The Effectiveness of R&D and Innovation Policy in Promoting Innovation in European SMEs: an Empirical Investigation of Additionality Effects

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ABSTRACT

Innovation is crucial for firms' growth and competitiveness. Yet, because knowledge is a public good, firms may underinvest in innovation activities to avoid freeriding and opportunistic behaviour. Besides market failures, another cause of underinvestment in innovation is associated with the concept of systems failures, advanced in the literature on systems of innovation. Potential adverse effects of market and systems failures provide scope for government intervention designed to foster investment in innovation and bring about innovation activities at the socially optimal level. This thesis investigates the effectiveness of innovation policy for small and medium-sized enterprises (SMEs) by exploring whether public support has an "additionality" effect on their innovation activities. First, we investigate the impact of public support on innovation output (output additionality) in traditional manufacturing industries. Second, we focus on the effect of innovation support programmes on innovative behaviour, particularly on networking and cooperation for innovation among Spanish SMEs (behavioural additionality). Finally, we assess both output and behavioural additionality among European SMEs.

In the evaluation of innovation policy, public support is treated as endogenous because of the selection bias that arises when firms self-select into government programmes, and/or when government agencies adopt a "picking-the-winner" strategy, whereby the selected firms are those most likely to succeed in innovation activities. Therefore, due to the endogeneity of public support, appropriate econometric techniques should be applied. Most cross-sectional studies apply matching estimations to assess the additionality of public support measures. One contribution of this thesis is the application of the endogenous switching regression model in estimating treatment effects.

1. The main findings of the thesis reveal important policy implications with regard to the distribution of public support and the magnitude of treatment effects. In the three empirical chapters, the respective "headline" results include the following.Public support for EU SMEs in traditional manufacturing industries could have a larger additional effect if randomly distributed to innovative firms rather than adopting a "picking-the-winner" strategy.

2. Public funding of Spanish SMEs has the largest effects on cooperation with government institutions and on R&D outsourcing, but rather small effects on cooperation with other networking partners, perhaps due to cooperation failure.
3. Finally, public support measures have a heterogeneous effect on innovation behaviour among European SMEs. Regarding output additionality, a random allocation of public support would yield an additionality effect among highly innovative firms, but not among less innovative SMEs. With respect to behavioural additionality, overall results indicate that a lottery system would benefit firms' innovative behaviour, although the magnitude of its impact would be the largest on cooperation with research organizations, while it would only marginally increase the probability of using online technology or knowledge brokers.

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PREFACE

Innovation policy has taken the centre stage among policy makers in the European Union (EU) (Edler et al., 2012b). Its importance stems from the key role innovation is playing in enhancing firms' performance and competitiveness. At the Lisbon Summit in 2000, policy makers set the major goal for the EU to become the world's most competitive knowledge economy by 2010 (Lundvall and Borrás, 2005, p. 623). With respect to investment in Research & Development (R&D) and innovation, the Lisbon Strategy set a goal of investing 3 per cent of Gross Domestic Product (GDP) on R&D by 2010. However, by 2011, official statistics indicated that the goal of 3 per cent had not been achieved as R&D expenditures were, on average, 2.03 per cent of GDP (ONS, 2011).

One of the three priorities put forward in a new EU strategy for economic growth and employment - Europe 2020 - is achieving and sustaining smart growth by developing an economy based on knowledge and innovation (European Commission, 2010). To achieve Europe 2020, the European Commission designed Horizon 2020, the 2014-2020 Framework Programmes for Research and Technological Development, with a generous budget of nearly 80 billion Euros to be invested in creating innovation-led growth and fostering research (CLORA, 2013). A key feature of Horizon 2020 is the emphasis placed on innovation that encompasses a broad perspective. It acknowledges not only R&D but also demand-driven innovation, through public procurement and the setting up of standards and regulations, as well as non-technological innovation and areas relevant for this type of innovation, such as design, service innovation and creativity (European Commission, 2013).

Another relevant feature of Horizon 2020 is the attention dedicated to small and medium-sized enterprises (SMEs), through policy instruments that will aim to support development, growth and internationalization of SMEs (European Commission, 2013a). Small and medium-sized enterprises are regarded as the engine of growth in the European economy, accounting for 66.5 per cent of all European jobs in 2012 and 57.6 per cent of gross value added (European Commission, 2013b). Innovations are among the most important means through which small and medium sized enterprises contribute to increased employment, economic growth and development.

Policy makers not only recognize the importance of innovation and its public support, but increasingly recognize the relevance of evaluating the impact of support measures (Edler et al., 2012a). Therefore, the central question within the evaluation debate is related to the effectiveness of public subsidies, i.e. whether firms indeed increase their innovative efforts as a result of public intervention. Evaluation of public innovation support attempts to answer this question through qualitative evaluation (including case studies and interviews) and through quantitative evaluation using econometric models and techniques. Referring to the latter, the key research questions arise as to whether public support measures induce larger investment in R&D and innovation than firms' private funding in the absence of public support programmes (input additionality); larger innovation output, such as the introduction of technological and non-technological innovations (output additionality); and, whether policy instruments establish changes in firms' innovative behaviour (behavioural additionality).

There are a large number of empirical studies investigating input additionality, whereas only recently has increased attention by researchers been devoted to output and behavioural additionalities. Furthermore, most cross-sectional empirical studies employ matching estimators, although their main disadvantage is the selection based on observables; i.e. unobserved firm characteristics cannot be taken into account, thus raising the issue of the robustness of empirical findings to unobserved heterogeneity. Moreover, very few studies examine the effectiveness of public innovation support measures for SME innovation. This research project aims to fill this gap by examining the impact of policy support at national, regional and EU level on SME innovation. Moreover, our focus is on the less investigated, but at least as important, output and behavioural additionalities.

Given the importance of innovation related policies and their quantitative evaluation, several research questions are identified which provide guidelines throughout the thesis.

1) How is innovation defined? What are theoretical contributions to understanding and conceptualizing innovation?
2) How do SMEs undertake innovation, and what are the main advantages and limitations of innovation in SMEs relative to innovation in large firms? What conceptual frameworks can be adopted to investigate innovation processes in SMEs?

3) How have innovation related policies evolved from science policy to systemic policy, and what does empirical evidence indicate in relation to input, output and behavioural additionalities?
4) Do government support measures increase SME innovation output? Is there a misallocation of public resources (i.e. if public funds are directed towards innovation projects that the firm would have undertaken anyway)? Do public agencies follow a strategy of "picking the winner" and select those innovation projects for support that are most likely to be successful?
5) Do public innovation measures induce behavioural additionality among Spanish SMEs and, more widely, among European SMEs? Does the treatment effect vary depending on the source of funding? Are estimated treatment effects robust to hidden bias (i.e. unobserved heterogeneity)? What policy recommendations can be deduced so that public intervention, in the domain of innovation, has a larger additionality effect?

Questions related to the effectiveness of public support will be answered through quantitative analysis. The originality of the approach stems first from applying a switching model, which, in the context of a cross-sectional analysis, is characterized by the ability to estimate programme effects conditional on both observed and unobserved firm characteristics. Another contribution of the thesis is related to the application of matching estimators, whereby sensitivity analysis was conducting to investigate the robustness of the empirical findings to unobserved heterogeneity. To investigate the research questions, we have utilized three cross-sectional datasets: the first is a unique dataset gathered within the EU Framework 7 project "GPrix", covering SMEs in traditional manufacturing sectors in seven EU regions during the period 2005-2009; the second is the Spanish Community Innovation Survey covering the period 2004-2006; and the third is a unique dataset gathered within the EU Framework 7 project "MAPEER", covering SMEs across Europe during the period 2005-2010.[1]

[1] Following the GPrix Deliverable 1.1 (2010a, p. 3): 'The main objective of the GPrix project is to identify good practices in innovation support measures to SMEs from the traditional sectors in seven European regions by developing a methodological framework for collecting internationally comparable data on existing Research and Innovation support programmes/measures in the public sector.' For more information, see the project's web page http://www.gprix.eu/. The main objective of the MAPEER project is to gather information on the design, implementation and impact of existing SME research and innovation support programmes and initiatives in the EU27 Member States and one non-EU country, Bosnia and Herzegovina. One EU country, Croatia, was not included in the survey, as it joined the EU in 2013. For more information, see the project's web page http://mapeer-sme.eu//.

The motivation behind testing the theory by employing three distinct datasets is manifold and stems from each dataset having different strengths and shortcomings. First, given our participation in the GPrix project, we were able to gain access to two unique datasets - the GPrix dataset as well as the MAPEER dataset. These datasets differ with respect to their country and industry coverage. Namely, the GPrix dataset contains information on the innovative activities of SMEs in six traditional manufacturing sectors in seven EU regions. Traditional industries include the manufacture of food products and beverages, textiles and textile products, leather and leather products, ceramics or other non-metallic mineral products, mechanical/metallurgy or basic metals and fabricated metal products, and automotive or motor vehicles, trailers and semi-trailers. Our definition of a traditional manufacturing sector is different from the OECD classification of "high", "medium" and "low-tech" industries, which is based on the R&D intensity of the industries. Instead we defined as "traditional" those manufacturing industries with the following characteristics: long established; once a main source of employment at the (sub-)regional level; recent decline; still a major source of wealth creation, employment and, in particular, exports; and retention of capacity for innovation. In contrast, the MAPEER dataset covers all manufacturing sectors as well as service sectors across 28 European countries.

As well as differing with respect to their country and industry coverage, the GPrix and MAPEER datasets also differ with respect to their range of innovation measures. Whereas the GPrix dataset includes many innovation output measures in the specific context of traditional manufacturing industry, the MAPEER dataset includes only a single measure of innovation output but several variables relevant to behavioural additionality in a more general sample of European SMEs. The GPrix dataset enables the evaluation of support measures in relation to a wide range of innovation output measures, including sub-categories of product, process, marketing and organisational innovation together with "innovation sales" (i.e. sales accounted for by recent product or process innovation). Relative to the GPrix dataset, the MAPEER dataset has broader country and industry coverage and, while including only a single measure of innovation output, enables behavioural additionality to be investigated. The MAPEER dataset contains information on the exploitation of several sources of external knowledge that are seldom available to researchers when investigating behavioural additionality, such as informal networking with other firms and with research organizations, as well as strategic alliances and non-equity alliances. Thus, besides investigating output additionality, similar to the analysis conducted on the GPrix data, the empirical analysis on the MAPEER dataset encompasses also behavioural additionality.

Next, we explain our decision to use the Spanish CIS dataset to evaluate the effectiveness of innovation support measures. Our initial intention was to use the CIS UK dataset to explore a range of research objectives from the literature on innovation studies. However, after 24 months of PhD studies, we did not manage to produce a single empirical analysis due to a range of practical difficulties encountered during the process of obtaining access to the data as well as analysing them. Not only was the process of obtaining access to the data extremely time consuming, it was also the case that, due to confidentially issues, researchers are not allowed to print or write down anything during their analysis. Moreover, researchers are required to finalize the analysis and interpret the findings by working in Essex, where the Secure Data Service, the CIS data provider, is located. For these reasons, we eventually decided to employ other available data sources to be able to finalize the PhD research in a timely manner. (In passing, we note that the obstacles to efficient access and use of UK CIS data make replication of published results all but impossible.) The motivation for using the Spanish CIS dataset is associated with the requirements of applying matching estimators. Namely, in the absence of longitudinal data and one or more valid exclusion restrictions, matching estimators are the only available econometric technique for estimated the treatment effects in the cross-sectional setting. However, because the selection on observables is achieved by matching the treatment and the comparison group, obtaining the appropriate size of the common support (i.e. matched pairs) requires a large dataset. As both the GPrix and the MAPEER data are not large-scale surveys (in comparison to the CIS), we opted to use the Spanish CIS data available on CD-ROM. Moreover, our intention to apply matching estimators in the thesis was motivated by the prevailing trend in the innovation literature, whereby most empirical studies, as discussed in Section 3.6, employ matching estimators, without reporting the results of sensitivity analysis. Our objective was to explore the underlying assumption, although not explicitly stated in the empirical studies, that participation in innovation support programmes is conditional only on firms' observed characteristics.

This thesis is structured as follows. Chapter I begins with the conceptualization of innovation and continues with a broad overview of two economic frameworks for analysing the innovation process: mainstream, neoclassical economic theory; and evolutionary theory. We briefly review Schumpeter's theorizing on innovation as he was the first scholar to recognize the key role of innovation in economic development and growth. Continuing Schumpeter's tradition of placing innovation in the centre of economic development, a new theoretical framework was developed within the evolutionary theory of the firm in the 1990s. Within this stream of literature, the concept of innovation systems was developed. In addition to theoretical developments within economics, another important stream of research, advanced within management science, is the resource-based view of the firm (Barney, 1991), which emphasises the role of internal human and financial resources for the firm's innovation performance and its competitive advantage. In the second part of this chapter, the evolution of economic thought on innovation is depicted through the evolution of innovation models, from the first generation of linear technology push and demand pull models, to the latest, fifth generation of system and networking models. The final section of the chapter provides a comprehensive overview of the internal and external determinants of innovation. The lack of a canonical theoretical model for identifying the determinants of innovation and, being consistent with this, the effectiveness of innovation support programmes, makes measuring the effects of innovation policy a particularly challenging task for economists – one to which we apply our recognised empirical tools, but with less guidance from theory than in many other areas of economic enquiry.

Chapter II focuses on small and medium-sized firms and the innovation process within this heterogeneous group of firms. After defining SMEs based on their headcount and turnover, we continue by discussing advantages and disadvantages of SME innovation relative to innovation activities in large firms. A key advantage of SMEs in comparison to large firms is their behavioural characteristics; due to their simple organizational structures and (small) size, SMEs can easily adapt to changes in market dynamics. In contrast, a major constraint that SMEs face in undertaking innovation is related to limitations on their human and financial resources. A final section of this chapter focuses on the innovation process, identifying a conceptual framework for analysing technological innovations in SMEs, as well as reviewing several taxonomies based on prominent innovation processes at the organizational level.

Chapter III discusses innovation related policies and quantitative evaluation methodology. The first part of the chapter, drawing upon the discussion in Chapter I, reviews two complementary rationales for public intervention: the neoclassical market-failure rationale; and the evolutionary system-failure framework. Our discussion continues by investigating the evolution of innovation related policy, from science and technology policy to modern innovation policy, and, in parallel, reviewing supply-side and demand-side policy instruments. After briefly presenting a theoretical framework for evaluating public support for innovation, we give an overview of qualitative evaluation methods together with their main advantages and shortcomings. This overview serves as a basis for the empirical literature review presented in the second part of the chapter. The review is organized by dividing empirical studies into two categories: studies applying matching estimators; and studies applying other evaluation methods. This division of empirical studies is motivated by the prevalence of matching estimators in empirical studies. The chapter concludes by reviewing the empirical evidence on input, output and behavioural additionalities as well as reviewing recommendations for policy makers and evaluators of innovation policies on how to progress, within the emerging field of innovation studies, policy effectiveness.

Chapter IV provides empirical evidence on the output additionality of innovation support programmes for SMEs operating in traditional manufacturing sectors across seven EU regions. The empirical analysis utilizes a unique cross-section dataset gathered within the GPrix project covering the period 2005-2009. The author participated in the GPrix project team. However, our role was limited to econometric analysis of the primary data. Therefore, we were not a part of the project team that designed the questionnaire and collected the primary data. Econometric analysis of the primary data included modelling and estimating baseline and augmented models by applying a binary endogenous switching model. In addition, a robustness check is conducted by estimating treatment effects using matching estimators.

Chapter V focuses on Spanish SMEs and investigates the behavioural additionality of regional, national and EU support programmes. Behavioural additionality is investigated from the narrow perspective of network additionality. Treatment effects are estimated by applying several matching estimators to data from the Spanish Community Innovation Survey conducted in 2006 and covering the period 2004-2006. Given that matching estimators cannot control for unobserved firm characteristics, the main contribution of this chapter is testing for unobserved heterogeneity through sensitivity analysis.

Chapter VI investigates output and behavioural additionality among European SMEs utilizing a unique dataset collected within the MAPEER project covering the period 2005-2010 and including 27 EU member states and one non-EU country, Bosnia and Herzegovina. The only EU country not included in the survey is Croatia, as it joined the EU in 2013. The rationale for using two datasets (the CIS and the MAPEER datasets) for investigating behavioural additionality is that the MAPEER dataset contains information on sources of external knowledge that are not included in the CIS survey questionnaire, but are particularly relevant for SMEs, such as informal networking. Two models - baseline and augmented - are estimated applying a binary endogenous switching model, similar to the analysis presented in Chapter IV. In addition, the participation in innovation support programmes is analysed separately for national and international programmes, as well as jointly for both streams of funding. The empirical results indicate that a random distribution of public support measures would yield behavioural additionality for most types of networking. The results are not directly comparable with the findings from Chapter V on the CIS dataset, given that the Average Treatment Effect (ATE) was not estimated in the latter (this is because matching methods typically do not yield estimates of ATE that are are statistically distinct from estimates of ATT). Therefore, the comparison of results is restricted to the estimated Average Treatment Effects on the Treated (ATT), which are, overall, suggesting an additionality effects on Spanish SMEs as well as on SMEs across Europe.

Finally, in Chapter VII, we summarize our empirical findings and formulate the conclusions of the thesis. After identifying the contributions to knowledge of this research, we also discuss its limitations, which can offer avenues for further research. In addition, we provide a set of policy recommendations based on the empirical evidence from previous chapters. The main policy implication stemming from our analysis is that *public support measure could have a larger additional effect if randomly distributed to innovative SMEs*. The results suggest a perverse selection into innovation support programmes with respect to output additionality in SMEs in traditional manufacturing sectors (GPrix data). Contrary to the consistent findings for this group of SMEs, empirical evidence on output additionality in European SMEs more generally is rather heterogeneous (MAPEER data). In this respect, a perverse selection into programme participation is found for more innovative firms, which would benefit from a random distribution of support measures. However, opposite findings are found for less innovation firms, for which a random distribution of support measures would further increase the crowding out effect reported for participating firms. Regarding behavioural additionality, the empirical analysis of Spanish SMEs revealed robust treatment effects for two open innovation practices: cooperation with government institutions; and outsourcing R&D. A lack of robust and large treatment effects for other networking partners might indicate a cooperation failure among Spanish manufacturing SMEs.Moreover, behavioural additionality was also a subject of investigation among the more general sample of European SMEs (MAPEER data) and here the empirical findings indicate that a random distribution of policy instruments would either increase the treatment effect, or, at least, reduce crowding out of public funding. The conclusions drawn from the analysis of the Spanish SMEs in Chapter V and European SMEs in Chapter VI are not directly comparable, as the former does not report the Average Treatment Effects (ATE). However, with respect to the Average Treatment on the Treated (ATT), both analyses report additionality of public support measures on innovative behaviour.

Policymakers and economic scholars around the world agree that the primary source of economic growth, competitiveness, and increases in standards of living in a globalized economy is innovation in the form of new products and services, more efficient production processes, and new business models.

(Atkinson and Audretsch, 2010, p. 163)

CHAPTER I

THEORETICAL APPROACHES TO INNOVATION

1.1 Introduction

Innovation is a subject of investigation in a large number of disciplines, such as economics, sociology, strategic management, entrepreneurship, economic history, psychology, human resources management, organization studies, technology, science and engineering, knowledge management, marketing and regional science. Innovation studies, as a scientific field, start to emerge during the 1960s. Although Schumpeter is regarded as the father of innovation studies, his contribution to economic theory and innovation economics was neglected until the 1960s. In the *early phase* of the emerging field of innovation studies, innovation was investigated mainly in economics and sociology, with almost no interaction between the disciplines. The economics of innovation focused on technological innovation and R&D as a measure of innovation and technological progress (Fagerberg et al., 2012).[2]

From the 1970s, the emerging field of innovation studies entered its *growth phase.* This phase is characterized by the increasing number of other social sciences whose researchers begin investigating innovation, particularly in the field of management. This rising interest in innovation across disciplines reflects the complex nature of innovation, resulting in dispersion of innovation studies across and between disciplines. From the 1980s, the field reached its more *mature phase*, particularly with the emergence of evolutionary economics and advances in relation to systems of innovation. The broadening of the field with respect to theoretical and methodological developments introduced a further diversity in the field. However, it is questionable whether the field is also deepening, given a continuous lack of interaction among researchers across disciplines. Communication failure among researchers from different disciplines added a further complexity and fuzziness to exploring innovation processes (Fagerberg, 2005). This, coupled with a complexity of conceptualizing and formalizing innovation, resulted in dispersion and a lack of cohesive and comprehensive theorizing

[2] Other disciplines, relative to the economics of innovation, differ with respect to their approach to exploring innovation activities. For instance, in sociology, Rogers 's (1962) book on the diffusion of innovation focused on the diffusion of innovation from a sociological perspective, examining the conditions that affect the adoption of innovation. Also, organizational sociology explores social changes within organizations caused by innovative activities. Behavioural aspects are explored by process sociologists, who study the impact of the cognitive processes of the workers and managers on innovation activities (Gopalakrishnan and Damanpour, 1997).

on innovation. Of importance is to note that although it is generally accepted that as an object of enquiry innovation is a multidisciplinary and interdisciplinary phenomenon (Fagerberg, 2005; Fagerberg et al., 2012), interaction between research communities was more pronounced in the early stages of innovation studies than in the later stages of development.

Moreover, in their review on recent developments in the economics of innovation, Nascimento and Teixeira (2010) note, among other trends in the field, that empirical research is increasing at a faster pace than theoretical advances, which they interpret as a sign of a disconnect between theory and empirical studies. Their findings suggest a lack of theoretical underpinnings in applied empirical research and, consequently, call for an increased use of economic theory in guiding empirical studies. In a similar vein, Galende (2006) notes the necessity for developing a common theoretical ground, which would serve as a basis for empirical analysis. However, it seems that few scholars are attempting to undertake such a complex and paramount task.

Since the 1950s, two strands of research within the economics of innovation emerged; one focusing on macroeconomic aspects of innovation and the role of innovation in driving economic development (i.e. neoclassical growth theory and the "Solow residual" measuring technical progress), and another strand identifying and analysing the determinants of innovation at the micro level (Galende, 2006). Within the discipline of Industrial Organization economics, the main research objectives are associated with analysing how external, market characteristics affect innovation. Following the Structure-Conduct-Performance paradigm (Mason, 1939; Bain, 1956), market structure has a profound effect on firms' conduct and, indirectly, on firm performance. Therefore, researchers within the field of industrial organization are interested in identifying external, market-specific determinants of innovation, such as market demand and competition. Internal determinants of innovation are mainly related to firm size (Asc and Audretsch, 1988).

In contrast to Industrial Organization economics, the resource-based view (RVB) of the firm deals with internal resources and their role in firms' realizing competitive advantages (Wernerfelt, 1984; Barney, 1991; Peteraf, 1993). The RBV originated with Edith Penrose (1959) who related firm diversification – which to a large extent overlaps the modern concept of innovation – to the firm's managerial and, in particular, entrepreneurial resources.

Among many internal resources, the RBV pays a specific attention to intangible assets, among which innovation and technological competences are of high importance. However, only those new technologies that are developed within the firm are considered as strategic resources, which are a critical factor in sustaining competitive advantage. Thus, new technologies generated externally, outside of the firm, are easily imitated and adapted by other, competing firms and cannot be regarded as inimitable strategic resources (Kostopoulos et al., 2002; Galende, 2006).

Finally, the current research on innovation is strongly related to the evolutionary theory (Galende, 2006). While the neoclassical analysis neglects the innovation process, treating it as a 'black' box and adopts a static, equilibrium framework in economic analysis, innovation and dynamic changes take the central stage in evolutionary theory (Nelson and Winter, 1982; Dosi and Nelson, 1994; Hodgson, 1998; Nelson and Winter, 2002). Firms, as heterogeneous economic agents, are not rational, but operate under bounded rationality (Simon, 1957). Instead of a profit maximising objective, firms adopt satisficing behaviour (Simon, 1957) based on organizational routines. In recent years, the basic evolutionary framework has been extended to incorporate networks and interactions between firms and institutions, for example in the systems of innovation framework (Lundvall, 1988; Lundvall, 1992; Rossi, 2002).

This chapter is organized as follows. Section 1.2 provides a review of various definitions of innovations, while Section 1.3 elaborates the economic theorizing on innovation and technological change, from neoclassical economics to evolutionary theory and the resourced-based view of the firm. Section 1.4 presents innovation models and identifies a broad range of determinants of innovation. Concluding remarks are presented in the final section.

1.2 Defining innovation

The significance of innovation is recognized at both the micro and the macro level of an economy. At a firm level, Zahra and Covin (1994, p.183) noted that 'Innovation is widely considered as the life blood of corporate survival and growth'. The process of innovation and its effect on firms’ performance is studied in different disciplines, as noted in Section 1.1, and is defined depending on the prevailing paradigm of a certain discipline. Its multidisciplinary aspect resulted in the absence of a general definition of innovation (Gopalakrishnan and Damanpour, 1997; Garcia and Calantone, 2002; Baregheh et al., 2009). Therefore, the term innovation is ambiguous, which hampers measurement and empirical research on innovation processes.

Schumpeter’s definition of innovation is often cited and has become a standard in 'innovation studies' (Fagerberg et al., 2012).[3] Schumpeter's notion of innovation refers to “new combinations” of existing factors of production (Schumpeter, 1934, p. 65), which include: 1) production of new goods or improvements of the existing goods; 2) introduction of the new methods of production; 3) entering into new markets; 4) use of new sources of raw materials and intermediate goods; and 5) new organization of production (Schumpeter, 1934, p.66). What is striking in Schumpeter’s definition of innovation is how similar it is to the definition of innovation in the *Oslo Manual* (OECD, 2005), the international source of guidelines for the collection and use of data on innovation activities. Building on the experience of early innovation studies, the OECD and Eurostat have created three editions of the *Oslo Manual* (1992, 1997 and 2005) with a purpose of formalizing and harmonizing innovation studies across countries. Nowadays, most European countries, but also the USA, Canada and New Zealand regularly conduct the Community Innovation Survey (CIS), a large-scale survey on innovative activities at the firm level (Moiresse and Mohnen, 2010). Based on the *Oslo Manual* (OECD, 2005), the following definition is proposed in the third wave of the Community Innovation Survey (CIS):

> Innovation is a new or significantly improved product (good or service) introduced to the market or the introduction within an enterprise of a new or significantly improved process. Innovations are based on the results of new technological developments, new combinations of existing technology or the utilisation of other knowledge acquired by the enterprise. Innovations should be new to the enterprise concerned; for product innovations they do not necessarily have to be new to the market

[3] Fagerberg et al. (2012, p. 1132) define innovation studies as 'scholarly study of how innovation takes place and what the important explanatory factors and economic and social consequences are’.

and for process innovations the enterprise does not necessarily have to be the first to have introduced the process (European Commission, 2005).

In the second edition of the *Oslo Manual* (OECD, 1997), the focus is only on the product and process innovations or technological innovations, because they are easier to define and measure. However, the third edition of the *Oslo Manual* (OECD, 2005) defines, besides technological innovations, also non-technological (organizational and marketing) innovations. Innovation as such is defined as the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations. In one respect, the modern definition of innovation is more restrictive than the Schumpeter's, because marketing innovation excludes "entering into new markets", specifically exporting. Corresponding to this restricted understanding is that firms' innovation and firms' exporting are treated in entirely different literatures even within economics, while, on the policy level, innovation and exports are promoted by different public agencies. Although this issue is of importance, we do not pursue it further in the thesis, given our focus on the effectiveness of the existing innovation related policies.

Each type of innovation is defined as follows:

- *Product innovation*: the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses;
- *Process innovation*: the implementation of a new or significantly improved production or delivery method;
- *Marketing innovation*: the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing;
- *Organisational innovation*: the implementation of a new organisational method in the firm's business practices, workplace organisation or external relations.

Baregheh et al. (2009) review definitions of innovation in seven disciplines: business and management; economics; organization studies; innovation and entrepreneurship; technology, science and engineering; knowledge management; and marketing. They gathered around sixty definitions of innovation and used a content analysis to identify key characteristics of innovation processes. The aim of the analysis is to derive a multidisciplinary and common definition of innovation. Their proposed definition of innovation is:

> Innovation is a multi-stage process whereby organizations transform ideas into new/improved products, services and processes, in order to advance, compete and differentiate themselves successfully in the market places (Baregheh et al., 2009, p. 1334).

Furthermore, the authors distinguish between different attributes of innovation:

- *Type of innovation*: the result of innovation (product, services, process and technical);
- *Nature of innovation*: new, improved or changed various types of innovation;
- *Stages of innovation*, often defined as "invention-innovation-diffusion";
- *Social context*: social systems, institutional set-up and agents involved in the innovation process;
- *Means of innovation*: financial, technical, human resources necessary for the innovation process;
- *Aim of innovation*: results that are achieved through innovative activities.

Another relevant classification of innovation is associated with the degree of novelty of innovation or the degree of technological change (new knowledge embedded in innovation). Namely, radical innovations are defined as fundamental advances in technological competences, whereas incremental innovations are minor changes to existing technology (Tushman and Romanelli, 1985; Dewer and Dutton, 1986). Drivers of innovation are often divided into market pull and technology push. Dosi (1988) notes that incremental innovations are driven by market demand, whereas radical innovations are often generated by technological opportunities.

Conditional on prevailing innovation types, Freeman and Soete (1987, p. 56) suggest the following division of technical change:[4]

- *Incremental innovation* (those innovations that are continuous and frequent);

[4] Often in the literature, the terms "technological" and "technical" innovations are used interchangeably; both terms refer to the same type of innovation (Baregheh et al., 2009).

- *Radical innovation* (discontinuous and unevenly distributed over sectors and time);[5]
- *New technological systems* based on a large number of incremental and radical innovations;
- *Changes of techno-economic paradigms* (technological revolutions), characterized by pervasive technological changes affecting almost the entire economic system, i.e. clusters of radical and incremental innovations.

A taxonomy of innovation is also provided within the literature on the management of technology, where the classification by Abernathy and Clark (1985) is considered to be the most important. Combining the market and technology dimensions, they created a 2x2 matrix, labelled the transilience map, to illustrate the impact of different forms of innovation on firms' competitive advantages. Four different types of innovation are classified as:

- *Architectural innovation*, referring to the development of new technologies that either create new or transform existing industries (the combination of new technologies and new market opportunities).
- *Niche creation (innovation in the market niche)*. This type of innovation creates new market opportunities by applying existing technological competences (the combination of existing technologies and new market opportunities). In most cases, it is associated with incremental changes in the established technology base.
- *Regular innovation*, refers to refinements in established technologies applied in existing markets (the combination of existing technologies and existing market opportunities). This type of innovation induces incremental changes in established technological competencies.
- *Revolutionary innovation*: The use of new technologies applied in existing markets (the combination of new technologies and existing market opportunities).

Abernathy and Clark's categorization of innovations is intended to contrast with Schumpeter's notion of 'creative destruction' (see Section 1.3.2 on Schumpeter's

[5] Radical and incremental innovations are also termed revolutionary and evolutionary innovations (Kline and Rosenberg, 1986).

theorizing on innovation) by emphasizing that innovation does not necessarily have to be disruptive or radical and render existing technologies obsolete, but can sometimes be incremental and thus enhancing established technology competences.

As a conclusion to our review of definitions of innovations, it can be inferred that scholars utilizing information provided in the Community Innovation Survey, uniformly adopt the definition and categorization of innovation advanced in the third edition of the *Oslo Manual* (OECD, 2005) (Mairesse and Mohnen, 2010). The lack of consensual or, indeed, any overarching theory either between or within disciplines leads researchers – at least quantitative empirical researchers - into a default position of accepting the theory and concepts underlying the design of the CIS and similar surveys, which are those of the *Oslo Manual*. Given the current state of theory and empirical evidence, this seems to be the prevailing approach, and we broadly adopt this approach in the thesis, which contributes to empirical evidence and policy development rather than to innovation theory. We would argue that 80 years after Schumpeter's definition of innovation, it is high time that a consensus is reached among scholars on a commonly accepted definition of innovation. Adopting a common definition of innovation can enhance interdisciplinary collaboration among researchers and provide a basis for theoretical advances in the field.

1.3 Different theoretical approaches to innovation

In this section, we will provide an overview of several but not all theoretical approaches to innovation, mostly but not exclusively from within the discipline of economics. Our review of theorizing on innovation can be broadly divided into four categories: 1) innovation within the neoclassical economics tradition; 2) Schumpeter's contributions to a theory of innovation; 3) evolutionary economics and the systems of innovation approach; and 4) the resource-based view (RBV) of the firm and innovation. Our choice of theoretical frameworks to be reviewed in the thesis is motivated by our research objective of assessing the effectiveness of innovation related policies. Namely, the design and implication of contemporary innovation policies is influenced by two complementary rationales: a market-failure rationale advanced within neoclassical economics; and a system-failure rationale proposed within the evolutionary economics framework. Therefore, before a detailed discussion on rationales behind innovation policies is provided in Section 3.2, we review the role of innovation within these theoretical frameworks. In addition, given the prominent role of Schumpeter's theorizing on innovation, the next section also briefly reviews Schumpeter's contribution to innovation studies. Finally, the resource-based view of the firm is included in our review of the literature on innovation – given the importance of limited resources to performing innovation in SMEs. The innovation processes in SMEs will be further elaborated in the following chapter.

1.3.1 Innovation in neoclassical economics

The origin of macroeconomic theorizing on economic growth and technological change is particularly identified with Solow (1956). According to Solow's seminal neoclassical growth model, the productivity level in an economy depends, *ceteris paribus*, on the capital-labour ratio. Yet, because capital accumulation is subject to diminishing returns, the growth-promoting potential of saving and investment at a constant technical level are limited. Under these circumstances - i.e. continued investment without technical progress - the model demonstrates that productivity growth approaches and eventually reaches a stable, no-growth steady state. In contrast, technical progress - or innovation - enables sustained productivity growth - i.e. per capita growth and increasing welfare - but is exogenous in Solow's model (Nelson and Winter, 1974; Freeman and Soete, 1997; Aghion and Howitt, 1998; Mulder et al., 2001) (The level of technology is present in Solow's model as a parameter and technical progress is correspondingly represented by increase in the value of this parameter;[6] however, neither the parameter nor its change are explained within the model.) Hence, Solow's model demonstrated the unique importance of innovation while remaining silent on its origins and mechanisms.

From the mid-1980s, new growth models were developed in which technological change (thus innovation) is treated as an endogenous determinant of economic growth. These models are labelled endogenous growth models, and among the first were those by Romer (1986) and Lucas (1988). In the former, a key determinant of economic growth is *technological change* embodied in new capital

[6] In general, parameters in the model are similar to exogenous variables, as they are pre-determined or treated as given variables. But the difference between parameters and exogenous variables is that the former are given by nature, such as technology and consumer preferences (Aghion and Howitt, 1998).

stock.. In the latter, a driving force of increase in aggregate income and production is the accumulation of human capital. Models of growth based on monopolistic competition were also developed, at around the same time, by Grossman and Helpman (1994). In their model in each period a new generation of technology is introduced that is more efficient than the previous one: a protection mechanism via the patent system allows the innovating firm to generate super-normal profit (i.e. rents), contrary to zero economic profit earned by firms using the previous generation technology. The innovator continues to earn rent until the following generation of new technology is introduced. Models such as this are called “neo- Schumpeterian”, because firms' main incentive for innovation is Schumpeterian profit leading to a temporary monopoly power.

In these models, innovation through "creative destruction" is crucial for economic growth (Rossi, 2002). Another model adopting the neo-Schumpeterian approach to economic growth was developed by Aghion and Howitt (1992). Again, the process of "creative destruction" is a key feature of technological progress; innovation in the form of quality improvement is a random process arising from firms' research activities. The innovating firm gains a temporary monopoly position, which is eliminated when someone else introduces the next innovation.

Parallel to the development of macroeconomic growth models, a neoclassical microeconomic analysis of innovation focussed on how firms introduce *process innovation* into the production process. Innovation regarded as technology is an integral element of the production function. Increase in the price of a production input (labour or capital) motivates firms to undertake process innovation, i.e. to introduce technical changes that will enable the firm to reduce the employment of a more expensive factor of production and increase the use of a cheaper factor. Internal technological changes, in this scenario, bring production back into equilibrium, as a new optimal combination of production factors is achieved along the original production function. Another way of introducing process innovation is the use of newly introduced external technology, which shifts the production function to a new isoquant, thus increasing the efficiency of the production inputs (Stoneman, 1983; Grilliches, 1998; Rossi, 2002).

1.3.1.1 Modelling product and process innovations in neoclassical economics

Stoneman (2010) presents a simple model of the determinants of firms' decisions to undertake process innovation. Most theoretical models explain the determinants of process innovation (for instance, see Dasgupta and Stiglitz, 1980; Link and Lunn, 1984; Levin and Reiss, 1988; Cohen and Klepper, 1996; Lee, 2002; Gonzáles and Pazó, 2004). The firm *i* sets a price at level p_i and quantity at level q_i, while q_j denotes the supply of other firms in the market. The unit costs of productions are c_i, and they are defined as the function of R&D expenditures (R_i) such as c_i=f(R_i). The profit function is defined as

$$\pi_i = q_i p_i\left(q_i, q_j\right) - c(R_i)q_i - R_i \tag{1.1}$$

Where π_{i} denotes profit determined by the levels of q_i and R_i. Profit maximization occurs under the following two conditions:

$$-\frac{q_i dc(R_i)}{dR_i} - 1 = 0 \tag{1.2}$$

$$p_i\left(q_i, q_j\right) + q_i\left(\frac{\delta p_i}{\delta q_i} + \frac{\delta p_i}{\delta q_j}\frac{dp_i}{dq_j}\right) - c(R_i) = 0 \tag{1.3}$$

Where dR_i denotes the differential of R_i; $dc(R_i)$ denotes a differential of the unit costs of production; δp_i is the first-order partial derivative of p_i; δq_{i} is the first-order partial derivative of q_i; δp_j is the first-order partial derivative of q_j; and dq_j denotes the differential of q_j.

The first condition (Equation 1.2) stipulates that the marginal reduction in production costs as a result of process innovation (i.e. investment in R&D aimed at cost reduction) is equal to the marginal cost of undertaking that reduction. The second condition (Equation 1.3) defines the equality of marginal cost and marginal revenue.

Jointly, these two conditions determine the level of investment in R&D, the unit costs of production, output and profit of firm *i*.

Equation 1.3 expressed through the first order conditions results in the following:

$$p_i(q_i, q_j)\left(1 + \frac{1}{\eta}\right) = c(R_i) \tag{1.4}$$

$$\frac{R_i}{p_i q_i} = \eta_{CR}(1 + \frac{1}{\eta}) \tag{1.5}$$

Where η denotes the firm *i* price elasticity of demand and η_{CR} represents the negative of the elasticity of unit costs related to R_i. Therefore, the ratio of R&D expenditures to sales is determined by the price elasticity of demand and the elasticity of unit costs in relation to R&D expenditures.

In a similar vein, a simple model of product innovation can be presented. The key difference between the model of product innovation, compared to the model of process innovation, is that it is assumed that product innovation, expressed as investment in R&D, affects the demand for the firm's product, rather than the unit costs of production. Before the model is demonstrated, it should be asserted that product innovation is less investigated in economic theory (Stoneman, 2010), but has received equal attention as that of process innovation in the literature on technology management and technology life cycle (see Meuller and Tilton, 1969; Utterback and Abernathy, 1975; Clark, 1985; Klepper, 1996; Adner and Levinthal, 2001).

In the model, it is assumed that the demand for the firm *i* product is a function of price p_i, the output of competitors q_j and the firm's expenditure on new product development (R&D expenditure) R_i. Moreover, the unit costs of production are assumed to be fixed and exogenous. The profit function is given as:

$$\pi_i = q_i p_i(q_i, q_j, R_i) - c_i q_i - R_i \tag{1.6}$$

As in the model of process innovation, the firm chooses the output q_i and the level of investment R_i in order to maximize profit. Profit maximization occurs under the following two conditions:

$$q_i \frac{\delta p_i}{\delta R_i} = 1 \tag{1.7}$$

$$p_i + q_i \left(\frac{\delta p_i}{\delta q_i} + \frac{\delta p_i}{\delta q_j} \frac{d q_j}{d q_i} \right) - c_i = 0 \tag{1.8}$$

Where δR_i is the first-order partial derivative of R_i. Equation 1.8 can be expressed as:

$$p_i(q_i, q_j) \left(1 + \frac{1}{\eta}\right) = c_i \tag{1.9}$$

The first condition (Equation 1.7) states that the marginal increase in revenue generated from the last unit of R&D expenditure is equal to the cost of R&D expenditure. The second condition (Equation 1.8) states that marginal cost is equal to marginal revenue. These two conditions jointly determine the level of R&D expenditure incurred for the new product development (i.e. product innovation), the output of the firm *i*, its profit, total costs and total revenue.

The first-order conditions of Equation 1.9 is given by:

$$\frac{R_i}{p_i q_i} = \eta_{PR} \tag{1.10}$$

Where η_{PR} represents the firm's price elasticity with respect to R_i.

Therefore, the ratio of R&D expenditures on new product development to sales depends on the firm's price elasticity with respect to R&D expenditures. However, it should be noted that the price elasticity related to R&D encompasses two effects: the impact of the firm's R&D expenditure on its price p_i, but also the impact of competitors' reactions to the firm's price p_i. Intuitively, when the firm undertakes product innovation, the firm's price elasticity of demand decreases, implying that the successful introduction of product innovation enables the firm to capture a larger market share and/or to sell at a higher price thereby increasing profit.

The models of product and process innovation presented above are mostly applied in empirical studies on the correlation between market concentration and innovation, to test Schumpeter's Mark I and Mark II hypotheses (Stoneman, 2010).[7] However, as the focus of the thesis is to investigate the effects of public intervention on innovation, we limit our exposition of neoclassical theorizing on innovation to these simple models of product and process innovation, to illustrate how technological innovations are analysed within neoclassical economics.

1.3.2 Schumpeter's contribution to innovation studies

Schumpeter's contribution to economic theory and analysis has three strands: an evaluation of classical and contemporary economic theory (*History of Economic Analysis*, 1954); the elaboration of a theory of economic evolution encompassing the books *The Theory of Economic Development* (1934) and *Business Cycles* (1939); and expansion of a theory of social and institutional changes in his 1942 book *Capitalism, Socialism and Democracy* (Giersch, 1984). Moreover, the concept of entrepreneurship cannot be fully understood without his contributions.

In his early work *The Theory of Economic Development* (1934), Schumpeter argues that entrepreneurs and entrepreneurial innovation are the main determinants of economic growth. Schumpeter's theory of economic development is elaborated on the basis of the Walrasian general equilibrium theory, which he names the circular flow theory. Circular flow is, according to Schumpeter (1934), a static state in which economic agents earn zero profit, the economy is closed, equilibrium is perpetually reached and there are no specific factors that disturb a static state. Schumpeter argues that the circular flow theory is unable to explain why economic change occurs (Frank, 1998). For Schumpeter, development is discontinuous (i.e. cyclical) and induced by dynamic changes caused by entrepreneurs and entrepreneurial innovation. Therefore, the primary cause of cyclical movement is innovation. Following Sweezy (1943), after discussing an economic system as a circular flow, Schumpeter continues to develop his

[7] For the discussion on Schumpeter's hypotheses, see the following Section 1.3.2.

method consisting of three steps: first, analysis of entrepreneur’s personal traits and motivations; second, introduction of the entrepreneur as a source of change and disturbance in the model of circular flow; and third, analysis of a process of economic development.

The essential feature of a capitalist system is constant evolution and Schumpeter argues that evolutionary changes are caused by endogenous factors. The reason why the entrepreneur and the entrepreneurial functions are emphasized in Schumpeter’s work is because he regarded them as exactly those internal factors causing economic change. Therefore, the endogenous changes do not occur on the consumption side of the economic process, but rather on the supply side (Heertje, 2006, p. 14). After indentifying the causal factor of economic development (i.e. entrepreneurs whose function is to undertake innovation and cause changes in the economy), Schumpeter continues to develop his theory by explaining the occurrence of business cycles. His analysis of a business cycle starts with the prosperity phase. Initial static equilibrium is disturbed by the introduction of innovation. Schumpeter defined innovation in the form of the production function. The production function, he argues, 'describes the way in which quantity of product varies if quantities of factors vary. If, instead of quantities of factors, we vary the form of the function, we have an innovation' (1939, p. 62). Therefore, he explicitly defines innovation as shifts in the production function, rather than changes along the production function. Heertje (2006, p. 19) notes that shift in the production function is the characteristic feature of technological innovations (i.e. product and process innovations).

Innovation leads to cost reduction in the production process of the innovative firm (i.e. process innovation) or the introduction of new products (i.e. product innovation), and lowering costs or commercializing a new product results in the increase of profit. Higher profits resulting from innovation-induced lower production costs are labelled Schumpeterian profit (Nordhaus, 2004). In addition, when the firm introduces a new product, it temporarily obtains a monopoly position and generates monopoly profit. The duration of a monopoly position hinges on the availability of protection mechanisms. For instance, if the firm successfully applies for a patent, it can maintain its monopoly position until the patent expiration.

However, the next phase in the innovation process is diffusion of innovation, where more firms start to produce new products or introduce new processes, supply increases, and prices start to fall, until the Schumpeterian profit is exhausted. Therefore, decline and eventual disappearance of economic profit is a direct consequence of the diffusion of innovation. Several processes enable the final stage of the innovation process, i.e. diffusion and imitation of innovation, and those processes include the expiration of the patent protection, a loss of the first-mover advantage and/or introduction of superior goods and services (Kurz, 2008). Firms incur losses soon after the price starts to decrease, which results in an economy entering into the second phase of the business cycle (i.e. depression) (Heertje, 2006, p. 78; Kurz, 2008). While experiencing a downturn in economic activity, entrepreneurs are temporarily discouraged from innovation, and thus from raising new funds. The primary cause of depression is the process of adaptation to the conditions caused by prosperity. That is, the economy cannot rapidly absorb radical innovation, which was the cause of disturbance of the initial equilibrium (Fagerberg, 2003). Eventually, the economy enters a recovery phase, in which entrepreneurs are more likely to engage in new innovations, because the system of economic values is again stable and reliable (Festré, 2002).

Schumpeter made a clear distinction between invention, which is a discovery of a new technique, and innovation, which is the practical and commercial application of an invention and the result from this application is a new production function. Innovation is carried out by entrepreneurs who are not necessarily inventors (Thanawala, 1994). The reason why Schumpeter stressed the differences is because innovation is a specific social activity with commercial purpose, while invention is not a part of the economic sphere and has no commercial use: 'Innovation is possible without anything we should identify as invention and invention does not necessarily induce innovation, but produces of itself no economically relevant effect at all' (Schumpeter, 1939, p. 84). Thus, invention is an exogenous factor in economic development, whereas the endogenous factors are innovation and the innovative activity of entrepreneurs, who are individuals doing things in new ways (Hagedoorn, 1996).

Schumpeter's definition of innovation has been a subject of criticism by many authors. One strand of criticism points out that definition is too narrow, because it includes only new firms and new entrepreneurs (Hagedoorn, 1994; McDaniel, 2002, p. 32). However, Schumpeter augmented the definition in his later work, *Capitalism,* *Socialism and Democracy* (1942), where existing, large firms are innovators in modern capitalism. Even in *The Theory of Economic Development*, Schumpeter refers to new firms as innovators in an earlier stage of capitalism, i.e. competitive capitalism as he termed it, but not in the later stages of "trustified" capitalist development (Schumpeter, 1934, p. 67).[8] Another strand of criticism refers to the broad and vague definition of innovation (Hagedoorn, 1996). The definition includes not only technical, but also marketing and organizational aspects of the innovative activities. Hagedoorn (1996) suggests that different aspects of innovation should be separated and limits innovation only to product and process innovation, i.e. new goods and new or improved methods of production. Thus, technological innovation should be separated from organisational and marketing innovations, which is the approach adopted in the latest version of the *Oslo Manual* (2005).

Schumpeter is also criticised for neglecting minor innovations (continuous learning and continuous technical development), because existing routinized technological changes have no impact on economic development (Hagedoorn, 1996).[9] However, in his later work *Capitalism, Socialism and Democracy* (1942), routinized innovations within large enterprises have a larger impact on business cycles and changes in the economic system.

Entrepreneurs are the only agents who are capable of carrying out new combinations, and lose the character of entrepreneurs as soon as their business is built up and return to capitalist routines: '(…) everyone is an entrepreneur only when he actually carries out new combinations, and loses that character as soon as he has built up his business, when he settles down to running it as other people run their businesses' (Schumpeter, 1934, p. 78). The personal traits of the entrepreneur are important in understanding his key role in Schumpeter's theory of economic development. Following Matis (2008), the entrepreneur is an innovator who is capable of recognizing new innovative ideas. His primary motive is not profit, but rather is driven by "the will to conquer", "the dream and the will to found a private kingdom" and "the joy of creating, of getting things done" (Schumpeter, 1934, p. 93). Moreover, the entrepreneur has

[8] Schumpeter distinguishes between two phases of capitalist development: competitive and trustified capitalism. In the latter, entrepreneurial leadership tends to disappear and is replaced by innovative activities incorporated as routines within large firms (Ebner, 2006).

[9] For instance, the *Oslo Manual* (2005) defines product innovation as introduction of new or significantly improved products, thus integrating minor innovations within the concept of innovation.

persistently to overcome social resistance to changes and innovation. It is also important to note that entrepreneurs are not capitalist or social class, but rather a special sociological type (Sweezy, 1943).

In his early work, Schumpeter emphasized the crucial role of the entrepreneur in economic development, but his later analysis of the capitalist system, the entrepreneurial function is assigned to formal R&D departments within large firms. Namely, in *Capitalism, Socialism and Democracy* (1942), Schumpeter argues that the main feature of the capitalist system is the introduction of new combinations (Heertje, 2006, p. 82). Introduction of “new combinations” is an endogenous process, which Schumpeter termed “creative destruction”. In this work, Schumpeter argues that large firms are fulfilling the entrepreneurial function, as innovation is the critical factor in maintaining their monopolistic position. Contrary to Schumpeter's early analysis, innovation is no longer, a radical, disturbing force, but rather a routinized activity, performed on a regular basis (Heertje, 2006, p. 83). Moreover, in *The Theory of Economic Development,* Schumpeter (1934) developed a theory of individual entrepreneurship, but, in later work on the capitalist system, circumvented a deeper analysis of corporate entrepreneurship.

This conceptual dualism of an early and a late Schumpeter, shifting from the “Schumpeter Mark I” model of individual entrepreneurship in new firms to the “Schumpeter Mark II” model of institutionalized research and development departments in large firms has been noted by many scholars.[10] The terms 'Schumpeter Mark I' and 'Mark II' are first mentioned in the works of Nelson and Winter (1982) and Kamien and Schwartz (1982). Schumpeter Mark I models industries with low barriers to entry, thus enabling new, entrepreneurial firms to enter the market at low cost, engage in innovative activities and disrupt the existing production processes. Therefore, the main feature of this model is “creative destruction” and the pattern of *widening* of technology and innovation bases as new, innovative firms enter the market and introduce new ways of organizing production and distribution. Conversely, Schumpeter Mark II model is pertinent to industries with high barriers to entry, which allow few incumbent firms, through the process of “creative accumulation”, to accumulate their technological base

[10] The former is proposed in *The Theory of Economic Development* (Schumpeter, 1934) and the latter in *Capitalism, Socialism and Democracy* (Schumpeter, 1942).

and enhance their innovative capabilities. This model is characterized by the *deepening* pattern of innovation processes (Malerba and Orsenigo, 1995; Breschi et al., 2000).

Several scholars attempt to explain why Schumpeter's conceptual dualism does not invalidate his theoretical reasoning. Following the industry life-cycle view, industries can experience both patterns of innovation activities, depending on the phases of their development (Malerba and Orsenigo, 1995). Namely, in early stages, the industry is populated with a large number of small firms without monopoly power, because low barriers to entry encourage the entrance of new, innovative firms. Due to absence of monopolistic power among incumbent firms, no firm has dominant technological and innovation competences that would lead to increase in technological barriers to entry. Yet in advanced stages of the industry life cycle, innovation activities tend to be concentrated in a few large, established firms with monopoly power that enables the creation of high barriers to entry.

Another line of argument in favour of the consistency of Schumpeter's dualism was advanced by Frank (1998), who argues that, in Schumpeter’s theory of economic development, the critical feature is the entrepreneurial function per se, while it is not of such importance whether this function is ascribed to the individual entrepreneur or to large firms, because historical facts are unpredictable ex ante. Therefore, it is not possible to predict who will fulfil the entrepreneurial function. Although entrepreneurial creative response introduces the element of indeterminateness into Schumpeter’s model, his theory is not inconsistent as different economic agents can fulfil the entrepreneurial function.

Finally, following Ebner (2006), the analytical consistency of Schumpeter’s theory of the entrepreneur can be validated through evaluating the historical specificity of entrepreneurship in specific phases of capitalist development, namely competitive capitalism during the nineteenth century and “trustified” capitalism in the twentieth century (see Table 1.1 for the main characteristics of both stages).[11] In competitive capitalism, individual entrepreneurs are the driving force of economic change, while in “trustified” capitalism large monopolistic enterprise play the main role in the economic development (Fagerberg, 2003). A similar argument can be found in Sweezy (1943),

[11] Schumpeter introduced the concept of "trustified" capitalism in his book *Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process* (Schumpeter, 1939).

who argues that Schumpeter's theory of economic change presented in *The Theory of Economic Development* is more suitable to the conditions inherent to competitive than to "trustified" capitalism.

Table 1.1. Varieties of entrepreneurship in competitive and "trustified" capitalism

	Competitive capitalism	**Trustified capitalism**
Type of enterprise	Family enterprises	Corporations and trusts
Type of entrepreneur	Merchant	Corporate director
Mode of innovation	Individual impulse	Organizational routine
Mode of behaviour	Intuitive creativity	Professional calculation
Selection mechanism	Market competition	Political compromise
Type of income	Entrepreneurial profit	Employee salary

Source: abridged from Ebner (2006, p. 326).

1.3.3 Innovation in evolutionary economics

Besides neoclassical and neo-Schumpeterian theories, the third strand of macroeconomic theorizing on economic growth is associated with the evolutionary economics where technological progress is taken as endogenous. Models of evolutionary economics are the models of economic growth at the macroeconomic level, but based on the evolutionary theory of technological change, rather than on the neoclassical moving equilibrium (Nelson and Winter, 1982; Dosi and Nelson, 1994; Nelson and Winter, 2002). Moreover, the microfoundations of the two theories are quite different (Nelson, 1995). Macroeconomic evolutionary models are based on explicit microfoundations; that is, macroeconomic models are tested using microeconomic data. The microeconomics of the evolutionary theory are based on the behavioural theory of the firm, in which learning and adaptive behaviour take a central stage (Metcalfe, 1994). Firms in evolutionary theory are heterogeneous agents with variations in technologies they use, in their productivity and growth. In contrast, neoclassical microfoundations are based on a "representative agent" and its characteristics are extrapolated to the entire population of firms. The central principle of evolutionary dynamics is Fisher's theorem of natural selection, which states that selection increases the average performance of the population, and the rate of increase is equal to the variance of performance. Therefore, the driving force of growth is variety. Variety (i.e. innovation) improves not only the performance of a firm, but also of the entire population of firms (Nelson and Winter, 1982; Dosi and Nelson, 1994; Mulder et al., 2001; Nelson and Winter, 2002; Fagerberg, 2003).

Often in the evolutionary economics literature we can find a distinction between "the old evolutionary economics", pertaining to Schumpeter's work, and "the new evolutionary economics", associated with Nelson and Winter's work and later contributions. Schumpeter is widely regarded as the most prominent evolutionary theorist (Hanusch and Pyka, 2007). According to Fagerberg (2003), there is a common core connecting these somewhat different strands of analysis. First, innovation is the driving force of long-run economic development in both "old" and "new" evolutionary economics. In the absence of innovation, the economic system would be in a static state. Second, both strands recognize strong regularities embedded in economic development and evolution, for instance, clustering of innovation, the sequence of innovation and imitation etc. Third, economic knowledge is a result of the set of routines adopted through repetition.

However, the "old" and the "new" strands differ in several aspects as well. First, although Schumpeter assigned the entrepreneurial function to large firms (according to Schumpeter Mark II hypothesis), unlike Nelson and Winter, he did not elaborate his concept of corporate entrepreneurship. Second, Schumpeter did not apply any biological principles or analogies in his economic analysis. Third, Schumpeter emphasized the role of radical innovations in the capitalist development, while Nelson and Winter allowed for minor (incremental) innovative activities (e.g. the learning process) in their model (Fagerberg, 2003). However, we cannot agree with the last argument. Schumpeter only focused on radical innovation in his theory of individual entrepreneurship (Mark I), while in his later work, following the Mark II hypothesis, he argued that incremental innovation is routinely undertaken in large firms, who played the key role in innovative activities.

The basic building blocks of the evolutionary process are heterogeneity of the population or agents (firms, countries or technologies), mutation (often in the form of technological innovation) and selection.

Heterogeneity: In evolutionary micro models, technological differences are the main source of heterogeneity between firms (Dosi and Nelson, 1994). Firms differ with respect to their capabilities, procedures and decision-making rules, which, in turn, determine their conduct (Mulder et al., 2001). In some evolutionary growth models, heterogeneity of firms is defined as differences in firms' technological capabilities (for instance, in the model by Conlisk, 1989). In other models (e.g. Chiaromonte and Dosi, 1993), heterogeneity is associated with both differences in technological competences and behavioural characteristics of firms.

Mutation refers to the process of learning (variation) and to the mechanisms by which firms adapt to novelties in the system. This is a point of departure from the neoclassical behavioural assumptions. In neoclassical theory, the basic behavioural assumption is that of rational agents who optimize their decisions, i.e. make decisions that will maximize their utility under the budget and other constraints. Contrary to the "rational" neoclassical models, evolutionary theories are based on the premises that agents adopt different forms of rule-guided behaviours, which lead to temporary and suboptimal adaptation but seldom to optimal behaviour (Dosi and Nelson, 1994). Decision-making is based on bounded rationality (Simon, 1957), stemming from the limited cognitive abilities of individuals and too much information, which cannot be fully comprehended.[12] Thus, instead of choosing the optimal solution, agents will seek a satisfactory solution. Agents follow the pattern of "satisficing" behaviour (Simon, 1957) and not of the rational one. At the firm level, this behavioural pattern implies that profit maximization is not the objective, but rather profit satisficing (Simon, 1957; Hodgson, 1998; Mulder et al., 2001; Rahmeyer, 2010). The concepts of bounded rationality and satisficing behaviour were initially developed to explain the behaviour of individuals. Following Fagerberg (2003), the most prominent contribution of Nelson and Winter (1982) is the application of these concepts to the behaviour of firms.

[12] According to Simon (1957), bounded rationality pertains to individual as well as organizational decision making processes. In the process of profit maximization within organizations, or of utility within consumer behaviour, economic agents are faced with an enormous amount of information, the processing and understanding of which transcends human cognitive abilities.

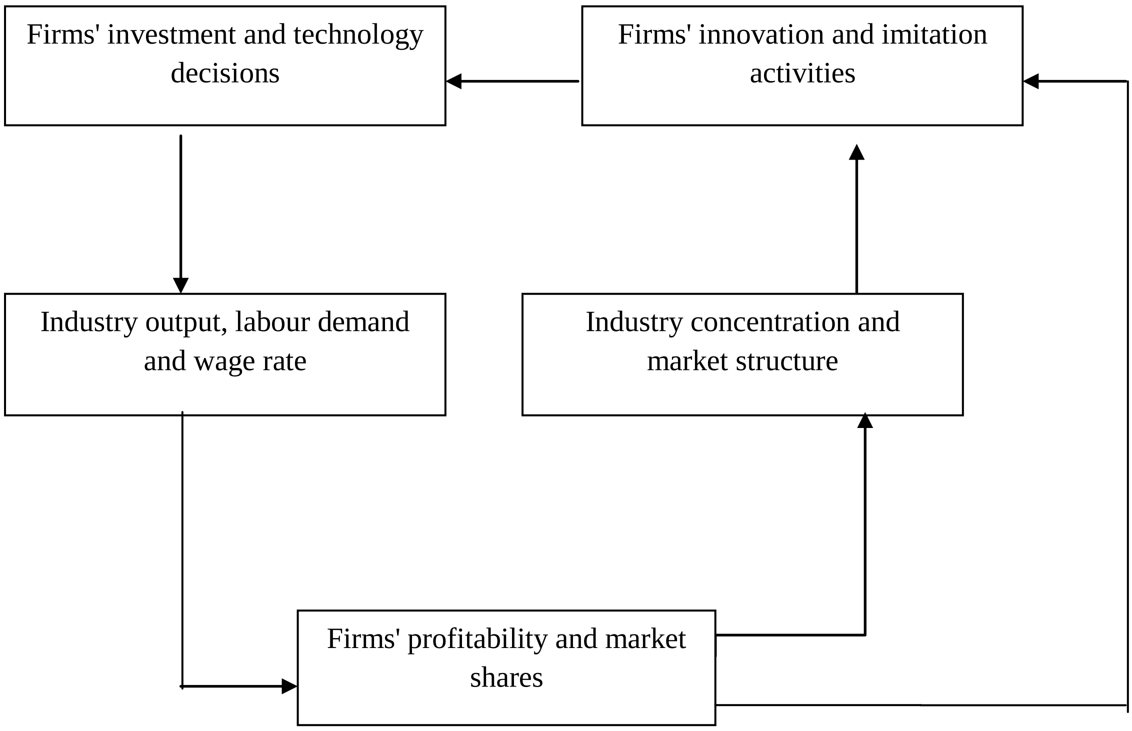
Various rule-guided behaviours are defined by Nelson and Winter (1982) as invariant routines, i.e. habits, customs and beliefs. Routines are the result of a learning process. The authors divided routines into three categories. First are "standard operating procedures", those that involve decisions about the level of production given the firm's capital stock and other relevant factors. Prominent among these routines are technologies. The second group includes routines pertaining to firm's investment decisions; and the third those that involve searching for novelty (i.e. searching for innovation).

Selection: Selection criteria are defined as variables that have an impact on the probability of survival of the population. Selection criteria are relatively invariant in natural sciences, which is not the case under many economic and social conditions. If the unit of selection is a firm, these selection criteria are often relatively simple, such as profit, prices, delivery conditions, etc. (Dosi and Nelson, 1994). The process of selection is inherent within a firm and between firms. Firms will imitate successful routines from other firms or innovative firms will introduce new routines and skills (Rahmeyer, 2010).

Nelson and Winter (1982) developed the first formalized evolutionary growth model in which the unit of analysis is heterogeneous firms. The analysis is restricted to one sector and only process innovation is considered. Firms' profitability determines the "fitness" (competitiveness) of technologies employed by firms, while technological competition is the driving force of the economic system. Search processes are intended to discover the ways to improve routines or replace them with those that are more profitable. Search may lead to *innovation*, if a new routine is developed, or to *imitation*, if an existing routine is adopted and used for other purposes (Fagerberg, 2003). Although routines might belong to any of three previously defined groups, Dosi and Nelson (1994) note that, in all of the Nelson-Winter models, search is aimed at discovering new production techniques or to improve old ones; thus, *search is determined by R&D activities within firms*. Other authors of similar models use the term "learning" to describe the stochastic search processes.

The structure of Nelson and Winter (1982) model is presented in Figure 1.1. The model exhibits a stochastic dynamic process of correlation between micro and meso (industry) levels. The behaviour of firms determines industry performance and, in turn, market conditions affect a firm's innovative activities and its technological and investment decisions. Due to the presence of a stochastic dynamic process, the model is too complex to be analytically tractable. Accordingly, the model can only be tested by means of computer simulation analysis (Castellacci, 2011).

Figure 1.1. The analytical structure of Nelson and Winter's (1982) model



Source: Castellacci (2011, p. 92).

One of the assumptions of the model is that retained profit is the only source for financing investments. Fagerberg (2003) argues that large firms with market power have a competitive advantage because they can invest more in R&D than can small firms, and the search process is likely to result in finding a better technology (routine). Moreover, due to higher volumes of production, the benefits of introducing new routines are larger for large firms. To overcome this bias, Nelson and Winter assumed that large firms have a higher price/cost ratio, and also that large firms do not necessarily create high barriers to entry, so new firms can enter the market.

Several authors developed variants of the Nelson-Winter model. Most prominent are the models by Soete and Turner (1984), Metcalfe (1988, 1992), Silverberg (1987) and Metcalfe and Gibbons (1989). The main difference between this class of models and the Nelson and Winter model is the absence of the stochastic introduction of new technologies. Instead, the models only deal with a given and fixed set of technologies. Increase in productivity is the results of two dynamics, the improvement of the individual technologies, as well as the extended use of more productive technologies (Dosi and Nelson, 1994). The model of Silverberg et al. (1988) considers the case when only two technologies are employed. Moreover, “learning by doing” is a complement to search activities (Fagerberg, 2003). Search processes are limited to improving a firm’s prevailing routines (technologies) through a learning process. Learning leads to increase in productivity, but other firms might be free-riders and imitate improvements in technology, if spillover of learning occurs. Firms are forward- looking agents, unlike firms in the Nelson-Winter model, and may realize that less productive technology has a potential of improvement to the level of the highest productivity, if a firm invests in its improvement and learns through its operation.

Recently, within the evolutionary theory, a new approach to analysing innovation has emerged, termed Systems of Innovation (IS) approach. The approach focuses on broader, institutional settings conducive to innovation and is elaborated in the next section.

1.3.4 Systems of innovation approach

Developed in the last decade, the systems of innovation (SI) approach is a conceptual framework for the study of innovation and technological change that explicitly acknowledges the collective and non-linear properties of innovation processes (see Section 1.4.1 on models of innovation). Edquist (1997, p. 14) defines systems of innovation as 'all important economic, social, political, organizational, and other factors that influence the development, diffusion and use of innovation'. The SI approach attempts to identify determinants of innovation, rather than to analyse the effects of innovation on firms’ performance or economic growth (Edquist, 2001).

Lundvall (1992, p. 13) distinguishes a narrow and a broad definition of a system of innovation. A system of innovation in a narrow sense specifies institutions and organisations that support searching and exploring processes in firms, such as R&D

departments, technological institutes and universities; whereas a broad definition includes subsystems involved not just in searching and exploring, but also in learning processes, such as the production system, the marketing system and the finance system. Lundvall (2007) defines the core of the innovation system as firms and their interaction with other firms (competition, cooperation and networking) as well as with the knowledge infrastructure (universities, research centres and technological institutes).

The systematic approach to innovation covers the concepts of national, regional, sectoral and technological systems as well as the concept of industrial clusters. Following Johnson et al. (2003), systems of innovation can be divided into three categories. Based on geographical or spatial criterion, innovation systems could be local, regional, national and supranational. The concept of National Innovation Systems (NIS) was introduced in the late 1980s in the context of debates over industrial policy in Europe.[13] Its aim was to challenge orthodox economic theory and its distinction between macro and micro- aspects of innovation. National innovation systems can be defined as a subsystem of interconnected institutions which contribute to generation and diffusion of new technologies (Sharif, 2006). Second, sectoral/technological innovation systems refer to either a particular product group or a particular technological field or a knowledge field. Technological innovation systems identify the general patterns of the emergence and development of new technologies. Finally, the third category – industrial clusters - refers to the breadth of activities and institutions included in an innovation system. Lundvall (2007) distinguishes between codified knowledge exchange (knowledge transfer through information flow) and tacit knowledge exchange (body-body contact) and continues to infer that the main difference between various levels of innovation systems is the role these two types of knowledge play in innovative activities.

Innovation according to this concept includes not only technological (product and process) innovation but also the determinants of innovation, which include the R&D activities of both the public and private sectors. Lundvall (2007, p. 101) notes that he prefers to define innovation 'as a process encompassing diffusion and use as well as the first market introduction'. Lundvall’s definition of innovation is thus broader than Schumpeter’s definition, because the former includes diffusion of innovation as an

[13] The concept is also termed National Systems of Innovation (NSI).

integral part of innovative activities. Lundvall continues to infer that the successful implementation of innovation critically relies on training and organizational change.

The systematic approach to innovation focuses on the interaction and influence of various institutions and organizations in the generation and diffusion of innovation. Hence, the SI approach stresses the central role of institutions and their influence in the innovation process as well as the importance of actors collaborating and interacting in networks. A broader definition of institutions as habits and practices or routines is based on the definition by Nelson and Winter (1982) (see Section 1.3.4). Furthermore, institutions refer to laws and regulations in a national economy. Such institutions reduce the uncertainty inherent in innovative activities and ensure stability for the firms and other actors in the system. Institutions should not be confused with organisations, defined as the tangible and legal parts of the innovation systems, which facilitate economic actors in the carrying out of innovative activities (Soete et al., 2010).

The concept encompasses a non-linear and multidisciplinary perspective on innovative activities.[14] Innovation does not occur in isolation, but firms innovate through complex interactions, which are characterized by many forms of feedback mechanisms. The multidisciplinary aspect refers to application of perspectives from different social science disciplines (Balzat and Hanusch, 2004). Lundvall (2007) maintains that the concept of NIS is an evolutionary concept, because knowledge and learning play a strategic role in the innovation system. Furthermore, the dynamics of innovation are often path dependent and evolve over time (Castellacci et al., 2005). National systems are at different stages of innovation generation and diffusion due to both different levels of production and trade specialization but also of the knowledge base. However, optimal or best practice innovation systems cannot be determined, because innovation processes are evolutionary and the notion of optimality is not applicable in an evolutionary framework.

Following Soete et al. (2010) the literature on innovation systems can be divided into three areas.

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[14] Non-linearity of innovation process suggests the presence of feedback mechanisms between the stages of the innovation process (see Section 1.4.1 on innovation models).

1. The first is based on Freeman (1987), where the Japanese NIS was analyzed. Freeman noted four elements comprising the Japanese NIS: public policy aimed at creating comparative advantages in the strategic industries; corporate R&D, which combined external knowledge from abroad with in-house technological advances; human capital and innovative forms of work organisation; and, finally, the conglomerate structure of the Japanese economy, which is characterized by both the absence of competition and consequently opportunities for vertical integration in the supply chains.
2. The second direction of the development of the NIS concept is related to Lundvall's (1992) theoretical contribution. Lundvall emphasizes interactive learning as the most important process and knowledge as the most important resource of innovation. Soete et al. (2010) identified three theoretical building blocks of the NIS concept developed by Lundvall, one of the first and also major innovations systems scholars.
    a. The first premise refers to sources of innovation, divided into two categories: learning; and search and exploration. Distinction is made between learning and R&D. R&D is a second source of innovation and covers corporate R&D or search activities as well as academic R&D or exploration.
    b. The second theoretical building block pertains to the nature of innovation, because Ludvall is mainly focused on incremental, rather than on radical innovations. Innovation in general is defined as a process, not a single event (Lundvall, 1992, p. 9). Incremental innovations are the results of continuous learning and searching processes in firms, and they also provide a feedback between innovators and imitators.
    c. The third premise is the role of non-market institutions in the systems of innovation. Lundvall distinguished two forms of non-market institutions: user-producer interaction; and the institutions in the system. The former refers to the communication between users and producers beyond market exchange, while latter emphasizes the role of institutions in risk reduction and provision of stability for firms in the inherently uncertain economic environment.
3. Finally, the third distinctive area in the development of the NIS concept is the empirical study of national innovation systems by Nelson (1993). Nelson's

approach is narrower than Lundvall's, focusing on institutions that facilitate formal R&D activities, especially the role of universities in supporting R&D.[15]

Furman et al. (2002) introduced the concept of national innovation capacity (NIC). It represents a combination of three related theoretical concepts: endogenous growth theory; the theory of international competitiveness (Porter, 1990); and the NIS concept. The NIC concept is based on three components: innovation infrastructure; the environment for carrying out innovative activities in industrial clusters; and the linkages between these two components (Balzat and Hanusch, 2004). The main contribution of the NIC concept is the linkage between endogenous growth theory and the contemporary, systemic approach to innovation. The major pitfall of the empirical literature is that it only models one measure of innovation, i.e. patent data.

Empirical studies of national innovation systems have developed in three directions: policy-oriented studies of innovation systems; the development of descriptive models; and the NIS studies of low and middle income countries (Balzat and Hanusch, 2004). The first strand was triggered by the political interest in deriving technology policy implications from the systemic analysis of national innovation systems. Within this trend, national benchmarking studies are conducted to identify "best practice" policies and to derive policy recommendations. Descriptive models of national innovation systems are aimed at identifying the structural specifics and performance of a national innovation system. Finally, studies of the NIS concept in developing countries focus on country–specific innovation patterns and different development stages of NIS in low and middle income countries (Balzat and Hanusch, 2004).

The most important impact of the concept, according to Lundvall (2007), is that policy makers realized the importance of national policy strategies that are aimed at promoting international competitiveness. Furthermore, *the concept induced policy makers to change their perspective from a linear to an interactive process of innovation*. The systematic approach to innovation gained its relevance after the Community Innovation Survey (CIS) was carried out. Innovation surveys pointed out not just the importance of R&D sources of innovation but also, and especially, the non-R&D

[15] The prominent triple helix model of university-industry-government relations is developed with the IS framework (Etzkowitz and Leydesdorff, 2000; Etzkowitz, 2003).

innovation inputs such as purchase of equipment, design and marketing (Soete et al., 2010).

The IS concept has its weakness. It is often argued that the definition of innovation systems is too broad, the boundaries of the system are not determined and thus it is not clearly specified what should be included in the system (Edquist, 2005, p. 186). Lundvall (1992, p. 14) noted that the broad definition of innovation systems stems from the relevance of interactive learning as a basis of innovation. A system of innovation based on the linear model of innovation could be defined in a narrow context. However, the non-linear and multidisciplinary approach to innovation processes inherent to the IS concept requires the broad definition of the system.

> It should be obvious that a definition of the system of innovation must, to a certain degree, be kept open and flexible regarding which sub-systems should be included and which processes should be studied (Lundvall, 1992, p. 14).

Based on the shortcomings of the IS concept, many scholars (see Lundvall, 2007; Edquist, 2005, p. 186) argue that the concept is not a theoretical concept or a formal theory, but rather an approach or a conceptual framework. However, the concept is important as a point of departure from neoclassical theory, which specifies one general rule of behaviour of economic agents, that of utility and profit maximisation. Systemic approach to innovation, as in the institutional approach, emphasises the importance of the economic structure and institutional set-up and their affect on learning and interaction between agents (Johnson et al., 2003).

1.3.5 Resource-based view of the firm and innovation

The resource-based view (RBV) is one of the most influential approaches to the study of strategic management (Hoskisson et al., 1999; Acedo et al., 2006; Newbert, 2007). The origins of the RBV can be traced back to the work of Edith Penrose (1959), in which she argues that firm growth depends on internal resources, in particular managerial and entrepreneurial resources. The RBV basically identifies firms’ resources as a key factor in achieving sustainable competitive advantage. It is important to note that the RBV is not a theory of the firm. As Foss (2011) notes, if it is a theory, then it is a theory of sustainable competitive advantage rather than a theory of the firm. Gavetti and Levinthal (2004) divide the RBV into "high-" and "low-church" RBV. The low–church RBV encompasses the following streams of research: the knowledge-based view of the firm; the evolutionary theory of the firm; the capabilities view of the firm; and the dynamic capabilities view of the firm (for reference see Foss, 2011).

The major contribution of high-church RBV is the identification of criteria that have to be jointly fulfilled (Foss, 2011). Only if these criteria are jointly met does a resource provide sustainable competitive advantage. Barney (1991) defines these criteria as follows:

- Valuable; either it seizes opportunities or mitigates threats;[16]
- Rare: either no other firm possesses the resource or only few;
- Costly to imitate; and
- Costly to substitute.

Peteraf (1993) adds new criterion to those formalized by Barney (1991), but also groups them under different terms (Foss, 2011):

- Relative resource immobility (new criterion);
- Resource heterogeneity (valuable and rare in Barney's framework);
- Ex ante limits to competition; and
- Ex post limits to competition (costly imitation and substitution in Barney's framework).

Further, it is important to distinguish between resources and capabilities. Resources are the tangible (physical and financial) and non-tangible (knowledge and skills, know how, organizational procedures etc.) assets of the firm. Capabilities are firm-specific processes developed for the exploitation of resources. Their purpose is to increase productivity of resources by deploying and coordinating inputs (resources) into outputs. The main distinction between resources and capabilities is that the latter are firm-specific, while resources usually are not (Barney, 1991; Peteraf, 1993; Kostopoulos et al., 2002). However, there is a group of resources that are firm-specific and thus non-tradable, such as human resources (e.g. leadership, managerial and

[16] In the SWOT analysis, opportunities are internal, while threats are external (Foss, 2011).

entrepreneurial resources) and those are strategic resources. *Only strategic resources can be a source of competitive advantage*, following the criteria formalized by Barney (1991) and Peteraf (1993).

Kostopoulos et al. (2002) note that the RBV identifies the critical link between firm's resources and innovation whereby internal resources and capabilities determine the innovative capacity of the firm. [17] The authors categorized resources pertaining innovative activities into three groups:

- *Financial resources* from internal and external funds;
- *Technical resources* (Information Technology- IT, equipment and machinery);
- *Intangible resources* (human capital and knowledge).

The knowledge-based view of the firm, as an extension of the RBV, is based on premises that the firm's stock and flow of both tacit and formal knowledge is a source of competitive advantage. Besides resources, capabilities also determine the innovative capacity of the firm and Kostopoulos et al. (2002) argue that the following capabilities have a positive effect on the firm's capacity for innovation:

- ***Entrepreneurship***, defined as 'the articulation of a long-term vision for the firm that aims at higher growth through the introduction of innovative products and technologies at the expense of short-run profit maximization' (Kostopoulos et al., 2002, p. 11). Thus, entrepreneurship is regarded as a long-term goal of firm growth through technological innovations.
- ***Learning***: Innovative activities are carried out through learning processes; firms' absorptive capacities depend on acquiring and applying new knowledge, on adapting to changing environments.
- ***Sense and response***: This capability refers to the firm's ability to rapidly react to market dynamics. We would argue that sense and response capability refers to the agile response to market conditions, one of recognized advantages of SMEs in innovation.

[17] The authors refer to organizational innovation, which, in their study comprises firm-level innovation encompassing product, process and administrative innovations. However, the OECD *Oslo Manual* (2005) defines organizational innovation as non-technological innovations pertaining to new organizational methods in any functional area of the firm (OECD, 2005). Thus, we would like to emphasise the difference between these two conceptualizations of organizational innovation.

- ***Marketing skills***: Successful commercialization is a critical aspect of the innovation process, and marketing competencies play a crucial role in the commercialisation of innovation.
- ***Dynamic capabilities***: the Firm's ability to adapt its competencies to respond to market conditions is regarded as its dynamic capabilities (Eisenhardt, 2000).

Finally, Kostopoulos et al. (2002) make an interesting observation that there is interaction and feedback between the firm's internal resources and innovation. Resources are inputs necessary for innovative activity, but innovation also affects resources in the sense that generation and application of innovation create new, specific resources that are difficult to imitate or substitute.

1.4 Models and determinants of innovation

1.4.1 Models of innovation

The focus of the thesis is not on macro-level analysis of the role of innovation in economic growth and development. Rather, our research objectives are associated with the firm-level investigations of contemporaneous issues regarding R&D and innovation policy. Accordingly, our review of theoretical developments in the economics of innovation will continue with a critical assessment of firm-level innovation models.

Different taxonomies of innovation models can be found in the innovation literature. Rothwell (1992) is the first scholar who divided the development of innovation models into five generations from the 1950s to the 1990s:

- First generation: technology push models;
- Second generation: demand pull models;
- Third generation: coupling or interactive models;
- Fourth generation: integrated models;
- Fifth generation: systems integration and networking models.

The prominent features of innovation models can be summarized as follows (Rothwell, 1992):

- Earlier models are not automatically substituted by the next-generation models, but rather co-exist.
- Appropriability of particular innovation models is contingent upon the industry in which the firm operates and on the type of prevalent patterns of innovation (for instance, whether incremental innovation is a dominant pattern of innovation activities or the firm mostly engages in radical innovation). With reference to industry-specific innovation models, an example would be the case of resource-intensive firms (de Jong and Marsili, 2006), that are less likely to adopt innovation models from the fifth generation, because those models emphasize the importance of interaction between firms and of cooperation with a broad network of partners.

Hobday (2005) reviews the models and discusses their explanatory power and their weaknesses. Of principal concern from a theoretical perspective is that Hobday notes the lack of an explicit theoretical base in the innovation models. However, he does not expand his criticism, but rather suggests a resource –based theory as a possible approach for providing theoretical underpinnings for innovation models. We discuss the resource-based view in Section 1.3.5, and proceed by presenting the summary of the five generations of innovation models in Table 1.2.

The first generation of the innovation models are the technology push models. The model is related to the "science push" model developed by Vannevar Bush in his 1945 report *Science: The Endless Frontier*. The model is simple and linear, in which the driving force for innovation is development of new technologies (Marinova and Phillimore, 2003, p. 46). Public policies for fostering innovative activities were focused on the interventions and instruments on the supply side, such as R&D subsidies and loans which, the model suggested, would result in additional R&D investments and, thus, increase in innovation activities. The stages of the model are presented in Figure 1.2.

Figure 1.2. The technology push linear model

Basic Science → Applied Science and Engineering → Manufacturing → Marketing → Sales

Source: Marinova and Phillimore (2003, p. 46); Hobday (2005).

Table 1.2. Five generations of innovation models

Innovation models	Characteristics
1st Generation Technology push (1950s to mid-60s)	• Simple linear sequential innovation process. • Key stage is investment in R&D. • Commercialization of R&D activities.
2nd Generation Market pull (mid-1960s–1970s)	• Simple linear sequential innovation process where market (i.e. consumers' needs) induce innovation activities. • Focus in the model is on marketing, as consumers' needs and preferences are the source of ideas and R&D activities are directed by the market. • R&D has a reactive role.
3rd Generation Coupling models (mid 1970s–1980s)	• Sequential innovation process, but with feedback loops from later to earlier stages. • Involves both R&D activities as an initial impetus to innovation as well as innovations induced by a combination of R&D- push and market- pull activities. • Both R&D and marketing activities are equally relevant for the innovation process. • Emphasis is on integration of internal R&D activities and marketing functions.
4th Generation Integrated model (early 1980s–1990)	• Parallel development with integrated development teams. • Relevance of networking and cooperation for innovation with suppliers and leading customers through joint ventures and strategic partnerships. • Emphasis on integration between R&D and manufacturing (e.g. design for manufacturability).
5th Generation Systems integration and networking (post-1990)	• Fully integrated parallel development model supported by advanced Information and Communications Technology (ICT). • Cooperation with leading customers is the key driver of innovation. • Cooperation with customers and suppliers (i.e. vertical cooperation) is through joint ventures, collaborative research groupings, collaborative marketing arrangements etc. • Emphasis on corporate flexibility and speed -to-market strategy (i.e. rapid commercialization of innovation).

Source: Hobday (2005, p. 123).

However, the stages of the linear model slightly differ depending on the source. Swann (2009) distinguishes the following stages (Figure 1.3):

Figure 1.3. The linear model

Research and Creativity → Invention → Design and Development → Innovation

Source: Swann (2009, p. 23).

The sequence of the model reflects the stages of the innovation process whereby research and creativity should lead to invention and further development and design should result in innovation. The linear model can be a model of technological innovation at both a firm and an economy level. At the micro level, it represents a sequence running from R&D into production engineering and then marketing, similar to the technology push model by Marinova and Phillimore (2003, p. 46). At the macro level, the model reflects the transition from basic research into applied R&D, then innovation and commercialisation of knowledge. The origin of the linear model can also be associated with the Schumpeterian trilogy, which distinguishes technological change in three different phases: invention; innovation; and diffusion. The first phase represents the generation of new scientific and technological ideas, while the second refers to the commercialization of novelties. Finally, the diffusion stage involves the distribution of innovation, over time and space (Swann, 2009).

The second generation is represented by the demand pull model, which is also a linear model of innovation but, contrary to the technology-push model, based on the recognition of the importance of the demand side in the innovation process. The key factor in the innovation process is the existing demand for a certain technology. The marketplace (i.e. customers' needs) is the main source of new ideas. The sequence of the model is depicted in Figure 1.4.

Figure 1.4. The demand pull linear model

Market place → Technology Development → Manufacturing → Sales

Source: Marinova and Phillimore (2003, p. 46); Hobday (2005).

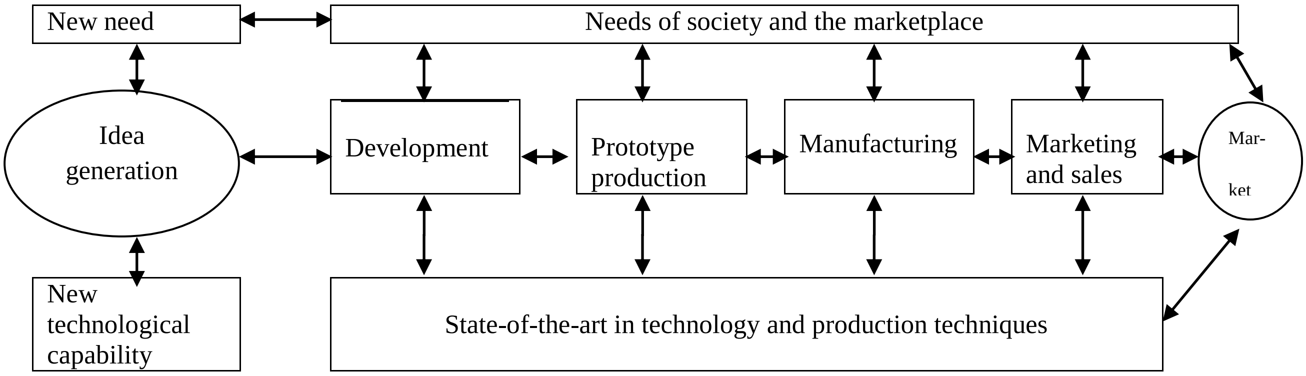
Development of the linear models of innovation, especially the technology push model, induced policy makers to recognize the importance of research and development in the innovation process as well as to recognize market failure and underinvestment in research activities at the firm level. The discussion on various market and systems failures can be found in Section 3.2 on the innovation policy. Another important contribution of the linear models is related to the concept of barriers to innovation and success factors which can be identified in both the supply (push) as well as the demand (pull) side of the innovation process. However, whether technology or market demand has a leading role in successful innovation remains open to debate: 'The question of what comes first - technology or need - has turned out to be a chicken and egg question, and that field of research has remained relatively quiet' (Marinova and Phillimore, 2003, p. 46).

The main strength of the linear model, i.e. its simplicity and clarity is also the source of much criticism. The actual process of innovation is neither linear nor simple, i.e. different stages of innovation process are interconnected and mutually interdependent. For example, information acquired during the diffusion stage provides an important feedback in improving a technology. Therefore, a more realistic representation of the innovation model would be to identify the feedback mechanisms and incremental patterns of development and avoid ordering them in strict sequential stages (Swann, 2009, p. 128). Hobday (2005) notes the main criticism of the linear models:

- the innovation process is not linear in the practice;
- feedback mechanisms occur between different stages of the innovation process;
- there is no systematic evidence to verify the models;
- the absence of external sources of knowledge, such as customers, suppliers, the private sector, universities;
- the stages of the innovation process are not explained; and
- the overestimation of rational processes underpinning the innovation process and the corresponding lack of recognition of bounded rationality in human behaviour and of alternative innovation routes.

The need for more sophisticated models of innovation, which incorporate feedback mechanisms and non-linear relations between different stages of the innovation process, led to the introduction of the third generation of interactive models of innovation. Such a model is presented in Figure 1.5. Innovation in the interactive models can occur at different stages in the innovation process. The process itself is no longer linear and sequential, but rather circular (iterative). The interactive models of innovation are derived from the systems approach to innovation (Hadjimanolis, 2003, p. 564).

Figure 1.5. The coupling or interactive model

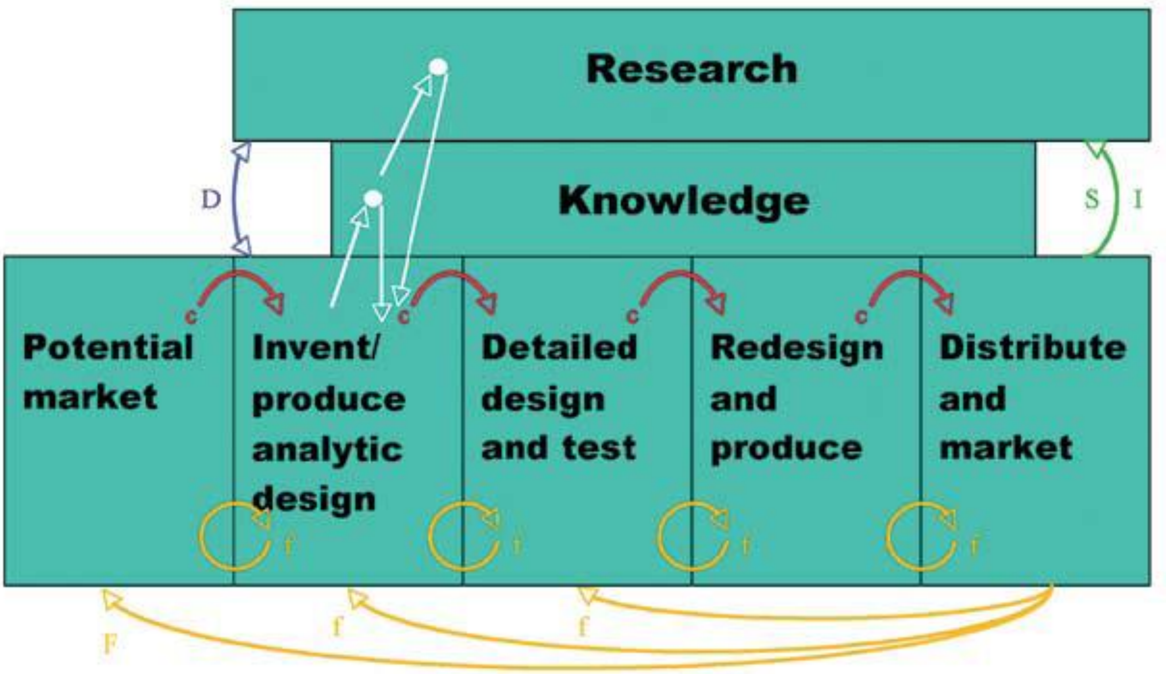


Source: Rothwell (1994, p. 10).

A well- known interactive model is the chain-link model developed by Kline and Rosenberg (1986) presented in Figure 1.6. Science is divided into two major parts - knowledge (known science) and research (pure science). The model contains five different paths of innovation processes. The central chain of innovation is labelled C. The second path, labelled F and f, represents a set of feedback mechanisms.[18] The third path refers to the links between the central path and knowledge and research (white arrows in Figure 1.6). The forth path marked by arrow D indicates potential radical innovations. Finally, the fifth path indicated by arrow I is the feedback loop from the innovation output to science. As noted by Kline and Rosenberg (1986, p. 293), the linear model with one central path for innovation and with the notion of science as the driving force of innovation is too simple and leads to distortion in understanding innovation processes.

[18] F indicates particularly important feedback.

Figure 1.6. The chain – link model proposed by Kline and Rosenberg (1986)

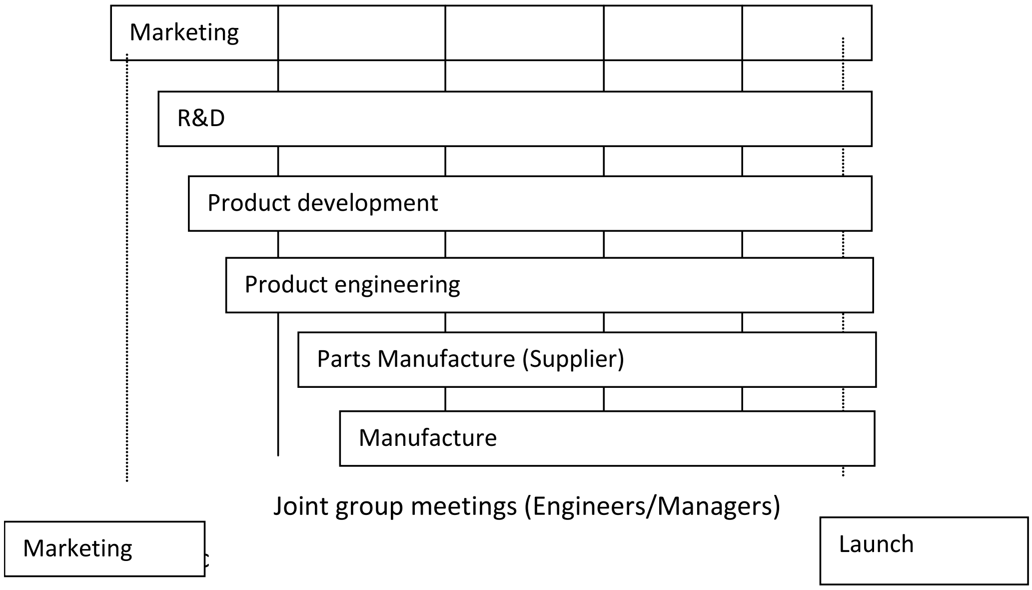


Source: Gulbrandsen (2009, p. 57).

The interactive models stress the importance of interaction and interdependence of different stages of the innovation process on both the supply and the demand side. Therefore, the models attempt to include both technology push and demand pull approaches to the innovation process and create a comprehensive innovation model. The distinguishing feature of the third generation compared to the first and second, is the explicit link between the decision-making of firms and both the marketplace and the public and private Science and Technology (S&T) community (Hobday, 2005). The main shortcoming of the interactive models is the insufficient elaboration of environmental factors, such as government regulations and the S&T community.

The fourth generation of the integrated models was developed in the 1980s, and their main feature is the functional overlap between different departments and activities in the firm. However, the models also incorporate external linkages with suppliers, customers, the public sector and research organizations. The model based on the Japanese automotive and electronics sectors is presented in Figure 1.7. Instead of the sequential flow of information immanent to previous innovation models, the integrated model is characterized by information sharing through joint group meetings that bring together R&D personnel (engineers) and managers from different departments in the firm. Besides functional integration and parallel activities across departments, firms establish and maintain close links to customers and suppliers, as well as other networking partners. Overall, the innovation process is regarded as cross functional and non-sequential, requiring both internal innovative capacities and external sources of knowledge.

Figure 1.7. The integrated model



Source: Rothwell (1994, p. 12).

The fifth generation systems integration and networking models extended the fourth generation integrated models by recognized the importance of vertical cooperation with suppliers and consumers and of horizontal cooperation with other firms. The main emphasis is on the learning processes and their flow between firms. Innovation is recognized as a networking process, in which the internal and external links of the firm are reinforced by the introduction of information technology (IT) and use of electronic tools (Information and Communication Technologies- ICT). The driving force of the innovation process is information exchange through ICT. The main criticism of the fourth and fifth generation models is that the empirical evidence does not suggest that the innovation process is conducted in the suggested manner. Furthermore, the benefits of IT systems on the innovation efficiency are disputable, as their introduction requires certain organisational changes and IT knowledge (Hobday, 2005).

Marinova and Phillimore (2003) extended Rothwells's typology and divided innovation models into six generations:

- First generation: the black box model;
- Second generation: linear models;
- Third generation: interactive models;
- Fourth generation: system models;
- Fifth generation: evolutionary models; and
- Six generation: innovation milieu.

These models refer to the process of technological innovation, not including other types of innovation, such as organizational and marketing innovations. The first generation - the black box model - is derived from Solow's (1956) neoclassical growth model, in which the process of innovation is treated as a black box (an exogenous parameter). The second generation - the linear models - were developed in the 1960s and 1970s including the technology push and demand pull models. These models are already discussed in this Section as well as the third generation, the coupling or interactive models.

The systems models belong to the fourth generation of innovation models. These models are derived from the systems of innovation approach, and the most well- known model is the national systems of innovation. The model emphasizes the systems features of the innovation process i.e. interaction and inter-connectedness among actors (firms, public sector and private and public research organizations). Marinova and Phillimore (2003, p. 48) argue that the main contribution of the systems models is in exploring the role of small firms in the innovation process. Small firms are able to survive and compete with large firms by interaction and collaboration within external innovation networks.

The next generation is the evolutionary model of innovation. Based on a conceptual model, Nelson and Winter (1982) were the first to develop a computer simulation of innovation. The main contribution of the model is in explaining the process of decision-making in firms, and also how agents in the innovation model interact to produce innovations.

Finally, the innovative milieu model focuses on regional clusters of innovation and the importance of geographical location in knowledge and technology transfer. The model contributes to explaining the successful innovative activities in SMEs, by focusing on the regional networks of innovation and the role of proximity and of the specific cultural and economic environment for generation and diffusion of innovation among SMEs (Marinova and Phillimore, 2003, p. 51). The concept of innovation clusters developed by Porter (1990) is related to the innovative milieu model in that the concepts of clusters and of networks are similar. However, clusters are a broader concept than networks, as they include all types of knowledge transfer and exchange in a certain location.

A few conclusions can be drawn from reviewing taxonomies of innovation models. First, attention shifted from exploring internal factor of innovative activities (such as R&D activities, marketing, and finance) to examining the role of external factors in the innovation process such as networks, clusters, public policy and geography. Second, the genesis and development of various models of innovation reflects difficulties in examining innovation processes. As Marinova and Phillimore (2003, p. 51) noted:

> What becomes apparent from this overview of the six generations of innovation models is that the more we study innovation, the more we realize how complex a process it is and how difficult it is to "master" it, whether at a corporate or government policy level.

1.4.2 Determinants of innovation

Although some authors argue that the question as to what are the determinants of technological innovations is out-dated, Souitaris (2002) notes that, after numerous studies were conducted in the 1950s, 1960s and 1970s, the debate remains open.

In their comprehensive review of the determinants of technological innovation in the manufacturing sector, Becheikh et al. (2006) examined the findings from 108 empirical articles published between 1993 and 2003. They identified around sixty variables, out of which forty concern the internal determinants of innovation and twenty the contextual determinants. The inspection of variables presented in Table 1.3 and Table 1.4 reveals an eclectic approach adopted towards empirical analysis in identifying determents of innovation.

Table 1.3. Internal determinants of innovation

Category	Subcategory	Variables
Firm's general characteristics	-	Firm size Firm age Ownership structure Past performance
Firms' global strategies	Strategy definition	The firm has a defined strategic orientation
	Corporate strategy	Diversification strategy Export/ internationalization External vs. internal growth
	Business strategy	Differentiation strategy Cost reduction strategy Protection mechanisms
Firm's structure	Formalization	Formal structure Flexible structure
	Centralization	Centralization of decision making Empowerment of employees
	Interaction	Interaction between firm's units
Control activities	-	Financial versus strategic control
Firm's culture	-	Resistance to change Total quality management Culture of support for innovation
Management team	Leadership variables	Presence of a project leader CEO characteristics CEO change
	Manager related variables	Qualification and experience Perception of risk Perception of innovation returns
Functional assets and strategies	R&D	R&D assets and strategies
	Human resource	Personnel qualification/experience Human resource strategies
	Operation and production	Advanced equipment/technologies Degree of capacity utilization
	Marketing	Marketing strategies Monitoring of competitors
	Finance	Financial autonomy Turnover/profit Budget/ funds availability

Source: Becheikh et al. (2006, p. 651).

Table 1.4. External determinants of innovation

Category	Variables
Firm's industry related variables	Sector Demand growth in the industry Industry concentration
Firm's regional variables	Geographic location of the firm Proximity advantage
Networking	Interaction with universities/research centres/consumers/suppliers etc.
Knowledge/ technology acquisition	Formal and informal knowledge and technology acquisition
Government and public policies	Government policies External financial support
Surrounding culture	Power distance/risk avoidance/feminity-masculinity/individualism-collectivism etc.

Source: Becheikh et al. (2006, p. 657).

Internal determinants of innovation encompass a broad range of variables: financial and human resources; firm size and age; firm strategy and structure; the firm's culture; and individual and professional characteristics of managers and directors. External or contextual determinants include industry and regional-specific characteristics, networking, public policy and support, knowledge acquisition and national culture.

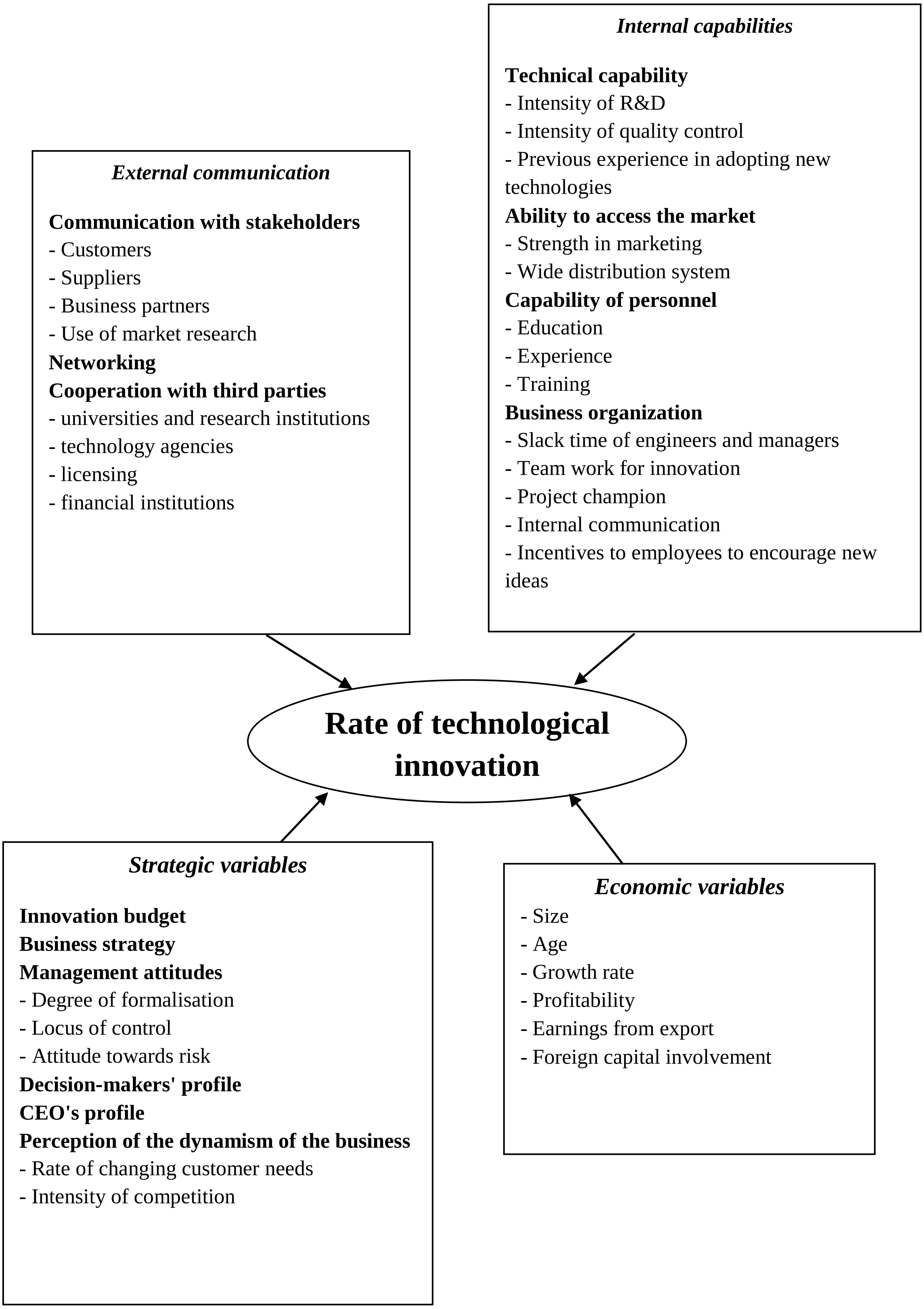
Furthermore, careful examination of variables included in Table 1.3 and Table 1.4 points to several caveats in exploring determinants of innovation. First, diversification can be regarded as an integral element of innovation, as it encompasses product diversification and international (market) diversification, i.e. introduction of new products and entering new markets (Lee and Jang, 2007). Therefore, it can be argued that diversification cannot be a determinant of innovation but is, rather, itself a measure of product and marketing innovation. Second, there may be a mutually causal link between innovation and firm performance, in the sense that past innovation influences firm performance, which, in turn, affects current innovative activities.

The diversity of determinants indicates the lack of a core (minimum) set of determinants; i.e. there is no consensus on a parsimonious model comprising the minimum set of variables that influence innovation. However, each category of determinants has its own theoretical background. The resource-based view of the firm emphases the importance of internal resources in achieving competitive advantage of the firm (see discussion in Section 1.3.5). The relationship between firm size, market structure and innovation is grounded in Schumpeter Mark I and Mark II (see Section 1.3.2). Individual characteristics of managers are examined in the entrepreneurship studies (for example, see Carland et al., 1984; Chell, 1985; Littunen, 2000). Strategic management recognizes the relevance of firm's strategy and culture and their impact on firm performance. The knowledge-based view of the firm recognizes the critical role of knowledge in achieving a firm's competitive advantage. Finally, the systems of innovation approach explores the institutional surrounding of the firm, including networking and public policy (see Section 1.3.4). Becheikh et al. (2006) note that the relevance of contextual or external determinants is the main reason for the emergence of various approaches to studying innovation, such as innovation clusters, the innovation milieu and national and regional systems (see Section 1.4.1 on innovation models).

We conclude that the inclusion of determinants suggested by different disciplines clearly indicates the multidisciplinary nature of innovation studies. However, a broad range of determinants of innovation seriously hampers the comparison between studies and generalization of their findings (Becheikh et al., 2006).

Souitaris (2002) maintains that theory cannot provide a general framework for analysing the innovation process and its determinants, because the process itself is firm-specific and depends on the industry and region in which the firm operates. The solution suggested by Souitaris (2002) is the adoption of a contingency approach in analysing the determinants. For that purpose, the author developed a portfolio model that illustrates the full range of determinants, the application of which depends on contingencies as defined by economic and social environments. This model is presented in Figure 1.8. A comparison of the determinants presented in Tables 1.3 and 1.4 with those in Figure 1.8 indicates similarities between the portfolio model by Souitaris (2002) and the list of variables in the study by Becheikh et al. (2006).

Figure 1.8. The portfolio model of the determinants of innovation



Source: Souitaris (2002, p. 884).

We would argue that a contingency approach might be a solution for empirical analysis of the determinants of innovation. External factors affect the innovative behaviour of firms, which is a subject of interest in the systems of innovation approach. On the other side, SMEs are a highly dispersed group of firms, and analysing SME innovation should take into account firm-specific characteristics as well as the industry and region in which the firm operates. Souitaris (2002) goes one step further by suggesting that instead of searching for a unified theory of innovation, researchers might adopt portfolio models as a way to identify determinants of innovation relevant in a particular context.

1.5 Conclusions

Although the importance of innovation at both micro and the economy level is long recognized, there is *no generally accepted theory of innovation* at the firm level. In economics, at least, such a theory would be widely supported, yield a parsimonious list of determinants and find overwhelming support from quantitative evidence. Within economics, both Schumpeter and neoclassical growth theory established the central importance of innovation in capitalist economic development. Among policy makers, promotion of innovation is the "holy grail", the means to revive economic growth without – indeed, while reversing - environmental degradation. Yet innovative behaviour and its determinants and, hence, how innovation may be promoted are not so well understood. This relative lack of microeconomic foundations is partly a consequence of the complexity and fuzziness of the concept of innovation *per se*. The heterogeneity of the various definitions of innovation advanced in the literature contributes to the lack of convergence towards a generally accepted definition of innovation.

Moreover, the absence of a canonical theory of innovation is further accentuated by its multidisciplinary nature, as the innovation process, its determinants, and its effects are all subject to investigation in many research disciplines, such as economics, strategic management and entrepreneurship. Furthermore, theories of the innovation process have evolved from a simple, linear model, that was dominant in the 1950s, to the complex, systems models of innovation in the 1990s. Given the complex and evolving nature of innovation theory, a large number of internal and external determinants of innovation are identified in the literature.

Joseph Schumpeter is regarded as the father of innovation studies, because of his two crucial contributions. First, Schumpeter was the first scholar to provide a definition of innovation, which is surprisingly similar to the latest definition advanced in the *Oslo Manual* (OECD, 2005). Second, Schumpeter was the first economist to recognize the crucial role of innovation in capitalist economic development. According to Schumpeter, the entrepreneurial function can be embedded in individual entrepreneurs in new firms but also in corporate entrepreneurship immanent to large firms. The former model, labelled 'Schumpeter Mark I', assigns the role of innovator to individual entrepreneurs who establish new firms to undertake innovation activities. The latter model, labelled 'Schumpeter Mark II', places the entrepreneurial function within large firms with formal R&D departments.

Within neoclassic economics, the macroeconomic analysis of innovation encompasses two distinct models: neoclassical exogenous growth models (Solow 1956, 1957) and endogenous growth models (e.g. Romer, 1986 and Lucas, 1988). Solow's model identified technological change as a driving force of economic growth. Treating technology (thus innovation) as exogenous is recognized as the main limitation of exogenous growth models, which resulted in the next generation of endogenous growth models, first formulated by Romer (1986) and Lucas (1988). The microeconomic analysis of innovation in the framework of neoclassical economics resulted in the first generation of innovation models, incorporating two linear models: a demand pull model; and a technology push model. Regarding the types of innovation, most theoretical models focused on process innovation (Stoneman, 2010), although product innovation was investigated to a lesser extent. As theoretical models predict that the introduction of technological product and process innovation, in general, depends on the price elasticity of demand, a large body of empirical studies examined the determinants of process and product innovations in relation to market structure, thereby effectively, in this context, testing Schumpeter's hypotheses on the relationship between firm size and innovation.

A point of convergence between neoclassical theorizing on innovation and innovation studies as a distinct field can be identified in two areas. First, innovation is treated as an endogenous driver of economic growth in both endogenous growth models as well as in innovation studies (Mulder et al., 2001; Rossi, 2002). Second, neoclassical economics advanced the rationale for policy intervention based on market failure. Discussion of market and system failures as both offering a rationale for government intervention is undertaken in Section 3.2.

Another strand of literature examining the impact of innovation on economics development is evolutionary economics. The main contribution of the evolutionary theory of the firm is that firms are considered as heterogeneous entities, with the main source of heterogeneity being the innovation process. Furthermore, innovation is treated as a dynamic and complex process, in which – in contrast to earlier linear models of innovation - stages of the process are connected through loops and feedback mechanisms. Arguments advanced in evolutionary economics found their place in the systems models of innovation. By introducing the concept of national innovation systems, evolutionary economics put forth the importance of the institutional setting and firms' environments in their innovation processes. Within the system, firms innovate by interacting with other firms and institutions.

Among evolutionary theories of the firm, the resource-based view of the firm recognized the relevance of firms' internal innovative resources in achieving comparative advantages. Among intangibles, strategic resources, innovation and technological competences play a significant role. While Industrial Organization economics emphasizes the effect of external determinants of innovation, such as market structure and networking , the resource-based view stresses a critical role of internal resources in innovation processes.

Innovation studies as a field of enquiry is currently in its mature phase (Fagerberg et al., 2012). Given its interdisciplinary nature, innovation is of relevance in many disciplines, such as economics, management, psychology and sociology (Fagerberg and Verspagen, 2009). However, as the field is rapidly *broadening*, it is questionable to what extent a multi-disciplinary, heterogeneous research community is cooperating and developing a common research agenda – which is a desirable basis for further advances and a *deepening* of the field.

This chapter provided an overview of theoretical approaches to the understanding of innovation within the disciplines of economics and management studies. The review of economic theorizing on innovation started with the macroeconomic contributions, advanced in Solow's neoclassical growth model, endogenous growth models, and Schumpeter's contributions to a theory of economic development. Because our main contribution is related to the firm-level evaluation of innovation support programmes, our focus subsequently shifted to microeconomic foundations of a theory of innovation.

Theoretical frameworks discussed in this chapter serve as a basis for the following two chapters of the thesis. Namely, in the next chapter, our focus is narrowed to the innovation processes in SMEs, where the resource-based view provides useful insights. Furthermore, Chapter III begins with the discussion on two rationales for the provision of public support in the domain of innovation. While the market-failure rationale is developed within the neoclassical economics framework, the more recent system-failure rationale was proposed by evolutionary economists. Thus, the theoretical approaches to innovation discussed in this chapter are extended in Chapter III into the area of public policy.

The overview of the determinants of innovation provides an guidelines for the econometric modelling of the impact of public support on innovation. The review of empirical studies presented in Section 3.6 will reveal a rather eclectic approach to selecting explanatory variables in empirical modelling. Thus, we would argue that, effectively, a contingency approach and portfolio model suggested by Souitaris (2002) and Becheikh et al. (2006) is a commonly adopted practice among practitioners undertaking the quantitative evaluation of innovation related policies. Given the absence of a canonical theoretical parsimonious model in estimating the effectiveness of public intervention, our preferred approach is associated with a contingency approach proposed in the literature on the determinants of innovation.

As a final remark, it can be noted that a dominance of practice over theory in this field is reflected in a fast-growing number of empirical studies. However, their comparison and the development of a consistent body of empirical evidence is limited by the lack of a unifying and parsimonious theoretical model that would both improve our understanding of innovation processes and serve as a basis for building a consistent body of empirical evidence on the relationship between innovation, firm performance and economic growth.

Encouraging innovation in small and medium sized enterprises (SMEs) remains at the heart of policy initiatives for stimulating economic development at the local, regional, national and European levels.

Edwards et al. (2005, p. 1119)

CHAPTER II

INNOVATION IN SMALL AND MEDIUM-SIZED ENTERPRISES (SMEs)

2.1 Introduction

Innovation is equally relevant for the survival and competitiveness of large as well as of small and medium sized firms (Hoffman, 1998; Edwards et al., 2005; Oke et al., 2007). While a broad overview of theoretical approaches to innovation is provided in Chapter I, this chapter shifts the attention to SMEs and the innovation process among this heterogeneous group of firms (Curran, 2000; Hadjimanolis, 2003). Similar to innovation, there is no broadly accepted definition of SMEs. Recently, practitioners across Europe increasingly have adopted the definition of SMEs by the European Commission given in the EU Recommendation 2003/361.

Schumpeter's Mark I and Mark II hypotheses initiated the debate within the economics of innovation as to whether small firms or their large counterparts are more able to engage in innovation. This chapter does not extensively discuss the link between firm size and innovation (for a review of empirical studies, see Damanpour, 1992; Camisón-Zornoza et al., 2004; Camisón-Zornoza et al., 2007; Damanpour, 2010; Cohen, 2010), but highlights the advantages and disadvantages of undertaking successful innovation in SMEs relative to innovation in large firms. The main advantages of SME innovation are associated with their behavioural characteristics, such as flexibility and motivation, whereas critical weaknesses are identified in relation to the limited pool of financial and human resources. Therefore, analysing the innovation process in SMEs is closely related to advances within the resource-based view of the firm, originating from Penrose (1959).

Within the disciplines of economics and management of innovation, one the main research questions is how innovation can affect firms' performance. Focusing on the innovation process in SMEs, Bolinao (2009) developed a conceptual framework for the management of technological innovation, connecting the building blocks of innovation as the explanatory variables and variables associated with the commercialization of innovation to firms' financial and non-financial performance.

Finally, Pavitt's (1984) taxonomy of firms in relation to their innovation processes motivated several authors (e.g Rizzoni, 1991; de Jong and Marsilli, 2006) to propose a taxonomy of SMEs based on their innovative activities. Taxonomies of SMEs can be a useful tool in analysing how SMEs undertake innovation, given the heterogeneity of their conduct and performance.

This chapter is organized as follows. Section 2.2 provides a review of various definitions of SMEs, while Section 2.3 elaborates on advantages as well as weaknesses pertinent to SME innovation. Section 2.4 presents the innovation process in SMEs and provides an overview of several taxonomies of firms based on the characteristics of their innovation processes. Concluding remarks are presented in the final section.

2.2 Defining small and medium-sized enterprises (SMEs)

Definition of small and medium-sized enterprises (SMEs) has changed over time and across countries. Rothwell and Zegveld (1982) discuss variations in definition and define SMEs with respect to the headcount as firms with less than 500 employees. In the 1980s, national definitions of SMEs varied from less than 500 and sometimes even 1000 employees. A complementary criterion for defining SMEs is the amount of turnover, and in relation to this criterion, the threshold of turnover varied from $1 million to $ 5 million and more (Rothwell and Zegveld, 1982, p. 7). In the European Union, starting from 2005, SMEs are defined on the basis of both the number of employees and the value of turnover (or alternatively the value of the balance sheet; see Table 2.1).

Table 2.1. Definition of SMEs in the European Union

Enterprise category	Headcount	Turnover	Or	Balance sheet total
Medium-sized	< 250	≤ € 50 million		≤ € 43 million
Small	< 50	≤ € 10 million		≤ € 10 million
Micro	< 10	≤ € 2 million		≤ € 2 million

Source: European Commission (2005).

In the UK, Sections 382 and 465 of the Companies Act 2006 define a small company as one that has a turnover of not more than £6.5 million, a balance sheet total of not more than £3.26 million and not more than 50 employees. A medium-sized company has a turnover of not more than £25.9 million, a balance sheet total of not more than £12.9 million and not more than 250 employees. However, this classification is not universally applied within the UK (Ahmed and Chowdhury, 2009). On the other side, the threshold for categorizing firm size in the USA is different than in the European Union. The U.S. Small Business Administration (SBA) categorizes firm size depending on the industry in which firms operate. On average, small firms are those with not more than 500 employees and with an annual revenue not exceeding USD $10 million (Hooghhoudt, 2010).

Nooteboom (1994) discuss the diversity as both a major characteristic of SMEs and a source of much confusion and misunderstanding and, hence, the reason why a generally accepted definition of SMEs is missing. The diversity between markets and industries is common among small, but also among large firms. What is specific to small firms in comparison to large firms is diversity of conduct and purpose within industries. He further discusses the conditions and sources of diversity. The conditions of diversity are associated with the profit objectives of the entrepreneur. Nooteboom (1994) suggests that entrepreneurs are more risk–averse than shareholders who can spread their risk in the portfolio, but are less risk-averse than managers in large firms who have a secure income.[19] Therefore, their profit objectives depend on the degree of risk-aversion. Sources of diversity are also related to the wider motives and goals of the entrepreneur, i.e. reasons for starting their own business. Three groups of factors influencing the entrepreneur's motive are identified: a) "push" factors (discontent with current job perspectives); b) "pull" factors (benefits and merits of self-employment); and c) coincidence (random reasons for self-employment).[20] Moreover, he notes that a particular definition of SMEs depends on the purpose of the study and the researcher's perspective.[21]

Therefore, past research on SMEs was hampered by the lack of consistent and unified definition of SMEs. The proposed EU framework for defining SMEs is helpful for research, because it enables comparison between cross-country and inter-temporal studies. Finally, even with a widely accepted definition of SMEs (at least in the EU), it is difficult to generalize or stylize facts about SMEs conduct due to their diversity among and within industries.

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[19] However, we would argue that the managers in large firms can be risk-loving to a greater extent than entrepreneurs if their income depends on their performance (i.e. incentive pay or "pay for performance", such as bonus system, share options etc.).

[20] For a detailed discussion on three categories, see Nooteboom (1994, pp. 330 - 331).

[21] His definition of SMEs is in accordance to the Dutch convention in the period of study: small firms employing less than 10, and medium between 10 and 100 employees.

2.3 Advantages and disadvantages of SMEs in innovation

Rothwell and Zegveld (1982) and Vossen (1998) identify the following advantages of carrying out innovation in SMEs:[22]

- **Marketing**: Small firms are often positioned in a market niche which enables them to establish and maintain close relations with their customers. Due to flat organizational structure and lack of bureaucratic inertia, they rapidly react to changing, dynamic market requirements.
- **Dynamic, entrepreneurial management**: It is argued that managers in small firms are risk-takers and thus more inclined to innovative activities than are managers in large firms, who are often limited in the decision-making process by their accountants.[23]
- **Internal communication**: Small firms often adopt informal internal communication, which is characterized by rapid information dispersion and prompt feedback mechanisms between managers and employees. Effective internal communication fosters rapid reaction to internal and external changes.

On the other side, SMEs have certain disadvantages relative to large firms:

- **Skilled workers**: Technological innovations often require the application of specific knowledge of scientists and engineers. However, SMEs are hampered in their ability to attract and keep qualified workers. However, it should be noted that the authors considered the relative disadvantages of SMEs in the 1980s taking into account just technological innovation. We would argue that lack of skilled workers is not so critical to the extent that firms are engaged in non-technological innovation, for which the need for specific knowledge may be significantly reduced. Moreover, cooperation between SMEs and universities and research centres has gained impetus, which diminishes the need for qualified

[22] For the overview of the barriers approach to innovation, see Hadjimanolis (2003).
[23] Not all small businesses are growth-oriented. On the contrary, the literature on SME growth suggests that, in most cases, the strategic objective of small firms is survival, rather than growth (Nooteboom, 1994; Holmes and Zimmer, 1994; McMahon and Stanger, 1995). Therefore, a dynamic and entrepreneurial management is imminent to small firms that are strategically focused on growth and, consequently, innovation. In that sense, this argument is similar to that of Penrose (1959), who explicitly notes that the focus of her analysis is on growing firms, whereas non-growing, stagnating firms are outside of the scope of her theory of the firm.

engineers and scientists working within SMEs. Yet, we would argue that building absorptive capacity is influenced by in-house expertise, thus the role of qualified workers remains relevant in the context of SMEs. In addition, SMEs could be more constrained in employing and accessing marketing experts (Freel, 1999), rather than facing constraints regarding technical expertise.

- **External communication**: Rothwell and Zegveld (1982) suggest that SMEs face difficulties in gathering information about technological advances, public policy measures, changes in markets etc. This limitation is associated with the previously noted constraints with respect to qualified engineers, scientists and other specialists, and their role in exploring external sources of information and knowledge in regard to technological advances as well as constraints arising from the lack of expertise in marketing, necessary for searching and identifying market needs. This information gap hampers SMEs in discovering new opportunities and forces them to seek new ideas internally.
- **Management techniques and practices**: Lack of adequate management expertise within SMEs may create problems in formulating and implementing strategic planning, which is a critical management tool in a dynamic and turbulent business environment. Besides lack of technical skills and managerial competencies, Freel (1999) also emphasizes poor marketing skills, which hampers successful innovation in SMEs.
- **Finance**: Difficulties in providing adequate financial resources for innovative activities are often identified as a barrier to innovation in SMEs, especially for high-risk projects. Moreover, small firms cannot engage in more innovative projects simultaneously, unlike large firms, which are able to diversify their portfolio and thus reduce the risk. The above points are all consistent with Penrose (1959) and the subsequent tradition of RBV; namely, that the constraint on growing firms – SMEs in particular – is their managerial and entrepreneurial resources from which arise their capabilities. Interestingly, Penrose (1959) also relates lack of finance to this constraint. After all, she argues, good entrepreneurs should be able to convince financiers to support them. If a firm lacks the entrepreneurial capability to convince financiers then that firm will probably lack the capability to convince customers.
- **Economies of scale**: Economies of scale are relevant for particular industrial sectors, such as automotive, electricity supply, consumer durable goods etc. There are a few solutions to this issue - to avoid entering these markets or to

specialize in supplying large firms with subcomponents. Economies of scale are not limited to production, but they occur in R&D as well; i.e. large firms can invest more in R&D (Hooghoudt, 2010).

- **Government regulation**: SMEs often suffer the burden of complying with various technical and social legislations, because the compliance can be time consuming, costly and requiring a particular expertise. The latter constraint is again in line with the RBV and difficulties arising from limited or otherwise inadequate managerial and entrepreneurial competences.
- **Absence of SMEs growth**: Many small firms do not grow even after many years in business. Rothwell and Zegveld (1982) review a few studies that identified potential problems causing the stagnation of small firms. One interesting finding is that some managers do not want to expand the business, because that would mean a loss of control but also of close interpersonal relations within a firm. Furthermore, lack of financial resources is also recognized as an important barrier to firm growth. Finally, expansion of the firm requires changes in management style and incumbent managers might lack the professional expertise required for the next phase in the firm life cycle. Again, this line of argument is consistent with Penrose's (1959) seminal work on the growth of firms and a subsequent theorizing in the RBV framework.

Given the above overview, advantages of SMEs are mainly behavioural (e.g. internal communication; dynamic management), while disadvantages are material or resource-related, particularly constraints in relation to financial (e.g. lack of internal financial funds for innovation, credit constraints) and human resources (e.g. lack of management and entrepreneurial competences, issues in employing and retaining skilled workers, lack of marketing expertise). Furthermore, difficulties in compliance with government regulation are also associated with the lack of financial and human capital. Finally, absence of growth of SMEs is an outcome of their weaknesses, again, mostly related to lack of financial and human resources.

When reviewing strengths and weakness of SMEs in the innovation process and diffusion of innovation, Nooteboom (1994) begins by identifying three core characteristics of small firms, and then formulates derived characteristics, which can be the source of either strengths or weakness in SME innovation (see Figure 2.1 for an illustration of Nooteboom's approach).

The author ascertains three core characteristics in the functioning of small firms:[24]

a) *Small scale* (in production, management and marketing). Small scale is self-explanatory; small firms are characterized by low volumes of production. Small scale of production also results in a small scale in distribution and marketing.
b) *Independence* (different goals and motivation of entrepreneurs relative to managers). Independence refers to autonomy from the goals and conducts dictated by the capital market. Larger firms are characterized by a separation of ownership and management. The main objective of managers is short-term profit maximization so that dividends can be paid to shareholders. If the managers do not pursue profit-maximization, they can be replaced.[25] Furthermore, we already mentioned that managers are often more risk-loving than entrepreneurs. On the other side, in small firms, ownership and management is often concentrated in one person, avoiding the separation. Further, entrepreneurs start their business either by borrowing financial capital from the banks, or by utilizing own resources. In either case, profit maximization might not be the goal or, at least, not the main objective of the entrepreneur. Nooteboom (1994) observes that some small business owners are not entrepreneurial, i.e. innovative and do not pursue firm growth. They rather want to keep the firm small and thus follow a traditional way of business conduct (craftsmanship).

[24] Nooteboom (1994) uses the terms small firms and SMEs interchangeably.
[25] Agency theory, in contrast, posits that managers attempt to maximize their utility function comprising job security, power, status, dominance, prestige and professional excellence (Williamson, 1963, 1964). Managerial opportunism, according to agency theory, can be prevented through several control mechanisms, such as the functioning of capital market (the reduction in the price of shares of less profitable firms results in a decrease in the market value, which, in turn, increases the probability of takeover) (Hoskisson et al., 2002). Another mechanism for aligning managers' objectives with those of shareholders is via the activism of institutional shareholders (for instance, pension funds and insurance companies). In modern companies, institutional shareholders emerged as the most important element in corporate governance (Hansen and Hill, 1991). Through their voice, institutional shareholders can impose their own short-term objectives onto industrial managers (Hoskisson et al., 2002).

Figure 2.1. Core and derived characteristics of SMEs, their advantages and weaknesses

DERIVED CHARACTERISTICS	*STRENGTHS*
Intertwined ownership and management	→ Motivated management/commitment
Integration of tasks in worker's variation and improvisation	→ Motivated labour
Few hierarchical levels; short communication lines	→ No bureaucracy; internal flexibility
Few and simple procedures; personal, direct, oral internal communication	→ Low costs and little distortion of internal communication
Personal and close relations with customers	→ Capacity for customization
Craftsmanship	→ Unique or scarce competencies
Tacitness of knowledge	→ Appropriability
Idiosyncratic perception	→ Originality of initiatives

Core characteristics

- Small scale
- Personality
- Independence

Core strategies

- Innovation through new products
- Niche markets
- External networks
- Independence

Weaknesses	
Idiosyncratic perception	→ Unopposed misapprehensions
"Tacit knowledge"	→ Limited absorptive capacity
Craftsmanship	→ Technical myopia
Few products and markets	→ Little spread of risk, limited synergy
Small volume of production	→ Diseconomies of small scale
No staff functionaries	→ Lack of functional expertise
Lack of managerial time	→ Ad hoc management
Much authority and many functions in one person	→ Vulnerability to discontinuity of management and staff
Few layers of hierarchy	→ Limited career opportunities
Low level of abstraction	→ Lack of information
Product or technique orientation	→ Errors in marketing and strategy
Possible Lack of finance	→ Lack of financial resources for growth

Source: Nooteboom (1994, p. 334).

c) *Personality* (personal characteristics and traits of the entrepreneur). The third core characteristic of small firms, besides small scale and independence, is personality. Personality refers to the overlapping of personal and professional life and work of the entrepreneur. For instance, she might have an office at home, her family could be involved in business, her objective could be to run a small business without a tendency to grow etc.

Based on the core characteristics of small business, Nooteboom (1994) identifies the derived characteristics of SMEs, which can be either advantages or disadvantages (see Figure 2.1). However, three derived characteristics can yield both strengths and weaknesses. Craftsmanship can lead to the development of competitive advantage in human capital (i.e. unique competencies), but can also result in the lack of attention to financial and commercial aspects of business operation (technical myopia). Tacit knowledge can be difficult to imitate or adopt (an appropriability issue).[26] However, a lack of formal education or skills and training might adversely affect small businesses with respect to acquiring, developing and adopting new knowledge (i.e. limit their absorptive capacity). Finally, idiosyncratic perception might create an organizational culture which promotes initiative and creativity.[27] On the other side, it might also lead to unopposed misapprehensions.

We would argue that, similar to Rothwell and Zegveld (1982), strengths and weaknesses identified by Nooteboom (1994) can be grouped into resources and behavioural characteristics. Resources would include: lack of finance; limited capacity for absorption of new knowledge (absorptive capacity); and lack of functional expertise. Behavioural characteristics refer to staff and management motivation; internal communication; internal flexibility; tacitness of knowledge (learning by doing); and unopposed misapprehensions associated with the peculiarities of entrepreneurial perception, initiative and creativity (Rothwell, 1989).

Further, Nooteboom (1994) suggests that SMEs can adopt three core strategies for innovation: new products; niche markets with differentiated goods; and external networks. The first strategy refers to radical innovation, and Nooteboom (1994) argues that only 10-20 per cent of SMEs carry out radical innovation. Furthermore, new products and niche markets offset the weakness of small scale, whereas the third strategy, networking could offset the lack of absorptive capacity within SMEs; because, through networking, small firms can acquire new knowledge. External networking is

[26] Appropriability of innovations is associated with the mechanisms of protecting innovation from imitation, which, in turn, is related to the possibility of reaping benefits from innovation (Breschi et al., 2000). High appropriability conditions indicate the existence of mechanisms for protecting innovations, whereas low appropriability is characterized by widespread spillovers arising from the difficulties in successfully protecting innovation (Breschi et al., 2000).

[27] Openness to new ideas, initiative and creativity are especially important in the first phase of the innovation process, idea generation. The innovation process will be discussed in the following section.

important for SMEs, as it can compensate the lack of absorptive capacity. However, the relation between radical innovation and firm size is ambiguous. Economic theory posits that small firms are more likely to introduce radical innovation (Sood and Tellis, 2005), and this hypothesis is substantiated by the theory of inertia (Hannan and Freeman, 1984; Cohen and Levin, 1989). [28] Namely, large firms are burdened with a complex organizational structure, organizational routines and bureaucratic inertia. Employees with a potentially successful innovation usually have to exert significant effort to overcome bureaucratic resistance. As a result, large firms are prone to slow reaction to radical product innovations.[29] Ettlie et al. (1984) found that centralization of decision making is a necessary condition for the introduction of radical innovation. In addition, individual innovators might have less incentive to introduce radical innovations in large firms, if they cannot reap the benefits of their efforts (Cohen, 1995). For instance, while moving and presenting their innovative efforts through layers of administration, their innovative ideas could be diluted (Chandy and Tellis, 2000). These impediments can seriously discourage individual innovators within large firms, who, faced with bureaucratic inertia and resistance, might decide to commercialize their radical innovation by starting their own enterprise.

In contrast, innovative activities in large firms, unlike in small firms, are not hampered by limited financial and human resources (Chandy and Tellis, 2000). This advantage over small firms would suggest that large firms should introduce radical innovation to a larger extent than small firms. Even in the case when radical innovation fails to commercialize, large firms with their enormous financial and human resources, are better equipped to neutralize the failure. In addition, Cohen and Levin (1989) and Freel (2000) posit that, due to capital market imperfections, large firms are more likely to obtain external funding than small firms. Other advantages of performing radical innovation in large firms are their ability to exhibit economics of scale in R&D and to spread risks across a number of innovative activities (Ali, 1994).

[28] Another theory explaining why small firms might be more innovative in respect to radical innovation is the willingness to cannibalize specialized investment, i.e. investment in current, old technology, that would be destroyed or rendered obsolete when new technology emerges (Chandy and Tellis, 1998). As large firms are more likely to incur larger specialized investment, due to their large pool of financial and human resources, they are less willing to adopt radical, new technologies, which would replace old technology.

[29] Ettlie et al. (1984) found that centralization of decision making is a necessary condition for the introduction of radical innovation.

Therefore, as theory posits ambiguous hypotheses in relation to firm size and radical innovation, empirical evidence could contribute to the on-going debate on what type of firms introduces radical innovations (Chandy and Tellis, 2000). For instance, Dewar and Dutton (1986) found that large firms are more likely to adopt radical innovation than are small firms in the footwear industry. Ettlie and Rubenstein (1987) found no relationship between firm size and radical innovation adoption in firms with less than 1,000 employees. Conversely, they found a positive relationship in firms having between 1,200 and 11,000 employees, whereas very large firms with more than 45,000 employees are unlikely to adopt radical innovation. In his review of empirical studies in the last fifty years, Cohen (2010) notes that empirical findings mostly suggest that large firms are more likely to introduce incremental innovation, while small firms pursue radical innovation to a larger extent. Moreover, Oke et al. (2007) conclude that small firms are more inclined towards radical innovation, because of their ability to adjust to changes necessary for generating radical innovation.

Other authors suggest a non-linear relationship between firm size and radical innovation. For instance, Ettlie and Rubenstein (1987), as noted above, found a bell-shaped relationship, whereby medium-sized firms are most likely to adopt radical innovation, because, unlike large firms, they are not prone to bureaucratic inertia, and, on the other side, their innovative capacity is larger than in small firms. In contrast, Pavitt (1990) suggests a U-shaped relationship, arguing that medium-sized firms are least engaged in radical innovation, as this category of firms exhibit weaknesses in innovation activities pertinent to both large and small firms, but without incorporating their strengths.

Hooghoudt (2010) identified additional strengths and weaknesses of SMEs in innovation. He argues that non-formalized innovation (i.e. informal R&D) is a distinct disadvantage. However, SMEs do not establish formal R&D departments, because of lack of financial resources. Therefore, this is not a distinct disadvantage, because it is embedded in the lack of resources. Furthermore, he argues that SMEs are more likely to introduce radical innovation, and this is characterized as their advantage. First, this is an outcome of SMEs advantages, not a distinct advantage. Second, as we have seen, there is mixed evidence on SMEs’ proclivity towards radical innovation. Nooteboom (1994), for instance, argues that only a small percent of SMEs carry out radical innovation. Further, Hooghoudt (2010) suggest that innovation is the long-term goal of SMEs, while large firms pursue short-term profit-maximization. However, not all SMEs are innovative. Innovation might be the main objective but only for entrepreneurial, i.e. innovative, SMEs or for SMEs that adopt an innovation orientation.[30] Further, the author argues that pursuing innovation as a long-term goal is derived from another SME advantage, and that is intertwined ownership and management. However, Nooteboom (1994) argues that this is a derived characteristic of SMEs which can lead to both strengths (motivated and committed management) and weaknesses (vulnerability to discontinuity of management and employees). We summarized the advantages and disadvantages of SMEs in innovation in Table 2.2 below.

Table 2.2. Advantages and disadvantages of SMEs and large firms in innovation

Large firms		**Small firms**		**Reference**
Advantages	***Disadvantages***	***Advantages***	***Disadvantages***	
	High bureaucracy	Low bureaucracy (rapid and effective internal communication, shorter decision chains, i.e. faster decision making)		Vossen (1998); Hooghoudt (2010); Rothwell and Zegveld (1982); Nooteboom (1994)
	Sluggish response to market dynamism	Agile response to market dynamism		Vossen (1998); Hooghoudt (2010)
Economies of scale in production, distribution and R&D			Diseconomies of scale in production, distribution and R&D	Hooghoudt (2010); Rothwell and Zegveld (1982); Nooteboom (1994)
Large resource base (absorptive capacity)			Small resource base	Vossen (1998); Hooghoudt (2010); Rothwell and Zegveld (1982); Nooteboom (1994)
Diverse resources			Narrow resources	Hooghoudt (2010)

[30] The goal of innovation orientation is innovation. Siguaw et al., 2006 (p. 560) define innovation orientation as: 'A multidimensional knowledge structure composed of a learning philosophy, strategic direction, and transfunctional beliefs that, in turn, guide and direct all organizational strategies and actions, including those embedded in the formal and informal systems, behaviors, competencies, and processes of the firm to promote innovative thinking and facilitate successful development, evolution, and execution of innovations'.

	Incremental innovation	Radical innovation		Hooghoudt (2010)
	Ownership-management separation	Ownership-management consolidation		Hooghoudt (2010); Nooteboom (1994)
	Profit-maximization as a goal	Innovation as a goal		Hooghoudt (2010)
	Closeness (low employees' fluctuation)	Openness (high employees' fluctuation)		Hooghoudt (2010)
Formal management skills		Motivated, committed and entrepreneurial management	Lack of adequate management techniques and practices	Vossen (1998); Rothwell and Zegveld (1982); Nooteboom (1994)
Diversification of risk		Risk taking	Little spread of risk and limited synergy	Vossen (1998); Nooteboom (1994)
		Tacitness of knowledge (learning by doing) and consequent appropriability		Nooteboom (1994); Vossen (1998);
Skilled workers		Motivated labour	Lack of functional expertise	Rothwell and Zegveld (1982); Vossen (1998); Nooteboom (1994)
		Marketing; capacity for customization		Rothwell and Zegveld (1982); Nooteboom (1994); Vossen (1998)
External communication, i.e. networking	Low cooperation	High cooperation		Rothwell and Zegveld (1982); Vossen (1998); Hooghoudt (2010)

Source: Adopted from Vossen (1998, p. 90) and Hooghoudt (2010, p. 16).

As both large and small firms have distinct strengths and weaknesses regarding innovation activities, scholars have attempted to provide empirical evidence on the relationship between firm size and innovative since Schumpeter advanced his two innovation models - Mark I and Mark II. However, the evidence is ambiguous (Nooteboom, 1994; Hooghoudt, 2010; Damanpour, 1992) and can be categorized into three groups: a positive relationship argued by ”classicists”; a negative relationship by “modernists”; and no relationship suggested by “nihilists” (Hooghoudt, 2010). However, Damanpour and Schneider (2006) observe that while single studies yield ambiguous results, aggregate findings from meta-analysis suggest a positive relationship between firm size and innovation (e.g. Damanpour 1992; Camisón-Zornoza et al., 2007).

There are two potential explanations for the inconsistency of the empirical findings. The first argument is associated with the methodological issues of measuring both firm size and innovation. Researchers recognize four measures of firm size: a) financial resources; b) physical capacity; c) number of employees; and d) the volume of tangible and intangible assets and outputs (Damanpour, 1992; Hooghoudt, 2010). Damanpour (1992) notes that different measures of firm size could contribute to ambiguity in empirical evidence on the link between firm size and innovation.

Further, defining and measuring innovation is also diverse. As early as 1962, Kuznets noted that ‘the greatest obstacle to understanding the economic role of technological development was a clear inability of scholars to measure it’ (Acs and Audretsch, 2005, p.7). To illustrate this claim, the authors review the state of the theory through the lenses of the introduction of different measures of innovation. Three categories of measures of technological change are indentified, depending on the stage of the innovation process:[31]

- A measure of the inputs in the innovation process (e.g. R&D expenditure);
- An intermediate output (e.g. number of patents);
- Direct measures of the output of the innovation process, including product and process innovation and the share of innovative sales in total sales.

The first measures of inputs were introduced in the literature in the 1950s and early 1960s, and the most frequently used was investment in R&D. The main criticism of this measure is that the level of innovation input does not reflect the level of innovation output proportionately, i.e. Innovation output cannot be appropriately measured by innovation input such as investment in R&D. Furthermore, this measure only captures formal R&D activities reported in financial statements and conducted in R&D departments. Informal R&D, particularly associated with the innovative activities

[31] As often in the literature, the authors use terms innovation and technological change interchangeably.

in SMEs, is absent. Moreover, in UK manufacturing firms, spending on technical design is much larger than spending on R&D but is not recorded. In this context, Livesey and Moultrie (2009), in their survey of 358 UK firms, found that only 8 per cent of surveyed firms report to claim R&D tax credits, while more than one third of firms report spending on technical design. Technical design overlaps greatly with R&D but is neither conceptually distinct not (therefore) measured. In their 2010 report, the Design Council identifies design as a 'coping stone of an innovation system' (p. 5), whereby the recent estimates of UK firms' spending on design exceed spending on R&D by five times.

In the mid-1960s, scholars were able to use a new measure of innovative activities, the number of patents. Although the number of inventions patented is superior to measuring innovative input, it was mistakenly interpreted as the measure of innovation output. However, not every invention is successfully commercialized. Therefore, it is appropriate to consider the number of patents as an intermediate output measure. Moreover, many inventions are not patented, even though they lead to successful innovation. In sum, the number of patents is a better measure of innovative activities than the measures of innovation input, but still it does not fully capture innovation output.

The traditional knowledge about technological change and innovation was based on insight from research employing these imperfect measures of the innovation process. Only when direct measures of innovation output (e.g. number of innovations; share of innovative sales in total sales) were introduced in the 1970s could the traditional approach be challenged. Schumpeter hypothesized that market power exercised by large firms is a necessary condition for bearing the risk and uncertainty inherent to innovation. Yet many subsequent empirical studies on balance indicate that innovative activities are not only conducted in large firms with market power, but also in small firms.

Moreover, empirical analysis based on the direct measures of innovation output has unambiguously rejected the conventional wisdom and indicated that small firms were also innovative. Earlier studies, employing the measure of innovation input (e.g. R&D expenditures), support the Schumpeterian hypothesis that firm size and innovation are positively related (i.e. large firms are more innovative than small). However, when patents were introduced into empirical studies, evidence for the Schumpeterian hypothesis was less overwhelming. Indeed, some empirical evidence even indicated that the propensity to patent is higher in SMEs than in large firms (Bound et al., 1984). With regard to a direct measure of innovation output, studies by Acs and Audretsch (1988, 1991) and Pavitt el al. (1987) report that small firms engage in a higher number of innovations relative to their innovation input, i.e. R&D expenditures, as a result of a decreasing returns to R&D relative to firm size. Vossen (1998) reviews several complementary arguments in favour of small firms outperforming large firms in producing innovation output: small firms are more cost efficient than large firms (Vossen, 1996); small firms are more efficient in utilizing knowledge spillovers from public research institutes and universities (Acs et al., 1994); and small firms are more efficient in employing and retaining engineers with higher ability and skills (Zenger, 1994). Therefore, the lack of standardized measures of innovation and firm size could result in mixed evidence on the effect of firm size on innovation (Damanpour, 1992). Cohen (2010) observes that this might be the most serious limitation in empirical analysis of the size- innovation relationship.

In conclusion, advantages of SMEs in innovation are associated with their behavioural characteristics (flexibility, motivation). On the other side, large firms have a large and diverse resource base as their main advantage (Nooteboom, 1994; Vossen, 1998; Andreassi, 2003). However, ambiguous empirical evidence and methodological issues pertaining to analysis of the firm size-innovation relationship do not provide a consistent answer. Reasons for the ambiguity are manifold. First, both innovation and firm size are multidimensional and heterogeneous concepts and these features hamper their conceptualization and operationalization (Damanpour, 1992; Hooghoudt, 2010). Second, Damanpour (1992) argues that exclusion of moderating factors could produce inconclusive evidence on the effect of firm size on innovation. Third, the issue of endogeneity of firm size is recognized as a relevant problem, which should be taken into account in reviewing empirical evidence and conducting empirical analysis (Symeonidis, 1996). Fourth, most studies focus on the effect of firm size on product innovation. It would be useful to shed light on the correlation between non-technological innovations and firm size.

Finally, Symeonidis (1996) argues that inconclusive findings of empirical studies indicate that the size-innovation relationship should be explored within specific industries, taking into consideration particular factors that are affecting innovative activities in a specific sector. In this way, researchers would not attempt to find a general pattern, because maybe it does not exist, but rather focus on factors fostering and hampering innovation at industry level. This reinforces Nooteboom's (1994) observation that both Schumpeter Mark I and Mark II are valid, and that a general conclusion is that both large and small firms are innovative. But this synthesis requires an additional explanation. Large firms are more likely to be innovative in some industries and at particular stages of the innovation process (e.g. following Nooteboom, 1994, large firms engage in invention to a larger extent than small firms, but small firms might have advantages in the implementation of invention), while small firms are more innovative in other sectors. We would add types of innovation as an important moderator. Therefore, from this perspective, innovation is industry-specific, but also innovation type-specific and contingent on the phase of the innovation process. Finally, empirical studies should encompass both quantitative and qualitative research methods, while employing both primary and secondary sources of data.

Next, we will discuss the stages of innovation process and a conceptual framework for managing innovation processes in SMEs.

2.4 The innovation process in SMEs

It is widely accepted that firm-level innovation is not a single event, but a process consisting of three overlapping stages: a) idea generation; b) problem solving; and c) implementation with potential diffusion. Idea generation is a result of design or technical proposal; problem solving leads to original technical solutions (i.e. invention); implementation is a commercialization of a new idea (i.e. innovation) and diffusion is a widespread use of innovation (Utterback, 1971). The innovation process, defined in this manner, encompasses invention, innovation and imitation. However, as Bolinao (2009) observes, diffusion is not a part of the innovation process, because it occurs in the firm's environment.[32]

[32] The *Oslo Manual* (OECD, 2005) defines diffusion of innovation as the spread of innovation across firms, industries and countries. The *Manual* emphasizes that, without diffusion, innovation would not have economic impact.

Nooteboom (1994) presents the innovation process in five stages: invention; development; tooling/production; introduction to practice/market; and diffusion. In the first stage, large firms have more advantages than do small firms, especially in fundamental research, because they can invest more in R&D. In the phase of developing inventions, small firms are more efficient in decision-making, due to flat organizational structure, less bureaucracy and more informal and hence faster communication. In the production and market phase, large firms can utilize economies of scale and scope, not just in production but also in marketing if the market is characterized by a large number of consumers.[33] However, small firms are better off in niche markets, with a small number of consumers who are in a close proximity to the firm. Finally, Nooteboom (1994) observes that small firms should position themselves in niche markets with differentiated products or could introduce a new product if close relations with customers are relevant for product development.

Bolinao (2009) developed a conceptual framework for analysing the innovation process in SMEs, with respect to the management of technological innovation.[34] He augmented a conceptual framework formalized by Atherton and Hannon (2000), which consists of four distinct phases:[35]

a) **Building blocks of innovation**:

- *Strategy for innovation* refers to the firm's ability to develop and improve its technology, to imitate new technologies, to invest in R&D and manage it;
- *Awareness of the external environment:* The firm's operation and performance is affected by political, social, technological and economic external factors (Utterback, 1971);
- *Innovative capability (i.e. absorptive capability)*: Absorptive capacity is the firm's ability to absorb and utilize external knowledge (Cohen and Levinthal, 1990).

b) **Innovation implementation**, defined as a process of appropriate use of the adopted innovation by employees. Therefore, human resources are critical in the process of diffusion of innovation throughout the organization. Failure in

[33] Economies of scale in marketing refer to use of distribution channels, advertising, promotions etc.
[34] Once more, we would like to stress that discussion on innovation defined in a broad manner encompassing both technological and non-technological innovation cannot be found in the innovation literature, regardless of the discipline (economics, management studies etc.). Our general observation is that technological innovations are more considered in the economics of innovation, whereas organizational innovation is in focus of management science.
[35]Innovation in this framework is defined as a management process, and the framework is developed in an attempt to evaluate innovative capacities of SMEs.

innovation implementation, not in innovation itself, is often a cause of sub-optimal benefits of innovation (Klein and Sorra, 1996).

c) **Commercialization of innovation** defined as turning innovation into a marketable product or service.[36] This stage requires utilization of the following factors (Rosa and Rose, 2007):

- Transfer and creation of knowledge (technical knowledge; knowledge of market conditions and of legislation);
- Skills and human resources (intellectual rights management, marketing);
- Financial and physical resources;
- Organizational management which incorporates identification of customers and suppliers; marketing strategy; selection of strategy for technical acquisition; and identification of obstacles to commercialization;

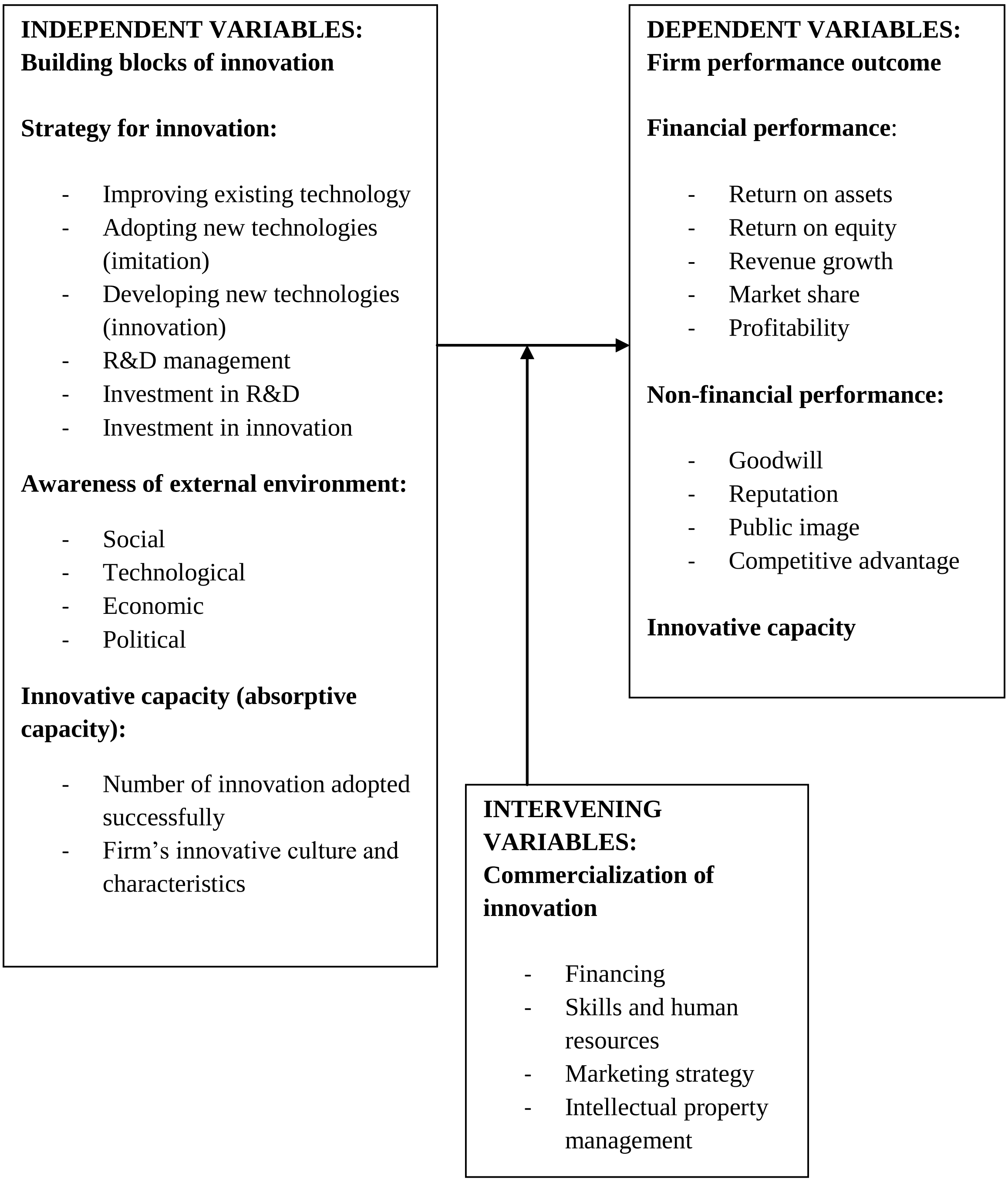
d) **Outcomes of firm performance**:

- Financial performance (return on assets, return on equity, revenue growth, market share, profitability);
- Non-financial performance (reputation, goodwill, public image, competitive advantage);
- Innovative capacity.

In this conceptual framework, Bolinao (2009) stresses the importance of the commercialization of the innovation phase. In the framework, commercialization of innovation plays a mediating role between generation and implementation of innovation as independent variables and firm performance measures as dependent variables (see Figure 2.2). Furthermore, he discusses the factors hampering successful commercialization. Two major barriers are the lack of financial resources and the lack of personnel specialized in promoting new products or services. Another, less pronounced obstacle is associated with rapid product obsolescence insofar as SMEs cannot promptly react to changed market demand.

[36] We found this framework to be somewhat puzzling. First, Utterback (1971) defines implementation as a phase in innovation process which incorporates commercialization of innovation. However, Atherton and Hannon (2000) separate innovation implementation from its commercialization. Furthermore, absorptive capacity is regarded as an integrative element of innovation (i.e. independent variable) but is also suggested as a measure of firm performance.

Figure 2.2. Conceptual framework for the management of technological innovation



Source: Bolinao (2009, p. 74).

Intervening variables related to commercialization of innovation are those factors that serve as mediators between a dependent variable (firm performance) and corresponding independent variables (the building blocks of innovation). Therefore, intervening variables capture conditions for effective commercialization of innovation.

With respect to SME innovation, two barriers to effective commercialization are the lack of financial resources and of human resources, i.e. specialized personnel for promotion and sale of innovative products (marketing team).

Coccia (2006) reviewed several taxonomies of firms based on their innovative activities (see also de Jong and Marsili, 2006). The ambiguity of classifications hinders both the theoretical advances in the various disciplines and comparison of empirical studies on innovation. Pavitt's sector taxonomy (1984) divides firms into four groups depending on the way firms generate innovation:

- *Supplier-dominated firms* which generate innovation through purchase of equipment and machinery;
- *Specialized suppliers* of capital goods and equipment;
- *Science –based firms* which generate innovation through in-house R&D departments;
- *Scale- intensive firms*, i.e. mass production companies.

In a later version, due to development of innovation technology, Pavitt replaced specialized suppliers with a new category, information-intensive firms (Tidd et al., 2001). As de Jong and Marsili (2006) note, Pavitt's taxonomy is developed from a sample that is skewed towards large firms. Small firms in the sample are mainly categorized into two groups: supplier-dominated and specialized suppliers (de Jong and Marsili, 2006). The lack of taxonomies of innovative small firms has motivated de Jong and Marsili (2006) to build a taxonomy of small and micro Dutch firms.[37] They identify four clusters of small firms:

- *Supplier-dominated firms*: Firms with a low innovative capacity. Firms establish and maintain a large network of cooperative partners, among which suppliers are the most important external source of knowledge.
- *Specialized suppliers*: Firms with a rather high innovative capacity. Customers are by far the most important source of innovation and formal cooperation between them is frequent. However, their degree of external knowledge exploitation and openness of the innovation process are generally low, as these

[37] Small firms in their study are defined as having less than 100 employees. Furthermore, the sample is skewed toward micro firms (firms with fewer than 10 employees).

SMEs are less likely to cooperate with other partners, such as suppliers, universities and research centres.

- *Science-based firms*: Firms with a high level of innovative capacity. These firms display the highest level of openness of innovation activities, frequently cooperating with a large number of partners, mainly with universities and research institutions, but also heavily involving customers in their innovative activities.
- *Resource- intensive firms*: Firms in this cluster are focused on developing in-house absorptive and innovative capacities by investing the largest proportion of financial and time resources to innovation compared to firms in other categories. However, these firms mainly maintain a low degree of networking relationships.

This taxonomy indicates a diversity and heterogeneity of SMEs with respect to their level of innovativeness as well as the intensity of use of various external sources of knowledge. Moreover, the taxonomy provides a broader categorization of small and micro firms than does Pavitt's taxonomy.

It is of interest to mention the taxonomy of small firms by Rizzoni (1991), who developed a taxonomy based on the theoretical and empirical advances in several prominent studies (e.g. Freeman, 1982; Pavitt, 1984). Her taxonomy is of importance because a large number of criteria are used in identifying the six following types of small firms:[38]

- ***'Static' small firms***: The main feature of firms belonging to this category is an absence of innovation activities, other than the purchase of machinery and equipment. These non-innovative small firms are family businesses established and organized to foster the social status of the owner-entrepreneur. Therefore, the firm's objective is survival, not growth.
- ***'Traditional' small firms***: These firms are very similar to Pavitt's (1984) category of supplier-dominated firms. Rizzoni (1991) notes that, typically, furniture, clothing and footwear industries are populated with traditional small firms. These firms engage in incremental innovation by imitating adopting

[38] The author utilized six criteria in categorizing small firms: the key determinant of the firm's survival and growth; the industry to which the firm belongs; the level of technological competences; types of innovations prevailing in the firms (radical versus incremental innovations); innovative strategy; corporate strategy; organizational structure (managerial and entrepreneurial skills); and barriers to innovation.

technological changes developed elsewhere. Traditional small firms are similar to static small firms, insofar as the firm's objective is short-run survival, rather than growth.

- ***'Dominated' small firms***: Firms in this category are suppliers to large firms, which implies that the only way these firms enter the market is through sub-contracting. Innovation activities are limited to user innovations, i.e. the external stimuli from the large firm in the supply chain. Firms' objectives are short-run survival and achieving a higher level of autonomy.
- ***'Imitative' small firms***: These small firms tend to innovate through imitation and by exploring and exploiting external sources of knowledge, mainly from large firms operating in the same sector. Innovations introduced in imitative small firms are complementary to innovation processes undertaken in large firms. Unlike firms belonging to the aforementioned categories, imitative small firms have medium-run growth objectives.
- ***'Technology-based' small firms***: This group of small firms undertakes in-house R&D activities, thus enhancing internal innovative capacities, but also are actively involved in cooperation for innovation with external partners. Technology-based small firms engage in significant product innovations, described as a consequence of significant technological change, but that cannot be categorized as either incremental or radical innovations. Their growth objective is focused on the development of distinctive competence and networking with other firms.
- ***'New-Technology-based' small firms***: Finally, firms belonging to this group are innovative firms at the frontier of technological development. They mainly introduce radical innovations, through internal R&D activities as well as through strong linkages with external partners, particularly research centres and universities. Growth is recognized as the firms' strategic goal, accomplished through technological leadership.

2.5 Conclusions

Given the importance of innovation to SME growth and competitiveness, this chapter elaborates on how SMEs innovate and indentifies their strengths and weaknesses relative to large firms. Before focusing our attention on innovative activities in SMEs, this heterogeneous category of firms should be defined and distinguished from their large counterparts. Although in the past research, most cross-country studies adopted the definition of SMEs prevailing within their national boundaries, the European Commission, with its EC Recommendation 2003/361, provided a uniform definition of SMEs across the European Union.

Regarding the innovation process in SMEs, the literature mainly emphasizes that the major obstacles to innovation in SMEs are related to limited human and financial resources, whereas the main advantages of SME innovation are associated with behavioural characteristics of small firms, such as a simple organizational structure, agile response to market demand, openness to cooperation with external partners etc. Therefore, in analysing and identifying determinants of innovation in SMEs, the resource-based view (RBV) of the firm seems to provide particularly useful insights into barriers to innovation within SMEs.

The review of the determinants of innovation given in Section 1.4.2 revealed a rather eclectic approach to modelling and analysing firms' innovative activities. To bring together the building blocks of innovation and their impact of SME firms' performance, Bolinao (2009) proposed a conceptual framework in estimating the effects of the innovation process (innovation inputs and outputs) on firms' financial and non-financial performance indicators. Finally, since Pavitt's (1984) taxonomy of innovating firms gave an impetus to analysing sectoral characteristics of firms regarding their innovative behaviour, several authors focused on examining taxonomies of innovative SMEs in relation to technological innovation, for instance, Rizzoni (1991) for manufacturing SMEs and de Jong and Marsili (2006) for Dutch SMEs.

As this chapter serves as a bridging chapter between Chapter I on the theoretical underpinnings of innovation and Chapter III on innovation related policies and evaluation methodology, its main role is to briefly elaborate on the general context of SME innovation, rather than to identify gaps in the literature and the knowledge contributions of the thesis. However, in the following chapter, the focus is on the particular contribution of this thesis; namely, on public intervention in the domain of innovation and on quantitative evaluation methodologies.

The new realities of a global, knowledge-based economy in the 21st century require a new approach to national economic policy, one that is based more on smart support for the building blocks of innovation and entrepreneurship and less on capital accumulation, budget surpluses, or social spending.

(Atkinson and Audretsch, 2010, p.165)

CHAPTER III

INNOVATION POLICY - EVALUATION METHODOLOGY AND EMPIRICAL LITERATURE REVIEW

3.1 Introduction

This chapter describes the rationales for government involvement in the domain of innovation. It provides an overview of evaluation methodology applied in assessing the effectiveness of innovation policy, and reviews empirical evidence with respect to additionality effects of public support. Moreover, this chapter identifies knowledge gaps and contributions of the thesis from the perspective of evaluation of innovation related policies.

In the last few decades, the evolution of contemporary policies for fostering and stimulating innovation has resulted in an increasingly complex mix of policies and programmes. For instance, the INNO-policy Trendchart database of innovation policy measures in Europe has reached more than 1,000 measures in 2009, compared to less than 200 in 1995 (Tsipouiri et al., 2008; Tsipouiri et al., 2009). The main reason for this increased complexity is the co-existence of two policy rationales; alongside the neoclassical market-failure rationale, an evolutionary-systemic rationale has emerged as a complementary basis for justifying public intervention in the domain of innovation. Whilst the market-failure rationale emphasizes the importance of investing in science and technology, the evolutionary-systemic rationale focuses on the interaction of organizations and institutions within systems of innovation. A direct consequence of the widening of policy rationales is the introduction and implementation of a large number of policy instruments. Besides traditional, hard innovation policy instruments, stemming from the neoclassical, market-failure approach, a set of soft and non-coercive policy instruments has been implemented, reflecting the proliferation of evolutionary, systemic policies. Therefore, the innovation policy domain is characterized by the existence of complementary policy rationales, accompanied by a complementary mix of policy instruments. To reflect the widening of policy rationales and a proliferation of various policy instruments, the concept of the innovation 'policy mix' has only recently emerged.

Among the reasons contributing to the bewildering multiplicity of innovation support programmes may be the following. The variety of theories of innovation, and uncertainly about what works and what does not work, provides a changing intellectual and policy climate that favours new initiatives and changes in policy. Moreover, bearing in mind the role in public choice theory of self-interested public-sector bureaucracies (Buchanan and Tullock, 1962), both officials and politicians may have interests in new initiatives: ambitious officials like novelty, as change offers better prospects of career advancement than does routine; and political changes bring new ministers and public officials into office who are generally keen to make their name by launching new initiatives (often irrespective of how well existing policies are working). Public choice theory also points to the role of interest groups who may resist the elimination of existing programmes even as new ones are introduced. Hence, new policies and programmes do not necessarily entail the retirement of existing ones, which may be subject to inertia irrespective of their effectiveness from the perspective of public policy.

Finally, the complexity of innovation policies is further actuated by the broadening of policy domains. More specifically, implementation of innovation policies is practically conducted at different administrative levels: local; regional; national; and supra-national (European Union). The implications are that a wide range of policy measures implemented at all administrative levels are interacting with one another. Given the interaction between various innovation instruments implemented at different administrative levels but in the same geographical area, difficulties arise in evaluating individual policy measures. Therefore, the emergence of the innovation policy-mix is accompanied by the emerging need for systemic evaluation, which takes into account interactions and interdependencies of modern innovation policies. An alternative, but complementary explanation for increasing emphasis on evaluation is the proliferation of programmes with uncertain results in what is now an era of austerity. Increasing concern with value for money, together with increasing awareness of the difference between previously mainly poor practice in evaluation (OECD, 2007) and the potential of current best practice, are driving increased interest in evaluation on the part of policy makers. Scholars and evaluators of innovation policies have only recently put forth the necessity for the systemic evaluation of innovation policies (Arnold, 2004; Molas-Gallart and Davies, 2006; Flanagan et al., 2011; Magro and Wilson, 2013). For instance, following a rising awareness of the best practice in the quantitative evaluation of SME programmes, Bakhshi et al. (2013) evaluated the impact of the Creative Credits, a UK innovation voucher initiative designed to encourage the establishment of cooperative partnerships between SMEs and creative service providers, by adopting a randomized trial control (RTC) approach.

In assessing the impact of innovation policy, scholars have traditionally investigated the market-failure concepts of input and output additionality (i.e. the influence of public measures on innovation inputs and outputs respectively). With the emergence of the evolutionary-systemic failure approach, attention has been drawn to behavioural additionality, that is, to the broader impact of innovation support measures on firms' innovative behaviour (Magro and Wilson, 2013). Systemic innovation policy evaluation should encompass all three categories of additionality, to reflect interrelated effects of various policy instruments implemented at different administrative levels or the effects of the same instrument awarded at two or all three levels (regional national and EU). However, following Magro and Wilson (2013), studies integrating different additionality measures are scarce. The aim of the thesis is to fill this gap in the evaluation literature and focus on the less investigated, but equally relevant output and behavioural additionality effects.

Assessing the effectiveness of innovation related policies encompasses a broad range of evaluation methods that can be grouped into two categories - structural and non-structural (reduced-form) models (Cerulli, 2010). The main difference between these two categories of evaluation models is that the former estimate the outcome equation and the participation equation separately, whereas the latter only estimate the outcome equation. Besides briefly reviewing each model, this chapter also discusses their main advantages and disadvantages, which will be used as the basis of the review of empirical evidence on three types of additionality - input, output and behavioural.

A critical element of any evaluation exercise is a proper modelling of participation in support programmes. Namely, treatment assignment into support measures should be regarded as endogenous due to selection bias arising in the process of application and distribution of public measures. The selection bias occurs because a) firms self-select themselves into programmes, and b) the government adopts a 'picking-the-winner' strategy during the selection process (selecting those firms that are more likely to succeed with their project) (Walsten, 2000; Aerts et al., 2006; Arundel et al. 2008; Heckman, 2008; Cerulli, 2010; Grilli and Murtinu, 2011; Antonioli and Marzucchi, 2012). Our review of empirical evidence is restricted to those studies conducting after 2000 because, in that year, David et al. (2000) published their influential work on the state of the art in the evaluation of innovation related policies.

Their work, among other relevant conclusions which will be discussed later, emphasizes that most studies conducted before 2000 treated public support as exogenous. Thus, we omit those studies from our review, and focus on empirical studies undertaken after 2000, starting with Busom (2000).

Our review of empirical studies reveals mixed empirical results for input and output additionality. With respect to input additionality, this is in line with previous descriptive and meta-analyses of empirical findings (e.g. David et al., 2000; García-Quevedo, 2004; Zúñiga-Vicente et al., 2014). As there is no meta-analysis of empirical evidence on output additionality, our review provides an assessment of findings and puts forward the need for conducting meta-analysis of this type of additionality. Furthermore, as the only meta-analysis of input additionality was published in 2004 by García-Quevedo, it has become necessary that another meta-analysis be undertaken, given the large body of research that has emerged since 2004. Finally, our review of the empirical evidence provides an unambiguous conclusion of positive behavioural additionality found in the few studies recently conducted within this stream of research.

This chapter is organized as follows. Section 3.2 sets the stage for further discussion by exploring two complementary rationales for public intervention in the domain of innovation. Section 3.3 provides an overview of the evolution of innovation related policies, from science and technology policies to innovation policies. In addition, various supply-side and demand-side public measures are discussed in this section. Section 3.4 presents a theoretical framework for understanding the effects of public support measures on firms' innovation processes. A brief overview of evaluation methods, with their main advantages and disadvantages, is presented in Section 3.5. Empirical literature review, provided in Section 3.6, reveals that empirical evidence on additionality of public support is inconclusive and mixed. Section 3.7 concludes.

3.2 Economic rationale for public policy

3.2.1 Market failure rationale

The traditional or neo-classical approach to public support of technology and innovation is based on the theory of market failures. Other approaches are those of evolutionary economics and systems of innovation, which focus on system failures. System -failure and market -failure approaches are not mutually exclusive, but rather complement each other. Accordingly, public policy addressing the issues of enhancing the innovative activities should take into account both types of failures (Hauknes and Nordgren, 1999).

Market failures refer to inefficient allocation of goods and services in a market due to externalities, asymmetric information, non-competitive markets, uncertainty and risk, appropriability issues, indivisibility of knowledge generation, imperfect capital markets and missing markets for high-risk investments. From the late 1950s onwards, the market failure rationale has provided a basis for public innovation policies. The Arrow-Nelson argument (Arrow 1962*;* Nelson 1959) refers to three basic market failures to provide an optimal level of innovation (Hauknes and Nordgren, 1999):

- Uncertainty and risk which are inherent to innovation processes;
- Appropriability problems arising from the public-good character of knowledge;
- Knowledge generation is often indivisible.

Market failure results in higher social returns from R&D and innovative activities than the private rates of return. Uncertainty affects private rate of return as firms face higher risks when realizing innovation project than those incurred by society. Therefore, the future rate of return of a firms' innovation project will be discounted at a higher rate than those society applies in investment appraisal. The result is underinvestment of private R&D and innovative activities in general. Furthermore, the difference in private and social rates of return reflects the problem of partial appropriability; i.e. the innovator cannot fully appropriate the outcome of innovation because of spillover effects or positive externalities (customers and competitors will also benefit from innovation). Finally, indivisibility arises when a firm has fewer resources than needed for a particular innovative activity (see Section 1.3.5 on the resource-based view of the firm). Innovation often requires investment in specific equipment (asset specificity) which, in case of a failure, leads to high sunk costs (Schröter, 2009).

Schröter (2009) noted two additional market failures relevant for justifying innovation policy:

- ***Asymmetric information***: When one party in a transaction has more information than the other, asymmetry of information can result in moral hazard or adverse selection. In the case of innovation processes, information asymmetry can arise in the exchange of knowledge, when the seller faces the risk of disclosing information while negotiating a higher price. The process of negotiation incurs the risk of disclosing information, where the price exhibits a positive function, because the prospect of a higher price gives an incentive to the seller to disclose more information. Because of the risk, the seller will propose a higher price than the true value of knowledge resulting in an inefficient transaction. There is also a problem from the buyers' perspective. The buyer can only know the full value of information once it has been purchased. Fearful of buying a "lemon" (Akerlof, 1970), the buyer offers a lower price than the value of the information or makes no offer at all. In other words, the market for information is subject to severe information asymmetries, which – as Akerlof predicted – tend to result in reduced volumes of trade or even entirely missing markets (Akerlof, 1970).
- ***Inflexibility***: Firms might lack the ability to adapt to new technologies. Various reasons causing inflexibility can be identified, such as: lack of resources; insufficient information; high sunk costs; internal resistance to change; and incompetence.

Cerulli (2010) notes additional types of market failure other than positive externalities in production.

- ***Imperfect capital markets***: Due to asymmetric information, lenders might be prone to high rationing of funding.
- ***Missing markets for high-risk investments***: Markets for investing in highly innovative projects are not developed. This type of market failure is consistent with Akerlof's (1970) insights into the consequences of missing information.
- ***High barrier to entry and exit***: High sunk costs are an obstacle for entering or exiting a market.
- ***Market power or lack of it***: Following the Structure-Conduct-Performance (SCP) paradigm, market structure affects the R&D performance of firms.

The market failure rationale is complementary to three trends in innovation literature and practice prevalent in the 1950s and 1960s (Hauknes and Nordgren, 1999):

- The innovation process is considered to be linear and sequential (the linear models of innovation; see Section 1.4.1). In the linear model, economic actors carrying out a particular stage of the innovation process can be identified: universities would be mainly a source of basic research; private research laboratories would conduct applied research; and firms would introduce new products and processes as a result of basic and applied researches (Cowan et al., 2009). Outcomes of basic research are mainly regarded as public goods (Arrow, 1962; Nelson, 1959), consistent with the Arrow-Nelson argument on market failures. This, in turn, implies that basic research will be undersupplied due to appropriability issues. Furthermore, due to opportunistic behaviour and free-rider problems, firms frequently use protection mechanisms such as patent protection and secrecy, when introducing product and process innovations.
- Capital accumulation is regarded as the main driving force of economic growth and technological advances.
- The innovation process is technology-induced (based on the first generation of technology push innovation models). As noted above, a technology push model of innovation emphasizes the role of basic and applied research in the innovation process. The public-good character of research creates problems with respect to reaping full benefits from research (i.e. appropriability issue), which is one of the essential market failures identified in the Arrow-Nelson argument.

The policy instruments in the market-failure approach are aimed at facilitating innovative activities and at protecting the use of the outcome. The instruments are designed to either lower the costs of private R&D and innovative activities or to raise the payoff from knowledge creation. The problem of under-investment in innovative activities stemming from uncertainty, risk and asymmetric information implies direct support in the form of subsidies and/or tax relief; while the appropriability problems resulting in a positive externality suggests either direct support or the provision of intellectual property rights (patents and copyrights) (Smith, 2000).

However, the major criticism of the traditional, mainstream approach to government intervention in knowledge creation and diffusion is the absence of analysis to determine the optimal rate of R&D (Hauknes and Nordgren, 1999). Moreover, this approach does not provide guidelines either for how to identify where market failures exist or for how to determine the adequate level of public support (Smith, 2000).

Martin and Scott (2000) suggested that market failures should be identified at an industry level, rather than at the country level. Depending on the innovation mode prevailing in a particular sector and on the type of market failure identified in that sector, government should design and implement policy measures. They identified four innovation modes and instruments for each type of innovation mode (see Table 3.1).[39]

The first mode of innovation, innovating input suppliers, refers to intermediate goods producers, whose products will be further used in vertically related downstream sectors. Market failures in this mode are associated with transaction costs in the financial markets (especially SMEs and start-ups) as well as with relatively low appropriability of the returns to innovation. Suggested instruments are aimed at lowering the barriers of entry, especially for SMEs by providing capital funding. However, the government should avoid direct funding, because of the difficulties in identifying a priori sectors with potential technological advances. Martin and Scott (2000) proposed the method of bidding as an efficient way of mitigating opportunistic behaviour of private agents. The auction mechanism, authors claim, would choose the best bidder, firms that can produce the best outcome at the lowest cost.

Innovating input users belong to the second mode of innovation. These firms innovate by improving products from upstream sectors and using them for their own production. Market failures occur due to limited appropriability of knowledge and asymmetric information. Suggested measure for overcoming market failures in these sectors is to establish extension services, i.e. networks or public institutions in the form of the cooperative research associations. These institutions would be most beneficial to SMEs, because they would provide timely and trusted information on relevant technological advances and would promote the diffusion of knowledge and research.

[39] The innovation modes are not mutual exclusive, as noted by the authors.

Table 3.1. Innovation modes, sources of sectoral innovation failure, and policy measures

Main mode of innovation	Sources of sectoral innovation failure	Typical sectors	Policy instrument
Development of inputs for using industries (intermediate goods industries)	Transaction costs facing SMEs in financial markets; risk associated with standards for new technologies; limited appropriability of generic technologies	Software, equipment, instruments	Support for venture capital markets; bridging institutions to facilitate standard adoption
Application of inputs developed in supplying industries	Small firm size, large external benefits; limited appropriability	Agriculture, light industry	Low-tech bridging institutions (extension services) to facilitate technology transfer
Development of complex systems	High cost, risk, limited appropriability	Aerospace, electrical and electronics technology, telecom/computer technologies, semiconductors	R&D cooperation, subsidies; bridging institutions to facilitate development of infrastructure technology
Applications of high-science-content technology	Knowledge base originates outside commercial sector; creators may not recognize potential applications or effectively communicate new developments to potential users	Biotechnologies, chemistry, materials science, pharmaceuticals	High-tech bridging institutions to facilitate diffusion of advances in basic research

Source: Martin and Scott (2000, p. 439).

The third mode of innovation, complex systems innovation, is where large firms are involved in the generation of radical innovations. The market failure is associated with the high risk and uncertainty and high cost of introducing radical innovations.

Moreover, firms adopting this mode of innovation are inclined to be first movers, introducing new products or processes at an industry level, because imitators bear a risk of falling rapidly behind competitors. The policy instruments should promote joint research, either through direct subsidies or through designing a competition policy that allows research cooperation. We would add that protection of Intellectual Property Rights (IPRs) through, for instance, patent protection would also be a relevant policy instrument for firms who are prone to be first-movers with respect to introducing innovation. Patent protection would reduce appropriability issues and ensuing free-rider problems (i.e. opportunistic behaviour).

Finally, the fourth mode of innovation pertains to sectors with high science-content technologies. The market failures in these sectors arise because of the absence or inadequate diffusion of basic research in the academic community to the private sector. Suggested policy measures are related to establishing bridging institutions to promote research cooperation between universities and industries, such as public research institutes or university-industry research parks. Moreover, in any collaborative partnership, mutual trust is a factor upon which the sustainability and success of collaboration critically depends (Lee et al., 2010; Barge-Gil, 2010). Therefore, bridging institutions should foster trust among universities and businesses, as previously noted.

With the emergence of the innovation system approach (see Sections 1.3.3 and 1.3.4), the system-failure rationale was advanced, which is the topic of the following section.

3.2.2 Systems failure rationale

The evolutionary approach of system failures has been developed since the 1990s as a corollary of the development of evolutionary economics and of a resource-based, evolutionary theory of the firm. The main criticism of the neoclassical theory pertains to the stringent assumptions of the model of perfect competition. However, we would note that the mainstream or neoclassical approach developed the model of perfect competition as a benchmark. Then, where markets are identified as “imperfect”, there is a potential rationale for public intervention. Perfect competition is a framework of analysis, to be regarded not as a description of reality, but as an abstraction for purposes of analysis. Another criticism is related to the concepts of equilibrium and the optimality assumptions under the static analysis of perfect competition, whichare inadequate for analysing dynamic and evolutionary innovation processes. Although the neoclassical approach does allow for dynamics, this is typically achieved by way of continuous adjustment to some equilibrium, even if this equilibrium may be never achieved or is achieved only temporarily. In contrast, dynamic and evolutionary approaches might argue that there is no equilibrium but, rather, continuous change and disruption of economic relationships (in the manner of Schumpeter's "waves of creative destruction"). In this view, the processes of change cannot be captured by the neoclassical framework of equilibrium and adjustment processes, even when this framework is enlarged to include periodic (radical) structural breaks.

Therefore, innovation policy in the systems of innovation approach is considered as an alternative to the policy based approach of the neoclassical theory of market failures (Schröter, 2009). However, the systems of innovation approach will not replace the neoclassical approach, until it demonstrates superiority in designing innovation policy, although some authors argue that, from a broader perspective, the evolutionary system-failure framework is incorporated in contemporary innovation policies (such as policy instruments facilitating university-industry links and of establishing and maintaining knowledge intermediaries, Nill and Kemp, 2009) and that this framework has taken a predominant role over the neoclassical market-failure argument (Bleda and del Rio, 2013).

The systems approach to public innovation policy emphasizes the role of institutions and innovation infrastructure. Innovation policy should enhance firms' access to knowledge by developing an institutional structure that is aimed at supporting innovation processes, i.e. an innovation system. The policy incorporates not just innovation-related activities, but also the domains of education and training, science, technology, the labour market and regulated industries (Hauknes and Nordgren, 1999). The market is just one constitutive element in the process of technological advances and innovation processes. The other element pertains to institutions and networks in the broad context of innovation systems. Therefore, the systems approach does not exclude the policy instruments designed to address market failures, but introduces additional instruments aimed at changing the institutional set-up under which innovation processes occur.

Although there is no clear consensus on what constitutes the concept of system failures (Magro and Wilson, 2013), several categorizations of the concept are advanced in the literature. Malerba (1998) discuses four types of system failures:

- ***Learning failures***: firms or sectors might not be able to adopt new technologies in a timely manner.
- ***Trade-offs and embedded imbalances between exploration and exploitation***: firms can be divided into two groups depending on the prevailing processes in the generation of innovation: the first group consists of firms with a lot of variety generation (exploration) but weak selection processes (exploitation); the other group includes firms with tough selection processes but little variety generation.
- ***Appropriability traps*** (i.e. lock-in to particular sources or owners of technology).
- ***Absence of relevant complementary competences*** in an industry or an innovation system. Complementarities are related to knowledge, skills, know-know and capacity (Woolthuis et al., 2005).

In addition, Carlsson and Jacobsson (1997) divide system failure into two categories:

- ***Network failures*** refer to inappropriate interaction between actors and organisations in a system. Distinction is made between strong (too much interaction) and weak network failures (little or no interaction). Strong network failure implies that actors in a system fail to exchange information and knowledge. It can be caused by myopia due to internal orientation, lack of weak ties and dependence on strong partners (Woolthuis et al. 2005).[40] Weak network failures lead to poor connectivity between actors. As Woolthuis et al. (2005) noted, this type of failure matches Malerba's (1998) concept of relevant complementary competences. Both weak and strong network failures hamper innovative activities. On the other hand, well-established networks lead to the

[40] Myopia and inertia might occur in long-lasting relationships, in which firms tend to focus more on internal cooperation and interaction, and not paying enough attention to the technological developments outside. External weak ties are relevant for overcoming myopia and inertia caused by internal orientation. Finally, when a firm cannot easily find an alternative partner, it might be locked in a relationship.

mutual exchange and accumulation of knowledge as well as to a common vision of future technological development. Therefore, government measures should be aimed at promoting cooperation between firms and research communities (universities, research centres, R&D laboratories etc.) through various policy instruments such as joint research, technology foresights and R&D grants for joint projects (Hauknes and Nordgren, 1999).

- ***Institutional failures***: Systems of innovation approaches divide institutions into two categories. Hard institutions are formal organisations, including the legal system (laws and regulations) and especially relevant for innovation, intellectual property rights (IPR), whereby a too stringent IPR might prevent the diffusion of technological developments (Woolthuis et al., 2005). Soft institutions are informal, social organisations including social norms, values and attitudes. Institutional failures in both hard and soft institutions adversely affect innovative activities in a system.

Alternatively, Smith (2000) identifies four system failures:

- ***Failures in infrastructural provision and investment***: physical infrastructure refers to supply of energy and of communications, while science-technology infrastructure refers to universities, research institutes, regulatory agencies and government ministries. Woolthuis et al. (2005) add accommodation (offices, laboratories) and transport (roads) to this category. These infrastructures have specific technical characteristics, such as long time span of investment and/or large scale of operation, which will likely result in inadequate returns to private investments.
- ***Transition failures***: transition from one technology to other can be difficult for firms if they lack absorptive capacity to adopt new technologies. Firms need flexibility, resources, competence and knowledge to be able to shift to new technologies. Lack of resources is especially salient for SMEs (see Section 2.3). Woolthuis et al. (2005) label this type of system failure as ‘capabilities’ failure’, while Malerba (1998) refers to it as ‘learning failure’.
- ***Lock-in failures***: the notion of path-dependency or “lock-in” to existing technologies is often emphasized in evolutionary economics. As firms face “learning failures” (Malerba, 1998) in adopting new technologies, industries and the socio-economic system can be locked-in to a particular technological

paradigm. Changes and adoption of new technologies require not only changes at the firm level, but also changes in the system in which technologies are embedded.

- ***Institutional failures***: The regulatory system (technical standards, risk-management rules, health and safety regulations, intellectual property rights etc.) affects firms' technological capabilities and their performance. Therefore, public policy should encompass monitoring and assessment of the regulatory system and, when a failure occurs, introduce adequate changes in the system.

Different categorizations of system failures point to what Woolthuis et al. (2005, p. 610) describes as 'the lack of standardization in the NIS literature'. Consequently, the same concepts appear under different names. For instance, Smith (2000) defines institutions as laws and regulation, whereas Carlsson and Jacobsson (1997) refer to organisations as institutions. In the systems of innovation approach, a sharp distinction is made between organisations and institutions (see Section 1.3.4 on the Innovation Systems approach). Woolthuis et al. (2005) suggest that the confusion in terminology can be avoided if institutions and organisations are divided into rules (institutions) and players (organisations). In a policy framework, players are the public sector, firms, and universities, while rules refer to the outcome of player's actions (e.g. laws and regulations, joint researches). System failures mostly occur when the rules are not properly designed or implemented, while rarely emerge from the perspective of economic agents, i.e. when a crucial organisation or institution is absent from a system. Moreover, following Woolthuis et al. (2005), lock- in/ path dependency are considered as a result of system failures not as their cause. For instance, network and/or capability failures can lead to lock-in in a certain technology regime or paradigm. However, no consensus in the systems of innovation literature is reached on the issue as to whether lock-in is actually a type of system failure or an outcome of network and capabilities failures (Schröter, 2009).

The main difference between the neoclassical and the evolutionary approach is that the latter focuses on the variety in firms' behaviour and their attempt to adjust to framework conditions, often referred to as "given technology". Therefore, the main focus is on how firms endogenise technological advances (Hauknes and Nordgren, 1999). Given the endogenous and systemic feature of innovation, the optimum allocation of resources cannot be determined. As Hauknes and Nordgren (1999, p. 15) suggest: 'There is no single, optimal public policy'. Recognizing the importance of the institutional setting in the generation and diffusion of technical changes and innovations leads to a shift in innovation policy, from optimizing to adaptive policy making. Adaptive policy implies the relevance of evaluation and assessment of public policies while, at the same time, encompassing the learning process through trial and error and experimentation. The innovation systems approach regards innovation as a cumulative process that is path dependent and context dependent. Therefore, the systems rationale for public policy points out that the instruments and mechanisms of government intervention are firm specific (or industry, region or country specific depending on the level of government intervention). That is the main reason why "best practice" cannot be inferred from one innovation system and transferred to another; and contrary to the principles of market failures, which can be applied universally (Lundvall and Borrás, 2005, p. 617).

Given the systematic framework of the innovation process, it is recommended that the stakeholders should be involved in the process of developing innovation policy. The methods used to identify the areas of system failure are benchmarking and best practice. The next step in designing public support is the choice of adequate policy instruments. Their selection depends on the nature of a system failure. Different instruments will be needed in the presence of institutional failure and others if a network failure exists. Failures in soft institutions could suggest changes in laws and regulations that affect suppliers' and consumers' behaviour, such as competition regulation, consumer protection, improving access to information etc. (see Table 3.2 for a review of policy instruments). Failures in hard institutions might imply changes in the working conditions of universities and research institutes, but also in support to new firms. Network failures reflect the weak cooperation and interaction between the actors in the innovation system. In the presence of network failures, public support might be in the form of establishing bridging institutions between firms and research community, managing technology forecasting, standardization etc. (Hauknes and Nordgren, 1999).

Whether the neoclassical market failure approach and the systems of innovation approach are complementary or supplementary remains an open question. Within the evolutionary system failure framework, two theoretical positions are advanced (Bleda and del Rio, 2013). The first theoretical perspective explicitly rejects the market failure argument, because of its failure to capture the complex evolutionary nature of innovation (Metcalfe, 2005; Nelson, 2009). Within the second position, the market failure rationale remains valid, but the system failure argument is regarded as a more general theoretical justification for public intervention and support for innovation (Bach and Matt, 2005; Aghion et al., 2009).

In contrast, some scholars raise the issue of the contribution of the system failure rationale to the development of innovation policy theory and practice. For instance, according to Schröter (2009), the systems of innovation policy approach adds nothing in comparison to the neoclassical theory of market failures. The author points out three reasons for the lack of a significant contribution:

a) *The systems of innovation approach to innovation policy mostly identifies the symptoms rather than causes of the failures*. This argument is closely linked with the second point and will be jointly discussed.
b) *System failures are very similar, if not identical to the market failures*. A review of system failures and their corresponding market failures is presented in Table 3.2. Schröter (2009) argues that each system failure has its corresponding market failure. Therefore, infrastructural failure arises from indivisibility problems. Innovation projects can be unprofitable if period of amortization is long or sunk costs are high if the project fails. Externalities (appropriability problems) might also be relevant for infrastructural failures. Knowledge created during infrastructural investments cannot be fully appropriated by the private sector, because of positive external effects (spillovers). Moreover, Schröter (2009) argues that infrastructural failures are not a type of market imperfection, but the consequence of market failures (indivisibility and externalities). Furthermore, Schröter (2009) distinguishes between capability and learning failures, on the one side, and transition failures on the other, although Woolthuis et al. (2005) suggest that capability, learning and transition failures are the same type of failures, just labelled under the different name. Both types of failures are considered as a consequence of inflexibility; but for transition failures, indivisibility and high sunk costs are additional causes of market inefficiency. Network failures are compared to the implications of the market theory in which division of labour and interaction among economic agents is salient for productivity growth. Weak network failures are related to the problem of asymmetric information and high transaction costs if an innovation project

requires specialized competencies. In such a case, searching for a partner and negotiating a contract incurs high transaction costs. Strong network failures correspond to the concept of overembeddedness, i.e. a situation where organizations' relations became long-lasting, trust-rich, thick, and eventually redundant. Firms can also be locked into a relationship because of asset specificity or the absence of alternative partners (Williamson, 1985).

Table 3.2. Comparison between system and market failures

System failures	Market failures
Infrastructural failures	Indivisibilities, externalities
Capability and learning failures	Inflexibilities
Transition failures	Consequence of inflexibilities indivisibilities and sunk costs
Network failures (strong and weak)	Market theory is a theory of interaction: transition costs due to asymmetric information; inflexibility and lock-in
Institutional failures (hard and soft)	Institutions taken for granted; option for policy measures (e.g. IPR, competition policy etc.)
Lock-in/path dependency failures	Inflexibilities due to asymmetric information and indivisibilities

Source: Schröter (2009, p. 13).

In the neoclassical framework, institutions are regarded as exogenous and a precondition for market functioning, but not a cause of market failure. However, the importance of institutions is recognized in policy creation. For instance, competition policy and IPR are policy instruments in the neoclassical framework. Finally, lock-in or path dependency, whether a specific type of system failure or the outcome of several combined system failures, may be understood as a result of market failure, rather than its cause. Firms' present and future innovative activities are determined by their past experience, capabilities and competencies. Firms are locked into old technologies because of the lack of information on technological advances (asymmetric information) or of high sunk costs in the presence of uncertainty and indivisibility pertaining to the introduction of new technologies.

c) Because the cost-benefit analysis of public interventions is not considered, the innovation systems framework imposes no limitations in designing public policy. The dimensions of government failures and of costs related to the public interventions are ignored in the innovation systems framework. Government failures refer to the problem of self-interested bureaucrats and rent-seeking private actors (a detailed discussion on government failure is relegated to Section 4.2). Furthermore, the design and implementation of public measures incur direct costs of the intervention, transaction costs and deadweight losses if government failures occur. Following Schroter (2009), the systems innovation approach can justify any public intervention as costs and benefits are not weighted, whereas the neoclassical framework requires a cost-benefit analysis. Therefore, the latter is a superior for designing innovation policy.

The only contribution of the system failure approach, according to Schröter (2009), *is recognizing the relevance of the institutional setting and interactions* among actors in an innovation system. Moreover, benchmarking is criticized on two grounds:

- *The choice of the reference innovation system*: What are the criteria for selecting the reference system? Schröter (2009) concludes that the choice and criteria for selection are left to the discretion of innovation policy makers. Lack of adequate instruments for identifying an appropriate reference system is a common issue for both neoclassical and systems of innovation approach, and along this line of argument, Schröter (2009, p. 21) concludes that 'the comparative institutional approach does not provide a superior framework for indentifying systemic failures'.
- *The interdependence of institutions in the system*: Institutions are mutually dependent and complementary, affecting one another's efficiency. Innovation systems vary in their functioning because institutions and interactions between them differ. Therefore, copying the design of a particular institution from one system to another is not effective, because institutions are embedded in a broader institutional framework. This implies that in achieving desired results, the whole system should be copied (Lundvall, 2007).

3.3 Science, technology and innovation policy

Following Bartzokas (2001, p. 13): ‘Technology and innovation related policies can be thought of as a specific set of policies that aim to improve the ability of firms to compete by promoting technological improvements through the generation, diffusion and adoption of process, product and organizational technological changes.’

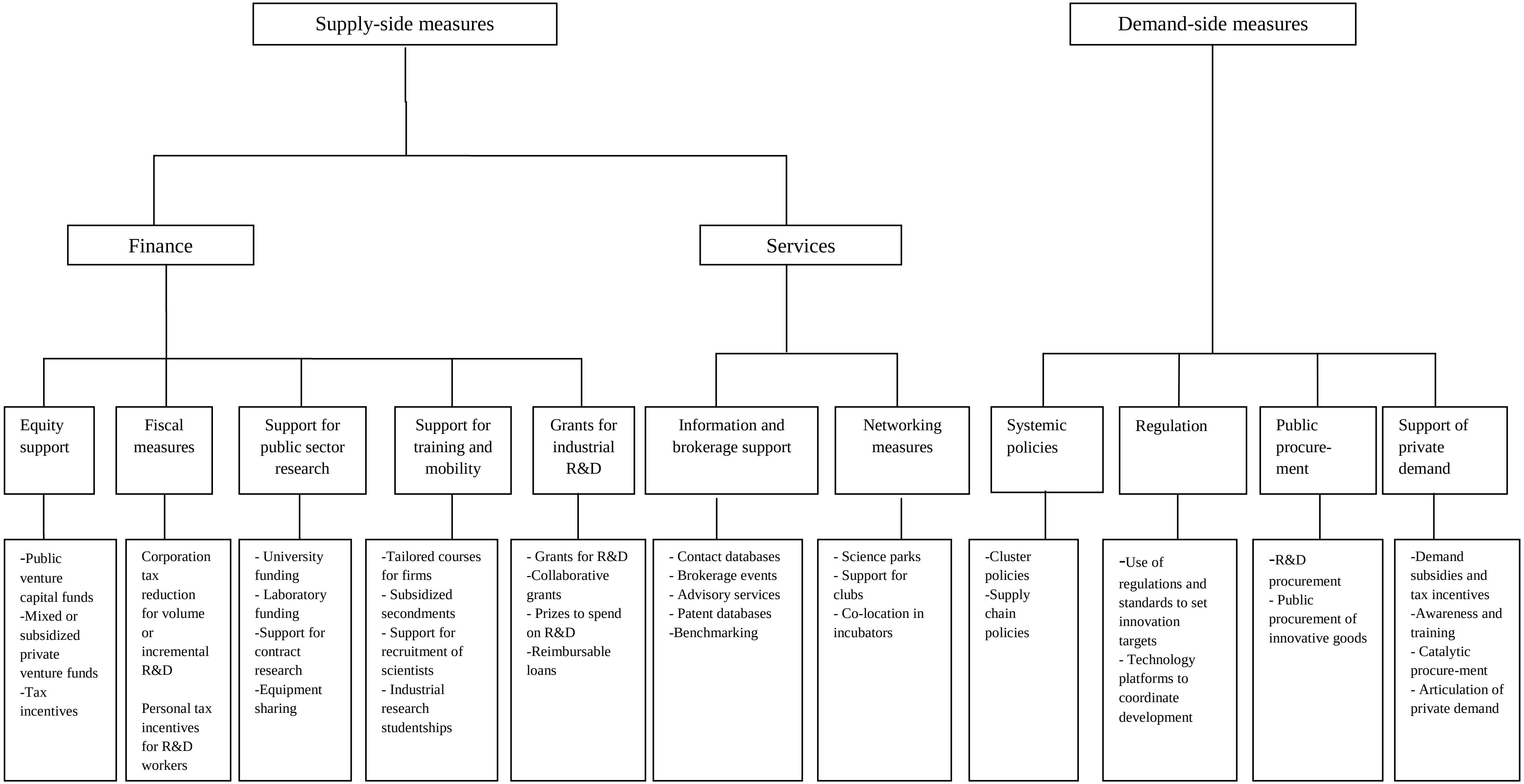
Public policies aimed at supporting and promoting innovation are divided into two broad categories: supply-side public measures and demand-side measures. Boekholt (2010, p. 334) defines a policy instrument as 'a government measure or programme that aims to change the behaviour and actions of the actors involved in the whole process from generating new ideas into innovative market introductions and solutions'. Supply-side measures stem from the linear innovation models, and have been the dominant category of public intervention in the domain of innovation since the market-failure rationale was advanced in theory and practice (Edler and Georghiou, 2007). The first generation of innovation models (see Section 1.4.1) represent a linear, technology-push model that focuses on the supply side in innovation policies, ignoring the demand for innovation and the market conditions, such as prices and other factors, that influence the profitability of innovation (Nemet, 2009). The second generation of demand-pull innovation models shifted the focus to the demand side of the innovation process but, at the same time, ignored the role of firms' technological capabilities in the innovation process (Brem and Voigt, 2009; Nemet, 2009). However, both models suffer from several pitfalls. First, both models formalize the innovation process as a linear, sequential process, without any interaction and feedback mechanisms betweens stages in the process (Nemet, 2009). Second, both the technology-push and the demand-pull linear models of innovation only take into account process innovation, without taking into consideration product innovation and/or non-technological innovations. While the technology-push models explain how radical innovations are introduced and developed (Walsh et at., 2002), the demand-pull innovation models focus on formalizing incremental technological innovations (Walsh et at., 2002; Nemet, 2009). Demand-side public measures were designed after the formalization of the third-generation interactive or coupling innovation models. These models, and specifically the Kline-Rosenberg chain-linked model (Kline and Rosenberg, 1986) (see Section 1.4.1) brought together the technology-push and the demand-pull arguments and emphasised several relevant features of the innovation process, not taken into consideration in linear innovation models (Edquist and Hommen, 1999): i) a crucial role in the innovation process is ascribed to the demand for innovation; ii) non-linearity of innovation is taken into account by incorporating interactions and feedback loops between stages in the innovation process; iii) contrary to linear models where research is identified as the only source of innovation, interactive or coupling innovation models suggest that the source of innovation is primarily design, thus shifting the focus from process innovation to product innovation;[41] and iv) interactive/coupling innovation models recognize the existence and relevance of linkage structure between the firm and other economic agents in the innovation process. It is of importance to note that the *Oslo Manual* is explicitly designed on the basis of the Kline-Rosenberg chain-linked model, rather than the linear model of innovation, thus acknowledging the non-linear and complex nature of the innovation process (Mytelka and Smith, 2002).

Boekholt (2010) reviews the historical evolution of Research, Technology Development and Innovation (RTDI) policy and identifies four generations of RTDI policies:

- **The first generation** covered the period from the 1950s to the 1980s and was mostly focused on science policy. The prevailing innovation model was the linear model, notably the technology-push model, whereby research was identified as the only source of innovation. Therefore, the government role was to provide funding for both basic and applied research within universities and research centres and, thus, the policy instruments were focused exclusively on the supply side of the innovation process.

[41] As noted in Section 1.3.1.1, product innovation was less investigated than process innovation in the neoclassical economics framework, and the introduction of interactive or coupling innovation models shifted the attention to product innovation and its role in firms' performance.

Figure 3.1. Taxonomy of innovation policy tools (Edler and Georghiou, 2007, p. 953).



- **The second generation** RTDI policy was introduced in the mid-1980s, where the shift in the innovation policy paradigm occurred with the development of the chain-linked innovation model (Kline and Rosenberg, 1986). In parallel to the development of the third generation innovation models, this period is characterized by the rising importance of clusters and value chains in the innovation process. However, in this period, the implementation of RTDI policy was lagging behind the advances in innovation theory, with the ensuing consequence of the reliance on the linear innovation model. In many countries, the main policy instrument was the direct funding of private R&D through soft loans and credits, R&D tax incentives and financing specific R&D projects. Although a direct funding was the prevailing policy tools, new measures were also introduced across industrialized countries, such as:
    - *Technology transfer mechanisms*. This category of new policy instruments was designed to encourage knowledge transfer from universities and public research centres to the business sector. One of the policy instruments among technology transfer mechanisms was the setting up of science parks, where universities would facilitate the creation of university spin-offs.
    - *Schemes to provide finance for innovation*. In order to overcome the problem of financing risky businesses and start-ups, governments across Europe began setting up schemes for risk finance, such as joint public-private venture capital funds and business angles networks.
- **The third generation** of RTDI policy stems from the innovation systems approach (see Section 1.3.4). Although theoretical advances on the innovation systems concept were forged in the 1990s, its application in the policy domain started a decade later, in the 2000s. A prominent feature of public instruments used in support of the innovation systems was further encouraging inter-linkages of various economic actors, i.e. firms, universities and public research centres. These so-called 'bridging instruments' mostly included public-private partnerships, competence centres (long-term research alliances connecting the private sector with universities aimed at undertaking basic but also applied research), and centres of excellence. Within the third-generation policy instruments, a prominent role within the European Union is assigned to those instruments promoting internationalization of R&D through transnational cooperative agreements covering a broad range of EU research initiatives and

agreements, such as the European Commission programmes (particularly the Framework Programmes).

- **The fourth generation** of RTDI policies encompasses investment in research and development in those areas that have crucial societal and economic effects, such as health care, climate change, energy supply etc. New concepts such as social innovation and eco-innovation have recently emerged to signify changes in the policy domain. Scholars put forth the proposition that sustainable innovation could bridge a gap between tensions arising from, on the one side, pursuing economic growth and on the other side, from environmental and social issues that are imminent to modern society (Shapira, 2010).

As innovation policies were evolving from one generation to another, new instruments were launched but older ones were seldom abolished (Boekholt, 2010). That is one of the reasons why nowadays a very large number of public measures exists. Another reason, as noted in the introductory section of this chapter, is associated with public choice theory (Buchanan and Tullock, 1962) and the behaviour of government officials and politicians, who, in the pursuit of their own political agendas, may introduce new initiatives irrespective of how well existing policies are working. Moreover, the lobbying of various interest groups can also have a significant impact on the conduct of public policy in general as well as on specific policies, such as those in a domain of innovation. Another more recent trend in the conduct of innovation policy is the reinforcement of the demand-side measures, particularly public procurement (Edler and Georghiou, 2007; Edler et al., 2012a). However, we circumvent further discussion on the use of the demand-side instruments, as our empirical strategy (see Chapters IV, V and VI) did not attempt to evaluate demand-side programmes.

Another consequence of the evolution of policies related to innovation is the shift in policy-making focus, from identifying the best policy instruments to formalizing a portfolio of instruments that will have a joint positive impact on innovation. A policy mix can be defined as 'the combination of policy instruments, which interact to influence the quantity and quality of R&D investment in public and private sectors' (Boekholt, 2010, p. 353). Finding a holistic solution based on the policy mix is not an easy task, as the synergetic effects of policy instruments might amplify or cancel each other’s' individual positive effects. Nowadays, proponents of the systems of innovation approach (e.g. Boekholt, 2010; Edler and Georghiou, 2007; Edler et al., 2012a) argue that the approach can provide an analytic tool in the construction of a policy mix that would increase innovative activities by removing deficiencies in the innovation system so they are most conducive to innovation.

Lundvall and Borrás (2005, p. 599) provide a brief discussion on the development of public policy from science to technology and innovation policy, although, according to Boekholt (2010, p. 333), clear distinction between them cannot be inferred. Science policy is a concept developed after the Second World War. The major focus is on the efficient allocation of resources to science. Therefore, supporting scientific research within universities, technological institutes, research centres and R&D laboratories is the main objective of science policy. An important policy tool is the evaluation of research, and the scientific community has developed its internal evaluation through peer review. However, internal evaluation is not without shortcomings, mainly with regard to difficulties in generating and especially in disseminating new ideas from interdisciplinary areas of research.

On the other hand, technology policy is oriented toward promoting specific technologies and industrial sectors. It is a common procedure to determine "strategic technologies" and those sectors developing them (strategic sectors). Lundvall and Borrás (2005, p. 608) noted the main issues in conducting technology policy:

- Should government support particular industries for commercial reasons?
- What technologies and industries should be promoted?
- At what stages of the innovation process should government provide support?
- Are there limitations in the provision of technological policy in regard to public competence?
- How can public support be combined with competition?

The main objective of technology policy is similar to science policy, i.e. promotion of scientific research in the scientific community, but the shift is made from universities' research activities to engineering and how universities and other research institutions cooperate and interact with industry. Policy tools vary depending on the public competence, sectors and technologies promoted etc. Besides instruments promoting university-industry links, they include public procurement, direct support in the form of subsidies, tax relief and protectionist trade policy. The evaluation of technology policy is also important and the public sector has several policy instruments at its disposal. For instance, technology forecasting is the policy tool useful for detecting the development of new technologies (Lundvall and Borrás, 2005, p. 610).

Finally, innovation policy appears in two different versions: the market failure approach of mainstream, neoclassical economics; and the system failure approach of the systems of innovation school. The similarities between these approaches are that in both the innovation policy covers all stages of the innovation process, and the emphasis is more on institutions and organisations than on science and technology policy. The differences between these approaches are mainly related to the methods prevailing in designing innovation policy. In the neoclassical approach, as mentioned earlier, there is a single, optimal innovation policy recommended to all countries; conversely, in the systems approach, innovation policy is country specific and, therefore, no single, optimal policy exists. Lundvall and Borrás (2005, p. 613) imply that the major distinction in innovation policy tools is between those instruments that support innovation in the existing institutional setting and those designed to alter the institutional structure to promote innovation processes. The first category of instruments is the same as those used in science and technology policy. The second category encompasses changes in the working conditions of universities and other research institutions but also changes in education, the labour market and regulated industries.

Therefore, as Figure 3.2 depicts, innovation policy is a broader concept than science and technology policy, including not just universities and technological sectors but also every part of the economy affecting the innovation processes, i.e. the national innovation system. This broad coverage of innovation policy implies that the instruments of science and technology policy are encompassed by innovation policy. Yet, in addition, innovation policy emphasizes the importance of institutions and organisations in engendering competence and in enhancing organisational performance. As Lundvall and Borrás (2005, p. 614) noted: 'Innovation policy calls for "opening the black box" of the innovation process, understanding it as a social and complex process.

Figure 3.2. Relationship between science, technology and innovation policy

Innovation policy

Focus: Overall innovative performance of the economy
Instruments: Horizontal policy instruments, combining "stick, carrot and sermon" effects, such as:
- Improving individual skills and learning abilities (through general education system and labour training)
- Improving organizational performance and learning (i.e. ISO 9000 standards, quality control)
- Improving access to information: information society
- Environmental regulation
- Bioethical regulation
- Corporate law
- Competition regulations
- Consumer protection
- Improving social capital for regional development (clusters and industrial districts)
- Intelligent benchmarking
- Intelligent, reflexive and democratic forecasting

Science policy

Focus: Production of scientific knowledge
Instruments:
- Public research funds granted in competition
- (Semi) Public research institutions (i.e. laboratories, universities, research centres)
- Tax incentives to firms
- Higher education
- Intellectual Property Rights (IPRs)

Technology policy

Focus: Advancement and commercialization of sectoral technical knowledge
Instruments:
- Public procurement
- Public aid to strategic sectors
- Bridging institutions (between research community and industry)
- Labour force training and improvement of technical skills
- Standardization
- Technology forecasting
- Benchmarking industrial sectors

Source: Lundvall and Borrás (2005, p. 615).

In relation to categorizing various policy instruments, Borrás (2009) identified four main categories:

- **Regulatory instruments**: This category of instruments includes laws and binding regulations relevant for fostering and promoting innovations. Examples of regulatory instruments are the regulation of IPRs, competition policy with respect to R&D and innovation activities, and the regulation of universities and public research centres.

- **Economic and financial instruments**: This type of instrument is extensively used as an innovation policy tool. The array of economic and financial instruments includes R&D tax incentives; support to venture capital; public support to universities and public research centres; and research funding (for both basic and applied research).
- **Soft instruments**: Instruments in this category are voluntary and non-coercive policy measures, aimed at providing information and guidelines for public organizations and firms in conducting innovation. Examples of soft instruments are standards, best practices, codes of conduct, public-private partnerships based on cost-sharing etc. These instruments are increasingly used since the 1990s, and most recently are focused on the establishment and maintenance of innovation networks. Freitas (2007) identified more than 80 soft instruments implemented in the UK since the 1990s.
- **Meta-instruments**: Provision of meta-instruments is focused on the design and implementation of innovation policy per se, not on the innovation process. Examples of meta-instruments are the development of innovation indicators, policy benchmarks and technology foresights.

3.4 A theoretical framework for evaluating public support

David et al. (2000) and David and Hall (2000) developed a structural model to illustrate how government intervention might affect private R&D investment. The model assumes profit maximising firms that reach an optimum level of R&D investment when the marginal cost (MC) of R&D investment is equal to the marginal rate of return (MRR). Marginal costs are opportunity costs of investing in R&D represented by an upward sloping curve, which implies that increased costs are a result of increased gearing (the ratio of debt to equity). Marginal rate of return is an internal rate of return on R&D investment represented by a downward sloping curve as firms will prioritize projects with higher rate of return. Furthermore, both marginal cost and marginal rate of return are a function of R&D investment and other variables. That is,

$$MC = f(R, X) \tag{3.1}$$

$$MRR = g(R, Z)$$

Where R denotes the firm's R&D expenditure, X is a vector of variables determining marginal costs (technological opportunities, appropriability conditions and demand conditions), and Z is a vector of variables reflecting innovation policy instruments, macroeconomic conditions and external costs of funding and availability of venture capital.

The firm's optimum level of R&D investment $R*$ is achieved when MC equals MRR, hence

$$R^* = h(X, Z) \tag{3.2}$$

Under the assumption of exogeneity of X and Z, Equation 3.2 is a reduced-form model of the structural model set out in Equation 3.1.

Finally, the actual level of R&D investment can be presented as:

$$R = R^* + H \tag{3.3}$$

Where H is the additional R&D expenditure induced by the subsidy S. Depending on the relation between H and S, we can identify several outcomes of a public support measure (subsidy).

H > S (additionality effect)

H = S (no additionality or crowding out)

0 < H < S (partial crowding out)

H = 0 (full crowding out)

H < 0 < S (more than full crowding out)[42]

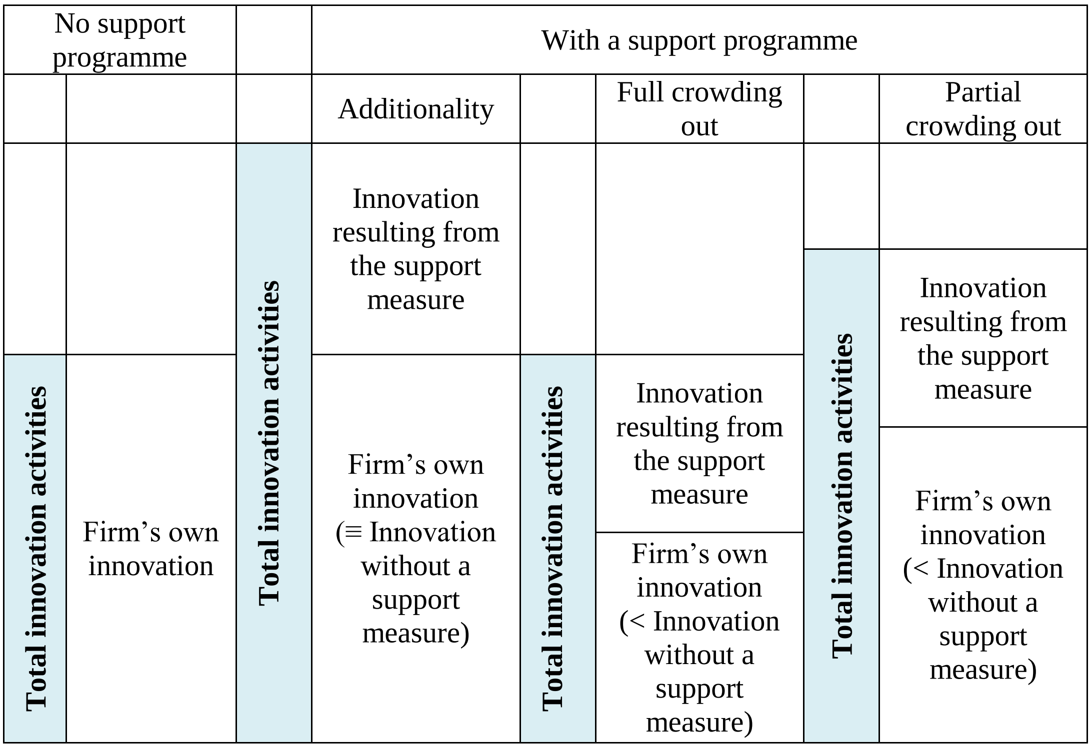
The task of empirical analysis is to determine the actual effect of public support in a specific context, as each of these cases can occur in practice.

[42] See Figure 3.3 below for the graphical illustration of the outcomes of a public support. Note that the second category 'no additionality or crowding out' and the fifth category 'more than full crowding out' are not illustrated, as Figure 3.3 is a simplified representation of the outcomes, disregarding the cost and illustrating only the effects of a public support.

The literature on innovation policy evaluation lacks clarity in defining the additionality effect. First, the authors agree that additionality represents the increase in R&D intensity (or innovation intensity, depending on the narrow or broader perspective on innovation) induced by a subsidy (Heijs and Herrera, 2004, p. 3). However, confusion arises in determining the exact magnitude of the increase in innovation intensity. Some authors argue that any increase in innovation intensity can be regarded as additionality (Heijs and Herrera, 2004). Others note that additionality refers to the increase in innovation intensity larger than the amount of subsidy (Cerulli and Potí, 2008).

Conversely, there is a consensus in defining full and partial crowding out effects. Full crowding out refers to 'a complete substitution of private by public funds, and this means that firms' total R&D expenses would be the same with or without subsidies' (Gonzáles and Pazó, 2008, p. 372). Cerulli and Potí (2008, p. 11) provide a very similar definition: 'total crowding-out: when the private R&D, compared to what the firm would have done in the absence of the grant, remains the same' (see also Busom, 2000; Streicher et al., 2004; Aerts and Schmidt, 2008; Gonzáles and Pazó, 2008). Therefore, a full crowding out effect implies that a firm reduces its private spending by the amount of the subsidy, so the total spending including a subsidy is the same had the firm not receive a subsidy. Finally, partial crowding out refers to a partial substitution of private spending. Partial crowding out occurs if firms raise their total R&D, but this amount is smaller than the subsidy itself (Gonzáles and Pazó, 2008, p. 372) (see also Cerulli and Potí, 2008; Streicher et al., 2004; Aerts and Schmidt, 2008). The hypothesis of a partial crowding-out effect can only be tested when the amounts of subsidies are available (Busom, 2000; Cerulli, 2010; Cerulli and Potí, 2008; Aerts and Schmidt, 2008, Gonzáles and Pazó, 2008).

Figure 3.3. Additionality and crowding out effects



Source: Author's own illustration.

Figure 3.3 gives a graphical presentation of additionality and crowding out according to the definitions followed in our research:

- ***Additionality***: the firm does not reduce its own innovation; instead, the firm’s innovation is greater than it otherwise would have been by an amount brought about by the support measure in addition to the firm’s own innovation.
- ***Full crowding out***: the firm reduces its innovation by an amount equal to the innovation brought about by the support measure; hence, the firm’s total innovation activities with the support measure are not greater than they would otherwise have been (the support measure substitutes fully for the firm’s own efforts).
- ***Partial crowding out***: the firm reduces its innovation but by an amount less than the innovation brought about by the support measure; hence, the firm’s total innovation activities are greater than they would otherwise have been but by an amount less than the full effect of the support measure (the support measure substitutes partly for the firm’s own efforts).

In addition to distinguishing between additionality versus crowding out effect, innovation policy literature recognizes several concepts of additionality. Falk (2007) grouped these concepts into three categories (see Figure 3.4):

A. Resource-based concepts

- *Project additionality* occurs when a project would be abandoned without public support;
- *Scale additionality* occurs when the project is undertaken at a larger scale due to a receipt of public support (Georghiou, 2002); [43]
- *Input additionality* refers to the effect of support measures on the private R&D expenditures (i.e. whether firms increase their private R&D investment when public funding is provided);

B. Results-based concepts

- *Output additionality* refers to the impact of subsidies on innovation outputs (i.e. patents, introduction of successful innovations and the share of sales resulting from product innovations (and/or process innovations);
- *Impact additionality* is associated with the effect of public support on firm's productivity or competitive position;

C. Process-based concepts

- *Scope additionality* occurs when firms, as a consequence of receiving public support, expand their activities, such as by entering new markets or by creating new partnerships (networking) (Georghiou, 2002);[44]
- *Cognitive capacity additionality* is defined as a positive impact of support on firms' competencies and expertise;
- *Acceleration additionality* occurs when public support has a positive effect on the duration of the project, either through a reduction of the implementation phase, or an earlier starting or ending date (Georghiou, 2002).

Falk (2007) defines behavioural additionality as the process-based concept of additionality.

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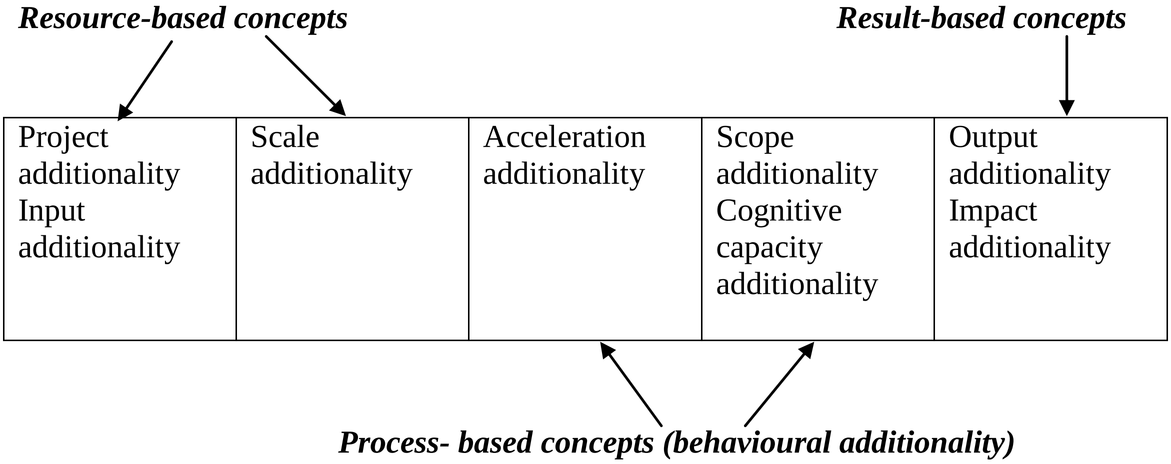
[43] Falk (2007) classifies scale additionality as a resource-based concept, although she notes that other authors categorize scale additionality as a sub-category of behavioural additionality.

[44] Falk (2007) points out that the effect of public support on cooperation could be classified as scope additionality, but also as cognitive capacity additionality.

Figure 3.4. Concepts of additionality



Source: Falk (2007, p. 668).

Falk (2007) points out that resource-based concepts of additionality might not be complementary. On the contrary, the firm might experience project and scope additionality, without increasing investment in R&D. Furthermore, the resource-based concept adopts the linear model of innovation, which is often an object of criticism because it proposes direct causality between innovation input and output. However, not every R&D investment results in a successful innovation, nor is every innovation a result of R&D activities (such as organisational and marketing innovations) (see Section 2.3).

Input and output additionalities are based on the linear model of innovation (see Section 1.4.1), where it is assumed that the innovation process is linear and sequential, without interactions and loops between the phases. An important shortcoming of input additionality is its focus on the allocation of resources, without exploring the effects of public intervention on innovation outputs and changes in the firms' innovative behaviour (Antonioli and Marzucchi, 2012). Another relevant limitation of input additionality is associated with the empirical strategies applied in most studies. Namely, the outcome variable can be operationalized in two manners, using either total R&D expenditures or net (private, own) R&D expenditures (equal to total R&D expenditures minus the amount of R&D subsidy). Only the latter is an appropriate outcome variable, because the objective of evaluation is to estimate the impact of public intervention on firms' own, private R&D investments (Cerulli, 2010). Our empirical review will reveal that most studies on input additionality, because constrained by the lack of data on the amount of subsidies, use total R&D expenditures as the outcome variable.

Investigating output additionality also suffers from several limitations. The first issue is associated with the definition of innovation output. The literature on innovation categorizes innovation outputs into two groups: intermediate (direct) innovation outputs (such as patents and publications); and indirect innovation outputs, such as the introduction of product and process innovations and the share of sales from new products and/or processes (i.e. innovative sales) (Clarysse et al., 2009) (see Section 2.3). In addition, measures of firms overall performance, such as productivity, profitability and value added can be used as proxies for innovation output. Using patents as a measure of innovation output is particularly problematic for investigating output additionality in SMEs operating in traditional industries, as the outcome of their innovative activities is seldom in the form of patents (Antonioli and Marzucchi, 2012). Second, the concept of output additionality assumes a direct link between innovation input and output, and this assumption is unlikely to hold (Clarysse et al., 2009; Antonioli and Marzucchi, 2012), given the non-linear nature of the innovation process, whereby the process is complex and non-linear, and may result not only in firms' improved innovation performance, but also in changes in their internal innovation behaviour. A non-linearity of the innovation process creates difficulties in investigating output additionality, especially when innovation output is operationalized using its indirect measures (Clarysse et al., 2009).

As the linear model of innovation was heavily criticized, with the development of evolutionary economics and of later generations of innovation models (from the Kline-Rosenberg chain-linked model to the fifth generation of networking models, see Section 1.4.1), the innovation process is regarded as a non-linear process, involving not just innovative firms but the entire innovation systems, including all economic actors and institutions and organizations affecting the firms' innovative activities. The emergence of evolutionary theorizing on innovation and system perspectives resulted in a shift in the design of innovation policy and its ensuing evaluation, by focusing on behavioural additionality (Antonioli and Marzucchi, 2012).

3.5 Evaluation models

Measuring the impact of a treatment includes economic agents (firms, households, and individuals), potential outcomes and treatment. We will refer to firms in our further discussion. If we denote T_i to be treatment (T_i =1 if a firm *i* received a treatment and T_i=0 if not) and Y_i (T_i) for outcomes of firms *i* = 1,..., N, where *N* is the total population of firms, $Y_i(1)$ is the outcome of treated firms, $Y_i(0)$ is the outcome of treated firms without a treatment, and Δ_i is a treatment effect for a firm *i*, then

$$\Delta_i = Y_i(1) - Y_i(0) \tag{3.4}$$

Equation 3.4 points to the fundamental evaluation problem. To evaluate the impact of a treatment, both outcomes with and without treatment should be simultaneously observed. Therefore, the outcome for treated firms had it not been treated (counterfactual outcome - $Y_i(0)$) cannot be observed and has to be estimated, which implies that the treatment effect itself cannot be observed and must be estimated (Aakvik et al., 2005; Heckman and Vytilacil, 2007).

Further, two effects are usually estimated in the evaluation literature. The Average Treatment Effect (ATE) indicates the difference in outcome between two counterfactuals: the outcomes for all firms if they were to be treated, $Y_i(1)$ (e.g. by programme participation); and the outcomes for all firms if they were not to be treated, $Y_i(0)$. As not all firms are treated and not all firms are untreated, both $Y_i(1)$ and $Y_i(0)$ are counterfactuals that have to be estimated.

$$ATE = E[Y(1) - Y(0)] \tag{3.5}$$

The Average Treatment Effect on the Treated (ATT) indicates the difference in outcomes of the treated firms with and without treatment and can be written as:

$$ATT = E[Y(1)|T = 1] - E[Y(0)|T = 1] \tag{3.6}$$

The second term $E[Y(0)|T = 1]$ is the expected outcome had treated firms not receive a treatment. This is a counterfactual outcome that is not observed. If the unconditional outcome of non-treated firms is taken to estimate the counterfactual outcome, then that would lead to selection bias, as treated and non-treated firms may differ even before a treatment assignment (Aakvik et al., 2005; Heckman and Vytilacil, 2007). The problem of selection bias can be solved by imposing certain identifying assumptions, which will be further discussed in this section. Thus, evaluation methods are designed to take into account the estimation of counterfactual outcomes as well as to control for selection bias.

Cerulli (2010) provides a comprehensive discussion on the evolution of econometric models for evaluating the impact of public support on R&D. [45] Furthermore, he suggests the following taxonomy according to:

- *Type of specification*: structural and non-structural (reduced-form) models;
- *Type of data* used: cross-sectional and longitudinal datasets;
- *Type of policy variable*: binary policy variable and policy variable in levels (the amount of subsidy).

Our discussion will be mainly focused on the distinction between structural and non-structural models. A basic structural model treated a policy variable (subsidy received) as exogenous. However, as Cerulli (2010) notes, there are three possible sources of endogeneity of public support.[46] First, simultaneity might occur if private investment in R&D and subsidies received mutually determine one another, i.e. private R&D investment affects subsidies, and vice versa. In this case, a government agency follows the 'picking the winner' strategy, which refers to the selection of firms that are more likely to innovate (Czarnitzki and Fier, 2002; Gonzáles et al., 2005; Aerts and Schmidt, 2008; Gelabert et al., 2009; Carboni, 2011; Alecke et al., 2012; Cerulli and Potí, 2012; Czarnitzki and Lopes-Bento, 2013). Another source of selection bias occurs when firms self-select themselves into support programmes (Busom, 2000; David et al., 2000; Aerts and Schmidt, 2008; Gelabert et al., 2009; Grilli and Murtinu, 2011). The second source of endogeneity is omitted-variable bias. The issue of omitting a relevant variable is especially prominent in the structural models, because these models only control for (some) observed characteristics of firms. Finally, the third potential source of endogeneity is error in measuring public support.

[45] See also Grilli and Murtinu (2011).
[46] See also Arundel et al. (2008).

Cerulli (2010) discusses several structural and non-structural evaluation models. Structural models are divided into two categories: early structural and selection models.

- ***Early structural models and recent improvements***: As aforementioned, a basic structural model considers a public policy to be exogenous, or pre-determined. When the public policy variable is exogenous, a structural model can be presented as a reduced-form model in which the investment in R&D is a function of subsidies received (S) and of the vector X of covariates.

$$R = f(S, X) \tag{3.7}$$

However, once the problem of endogeneity was recognized, researchers developed structural models taking into account the potential endogeneity of public support. These models can be estimated by Instrumental Variables (IV) estimation (for a review of models see Cerulli, 2010). The main practical issue in innovation evaluation literature is associated with the lack of valid instruments or exclusion restrictions. Furthermore, Cerulli (2010) argues that another pitfall of these models is that the selection decision remains a black box, as it is only implicitly modelled. In contrast, selection models take into account the selection process by estimating a system of equations consisting of both selection and outcome equations.

- ***Selection models***: The major advantage of selection models is an explicit modelling of the selection process. The models are estimated as a system of two equations: the selection and the outcome equation. However, the main limitation of selection models is the assumption of normality of the errors, which cannot be tested. Selection models can be estimated by IV estimation and by the Heckman two-step estimator (Heckit approach) (Blundell and Costa Dias, 2009). The latter has an advantage of not requiring an instrument for consistent estimation. However, a problem arises in the presence of heteroscedastic errors, which renders it an inconsistent estimator. If the researcher can identify a valid instrument, then IV estimation is preferred to the Heckit approach, because the estimation is consistent even in the case of heteroscedastic errors.

The second category of evaluation models are non-structural (or reduced-form) models, which include matching models (e.g. Propensity Score Matching), linear regression models and Difference-in-Difference (DiD) models. The major advantage of these models is that no assumptions are necessary about the distribution of errors or on the functional form of the selection equation. However, the non-structural models in a cross-sectional setting control only for observed characteristics of treated and non-treated firms (Cerulli, 2010; Cerulli and Potí, 2008).

Moreover, non-structural models cannot take into account spillover effects from government support. For instance, the comparison group in the matching method represents non-treated firms that are similar to treated firms based on chosen characteristics included in the vector *X*. Under the assumption that similar firms are more likely to cooperate, then non-treated firms could indirectly benefit from government support through linkages with treated firms. The occurrence of positive spillover hinders the accurate estimation of additionality (Grilli and Murtinu, 2011). Further, it is not clear whether the presence of spillover entails underestimation or overestimation of the R&D activities in non-treated firms. Economists argue that both cases are possible: the latter if negative spillovers occur, such as in the case of competition in product development; whereas the former is associated with the long-standing argument that R&D spillovers have a positive effect as new knowledge is transferred to non-treated firms. Finally, treated firms can also be affected by spillovers. Cerrulli (2010) terms the effect of R&D spillovers as 'spillover bias'. In order to econometrically deal with the spillover bias, the author suggest the inclusion of a variable measuring spillover effects. The problem is that the literature does not suggest any variable for capturing R&D spillovers (Grilli and Murtinu, 2011). However, the most severe problem caused by presence of spillovers is that the hypothesis of Stable Unit Treatment Value Assumption (SUTVA) is violated, which implies that the estimation results are biased regardless of the applied evaluation method (Rubin, 1980; Guo and Fraser, 2010; Grilli and Murtinu, 2011). Moreover, Cerulli (2010) notes that the spillover bias is more pronounced when estimating the impact of public support on innovation output, i.e. output additionality, than in the case of estimating input additionality. In economic models, spillovers are assumed to have a direct impact on firm's performance and only an indirect effect on R&D level. Table 3.3 depicts the main advantages and pitfalls of each evaluation model.

Table 3.3. Evaluation methods - advantages and limitations

Method	Advantages	Limitations
Matching estimators	- The method does not require exclusion restrictions (i.e. instruments). - The existence of several matching estimators provides a solid basis for robustness checks. - The model does not require specification of a functional form.	- The method controls only for observable firm characteristics (issue of hidden bias). - For Nearest Neighbour (NN) matching estimator the variance estimation is problematic (bootstrapping is not valid). - Trade off between precision and bias. - Propensity Score Matching (PSM) cannot disentangle the differentiated effect that covariates have on treatment assignment and on the outcome. - Small region of common support can lead to biased estimates of the ATT. - The estimator requires a large number of variables. - All pre-treatment variables are not usually available. - Propensity Score Matching (PSM) limits the population of inference to those units which are within the region of common support. - Conditional independence assumption cannot be tested.
Instrumental Variable (IV) approach	- The method controls for unobserved firm characteristics.	- The method requires exclusion restrictions.
Selection models	- Structural model whereby both the selection equation and the outcome equation are modelled and estimated.	- The method requires exclusion restrictions. - Strong underlying distribution assumption - joint normal distribution of the error terms of both the selection equation and the outcome equations. - Parametric structure of both the selection and the outcome equations.
Regression Discontinuity Design (RDD) approach		- The treatment effect is estimated at the threshold level.
Difference-in-difference estimator	- The outcome equation does not require a functional form or even a regressor. - The estimator accounts for time-unvarying unobserved characteristics and for macroeconomic trends. - The estimator does not require an exclusion restrictions. - It is not necessary to model the selection equation.	- The estimator does not control for firm-specific time-varying effects. - Macroeconomic shocks might not have the same or similar impact on both treated and untreated firms.
The conditional difference-in-difference estimator	- The estimator accounts for time-unvarying unobserved characteristics and for macroeconomic trends. - The estimator does not require an exclusion restrictions.	- The estimator does not control for firm-specific time-varying effects. - Macroeconomic shock might not have the same or similar impact on both treated and untreated firms.

Source: Blundell and Costa Dias (2009); Guo and Fraser (2010); and Grilli and Murtinu (2011).

The *OECD Framework* (2007) adopts the taxonomy of evaluation methodology suggested by Storey (2000) in which evaluation is divided into six steps. Step I measures a response rate of public support measures,[47] step II gathers information on the recipients' opinion about the delivery of support measures and step III provides recipients' self-assessment of the economic impact (additional effect or additionality) of support measures. Step I, II and III are related to monitoring of public intervention (Greene, 2009) and to qualitative evaluation (OECD, 2007). Step IV, V and VI seek to evaluate public support and are more associated with quantitative evaluation. These steps require the comparison of treated (participating) firms with a control or comparison group of non-treated (non-participating) firms. The difference between these three levels of evaluation is the choice of a control group as well as the treatment of selection bias. Step IV is a type of evaluation in which a control group consists of 'average' or 'typical' firms. However, as Curran (2000) observes, comparing treated firms with average firms does not provide reliable benchmarks due to the high heterogeneity of SMEs. This shortcoming is corrected in step V, where treated firms are compared with 'matched' non-treated firms. Matching is done on observable firm characteristics, such as firm size, industry, competition pressure, age, etc. The problem in step V arises from using econometric methods controlling only for observables. Other, unobservable characteristics, such as managers' abilities and motivation, can also have an impact on the additionality of support measures. Step VI resolves this issue by applying econometric methods that take into account both observable and unobservable factors, and hence controlling for selection bias.

3.6 Empirical literature review

The long-standing issue of the effectiveness of public policy on firms' innovation effort has been investigated in two streams of research. One stream adopts a rather empirical perspective, whereby the approach to the evaluation of innovation related policies is a-theoretical, empirical and data driven, without much consideration of theoretical underpinnings (termed 'measurement without theory' by Cerulli, 2010, p. 424). Another

[47] The first step usually includes information on the number of participating firm, their size, regional and sectoral distribution. As Storey (2000) notes, this steps seldom provides information on the amount of public support measures received by individual firms, due to confidentiality clauses stipulated in contracts between firms and the government.

stream attempts to develop a more theoretically based modelling approach (Cerulli, 2010). The former approach is based on the empirical findings from studies employing non-structural models that are estimated by matching estimators. The latter encompasses those studies that develop structural models, wherein explicitly modelling both the selection mechanism as well as the outcome equation.

Although structural models, by explicitly modelling and estimating the selection equation, can provide a more detailed evaluation, they are less applied than are non-structural models. Among non-structural models, matching estimators seem to be the preferred evaluation method (Gonzáles and Pazó, 2008; Hussinger, 2008; Cerulli, 2010; Carboni, 2011). Cerulli (2010) argues that the prevalence of non-structural models in empirical studies stems from their 'objectivity'- as theoretical considerations are reduced to a minimum, and the results are more data-driven than those from structural models. Another argument for the primacy of empirics over theory is the influence of evolutionary and Neo-Schumpeterian economics on the field of innovation studies. Namely, evolutionary and innovation systems approaches are descriptive and qualitative in nature, criticized for their lack of formal (mathematical) modelling. This limited application of economic modelling is then translated into innovation studies as a rather eclectic approach to estimating the effectiveness of policies in the domain of innovation. Arvanitis (2013), in line with discussion by Cerulli (2010), notes that there is no commonly accepted theory of public support to explain the selection process, because the process itself is specific and hinges on objectives set by the government. This could be the reason why David et al. (2000) and David and Hall (2000) suggest that, theoretically, both treatment effects (additionality and crowding out) are possible, thus, leaving the resolution of the issue to empirical analysis. However, following Klette et al. (2000), developing structural models in estimating the impacts of public support could provide valuable insights into the selection mechanisms, and thus facilitate the analysis of the success of government agencies in implementing operational procedures for indentifying those innovation projects with high social returns.

We would extend Cerulli's argument in two directions; first, non-availability of longitudinal, panel data restricted the choice of evaluation methods to be applied. Our argument is consistent with Bloch and Graversen (2012), who note that, in a cross-sectional analysis when the amount of subsidies is not available, 'matching methods are the only feasible option' (p. 209). Second, surveys such as Community Innovation

Survey (CIS) are not specifically designed for the evaluation of innovation related policies. As such, they do not contain suitable exclusion restrictions (instrumental variables), necessary for estimating selection models using IV approaches, Heckman selection models and endogenous switching models. Therefore, our argument for the prevalence of matching estimators in empirical studies is based on restrictions with regard to available data. In addition, following Cerulli (2010), matching is a more empirical, data driven method and that is the reason why the literature does not provide a core (parsimonious) evaluation model. Rather, modelling the outcome equation (in the case of propensity score matching, it is the propensity score equation) is data-driven, which can also be observed in the literature review given in this chapter.

The current state of evaluation innovation studies indicates a primacy of empirical analysis over theory, which creates manifold problems. An absence of a core theoretical model prevents comparability of empirical evidence across countries and over time (Cerulli, 2010). This, in turn, means that the innovation field is severely restricted in building a cohesive body of evidence to inform policy makers. Moreover, matching estimators cannot control for unobserved characteristics, thus creating two additional issues in evaluating public measures: treating the selection process as a 'black box'; and producing potentially biased treatment effects. Greene (2009), in his evaluation of the Prince's Trust programme, concludes that less sophisticated evaluation methods, following Curran's (2000) and the OECD (2007) taxonomy of evaluation methodology, yield more favourable treatment effects than do more sophisticated approaches to evaluation. His conclusion is in line with Papa (2012) and Hujer and Radic (2005), who, in the field of innovation related policies, conclude that unobserved characteristics play a significant role in the public support provision. According to Hujer and Radic (2005), the magnitude of the estimated treatment effects decreases as more variables controlling for both observed and unobserved factors are included in the model, thus improving our understanding of the selection mechanism. Moreover, Siegel et al. (2003), similar to Cerulli (2010), in their discussion on ambiguous empirical results on input additionality, call for more sophisticated evaluation methods.

Arvanitis (2013) argues that the major drawback of quantitative evaluation of innovation policy in general is associated with data limitations, most notably, non-availability of data before and after treatment assignment, as well as availability of only a few variables, which prevents practitioners from adequately modelling selection processes as well as firms' innovation processes (see also Cerulli, 2010; Grilli and Murtinu, 2011; Zúñiga-Vicente et al., 2014). However, Arvanitis (2013) notes that the major impediment in quantitative policy evaluation is present at the empirical level, implying that improvements in innovation databases would substantially enhance their reliability. Following this line of argument, Cerulli (2010) argues that the preferred approach to evaluating innovation-related public support is a dominance of empirical analysis over theoretical considerations or, as he termed it, 'measurement without theory' (p. 439).[48] However, his expectations in relation to empirical analysis in the near future are associated with an increased application of selection models, although matching estimations will still play a relevant role in quantitative evaluation in the domain of innovation. Research presented in this thesis is in accordance with Cerulli's suggestions; although we apply selection models in Chapters IV and VI, we also utilize matching estimators in Chapter V.

Following García-Quevedo (2004), theoretical considerations on the additionality versus crowding-out effect of private innovation subsidies imply that both effects are plausible.[49] Public support might provide incentives for firms to increase their investment in innovation, but might also lead to a reduction in investment in own R&D or innovation, as public funds substitute for private R&D investments. David et al. (2000) provide an extensive review of empirical evidence regarding the effect of public support on innovation and conclude that, although more empirical studies indicate complementarity rather than substitutability between public and private R&D funding, the overall conclusion is still ambiguous. Lööf and Heshmati (2005) in their review of more recent empirical evidence, draw the same conclusion. The meta-analysis conducted by García-Quevedo (2004) also does not provide a definite answer; the results indicate very weak evidence of crowding-out at the firm level.[50]

Another conclusion from García-Quevedo (2004) is that the problem of establishing control groups severely impedes the evaluation of public support, which implies that policy-makers should incorporate the requirements of best practice

[48] As noted in Section 1.4.2, Hong et al. (2012) argue that empirical studies on the determinants of innovation outweighed theoretical work in the field of innovation studies. In addition, Arundel et al. (2008) conclude that the availability of the CIS data resulted in the exponential increase of empirical studies on innovation.
[49] Most empirical research to date deals with R&D subsidies, which is not surprising, as public policy was focused and is largely still focused on R&D activities rather than on innovation in a broader sense as defined in the *Oslo Manual* (OECD, 2005).
[50] The meta -regression analysis covered 39 studies, out of which 17 are at the firm level.

evaluation into the design and budget of innovation policies. Best practice evaluation methodology is characterised by the use of a control group – or, at least – a comparison group - and a serious approach to selection bias: García-Quevedo (2004) insist that government support should always be treated as endogenous, due to the simultaneity and selection bias in the process of applying for support and in the selection process (David et al., 2000; Cerulli, 2010; Antonioli and Marzucchi, 2012). As Lööf and Heshmati (2005, p. 5) observe: 'It is well documented in the literature that firms funded by the government are likely to be among those with the best ideas.'

Lööf and Heshmati (2005) point out three suggestions for the advancement of research on innovation public support. First, researchers should focus on developing structural models in which government decisions are explicitly modelled. This leads to the second recommendation and that is the identification of the determinants of government selection decisions. Finally, common methodology for evaluation of innovation public policy should be developed. The first and second recommendations are difficult to implement, as information on the selection process are rarely publicly available. However, agreement on common methodology would enable comparison between studies and the provision of better policy recommendations. In our opinion, the advance of a common methodology is especially relevant in the context of the European Union, where funding is provided to innovative firms through the Framework Programmes and any evaluation of these programmes requires measuring evaluation effects across countries. Furthermore, common methodology would also enable the comparison of studies using the CIS datasets at national level. At the moment, comparison across countries (and even within countries) is seriously hampered in the absence of common methodology, as our empirical literature review reveals. In addition, the CIS questionnaire should be modified, by including more questions on firms' participation in innovation support measures. This modification would facilitate evaluation of innovation policies.

We review only firm-level studies (for a review of studies at industry and macro level see David et al., 2000; García-Quevedo, 2004) and only those conducted on data from European countries, because our analysis in the later chapters is focused on European SMEs. Our choice of focusing on European studies is in accordance with the trend of geographical coverage of empirical studies. Namely, investigating the impact of public support in the US was prevalent in the literature until the 1990s but, later, the focus shifted to EU countries (Zúñiga-Vicente et al., 2014). One example of the importance of innovation policy in the EU can be illustrated with the Community Innovation Survey (CIS), which was launched across Europe at the beginning of the 1990s (Mairesse and Mohnen, 2010; Hong et al., 2012), whereas the first CIS wave in the US was conducted in 2009 (Business R&D and Innovation Survey -BRDIS) (Hong et al., 2012; Jankowski, 2013).

Regarding empirical studies, three types of additionality have been investigated: input; output; and behavioural additionality. Although the focus of our thesis is on output and behavioural additionality, we also include input additionality in our empirical review, because we believe that insights from empirical studies on input additionality can provide useful guidelines in investigating other types of additionality such as output and behavioural additionalities, particularly in regard to evaluation methodology and the empirical strategies adopted in these studies.

Our empirical review is divided into two segments: empirical studies applying matching estimators (see Appendix I, Tables A1.1 and A1.2); and those applying other evaluation methods (see Appendix I, Tables A1.3 and A1.4).[51]

3.6.1 Input additionality

Input additionality is the subject of the largest number of studies (Clarysse et al., 2009; Clausen, 2009; Cunningham et al., 2013). In our literature review, out of 36 studies investigating input additionality, a majority (25 studies) applies matching estimators. Few studies cover more than one country, and those are Aerts and Schmidt (2008) on Belgium and Germany, Marzucchi (2011) on Italy and Spain, and Czarnitzki and Lopes-Bento (2012) on Belgium, Germany, Luxembourg, Spain and South Africa. Most studies are conducted for one of two countries:

- **Germany** by Czarnitzki and Fier (2002), Almus and Czarnitzki (2003), Czarnitzki and Hussinger (2004), Czarnitzki and Licht (2006), Aerts and

[51] Table A1.2 is a continuation of Table A1.1, that is, Table A1.2 provides further details of studies reviewed in Table A1.1. Similarly, Table A1.4 is a continuation of Table A1.3, that is, Table A1.4 provides further details of studies reviewed in Table A1.3.

Schmidt (2008), Hussinger (2008), Aschhoff (2009), Reinkowski et al. (2010), Alecke et al. (2012), Czarnitzki and Lopes-Bento (2012);

- **Spain** by Busom (2000), Heijs and Herrera (2004), González et al. (2005), Gonzáles and Pazó (2008), Gelabert et al. (2009), Herrera et al. (2010), Marzucchi (2011), Czarnitzki and Lopes-Bento (2012) and Herrera and Sánchez-González (2012).

Among all studies under review, only two studies investigate additionality in SMEs: Alecke et al. (2012) on input additionality of German SMEs; and Foreman-Peck (2013) on output additionality of British SMEs. Other studies cover both SMEs and large firms. Seventeen studies use Community Innovation Survey (CIS) databases.[52] The variable representing public support in the CIS datasets is a binary indicator, only identifying whether or not a firm received a support. The amount of subsidy is unknown, which means that partial crowding out cannot be empirically investigated. In general, any study using a binary indicator for public support can only test the hypothesis of additionality versus full crowding out, as noted in Section 3.4. A corollary of this limitation, according to Cerulli (2010), is that researchers cannot fully investigate the effectiveness of public support.

Arundel et al. (2008) and Cerulli and Potí (2008) point out other issues in the CIS data on public support. Besides the binary indicator for support, the CIS data is limited as to what type of support is received; i.e. it excludes tax incentives and only includes direct grants and loans. Another shortcoming of the CIS data is that the survey itself was not specifically designed for evaluating the effectiveness of innovation related policies, as previously noted in this Section (the CIS questionnaire, irrespective of the survey wave, contains a single question on the receipt of innovation support measures). Notwithstanding its shortcomings, the CIS survey has its advantages as well. First, it is a large-scale survey gathering extensive information on firms' innovative activities (Arundel et al., 2008; Mairesse and Mohnen, 2010). Having a large number of relevant variables is of high importance particularly when matching estimators are applied, given that the assumption of selection on observables critically hinges on the inclusion of all variables affecting the innovation process (see Section 5.3.1 for a detailed discussion on matching estimators). A second advantage of the CIS data is that both participating and

[52] The Mannheim Innovation Panel is the German innovation survey using the CIS questionnaire. The survey is conducted every two years (Arundel et al., 2008).

non-participating firms are covered by the survey. Following Smith and Todd (2005), the matching method can be applied if three conditions are met:

a. Information on participating and non-participating firms should be contained in the same data source;
b. A dataset contains a large set of variables for modelling the participation decision;
c. Both participating and non-participating firms operate in the same market.

The CIS database fulfils the first condition, as already noted. The third condition is met by controlling for market characteristics through the inclusion of industry dummy variables. However, regarding the second condition, a limitation common to most studies in the field of evaluation of innovation related policies is a lack of information on the selection process, as previously noted in this Section (Aerts et al., 2006; Cerulli, 2010; Arvanitis, 2013; Zúñiga-Vicente et al., 2014). Also, as previously mentioned, the CIS dataset contains a single question on whether the firm received public support measures (sources of funding are usually divided into local/regional, national and EU level, similar to the Spanish CIS dataset used in Chapter V). Fortunately, two new datasets analysed in this thesis (the GPrix data in Chapter IV and the MAPEER dataset in Chapter VI) were specifically designed for exploring issues related to the participation of SMEs in innovation support programmes.

Next, we discuss the estimation results and possible limitations of the studies under review. Four possible treatment effects can be reported: a full crowding-out effect (a negative and statistically significant ATT effect); a partial crowding-out effect (the sign of the ATT effect varies with the amount of subsidy);[53] no additionality (a statistically insignificant ATT effect); and additionality (a positive and statistically significant ATT effect). Most studies reject a full crowding-out effect (22 studies that apply matching estimators and 5 studies applying other methods) and provide evidence of additionality (19 studies that apply matching estimators and 5 studies applying other methods). A partial crowding-out effect cannot be rejected in three studies; two studies applying the Generalized Propensity Score (GPS) method, by Marino et al. (2010) and

[53] As already noted in Section 3.4, a partial crowding-out hypothesis can be tested only when the amount of subsidies is available.

Marino and Parrota (2010), while the study by Görg and Strobl (2007) applies a conditional difference-in-difference (DiD) method. Finally, no additionality is reported in four studies applying matching estimators, and those are by Duguet (2004), Kaiser (2004), Lööf and Hesmati (2005) and Gonzáles and Pazó (2008). Lach (2002) found an insignificant treatment effect on large Israeli firms and Klette and Møen (2012), applying the Fixed Effects (FE) estimator found no input additionality in Norwegian firms. In addition, a full-crowding out effect cannot be rejected in 30 per cent of participating firms in Busom (2000), while Gelabert et al. (2009) found a crowding-out effect for firms with the highest level of appropriability. Catozzella and Vivarelli (2011) investigate the impact of public support on input-output efficiency using a bivariate endogenous switching model and report a full crowding-out effect.

Regarding the differential impact of public support depending on firm size, several studies, such as by Lach (2002), Gonzáles et al. (2005), Gonzáles and Pazó (2008), Lööf and Hesmati (2005), Herrera et al. (2010) and Herrera and Sánchez-Gonzáles (2012) provide evidence that input additionality is likely to be found in SMEs. Conversely, Cerulli and Potí (2012) report no input additionality in micro firms (from 10-19 employees).

Further, after matching, it is necessary to estimate variance using one of the following methods: bootstrapping; variance estimation by Lechner (2001); and the variance estimator by Abadie and Imbens (2006). Three studies apply a nearest neighbour matching (NN) with bootstrapped standard errors (Almus and Czarnitzki, 2003; Czarnitzki and Fier, 2002; Heijs and Herrera, 2004). Recently, Abadie and Imbens (2008) suggested that bootstrapping is not valid for NN matching, which implies that the results from these studies could be misleading. Moreover, several studies (Kaiser, 2004; Lööf and Hesmati, 2005; Czarnitzki and Licht, 2006; Cerulli and Potí, 2008; Herrera et al., 2010) do not report what variance estimation methods are applied.

Another relevant issue in PSM is the choice of matching technique (algorithm). Most studies apply the nearest neighbour estimator, without any robustness check by using other matching techniques. The literature on matching estimators (Morgan and Harding, 2006; Guo and Fraser, 2010) suggests that researchers should use several matching estimators, as there is no consensus on which estimator is superior to other estimators. Following Caliendo and Kopeinig (2008), asymptotically all matching estimators should yield similar results. However, finite properties of various matching algorithms are not fully explored. For instance, Alecke et al. (2012) apply kernel matching on their sample of 1,267 firms (284 treated) as kernel matching has good finite sample properties (Fröhlich, 2004). Further, Kaiser (2004) argues that the sample in his study is small (1,115 firms, 129 treated) and applies several matching algorithms (NN, Kernel matching and stratification) for a robustness check.

3.6.2 Output additionality

In contrast to the large body of empirical studies on input additionality, few studies investigate output additionality (Clarysse et al., 2009), although the number of studies has grown in recent years (Cunningham et al., 2013). Our review includes 11 studies applying matching estimators and two studies applying other methods: Hujer and Radic (2005), who applied an IV approach and conditional difference-in-difference methods as a robustness check to their matching estimators; and Hussinger (2008), who applied semi-parametric and parametric selection models. In addition, three studies report the ATE effects; those by Garcia and Mohnen (2010), Schneider and Veugelers (2010) and Hewitt-Dundas and Roper (2010).

In most studies, output additionality is measured as either propensity to patenting or patent counts. A few studies use innovative sales as a proxy for innovation output (studies by Cerulli and Potí, 2008; Hussinger, 2008; Aschhoff, 2009; Garcia and Mohnen, 2010; Schneider and Veugelers, 2010; Hewitt-Dundas and Roper; 2010; Marzucchi, 2011; Herrera and Sánchez-Gonzáles, 2012), the introduction of product innovation (studies by Hujer and Radic, 2005; Hewitt-Dundas and Roper, 2010) and the introduction of process innovation (a study by Marzucchi, 2011). Foreman-Peck (2013) measures innovation output as either the introduction of product or process innovation. Other indicators of innovation output such as firm performance (productivity, profitability, etc.) are not taken into account. The argument justifying an absence of studies investigating other output measures is associated with the lack of longitudinal data, because public support is likely to have a medium or long-run effect on innovation output (Hyvärinen and Rautiainen, 2007; Busom and Fernández-Ribas, 2008; Clarysse et al., 2009; Grilli and Murtinu, 2011; Alecke et al., 2012).

Most studies report a positive output additionality; studies by Hussinger (2008), Aschhoff (2009), Herrera et al. (2010), Reinkowski et al. 2010 (but the estimated treatment effect is insignificant for micro firms), Alecke et al. (2012), Herrera and Sánchez-Gonzáles (2012) (output additionality found for small firms, but not for medium-sized firms) and Foreman-Peck (2013). Two studies found insignificant treatment effects, those are Aerts and Czarnitzki (2004) and Cerulli and Potí (2008). Finally, a partial crowding out is reported by Marino and Parrota (2010).

Marzucchi (2011) reports a differential impact of public support on Italian firms depending on the measure of innovation output. Namely, the ATT effects of regional support programmes are negative and statistically significant when the outcome variables are the introduction of product innovation and innovative sales from products new to the firm; no treatment effect is reported for patent applications and innovative sales from products new to the market; and a positive and statistically significant effect on the introduction of process innovation. In similar vein, the impact of Italian national support programmes is only positive when the innovation output is proxied by the introduction of process innovation; for other measures, empirical evidence suggests no additionality. Different results are, however, reported for Spain, where regional support programmes have a positive impact on patent applications, the introduction of product innovations and innovative sales from products new to the market. Very similar results are presented for national support programmes; positive treatment parameters are estimated for patent application and innovative sales from products new to the market.

Hujer and Radic (2005) applied a matching approach to evaluate the impact of R&D subsidies on innovation output. The results indicate output additionality for both measures (new products and innovative sales). Yet, once other methods that allow for control of unobservable firm characteristics were applied, the impact of public support becomes negative and crowding out cannot be rejected.

Only one study specifically focuses on output additionality in SMEs. That is the study by Foreman-Peck (2013), who uses the CIS4 dataset to investigate the impact of public support on technological innovations in UK SMEs using the Nearest Neighbour matching estimator. The results report a positive and significant treatment effect on SME innovation for both firms receiving R&D tax credits and those supported by non-tax public support.[54] Interestingly, empirical findings suggest a differentiated effect of R&D tax credits on small and medium-sized firms. The additionality effect of R&D tax credits is higher in medium sized firms (almost 30%), while in small firms it is only 15%. For non-tax public support, the results are reverse; the ATT for small firms is twice as large in small firms as in medium-sized enterprises. These results are in line with the expected impact of support measures depending on the firm size. Namely, medium firms benefit most from financial support, while small firms benefit most from non-financial support.

3.6.3 Behavioural additionality

The concept of behavioural additionality (BA) should be regarded as a complement, not a substitute to input and output additionalities (Clarysse et al., 2009; Cunningham et al., 2013). Although the literature advances a broad perspective on BA, most empirical studies investigate only one segment of BA;[55] that is the impact of public intervention on firms' cooperative behaviour (scope additionality as defined by Falk, 2007; or network additionality following the OECD, 2006a, definition). Compared to a large number of empirical studies on input additionality and to a lesser extent on output additionality, behavioural additionality has been the subject of only a few studies. An interesting feature of the empirical analysis of behavioural additionality is that matching estimators are the only estimation methods that have been employed. The reason for this is associated with impediments imposed by the data at hand. Innovation studies, in general, mostly report empirical findings from Community Innovation Survey (CIS) datasets. The main issues with this large-scale survey are twofold: first, the survey is not longitudinal by design, which typically precludes panel analysis; and, second, other evaluation methods, such as selection models and Instrumental Variable (IV)

[54] The UK CIS1, CIS2 and CIS3 survey questionnaires included two questions on public support participation; the first was a generic question on the sources of public support from different administrative levels (regional, national, and EU), whereas the second question further ask respondents if they participated in various government and EU schemes, such as: Technology Development programmes (e.g. LINK, SMART); Technology Acquisition (e.g. Teaching Company Scheme, Demonstration Projects); Management Information Programmes (e.g. Industry CLUBs); and European programmes (e.g. Framework, Eureka). The CIS4 survey questionnaire included one question on the firms' participation in support measures, but with a sub-question about the firms' claim of R&D tax credits. The CIS 5 survey questionnaire excluded the question on public support altogether. The CIS6 and CIS7 survey questionnaires reintroduced the question on the participation in public support measures, but excluded the sub-question about the firms' claim of R&D tax credits.

[55] Our study suffers from the same limitation; available data do not allow for exploring other categories of behavioural additionality.

approaches require a valid instrument, which is hard if not impossible to find in CIS surveys (Busom and Fernández-Ribas, 2008; Czarnitzki et al., 2007; Aerts and Schmidt, 2008).

Among the first studies to investigate behavioural additionality is the one by Fier et al. (2006), who assessed the impact of public support on the innovation behaviour of German firms in manufacturing sectors. Behavioural additionality is measured by three types of cooperation: with other businesses; with scientific institutions; and a combination of both. The results from matching estimation on the third and fourth CIS datasets are positive for all three types of cooperation. Moreover, the results indicate the heterogeneity of the impact; the largest effect of public support is on combined cooperation, and the smallest on cooperation with other businesses.

Busom and Fernández-Ribas (2008) used a subsample of Spanish manufacturing firms participating in the CIS survey in 1999 to explore the impact of national support programmes on vertical cooperation (with suppliers and customers) and with private-public partnerships (cooperation with universities or public laboratories). National programmes have a positive effect on both types of cooperation, but the effect on private-public partnership is more prominent; the Average Treatment Effect of the Treated (ATT) on this type of partnership is twice the effect on vertical cooperation. The study also reports the Hausman test for endogeneity of treatment assignment from a bivariate probit model. The results indicate that selection bias could affect the estimated treatment effects on public-private partnerships, but the effects on vertical cooperation are robust to unobserved factors.

Fernández- Ribas and Shapira (2009) investigate how local and national support programmes affect cooperation with international partners among manufacturing firms in Catalonia. The authors use the third CIS survey covering the period 1998 -2000. The estimated ATT effect is positive, but fairly small (8 percentage points). However, the econometric results from three different matching estimators (kernel, NN matching and stratification) are not consistent; for instance, for firms that cooperate with any international partner, the estimated ATT effect from the NN and kernel matching is statistically insignificant, but significant when stratification matching is applied. This inconsistency of results suggests that we should exercise caution when discussing their findings.

Afcha- Chàvez (2011) explores behavioural additionality using the Spanish ESEE survey of business strategy for the period 1998-2005. The treatment effects are estimated for vertical cooperation and private-public partnerships while separating regional from national programmes. Estimated programme effects are significantly positive only for private-public cooperation for both sources of funding, but not significant for vertical cooperation. Marzucchi (2011) provides a comparative analysis of the forth CIS survey for Spain and Italy. They found no effect of Italian regional policies on any type of cooperation (horizontal, vertical, and private-public); but report a positive effect of national policies on each type of cooperation. Findings from Spanish data indicate a positive impact of both regional and national policies on each type of cooperation.

Antonioli et al. (2012) investigate the impact of a specific regional innovation policy (PRRITT) in the Italian region of Emilia-Romagna. The results are contrary to previous studies – the authors report no effect of public support on regional cooperation. Furthermore, regional policy shows a negative effect on horizontal cooperation. In summary, most studies report behavioural additionality, i.e. a positive impact of public support on firms' cooperation. However, the magnitude and significance vary depending on sources of funding and types of cooperative partners.

In their book on open innovation activities, Spithoven et al. (2012) investigate, among other issues, the impact of public funding on Belgian firms using two waves of the CIS survey. Similar to our analysis, three sources of funding (regional, federal and EU) are analysed separately. To our knowledge, this is the first study to employ any method other than matching to investigate behavioural additionality. Namely, having two waves of the data at their disposal, Spithoven et al. (2012) apply a bivariate probit model, using lagged values of control variables as instruments. However, regarding cooperative partners, due to a small sample size, they only distinguish between two types of partnerships: cooperation with other businesses; and private-public partnerships. The results suggest a differential effect of different sources of funding. Only participation in regional funding has a positive and statistically significant effect on both types of partnership. National support has no impact on research cooperation, whereas EU support has a positive impact on private-public partnerships. As a robustness check, the study reports treatment effects estimated by matching. However, results are only broadly consistent with, but more optimistic than, those reported from a bivariate probit model. Overall, all three sources of funding have a positive and statistically significant effect on both types of partnerships.

3.6.4 Overview of the empirical evidence

The empirical review reveals heterogeneity among studies in various aspects. First, a broad range of explanatory variables are modelled. Lööf and Heshmati (2005) note the absence of robust theoretical guidelines on the choice of the independent variables. As a consequence, economic theory does not provide a core (parsimonious) model for investigating the effectiveness of innovation policy. Namely, theory is not developing at the same pace as empirical studies, where practitioners apply sophisticated econometric methods disregarding the lack of theoretical development (Aerts et al., 2006).

In general, the explanatory variables used in modelling evaluation methods can be divided into three categories:

- ***Firm characteristics***: firm size, age, export, belonging to a group, firm ownership, cooperation with competitors and institutions, financial and skill constraints, variables measuring human capital, such as the share of employees with a university diploma etc.

- ***Financial data***: cash flow per employee, debt per employee, capital stock per employee, equity per employee and capital intensity.

- ***Market and sectoral characteristics***: competition (market concentration, market power) and industrial sectors.

Most studies use cross-sectional data, thus the medium- and long-run impact of public support are not investigated (Arundel et al., 2008; Cerulli, 2010; Grilli and Murtinu, 2011). Most studies are constrained by the available data to use a binary treatment variable, not the amount of subsidies (Arundel et al., 2008; Cerulli, 2010; Grilli and Murtinu, 2011; Zúñiga-Vicente et al., 2014). Regarding input additionality, the outcome variable can be measured in two manners: total R&D expenditures; and net (private or own) R&D expenditures (equal to total R&D expenditures minus the amount of R&D subsidy). Only the latter is an appropriate outcome variable, because the objective of evaluation is to estimate the impact of public intervention on firms' own, private R&D investments (Cerulli, 2010). However, as most studies are characterized by a lack of data on the amount of subsidies, empirical results might be biased, but the direction of bias cannot be determined a priori, because public measures can have a positive effect (additionality) or a negative (crowding-out) effect.

Matching is the preferred evaluation method (Cerulli, 2010). However, Cerulli (2010) notes that unobserved characteristics might occur in the process. Given that researchers do not possess information on the quality of the proposed R&D projects (Grilli and Murtinu, 2011), assuming that unobserved factors have no impact on the treatment effects will give rise to biases in the estimated treatment effects. In this context, it is of high importance that empirical studies report sensitivity analysis (Guo and Fraser, 2010).[56] However, only one study (by Alecke et al., 2012) reports the results of sensitivity analysis.

Moreover, looking at the reported treatment effects in all studies using matching estimators, it is striking that not a single study reports a negative treatment effect. On the contrary, the estimated ATT effects are either positive and statistically significant or positive and statistically insignificant. Cunningham et al. (2013) observe that although a negative behavioural additionality is theoretically viable, there are no empirical studies reporting it. They proceed with their argument suggesting that behavioural additionality is sometimes reported to disguise the suboptimal findings on input and output additionality (Gök and Edler, 2012). We would extend their observation by noting that matching is the single evaluation method applied in investigating behavioural additionality. Thus, Cerulli's (2010) argument on studies disregarding the unobserved factors is easily confirmed in the domain of behavioural additionality and, to a lesser extent, output additionality. However, our rationalizing on the possible publication bias can only be confirmed through meta-analysis, which is absent for output additionality (Cunningham et al., 2013) and, we would add, for behavioural additionality.

The issue of positive bias associated with choice of methodology in this literature is further exacerbated by the lack of robustness checks. Guo and Fraser (2010) emphasize the importance of applying several evaluation methods before reaching a final conclusion regarding the effectiveness of treatment assignment. Our review reveals

[56] A detailed discussion on sensitivity analysis when applying matching estimators is relegated to Section 5.4.1.

that few studies apply more than one evaluation method as a robustness check, and those are the studies by Lach (2002), Hujer and Radic (2005), Cerulli and Potí (2008), Gelabert et al. (2009), Marino et al. (2010), Spithoven et al. (2010) and Czarnitzki and Lopes-Bento (2013). Among these studies, most authors report that crowding out effects cannot be rejected, either in the full sample (for instance, Hujer and Radic, 2005; Gelabert et al., 2009,; and Marino et al., 2010) or in the subsamples of certain characteristics (for instance, Lach, 2002, found a positive treatment effect on small firms, but no effect on large firms).[57]

In recent years, researchers increasingly investigate more than one type of additionality (see, for instance, Aerts and Czarnitzki, 2004, Hussinger, 2008; Cerulli and Potí, 2008; Aschhoff, 2009; Herrera et al., 2010; Reinkowski et al., 2010; Marino and Parota, 2010; Alecke et al., 2012; Marzucchi, 2011; Herrera and Sánchez-Gonzáles, 2012). Again, most of these studies use matching estimators, and echoing the proposition by Cerulli (2010), we emphasise the necessity of applying other evaluation methods.

Finally, the coverage of empirical studies is usually limited to one country. Among studies included in our review, only three studies analyse additionality in more than country, and even those cover mostly two countries; Aerts and Schmidt (2008) for Belgium and Germany; Marzucchi (2011) for Italy and Spain; Czarnitzki and Lopes-Bento (2012) for Spain, Germany, Belgium, Luxembourg and South Africa; and Hewitt-Dundas and Roper (2010) for Ireland and Northern Ireland. Thus, limited country coverage together with heterogeneous model specifications and evaluation methods seriously hampers international comparison and consistent policy recommendations.

3.7 Conclusions

Economic theory advanced two complementary rationales for public intervention in the domain of innovation. Historically, the first argument on market failures was developed within neoclassical economics. The market-rationale argument explores different reasons for the failure of markets to provide adequate incentives for innovative activities at the organizational level. An ensuing consequence is the underinvestment of private

[57] We excluded from the list those studies applying OLS regression, because selectivity and endogeneity cannot be taken into account in OLS models, thus the results are inconsistent and biased.

R&D below a socially optimal level. Second, the evolutionary system-failure rationale broadened the scope of public intervention by addressing failures in the functioning of innovation systems. From the perspective of a contemporaneous innovation policy, both rationales are valid and contribute to policy design and implementation, by emphasising the failures in markets to provide sufficient incentives for firms to invest in R&D and innovation at a socially optimal level, as well as institutional, network and other system failures stemming from interaction and connectedness of economic agents within broad boundaries of innovation systems.

Evaluation of the effectiveness of innovation policies has been conducted during the last 30 years. A broad range of evaluation methods is applied in the quantitative evaluation of innovation policy. These methods can be divided into two categories - structural and non-structural models. The former adopt a modelling strategy of developing a system of equations to reflect two processes: the selection process by government agencies; and the innovation process within firms. These models can be estimated by applying an Instrumental Variable (IV) approach (such as 2SLS and Heckman model) and/or selection models (such as the Heckit model and endogenous switching selection models). Their main advantage over non-structural models is the ability to control for both observed and unobserved firm characteristics. Conversely, non-structural models are characterized by modelling only the innovation process (the outcome equation) without explicitly accounting for the selection process. Among these, matching estimators are the most applied evaluation method. The main drawback of matching is inability to control for unobservables.

The main research question in the quantitative evaluation is whether public measures induce additional effects (additionality hypothesis) or if firms substitute their private investment with public funding (crowding out hypothesis). By far, the most investigated issue is the impact of public support programmes on firms' innovation input (input additionality). Notwithstanding a large number of empirical studies, empirical evidence on input additionality remains inconclusive, although evidence of a positive treatment effect seems to prevail (García-Quevedo, 2004; Zúñiga-Vicente et al., 2014). In addition to input additionality, more recently the focus of empirical studies has shifted to output additionality, and most recently, to behavioural additionality. With respect to the former, the empirical evidence is qualitatively very similar to that on input additionality. Namely, although most studies find a positive treatment effect, overall the empirical evidence is still mixed. Currently, only empirical evidence on behavioural additionality seems to provide a clear picture of positive, additional treatment effects. However, the main issue with this body of evidence is that all studies apply matching estimators, without attempting to conduct any robustness check by applying other evaluation methods, and particularly without applying sensitivity analysis. A lack of sensitivity analysis in studies applying matching estimators is endemic, thus seriously hampering, among other factors, the reliability of empirical findings. In addition, the literature on evaluation methodology suggests that less sophisticated methods yield more favourable effects of innovation policies (OECD, 2007; Greene, 2009).

The most recent trend in European innovation policy is a shifting focus towards a systemic innovation policy, that would consider broader, social and environmental effects of innovation. A necessity to design and implement a systemic innovation policy is accompanied by a necessity to develop and conduct systemic policy evaluation. Although these considerations are at early stage of development among scholars and policy makers, one recommendation is already put forward regarding policy evaluation; namely, that all three types of additionality should be explored in an integrated approach (Bach and Matt, 2005; Gök and Edler, 2012; Magro and Wilson, 2013). Our review of empirical studies shows that this practice is slowly gaining grounds and the most recent studies (e.g. Cerulli and Potí, 2008; Herrera et al., 2010; Alecke et al., 2012; Herrera and Sánchez-Gonzáles, 2012) are not solely focusing on exploring input additionality.

The research objectives of this thesis are related to above discussion. We do not investigate input additionality for several reasons. First, the dataset used in the following chapter does not contain information on firms' R&D expenditures. Second, all three datasets used in this thesis contain only a binary measure of public subsidies, thus preventing us from distinguishing between private (net) R&D expenditures and the amount of subsidy (Cerulli, 2010). Third, as the focus of the thesis is on SMEs, the literature suggests that these firms either invest in R&D to a lesser degree than do large firms, or that their R&D efforts are informal, particularly in firms without a formal R&D department (Lefebvre and Lefebvre, 1993; Hölzl, 2009; Ortega-Argilés et al., 2009). However, in line with suggestions on systemic evaluation, we investigate output and behavioural additionality of SMEs across Europe. Another novelty of the research is the application of structural models estimated by selection models. According to Cerulli (2010), in the near future, empirical research might be directed towards an increased application of structural models, although non-structural, most notably, matching estimators will remain a relevant evaluation method.

Finally, in this chapter, major limitations in the quantitative evaluation of innovation policy have been noted. Following Cerulli (2010), the preferred approach to evaluating public support is 'measurement over theory', that is, the dominance of empirical analysis over theory. Furthermore, the issue of data availability that is widespread in empirical studies, and this issue encompasses a number of data limitations. First, the lack of longitudinal data prevents empirical studies of medium- and long-term impacts of public interventions. Moreover, the availability of panel data would enable the application of estimators that can adequately treat the simultaneity and selection bias arising from participation in public support measures. Second, a lack of data on the amount of subsidies restricts the analysis of potential partial crowding out effects. In addition, input additionality cannot be properly modelled and investigated without knowing the size of support measures. Finally, the available data, particularly large-scale datasets such as the Community Innovation Survey (CIS), do not contain any information about the selection mechanisms, contributing to a lack of knowledge about the selection process (Aerts et al., 2006; Cerulli, 2010; Grilli and Murtinu, 2011). Internationally comparable empirical studies are scarce, as access to the CIS data is restricted to the Eurostat Safe Centre in Luxembourg or the anonymized data available on CD-ROM, which do not include all the countries conducting the CIS survey.

CHAPTER IV

THE IMPACT OF INNOVATION SUPPORT PROGRAMMES ON SME INNOVATION IN TRADITIONAL MANUFACTURING INDUSTRIES

4.1 Introduction

This Chapter reports the findings on the effectiveness of public innovation support programmes for small and medium enterprises (SMEs) in traditional manufacturing industries. Throughout the European Union, there are around 400 such programmes. Yet, in the absence of best practice evaluation, they are of unknown effectiveness, which precludes identification and spreading of best practice (OECD, 2007, pp.11 and 27; also, pp.50 and 52; see also Lenihan et al., 2007). Responding to this lacuna, the European Commission's DG-Research commissioned the multi-methods GPrix project.[58] The quantitative dimension of the evaluation required a new questionnaire survey. This Chapter reports the econometric analysis of the survey database, which informed the main GPrix policy recommendations.

In recent years, empirical analysis of the impact of public support on firms' innovative activities has been mainly concerned with additionality/crowding out. Most empirical studies investigate input additionality, i.e. the effect of subsidies on firms' R&D expenditure, as discussed in Section 3.6.1. The analysis in this Chapter, in contrast, focuses on output additionality, by which we mean the effect of subsidies on firms' innovation: operational innovations (product, process, marketing and organisational innovations);[59] and innovative sales (sales resulting from product and/or process innovations) (see Section 3.6.2).

The main challenge to innovation policy evaluation is the potential endogeneity of programme participation and its corollary, selection bias. Firms' innovation and a receipt of public subsidies are likely to be codetermined, because both are influenced not only by the observable characteristics of firms (those available to researchers such as measures of firm size) but also by unobservable characteristics (those generally not available to researchers such as management quality) (see Section 3.5). In principle (Curran and Storey, 2002), support may be endogenous to innovation either because firms that are more innovative are more likely to apply for a subsidy (self-selection of firms) and/or firms that are more innovative are more likely to receive a subsidy

[58] The GPrix project research and corresponding policy recommendations are all described and available from the project website: http://www.gprix.eu/ (under the "Reports" tab).
[59] For these definitions, see the *Oslo Manual* (OECD, 2005).

(government agencies select firms for participation by "cream skimming").[60] In either case, favourable (unfavourable) observable and/or unobservable characteristics may increase (decrease) both firms' participation in support programmes and their innovation behaviour. This introduces selection bias into programme evaluation. If evaluators assume that public funding is exogenous with respect to firms' innovation behaviour then they will mistakenly attribute influences arising from underlying observable and unobservable firm characteristics to programme participation, which causes the impact of programme participation to be overestimated.

To address programme endogeneity and consequent selection bias in policy evaluation, various empirical strategies are employed. The major distinction between them lies in the treatment of the unobservable heterogeneity of firms (see Section 3.5). Matching methods, which are most commonly used, can only control for observables (see Section 5.3.1 for a detailed discussion on matching estimators), whereas selection models control for both selection on observables and selection on unobservables (Cerulli and Potí, 2008; Czarnitzki and Lopes Bento, 2013). Our preferred approach is the selection model supplemented by matching estimates as a robustness check.

This chapter is organized as follows. Section 4.2 briefly surveys sources of potential government failure in innovation policy that, together, suggest reasons why public support programmes may fail to achieve additionality. Section 4.3 examines the methodology, model and the data. Section 4.4 discusses the results. Section 4.5 concludes with policy recommendations.

4.2 Government failure in innovation policy

Many empirical studies[61] note that governments might follow a "picking winners" strategy (Czarnitzki and Lopes-Bento, 2013; Nooteboom and Stam, 2008; Zúñiga - Vicente et al., 2014), but empirical evidence suggest that the effects of various programmes are, at best, rather small (see Section 3.6). In this Section, we consider reasons for the lack of substantial additionality - even a crowding out effect - of public support. As Stiglitz and Wallsten (1999, p. 58) note: 'Ironically, underlying the current

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[60] The terms "cream skimming", "cherry-picking" and "picking winners" are synonyms.
[61] Several studies empirically confirm this argument (Heijs, 2003; Cantner and Kosters, 2009; Hussinger, 2008).

drive for private-public partnerships is the widespread belief that government is not very effective in choosing good projects (i.e., picking winners) and managing research.'

The rationale for the provision of support measures arises from the occurrence of market failures. However, public interventions to mitigate market inefficiency can be impaired by various "government failures" (Nooteboom and Stam, 2008; Stiglitz and Wallsten, 1999; Wallsten, 2000). Firstly, due to measurement difficulties and asymmetric information, public agencies are hampered in selecting those firms with promising innovative projects that would not be undertaken without public support. Secondly, public agencies might be captured by the private interests of lobby groups. Thirdly, even in the presence of perfect information and making decisions independently, public choice theory suggests that public agencies would have incentives to “cream skim” – i.e. to subsidise those firms likely to do research and innovate in any case - to maximise apparent commercial returns and so justify and perpetuate agency resources. Fourthly, according to Wallsten (2000) adverse selection of inframarginal projects (those that generate positive private returns and would be undertaken by firms even without a public intervention) rather than marginal innovation projects (those that are not profitable for firms yet entail social benefits) arises because risk-averse governments fear loss of electoral support as a consequence of selecting programmes with higher probability of failure.

Finally, Crespi and Antonelli (2012) suggest another form of government failure related to asymmetric information. The so called "Matthew effect" arises when public agencies select firms based on their previous record of programme participation. In particular, programme managers have difficulties in assessing applications with a low level of scientific content and may accordingly rely on the firm's past record of programme participation. Together, these forms of potential government failure lead us to hypothesise that the estimated representative effects of public support measures to increase private innovation may be disappointing compared to the effects typically claimed by public agencies.

4.3 Methodology

4.3.1 The model and estimation

This section sets out a parsimonious model for econometric estimation of the innovation effects of programme participation on SMEs. This model was first set out publicly in Deliverable 1.3 of the GPrix project (GPrix, 2010b, pp. 11-21). The prepublication of models helps to assure the validity of results from subsequent estimation. That is, by setting out our model in advance of data analysis, we limit our options with respect to specification search, which is a well-known source of publication or selection bias in econometric literatures (Stanley, 2005).

The first problem to address is that there are many potential control variables (Becheikh et al., 2006, identify over 60 determinants of innovation) (see Section 1.4.2). Moreover, even within disciplines, let alone between them, there is no "canonical" model of the determinants of firms' innovation. In the absence of such a model, a parsimonious model is specified as follows.

- Dummy variables are used wherever possible to aggregate the effects of the many possible individual effects. *Country dummy variables* control for all country effects (i.e., all those variables associated with the "national innovation systems" approach as well as with other institutional effects and with macroeconomic effects); *Regional dummies* substitute for all regional effects (i.e., all those variables associated with the "regional innovation systems" approach); and *Industry dummies* substitute for all industry effects (i.e., all those variables associated with the "technological regimes" approach, e.g., technological opportunities and appropriability conditions, and demand conditions, etc).
- *Firm level "quasi" fixed effects* (or initial conditions) are used to capture *otherwise unobservable* firm and ownership effects. Here we adapt an approach suggested by Blundell et al. (1995); namely, we propose aggregating most time invariant (or, at least, "slow moving") firm-level and ownership influences on innovation by *'including a variable in the regression that approximates the build-up of knowledge of the firm at its point of entry into the sample'* (p. 338). According to Blundell et al. (1995, p. 338), such a proxy for 'the "permanent" capacities of companies

successfully to commercialise new products and processes' is designed to capture the aggregate effect of firm-level time invariant influences on innovation.

In this approach, there is a crucial assumption; namely, that the variables substituted by country, regional and industry fixed effects, or by firm "quasi" fixed effects, are time invariant or, at least, "slow moving" (Blundell et al., 1995). Our intention to evaluate programmes recently undertaken by firms (from 2005 to 2009) helps to make this assumption more reasonable than if we were taking a very long period into consideration.

The basic model has two equations: the second equation models the participation decision (the probability that a firm will participate in an innovation support programme); and the first equation is an innovation model, which estimates the innovation effect on firms of participating in an innovation support programme conditional on both other influences on innovation and the probability of participating in an innovation support programme.

$$\begin{aligned} Innovation_i = \hat{C} + \hat{\gamma} Participation_i + \hat{\beta}_1 Size_i + \hat{\beta}_2 MPower_i \\ + \hat{\beta}_3 Export_i + Industry_I \hat{\phi}_1 + Region_R \hat{\phi}_2 \\ + Country_C \hat{\phi}_3 + QFFE_i \hat{\alpha} + u_i \end{aligned} \tag{4.1}$$

$$\begin{aligned} Participation_i \\ = \hat{I} + \hat{\lambda}_1 Size_i + \hat{\lambda}_2 MPower_i + \hat{\lambda}_3 Export_i \\ + Industry_I \hat{\rho}_1 + Region_R \hat{\rho}_2 + Country_C \hat{\rho}_3 \\ + QFFE_i \hat{\delta} + Obstacle_i \hat{\theta} + \varepsilon_i \end{aligned} \tag{4.2}$$

Subscript *i* indexes each firm in the sample 1…n, where n is the number of firms; ^ indicates "to be estimated"; *C* and *I* represent the intercept in Equations 4.1 and 4.2 respectively; the γ coefficient measures the innovation effect of programme participation; the β and λ coefficients measure, respectively, the innovation and participation effects of control variables commonly identified in the literature (firm size, market power and the proportion of turnover exported); the k×1 ϕ and ρ vectors contain coefficients that measure, respectively, the innovation and participation effects of 1×k vectors of *Industry*, *Region* and *Country* dummies, where subscripts *I*, *R* and *C* index industries, regions and countries, respectively; the k×1 α and δ vectors contain coefficients that measure, respectively, the innovation and participation effects of 1×k vectors of firm level 'quasi' fixed effects; the k×1 θ vector contains coefficients that measure the participation effects of a 1×k vector of indicators of firms' views on factors promoting or impeding programme participation (*Obstacle*), which are the anticipated identifying variables; and *u* and ε are the error terms, which capture the unobserved influences on the respective dependent variables. Full definitions and descriptive statistics for each variable are presented in Appendix II, Table A2.1 and A2.2.

An augmented model is specified by including a variable *Collaboration* (=1 if the firm responded "yes" to the question "From 2005 to 2009 did your enterprise co-operate on any of your innovation activities with other enterprises or institutions?"; otherwise zero) (see Appendix II, Table A2.1).

The independent variables must include (for econometric reasons) all the control variables from the outcome Equation 4.1 together with at least one variable to identify Equation 4.2.[62] This identifying variable (*Obstacle*) must influence the programme participation decision but not the innovation decision. From the theoretical perspective, factors impeding programme participation have a direct effect on the probability of treatment assignment, but have no impact on firms' innovative activities, as they are specifically associated with the selection process, not the innovation process. For this purpose, the survey included a question related only to programme participation. Whereas previous questions related directly to firms' own, particular innovation behaviour, Question 31 asked firms about SME needs in general: "What are the specific needs for SMEs to enable them to participate in innovation support programmes?" In all 18 parts of this question (see Appendix II, Table A2.2), the corresponding indicator variable was defined as 1 if the response was "Very high importance" and 0 otherwise ("No importance", "Low importance", "Important" or "High importance"). Table A2.2 demonstrates that most of these display widely varying proportions between participants and nonparticipants.

[62] In practice, identifying variables may be desirable rather than essential. Lokshin and Sajaia (2011, p. 381) report that their estimator is 'relatively robust in terms of identification of the model'.

Equation 4.1 is constructed to test the hypothesis that whether or not a firm innovates depends on whether or not the firm participates in a support programme. This makes *Participation* a switching variable: according to the hypothesis, if the firm participates (*Participation* = 1) then the firm enters a state in which innovation is more likely (Regime 1); if the firm does not participate (= 0) then the firm remains in a state less conducive to innovation (Regime 0).

Because the outcome variable, *Innovation*, can exist in one of two regimes, equation 1 should be estimated over both regimes 1 and 0, in which case *Participation* disappears as a separately estimated variable. Instead of the single Equation 4.1, we now have two equations, 4.1a and 4.1b, differentiated by an additional subscript: 1 for Regime 1 (all firms that participated in a support programme – i.e. *Participation* = 1); and 0 for Regime 0 (all firms that did not participate in a support programme – i.e. *Participation* = 0). Equation 4.1a estimates the probability of innovating for firms that participated in a support programme, whereas Equation 4.1b estimates the probability of innovating for firms that did not participate in a support programme. Equations 4.1a and 4.1b, together with Equation 4.2 are estimated simultaneously by the full information maximum likelihood estimator (Lokshin and Sajaia, 2011).

Regime 1 (*Participation* =1; i.e. participants)

$$\begin{aligned} Innovation_{i1} = {} & \hat{C}_1 + \hat{\beta}_{11} Size_{i1} + \hat{\beta}_{21} MPower_{i1} + \hat{\beta}_{31} Export_{i1} \\ & + Industry_{I1} \hat{\phi}_{11} + Region_{R1} \hat{\phi}_{21} \\ & + Country_{C1} \hat{\phi}_{31} + QFFE_{i1} \hat{\alpha}_1 + u_{i1} \end{aligned} \tag{4.1a}$$

Regime 0 (Participation =0; i.e. nonparticipants)

$$\begin{aligned} Innovation_{i0} = {} & \hat{C}_0 + \hat{\beta}_{10} Size_{i0} + \hat{\beta}_{20} MPower_{i0} + \hat{\beta}_{30} Export_{i0} \\ & + Industry_{I0} \hat{\phi}_{10} + Region_{R0} \hat{\phi}_{20} \\ & + Country_{C0} \hat{\phi}_{30} + QFFE_{i0} \hat{\alpha}_0 + u_{i0} \end{aligned} \tag{4.1b}$$

This switching process is endogenous if unobserved influences on *Innovation* (u_{i1} in Equation 4.1a and/or u_{i0} in Equation 4.1b) are correlated with unobserved influences on *Participation* (ε_i in Equation 4.2). In our three equation model (4.2, 4.1a and 4.1b), a bivariate outcome (*Innovation*) is partitioned into two regimes by a potentially endogenous bivariate switching variable (*Participation*). The three equations are linked by both common observed variables and, potentially, by common unobserved variables. The correlations between the unobservables are denoted as follows:

- between the error terms of the selection equation (ε_i) and of the outcome equation in regime 1 (u_{i1}), ρ_1 (rho1);
- between the error terms of the selection equation (ε_i) and of the outcome equation in regime 0 (u_{i0}), ρ_0 (rho0); and
- between the error terms of the two outcome regimes, ρ_{10}.

The two correlations *rho1* and *rho0* are particularly important, because they give insight into whether or not the selection process is endogenous. If *rho1* and *rho0* are both zero, then the error terms are independent across equations, which "does not allow for selection on unobservables" to be related to the innovation outcome equations (4.1a and 4.1b) (Aakvik et al., 2005, p. 36). In this case, the selection process can be treated as exogenous.

The appropriate estimator for our model was developed by Aakvik et al. (2005) and has been made available as the *switch_probit* command for STATA by Lokshin and Sajaia (2011). The estimated switching probit model can be used to generate counterfactual probabilities of innovation for firms in different regimes of programme participation (Lokshin and Glinskaya, 2009, pp. 489 and 503). In turn, these enable statistics to be calculated that enable the effect of programme participation to be defined and measured "in terms of impact evaluation" (Lokshin and Glinskaya, 2009, p. 492). Three such statistics are of interest in the present analysis (see Section 3.5).

- The effect of the treatment on the treated (TT) statistic 'estimates the effect of the programme on the entire group of people who participate in it' (Aakvik et al., 2005, p. 22). In the present context, *TT* is the difference between the predicted probability of innovation for a participating firm and the probability of innovation had that firm not participated (Lokshin and Glinskaya, 2009, p. 490). The average TT effect (ATT) is obtained by averaging TT over the subsample of participating firms (Lokshin and Glinskaya, 2009).

- The average treatment effect on the untreated (ATU) estimates the effect of a programme on the firms who did not participate (the control group) (Lokshin and Glinskaya, 2009).
- The average treatment effect (ATE) is a sample estimate of the effect of programme participation on the innovation of a firm randomly selected from the population (Aakvik et al., 2005, p. 20).

4.3.2 Data

The population of interest is innovative or potentially innovative SMEs in traditional manufacturing industries. Resources dictated sampling from seven EU regions characterised by high employment shares in six traditional industries.[63] The sample includes 312 SMEs, comprising 145 participating and 167 non-participating firms. Data were gathered in 2010 from seven EU countries - the United Kingdom, Germany, Italy, Spain, Portugal, France and the Netherlands - and cover the period from 2005-2009. Detailed descriptive statistics on the survey sample are presented in Tables A2.2, A2.3 and A2.4 (see Appendix II). The GPrix survey sample has the desired characteristics; namely: a good balance between participants and non-participants; and similar characteristics between participants and non-participants with respect to demographic and market characteristics.

Table A2.2 contains descriptive statistics of the variables used in the empirical analysis.[64] These are reported separately for participants and nonparticipants in support programmes for all firms in the database that satisfy the standard EU definition of SMEs (including micro enterprises). Participants are more likely to introduce innovation than nonparticipants, for all aggregate types of innovation as well as for each of the disaggregated categories. For example, for aggregate product innovation - i.e. product

[63] For evidence that the regions selected for the GPrix project represent the diversity of regional situations concerning traditional industry in the EU, see GPrix Deliverable 2.2 (2012a) http://www.gprix.eu/. GPrix Deliverable 3.3 (2012b) gives detail and examples of how the sample was obtained; see http://www.gprix.eu/.

[64] The name of each variable is included as it appears in the dataset to enable the appropriate variable(s) to be identified in the dataset; hence, replication.

innovation in both goods and services - 93 per cent of participants engage in product innovation, compared to 73 per cent of the nonparticipants.

Turning to the independent variables in the model, strikingly similar as well as different characteristics can be observed for participants and nonparticipants. Participating and non-participating SMEs have the same average number of employees. Micro and small firms also have a similar average number of employees in both categories, whereas medium-sized participating firms have, on average, 5 employees more than non-participating firms. Furthermore, non-participating firms perceive a slightly higher level of competitive pressure than do participating firms (22% of participants and 25% of non-participants experience "very strong" competitive pressure, which is the highest category, *Q4t_5*). Industries included in our sample exhibit differences with respect to firms' participation in support programmes: leather (*Q3t_1*), textiles (*Q3t_3*), automotive (*Q3t_5*) and food products (*Q3t_6*) have a higher proportion of non-participating firms; whereas ceramics (*Q3t_2*) and metallurgy (*Q3t_4*) have a higher proportion of participating firms.

A significantly higher proportion of participating firms invested fewer resources in innovative activities in the past (*Q12t_1*) than they do currently (52% of participants and 29% of non-participants). This variable is one of five included in the model to control for initial conditions. The other four variables included in the model to control for initial conditions indicate firms' perceptions of their innovative capacities with respect to different types of innovation in 2005. For product innovation, 31 per cent of participating firms perceive their past innovative capacities as above average or leading (*Prodin_2005*), compared to 24 per cent of non-participating firms. For process innovation, the difference is even higher; 27 per cent of participating firms and 17 per cent of non-participating firms indicated their innovative capacities as above average or leading (*Procin_2005*). However, for non-technological (organisational and marketing) innovation, there is no substantial difference in past innovative capacities between those participating and non-participating firms that perceive their past capacities as lagging (*Q16_3t_1* and *Q16_4t_1* respectively). Considering export activities (*Q5_export*), participating firms are slightly more export-oriented (23 per cent) relative to non-participating firms (17 per cent). Participating firms have greater propensity to collaboration (*Q18_yes*) than non-participating firms (84% and 33 % respectively).

With respect to obstacles to participating in support programmes, a higher number of participating firms indicate each category of administrative needs to be of very high importance (*Q31_1t_5, Q31_2t_5, Q31_3t_5, Q31_4t_5, Q31_5t_5 and Q31_6t_5*). However, almost the same proportion of participating and non-participating firms recognizes financial needs as an obstacle to participation (*Q31_7t_5, Q31_8t_5* and *Q31_9t_5*). Further, a higher proportion of participating firms suggest that internal as well as external needs of SMEs are of very high importance (*Q31_10t_5, Q31_11t_5, Q31_12t_5, Q31_13t_5, Q31_14t_5, Q31_15t_5, Q31_16t_5* and *Q31_17t_5*). Only for appropriate general economic conditions (*Q31_18t_5*) does almost the same proportion of participating and non-participating firms perceive a very high obstacle to participation.

The balance between total participants and non-participants is as follows: participants, 46 per cent; non-participants, 54 per cent. By country, the range is from Germany (66%; 34%) to the UK (34%; 66%) (Table A2.3). Pleasingly, both participants and non-participants have similar characteristics with respect to demographics – e.g. the number of employees in 2009 and the mean number of employees in micro, small and medium- sized firms – and economic position (e.g. market power/strength of competition) (Table A2.2). Conversely, as expected, there are systematic differences between participants and non-participants in all categories of innovation. Moreover, formal balancing tests – referred to in Section 4.4.3 below as part of the robustness checking – confirmed that most variables are balanced even before matching. In sum, the GPrix survey sampling strategy resulted in a sample well balanced between participants and non-participants with similar demographic and market characteristics. These similar characteristics are necessary for the non-participants to be a suitable comparison group.

Country dummy variables are included in the model to control for country and regional-specific firm characteristics. Table A2.3 presents the number of participating and non-participating firms by country. Germany and Spain have much higher proportions of participating than non-participating firms. However, Italy, Netherlands and the UK have a smaller share of participating firms than non-participating firms, while Portugal and France have similar proportions.

Table A2.4 presents data on innovative firms that have received support measures. The sample contains similar numbers of participating and non-participating firms in each category of innovation output. For each category and sub-category of innovation outcomes, both operational (product, process, organisational and marketing innovation) and economic (proportions of sales attributed to new or improved products and/or processes) outcomes, the number of innovative participating firms is around half of the total number of innovative firms.

To investigate whether or not there are extreme differences in the innovation behaviour of firms between either the countries or the industries appearing in our dataset, we conducted one-way ANOVA analysis on each of the aggregate categories of operational innovation investigated in our econometric analysis.

Table 4.1. Tests of differences in mean percentages of firms undertaking different types of innovation (1) between countries and (2) between industries: p -values from one-way ANOVA model F-tests

	Product innovation	**Process innovation**	**Organisational innovation**	**Marketing innovation**
By country	0.35	0.02	0.07	0.19
By industry	0.37	0.04	0.07	0.00

Note: p≥0.5 (p≥0.1) indicates no statistically significant difference at the five per cent (one per cent) level.

Table 4.1 reports the p-values from the F-tests of the null that the means are the same across, respectively, countries and industries: by country there is a significant difference in firms' behaviour only in relation to process innovation; and by industry in relation to both process and marketing innovations. However, the significant country variation for process innovation is driven entirely by the Netherlands; without the Netherlands, the null of no significant difference in country means cannot be rejected (p= 0.21). Similarly, the significant industry variation in process innovation is driven by the leather industry (excluding leather, p=0.69); and in marketing innovation by the ceramics and textile industries (excluding these, p= 0.81). Overall, variation in firms' innovation behaviour varies more by industry than by country. To anticipate, this is reflected in our econometric results by the general lack of significance of country variables and by the more common significance of industry dummies.

4.4 Results

First, we present results from estimating our baseline model, focusing on the programme effects (Table 4.2). Then we report results from two major robustness checks: (1) from estimating our augmented model for the same 20 outcome variables (Table 4.3); and (2) from estimating the baseline model using Nearest Neighbour (NN) matching without replacement and with a caliper (Table 4.5).

4.4.1 Baseline model

From the perspective of evaluating the impact of publicly funded support programmes on SME innovation in traditional manufacturing industry, the most important results are the treatment effects defined in Section 4.4.1: ATE; ATT; and ATU. The validity of these postestimation statistics depends on the validity of the regressions that are used to generate the counterfactuals from which they are calculated.

The model set out in equations 4.1a, 4.1b and 4.2 was estimated separately for 20 dependent variables: 16 binary variables indicating whether or not firms enacted a particular type of operational innovation (product, process, organisational and marketing innovation together with sub-categories of each); and four indicating economic outcomes (proportions of sales attributed to new or improved products and/or processes - innovative sales) (see Tables A2.1 and A2.2 for variable descriptions and descriptive statistics).

In each of the 20 cases, we undertook a testing down procedure to achieve parsimonious models consistent with both valid and efficient estimation. This is similar to Aakvik et al. (2005, p. 26), who do not include all variables from their initial specification in their final model. Because we begin with a theoretically guided and pre-published parsimonious model, we were cautious in deleting variables. Hence, rather than simply deleting variables not estimated at conventional levels of statistical significance, we were guided by the paramount importance of the statistical validity of the model. The typical results of our testing down procedure were threefold.

- In all 20 preferred models, two or three Question 31 variables proved to be satisfactory instruments (see Section 4.3.1 above).
- The country dummies were typically found to be insignificant at conventional levels in the outcome equations, whereas in the selection equation only two – for Germany and Spain – were significant influences. Some insight into the reason for this can be gained by consulting Table A2.2. The base (omitted) country is the UK, which has a lower proportion of participants than nonparticipants. Hence, both Germany and Spain with much higher proportions of participants provide a stronger contrast to the UK than do the other countries. Accordingly, in the models where the Germany and Spain dummies influence the selection process but not innovation outcomes these become additional identifying variables.

Otherwise, all variables in the parsimonious model outlined above are included in all 20 final specifications. The final specifications differ only according to variations in the identifying variables and, in the few cases where these display statistical significance, inclusion of one or two country dummies in the output equations.

Baseline models for all four aggregate categories of operational innovations are reported in full in Table A2.4 (see Appendix II). Each estimated model is the platform for deriving the post estimation treatment effects. For reasons of space, we do not interpret the estimated models; however, a representative model is interpreted as follows. As an example, we interpret the results for the model with the dependent variable "*product innovation in both goods and services (combined)*". First, the statistically significant coefficients will be discussed. In the selection equation, the coefficient on one of the variables denoting the initial conditions[65] (whether a firm devoted fewer, the same or more resources to innovation five years ago, variable *Q12t_1*) is statistically significant at the one per cent level. The initial conditions have a positive and significant effect on participation in support programmes; i.e. those firms which devoted more resources to innovation in 2009 than they did five years previously are more likely to participate in support programmes. As we are estimating the endogenous selection model, the model should include at least one identifying variable,

[65] Initial conditions - or quasi firm fixed effects - control for firm's innovation capacities at the beginning of the sample period (see Section 4.3.1).

i.e. the instrument. Four identifying variables are included in the model for combined product innovation: two country dummy variables, for Germany and Spain; and indicators for two parts of question 31 referring to different specific needs for SMEs in relation to programme participation (the first part indicates the importance of adequate external assistance and guidance after the support project, *Q31_17t_5*, and the second part indicates the importance of appropriate general economic conditions, *Q31_18t_5*). Both coefficients on the country DVs are statistically significant (Germany at the 5% level and Spain at the 1% level). Although the indicator on appropriate general economic conditions (*Q31_18t_5*) is statistically insignificant, it was included in the model; otherwise, the model would not converge. Finally, the indicator for adequate external assistance and guidance after the project (*Q31_17t_5*) has a positive and significant impact on programme participation.

In the output equation for participating firms (regime 1), high competitive pressure (*Q4t_5*) has a negative and significant effect on product innovation, which suggests that firms facing strong competition are less likely to introduce product innovation. Furthermore, two variables used to proxy initial conditions (i.e. innovation capabilities regarding product and process innovation, variables *Prodin_2005* and *Procin_2005* respectively) have a positive and significant impact on product innovation. Firms with leading innovation capabilities in the past are more likely to engage in product innovation. However, initial conditions related to organisational innovation (*Q16_4t_1*) have a negative effect on product innovation. Sectoral DVs (*Q3t_2, Q3t_3, Q3t_4, Q3t_5* and *Q3t_6*) are all statistically significant, except for the leather industry (*Q3t_1*). Finally, exporting firms (*Q5_export*) are more likely to engage in product innovation (the coefficient is significant at the 5% level).

For non-participating firms (regime 0), three variables have a significant effect on the probability of product innovation. Initial conditions related to the resources devoted to innovation (*Q12t_1*) have a positive and significant effect on product innovation, which indicates that development of innovation capacities increases the probability of engaging in product innovation for both participating and non-participating firms. Similar to participating firms, non-participating firms with leading innovation capabilities for product innovation in the past (*Prodin_2005*) are more likely to innovate. However, leading innovation capabilities in organisational innovation

(*Q16_4t_1*) have a negative impact on product innovation, again, for both participating and non-participating firms.

For each model, the estimated coefficients are used to calculate the programme effects: ATT; ATE; and ATU. These estimated effects are presented in Table 4.2, columns 7-14 (following Lokshin and Sajaia, 2011, standard errors are calculated by bootstrapping). In Table A2.2, the raw or unconditional means suggest that both overall and in each separate category of innovation participating firms innovate more than do non-participating firms. Yet the estimates of ATT, ATE and ATU tell a very different story, which suggests the importance of controlling for selection (Aakvik et al., 2005).

The statistical properties of the 20 estimated models are as follows. First, columns 3 and 4 report the correlation coefficients, *rho1* and *rho0*. In 7 from 20 cases, one of the two correlation coefficients has a value of absolute unity. In other cases, correlation coefficients are estimated imprecisely (i.e. with relatively large standard errors). Following Aakvik et al. (2005, p. 37) we report the border values (1 and -1) as problematic; yet, with respect to the latter, we are "reluctant" to disregard large correlation coefficients "even if imprecisely estimated", because this would be to disregard the potential endogeneity of the selection process. Secondly, the Wald test (reported in column 6) should reject the null of the independence of the selection and output equations. We find that in 16 from 20 cases the Wald test rejects the null of no selection bias due to unobservables at the 10 per cent level or lower (following Lokshin and Sajaia, 2011, p. 379, with respect to the size of the test); the other four are not sufficiently overwhelming to disregard the potential endogeneity of the selection process,[66] which is grounded in theory and supported by the correlation coefficients, *rho1* and *rho0*.

[66] The respective p-values are: 0.125; 0.140; 0.146 and 0.151.

Table 4.2. Baseline model - programme participation effects on innovation outputs: the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU) and the average treatment effect (ATE) (Bootstrapped standard errors, 1,000 replications)

Output dependent variable	rho1	rho0	Problem with a model?	Wald test (p value)	Average treatment effect on the treated - ATT			Average treatment effect on the untreated - ATU			Average treatment effect - ATE		
					No of obs.	Coeff.	Bootstr. SEs	No of obs.	Coeff.	Bootstr. SEs	No of obs.	Coeff.	Bootstr. SEs
Product innovation in goods	0.300 (0.422)	0.792 (0.159)	NO	0.0713	104	-0.076***	0.021	132	0.169***	0.031	236	0.061***	0.019
Product innovation in services	-1	0.846 (0.263)	rho1=-1	0.0002	96	-0.196***	0.037	123	0.542***	0.026	219	0.228***	0.018
Product innovation - combined	-0.999 (0.004)	0.871 (0.417)	NO	0.0232	108	-0.011	0.018	134	0.224***	0.025	242	0.118***	0.015
Process innovation - processes for manufacturing goods	-0.694 (1.832)	0.754 (0.305)	Wald test p=0.1252	0.1252	105	-0.046**	0.020	132	0.359***	0.021	237	0.180***	0.013
Process innovation - logistics, delivery or distribution processes	-0.197 (0.474)	0.829 (0.203)	Wald test p=0.1402	0.1402	104	-0.426***	0.027	139	0.129***	0.024	243	-0.113***	0.017
Process innovation - support processes	-0.046 (0.376)	0.957 (0.059)	NO	0.0305	108	-0.299***	0.011	141	0.057***	0.014	249	-0.097***	0.006
Process innovation – combined	-0.406 (0.588)	0.999 (0.002)	NO	0.0183	116	-0.078***	0.010	145	0.224***	0.018	261	0.084***	0.010

Organisational innovation - new business practices for organising procedures	-0.207 (0.403)	1	rho0=1	0.0147	110	-0.378***	0.016	138	0.140***	0.025	248	-0.089***	0.013
Organisational innovation - new methods of organising work responsibilities	-0.768 (0.284)	0.802 (0.195)	NO	0.0293	113	-0.398***	0.023	143	0.460***	0.018	256	0.082***	0.017
Organisational innovation - new methods of organising external relations	-0.469 (0.291)	-0.999 (0.003)	NO	0.0091	105	0.526***	0.015	131	0.458***	0.017	236	0.492***	0.010
Organisational innovation – combined	-0.642 (0.330)	0.728 (0.260)	NO	0.0488	115	-0.160***	0.013	140	0.314***	0.018	255	0.102***	0.011
Marketing innovation - changes to design or packaging	-0.566 (0.322)	0.591 (0.337)	Wald test p=0.1512	0.1512	105	-0.204***	0.025	137	0.371***	0.021	242	0.116***	0.017
Marketing innovation - new media or techniques for product promotion	-0.597 (0.345)	0.729 (0.486)	NO	0.0964	106	-0.129***	0.045	137	0.416***	0.027	243	0.176***	0.232
Marketing innovation - new methods for sales channels	-1	0.503 (0.366)	rho1=-1	0.0015	108	-0.028	0.037	135	0.694***	0.026	243	0.374***	0.021
Marketing innovation - new methods of pricing	-0.711 (0.229)	0.104 (0.628)	Wald test p=0.1463	0.1463	109	-0.062***	0.023	139	0.463***	0.017	248	0.231***	0.015
Marketing innovation – combined	-1	0.440 (0.493)	rho1=-1	0.0111	106	-0.068**	0.030	131	0.393***	0.025	237	0.195***	0.018
Innovative sales > 5 %	-0.488 (1.480)	0.805 (0.157)	NO	0.0902	113	-0.088 ***	0.015	137	0.166***	0.020	250	0.051 ***	0.011

Innovative sales > 10 %	-1	0.243 (0.833)	rho1=-1	0.0103	110	0.007	0.024	133	0.430***	0.026	243	0.240***	0.017
Innovative sales > 15 %	1	-0.130 (0.494)	rho1=-1	0.0102	109	0.113***	0.029	132	0.569***	0.022	241	0.363***	0.017
Innovative sales > 25 %	-1	-0.200 (0.813)	rho1=-1	0.0001	109	0.160***	0.025	132	0.731***	0.019	241	0.477***	0.015

In sum, 13 from 20 correlation coefficients and 16 from 20 Wald tests support the validity of our estimation approach. Column 5 notes whether or not there are problems concerning the statistical validity of the estimated model in either of these respects (9 from 20 models are satisfactory in both respects).

In the results for the baseline models, the ATT effect is smaller than the ATE in almost every case (19 out of 20 models). For the ATT effect, 16 from 20 estimates are negative, of which 14 are significantly different from zero. In sum:

- ATT: the mean of the 20 values is -0.09 with a range from -0.43 to 0.53.

In contrast, for ATE 17 from 20 estimates are positive and statistically significant. In sum:

- ATE: the mean of the 20 values is 0.16 with a range from -0.11 to 0.49.

These results suggest that programme participation typically reduced the probability of innovation by programme participants by 9 percentage points but would have increased the probability for firms randomly selected from the entire population by 16 percentage points. Together these results suggest that randomly selected firms would benefit more from programme participation than do participants (Aakvik et al., 2005, p. 48). This implies that selection of SMEs into support programmes is perverse with respect to innovation outcomes (Aakvik et al., 2005, p. 41).

The results for the four categories of innovative sales are somewhat different than for operational innovations. For two categories of innovative sales (more than 15% and more than 25%), the ATT effect is positive and statistically significant, while the dominant pattern of smaller ATT than ATE is maintained. These results might suggest that support measures have a positive effect on more innovative firms, when innovative activities are proxied by the share of sales from new product and process innovations.

The finding that the ATT effect is systematically smaller than the ATE effect is reflected in the estimates of the ATU effect (see Table 4.2, columns 9-11). For the ATU effect, all 20 estimates are positive and statistically significant. The mean of the 20 values is 0.36 with a range from 0.06 to 0.73.

To study the relationship between unobservable characteristics related to programme participation and the treatment effects, we interpret the correlation coefficients, *rho1* and *rho0* (Aakvik et al., 2005, pp. 41-42). In 16 of the 20 models, *rho1* is negative (five statistically significant at 10% or less) and *rho0* is positive (ten significant); in two, both *rho1* and *rho0* are negative; in one, both *rho1* and *rho0* are positive; and in one, *rho1* is positive and *rho0* is negative. As an example of the dominant pattern, in the model where the dependent variable is *process innovation - processes for manufacturing goods or providing services*, the correlation between the unobservables from the selection equation and the unobservables from the output equation for participants (*rho1*) is -0.694 (although not statistically significant), while the correlation between the unobservables from the selection equation and the output equation for non-participants (*rho0*) is 0.754 (and significant). The economic interpretation is as follows. The negative *rho1* indicates that the unobservable characteristics of the firms participating in the support programmes are negatively correlated – although not significantly - with the innovative activities; and the positive *rho0* indicates that unobservable characteristics of the non-participant firms are positively correlated with the innovative activities. In other words, firms whose unobservable characteristics suggest that they are more likely to participate in the support programme are less likely or – taking statistical significance into account – no more likely to innovate relative to a random firm from the sample; whereas firms whose unobservable characteristics suggest that they are less likely to participate in the support programme have a higher propensity to innovate.

Therefore, the results suggest that the effect of support programmes on innovative activities is lower for the firms that are more likely to participate in the programmes. As Aakvik et al. (2005, p. 42) note for similar results, albeit in a different context, 'selection is perverse on unobservables: treatment effects are the lowest for those most likely to participate'. The implication of “perverse selection” is consistent with the characteristic contrast between a smaller ATT and a larger ATE identified above.

4.4.2 Augmented model

The results for the augmented models presented in Table 4.3 show that the ATT effect is smaller than the ATE in 13 out of 19 models.[67] For the ATT effect, 17 from 19 estimates are negative, of which 15 are significantly different from zero. In sum:

- ATT: the mean of the 19 values is -0.18 with a range from -0.47 to 0.23.

In contrast, for ATE 14 from 19 estimates are positive and statistically significant. In sum:

- ATE: the mean of the 19 values is 0.10 with a range from -0.24 to 0.41.

These results suggest that programme participation typically reduced the probability of innovation by programme participants by 18 percentage points but would have increased the probability for firms randomly selected from the entire population by 10 percentage points.

[67] We do not take into account results for the case where the output variable is product innovation - combined, as the statistical properties of the model are problematic with respect to the Wald test (p-value=0.92).

Table 4.3. Augmented model- programme participation effects on innovation outputs: the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU) and the average treatment effect (ATE) (Bootstrapped standard errors, 1,000 replications)

Output dependent variable	rho1	rho0	Problem with a model?	Wald test (p value)	Average treatment effect on the treated - ATT			Average treatment effect on the untreated - ATU			Average treatment effect - ATE		
					No of obs.	Coeff.	Bootstr. SEs	No of obs.	Coeff.	Bootstr. SEs	No of obs.	Coeff.	Bootstr. SEs
Product innovation in goods	0.100 (0.488	0.764 (0.181)	NO	0.0839	104	-0.028	0.023	129	0.257***	0.028	233	0.130***	0.018
Product innovation in services	-1	0.507 (0.933	rho1=-1	0.0037	97	-0.008	0.041	121	0.551***	0.027	218	0.311***	0.024
Product innovation - combined	-0.999 (0.000)	0.300 (0.598)	Wald test p=0.9173	0.9173	108	0.127***	0.028	130	0.001	0.041	238	0.058**	0.026
Process innovation - processes for manufacturing goods	-0.400 (0.481)	1	rho0=1	0.0032	106	-0.043*	0.023	131	0.323***	0.026	237	0.153***	0.016
Process innovation - logistics, delivery or distribution processes	-0.649 (0.454)	1	rho=1	0.0031	97	-0.441***	0.035	129	0.274***	0.028	226	-0.051**	0.023
Process innovation - support processes	-0.697 (0.199)	0.598 (0.457)	NO	0.0689	100	-0.179***	0.022	129	0.324***	0.025	229	0.106***	0.021
Process innovation – combined	-0.984 (0.056)	0.990 (0.013)	NO	0.0729	116	-0.078***	0.010	142	0.251***	0.017	258	0.099***	0.012

Organisational innovation - new business practices for organising procedures	-0.477 (0.375)	1	rho=1	0.0083	107	-0.358***	0.019	131	0.123***	0.024	238	-0.093***	0.015
Organisational innovation - new methods of organising work responsibilities	-0.605 (0.268)	1	rho=1	0.0055	105	-0.436***	0.022	133	0.350***	0.023	238	-0.003	0.018
Organisational innovation - new methods of organising external relations	-0.731 (0.265)	0.665 (0.587)	NO	0.0270	105	-0.123***	0.028	128	0.553***	0.019	233	0.250***	0.018
Organisational innovation – combined	-1	0.856 (0.178)	rho1=-1	0.0065	115	-0.208***	0.021	137	0.345***	0.020	252	0.095***	0.013
Marketing innovation - changes to design or packaging	1	0.576 (0.517)	rho1=-1	0.0480	102	-0.156***	0.027	134	-0.278***	0.020	236	-0.237***	0.015
Marketing innovation - new media or techniques for product promotion	-0.700 (0.298)	1	rho0=1	0.0002	103	-0.379***	0.034	130	0.539***	0.032	233	0.124***	0.031
Marketing innovation - new methods for sales channels	-0.728 (0.312)	1	rho0=1	0.0223	105	-0.304***	0.033	128	0.538***	0.031	233	0.145***	0.026

Marketing innovation - new methods of pricing	-0.553 (0.303)	1	rho0=1	0.0096	106	-0.473***	0.029	131	0.365***	0.022	237	-0.020	0.022
Marketing innovation – combined	-1	0.742 (0.277)	rho1=-1	0.0754	109	-0.191***	0.025	134	0.456***	0.022	243	0.157***	0.020
Innovative sales > 5 %	-0.688 (0.417)	0.818 (0.237)	NO	0.0692	110	-0.087***	0.017	131	0.159***	0.019	241	0.049***	0.013
Innovative sales > 10 %	-0.231 (0.797)	1	rho0=1	0.0170	111	-0.261***	0.019	133	0.121***	0.021	244	-0.057***	0.014
Innovative sales > 15 %	-1	-0.527 (0.545)	rho1=-1	0.0011	110	0.232***	0.023	131	0.538***	0.020	241	0.409***	0.016
Innovative sales > 25 %	-1	0.080 (1.258)	rho1=-1	0.0009	110	0.007	0.025	131	0.719***	0.021	241	0.401***	0.022

Summary results for both the baseline and the augmented models are presented in Table 4.4. The first conclusion is a systematically smaller ATT than ATE in both models. In models without diagnostic problems, this dominant pattern is found in 8 from 9 cases in the baseline model (in 7 cases both programme effects are statistically significant); and in all 5 cases in the augmented model (in 4 cases both programme effects are statistically significant). In models with one diagnostic problem, ATT is smaller than ATE in 11 from 11 cases in the baseline model (in 9 cases both programme effects are statistically significant); and in 13 from 14 cases in the augmented model (in 9 cases both programme effects are statistically significant).

The second conclusion is only slightly less systematic, namely a negative ATT and a positive ATE. In models without diagnostic problems, this pattern is found in 7 from 9 cases in the baseline model (in 6 cases both programme effects are statistically significant); and in 5 from 5 cases in the augmented model (in 4 cases both programme effects are statistically significant). In models with one diagnostic problem, a negative ATT and a positive ATE is reported in 6 from 11 cases in the baseline model (in 5 cases both programme effects are statistically significant); and in 6 from 14 cases in the augmented model (in 5 cases both programme effects are statistically significant).

Table 4.4. Programme effects from the baseline and augmented models: summary

Model	Number of models	Models without diagnostic problems	Models with one diagnostic problem	Models without diagnostic problems				Models with one diagnostic problem			
1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
				ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant	ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant
Baseline	20	9	11	8	7	7	6	11	9	6	5
Augmented	19	5	14	5	4	5	4	13	9	6	5

Note: As a guide to reading Table 4.4, compare numbers in columns 5-8 with column 3; for example, in the Baseline Model, eight (column 5) from nine models without diagnostic problems (column 3) yield ATT<ATE. Similarly, compare columns 9-12 with column 4

4.4.3 Matching estimation

To further check the robustness of our estimated effects, we apply Nearest Neighbour (NN) matching without replacement with a caliper of 0.25 of the standard deviation of the estimated propensity score (see Table 4.5) (for a discussion on matching estimators, see Section 5.3.1).[68] We report results for the 20 baseline models. For each model we used the same specification as the respective baseline switching selection model. Balancing tests show that each variable is balanced after matching; indeed, that most variables are balanced even before matching.[69] This matching quality indicates that our sample is well balanced between treated and non-treated firms for most observed firm characteristics, which reinforces our discussion on the properties of our sample (see Section 4.3.2 and Table A2.2).

Compared to the estimated effects reported in Tables 4.2 and 4.3, the findings from the matching estimator are skewed towards positive treatment effects; i.e. both ATT effects and ATEs are either positive or statistically insignificant. However, qualitatively the results are consistent with the those reported above, insofar as across the models the ATT is systematically smaller or the same as the ATE. Finally, we applied a Rosenbaum bound approach (Rosenbaum, 2002) to test for unobserved heterogeneity that can arise when unobserved firm characteristics have a significant impact on the effectiveness of innovation policy (see Section 5.5). In 15 of the 20 baseline models, the test indicates that the ATT might be overestimated.[70] These findings suggest that unobserved heterogeneity should be taken into account in the impact evaluation of innovation policy and supports the application of an endogenous switching model in our analysis.

[68] The choice of matching estimator reflects the consideration that the Rosenbaum bound approach (Rosenbaum, 2002) (see Section 5.5 on sensitivity analysis) can only be applied to NN matching without replacement. In order to increase the efficiency of the estimated effects, we used a caliper of the size suggested in the literature, because it removes 98 per cent of the initial bias due to covariates (Austin, 2011b).

[69] Balancing tests include standardized differences in the sample means of participating and non-participating firms (Rosenbaum and Rubin, 1985) and the t-test of the equality of the sample means of participating and non-participating firms (see, for instance, Czarnitzki and Lopes Bento, 2013).

[70] The test cannot be conducted for the ATU or the ATE effects.

Table 4.5. Results from the Nearest Neighbour (NN) estimators - baseline model

Output dependent variable	NN without replacement and caliper of 0.25 of SD of propensity score		NN without replacement and caliper of 0.25 of SD of propensity score		Hidden bias (overestimation)
	Average treatment effect on the treated - ATT		Average treatment effect - ATE		
	Common support	Coeff. (subsampled SEs)	Common support	Coeff. (subsampled SEs)	
Product innovation in goods	230	0.222*** (0.082)	185	0.200*** (0.078)	No
Product innovation in services	220	0.167** (0.010)	176	0.193** (0.079)	Yes
Product innovation - combined	235	0.194*** (0.058)	193	0.212*** (0.058)	No
Process innovation - processes for manufacturing goods	242	0.213*** (0.079)	195	0.221*** (0.070)	No
Process innovation - logistics, delivery or distribution processes	228	0.035 (0.097)	175	0.034 (0.089)	Yes
Process innovation - support processes	236	0.000 (0.094)	188	0.037 (0.085)	Yes
Process innovation – combined	235	0.143** (0.065)	189	0.138** (0.058)	Yes
Organisational innovation - new business practices for organising procedures	235	0.035 (0.100)	179	0.017 (0.090)	Yes
Organisational innovation - new methods of organising work responsibilities	240	-0.022 (0.096)	192	0.010 (0.085)	Yes

Organisational innovation - new methods of organising external relations	237	0.231** (0.093)	188	0.250*** (0.083)	No
Organisational innovation – combined	242	0.133 (0.084)	200	0.120 (0.074)	Yes
Marketing innovation - changes to design or packaging	239	0.078 (0.080)	189	0.074 (0.085)	Yes
Marketing innovation - new media or techniques for product promotion	230	0.085 (0.094)	174	0.092 (0.085)	Yes
Marketing innovation - new methods for sales channels	244	0.237*** (0.080)	200	0.235*** (0.078)	No
Marketing innovation - new methods of pricing	244	0.021 (0.080)	198	0.056 (0.072)	Yes
Marketing innovation – combined	228	0.116 (0.086)	175	0.126 (0.081)	Yes
Innovative sales > 5 %	233	0.141** (0.076)	188	0.154** (0.071)	Yes
Innovative sales > 10 %	232	0.058 (0.094)	177	0.062 (0.078)	Yes
Innovative sales > 15 %	234	0.023 (0.095)	189	0.069 (0.081)	Yes
Innovative sales > 25 %	221	0.088 (0.089)	240	0.090 (0.079)	Yes

4.5 Summary

Summary results from the switching regressions and from matching estimations are reported in Table 4.6. The first conclusion is that the ATT effect is systematically smaller than the ATE. For models estimated by the endogenous switching method, this finding is reported in 19 from 20 cases in the baseline model (in 16 cases both programme effects are statistically significant); and in 18 from 19 cases in the augmented model (in 13 cases both effects are statistically significant). For the baseline models estimated with the matching method, the ATT is smaller than the ATE in 13 cases (in 5 cases both effects are statistically significant).

The second conclusion arises from the somewhat less systematic finding of a negative ATT and a positive ATE. For models estimated by the endogenous switching method, this pattern is reported in 13 from 20 cases in the baseline model (in 11 cases both effects are statistically significant); and in 11 from 19 cases in the augmented model (in 9 cases both effects are statistically significant). However, results from matching are somewhat different, insofar as both ATT and ATE are positive in 12 from 20 cases (in 5 cases both effects are statistically significant). As discussed in Section 4.4.3, positively skewed programme effects estimated by matching methods are consistent with the proposition advanced by Hujer and Radic (2005) and Greene (2009) that evaluation methods that take into account only observed firm characteristics (such as matching methods) yield larger programme effects than those methods controlling further for unobserved influences.

Table 4.6. Programme effects from the switching regressions and from matching estimators: summary

Model	Number of models	ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant	ATT & ATE both positive	ATT & ATE both positive; both statistically significant
Switching regression - baseline model	20	19	16	13	11	4	3
Switching regression - augmented model	19	18	13	11	9	2	1
Matching estimators - baseline model	20	13	5	1	0	12	5

Finally, two issues concerning the validity of the estimates are considered: first, the potential endogeneity of our *Export* variable; and, second, the sensitivity of the switching estimator to ‘model identification and the assumptions about the distribution of the error terms’ (Lokshin and Sajaia, 2011, p. 379).

The repeated significance in the reported regressions of one or more of our five firm-level ‘quasi’ fixed effects (or initial conditions) is not only informative regarding the determinates of innovation but also increases confidence in the statistical validity of our estimates. There is limited scope within a cross-sectional study, particularly one analysing survey data, to address the potential endogeneity of regressors. Moreover, no estimator can address all potential specification issues. By estimating an endogenous switching model we address the main endogeneity issue in programme evaluation, that of endogenous selection (i.e. the potential endogeneity of the participation dummy). However, there may be particular concern that firms’ export activities may not be exogenous with respect to innovation. If so, then endogeneity arises from omitted variables rather than simultaneity. Simultaneity assumes that causation runs directly in both directions between innovation and exports. Conversely, we argue that if exporting is potentially endogenous then this is because innovation and exports are both dependent on similar determinants, in which case they are correlated but do not cause one another. This perspective on the potential endogeneity of exports is supported by three arguments. First, in theory, exporting may be regarded as a species of innovation. This view goes back at least to Schumpeter (1942, p. 83) who identified the main forms of innovation giving rise to the ‘process of Creative Destruction’:

> The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers’ goods, the new methods of production or transportation, the new markets, the new forms of industrial organisation that capitalist enterprise creates. (...) that incessantly revolutionises the economic structure from within (...).

Secondly, both case study interviews and survey data from the GPrix project suggest that SMEs in traditional manufacturing regard exporting as innovatory activity. In the GPrix survey all the examples for respondents of types of innovation followed the *Oslo Manual* (OECD, 2005), in which marketing innovation is restricted to varieties of marketing techniques but excludes entry into new markets. Yet, when asked to name the most useful innovation support measures in which they had participated, more than 10 per cent or respondents named export promotion programmes. Thirdly, in the respective literatures, models of SME innovation and of SME exporting behaviour typically have determinants in common: for example, firm size and dummies for industry and region.

The analysis presented in this chapter is limited in addressing the potential endogeneity of exports. For reasons explained above, we estimate a parsimonious model and so are unable to include all possible observable influences on firms' export behaviour in the model. With panel data, we could use firm-level fixed effects to capture unobserved influences, thereby excluding them from the error term and precluding endogeneity arising from omitted variables. To mimic this approach in our cross-section model, we include, as explained above, firm-level 'quasi' fixed effects (or initial conditions) to capture otherwise unobservable firm and ownership effects. These five variables are derived from questions to firms about their innovation behaviour at the beginning of the sample period and are designed to aggregate the effects of all unobserved firm-level time invariant (or, at least, slowly moving) influences on all types of innovation, which include diversification into new markets, especially into export markets. By specifying our model to include firm-level 'quasi' fixed effects we prevent – or, at least, reduce – the presence in the error term of unobserved but systematic influences on firms' innovation, including exporting, which eliminates – or, at least, attenuates – endogeneity arising from omitted variables.

It is noted in Section 4.3.1 that the estimation approach 'relies on an assumption of joint normality of the error terms of the estimates' (Lokshin and Sajaia, 2011, p. 369). However, there is no test for whether this assumption holds in the data. Instead, Lokshin and Sajaia (2011, p. 379) undertake Monte Carlo simulations to investigate the sensitivity of their estimator to 'model identification and the assumptions about the distribution of the error terms'. Their results indicate that their estimator is 'relatively robust in terms of identification of the model'. Moreover, the authors note that this finding is consistent with Wilde (2000) who found that 'in recursive multiple-equation probit models with endogenous dummy regressors no exclusion restrictions for the exogenous variables are needed if there is sufficient variation in the data' (cited by

Lokshin and Sajaia, 2011, p. 381).[71] Conversely, specification where the error terms are nonnormally distributed 'results in biased estimates for both ATE and ATT effects'. Moreover: 'The bias is larger for estimations based on smaller sample sizes.' However, the bias for both ATE and ATT effects is in the same direction: for a sample of similar size to the one analysed in this paper, true ATE of -0.175 is estimated at about -0.120 and true ATT of -0.336 is estimated at about -0.240; in both cases, an upward bias of about 30 per cent. In these simulations, the errors are $\chi 2$ distributed and 'simulation based on different functional forms for the nonnormal distribution of the shocks (…) produces similar estimates' (Lokshin and Sajaia, 2011, p. 381).

It can be concluded for our analysis, that while this evidence on the effects of failure of the distributional assumption in extreme forms puts a question mark over the precise size of our estimates of ATT and ATE, it does not undermine our main finding that estimated programme effects on SME participants (ATT) are systematically smaller than the estimated effects on randomly selected SMEs (ATE). In turn, it is this finding that underpins our main policy recommendation; namely, that a more inclusive selection procedure could improve the effectiveness of innovation support programmes for SMEs in traditional manufacturing industry.

4.6 Conclusions

In the context of a population of mainly innovating SMEs, estimated programme effects consistently reveal smaller innovation effects on participating firms than could have been realised from randomly selected programme participants. Moreover, consistent with this finding of smaller ATT than ATE effects, analysis of the unobserved effects captured by our models suggests that the more likely firms are to participate in a support programme as a consequence of their unobserved characteristics the less likely they are to innovate *as a consequence*. Conversely, firms that are less likely to participate as a consequence of their unobserved characteristics would be more likely to innovate *as a consequence* (i.e. were they to participate).[72]

[71] Monte Carlo simulations of ATE and ATT for the specification with normally distributed error terms demonstrate that: 'Even for smaller sample sizes, the method produces efficient and unbiased estimates of ATE and ATT effects' (Lokshin and Sajaia, 2011, p. 381).

[72] These findings are similar to the canonical study by Aakvik et al. (2005, p. 37) who also find that 'those most likely to participate in the program are those who benefit least from it'.

The results are consistent with the hypothesis advanced in Section 4.2; namely, because of potential government failure in innovation policy, the effects of public support measures to increase private innovation may be disappointing compared to the effects typically claimed by public agencies. Yet our results also suggest a direction for policy reform to overcome government failure, thereby increasing the potential additionality of innovation support programmes. We find that cream-skimming of firms on the basis of characteristics positively associated with innovation is less effective in promoting innovation than would be a strategy of randomly selecting participants. The policy implication is that *the selection process of firms into innovation support programmes should be reformed by moving away from "cream skimming" towards random allocation.* There is potential for improving the overall innovation outcomes of innovation support programmes for SMEs in traditional manufacturing industry by selecting typical firms with the most to gain from support rather than selecting those with the greatest propensity to innovate but the least to gain from support.[73] In other words, a more inclusive selection procedure could improve the effectiveness of innovation support programmes for SMEs in traditional manufacturing industry. Of course, some continued selection on observables (e.g. due diligence with respect to size and solvency) will still be needed to ensure that participating firms meet eligibility requirements for participating in public support programmes.

Consistent with these proposals, the case for random allocation is gaining influence amongst policy makers. Two recent examples of successful lottery distribution of innovation vouchers are in the Netherlands and in the United Kingdom. Cornet et al. (2006) investigated the effectiveness of a Dutch innovation voucher programme for SMEs, under which vouchers were allocated by lottery. The evaluation of the programme indicates that 8 out of 10 vouchers were used to introduce innovations which, without public support, would not have been realized. This is a very large treatment effect, especially given that empirical studies, if reporting additionality at all, typically report small programme effects.

In addition, Bakhshi et al. (2011) evaluated the short-term effects of the Creative Credits programme and report a high level of additionality, which quantitatively is

[73] Again, reflecting similar results, this echoes a conclusion from Aakvik et al. (2005, p. 48): 'There is a potential for improving the overall employment-promoting effect of VR training by selecting those who gain the most from training rather than choosing the most employable persons.'

similar to the effects of the Dutch programme discussed above. Evaluators of both voucher schemes highlight the advantages of a random distribution according to lottery:

1. to increase programme effectiveness, as argued in this paper; and
2. to "build in" evaluation by random controlled trials (RCT) and so feed back into enhanced programme effectiveness.

The analysis conducted in this chapter has a number of novel features but also some limitations. Novel or at least unusual features include: prepublication of the model to be estimated; focus on the effectiveness of public innovation support programmes for SMEs in traditional manufacturing industries; and focus on output additionality in relation to both technological and non-technological innovation. Finally, the econometric method applied in the study allows for selection on both observed and unobserved firm characteristics.

There are four main limitations of the analysis. The first is inherent to all cross-section analysis; namely, inability to account fully for the cumulating of effects over time and to identify the dynamic manner in which this occurs. The GPrix survey design compensated as far as possible for this deficiency by asking firms questions to establish initial conditions for firms' current innovation activities. The second limitation is that we cannot test the distributional assumption of the estimator used in this study. However, as we argue in Section 4.5, the evidence on the effects of the failure of this assumption does not undermine our main finding that estimated effects on SME participants (ATT) are systematically smaller than the estimated effects on randomly selected SMEs (ATE). The third limitation is associated with the sample size. Although our sample size is small, the sample has desirable characteristics, in particular with respect to balance between treatment and comparison groups. Moreover, our estimates typically display characteristics associated in the literature with statistical validity (namely, the Wald test for independence and the size and significance of the model correlation coefficients). The fourth limitation is that we were unable to test for partial crowding out. Although the survey questionnaire includes a question on the value of support, most participating firms did not report this amount, because respondents did not know the amount of subsidy their firms received from 2005-2009. Therefore, we are unable to utilize this variable in our econometric model. However, the absence of the amount of subsidy is a general issue in the literature on the evaluation of innovation policy (Zúñiga -Vicente et al., 2014).[74] Surveys such as the Community Innovation Survey (CIS) do not contain a question on the amount of subsidies. Even when researchers collect primary data, the response rate to questions on the amount of subsidy is very low, because respondents simply do not know the amount of subsidy, which is the case in our study.

Finally, we comment on the external validity of the findings. Edith Penrose's classic *The Theory of the Growth of the Firm* (1959, p. 7), addressed a similar issue: 'Many firms do not grow, and for a variety of reasons (…) I am not concerned with such firms, for I am only concerned with (…) those firms that do grow.' By analogy, policy makers are concerned to encourage innovative or potentially innovative SMEs to more fully exploit their innovative potential. Correspondingly, the GPrix sample firms are overwhelmingly recent innovators (and the rest are at least sufficiently oriented towards innovation to engage with an innovation survey). As long as such firms are a priority for policy makers, then it is valid to use our results to inform policy.

[74] Loss of information due to lack of data on the amount of subsidy are endemic in programme evaluation (Aakvik et al., 2005, p. 26) (see Section 3.6).

CHAPTER V

EFFECTIVENESS OF PUBLIC SUPPORT FOR INBOUND OPEN INNOVATION

5.1 Introduction

The evaluation of innovation policies, until recently, was mainly concerned with input and output additionality. Focusing on innovation inputs and outputs, however, means that we stay outside the “black box” of innovation processes, but rather observe the beginning (innovation inputs) or end results (innovation outputs) of those processes (OECD, 2006a). Behavioural additionality enables us to go beyond input and output additionality and assess the impact of public measures on firms' innovative behaviour. Following the discussion in Section 3.6.3, the literature on additionality lacks a common definition of behavioural additionality. Most empirical studies explore network additionality (Georghiou and Clarysse, 2006), which occurs when firms expand their networks and cooperative activities as a result of participation in support programmes.

The narrow perspective on behavioural additionality, by focusing on network additionality, can be associated with the concept of open innovation, i.e. the impact of public funding on open innovation, specifically the effect on external networking. In 2003, open innovation emerged as a new conceptual framework in the management literature, emphasizing the role of networking and knowledge exchange on firms' innovativeness, and their critical role in creating and sustaining competitive advantages (Chesbrough, 2003). The literature distinguishes between two types of open innovation practices: inbound and outbound open innovations. While the former refers to knowledge transfers relevant for the development of internal innovation, the latter encompasses marketing activities related to the commercialization of innovation. Open innovation is the subject of an increasing number of empirical studies, mainly focusing on the determinants of open innovation strategies and their impact on innovation and firm performance (for a comprehensive review, see Schroll and Mild, 2012).

Drawing on Community Innovation Survey (CIS) 2006 data, we employed several matching estimators to investigate the impact of public support on open innovation practices in Spanish small and medium-sized enterprises (SMEs). As discussed in Section 3.6, due to often noted factors hampering econometric analysis (such as, lack of longitudinal data and of valid instruments for selection models), matching estimation has become a widely used evaluation method in the literature on the effectiveness of innovation policy.[75]

In this chapter, we address three research questions, two on substantive issues related to inbound innovation and one related to research methodology.

a. Does public funding for innovation foster inbound open innovation in SMEs? If so, does it have the same or differential effects on various open innovation practices?
b. Are there differences in impact on inbound open innovation between local/regional, federal government funding and EU funding?
c. Are estimated treatment effects robust to unobserved heterogeneity?

This chapter contributes to the evaluation literature by providing the first empirical findings on the impact of public innovation support on three open innovation practices: cooperative behaviour in SMEs (behavioural additionality); outsourcing R&D; and acquiring other external knowledge (e.g. patents and know-how). The treatment effects are reported for three separate sources of funding: local/regional; national; and EU programmes. Following the literature on the determinants of R&D cooperation, we explicitly take into account incoming spillovers, knowledge flows from different sources (suppliers, customers, competitors, government and Higher Education Institutions) and include barriers to innovation and to cooperation in our methodological framework. Finally, we report the results of sensitivity analysis, conducted to check for unobserved heterogeneity in the model.

The chapter is organised as follows. Section 5.2 defines the concepts of open innovation and behavioural additionality. Section 5.3 formulates the methodological framework, discusses model specification and data used in the study. Section 5.4 gives the main results from matching, while Section 5.5 discusses findings from sensitivity analysis. Empirical findings for the subsample of innovative firms are presented in Section 5.6. Section 5.7 concludes.

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[75] These limiting factors are noted in most studies on additionality of public support (see, for instance, Czarnitzki et al., 2007; Busom and Fernández-Ribas, 2008; Czarnitzki et al., 2011).

5.2 Open innovation

The significance of cooperation in firms' innovation activities is reinforced with the concept of open innovation. With Chesbrough's (2003) seminal book, open innovation emerged as a new conceptual framework in innovation literature, opposite to closed innovation systems (Lichtenthaler, 2011). This new paradigm acknowledges firms' limited internal innovative capacities and suggests that generating external knowledge is necessary for innovation processes as firms no longer can be successful innovators by relying solely on internal capabilities.

Open innovation is defined as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and to expand the markets for external use of innovation, respectively" (Chesbrough et al., 2006, p. 1). Knowledge flows aiming at fostering internal innovation are termed inbound open innovation (technology exploration or acquisition), while the market expansion focusing on the commercialisation phase of the innovation process is termed outbound open innovation (technology exploitation or commercialization) (Van de Vrande et al., 2009; Dahlander and Gann, 2010; Lichtenthaler, 2008; Lichtenthaler, 2011).[76] The process of technology exploration or acquisition (i.e. inbound open innovation) encompasses the following practices (Van de Vrande et al., 2009; Parida et al., 2012):[77]

- *Technology scouting*, that is, a process of gathering information and knowledge from the technological environment (Cohen and Levithal, 1990; Lichtenthaler and Lichtenthaler, 2009; Dahlander and Gann, 2010).
- *Customer involvement*: Customers can be involved in firms' internal innovation processes, which enables firms to develop new products or to modify the existing ones according to customers' needs and preferences.
- *External networking*: Networking on innovation is an important component of open innovation, and it encompasses both formal (e.g. R&D alliances) and informal cooperation on innovation with individuals and organisations.

[76] Inbound open innovations is also referred to as the outside-in process of open innovation, whereas outbound open innovation is referred to as the inside-out process of open innovation (Enkel et al., 2009).
[77] Dahlander and Gann (2010) divided inbound and outbound open innovation practices into two categories - pecuniary and non-pecuniary, whereby revealing and selling are non-pecuniary and pecuniary outbound innovation respectively, and sourcing and acquiring are non-pecuniary and pecuniary inbound innovation respectively.

- *External participation*: This form of open innovation is associated with equity investment in other companies in order to access their knowledge or to benefit from other synergies.
- *Outsourcing R&D:* Extramural R&D activities performed by other firms or private and public organizations are an important alternative to intramural R&D.
- *Inward IP licensing (licensing-in)*: Firms can benefit from external knowledge through purchasing patents, trademarks, copyrights and other forms of IPs (Dahlander and Gann, 2010).

The process of technology exploitation or commercialization (i.e. outbound open innovation) includes several strategies:

- *Venturing*: In the context of open innovation, venturing refers to spin-offs, i.e. establishing new firms based on a firm's internal knowledge.
- *Outward licensing of Intellectual Property (IP)(licensing-out)*: This practice allows companies to generate profit from selling IPs to other companies (Dahlander and Gann, 2010; Lichtenthaler, 2011).

Lichtenthaler and Lichtenthaler (2009) develop a conceptual framework for open innovation, identifying relevant organisational capabilities which are a basis of dynamic capabilities of managing open innovation. The framework is regarded as a complement to the concept of absorptive capacity and proposes six 'knowledge capacities' that combine knowledge exploration, retention and exploitation:

- *Inventive capacity,* which relates to firms' ability for internal knowledge exploration, i.e. creating new knowledge within a firm. Inventive capacity is not only associated with creation of new knowledge, but also with a process of incorporating new knowledge into an existing knowledge base within a firm.
- *Absorptive capacity* is defined as a firm's ability for external knowledge exploration (Cohen and Levinthal, 1990). Firms' increase their absorptive capacity by absorbing additional knowledge into prior related knowledge. Therefore, the firms' existing knowledge base plays an important role in enhancing both, inventive and absorptive capacity.
- *Transformative capacity,* which refers to firms' ability to retain and reactivate knowledge within the organisation over time. Again, an existing knowledge base

is relevant in developing transformative capacity, insofar as a larger base enables easier retention and exploitation of new knowledge.

- *Connective capacity* is associated with firms' ability to maintain sources of external knowledge over time; for instance, by establishing long-term relationships with cooperative partners. In contrast to transformative capacity, connective capacity is focused on the retention and maintenance of inter-firm relations (external networks).
- *Innovative capacity* relates to firms' ability for internal knowledge exploitation. Besides developing internal and external capacities for knowledge exploration and retention, firms need to develop a capacity for exploiting a knowledge base. Innovative capacity is regarded as a realized absorptive capacity.
- *Desorptive capacity*, which refers to external knowledge exploitation, for instance through outward licensing of IP or venturing. The practice of active outward knowledge transfer is a recent trend in firms' management strategies.

Open innovation practices are the subject of an increasing number of empirical studies over the last few years. The main research objectives are aimed at identifying the determinants of inbound and outbound open innovation strategies, and assessing their impact on firms' innovation performance (for a comprehensive review of empirical studies, see Schroll and Mild, 2012). Both large firms and SMEs can greatly benefit from external knowledge. Open innovation is particularly relevant to SMEs, because limited human and financial resources are critical barriers to internal innovation in those firms (Van de Vrande, 2009; Parida et al, 2012). Conversely, limited resources can have a detrimental effect on open innovation in SMEs, for instance, in acquiring extramural R&D or maintaining collaborative networks (Huizingh, 2011). Indeed, empirical evidence suggests that large firms engage in open innovation to a larger extent than SMEs (Lihtenthaler, 2008; Bianchi et al., 2011) and, within SMEs, medium-sized firms are more prone to opening up innovation processes than are small firms (Van de Vrande et al., 2009). Furthermore, Van de Vrande et al. (2009) state SMEs mostly engage in user innovation (customer involvement) and in external networking. Conversely, the least practiced open innovations are outward and inward IP licensing, venturing and external participation, They argue that the latter require substantial financial resources, unlike customer involvement and external networking, which are often informal and need not entail significant financial investment.

Firms' strategic decisions on whether to develop new technologies and innovations by increasing in-house R&D or by external knowledge acquisition depend on the type of technology. Innovation processes than involve generic (standardized) technological competences, should be developed by external knowledge exploitation either through cooperation or subcontracting (Narula, 2001). However, core technological competencies, which are the main source of firms' competitive advantage, should be developed internally. Furthermore, in discriminating between cooperation and R&D subcontracting, following the argument advanced in transaction costs economics, firms have incentive to opt for the latter when opportunism and free riding are more likely to occur, thus increasing transaction costs (Dhont-Peltrault and Pfister, 2011). If we assume that opportunistic behaviour decreases with the increase in the level of technology standardization, this would mean that R&D subcontracting is more suitable for developing or enhancing standardized technologies (the 'standardization' hypothesis). Moreover, standardized technologies usually lack a degree of novelty sufficient to be patentable, thus suggesting that appropriability issues are less likely to occur.

Conversely, due to potential cooperation failure, firms can opt for R&D subcontracting for developing strategic, core technologies (the 'incentive' hypothesis). Cooperation failure refers to reduced R&D effort in cooperative partnerships when cooperating firms do not clearly specify which partner will be assigned the exclusive property rights (Dhont-Peltrault and Pfister, 2011). For instance, Cassiman and Veugelers (2002) report a negative relationship between vertical cooperation and the effectiveness of appropriation methods. Moreover, Leiponen and Byma (2009) argue that small firms with close links to cooperative partners might face difficulties in protecting their returns to innovation. Unlike large firms, small firms utilize formal methods of protecting IPs (such as patenting) to a lesser extent, and rely more on informal methods such as secrecy and lead time (Leiponen and Byma, 2009). Therefore, to assure the maximum level of R&D effort, firms can assign exclusive property rights to the subcontractors, thus avoiding appropriability issues.

Finally, assessing the impact of public support on open innovation strategies is closely related to the concept of behavioural additionality (BA). While input and output additionality leave the black-box of innovation process unopened, BA goes beyond innovation inputs and outputs and aims at explaining what is happening inside the box.

It is associated with intermediate effects of public support on firms' innovative behaviour (Georghiou and Clarysse, 2006). Following Busom and Fernández-Ribas (2008), BA assesses the short-term impact of public programmes. Although the literature advances a broad perspective on BA, most empirical studies investigate only one segment of BA; that is the impact of public intervention on firms' cooperative behaviour (scope additionality as defined by Falk, 2007; or network additionality following the OECD, 2006a, definition).[78] This narrow concept of BA encompasses the impact of public funding on inbound open innovation, specifically the effect on external networking. As previous studies do not investigate other forms of behavioural additionality, this inquiry, unlike other studies, expands research beyond cooperative networking to include two additional inbound open innovation strategies: outsourcing R&D; and acquisition of other external knowledge.

5.3 Methodology

5.3.1 Matching estimation

The main advantage of matching estimators, compared to selection models and IV approaches, is that they do not require any distributional assumptions regarding the error terms in the selection equation and in the outcome equation. However, matching estimators control only for firms' observed characteristics. In cases when unobserved inferences are suspected to influence the treatment assignment, matching yields biased estimates of treatment effects.

The literature on evaluation methods distinguishes between four categories of estimators that control for bias due to observable variables: regression estimators; matching estimators; propensity score methods; and a combination of these estimators, usually regression with matching (Imbens, 2004). Matching estimators are further divided into covariate matching and propensity score matching (Zhao, 2004). Propensity score methods are non-parametric evaluation methods, which are based on the premise that participants should be matched with non-participants (a control group) conditional on pre-treatment observed characteristics (covariates) X. Outcomes are then compared between matched units and the difference in outcomes is attributed to the treatment.

[78] Our study suffers from the same limitation; available data do not allow for exploring other categories of behavioural additionality.

Propensity score methods include weighting on propensity score, matching on propensity score, stratification on propensity score and regression on propensity score (covariate adjustment on propensity score) (Imbens, 2004).

Matching as an evaluation method is based on two assumptions. The first identifying assumption is referred to as the conditional independence assumption (CIA), unconfoundedness or selection on observables (Imbens, 2004; Imbens and Wooldridge, 2009).

$$\big(Y(0), Y(1)\big) \coprod T|X \tag{5.1}$$

This condition states that potential outcomes, $Y(0)$ and $Y((1)$, are independent ($\coprod$) of a treatment assignment (T), conditional on observed covariates, X, that are not affected by a treatment (pre-treatment variables). The CIA is a strong assumption and requires that all relevant observed variables are included in the estimation of treatment effects and that variables are measured before treatment assignment.

The second identifying assumption refers to the overlap or common support condition, which states that perfect predictability of a treatment assignment conditional on X is avoided. Therefore, both treated and non-treated firms have a positive probability of receiving a treatment or not. The condition can be written as:

$$0 < P(T = 1|X) < 1 \tag{5.2}$$

The overlap or common support condition states that if it is completely certain that some firms will participate (P = 1) and that other will not (P = 0), then there is no observable basis for comparison between treated and non-treated firms.

Caliendo and Kopeinig (2008) note that for the estimation of the ATT both assumptions can be relaxed into unconfoundedness for non-treated firms (a comparison group) and the weaker overlap condition, given by:

$$P(T = 1|X) < 1 \tag{5.3}$$

An additional assumption is the Stable Unit Treatment Value Assumption (SUTVA), which refers to independence of the impact of a treatment on firms, i.e. the outcome in one firm is not affected by the treatment of any other firms (no spillover effects). This assumption requires a careful selection of firms in the control group, so as to minimize the occurrence of spillovers (Stuart, 2010).

The crucial step in the matching procedure is the choice of covariates *X*. The literature suggests that all observed variables that simultaneously affect a treatment and outcome should be included in the estimation of propensity scores (the selection equation) (Austin, 2011a; Ho et al., 2007; Caliendo and Kopeinig, 2008; Steiner et al., 2010). Following Steiner et al. (2010), in situations when researchers have little or no information on the selection mechanism, the optimal modelling strategy is to include a large set of covariates, because this approach increases the probability of satisfying the assumption of selection on observables, i.e. strong ignorability.

The next step in the propensity score matching is the estimation of the propensity score. Since the propensity score is a probability of receiving a treatment (in our case, public subsidies), researchers can choose any discrete choice model, because both probit and logit models usually yield similar results (Caliendo and Kopeinig, 2008).

For the sake of brevity, we will not review a full range of matching estimators, but instead will focus on those applied in our study (for a review of matching estimators, see Stuart, 2010; Morgan and Harding, 2006; Austin, 2011a; Imbens, 2004). Nearest Neighbour (NN) matching is the most commonly used matching estimator in the innovation literature (Czarnitzki et al., 2007). The propensity score can be used to construct matched pairs applying three methods (Guo and Fraser, 2010): i) nearest matching on the estimated propensity score; ii) Mahalanobis metric matching including the estimated propensity score with other matching variables;[79] and iii) nearest Mahalanobis metric matching with calipers based on the propensity score. The third method is superior to others with respect to balancing of the covariates between a treatment and comparison group (Rosenbaum and Rubin, 1985). In choosing the optimal caliper size, Cochran and Rubin (1973) note that 98% of the bias on a normally distributed covariate is removed with the caliper of 0.2 of the standard deviation of the estimated covariate (in the case of PSM, the caliper is based on the estimated propensity score).

[79] This matching method is termed hybrid matching (Czarnitzki et al., 2011).

The purpose of matching estimators is to balance observed covariates *X* between treated and untreated units. As discussed, nearest Mahalanobis metric matching with caliper based on the propensity score results in the best balancing quality, and that is the reason why we have chosen to apply this estimator. Matching arguments, besides the estimated propensity score, are a DV for small firms and industry DVs. The inclusion of additional matching arguments is motivated by the arguments advanced in the literature on SME innovation, whereby SMEs are a heterogeneous group of firms and their innovative activities should be analysed at industry level (Nooteboom, 1994; for the same empirical strategy see Czarnitzki et al., 2007; Czarnitzki et al., 2011; Spithoven et al., 2012). Stuart (2010) notes that NN matching with the Mahalanobis metric is not the best choice if the number of matching arguments in the metric is larger than 8 or if covariates are not normally distributed (Stuart, 2010). Although the Mahalanobis metric in our models included fifteen matching arguments (thirteen industry DVs, DV for small firms and the estimate propensity score), all four balancing tests indicate a high matching quality.

After the estimation of the propensity score, but prior to applying a chosen matching estimator, a balancing test should be conducted. The purpose of a balancing test before matching (stratification test) is to check how well the estimated propensity score has succeeded in balancing covariates.[80] This approach requires the division of the sample into strata conditional on the propensity score, and checking whether there are no statistically significant differences between the means of the propensity score of the treated and non-treated firms. If the difference in means is statistically insignificant, then covariates are well balanced between matched pairs (Austin, 2011a; Stuart, 2010; Caliendo and Kopeinig, 2008; Lee 2013). High matching quality indicates a good balance of covariates between the treatment and comparison groups. Low matching quality, on the other hand, indicates either misspecification of the model or weak comparability between treated and non-treated firms. If the propensity score model is correctly specified, then observed covariates *X* should be balanced before matching. Therefore, checking the covariate balance after estimating the propensity score model also means checking model specification. If the propensity score model is not properly specified then matching should be repeated on a model containing interaction terms and higher-order terms (Rosenbaum, 2005). However, if the matching quality remains low

[80] Balancing tests before matching should not be confused with balancing tests after matching.

even after re-specifying the model, that would indicate that the treated firms and matched firms in the control group have quite different characteristics, which makes them bad candidates for matching. In this case, one should use alternative evaluation methods other than matching (Caliendo and Kopeinig, 2008).

The literature identifies several approaches for assessing the matching quality after matching. The first approach consists of comparing the standardized bias before and after matching. The formula for calculating the standardized bias was proposed by Rosenbaum and Rubin (1985) and is constructed as the ratio of the difference in sample means of treated and non-treated firms divided by the square root of the difference between the variances in both groups multiplied by 0.5. Hence, for a continuous covariate, the standardized difference is defined as:

$$d = \frac{\bar{x}_t - \bar{x}_c}{\sqrt{\frac{s_t^2 + s_c^2}{2}}} \tag{5.4}$$

Where d denotes the standardized difference; $\bar{x}_t$ and $\bar{x}_c$ denote the sample mean of the covariate in treated and untreated units, respectively; and s_t^2 and s_c^2 denote the sample variance of the covariate in treated and untreated subjects respectively (Austin, 2011b).

For a dichotomous variable, the standardized difference is given by:

$$d = \frac{(\hat{p}_t - \hat{p}_c)}{\sqrt{\frac{\hat{p}_t(1-\hat{p}_t) + \hat{p}_c(1-\hat{p}_c)}{2}}} \tag{5.5}$$

Where $\hat{p}_t$ and $\hat{p}_c$ denote the mean of the dichotomous variable in treated and untreated units respectively.

The issue with this approach is that the evaluation literature does not provide a precise guide as to how small the standardized bias should be after matching (Becker and Egger, 2013). The rule of thumb adopted in most empirical studies is that a standardized bias below 3% or 5% is acceptable (Caliendo and Kopeinig, 2008). However, some authors argue for larger standard differences, for instance, Austin

(2011a) adopts the proposal by Normand et al. (2001) that any difference lower than 10% indicates a negligible difference in the mean. Rosenbaum and Rubin (1985) and Stuart and Rubin (2008) adopt a less conservative approach arguing that standardized bias should not be larger than 20 per cent. Conversely, Steiner and Cook (2013) suggest that the difference should be close to zero, especially for large-effect variables.

The second approach is based on the t-test statistics, whereby we check whether there are statistically significant differences in the means of covariates X after the matching. Significant differences after matching imply low matching quality. Finally, the matching quality can be assessed by checking the joint significance of all covariates in the selection equation based on the likelihood-ratio (LR) test. All variables should be jointly significant before matching, and jointly insignificant after matching. Furthermore, one can estimate the propensity score only for matched treated and non-treated firms and compare the pseudo- R^2 before and after matching. Low pseudo-R^2 after matching indicates a good matching quality (Sianesi, 2004; Caliendo and Kopeinig, 2008).

Treatment effects of any matching estimator based on the propensity score are only estimated in the region of common support (see Equation 5.2). Thus, it is necessary to check the overlap of the propensity score between treated and non-treated firms after matching. The method applied in this study is based on identifying a minimum and a maximum propensity score and then deleting those observations for which the propensity scores in the treatment group are smaller than the minimum, and larger than the maximum propensity score in the comparison group. In this case, causal estimates are narrower treatment effects than estimates of the ATT: the common-support treatment effect for the treated (Morgan and Harding, 2006).

Finally, analytical standard errors of the treatment effect are not valid for casual inference, as they do not take into account the estimation of the propensity score and the limitation of the sample to the common support region. The literature suggests three approaches for the variance estimation (we briefly mention the two applied in this study). Bootstrapping is the most frequently used method, although there is no formal justification for its application in the variance estimation (Imbens, 2004). Recently, Abadie and Imbens (2008) demonstrate that bootstrapping is not valid for NN matching with replacement with more than one continuous covariate. However, it is still valid for kernel matching (Heckman et al., 1997). The second approach, developed by Abadie and Imbens (2006), requires the estimation of the sample average treatment effect on the treated (SATT) and then the estimation of the variance of the SATT. Two options are available for the variance estimation: homoscedastic and heteroscedastic standard errors. The latter is applied in the analysis.

Finally, based on the previously explained steps, a matching protocol can be presented (see Figure 5.1).

For a robustness check, three matching estimators were employed. The first is kernel matching, which uses weighted averages of most units in the control group to estimate a counterfactual outcome.[81] The major advantage of this non-parametric estimator is the reduction in variance as the entire sample of the control group is used in matching algorithm. Kernel matching requires the selection of the kernel function and of the bandwidth parameter, although the former is not very relevant in practice. The choice of bandwidth is associated with the following bias; high bandwidth yields a diminishing variance at the price of biased estimates and vice versa (Caliendo and Kopeinig, 2008).

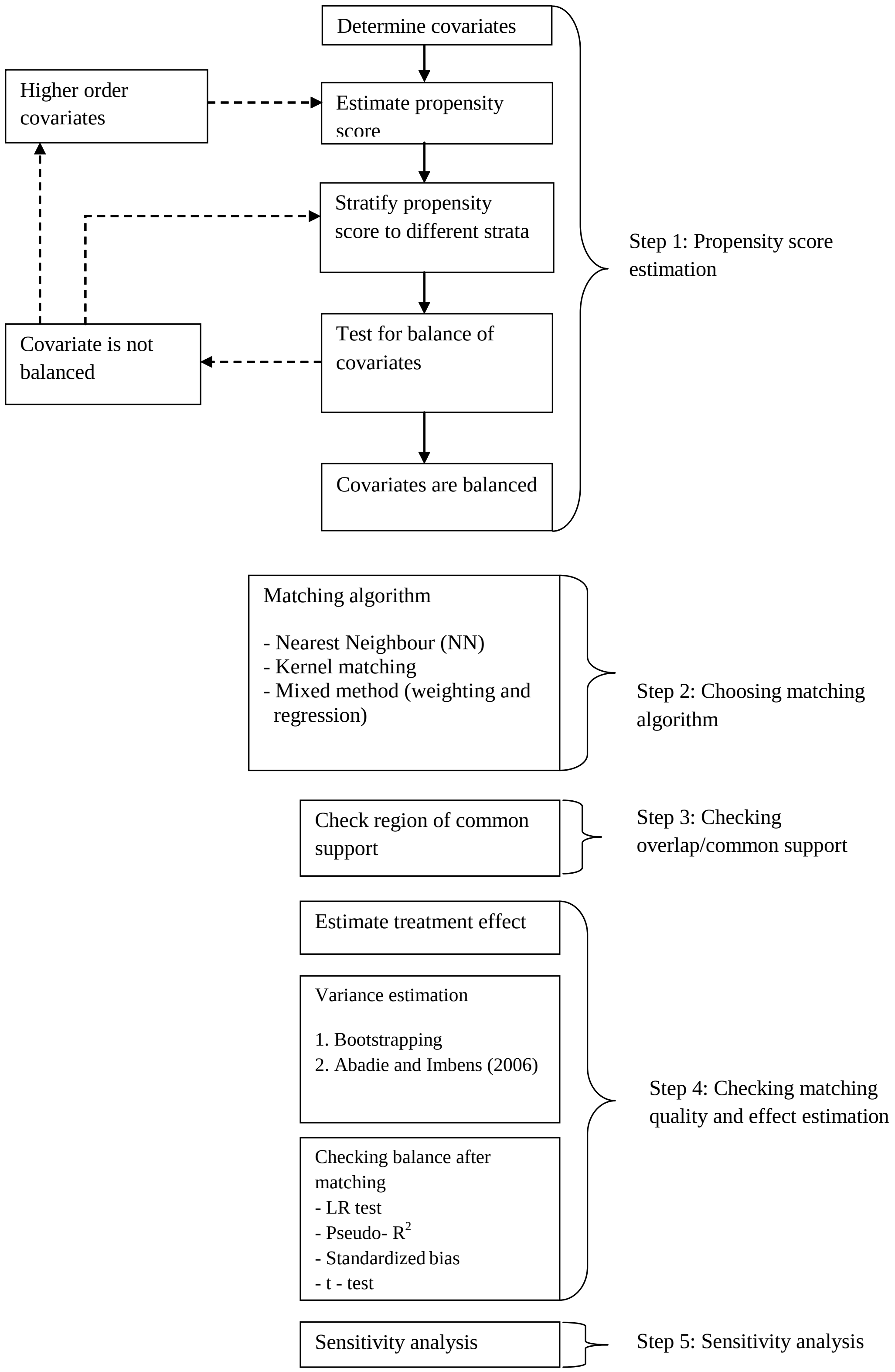
The second is bias-adjusted covariate matching proposed by Abadie and Imbens (2006) and implemented in Stata software by Abadie et al. (2004). The main advantage of this estimator is the reduction of bias when matching is not exact and so treated and control units do not have the same characteristics, i.e. there is at least one continuous covariate. Bias reduction is achieved by adjusting the estimated non-observed (counterfactual) outcome for the difference between treated and its matched control unit. Bias-adjusted matching estimator combines matching with a regression adjustment. In the first step, the outcome variable is regressed by OLS on the covariates using only the matched sample.

In the second step, the estimated coefficients from OLS regression are used for predicting the outcomes for treated units and their matched untreated units. Finally, to obtain a counterfactual outcome of the treated units, the difference between these two estimated outcomes (i.e. for treated and their matched untreated units) is added to the

[81] How many comparison units will be used depends on the choice of bandwidth.

observed outcome of the matched treated units (Abadie et al., 2004; Gonzàles and Pazó, 2008).

Figure 5.1. Matching protocol



Source: Adopted from Li (2012).

We have estimated 1:4 bias-adjusted estimator, whereby 1:4 refers to the number of control units used in matching (four control units were used to match each treated unit). Ratio matching be used if there is a large number of control units (Stuart, 2010). Selecting multiple controls entails a bias-variance trade-off; multiple matches increase bias but reduce variance. What is not clear from the literature is how to choose an optimal number of matches (Huber et al., 2010). Following the practical example in Abadie et al. (2004), we used four matches, as 'it offers the benefit of not relying on too little information without incorporating observations that are not sufficiently similar' (p. 298).

The third PSM estimator is Inverse Probability of Treatment Weighting (IPTW) based on propensity score, which uses weights based on the propensity score to create an artificial population in which treatment assignment is independent of the exogenous covariates *X*. The purpose of weighting is similar to using survey sampling weights to obtain weighted survey samples that are representative of the population (Austin, 2011a). Weights (ω_{Ti}) used for the estimation of the ATT are set to equal to 1 for treated units (normalization of weights), i.e. ω_{Ti}=1 and for untreated units, $\omega_{Ti}=\frac{P(X)_i}{1-P(X)_i}$, where $P(X)_i$ is the estimated propensity score (probability of receiving a treatment) for the *i*th subject (Nichols, 2008; Emsley et al., 2008).

After estimating the weights, the next step is to estimate the regression function by weighted least squares, whereby the outcome variable is regressed on the treatment indicator and covariates *X*. The weights, in this case, ensure that the treatment indicator is not correlated with the covariates. The variance estimation of the IPTW estimator has to take into account that weights are used to create an artificial sample. It is a common practice to use robust variance estimation (Emsley et al., 2008; Austin, 2011a). This estimator belongs to a group of double robust estimators, which require modelling both the propensity score model and a regression model in the same estimator. Namely, the treatment effects are not estimated as a difference in outcomes between treated and non-treated firms, which is a common practice in other matching methods, but rather are estimated using a regression model. The importance of this estimator lies in its double robustness property, i.e. it remains consistent if either the propensity score model is correctly specified or the regression model or both. Therefore, only one model needs to be correctly specified for consistent estimation (Imbens, 2004; Imbens and Wooldridge, 2009).

5.3.2 Model specification

Available data allows us to explore how public support affects several inbound open innovation strategies, which are: external networking; outsourcing R&D; and acquisition of other external knowledge. As the CIS data do not contain information on outbound open innovation, we are not able to assess the effectiveness of public support on those open innovation practices.

Busom and Fernández-Ribas (2008) do not assess the impact of subsidies received from the European Union (EU), because often cooperation on innovation is a pre-requisite for applying for EU funding. This obvious selection bias is partially addressed by matching on observed firm characteristics. Although the literature on EU funding emphases that cooperation is a pre-requisite for applying for this source of funding (Defazio et al., 2009; Busom and Fernández-Ribas, 2008; Teirlinck and Spithoven, 2012), researchers interpret this condition differently. For instance, Defazio et al. (2009) explicitly note that, since the first EU Framework Programme, firms applying for funding must be organized in networks. However, according to these authors, in practice this precondition is irrelevant , because the required cooperative networks can be established either shortly before an application or, effectively, shortly after receipt of EU funding for the purpose of satisfying the conditions of EU funding. On the other hand, Teirlinck and Spithoven (2012) argue that firms have to have had long-standing cooperation on innovation before accessing the selection process. This discrepancy in the literature suggests that two types of selection bias might arise. Namely, if it is necessary for firms to establish cooperative networks well prior to participating in EU funding, this would imply an obvious selection bias in assessing the effectiveness of EU programmes on cooperation. In this case, findings of a large additional effect would be spurious, as large treatment effects would be overestimated due to selection bias. (EU funding to encourage firms to cooperate would go only to firms already engaged in long-standing cooperation, thereby invalidating findings of additionality.) If, however, firms establish cooperative networks either shortly before or, effectively, shortly after the provision of EU funding, then self-selection bias might invalidate causal interpretation of the estimates. (In this case, participating firms are not typical but a self-selecting group.) In either case, treatment effects would be highly sensitive to unobserved heterogeneity. Therefore, we can hypothesize that participation in EU funding may have a large and positive effect on cooperation, but that this effect is likely to be overestimated due to selection bias.

The presence of selection bias has strong implications for the empirical strategies to be adopted for analysing the effectiveness of EU programmes designed to promote cooperation among firms. Not only is it likely that evaluation findings for EU programmes will be influenced by selection bias but also it is possible that evaluations that do not differentiate between programmes administered at the EU and other levels – treating them as homogeneous support programmes - will also be biased. In turn, this suggests that evaluators either should have information about the selection process or should apply those evaluation methods that control for unobserved heterogeneity (such as the difference-in-difference estimator). Finally, to anticipate, this discussion does not alter the conclusions from our analysis reported below. The reason is that sensitivity analysis revealed no treatment effects that are robust to unobserved heterogeneity among firms that participated in EU funding; our robust findings are all for programmes that are administered at the national or the regional level. Accordingly, as our focus is on drawing conclusions from robust treatment parameters, the concluding remarks omit any reference to the estimated treatment effects of treatment assignment to EU funds.

Further, we separately analyse receipt of local or regional support (*FUNLOC*) and of national support (*FUNGMT*). From the perspective of distinguishing between three sources of funding, our analysis is similar to the analysis by Spithoven et al. (2012), who found that national support has the largest effect on open innovation in Belgian firms.

Outcome variables are defined as follows (see Appendix III, Table A3.1. for variable definition and descriptive statistics):

- Aggregate cooperation (*COOPERATION*): DV=1 if firms cooperate with any partner: consumers, suppliers, universities or other higher education institutions (HEIs), consultants, government or competitors; otherwise zero;

- Cooperation with consumers (*COOP_CUSTOMERS*): DV=1 if firms cooperate with clients or customers, otherwise zero;
- Cooperation with suppliers (*COOP_SUPPLIERS*): DV=1 if firms cooperate with suppliers, otherwise zero;
- Cooperation with competitors (*COOP_COMPETITORS*): DV=1 if firms cooperate with competitors or other firms in the sector, otherwise zero;
- Cooperation with consultants (*COOP_CONSULTANTS*): DV=1 if firms cooperate with consultants, commercial labs or private R&D institutes, otherwise zero;
- Cooperation with HEI (*COOP_HEI*): DV=1 if firms cooperate with universities or other higher education institutions, otherwise zero;
- Cooperation with government (*COOP_GOVERNMENT*): DV=1 if firms cooperate with government or public research institutes, otherwise zero.
- Outsourcing R&D (*OUTSOURCING_RD*): DV=1 if firms conduct extramural R&D activities, otherwise zero;
- Acquisition of other external knowledge (*EXTERNAL_KNOWLEDGE*): DV=1 if firms purchase or license patents, know-how, and other types of knowledge from other firms, otherwise zero.

Although our sample is restricted to SMEs, we further include a dummy variable for small firms (*SM*) with more than 10 and fewer than 50 employees. SMEs are a heterogeneous category, and public support could have a differential effect on small firms relative to medium-sized firms (Curran, 2000).

A novelty of this study is the inclusion of barriers to innovation in the estimation of propensity scores (Becker and Dietz, 2004). The correlation matrix between seven variables measuring barriers to innovation indicates that multicollinearity might exist between these constraining factors (the correlation matrix is presented in Table A3.2).[82] Thus, to avoid multicollinearity, we omit four and include three variables: too high innovation costs (*BARRIER3*); a lack of qualified personnel (*BARRIER4*); and

[82] The seven barriers are as follows: lack of funds within enterprise or group (*BARRIER1*); lack of finance from sources outside a firm (*BARRIER2*); innovation costs too high (*BARRIER3*); lack of qualified personnel (*BARRIER4*); lack of information on technology (*BARRIER5*); lack of information on markets (*BARRIER6*); and difficulty in finding cooperation partners for innovation (*BARRIER7*). They are grouped into two categories - financial and knowledge obstacles to innovation. We assume that the reason why collinearity might occur is because some barriers belong to the same group, i.e. measure similar hampering factors. For instance, *BARRIER1*, *BARRIER2* and *BARRIER3* indicate financial barriers to innovation. The correlation matrix indicates high collinearity between these three obstacles.

difficulties in finding cooperative partners (*BARRIER7*) (the variables are measured as scores: 0 - no importance; 1 - low importance; 2 - medium importance; and 3 - high importance). The resource-based theory of the firm posits that resources are a crucial determinant of firms' competitive advantages (Barney, 1991; Peteraf, 1993). For SMEs, limited human and financial resources are critical factors in hampering innovation activities and justify the inclusion of the aforementioned barriers to innovation. In addition, limited internal resources and competencies can, at least partially, be compensated through cooperation with network partners (Lee et al., 2010; Parida et al., 2012).

The following variables are included to control for firms' absorptive capacity:

- Patent activities (*PROPAT*): In the empirical literature on R&D cooperation, patents are regarded as a measure of the appropriation effort; i.e. those firms that actively use mechanisms to protect their intellectual property are more likely to successfully commercialize their inventions (Faems et al., 2005).
- Whether firms continuously innovate (*CONTINUOUS_RD*). The reason to model these variables is that public agencies could adopt a strategy of picking the winners (Czarnitzki et al., 2007; Spithoven et al., 2012). In that case, government selects those firms that have a record of successful innovation.

The model also includes a dummy variable for belonging to a group (*GP*). This variable can have a twofold effect; it can have a positive effect on cooperation, as firms that are a part of the enterprise group could be more likely to cooperate with other firms within a group (Czarnitzki et al., 2007). On the other hand, being a part of the group can have an adverse effect on the probability of receiving support. Some support measures are restrictive insofar SMEs that are part of a group are not eligible to apply for them. Thus, belonging to a group can be a barrier to participation in support programmes (Almus and Czarnitzki, 2003).

Exporting activities (*EXPORT*) are modelled as a binary indicator equal to one if firms export and zero otherwise. Exporting can have a positive impact on cooperation, given that exporters potentially could have a larger network of cooperation partners than do non-exporting firms. Furthermore, exporting firms might have more incentive to innovate as a result of competitive pressure on international markets (Busom and Fernández-Ribas, 2008; Czarnitzki and Lopes-Bento, 2013).

Another novelty of our study is the inclusion of sources of information in the selection equation. In the literature on determinants of R&D cooperation, sources of information are used as a proxy for knowledge spillovers. Several empirical strategies can be employed for measuring the complexity of knowledge:

- A single variable to capture different sources of information. For instance, Spithoven et al. (2012) measure incoming knowledge spillovers by the average score of the importance of information from suppliers, consumers, competitors, universities, government, professional conferences, journals and exhibitions.
- Only particular sources of information are included as a measure of incoming knowledge spillovers; these are conferences, trade fairs, exhibitions, scientific journals and publications, and professional and industry associations (Cassiman and Veugelers, 2002; de Faria et al., 2010; Chun and Mun, 2012).
- All sources of information are included. For instance, Belderbos et al. (2004) control for incoming spillovers by including five sources of information: from suppliers; customers; competitors; universities and research institutions (institutional incoming spillovers); and from public sources (importance of patents, databases and trade fairs).

The third strategy was chosen, whereby incoming spillovers are proxied by the importance of various sources of information, such as: (a) conferences, trade fairs and exhibitions (*INCOMING1*); (b) scientific journals and publications (*INCOMING2*) and (c) professional and industry associations (*INCOMING3*). Furthermore, the following variables are included in the model:

- Internal source of information to measure the importance of information within a firm or enterprise group (*INFO_INTERNAL*);
- Market sources of information: from customers (*INFO_CUSTOMERS*); from suppliers (*INFO_SUPPLIERS*); competitors (*INFO_COMPETITORS*); and consultants, commercial labs or private R&D institutes (*INFO_CONSULTANTS*); and
- Institutional sources: from universities (*INFO_HEI*) and from government or public research institutes (*INFO_GOVERNMENT*).

All variables are measured as scores (0 - no importance; 1 - low importance; 2 - medium importance; and 3 - high importance). In addition, the balancing test before matching reported that the two variables (*INFO_INTERNAL* and *INFO_SUPPLIERS*) were not balanced in the propensity score model where the treatment variable is government support (*FUNGMT*). Following the literature on matching estimators discussed in Section 5.3.1, if the propensity score model is not balanced before matching, it should be re-specified by adding interaction terms and/or polynomials. We added two covariates (*INTERNAL_SM and SUPPLIERS_SM*), created as interaction terms between a binary indicator for small firms and two unbalanced covariates (*INFO_INTERNAL* and *INFO_SUPPLIERS*). After these additional covariates were added to the propensity score model, covariate balance before matching was achieved. We used this specification of the propensity score model for each treatment variable, which will enable us to compare the treatment effects of all three sources of funding.

To control for industry heterogeneity, based on the NACE classification at the 2-digit industry level, we include in our model sectoral DVs for fourteen manufacturing industries (see Table A3.1. for variable definitions and Table A3.2 for NACE classification).[83] The base category is *INDUSTRY9* (sector 25 - Manufacture of rubber and plastic products.

5.3.3 Data

The analysis employs Spanish CIS2006 survey data covering the period 2004-2006. Anonymised micro-data are provided by Eurostat. The sample consists of 8,022 small and medium-sized enterprises (SMEs) in manufacturing sectors. For a robustness check, following Busom and Fernández-Ribas (2008), the sample is restricted to those firms

[83] There are two discrepancies between the NACE two-digit classification and the CIS microdata (see Table A3.2 for NACE classification). Firstly, sector 31 - Manufacture of electrical machinery and apparatus is a medium-high tech sector, but it is aggregated with three high-tech sectors: 30 - Manufacture of electrical and optical equipment; 32 - Manufacture of radio, television and communication equipment; and 33 - Manufacture of medical, precision and optical instruments. Secondly, sector 23 - Manufacture of coke, refined petroleum products and nuclear fuel is a medium low tech sector but is aggregated with sector 24 - Manufacture of chemicals and chemical products, which is a medium high tech industry.

that reported positive intramural R&D expenditures, which enables us to focus on innovative firms.[84]

Our sample consists of 5,115 small and 2,907 medium-sized firms.[85] Around a quarter of the sample participated in local or regional programmes (1,854 SMEs or 23.1 per cent) and less than 20 per cent received national government support (1,312 firms or 16.4 per cent). Only 182 firms (2.3 per cent) received support from EU funding. Furthermore, 534 firms received both local/regional and government support, but very few firms (59) received all three types of support.

Descriptive statistics are presented in Table A3.1 (see Appendix III). Only one-fifth of SMEs cooperate on innovation (22.2 per cent). Regarding cooperation partners, the largest number of firms cooperate with suppliers (10.7 per cent) followed by government institutions (8.8 per cent) and universities (7.0 per cent). The smallest numbers of firms engage in horizontal cooperation with competitors (3.6 per cent). With respect to innovation activities, only 11.3 per cent applied for a patent in the period covered by the survey, while 34.5 per cent of firms continuously engage in R&D activities, and one-fourth of SMEs undertook extramural R&D activities (24.7 per cent). Furthermore, a large number of SMEs are exporters (68.6 per cent). Among various sources of information, the most important are internal sources (mean value of 2.1), followed by customers and suppliers (mean values of 1.4 and 1.5 respectively). The least important source of information is from government and public research institutes (mean value of 0.4).

Table A3.4 (see Appendix III) presents numbers and percentages of SMEs according to their cooperative behaviour and participation in support programmes. Out of 8,022 firms, more than two-thirds of firms neither cooperate on innovation nor participate in support programmes (63.5 per cent of firms from the perspective of local/regional support; 67.6 per cent of firms from the perspective of government support; and 76.6 per cent for EU support). By contrast, the percentage of firms that both cooperate and participate in public funding is rather low (8.9 per cent of firm receiving local/regional support; 6.1 per cent of firms receiving national support; and

[84] In addition, this empirical strategy enables comparison between findings from our study and those from Busom and Fernández-Ribas (2008).

[85] Small firms are defined as those employing more than 10 and fewer than 50 workers, while medium-sized firms employee between 50 and 250 workers.

1.1 per cent of firms participating in the EU support). A similar pattern is found for participating firms that undertake extramural R&D activities (10.1 per cent of firms participating in local/regional support measures; 7.1 per cent of firms receiving federal government support; and 1.0 per cent of firms participating in the EU support). A very modest share of participating firms acquires other types of external knowledge (0.8 per cent of firms participating in local/regional funding; 0.7 per cent of firms receiving national support; and 0.1 per cent of firms receiving the EU support). Table A3.5 (see Appendix III) shows that the number of cooperating firms participating in support programmes is smaller than those that do not participate, although the largest discrepancy is found for EU support. The only exception is cooperation with government institutions of firms receiving local/regional support, where 378 are participating and 330 are non-participating firms.

5.4 Main results

We estimated the impact of public support on various types of cooperation (vertical, horizontal, and private-public partnerships etc.) and two additional open innovation practices: outsourcing R&D; and acquisition of other external knowledge. As discussed in Section 5.3.1, the first step in matching is to estimate the propensity score. The results of three probit models are shown in Table A3.6. We do not interpret the results of probit estimations, because probit models in the case of matching are used to obtain the propensity score. Furthermore, a critical step in estimating probit model is to check whether covariates between matched pairs of treated and untreated firms are balanced given the estimated propensity scores. The literature on matching suggests the inclusion of even those covariates that are statistically insignificant, because their inclusion does not increase bias in subsequent matching estimations. Moreover, our study is limited by a lack of information on the selection process, which means that a large number of covariates should be modelled in the estimation of the propensity score (Steiner et al., 2010)**.**

The choice of three matching estimators is motivated by suggestions advanced in the literature on matching. Following a discussion in Section 5.3.1, we estimated the Nearest Neighbour (NN) matching with the Mahalanobis metric and a caliper of 0.2 of the standard deviation of the propensity score, because this estimator results in the best covariate balance after matching (D'Agostino, 1998; Cochran and Rubin, 1973). However, in our study, the number of matching arguments in the Mahalanobis metric amounted to eleven, which could be the reason why the matching balance was worse than found after kernel matching. For a robustness check we applied three additional matching estimators: kernel matching; 1:4 bias-adjusted covariate matching with the Mahanalobis metric; and IPWT estimator.

Table 5.1 presents the Average Treatment Effect on the Treated (ATT) for three sources of funding. With respect to behavioural additionality, the overall results strongly indicate a positive but differential impact of public support for each source of funding. The hypothesis advanced in Section 5.3.1 regarding the impact of EU funding on cooperation cannot be rejected: relative to local/regional and government supports, the EU funding has the largest effect on each type of cooperation and for an aggregate category of cooperation (*COOPERATION*). However, following discussion advanced in Section 5.3.1, interpreting these results as evidence of a large additional effect would be spurious, given that selection bias is unavoidable in assessing the impact of EU programmes. Indeed, the results of sensitivity analysis reported in the next section, confirm our discussion; only one model, estimated on the whole sample, for the effect of EU funding is robust to hidden bias.

Although estimated ATT effects are fairly consistent across the four matching estimators, we will interpret the results from kernel matching, because the latter resulted in the best balance after matching for each source of funding. The results of balancing tests are reported in Table 5.2 below. Moreover, the regions of common support for each estimator are presented in Table A3.8 (see Appendix III). Very few observations are lost due to the common support restrictions, which indicates a large overlap of estimated propensity scores among treated and untreated SMEs. Finally, Figure A3.1 (see Appendix III) shows kernel densities of the estimated propensity scores before and after matching. After the matching procedures, the distribution of propensity scores for treated and untreated firms are identical. These results suggest that the propensity score are very well aligned after matching.

The ATT effect of local/regional programmes on aggregate cooperation is 14.1 percentage points (p.p.) of an increase in the probability of cooperating on innovation; of national programmes 8.5 percentage points of an increase in the probability of cooperating on innovation; and of EU support is 17.0 p.p. of an increase in the probability of cooperating on innovation.[86] A comparison between treatment effects of local/regional and government support reveals that participation in local/regional programmes has a larger effect on any type of cooperation than does participation in national programmes, except for cooperation with competitors (horizontal cooperation) and for cooperation with HEIs. Moreover, the largest ATT effect is found for cooperation with government institutions for both sources of funding (for local/regional programmes, 11.8 p.p. of an increase in the probability of cooperating with government institutions; and for national support, 8.4 p.p. of an increase in the probability of cooperating with government institutions). On the other hand, the smallest ATT effect of local support is reported for cooperation with competitors (2.7 p.p. of an increase in the probability of cooperating with competitors), and of national support for vertical cooperation (2.9 p.p. of an increase in the probability of cooperating with customers and 2.6 p.p. of an increase in the probability of cooperating with suppliers) together with cooperation with consultants (2.8 p.p. of an increase in the probability of cooperating with consultants). However, as reported in Table A3.7, the 95 per cent confidence intervals overlap for each outcome variable, except for the model in which aggregate cooperation is the outcome variable. Therefore, the differences between estimated treatment effects are not statistically significant, except, as noted, in one model.

Turning to open innovation strategies other than cooperation, the most interesting finding is reported for outsourcing R&D. Participation in both local/regional and government support programmes results in a larger effect on extramural R&D activities, than on either aggregated or disaggregated categories of cooperation. The pattern is reversed in the case of EU funding; i.e. a substantially larger effect (17.0 p.p.) on aggregate cooperation than on extramural R&D activities (9.6 p.p. of an increase in the probability of outsourcing R&D). In contrast, receiving public support from regional and EU programmes has no effect on the acquisition of external knowledge, and has a small effect on SMEs participating in government programmes (1.2 p.p. of an increase in the probability of acquiring other external knowledge).

[86] We conducted two kernel matching estimations for EU funding: the first estimator with a bandwidth of 0.06; and the second with 0.001. Matching quality was poor after the former, which motivated our decision to reduce the bandwidth to improve the balance. Indeed, a smaller bandwidth results in improved and satisfactory matching quality. Therefore, we present results from kernel matching with bandwidth of 0.001.

Table 5.1. Average Treatment Effects (ATTs) for the whole sample of Spanish SMEs

Dependent variable	Local/regional support				Government support				EU support			
	NN matching with Mahalanobis metric and caliper 0.02	**Kernel matching (Epanechnikov kernel, bw=0.06)**	**1:4 bias adjusted covariate matching with Mahalanobis metric**	**IPTW**	**NN matching with Mahalanobis metric and caliper 0.02**	**Kernel matching (Epanechnikov kernel, bw=0.06)**	**1:4 bias adjusted covariate matching with Mahalanobis metric**	**IPTW**	**NN matching with Mahalanobis metric and caliper 0.004**	**Kernel matching (Epanechnikov kernel, bw=0.001)**	**1:4 bias adjusted covariate matching with Mahalanobis metric**	**IPTW**
	ATT (sub-sampled SEs)	**ATT (bootstrapped SEs)**	**ATT (Abadie and Imbens SEs)**	**ATT (robust SEs)**	**ATT (sub-sampled SEs)**	**ATT (bootstrapped SEs)**	**ATT (Abadie and Imbens SEs)**	**ATT (robust SEs)**	**ATT (sub-sampled SEs)**	**ATT (bootstrapped SEs)**	**ATT (Abadie and Imbens SEs)**	**ATT (robust SEs)**
Aggregate cooperation	0.157*** (0.020)	0.141*** (0.014)	0.152*** (0.013)	0.142*** (0.014)	0.099*** (0.026)	0.085*** (0.014)	0.100*** (0.015)	0.089*** (0.016)	0.156*** (0.066)	0.170*** (0.035)	0.218*** (0.039)	0.175*** (0.038)
Cooperation with customers	0.054*** (0.012)	0.053*** (0.009)	0.057*** (0.008)	0.054*** (0.009)	0.030* (0.017)	0.029*** (0.010)	0.032*** (0.010)	0.031*** (0.010)	0.138*** (0.049)	0.129*** (0.030)	0.137*** (0.029)	0.127*** (0.031)
Cooperation with suppliers	0.047*** (0.016)	0.039*** (0.010)	0.042*** (0.010)	0.042*** (0.010)	0.040** (0.020)	0.026** (0.013)	0.029** (0.012)	0.028** (0.012)	0.113** (0.047)	0.106*** (0.034)	0.116*** (0.033)	0.103*** (0.033)
Cooperation with competitors	0.025** (0.010)	0.027*** (0.007)	0.025*** (0.007)	0.026*** (0.007)	0.045*** (0.013)	0.045*** (0.008)	0.044*** (0.009)	0.045*** (0.008)	0.106*** (0.040)	0.106*** (0.027)	0.124*** (0.026)	0.112*** (0.027)
Cooperation with consultants	0.031** (0.012)	0.037*** (0.009)	0.042*** (0.008)	0.037*** (0.009)	0.034** (0.017)	0.028*** (0.010)	0.026*** (0.010)	0.030*** (0.010)	0.106** (0.045)	0.087*** (0.030)	0.119*** (0.029)	0.103*** (0.030)
Cooperation with HEI	0.047*** (0.013)	0.042*** (0.010)	0.049*** (0.008)	0.044*** (0.010)	0.032* (0.019)	0.047*** (0.011)	0.052*** (0.010)	0.051*** (0.012)	0.081* (0.049)	0.107*** (0.034)	0.143*** (0.030)	0.113*** (0.033)
Cooperation with government	0.115*** (0.014)	0.118*** (0.012)	0.128*** (0.010)	0.117*** (0.011)	0.069*** (0.019)	0.084*** (0.012)	0.097*** (0.012)	0.086*** (0.013)	0.181*** (0.058)	0.169*** (0.036)	0.184*** (0.034)	0.166*** (0.035)
Outsourcing R&D	0.163*** (0.020)	0.168*** (0.013)	0.177*** (0.013)	0.167*** (0.014)	0.117*** (0.025)	0.122*** (0.013)	0.134*** (0.015)	0.124*** (0.016)	0.131** (0.067)	0.096** (0.038)	0.134*** (0.039)	0.106*** (0.038)
Acquisition of other external knowledge	-0.002 (0.009)	0.007 (0.005)	0.010** (0.005)	0.007 (0.005)	0.013 (0.009)	0.012* (0.006)	0.015** (0.006)	0.012* (0.006)	0.000 (0.025)	0.000 (0.016)	0.005 (0.014)	-0.000 (0.014)

Table 5.2. Balancing tests for the whole sample

Matching estimator	Local/regional support				Government support				EU support			
	Pseudo-R^2	p-value of LR test	Mean bias	t-test	Pseudo-R^2	p-value of LR test	Mean bias	t-test	Pseudo-R^2	p-value of LR test	Mean bias	t-test
NN matching without replacement and caliper	0.002	1.000	1.8	Yes	0.004	0.999	2.0	Yes	0.027	0.998	5.7	Yes
NN matching with Mahalanobis metric and caliper	0.001	1.000	0.8	Yes	0.004	0.996	1.5	No at the 5% l.s.[a]	0.017	1.000	2.7	Yes
Kernel matching Epanechnikov kernel, bw=0.06 (0.001 for EU support)	0.000	1.000	0.9	Yes	0.001	1.000	1.7	Yes	0.002	1.000	1.4	Yes

Notes: [a] l.s. denotes level of significance. Following the discussion on matching quality in Section 5.3.1, low values of pseudo-R^2 indicate a good matching quality. Very high p-values of the likelihood-ratio (LR) test suggest that there is insufficient evidence to reject the null of joint insignificance of covariates at 1 % level of significance. Mean biases for each estimation are below 3 %, except for NN matching without replacement estimating the impact of EU support, which is slightly below 6 %. The forth balancing test, t-test statistics, is satisfied in each estimation (i.e. Yes - there are statistically insignificant differences in the means of covariates after matching), except for NN matching with Mahalanobis metric estimating the impact of government support.

5.5 Sensitivity analysis

As noted in Section 5.3.1, the main drawback of matching as an evaluation method is that it only controls for selection on observables. Yet firms' innovative behaviour as well as the selection process can be affected also by unobserved characteristics, such as managerial attitude toward innovation (Busom and Fernández-Ribas, 2008). This unobserved heterogeneity is referred in evaluation literature as 'hidden bias'. The presence of 'hidden bias' indicates a failure of the identifying assumption on unconfoundedness or the selection on observables (CIA). The evaluation literature proposes several tests that can be applied to test for the presence of 'hidden bias'. The results of such tests should be taken with caution, as they cannot directly confirm whether the CIA holds. Rather, they can indicate whether 'hidden bias' arises or not. However, testing for unobserved heterogeneity should always complement a propensity score analysis, as the assumption on unconfoundedness cannot be tested directly (Guo and Fraser, 2010). Naturally, the ideal robustness check would be to apply those evaluation methods that control for unobserved heterogeneity. However, as discussed in the introductory section, the lack of valid instruments precludes this empirical strategy.

Sensitivity analysis is not common in empirical studies on additionality of innovation policy. Indeed, no previous study on behavioural additionality reports any type of sensitivity analysis. Moreover, to our knowledge, only the study on input additionality by Alecke et al. (2012) reports the results of sensitivity analysis.[87] The authors adopted the same Rosenbaum bound approach (Rosenbaum, 2002) as in our analysis.

The idea behind the Rosenbaum bounds approach is to determine how large the impact of an unobserved 'confounding' variable should be to render the treatment effect statistically insignificant, under the assumption that this variable simultaneously affects a treatment assignment and the outcome variable (DiPrete and Gangl, 2004). Sensitivity of the estimated results with respect to 'hidden bias' would indicate that the results are not robust (Caliendo and Kopeining, 2008; Becker and Caliendo, 2007).

[87] However, we believe that the authors did not correctly apply the test using the Stata software. The user-written command *mhbounds* can only be used for two types of matching estimators: NN matching without replacement; and stratification. Alecke et al. (2012) employ kernel matching; and, to our understanding, *mhbounds* cannot be applied to kernel matching.

The probability of treatment assignment is given by (Becker and Caliendo, 2007):

$$P_i = P(x_i, u_i) = P(T_i = 1|x_i, u_i) = F(\beta x_i + \gamma u_i) \quad (5.6)$$

Where x_i are observed characteristics for unit i, u_i is the unobserved variable, T_i denotes treatment assignment, β is the effect of observed characteristics x_i and γ is the effect of unobserved variable u_i on the probability of treatment assignment. When a treatment effect is robust to hidden bias, γ is equal to zero. However, in the presence of unobserved heterogeneity, γ is larger than zero and two matched units i and j will have a different probability of receiving a treatment. Under the assumption that F is a logistic distribution, the odds that unit i will receive a treatment is $P_i(1-P_i)$ and the odds that unit j will receive a treatment is $P_j(1-P_j)$, while the odds ratio is then:

$$\frac{\frac{P_i}{1-P_i}}{\frac{P_j}{1-P_j}} = \frac{P_i(1-P_j)}{P_j(1-P_i)} = \frac{\exp(\beta x_i + \gamma u_i)}{\exp(\beta x_j + \gamma u_j)} \quad (5.7)$$

As both units i and j have the same observed covariates, the vector x cancels out and what remains is:

$$\frac{\exp(\beta x_i + \gamma u_i)}{\exp(\beta x_j + \gamma u_j)} = \exp\{\gamma(u_i - u_j)\} \quad (5.8)$$

The odds ratio is equal to one (i.e. no hidden bias) in two cases:

- if $u_i - u_j = 0$, i.e. no differences in unobserved covariates and their impact on matched pairs of treated and untreated units; and
- if $\gamma = 0$, i.e. the effect of unobserved variables on the participation decision is zero.

However, when these conditions do not hold, meaning that the study is sensitive to hidden bias, we want to determine how changes in γ and $(u_i - u_j)$ affect the estimated treatment effects. The upper and lower bounds for the odds ratio denoted gamma (Γ) in Equation 5.7 are as follows (Rosenbaum, 2002):

$$\frac{1}{e^{\gamma}} \leq \frac{P_i(1-P_j)}{P_j(1-P_i)} \leq e^{\gamma} \qquad (5.9)$$

Where e denotes exponentiation. The value of gamma (Γ) shows how much matched pairs differ in their odds of treatment assignment. When gamma has a value of 1 (which can only be the case when γ=0), that means that the treatment effect is free of hidden bias. In other words, if unobserved characteristics have no influence on the causal inference, then the estimated ATT and its confidence intervals are unbiased (Li, 2012). Higher values of gamma indicate a departure from random assignment (selection) on observables. For instance, if gamma is equal to two, treated units are twice as likely to receive treatment as untreated (control) units. Keele (2010) notes that using gamma between 1 and 2 is sufficient for sensitivity analysis, as for larger values of gamma, most treatment effects are not robust to hidden bias.

Under the assumption that the unobserved covariate is binary, Becker and Caliendo (2007) developed the Stata user-written command *mhbounds* for binary outcomes, which provides p - values for the upper and lower bounds in Equation 5.9 calculated from the sample data. These p-values reflect the critical values associated with the Mantel-Haenszel test statistics (Q_{MH}), which are based on the values of gamma. The test statistic Q_{MH} is calculated for each value of gamma. If Q^{+}_{MH} denotes the test statistics when the treatment effect is overestimated (the upper bound), and Q^{-}_{MH} is the test statistics when the treatment effect is underestimated (the lower bound), then the upper bound is given by (Becker and Caliendo, 2007):[88]

$$Q^{+}_{MH} = \frac{\left|Y_1 - \sum_{s=1}^{S} \tilde{E}^{+}_{s}\right| - 0.5}{\sqrt{\sum_{s=1}^{S} Var(\tilde{E}^{+}_{s})}} \qquad (5.10)$$

[88] If there is an unobserved selection bias, we expect it to be positive (i.e. overestimation of the treatment effect). For the calculation of the lower bound, see Becker and Caliendo (2007). It is important to note that each component of Equation 5.10 is observable.

The number of successful treated units is Y_{1s}, the number of successful untreated units is Y_{0s} and the number of total successes in stratum s is Y_s.[89] The number of successful treated units in the whole sample is denoted Y_1.

$\tilde{E}_s^+$ and $Var(\tilde{E}_s^+)$ are the large-sample approximations of the expectation and variance of the number of treated units for given γ.

The large-sample approximation of $\tilde{E}_s^+$ is the unique root of the Equation 5.11:

$$\tilde{E}_s^2(e^\gamma - 1) - \tilde{E}_s\{(e^\gamma - 1)(N_{1s} + Y_s) + N_s\} + e^\gamma Y_s N_{1s} \qquad (5.11)$$

where N_{1s} and N_{0s} are the numbers of treated and untreated units in stratum s respectively and $N_s = N_{0s} + N_{1s}$.

The decision on which root to use is based on the following condition:

$$\max(0, Y_s + N_{1s} - N_s) \leq \tilde{E}_s \leq \min(Y_s, N_{1s}) \qquad (5.12)$$

Finally, the large-sample approximation of the variance is given by:

$$Var(\tilde{E}_s^+) = \left\{\frac{1}{\tilde{E}_s^+} + \frac{1}{Y_s - \tilde{E}_s^+} + \frac{1}{N_{1s} - \tilde{E}_s^+} + \frac{1}{N_s - Y_s - N_{1s} + \tilde{E}_s^+}\right\}^{-1} \qquad (5.13)$$

The literature on a sensitivity analysis does not provide clear guidance as to which value of gamma should be taken as a threshold for concluding whether a study is robust to hidden bias. Based on the proposal advanced by DiPrete and Gangl (2004) that a critical value of gamma depends on the research question, Lee and Lee (2009, p. 103) argue in their labour market study:

> If more track records for the sensitivity parameters are established in future through more applications so that researchers can agree on how big is big for sensitivity analysis parameters, then the sensitivity analysis may become useful tools in dealing with unobserved confounders.

[89] In our case, successful treated units are those participating firms who introduced a particular open innovation activity (i.e. outcome variable=1). Consequently, successful untreated units are those non-participating firms who engaged in open innovation activities.

Given that only one study in the literature on R&D and innovation policy includes a sensitivity analysis (that of Alecke et al., 2012)[90], we consulted empirical studies in labour market economics (Aakvik, 2001; Hujer et al., 2004; Caliendo et at., 2005) and, accordingly, adopt the threshold of Γ=1.5. Therefore, if a significance level - p-value - is above 5% for $\Gamma \leq 1.5$, we report that a model is sensitive to unobserved heterogeneity. Conversely, if a significance level is below 5% for $\Gamma > 1.5$, we conclude that a model is robust to hidden bias. In the analysis, we set the maximum value for Γ to 2 with increments of 0.05.

Table 5.3. reports the results of a sensitivity analysis of the main empirical results. We estimated the ATT effects from NN matching without replacement and with a caliper of 0.2 of the standard deviation of the estimated propensity score. The rationale for using this particular estimator is twofold. First, as previously mentioned, the Stata command for a sensitivity analysis can only be applied for NN matching without replacement. Second, we used the same caliper size as in Section 5.4, to be able to compare results from NN Mahalanobis metric matching with replacement (reported in Table 5.1.) and NN matching without replacement (reported in Table 5.3. below).

Besides the ATT effects estimated applying NN matching without replacement, Table 5.3. reports those gamma values for which the 5% significance levels of the upper bounds indicate whether the results are sensitive to unobserved heterogeneity; the null hypothesis is no treatment effect (columns titled Hidden bias at 5%), i.e. an unobserved covariate renders the ATT insignificant. The implication of a non-rejection of the null is that the reported ATT effect is spurious, because it does not take into account variations in unobservables. We expect a positive (unobserved) selection bias, meaning that those firms that are more likely to participate in public funding, are also more likely to undertake open innovation. For positive treatment effects, we are interested in the upper bounds indicating a possible overestimation of the true treatment effects (Becker and Caliendo, 2007).[91]

[90] The threshold in their study is Γ=3.
[91] The null hypothesis of underestimated effects is rejected at the 1 % significance level in most cases.

Table 5.3. Sensitivity analysis- Rosenbaum bound approach

Open innovation strategies	Local support		Government support		EU support	
	NN without replacement and caliper 0.02	Hidden bias at 5 % (overestimation) [b]	NN without replacement and caliper 0.02	Hidden bias at 5 % (overestimation)	NN without replacement and caliper 0.004	Hidden bias at 5 % (overestimation)
	ATT (subsampled SEs) [a]		ATT (subsampled SEs)		ATT (subsampled SEs)	
Aggregate cooperation	0.135*** (0.016)	No when Γ≤1.70	0.079*** (0.020)	Yes when Γ≥1.25	0.126** (0.057)	Yes when Γ≥1.20
Cooperation with customers	0.047*** (0.010)	Yes when Γ≥1.50	0.042*** (0.014)	Yes when Γ≥1.35	0.132*** (0.044)	No when Γ≤1.70
Cooperation with suppliers	0.041*** (0.013)	Yes when Γ≥1.25	0.022 (0.015)	Yes when Γ≥1.00 At Γ≥1.45 changes sign	0.088* (0.053)	Yes when Γ≥1.10
Cooperation with competitors	0.024*** (0.008)	Yes when Γ≥1.35	0.047*** (0.011)	No when Γ≤1.85	0.093** (0.037)	Yes when Γ≥1.45
Cooperation with consultants	0.031*** (0.010)	Yes when Γ≥1.25	0.023 (0.014)	Yes when Γ≥1.05 At Γ≥1.65 changes sign	0.093** (0.043)	Yes when Γ≥1.25
Cooperation with HEI	0.043*** (0.011)	Yes when Γ≥1.35	0.039* (0.015)	Yes when Γ≥1.15	0.104** (0.044)	Yes when Γ≥1.25
Cooperation with government	0.110*** (0.012)	No when Γ≤2.00	0.086*** (0.016)	No when Γ≤1.65	0.148*** (0.048)	Yes when Γ≥1.50
Outsourcing R&D	0.169*** (0.017)	No when Γ≤1.90	0.112*** (0.018)	Yes when Γ≥1.45 At Γ≥1.90 changes sign	0.049 (0.061)	Yes when Γ≥1.00 At Γ≥1.80 changes sign
Acquisition of other external knowledge	0.007 (0.006)	Yes when Γ≥1.00 At Γ≥1.85 changes sign	0.012 (0.008)	Yes when Γ≥1.00	-0.011 (0.023)	Yes when Γ≥1.00

Notes: [a] *** ATT estimated at the one per cent level of significance; ** ATT estimated at the five per cent level of significance; * ATT estimated at the ten per cent level of significance.[b] Interpretation as follows: for example, in the case of “No when Γ≤1.70”, the upper bound is significant at the 5 per cent level when Γ is below or equal 1.7 (so Γ at the threshold level of 1.5 is statistically significant); “Yes when Γ≥1.50” means that the upper bound becomes insignificant at the 5 per cent level when Γ is 1.5 (so Γ at the threshold level of 1.5 is statistically insignificant); and “Yes when Γ≥1.25” means that the upper bound becomes insignificant at the 5 per cent level when Γ exceeds 1.25 (so Γ at the threshold level of 1.5 is statistically insignificant).

Sensitivity analysis reveals that most estimated treatment effects are sensitive to hidden biases. Secondly, analysing each source of funding separately, sensitivity analysis suggests the following: [92]

- In the case of regional support, the models that are less sensitive to unobserved heterogeneity are those with the following outcome variables: aggregate cooperation; cooperation with government (least likely to be affected by hidden bias); and outsourcing R&D. The remaining models are rather sensitive to selection bias.
- In the models of national treatment assignment, deviations from the underlying conditional independence assumption (CIA) are less likely to occur in the models with horizontal cooperation and with public institutions. For the remaining models, Rosenbaum's bounds indicate that ATT effects are sensitive to hidden bias.
- Finally, for EU funding, most models are sensitive to unobserved heterogeneity at fairly low values of gamma. Two exceptions are the models with cooperation with customers and with public institutions, with high values of gamma (1.70 and 1.50 respectively).

It is important to notice that the results from a sensitivity analysis adopting the Rosenbaum bounds are the worst-case scenarios (DiPrete and Gangl, 2004). For instance, in the model with the cooperation with suppliers (for local/regional support), the estimated ATT effect is sensitive to hidden selection bias for $\Gamma \geq 1.25$. However, this does not mean that there is no true positive effect of public support on cooperation with suppliers. The result suggests that, if there is a confounding variable with a large effect on both a treatment assignment and the outcome variable and if that variable increases the odds ratio of receiving a treatment for participating firms by 25 per cent (i.e. $\Gamma=1.25$) then the confidence interval for the ATT effect would include zero (DiPrete and Gangl, 2004).

[92] In five models, the significance levels of the Mantel-Haenszel test statistics on the upper bounds firstly fall but then begin to rise. At the point of rising significance levels, the treatment effects change sign and become significant (Becker and Caliendo, 2007). For instance, in the case of the ATT effect of government support on cooperation with suppliers, the point estimate is positive and statistically insignificant (ATT=0.022). The null hypothesis of no treatment effect cannot be rejected at a gamma value of 1. When gamma increases to 1.45 (the odds of treated firms receiving treatment relative to untreated firms), the significance levels indicates that the ATT effect becomes negative and statistically significant (see Appendix III, Table A3.9 for the Stata output).

The overall conclusion from sensitivity analysis suggests that hidden bias is unlikely to occur only in the case of cooperation with government agencies, and to a lesser extent, in models with cooperation with customers. On the other side, hidden bias is likely to arise in modelling cooperation with suppliers, consultants and Higher Education Institutions. Finally, the models in which the outcome variable is the acquisition of external knowledge are least robust to unobserved heterogeneity, as hidden bias arises even at gamma equal to 1.

Our findings raise several issues. First, sensitivity analysis should be a necessary step when the effectiveness of R&D and innovation policy is assessed with the PSM analysis, as the findings indicate that treatment effects could be overestimated when firms' unobserved characteristics are not controlled for. Although a sensitivity analysis is considered to be an integral part of the PSM analysis, (Guo and Fraser, 2010; Caliendo and Kopeinig, 2008), it is not adopted as a common practice in empirical innovation studies. However, a lack of sensitivity analysis is not only pertinent to innovation studies; Pearl (2009) points out that researchers often assume that the assumption of strong ignorability (i.e. CIA) holds because a large number of covariates is included in estimating a propensity score. However, it is not enough to recognize the major limitation of the PSM analysis; we should also examine whether selection on observables is likely to be satisfied. Although a sensitivity analysis cannot directly test the assumption, it can gauge the level of robustness of empirical findings to hidden bias.

Second, given the dominance of matching estimators in empirical studies, empirical evidence should be treated with caution. Most empirical studies reviewed in Section 3.6 report a positive impact of public support on firms' cooperation on innovation. Our results suggest that, depending on the type of cooperative partners, particular treatment effects could be overestimated. Third, our results indicate that unobserved heterogeneity is more prominent in the models with vertical cooperation, than in those with other types of cooperation. It could be that other factors, not considered in empirical studies to date, influence the effectiveness of innovation support on cooperation with customers and suppliers. Finally, regarding open innovation practices, the model with the outcome variable measuring the acquisition of other external knowledge is extremely sensitive to a positive unobserved selection for each stream of funding.

5.6 Results for the subsample of innovative firms

As noted in Section 5.3.3, we employed the same matching estimators on the subsample of innovative firms. Following Busom and Fernández-Ribas (2008), innovative firms are defined as those firms reporting positive intramural R&D expenditures in the period 2004-2006.[93] The subsample consists of 3,861 SMEs, out of which 2,271 are small- and 1,590 are medium-sized enterprises. Results from the probit models are presented in Table A3.10 (Appendix III). Again, based on four balancing tests, the best balance is achieved with kernel matching (see Table A3.11, Appendix III). Therefore, the ATT effects presented in Table 5.4 are interpreted using the estimated treatment effects from kernel matching.

The first interesting finding is that, qualitatively, the results for innovative firms are consistent with the main results. However, quantitatively, treatment effects for the whole sample are uniformly smaller than those reported for innovative firms, although the differences, on average, are not large. This pattern of larger treatment effects on innovative firms could suggest two stylized facts.

- Unobserved firm characteristics have a smaller influence on causal estimates, because the sample is more homogenous (i.e. only innovative firms).
- Public support, overall, is more effective in supporting open innovation practices in those SMEs that engage in intramural R&D activities, suggesting the importance of moderating influences related to firms' internal innovative capacities.

The findings for each stream of funding are as follows. Participation in local/regional support programmes has a positive and statistically significant effect on all open innovation practices; a very small, but significant effect is even reported for acquisition of other external knowledge (1.1 p.p. of an increase in the probability of acquiring other external knowledge). Moreover, the largest treatment effect is estimated for extramural R&D activities (20.2 p.p. of an increase in the probability of outsourcing R&D), which is a slightly higher estimate than for the aggregate cooperation (17.7 p.p.). The smallest effect is found for horizontal cooperation (3.3 p.p.).

[93] Spithoven et al. (2012) also estimated the treatment effects in the subsample of innovative Belgian firms. However, the authors do not explain how innovative firms are defined in the Belgian CIS questionnaire.

Table 5.4. Average Treatment Effects (ATTs) from the subsample of innovative Spanish SMEs

Dependent variable	Local/regional support				Government support				EU support			
	NN matching with Mahalanobis metric and caliper 0.02	Kernel matching (Epanechnikov kernel, bw=0.06)	1:4 bias adjusted covariate matching with Mahalanobis metric	IPTW	NN matching with Mahalanobis metric and caliper 0.02	Kernel matching (Epanechnikov kernel, bw=0.06)	1:4 bias adjusted covariate matching with Mahalanobis metric	IPTW	NN matching with Mahalanobis metric and caliper 0.006	Kernel matching (Epanechnikov kernel, bw=0.001)	1:4 bias adjusted covariate matching with Mahalanobis metric	IPTW
	ATT (sub-sampled SEs)	ATT (bootstrapped SEs)	ATT (Abadie and Imbens SEs)	ATT (robust SEs)	ATT (sub-sampled SEs)	ATT (bootstrapped SEs)	ATT (Abadie and Imbens SEs)	ATT (robust SEs)	ATT (sub-sampled SEs)	ATT (bootstrapped SEs)	ATT (Abadie and Imbens SEs)	ATT (robust SEs)
Aggregate cooperation	0.167*** (0.028)	0.177*** (0.017)	0.190*** (0.019)	0.178*** (0.018)	0.103*** (0.030)	0.108*** (0.020)	0.121*** (0.020)	0.108*** (0.020)	0.227*** (0.084)	0.215*** (0.050)	0.299*** (0.048)	0.229*** (0.044)
Cooperation with customers	0.049*** (0.018)	0.071*** (0.013)	0.079*** (0.013)	0.072*** (0.013)	0.038* (0.023)	0.038*** (0.014)	0.041*** (0.015)	0.037** (0.015)	0.182** (0.075)	0.148*** (0.045)	0.184*** (0.042)	0.166*** (0.042)
Cooperation with suppliers	0.047** (0.023)	0.058*** (0.016)	0.061*** (0.015)	0.060*** (0.014)	0.014 (0.024	0.036** (0.017)	0.034** (0.016)	0.035** (0.016)	0.164** (0.074)	0.129** (0.051)	0.159*** (0.044)	0.138*** (0.042)
Cooperation with competitors	0.014 (0.014)	0.033*** (0.009)	0.029*** (0.010)	0.033*** (0.009)	0.054*** (0.016)	0.063*** (0.010)	0.064*** (0.012)	0.062*** (0.011)	0.145** (0.067)	0.140*** (0.036)	0.157*** (0.036)	0.152*** (0.037)
Cooperation with consultants	0.029 (0.019)	0.043*** (0.014)	0.047*** (0.012)	0.042*** (0.013)	0.020 (0.021)	0.035** (0.016)	0.025* (0.014)	0.035** (0.014)	0.136** (0.069)	0.090** (0.042)	0.154*** (0.039)	0.125*** (0.039)
Cooperation with HEI	0.054*** (0.019)	0.058*** (0.013)	0.061*** (0.012)	0.058*** (0.014)	0.046** (0.023)	0.057*** (0.017)	0.061*** (0.015)	0.057*** (0.017)	0.118 (0.077)	0.122*** (0.044)	0.171*** (0.043)	0.143*** (0.043)
Cooperation with government	0.147*** (0.023)	0.152*** (0.016)	0.164*** (0.015)	0.152*** (0.015)	0.090*** (0.026)	0.109*** (0.018)	0.120*** (0.017)	0.108*** (0.017)	0.173** (0.081)	0.189*** (0.048)	0.226*** (0.047)	0.204*** (0.045)
Outsourcing R&D	0.199*** (0.028)	0.202*** (0.016)	0.227*** (0.019)	0.201*** (0.018)	0.165*** (0.031)	0.154*** (0.021)	0.174*** (0.021)	0.151*** (0.020)	0.173** (0.085)	0.097* (0.051)	0.175*** (0.050)	0.109** (0.046)
Acquisition of other external knowledge	0.011 (0.011)	0.011* (0.006)	0.013* (0.007)	0.011* (0.007)	0.006 (0.012)	0.011 (0.008)	0.014* (0.008)	0.011 (0.008)	0.000 (0.034)	-0.001 (0.019)	0.004 (0.020)	0.005 (0.018)

Receiving government funding has a positive and statistically significant effect on all open innovation practices, except for acquisition of other external knowledge. Similar to participation in local/regional programmes, the largest effect of government support is on outsourcing R&D (15.4 p.p.), followed by aggregate cooperation (10.8 percentage points) and cooperation with government institutions (10.9 p.p.). Contrary to receiving local/regional support, the smallest effect of government support is on cooperation with consultants (3.5 p.p.) and on vertical cooperation (with customers 3.8 p.p. and with suppliers 3.6 p.p.). Similar to findings for the whole sample, the 95 per cent confidence intervals for the subsample of innovative firms (see Table A3.12, Appendix III) overlap for each outcome variable. Therefore, the differences between estimated treatment effects are not statistically significant.

The third source, EU funding, has the largest effect on cooperative behaviour of innovative firms, compared to other streams of funding. The ATT effect on aggregate cooperation is 21.5 p.p., followed by the effect on cooperation with government institutions (18.9 p.p.). Compared to local/regional and government support, the effect of EU funding is relative larger for each type of cooperative partners. For instance, the smallest effect is found for cooperation with consultants (9.0 p.p.). Another dissimilarity, relative to other sources, is that EU funding has a larger effect on cooperation, both aggregate and separately, than on extramural R&D activities (9.7 p.p.). Finally, receiving funding from the EU has no effect on acquisition of other external knowledge.

Table 5.5 shows results from a sensitivity analysis of the subsample of innovative SMEs. The results confirm those reported for the whole sample. In addition, the results of the Rosenbaum bound approach for the subsample indicate that, overall, treatment effects are less sensitive to hidden bias, as more models are reported to be robust to overestimation (see also Table 5.6). This finding is consistent with our argument about the smaller influence of unobservables due to the more homogenous group of firms in the subsample.

For instance, for government support, the ATT effect on extramural R&D activities is not sensitive to unobserved heterogeneity for gamma values lower than 1.60. Moreover, for innovative SMEs participating in EU funding, the results of sensitivity analysis suggest that the treatment effect estimated for aggregate cooperation for gamma value lower than 1.75 is robust; and the ATT effects on cooperation with competitors are rather robust (gamma value should be above 2 to alter the estimated effect).

Table 5.5. Sensitivity analysis for a subsample of innovative SMEs

Open innovation strategies	Local support		Government support		EU support	
	NN without replacement and caliper 0.02	Hidden bias at 5 % (overestimation)	NN without replacement and caliper 0.02	Hidden bias at 5 % (overestimation)	NN without replacement and caliper 0.006	Hidden bias at 5 % (overestimation)
	ATT (subsampled SEs)		ATT (subsampled SEs)		ATT (subsampled SEs)	
Aggregate cooperation	0.162*** (0.023)	No when Γ≤1.75	0.095*** (0.025)	Yes when Γ≥1.30 At Γ≥1.75 changes sign	0.244*** (0.066)	No when Γ≤1.75
Cooperation with customers	0.061*** (0.015)	Yes when Γ≥1.40	0.027 (0.018)	Yes when Γ≥1.00 At Γ≥1.60 changes sign	0.157*** (0.057)	Yes when Γ≥1.50
Cooperation with suppliers	0.047** (0.018)	Yes when Γ≥1.15	0.014 (0.021)	Yes when Γ≥1.00 At Γ≥1.35 changes sign	0.118* (0.061)	Yes when Γ≥1.15
Cooperation with competitors	0.030** (0.012)	Yes when Γ≥1.25	0.058*** (0.014)	No when Γ≤1.75	0.165*** (0.053)	No when Γ<2.0
Cooperation with consultants	0.026* (0.014)	Yes when Γ≥1.05 At Γ≥1.60 changes sign	0.037** (0.016)	Yes when Γ≥1.10 At Γ≥1.80 changes sign	0.118** (0.052)	Yes when Γ≥1.25
Cooperation with HEI	0.039** (0.017)	Yes when Γ≥1.15 At Γ≥1.65 changes sign	0.044** (0.019)	Yes when Γ≥1.10 At Γ≥1.70 changes sign	0.157*** (0.057)	Yes when Γ≥1.40
Cooperation with government	0.152*** (0.018)	No when Γ<2.0	0.101*** (0.021)	No when Γ≤1.55	0.181*** (0.063)	Yes when Γ≥1.45
Outsourcing R&D	0.192*** (0.022)	No when Γ≤1.90	0.152*** (0.024)	No when Γ≤1.60	0.087 (0.066)	Yes when Γ≥1.00
Acquisition of other external knowledge	0.013 (0.008)	Yes when Γ≥1.05	0.004 (0.010)	Yes when Γ≥1.00 At Γ≥1.80 changes sign	0.016 (0.026)	Yes when Γ≥1.00

5.7 Conclusions

This chapter reports on the positive, but heterogeneous impact of public support on open innovation in Spanish SMEs. However, sensitivity analysis suggests that the programme effects could be overestimated due to unobserved heterogeneity, which matching estimators cannot account for. Notably, the results for two cooperative partners - cooperation with suppliers and with HEIs - seem to be highly sensitive to hidden bias. This is not to say that there is an issue of unobserved heterogeneity from the perspective of either suppliers or HEIs. On the contrary, through cooperative networking, they obtain all the necessary information about the firm. The issue of hidden bias is associated with unobserved firm characteristics, such as managerial abilities and attitudes, which are generally inaccessible to researchers.

Furthermore, results from the Rosenbaum bound approach are broadly in line with those reported by Busom and Fernández-Ribas (2008), who conducted the Hausman test and found that private-public partnerships might be affected by hidden bias, whereas vertical cooperation with customers and suppliers is unlikely to be sensitive to this source of bias. However, our analysis goes one step further and examines cooperative partners separately. Among private-public partnerships, we found that our estimates of the effect on partnerships with HEIs might be affected by a positive selection bias, but the opposite holds for the estimated effects on cooperation with government agencies, which are rather robust to unobserved firm characteristics. Regarding our estimates of the effect on cooperation with other firms, our sensitivity analysis indicate that the estimated effects on cooperation with customers are less sensitive, while the treatment effects on cooperation with suppliers are more sensitive to hidden bias.

Given the lack of sensitivity analysis in empirical studies, empirical evidence from matching studies should be treated with caution. The issue of unobserved heterogeneity is further exacerbated by the absence of valid instruments in available datasets (prominently the CIS data), which precludes researchers from applying other evaluation methods, not only as a robustness check but also as a way of controlling for selection on unobserved firm characteristics. In the absence of a robustness check in this context, the importance of a sensitivity analysis is even more pronounced.

The robustness of treatment effects to unobserved factors is summarised in Table 5.6. In total, 27 treatment effects were estimated in the whole sample and the same number for the subsample of innovative SMEs. Six estimated effects in the whole sample are rather robust to selection bias, and eight estimates in the subsample (perhaps due to a more homogenous sample). In total, out of 54 treatment effects, only 14 are less likely to be overestimated. Finally, across both the whole sample and the subsample, five ATT effects are robust to hidden bias:

- For local/regional support, three effects on the following open innovation activities: aggregate cooperation; cooperation with government institutions and outsourcing R&D;
- For national (government) support, two effects - on horizontal cooperation and cooperation with government agencies.

Table 5.6. Summary of results with respect to hidden bias

	Number of models	**Models robust to hidden bias**
Whole sample	27	6
Subsample of innovative firms	27	8

Overall, we find that public support most robustly increases SME cooperation with government institutions; only slightly less robust is that the largest treatment effects of public support - both regional (a robust finding) and federal (borderline robust) - are for outsourcing R&D activities. Yet there is not so much robust evidence that public support increases cooperative and innovative behaviour more generally. Recent work on cooperation failure can help us to make sense of this contrast, suggesting that it may be of systematic rather than merely contingent significance.

By analysing treatment effects of different types of inbound open innovations, our analysis discriminates between the effects of public intervention on cooperation for innovation and on R&D and innovation outsourcing (extramural R&D investments and acquiring other external knowledge). The results suggest that, depending on the source of funding, SMEs are more likely to respond to public support by increasing either their cooperation with government institutions or their investment in extramural R&D than by establishing and maintaining cooperative networks. Following our discussion in Section 5.2, acquiring external knowledge through cooperation could be subject to cooperation failure. In this case, compared to cooperation with other firms, either increased cooperation with government institutions may be facilitated by greater trust that these are unlikely to appropriate the firm's intellectual; property; or/and R&D subcontracting is a more viable option. This issue deserves further attention from both practitioners and policy-makers. For example, to increase the effectiveness of public support for cooperation between firms – including customers and suppliers – policy makers should place particular emphasis on measures designed to attenuate cooperation failures (Zeng et al., 2010).

Another relevant finding is associated with the larger treatment effect of regional support on outsourcing R&D than on networking (either aggregate or disaggregate). These results might suggest that SMEs compensate their limited internal innovative capacity by increasing their investment in extramural R&D activities, rather than by utilizing external knowledge through cooperative networking.

Furthermore, the estimated treatment effects and a subsequent sensitivity analysis of the subsample of innovative firms revealed a relevant implication regarding empirical strategy. Namely, matching should be applied when estimating treatment effects in more homogenous groups of firms, e.g. innovative firms, because they are less likely to be affected by heterogeneous unobserved influences. Moreover, bias reduction achieved by matching is based on the premise that matched units are similar in their observed characteristics. We can assume that innovative firms have more common characteristics with other innovative firms rather than with non-innovative firms. Finally, following the same line of argument, it can be assumed that innovative firms are similar in both observed and unobserved factors, implying that hidden bias is less likely to occur among a more homogenous group of innovative firms.

In sum, empirical evidence point out to several conclusions regarding the evaluation of innovation policies:

- Previous studies mainly grouped cooperative partners into more aggregate categories of public-private partnerships and cooperation with businesses (horizontal and vertical cooperation) (Fier et al., 2006; Busom and Fernández-Ribas, 2008; Spithoven et al., 2012, p. 171 and p. 181). Our results suggest that each type of cooperative partner should be considered separately. For instance, with respect to public-private partnerships, the treatment effect is significantly larger for cooperation with government institutions than for cooperation with HEIs. Furthermore, the findings from sensitivity analysis also confirm this conclusion. Namely, robustness of treatment effects to unobserved heterogeneity varies depending on the type of cooperative partner.

- Sources of funding have a differential effect on open innovation and should be investigated separately (Busom and Fernández-Ribas, 2008). A similar conclusion is advanced by Spithoven et al. (2012), who investigated network additionality in Belgian firms and found that 'there are, indeed, substantial differences in impact between different types of funding' (p. 170).
- Public support has a differential effect on open innovation practices. Our results echo the findings reported in other studies investigating network additionality (Fier et al., 2006; Busom and Fernández-Ribas, 2008; Spithoven et al., 2012). Moreover, our study is the first to explore the effectiveness of public funding on extramural R&D and acquisition of other external knowledge. In the case of these open innovation practices, the results are again heterogeneous.

A separate analysis of three administrative levels of public funding (local/regional, national and EU) was conducted with the objective to empirically investigate whether the effectiveness of innovation support measures differs depending on the source of funding. In particular, we investigate whether regional public agencies are more effective in promoting SME innovation than are federal bodies. This procedure is similar to Spithoven et al. (2012), who investigated behavioural additionality among Belgian firms. Their empirical strategy treated each source of funding separately (regional, federal and EU), as regional support programmes are the most important source of R&D subsidies in Belgium. Empirical findings reported by Spithoven et al. (2012) indeed suggest that the only effective source of funding, with respect to behavioural additionality, is regional support. However, the empirical results reported in Chapter V indicate that, in the context of Spanish SMEs, all sources of funding have positive and highly statistically significant ATT effects. Although the ATT effects presented in Table 5.1 for the whole sample of Spanish SMEs are overall higher for local/regional support programmes than for federal programmes, the 95 per cent confidence intervals shown in Table A3.7 indicate that there are no systematic differences between the ATT effects estimated separately for these sources of funding (i.e. the confidence intervals overlap). This conclusion is confirmed in the analysis of the subsample of innovative firm reported in Table 5.4, for which the 95 per cent confidence intervals are shown in Table A3.12.

Research conducted as part of the GPrix project (not reported in this thesis) may qualify this conclusion of "no difference". Namely, the finding of no systematic differences between the regional and national support programmes could be explained by measurement/recording error, which would occur in the case when regional public agencies are simply administrating national or EU programmes. This view arose in the GPrix team for two reasons. First, the only questions that failed to generate survey data with complete or almost complete responses and that required "cleaning" were those on the source and (monetary) value of support received. Second, the underlying reasons for this failure of the question on the source of funding were revealed in interviews with owners and managers of SMEs participating in the GPrix survey, which revealed that managers usually are either not aware of which level of administration had provided support measures or simply recorded the delivery body. Hence, there was a non-trivial probability of either a non-response or a misleading response (reflecting, for example, that a national of EU programme could be delivered by a regional body). In addition to measurement error, there is not much in the way of theoretical reasoning as to why programme effectiveness may differ by administrative level. We offer two brief but offsetting suggestions. On the one hand, local/regional programmes may be more specifically designed for SMEs in the particular area, whereas national/international programmes are, perforce, more generic. On the other, national agencies may have higher quality personnel and be more experienced in administrating and distributing public funding than are regional agencies. This argument draws some support from comparison of the quality of evaluations conducted at, respectively, regional and national levels; namely, another finding by the GPrix project was that the quality of evaluations performed by higher-level bodies are generally of higher quality than those of regional public agencies. This is a topic that requires further investigation.

Empirical investigation into behavioural additionality is still in its nascent years. Our analysis is the first to investigate the impact of public innovation measures on open innovation practices other than cooperative behaviour. However, available data does not allow for assessing public effectiveness on other categories of firms' behaviour, such as changes in competencies and expertise (Busom and Fernández-Ribas, 2008; Fier et al., 2006). Moreover, effectiveness of public support on outbound open innovation (such as venturing or outward licensing of IPs) could also be a subject of future research. Furthermore, the lack of longitudinal data inhibits exploring the medium- to long-run effects of programme participation on cooperative behaviour (Busom and Fernández-Ribas, 2008). Finally, we do not have information on the number of cooperative partners, as it would be interesting to explore whether additionality of a support programme would be affected by the magnitude of cooperation.

CHAPTER VI

THE EFFECT OF R&D POLICY ON INNOVATION IN EUROPEAN SMEs

6.1 Introduction

Few empirical studies on the effectiveness of R&D and innovation public support investigate the impact of public intervention on SMEs in several countries and across a wide range of industries. Although empirical analysis presented in Chapter IV covers seven EU countries, all the surveyed SMEs belong to traditional manufacturing industries. In this Chapter, we utilize a unique dataset on R&D policy for SMEs operating in both manufacturing and service sectors across 28 European countries. The focus of analysis is the effect of policy both on innovation output and on open innovation practices in European SMEs. Thus, the two main research questions in this chapter refer to assessing the output additionality and behavioural additionality of R&D support programmes.

The chapter is organised as follows. In Section 6.2 we review additional forms of cooperation and networking among firms, as our dataset enables us to further explore network additionality. The features of the dataset and the main descriptive statistics, together with the research methodology of the chapter will be discussed in Section 6.3. The empirical results will be elaborated in Section 6.4. Finally, Section 6.5 will summarize the findings and conclude.

6.2 Open innovation practices revisited

Advantages of networking and outsourcing are numerous. First, open innovation reduces costs, because firms can explore economies of scale and scope in R&D activities (Narula and Hagedoorn, 1999; Teirlinck and Spithoven, 2013). Second, through cooperation and outsourcing firms share risks and uncertainty related to innovation processes (Hagedoorn, 1993; Rese and Baier, 2011). Third, the transaction costs theory suggests that firms will opt for a 'buy' strategy, instead of 'make', when transaction costs are low. Therefore, internalization of innovation activities is pertinent to high transaction costs, while cooperation, outsourcing and other types of open innovation strategies are pursued when technological transactions entail low transaction costs (Williamson, 1985).

Networking and inter-firm cooperation for innovation offer time advantage compared to internal technology and innovation development, meaning that firms can commercialize their inventions in a shorter time interval (Rese and Baier, 2011). This is particularly relevant for small firms, insofar as patenting and other formal mechanisms for appropriating intellectual assets are less often utilized by SMEs. The reasons are usually related to high costs of patent application and difficulties in maintaining secrecy in collaborative relationships. Leiponen and Byma (2009) found that the most important method of protecting IPs in Finish SMEs is speed to market. Therefore, in order to capture innovation returns and overcome appropriability issues, the most effective mechanism is quick market launch of new or improved technologies and innovations.

Mutual trust between partners is often identified as a key success factor in collaborative relationships (Lee et al., 2010; Barge-Gil, 2010). As a potential licensee can behave opportunistically and obtain information about new technologies without paying for them, firms may lack incentives to reveal their internal inventions. To avoid this 'disclosure paradox', inventors often require a formal agreement with a licensee (Dahlander and Gann, 2010). A recent study by Love and Roper (2005) confirms this argument, suggesting that firms, when deciding whether to internalize or outsource technological competencies, are primarily concerned with protecting information leakages rather than with exploring economies of scale and scope. Barge-Gil (2010) concludes that forcing firms to collaborate can be counterproductive and create a climate of mistrust. Lee et al. (2010) discuss potential negative effects of cooperation in the context of small and medium-sized firms: increased likelihood of leakage of core knowledge, which can jeopardize firms' competitive advantage; and higher levels of mistrust that require monitoring of a partner's behaviour which, in turn, increases costs.

Besides strong appropriation mechanisms, another way of avoiding cooperation failure is the use of knowledge and innovation brokers (Lee et al., 2010). These intermediary organisations can facilitate SMEs in finding appropriate collaborative partners and creating a climate of trust between partners and, at the same time, preventing involuntary information leakage among partners. Huizingh (2011) argues that both large and small firms can benefit from intermediaries, particularly for outbound open innovation. The questionnaire used in our study contains questions on the extent of use of online technology and knowledge brokers/intermediaries as sources of external knowledge. We utilize this question to measure the openness of innovation processes and the use of knowledge brokers.

Another source of external knowledge included in the analysed survey is strategic alliances. Narula and Hagedoorn (1999) refer to strategic alliances as cooperative agreements aimed at long-term profit optimisation. They argue that the form of cooperative agreement depends on the underlying motives: establishing and maintaining vertical cooperation with customers and suppliers is mainly motivated by cost reduction and short-term profit increase; whereas firms enter strategic alliances to increase the value of the firm and it long-term market position. However, SMEs are less likely to form strategic alliances than are large firms, due to a higher level of physical resources needed for this type of open innovation (Narula and Hagedoorn, 1999; Narula, 2004). We extend this argument by pointing out that partnerships, through strategic alliances, would also require certain entrepreneurial/managerial resources and competencies, identified as the major constraint in the resource-based view of the firm (see Section 1.3.5). Furthermore, the high failure rate of strategic alliances is also associated with higher levels of investment and involvement required for this type of cooperation (Narula and Hagedoorn, 1999). But, if SMEs do cooperation through strategic alliances, their impact on SME performance and innovativeness is positive, suggesting that this form of networking is an important source of external knowledge (Lee et al., 2010). Furthermore, irrespective of the firm size, strategic alliances as a form of networking on technology transfer are particularly relevant for capital and knowledge-intensive industries, where the introduction of product and process innovations entails high risk and uncertainty and new technologies are constantly and rapidly developed (Narula and Hagedoorn, 1999; Wynarczyk et al., 2013).

In addition, our dataset contains information on non-equity alliances, defined as a type of alliance that is not based on formal economic return for either party. Following Hagedoorn (2002), non-equity alliances are more relevant for firms in high-tech and ICT sectors than for firms in medium and low-tech industries. Emden et al. (2006, p. 338) define co-development alliances as 'non-equity-based relationships in which each party contributes a significant portion of the end solution'. A unique feature of non-equity alliances is that partners maintain a certain level of competitiveness towards one another, while cooperating through this type of alliances. In their partner selection process model, three components are identified as important for realizing potentials for value creation in non-equity alliances: technological alignments of the partners (resource complementarities); relational alignments (cultural and operational compatibilities); and strategic alignments (a similar motivation and noncompeting goals with respect to entering alliance relationships).

6.3 Methodology

6.3.1 Data

The dataset used in the analysis was gathered in 2010 within the MAPEER project commissioned by the European Commission's DG-Research. [94] The survey questionnaire covered the period 2005-2010. The sample includes 763 SMEs from 28 European countries. The survey was targeted at the population of SMEs with less than 250 employees and an annual turnover of less than 50 million Euros (EU definition of SMEs - Article 2 of the Annex of Recommendation 2003/361/EC) (European Commission, 2005). Within the group, micro-sized firms are defined as those with less than 10 employees, small firms with 10 or more and less than 50 employees and medium-sized firms with 50 or more and less than 250 employees. The sample consists of 376 micro firms, 242 small firms and 145 medium-sized firms. Given the small number of firms from individual countries, we grouped them into four categories following the European Innovation Scoreboard (European Commission, 2011).[95] The categories are as follows:

- *'Innovation leaders'*, countries whose innovation performance is well above the EU27 average.[96] Our sample consists of 146 SMEs operating in countries from this category.
- *'Innovation followers'*, countries with performance close to the EU27 average (219 firms in our sample; this is the base or reference category);

[94] The description of and information about the project are given on the project's web page http://mapeer-sme.eu/.
[95] The European Innovation Scoreboard publishes the average innovation performance based on a composite indicator, encompassing 24 individual indicators. The innovation performance of each Member State is then compared to the average innovation performance of all 27 EU Member States. The Innovation Scoreboard in 2011 refers to innovation performance in the years 2009/2010. We have utilized this report because the survey data were gathered in 2010.
[96] For the list of countries in each category, see Table A4.1.

- *'Moderate innovators'*, countries whose performance is below that of the EU27 average (284 firms in the sample); and
- *'Modest innovators'*, representing countries whose performance is well below that of the EU27 average (114 firms in the sample).

Grimpe and Sofka (2008) control for heterogeneity in national innovation systems by grouping 13 EU countries on the basis of their total national R&D expenditure (GERD) as a share of each countries' GPD. For a robustness check, they grouped countries based on the share of firms performing R&D on a continuous basis. We opted to control for distinct national innovation systems based on both innovation inputs and outputs, and not just on innovation inputs (such as R&D expenditure).[97]

Table A4.1 (Appendix IV) shows means and standard deviations for treatment variables, output dependent variables and control variables. Half of the surveyed SMEs (52.9 per cent) participated in national/regional R&D programmes in the period covered by the survey. Less than a third of firms (27.4 per cent) received public support from international sources, whereas the largest number of firms (59.9 per cent) participated in either national or international support measures. Innovation output is proxied by innovative sales, i.e. the share of sales from new or substantially improved products and processes. Slightly more than two thirds of firms report to have generated more than 10% of innovative sales (67.2 per cent of firms); more than half of firms report more than 20% of innovative sales (57.2 per cent of firms); less than half of firms report more than 30 % of innovative sales (46.7 per cent of firms); more than one third of firms report more than 40 % of innovative sales (39.7 per cent of firms); and slightly more than one third of firms report more than 50 % of innovative sales (34.7 per cent of firms).

When considering open innovation practices, the largest number of firms (62.3 per cent) utilizes informal networks with other firms as a source of external knowledge, followed by customer involvement (58.3 per cent of firms) and informal networks with research organizations (52.7 per cent). The least practiced open innovation is non-equity alliances with other firms (25.5 per cent). With regard to firm characteristics, the modal group of SMEs' reported total R&D expenditures as a percentage of total expenditure is

[97] A composite index is calculated based on individual indicators grouped in five categories: three of them measure innovation input; and two categories represent innovation outputs.

the range of 11 to 20 per cent, two-thirds of firms are exporters (66.2 per cent), and a similar proportion of SMEs reports a high competitive intensity (62.8 per cent). Moreover, almost 40 per cent of firms have a separate R&D department, while almost half of the sample firms have a defined R&D and innovation strategy for the period 2010-2015. Less than a third of firms are located in technology parks/areas[98] and have integrated a technology platform[99] (26.7 and 23.2 per cent respectively). Finally, regarding barriers to participation, the largest number of firms identified administrative needs to be the most important specific SME need, particularly simple application procedures (54.7 per cent) and simple reporting requirements (44.1 per cent). Besides administrative needs, almost half of the firms reported financial needs (in particular, high funding rates) and internal needs associated with compliance of programme aims to SMEs interests (41.8 and 41.7 per cent respectively).

6.3.2 Model specification

Our empirical strategy encompasses estimating two models - a parsimonious (baseline) model and an augmented (final) model. In the models assessing output additionality, the outcome variable is innovation output measured as the share of sales from new or substantially improved product and process innovations. As innovative sales is a categorical variable, it was necessary to create binary outcome variables to enable the estimation of an endogenous switching model. Thus, five outcome variables were generated with increasing proportions of innovative sales:

- Innovative sales more than 10 % (variable *Q14_morethan10*);
- Innovative sales more than 20 % (variable *Q14_morethan20*);
- Innovative sales more than 30 % (variable *Q14_morethan30*);
- Innovative sales more than 40 % (variable *Q14_morethan40*); and

[98] Usually, the literature on agglomeration and networking for innovation does not distinguish between science and technology parks (STPs). However, Albahari et al. (2013) suggest a division between them as the latter have no university shareholding, whereas the former are characterized by a university shareholding. Firms locate their businesses in technology parks to exploit the benefits of agglomeration externalities arising from spatial proximity. Because of physical closeness, firms located in technology parks can easily establish and maintain linkages and engage in knowledge transfer, particularly in exchanging tacit knowledge (Howells, 2002; Boschma, 2005).

[99] Technology platforms are defined as 'technologies with wide and swift applicability across a range of related and unrelated sectors' (De Propris and Corradini, 2013). In other words, technology platforms are established among firms operating in a range of industries, with the aim of developing complementary products, technologies or services by utilizing common resources (Gawar, 2010).

- Innovative sales more than 50% (variable *Q14_morethan50*).

Regarding behavioural additionality, the dataset contains information about two inbound open innovation practices (external networking and close involvement of end users/customers). External networking encompasses six different sources of external knowledge:

- Use of online technology or knowledge brokers/intermediaries;
- Informal networking with other firms;
- Informal networking with research organizations;
- Strategic alliances with other firms;
- Non-equity alliances with other firms (a type of alliance that is not based on formal economic return for either party); and
- Participation in innovation networks, S&T parks, clusters, etc.

Moreover, our dataset contains information on customer involvement (i.e. close involvement of end users/customers in idea generation/concept development). Each inbound practice is measured on a five-point scale (from 'Don't apply at all' to 'Apply expensively'). Based on the scale, binary indicators were created for each type of open innovation practice, where the indicator is equal to 0 if the firm reports either of three categories ('Do not apply at all'; 'Do not apply'; or 'Neutral') and is equal to 1 if the firm reports either 'Apply' or 'Apply extensively' for a particular type of open innovation.

Furthermore, sources of funding are separated into national and international innovation programmes. As the first robustness check, and given the issues with diagnostics when streams of funding are analysed separately, we also estimated the model with a joint source of funding (the firm participated in either national or international programmes).

The treatment parameters are obtained by estimating an endogenous switching model. Following the discussion in Section 4.3.1, the endogenous switching model has two equations: the second equation models the participation decision (the probability that a firm will participate in an R&D support programme); and the first equation is an innovation model, which estimates the innovation effect on firms of participating in an

R&D support programme conditional on both other influences on innovation and the probability of participating in an R&D support programme.

$$\begin{aligned} Innovation_i = \hat{C} + \hat{\gamma} Participation_i + Absorptive\ capacity_A \hat{\alpha}_1 \\ + Firm\ characteristics_F \hat{\alpha}_2 + External\ factors_E \hat{\alpha}_3 \\ + Industry_I \hat{\phi}_1 + Country_C \hat{\phi}_2 + QFFE_i \hat{\beta} + u_i \end{aligned} \tag{6.1}$$

$$\begin{aligned} Participation_i \\ = \hat{I} + Absorptive\ capacity_A \hat{\rho}_1 + Firm\ characteristics_F \hat{\rho}_2 \\ + External\ factors_E \hat{\rho}_3 + Industry_I \hat{\delta}_1 + Country_C \hat{\delta}_2 \\ + QFFE_i \hat{\rho} + Barriers_i \hat{\theta} + \varepsilon_i \end{aligned} \tag{6.2}$$

Subscript i indexes each firm in the sample 1…n, where n is the number of firms; ^ indicates "to be estimated"; C and I represent the intercept in equations 6.1 and 6.2 respectively; the γ coefficient measures the innovation effect of programme participation; the α and ρ coefficients measure, respectively, the innovation and participation effects of control variables controlling for absorptive capacity, firm characteristics and external (environmental) factors; the k×1 ϕ and δ vectors contain coefficients that measure, respectively, the innovation and participation effects of 1×k vectors of industry and country group dummies, where subscripts I and C index industries and country groups, respectively; the k×1 β and ρ vectors contain coefficients that measure, respectively, the innovation and participation effects of 1×k vectors of firm level 'quasi' fixed effects; the k×1 θ vector contains coefficients that measure the participation effects of a 1×k vector of indicators of firms' views on factors promoting or impeding programme participation (*Barriers*), which are the anticipated identifying variables (exclusion restrictions); and u and ε are the error terms, which capture the unobserved influences on the respective dependent variables.

Control variables are grouped into three categories: those measuring firms' absorptive capacity; those controlling for firm characteristics; and those controlling for external, environmental (external) influences.

Absorptive capacity. Firms' absorptive capacity is usually measured by internal R&D activities, proxied by several measures: internal (intramural) R&D expenditures; the share of R&D personnel; and the presence of a separate R&D department (Spithoven et al., 2010). Our dataset contains information on each measure, but the variable measuring R&D expenditures (*RD_expenditure*) represents total R&D expenditures, thus including the following categories: R&D staff salaries; contracts to outside R&D performers; acquisition of machinery, equipment and software; purchase of patents and know-how from other organizations; training in R&D; and, market introduction of innovations. Having a separate R&D department is measured as a binary variable (=1 if a firm has a separate R&D department; 0 otherwise; *RD_department*) (see Table A4.1, Appendix IV for the variable definition). However, the variable measuring R&D expenditures *(RD_expenditure)* is highly correlated with the variable measuring the share of R&D personnel (the correlation coefficient is 0.79), suggesting a potential problem with multicollinearity if both variables were to enter the model (Greene, 2005). Hence, the model specification includes only the former, because it is a broader measure of innovation input. In the final (extended) model estimated as a robustness check, we have also included a binary variable *RD_strategy* equal to 1 if the firm has defined a R&D and innovation strategy for the next five years (zero otherwise).

Firm characteristics. We control for a firm's degree of internationalization by including a binary indicator that is equal to 1 if a firm undertakes exporting activities (*Export*). Exporting firms tend to have more incentive to innovate as a result of competitive pressure on international markets (Busom and Fernández-Ribas, 2008; Parida et al., 2012). SMEs are a heterogeneous group of firms; correspondingly, we created three binary indicators for micro firms with less than 10 employees (*Micro_firms*),[100] small firms having between 10 and 49 employees (*Small_firms*) and medium-sized firms having between 50 and 249 employees (*Medium_firms*). Moreover, the final (extended) model includes two variables to control for firm-level "quasi" fixed effects (or initial conditions) (see Section 4.3.1 for a discussion). The first variable (*Q18a_leading*) is equal to 1 if firms report that their research and innovation record was leading compared to other firms in the industry five years prior to the survey (zero otherwise). The second variable (*Q19_fewer*) is equal to 1 if firms report having devoted fewer resources to innovation five years prior to the survey (zero otherwise).

Environmental (external) factors. Our model also takes into account environmental factors (Lichtenthaler, 2009), such as competitive pressure, industry

[100] Micro firms are the base category.

characteristics, and whether firms operate in technology parks and integrate technology platforms. Competitive intensity is measured as a binary indicator, equal to 1 if a firm reports that the competition is strong in its main markets (zero otherwise) (*Competition*). Furthermore, the final (extended) model includes two binary indicators for firms located in technology parks (*Tech_parks*), and for those that integrate a cluster/technology platform (*Tech_platform*). Finally, we control for sectoral heterogeneity by constructing six industry categories: high tech; medium high tech; medium low tech; low tech; Information and Communication Technology (ICT); and services (as the base category).[101]

Barriers to participation (identifying variables or exclusion restrictions). Following the discussion in Section 4.3.1, the selection question must include all the control variables from the outcome equation together with at least one variable to identify the selection equation. Identification restrictions are imposed on the model by including variable(s) that influence the participation decision, but do not directly affect the innovation decision. The survey questionnaire within the MAPEER project, similar to the GPrix survey, included questions related only to programme participation. Questions 53, 54, 55 and 56 asked firms about SME needs in general: "Which would you say are the specific needs for SMEs in order to participate in R&D programmes?" In all 21 parts of this question (see Table A4.1, Appendix VI), the corresponding indicator variable was defined as 1 if the response was "Most important" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important").

6.4 Results

6.4.1 Output additionality

For evaluating the impact of programme participation on innovation output, we estimated three treatment parameters - the Average Treatment Effect on the Treated (ATT); the Average Treatment Effect on the Untreated (ATU); and the Average Treatment Effect (ATE - from fifteen parsimonious (baseline) models, five for each stream of funding (national, international and joint funding). Estimated treatment effects

[101] Manufacturing industries – the first five categories - are grouped based on NACE classification according to technology intensity (OECD, 2006b) (see Table A4.2, Appendix IV).

for each model are presented in Table 6.1 (baseline specification) and in Table 6.2 (augmented specification).

Out of 15 baseline models, only two are without diagnostic problems[102]; in other models either correlation coefficients are equal to the extreme values of the absolute unity or the likelihood-test ratio suggests no selection bias. However, as discussed in Section 4.4.1, we report the border values (1 and -1) as problematic; but we are “reluctant” to disregard large correlation coefficients "even if imprecisely estimated”, because this would be to disregard the potential endogeneity of the selection process (Aakvik et al., 2005, p. 37). Moreover, the likelihood-ratio test (reported in column 5) should reject the null of the independence of the selection and output equations. We find that in 8 from 15 cases the likelihood-ratio test rejects the null of no selection bias due to unobservables at the 10 per cent level or lower. However, it is highly unlikely that the assignment of public innovation measures is free of selection bias, and for this reason the literature on R&D and innovation policy argues that public support should always be treated as endogenous variable (for a discussion on selection bias see Section 3.4).

The interpretation of the treatment effects begins with the two models without diagnostic problems. Interestingly, both models refer to participation in national support programmes. For a broader measure of innovation output (innovative sales more than 20%), both treatment effects are negative and statistically significant at the 1 per cent level. However, the ATE effect is smaller than the ATT effect, and the 95 per cent confidence intervals do not overlap, indicating that in this case random allocation of national funding would further reduce the probability of innovation. Namely, on average, receiving national public funding reduces the probability of innovation by programme participants by 23.3 percentage points; in comparison, receiving national public funding would have reduced the probability of innovation for firms randomly selected from the entire population by 35.6 percentage points. However, this comparison is not replicated in the second model for more innovative firms (innovative sales more than 40%). In this case, both treatment effects are statistically significant at the 1 per cent level, but the ATT effect is smaller than the ATE effect. On average, receiving national public funding reduces the probability of innovation by programme participants by 30.4 percentage points. Conversely, receiving national public funding

[102] Stata outputs for these models are shown in Appendix IV, Tables A4.3 and A4.4 respectively. For the sake of space, we do not report Stata outputs for the remaining 13 baseline models.

would have increased the probability of innovation for firms randomly selected from the entire population by 13.7 percentage points.

If we draw attention to the models with diagnostic problems, a prevailing pattern of negative ATT and positive ATE emerges. As the confidence intervals reported for both treatment effects (see Table 6.1) are not overlapping in any case, we can conclude that there is a systematic difference between the treatment effects across all models.

For the ATT effect, all 13 estimates are negative and significantly different from zero at the 1 per cent level. In sum:

- ATT: the mean of the 13 values is -0.241 with a range from -0.445 to -0.099.

In contrast, for the ATE effect, 11 from 13 estimates are positive and statistically significant at the 1 per cent level. In sum:

- ATE: the mean of the 13 values is 0.055 with a range from -0.342 to 0.224.

These results suggest that programme participation typically reduced the probability of innovation by programme participants by 24.1 percentage points but would have increased the probability for firms randomly selected from the entire population by 5.5 percentage points. Overall results, therefore, indicate that random distribution of support measures among European SMEs would result in a small, but positive additional effect. In contrast, the empirical evidence reveals that programme assignment is perverse regarding innovation output.

Furthermore, besides estimating treatment parameters for participation in a variety of support measures (national, international and joint national/international), another robustness check was conducted by including additional control variables in the model specification to construct an augmented model.[103] The additional control variables, as noted in Section 6.3.2, are as follows: DV for resources devoted to innovation (*Q19_fewer*); DV for the firm's research and innovation record in 2005 (*Q18a_leading*); DV for the location of the firm in technology park/area (*Tech_park*); DV for the integration of a cluster/technology platform (*Tech_platform*); and DV for the development of R&D and innovation strategy (*RD_strategy*) (see Table A4.1).

[103] Some models also include additional exclusion restrictions, if they were statistically significant in the selection equation and statistically insignificant in the outcome equation.

Treatment effects for the augmented models are presented in Table 6.2. Out of 15 baseline models, only two are without diagnostic problems; in other models either one of the correlation coefficients is equal to the extreme value of absolute unity or the likelihood-test ratio suggests no selection bias. In 12 from 15 cases the likelihood- test rejects the null of no selection bias due to unobservables at the 10 per cent level or lower. Regarding the remaining three cases, one is on the borderline (p-value is equal to 0.1056, in the model estimating the treatment effects of international programme participation on firms with innovative sales above 30 %), but the other two cases are problematic, as the p-values overwhelmingly suggest that the null of no selection bias cannot be rejected.

Our initial focus is on two models without diagnostic problems.[104] The first model reports the impact of participation in international support measures on rather innovative firms with innovative sales above 40%. Both treatment effects are statistically significant at the 1 per cent level of significance, while he ATT is negative and the ATE is positive. On average, receiving international public funding reduces the probability of innovation by programme participants by 38.3 percentage points. With respect to the ATE effect, the findings suggest that, on average, receiving international public funding would have increased the probability of innovation for firms randomly selected from the entire population by 21.9 percentage points. Another relevant finding is associated with the estimated correlation coefficients *rho1* and *rho0* in this model, whereby their signs and statistical significance indicate perverse selection on unobservables: for the highly innovative SMEs participating in international support measures (i.e. those reporting innovative sales in excess of 40 per cent of turnover), unobservables that positively affect the probability of participation in international support measures have a negative impact on the probability of having a large share of innovative sales (rho1=-0.725; statistically significant at the 1% level). In contrast, for the highly innovative non-participating SMEs, the unobservables promoting participation in international programmes are positively correlated with a large innovation output (rho0=0.569; statistically significant at the 5% level).

The second model without diagnostic problems estimates the impact of joint support (either receiving national or international support) on highly innovative firms

[104] Stata outputs for these models are presented in Appendix IV, Tables A4.5 and A4.6. For the sake of space, we do not report Stata outputs for the remaining 13 augmented models with diagnostic problems.

with innovative sales above 50%. Both treatment effects are statistically significant at the 1% level of significance. While the pattern of smaller ATT than ATE effect is maintained, both effects are negative. More precisely, on average, receiving either national or international public funding reduces the probability of innovation by programme participants by 49.6 percentage points. With respect to the ATE effect, the findings suggest that, on average, receiving either source of public funding would have reduced the probability of innovation for firms randomly selected from the entire population by 11.6 percentage points. Moreover, similar to the above model on the impact of international support, the estimated correlation coefficients *rho1* and *rho0* in this model indicate perverse selection on unobservables: for the most innovative SMEs participating in either support measures (i.e. those reporting innovative sales in excess of 50 per cent of turnover), unobservables that positively affect the probability of participation in joint support measures have a negative impact on the probability of having a large share of innovative sales (*rho1*= -0.720; statistically significant at the 5% level). In contrast, for the most innovative non-participating SMEs, the unobservables promoting participation in either stream of funding are positively correlated with a large innovation output (*rho0*=0.809; statistically significant at the 1% level).

Focusing on the treatment parameters in the augmented models with diagnostic problems, a pattern of smaller ATT than ATE is reported across all, but one model, which is in line with the results from the baseline models. Furthermore, treatment effects are systematically different given a lack of overlap in the confidence intervals in all models (see Table 6.2).

For the ATT effect, 12 of 13 estimates are negative and significantly different from zero at the 1 per cent level. In sum:

- ATT: the mean of the 13 values is -0.211 with a range from -0.435 to -0.004.

In contrast, for the ATE effect, 12 from 13 estimates are positive and statistically significant at the 1 per cent level. In sum:

- ATE: the mean of the 13 values is 0.086 with a range from -0.351 to 0.199.

Table 6.1. Baseline model - programme participation effects on innovation outputs: the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU) and the average treatment effect (ATE) (Bootstrapped standard errors, 1,000 replications)

Output dependent variable	rho1	rho0	Problem with a model?	LR test (p value)	Average treatment effect on the treated - ATT			Average treatment effect on the untreated - ATU		Average treatment effect - ATE		
					No of obs.	Coeff. (bootstr. SEs)	95 % confidence intervals	No of obs.	Coeff. (bootstr. SEs)	No of obs.	Coeff. (bootstr. SEs)	95% confidence intervals
	National support (N=763)											
Innovative sales >10%	-1	0.689 (0.380)	rho1= -1	0.0016	314	-0.218*** (0.008)	[-0.234 -0.202]	283	0.365*** (0.012)	597	0.062*** (0.007)	[0.049 0.076]
Innovative sales > 20%	0.934 (0.089)	0.583 (0.396)	No	0.0485	315	-0.233*** (0.006)	[-0.245 -0.222]	282	-0.490*** (0.010)	597	-0.356*** (0.004)	[-0.363 -0.349]
Innovative sales > 30%	-0.999 (0.002)	0.373 (0.625)	rho1= -0.999	0.0303	324	-0.207*** (0.007)	[-0.221 -0.194]	288	0.570*** (0.012)	612	0.157*** (0.009)	[0.139 0.175]
Innovative sales > 40%	-0.950 (0.085)	0.526 (0.486)	No	0.0503	324	-0.304*** (0.007)	[-0.318 -0.290]	288	0.629*** (0.011)	612	0.137*** (0.011)	[0.115 0.159]
Innovative sales >50%	-0.994 (0.048)	0.762 (0.268)	rho1= 0.994	0.0076	324	-0.445*** (0.008)	[-0.460 -0.430]	288	0.697*** (0.011)	612	0.093*** (0.013)	[0.068 0.118]
	International support (N=763)											
Innovative sales >10%	-0.594 (0.586)	0.570 (0.443)	LR test p= 0.2967	0.2967	180	-0.206*** (0.009)	[-0.223 -0.188]	444	0.248*** (0.006)	624	0.117*** (0.006)	[0.105 0.129]
Innovative sales >20%	-0.284 (0.520)	0.329 (0.411)	LR test p= 0.6427	0.6427	180	-0.152*** (0.008)	[-0.168 -0.135]	444	0.178*** (0.006)	624	0.083*** (0.005)	[0.073 0.094]
Innovative sales >30%	-0.553 (0.503)	0.153 (0.460)	LR test p= 0.6473	0.6473	183	-0.099*** (0.009)	[-0.116 -0.081]	450	0.353*** (0.006)	633	0.224*** (0.007)	[0.211 0.236]
Innovative sales >40%	1	0.313 (0.584)	LR test p= 0.4659 & rho1 = 1	0.4659	186	-0.245*** (0.009)	[-0.262 -0.228]	492	-0.380*** (0.010)	678	-0.342*** (0.006)	[-0.353 -0.331]

Innovative sales >50%	-0.456 (0.434)	0.254 (0.459)	LR test p= 0.5774	0.5774	180	-0.232*** (0.011)	[-0.253 -0.211]	444	0.220*** (0.006)	624	0.090*** (0.007)	[0.078 0.103]
	Joint support (N=763)											
Innovative sales >10%	-1	0.508 (0.536)	rho1= -1	0.0196	383	-0.205*** (0.007)	[-0.220 -0.191]	250	0.376*** (0.013)	633	0.022*** (0.008)	[0.007 0.037]
Innovative sales >20%	-0.774 (0.290)	0.634 (0.451)	LR test p= 0.1736	0.1736	372	-0.282*** (0.006)	[-0.294 -0.269]	240	0.412*** (0.011)	612	-0.008 (0.007)	[-0.023 0.006]
Innovative sales >30%	-1	0.493 (0.766)	rho1= -1	0.0167	380	-0.314*** (0.007)	[-0.327 -0.300]	249	0.577*** (0.014)	629	0.038*** (0.010)	[0.017 0.058]
Innovative sales >40%	-0.873 (0.181)	0.190 (0.757)	LR test p= 0.2267	0.2267	372	-0.203*** (0.007)	[-0.216 -0.190]	240	0.560*** (0.012)	612	0.098*** (0.011)	[0.076 0.120]
Innovative sales >50%	-0.999 (0.000)	0.484 (0.540)	rho1= -0.999	0.0613	372	-0.332*** (0.008)	[-0.348 -0.317]	240	0.686*** (0.014)	612	0.067*** (0.013)	[0.040 0.093]

Table 6.2. Augmented model - programme participation effects on innovation outputs: the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU) and the average treatment effect (ATE) (Bootstrapped standard errors, 1,000 replications)

Output dependent variable	rho1	rho0	Problem with a model?	LR test (p value)	Average treatment effect on the treated - ATT			Average treatment effect on the untreated - ATU		Average treatment effect - ATE		
					No of obs.	Coeff. (bootstr. SEs)	95% confidence intervals	No of obs.	Coeff. (bootstr. SEs)	No of obs.	Coeff. (bootstr. SEs)	95% confidence intervals
	National support (N=763)											
Innovative sales >10%	-1	0.604 (0.580)	rho1= -1	0.0014	324	-0.212*** (0.009)	[-0.230 -0.195]	288	0.364*** (0.013)	612	0.062*** (0.008)	[0.046 0.078]
Innovative sales > 20%	-1	0.230 (0.783)	rho1= -1	0.0140	324	-0.134*** (0.010)	[-0.154 -0.113]	288	0.477*** (0.015)	612	0.154*** (0.010)	[0.134 0.174]
Innovative sales > 30%	0.999 (0.000)	0.554 (0.395)	rho1= 0.999	0.0118	315	-0.283*** (0.010)	[-0.302 -0.264]	282	-0.424*** (0.014)	597	-0.351*** (0.006)	[-0.364 -0.339]
Innovative sales > 40%	-1	0.475 (0.556)	rho1= -1	0.0025	324	-0.294*** (0.009)	[-0.312 -0.276]	288	0.645*** (0.012)	612	0.150*** (0.012)	[0.126 0.174]
Innovative sales >50%	1	0.738 (0.273)	rho1= 1	0.0012	324	-0.435*** (0.010)	[-0.455 -0.416]	288	0.688*** (0.012)	612	0.097*** (0.014)	[0.070 0.124]
	International support (N=763)											
Innovative sales >10%	-1	0.999 (7.192)	rho1= -1 rho0= 0.999	0.0596	180	-0.258*** (0.015)	[-0.286 -0.229]	444	0.333*** (0.009)	624	0.159*** (0.008)	[0.143 0.175]
Innovative sales >20%	0.440 (0.544)	0.371 (0.385)	LR test p=0.4914	0.4914	180	-0.184*** (0.011)	[-0.205 -0.162]	444	0.247*** (0.007)	624	0.123*** (0.007)	[0.109 0.138]
Innovative sales >30%	-0.691 (0.323)	0.586 (0.326)	LR test p=0.1056	0.1056	180	-0.322*** (0.012)	[-0.346 -0.299]	444	0.407*** (0.008)	624	0.199*** (0.009)	[0.182 0.216]
Innovative sales >40%	-0.725 (0.251)	0.569 (0.289)	No	0.0592	180	-0.383*** (0.012)	[-0.407 -0.359]	444	0.461*** (0.009)	624	0.219*** (0.011)	[0.198 0.241]

Innovative sales >50%	-0.389 (0.391)	-0.243 (0.491)	LR test p=0.5962	0.5962	180	-0.004 (0.013)	[-0.030 0.022]	421	0.143*** (0.009)	601	0.099*** (0.008)	[0.085 0.114]
	Joint support (N=763)											
Innovative sales >10%	-1	0.277 (0.558)	rho1= -1	0.0015	372	-0.167*** (0.009)	[-0.185 -0.149]	240	0.367*** (0.016)	612	0.043*** (0.009)	[0.024 0.061]
Innovative sales >20%	-1	0.035 (0.703)	rho1= -1	0.0156	372	-0.090*** (0.010)	[-0.110 -0.071]	240	0.483*** (0.015)	612	0.133*** (0.011)	[0.112 0.154]
Innovative sales >30%	-1	-0.090 (0.765)	rho1= -1	0.0112	372	-0.073*** (0.011)	[-0.094 -0.052]	240	0.563*** (0.016)	612	0.175*** (0.012)	[0.152 0.197]
Innovative sales >40%	-1	0.311 (0.633)	rho1= -1	0.0950	367	-0.285*** (0.010)	[-0.305 -0.266]	238	0.622*** (0.017)	605	0.071*** (0.014)	[0.043 0.099]
Innovative sales >50%	-0.720 (0.290)	0.809 (0.221)	No	0.0285	365	-0.496*** (0.008)	[-0.512 -0.480]	237	0.460*** (0.013)	602	-0.116*** (0.012)	[-0.140 -0.092]

These results suggest that programme participation typically reduced the probability of innovation by programme participants by 21.1 percentage points but would have increased the probability for firms randomly selected from the entire population by 8.6 percentage points. Overall results confirm the findings from the baseline models; i.e. random distribution of public funding among firms similar to those in our sample of mostly innovating SMEs (two thirds of firms reported to have generated more than 10% of innovative sales, as noted in Section 6.3.1) would yield a positive additional effect on SME innovation performance.

6.4.2 Behavioural additionality

The impact of public support on SME innovative behaviour is limited to the assessment of network additionality, whereby binary outcome variables represent the seven categories of networking and cooperation for innovation detailed in Section 6.3.2.

In line with the empirical strategy adopted for assessing output additionality, twenty one parsimonious (baseline) models were estimated to assess the impact of three sources of funding (national, international and joint support) on seven types of networking activities. The treatment effects are presented in Table 6.3. Out of 21 models, only two are without diagnostic problems; in other models either correlation coefficients are equal to the extreme values of the absolute unity or the likelihood-ratio test indicates no selection bias. As previously discussed in Section 3.4, public support in a domain of innovation cannot be treated as an exogenous, pre-determined variable, given the sources of selection bias acknowledged in the literature. The two models without diagnostic issues refer to SMEs participating in joint support: in the first model the outcome variable is the use of online technology or knowledge brokers; and in the other model the outcome variable is participation in innovation networks, S&T parks and clusters.[105]

The estimated treatment effects are rather heterogeneous across different network activities. We first focus on the interpretation of the two models without problems with diagnostic tests. The relationships between treatment effects and their

[105] Stata outputs for these models are presented in Appendix IV, Tables A4.7 and A4.8 respectively. For the sake of space, Stata outputs for the remaining 19 baseline models are not presented.

signs and statistical significance are consistent across both models. Namely, both treatment effects are negative and statistically significant at the 1 per cent level, and for both models the ATT effect is smaller than the ATE. The interpretation of the programme effects is as follows. Participation in either national or international programmes reduces the probability of the use of online technology or of knowledge brokers by programme participants by 47.2 percentage points and would have also decreased this probability for firms randomly selected from the entire population by 42.4 percentage points. Likewise, receiving either national or international support decreases the probability of participation in innovation networks by 44.9 percentage points and would have reduced the probability for firms randomly selected from the entire population by 29.9 percentage points.

Table 6.3. Baseline model - programme participation effects on innovation behaviour: the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU) and the average treatment effect (ATE) (Bootstrapped standard errors, 1,000 replications)

Output dependent variable	rho1	rho0	Problem with a model?	LR test (p value)	Average treatment effect on the treated - ATT			Average treatment effect on the untreated - ATU		Average treatment effect - ATE		
					No of obs.	Coeff. (bootstr. SEs)	95% confidence intervals	No of obs.	Coeff. (bootstr. SEs)	No of obs.	Coeff. (bootstr. SEs)	95% cnfidence intervals
	National support (N=763)											
Use of online technology or knowledge brokers/intermediaries	-1	-0.206 (1.072)	rho1= -1	0.0587	312	0.073*** (0.008)	[0.057 0.089]	280	0.674*** (0.006)	592	0.359*** (0.007)	[0.345 0.372]
Informal networking with other firms	-0.693 (0.620)	0.999 (0.001)	LR test (p=0.4467) & rho0=0.999	0.4467	329	-0.303*** (0.006)	[-0.314 -0.291]	283	0.415*** (0.007)	612	0.031*** (0.007)	[0.018 0.044]
Informal networking with research organizations	-0.999 (0.116)	0.281 (0.533)	rho1= -0.999	0.0482	314	0.071*** (0.009)	[0.053 0.089]	271	0.633*** (0.011)	585	0.332*** (0.009)	[0.315 0.349]
Strategic alliances with other firms	-1	0.812 (0.216)	rho0= -1	0.0350	305	0.507*** (0.010)	[0.487 0.527]	272	-0.325*** (0.011)	577	0.114*** (0.008)	[0.099 0.129]
Non-equity alliances with other firms	-1	0.027 (0.618)	rho1= -1	0.0016	306	0.046*** (0.010)	[0.026 0.065]	271	0.753*** (0.006)	577	0.381*** (0.007)	[0.367 0.395]
Participation in innovation networks, S&T parks, clusters etc.	0.023 (0.771)	1	rho0= 1	0.0120	311	-0.475*** (0.009)	[-0.493 -0.458]	271	0.200*** (0.012)	582	-0.160*** (0.008)	[-0.177 -0.144]
Close involvement of end users/customers	-0.413 (0.766)	0.522 (0.506)	LR test p=0.5935	0.5935	300	-0.227*** (0.010)	[-0.246 -0.209]	267	0.316*** (0.009)	567	0.029*** (0.010)	[0.010 0.048]

	International support (N=763)											
Use of online technology or knowledge brokers/intermediaries	0.999 (0.019)	0.364 (0.381)	rho1=0.999	0.0127	179	-0.325*** (0.011)	[-0.348 -0.303]	435	-0.348*** (0.004)	614	-0.342*** (0.004)	[-0.349 -0.335]
Informal networking with other firms	-1	0.999 (0.004)	rho1= -1 & rho0= 0.999	0.0455	177	-0.313*** (0.015)	[-0.343 -0.283]	409	0.390*** (0.006)	586	0.178*** (0.007)	[0.164 0.191]
Informal networking with research organizations	-0.999 (0.026)	-0.002 (0.490)	rho1= -0.999 & LR test (p=0.1427)	0.1427	176	0.188*** (0.014)	[0.160 0.215]	409	0.555*** (0.009)	585	0.444*** (0.008)	[0.428 0.459]
Strategic alliances with other firms	-0.213 (0.477)	-0.062 (0.447)	LR test p=0.9004	0.9004	171	0.225*** (0.016)	[0.194 0.256]	404	0.322*** (0.010)	575	0.293*** (0.009)	[0.276 0.310]
Non-equity alliances with other firms	1	-0.999 (0.231)	rho1= 1 & rho0= -0.999	0.0004	172	0.298*** (0.016)	[0.267 0.330]	393	-0.236*** (0.008)	565	-0.070*** (0.005)	[-0.081 -0.060]
Participation in innovation networks, S&T parks, clusters etc.	-0.647 (0.373)	0.223 (0.550)	LR test p=0.4159	0.4159	176	0.014 (0.015)	[-0.016 0.044]	404	0.542*** (0.008)	580	0.383*** (0.009)	[0.365 0.402]
Close involvement of end users/customers	-0.465 (0.446)	0.488 (0.579)	LR test p=0.4653	0.4653	169	-0.207*** (0.012)	[-0.229 -0.184]	391	0.289*** (0.008)	560	0.140*** (0.008)	[0.125 0.155]
	Joint support (N=763)											
Use of online technology or knowledge brokers/intermediaries	0.956 (0.122)	0.649 (0.413)	No	0.0871	366	-0.472*** (0.009)	[-0.489 -0.455]	232	-0.347*** (0.010)	598	-0.424*** (0.006)	[-0.437 -0.412]
Informal networking with other firms	0.032 (1.146)	0.551 (0.553)	LR test p=0.7527	0.7527	371	-0.181*** (0.006)	[-0.193 -0.169]	233	0.132*** (0.009)	604	-0.060*** (0.006)	[-0.072 -0.048]
Informal networking with research organizations	-0.999 (0.038)	0.432 (0.450)	rho1= -0.999	0.0296	358	-0.006 (0.008)	[-0.022 0.010]	227	0.677*** (0.012)	585	0.259*** (0.010)	[0.240 0.278]
Strategic alliances with other firms	0.810 (0.318)	0.475 (0.725)	LR test p=0.3041	0.3041	360	-0.136*** (0.010)	[-0.155 -0.116]	235	-0.279*** (0.010)	595	-0.193*** (0.008)	[-0.207 -0.179]

Non-equity alliances with other firms	-1	0.202 (0.707)	rho1= -1	0.0031	352	-0.027** (0.012)	[-0.050 -0.003]	225	0.761*** (0.009)	577	0.283*** (0.010)	[0.263 0.302]
Participation in innovation networks, S&T parks, clusters etc.	0.522 (0.395)	0.966 (0.049)	No	0.0005	353	-0.449*** (0.009)	[-0.466 -0.433]	224	-0.061*** (0.012)	577	-0.299*** (0.008)	[-0.314 -0.284]
Close involvement of end users/customers	1	-0.181 (0.793)	rho0= 1	0.0750	350	-0.374*** (0.008)	[-0.391 -0.358]	225	0.197*** (0.012)	575	-0.152*** (0.009)	[-0.169 -0.134]

In the model where the outcome variable is the use of online technology and of knowledge brokers, the correlation coefficient *rho1* is positive and statistically significant at the 1 per cent level. This demonstrates that, for SMEs participating in either national or international support measures, unobservables positively affecting the probability of participation in joint support measures have also a positive impact on the probability of the usage of online technologies or of knowledge brokers (*rho1*=0.956). This finding may be explained by the argument that participation in support programmes could be regarded as cooperation with government institutions, and thus is consistent with the unobservables having a positive effect on other types of cooperation. In the model where the outcome variable is participation in innovation networks, the positive and statistically significant correlation coefficient *rho0* indicates that, for non-participating SMEs, the unobservables promoting programme participation are positively correlated with participation in innovation networks (*rho0*= 0.966). This finding is in line with the previous argument about considering treatment assignment into public funding as a type of cooperation, in this case with government.

Following the same empirical strategy that was applied to assessing output additionality by way of estimating the baseline specification, we estimated the augmented specification for all seven outcome variables measuring networking activities (see Table 6.4). Out of 21 models, only two were estimated without problems indicated by diagnostic testing. Both of these models assess the effectiveness of participation in joint support programmes, whereas the respective outcome variables are informal networking with other firms and informal networking with research organizations.[106] The pattern of smaller ATT and larger ATE pertains in both models.

The estimated treatment effects in the model where the outcome variable is informal networking with other firms indicate that programme participation reduces the probability of networking by programme participants by 29.2 percentage points and would have decreased the probability for firms randomly selected from the entire population by 3.6 percentage points. Moreover, a positive and statistically significant correlation coefficient *rho0* demonstrates that for non-participating SMEs the unobservables promoting programme participation are positively correlated with

[106] Stata outputs for these models are shown in Appendix IV, Tables A4.9 and A4.10 respectively. For the sake of space, Stata outputs for the remaining 19 augmented models are not presented.

informal networking with other firms (*rho0*=0.862). The coefficient *rho1* is not statistically significant at the 10 per cent level of significance or below.[107]

In addition, participation in either national or international support measures decreases the probability of informal networking with research organizations by participating SMEs by 11.9 percentage points, but would have increased the probability for firms randomly selected from the entire population by 17.4 percentage points. Moreover, a negative and statistically significant correlation coefficient *rho1* suggests a perverse selection on observables; for participating SMEs, unobservables that positively affect the probability of participation in joint support measures have a negative impact on the probability of informal networking with research organizations (*rho1*= -0.842). The coefficient *rho0* is statistically insignificant.

[107] The criteria for statistical significance of the *rho* coefficient are: 1.65 of the standard error (SE) for the 10 per cent level of significance; 1.96 of the SE for the 5 per cent level of significance; and 2.63 of the SE for the 1 per cent level of significance.

Table 6.4. Augmented model - programme participation effects on innovation behaviour: the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU) and the average treatment effect (ATE) (Bootstrapped standard errors, 1,000 replications)

Output dependent variable	rho1	rho0	Problem with a model?	LR test (p value)	Average treatment effect on the treated - ATT			Average treatment effect on the untreated - ATU		Average treatment effect - ATE		
					No of obs.	Coeff. (bootstr. SEs)	95% confidence intervals	No of obs.	Coeff. (bootstr. SEs)	No of obs.	Coeff. (bootstr. SEs)	95% confidence intervals
	National support (N=763)											
Use of online technology or knowledge brokers/ intermediaries	-1	-0.999 (0.000)	rho1= -1 & rho0= -0.999	0.0017	330	0.307*** (0.008)	[0.292 0.322]	286	0.665*** (0.010)	616	0.477*** (0.006)	[0.466 0.488]
Informal networking with other firms	-1	-0.520 (0.625)	rho1= -1	0.0680	329	0.452*** (0.009)	[0.435 0.470]	279	0.447*** (0.008)	608	0.451*** (0.005)	[0.441 0.460]
Informal networking with research organizations	-0.764 (0.333)	0.009 (0.638)	LR test p= 0.4861	0.4861	323	0.190*** (0.009)	[0.172 0.209]	276	0.562*** (0.010)	599	0.362*** (0.008)	[0.346 0.377]
Strategic alliances with other firms	0.095 (0.588)	1	rho0= 1	0.0240	300	-0.492*** (0.013)	[-0.517 -0.466]	273	-0.013 (0.011)	573	-0.267*** (0.007)	[-0.281 -0.252]
Non-equity alliances with other firms	-1	0.142 (0.540)	rho1= -1	0.0001	300	-0.064*** (0.012)	[-0.088 -0.040]	265	0.708*** (0.009)	565	0.304*** (0.011)	[0.283 0.325]
Participation in innovation networks, S&T parks, clusters etc.	-0.450 (0.537)	1	rho0= 1	0.0024	305	-0.463*** (0.012)	[-0.486 -0.440]	266	0.436*** (0.012)	571	-0.041*** (0.011)	[-0.063 -0.020]
Close involvement of end users/customers	0.053 (0.607)	0.999 (0.001)	rho0= 0.999	0.0048	300	-0.362*** (0.012)	[-0.386 -0.339]	267	0.081*** (0.015)	567	-0.155*** (0.010)	[-0.174 -0.135]
	International support (N=763)											
Use of online technology or knowledge brokers	1	0.442 (0.325)	rho1= 1	0.0031	178	-0.361*** (0.015)	[-0.390 -0.332]	410	-0.344*** (0.006)	588	-0.350*** (0.005)	[-0.359 -0.340]

Informal networking with other firms	-1	0.732 (0.546)	rho1= -1	0.0399	179	-0.280*** (0.016)	[-0.312 -0.248]	412	0.390*** (0.006)	591	0.186*** (0.008)	[0.172 0.201]
Informal networking with research organizations	-1	-0.182 (0.396)	rho1= -1	0.0235	176	0.229*** (0.016)	[0.198 0.260]	425	0.551*** (0.112)	601	0.455*** (0.009)	[0.437 0.473]
Strategic alliances with other firms	0.426 (0.886)	0.979 (0.046)	LR test p=0.1139	0.1139	171	-0.379*** (0.018)	[-0.414 -0.345]	418	-0.056*** (0.011)	589	-0.152*** (0.009)	[-0.170 -0.134]
Non-equity alliances with other firms	-1	0.865 (0.259)	rho1= -1	0.0223	172	-0.557*** (0.015)	[-0.586 -0.528]	413	0.745*** (0.007)	585	0.365*** (0.119)	[0.342 0.389]
Participation in innovation networks, S&T parks, clusters etc.	-0.844 (0.277)	1	rho0= 1 & LR test p= 0.1057	0.1057	176	-0.445*** (0.016)	[-0.476 -0.414]	404	0.606*** (0.011)	580	0.287*** (0.011)	[0.265 0.310]
Close involvement of end users/customers	-1	0.573 0.643	rho1= - 1	0.0235	169	-0.253*** (0.017)	[-0.287 -0.220]	391	0.426*** (0.010)	560	0.219*** (0.010)	[0.201 0.238]
	Joint support (N=763)											
Use of online technology or knowledge brokers/intermediaries	0.601 (0.635)	0.882 (0.193)	LR test p= 0.1909	0.1909	359	-0.638*** (0.008)	[-0.653 -0.623]	229	-0.284*** (0.013)	588	-0.500*** (0.007)	[-0.515 -0.486]
Informal networking with other firms	-0.562 (0.435)	0.862 (0.213)	No	0.0989	371	-0.292*** (0.007)	[-0.305 -0.279]	233	0.372*** (0.010)	604	-0.036*** (0.008)	[-0.052 -0.020]
Informal networking with research organizations	-0.842 (0.231)	0.579 (0.369)	No	0.0766	353	-0.119*** (0.009)	[-0.137 -0.101]	225	0.628*** (0.013)	578	0.174*** (0.011)	[0.153 0.195]
Strategic alliances with other firms	0.390 (0.486)	1	rho0= 1	0.0014	360	-0.464*** (0.011)	[-0.485 -0.442]	235	-0.098*** (0.011)	595	-0.320*** (0.007)	[-0.334 -0.307]
Non-equity alliances with other firms	-0.680 (0.454)	1	rho0= 1	0.0269	349	-0.701*** (0.009)	[-0.720 -0.682]	222	0.452*** (0.014)	571	-0.252*** (0.014)	[-0.279 -0.224]
Participation in innovation networks, S&T parks, clusters etc.	-0.208 (0.805)	1	rho0= 1	0.0004	353	-0.473*** (0.011)	[-0.494 -0.451]	224	0.309*** (0.015)	577	-0.166*** (0.011)	[-0.187 -0.145]
Close involvement of end users/customers	-0.760 (0.246)	1	rho0= 1	0.0134	350	-0.373*** (0.010)	[-0.393 -0.354]	225	0.416*** (0.016)	575	-0.066*** (0.011)	[-0.087 -0.045]

6.4.3 Summary

Summary results for output additionality are reported in Tables 6.5 and 6.6. If we combine results from both baseline and augmented models, then in 26 of 30 models, the ATT effect is smaller than the ATE (in 13 baseline models and 13 augmented models; in both cases, 12 of the respective models estimate both treatment parameters at conventional levels of statistical significance). Furthermore, in 25 models, the ATT effect is negative (12 baseline and 13 augmented models), whereas the ATE effect is positive (and in 24 from these 25 models, both treatment parameters are statistically significant).

Summary results for behavioural additionality are reported in Tables 6.8 and 6.9.[108] In 17 of the 21 baseline (parsimonious) models, the ATT effect is smaller than the ATE (and in 15 of these models both treatment parameters are statistically significant). Similarly, in 19 of the 21 augmented models, the ATT effect is smaller than the ATE (and both treatment effects in all 19 are statistically significant). However, a pattern of positive ATT and negative ATE is not so prominent in the models assessing behavioural additionality. Namely, this pattern is found in only 6 baseline models and in the same number of augmented models.

[108] After checking whether confidence intervals overlap, we identified one baseline model in which the confidence intervals for the ATT and ATE effects overlap; the outcome variable in the model is the use of online technology and knowledge brokers and the treatment variable is international support. Therefore, the treatment estimates for this model are not reported in Tables 6.7 and 6.8. Moreover, confidence intervals overlap in two augmented models. The first model estimated the impact of national support on informal networking with other firms, and the second model reports the effect of participation in international programme measures on the use of online technology and knowledge brokers. Again, the results from these models are not reported in Tables 6.7 and 6.8.

Table 6.5. Programme effects for output additionality: summary

Model	Number of models	Models without diagnostic problems	Models with one diagnostic problem	Models with two diagnostic problems	Models without diagnostic problems				Models with diagnostic problems			
13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.
					ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant	ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant
Baseline	15	2	12	1	1	1	1	1	12	11	11	11
Augmented	15	2	12	1	1	1	1	1	12	11	12	11

Note: As a guide to reading Table 6.5, compare numbers in columns 6-9 with column 3; for example, in the augmented models, one (column 6) from two models without diagnostic problems (column 3) yields ATT<ATE. Similarly, compare columns 10-13 with columns 4 and 5 together.

Table 6.6. Programme effects for output additionality: summary

Model	Number of models	ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant
Baseline model	15	13	12	12	12
Augmented model	15	13	12	13	12

Table 6.7. Programme effects for behavioural additionality: summary

Model	Number of models	Models without diagnostic problems	Models with one diagnostic problem	Models with two diagnostic problems	Models without diagnostic problems				Models with diagnostic problems			
1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
					ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant	ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant
Baseline	21	2	15	4	2	2	0	0	15	13	6	5
Augmented	21	2	17	2	2	2	1	1	17	17	5	5

Note: As a guide to reading Table 6.7, compare numbers in columns 6-9 with column 3; for example, in the augmented models, one (column 6) from two models without diagnostic problems (column 3) yield ATT<ATE. Similarly, compare columns 10-13 with columns 4 and 5 together.

Table 6.8. Programme effects for behavioural additionality: summary

Model	Number of models	ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant
Baseline	21	17	15	6	5
Augmented model	21	19	19	6	6

6.5 Conclusions

In this chapter, we investigated the impact of R&D policy on SME innovation, in particular, focusing on output and behavioural additionality. Before interpreting the main findings, it should be noted that the results should be taken with caution, given the problems with diagnostic tests in most of our estimated models. Although our dataset is the largest achievable with the resources that were available, it is relatively small for the required estimator, particularly taking into account the number of countries covered with the survey. Difficulties with diagnostic testing might be associated with heterogeneity of the data with respect to survey coverage; i.e. the MAPEER dataset includes firms from 28 countries and from both manufacturing and service sectors. Accordingly, we proceed with the interpretation of the findings, but mainly focus on results from the models without diagnostic problems.

In assessing the effectiveness of R&D policy on innovation output (i.e. output additionality), robust results are reported for two baseline models and two augmented models. In the former, both models are estimated for participation in national support programmes. A common finding in both models is that public intervention seem to have a crowding-out effect, demonstrated by a negative and statistically significant ATT effect. Estimated ATE effects, however, are not consistent across two models. For less innovative firms (innovative sales more than 20%), the ATE effect is negative and even smaller than the ATT effect, suggesting that in this case allocating public funding randomly would not reduce – indeed, in comparison would worsen - the adverse effect found for participating firms. Conversely, in highly innovative firms (innovative sales more than 40%), the estimated ATE effect is positive and statistically significant. Therefore, for this category of SMEs, public intervention in the form of randomly allocated funds would have a significant additional effect. Notwithstanding the problems with diagnostic testing, this finding is replicated across all but one model with diagnostic problems.

Another finding from the models without diagnostic problems points to perverse selection into public support. In three from four models, negative and statistically significant correlation coefficients between the error terms of the selection equation and the outcome equation in regime 1 (regime conductive to innovation) suggests a perverse selection on unobservables for participating firms.

As estimated treatment effects in the augmented models are broadly consistent with those from the baseline models, the overall results – a prevailing pattern whereby ATT<ATE - seem to suggest that firms receiving public support are less likely to increase their innovation output as a consequence of treatment assignment. In this respect, the findings from the analysis of the MAPEER dataset are consistent with those reported in Chapter IV on the analysis of the GPrix survey. In both analyses, empirical evidence indicate that the 'picking-the-winner' strategy adopted by government agencies yields no additional effect, if not even a crowding-out of private funding.

In this chapter, we also estimated programme effects on firms' innovative behaviour, specifically on networking and cooperation for innovation (i.e. behavioural additionality). Again, most parameters are imprecisely estimated, but four models report robust and consistent findings of a smaller ATT than ATE effect. Analysing each type of networking separately, the results suggest that a distribution of support measures via a lottery system would only marginally increase the probability of using online technology or knowledge brokers [109], but would have significantly increased the probability of informal networking with other firms[110] as well as of participation in innovation networks. The largest potential effect of random distribution is implied by the results for informal networking with research organizations, for which the ATT effect is significantly negative and the ATE significantly positive. Finally, if we take into account the findings for each open innovation practice and from both baseline and augmented models, the dominant pattern is still of smaller ATT than ATE. Therefore, the overall results seem to indicate that, for most types of networking and cooperation for innovation, a random distribution of R&D support measures would have a substantially larger effect - even if only by reducing crowding out - than using the current selection criteria.

[109] This conclusion does not hold for the case of participation in international support programmes, because the treatment effects are not statistically different in either the baseline or in the augmented model.
[110] In the augmented model, treatment effects are not statistically different for firms participating in national funding. Again, we emphasize the indicative nature of our findings.

CHAPTER VII

CONCLUSIONS AND POLICY IMPLICATIONS

7.1 Introduction

The aim of this thesis was to analyse the effectiveness of innovation support programmes on SME innovation. The focus of this thesis is on output and behavioural additionalities in the specific contexts of, respectively, traditional manufacturing SMEs (the GPrix dataset), European SMEs operating in both manufacturing and service sectors (the MAPEER dataset), and Spanish manufacturing SMEs (the CIS2006 dataset). Innovation policy and its effectiveness are of high importance for policy-makers at the national and supra-national levels, because innovation is regarded as the key to achieving sustainable economic growth and high employment. At the firm level, special attention is devoted to the innovation processes in SMEs, because of the contribution of this heterogeneous group to employment and production (European Commission, 2013b).

Two main issues in the evaluation of innovation policies are related to the presence of selection bias in the distribution of public support and to the necessity of having a group of participating (treated) firms and of non-participating (control) firms in order to empirically estimate treatment effects. The first issue of selection bias occurs for two reasons: a) firms' self-select themselves into support programmes; and b) government agencies are more likely to select those firms with the higher probability of successful innovation projects. Therefore, estimating the impact of innovation policies requires an adequate treatment of participation in support programmes as an endogenous factor. The second issue is associated with the evaluation methodology. Programme effects – additionality and crowding out – cannot be observed and so must be estimated. In turn, the estimation of programme effects requires the estimation of counterfactual outcomes (e.g. the treatment effect on non-participating firms and the effect of non-treatment on participating firms), which requires that evaluators should have data on both treated and non-treated firms (i.e. treatment and control groups respectively).

The empirical work in the thesis is based on three extensive enterprise surveys: a) the GPrix survey of SMEs in traditional manufacturing sectors in seven EU regions;

b) the large-scale Community Innovation Survey (CIS) of Spanish SMEs, and c) the MAPEER survey of SMEs across Europe.

The evidence presented supports the proposition that public measures have a less favourable effect on SMEs' innovation output and innovative behaviour than the claims of policy makers and programme managers would suggest. We find that there is a pervasive selection bias into support programmes, whereby public agencies adopt a 'picking-the-winner' strategy that yields a smaller additional effect of programme support than would randomly allocating public support among innovative SMEs. Furthermore, regarding behavioural additionality, participating in public support measures induces a typically small treatment effect among Spanish SMEs, while the largest effects on participating firms are found for cooperation with government institutions and for outsourcing R&D. Moreover, by analysing behavioural additionality among European SMEs (the MAPEER dataset), the empirical evidence indicates that, similar to output additionality, a random allocation of public measures to relatively innovative SMEs would induce a larger additionality effect than does the current selection process.

Overall, the empirical evidence is contrary to those reported in most empirical studies. Namely, as our review of the empirical literature argued in Section 3.6, there is a sharp distinction between findings reported from studies applying matching estimators and those applying selection models. While the former uniformly report positive treatment effects, the evidence from latter are mixed. Our findings are consistent with this observation. The detailed discussion of the main findings in the thesis is provided in the following section.

7.2 Main findings

The first research question refers to the theoretical contributions to conceptualizing and modelling the innovation process at the organizational level. The review of two streams of literature, neoclassical economics and evolutionary theory, reveals the absence of a canonical theoretical model for the determinants of innovation. This conclusion is consistent with the current advances in the literature on the effectiveness of innovation support programmes, surveyed in Chapter III. The prevailing approach to modelling and analysing the determinants of innovation as well as the impact of public intervention in relation to innovation is an eclectic one. This poses a particular challenge to economists who are trained to derive empirical specifications from theory: for, in the area of innovation generally and in the evaluation of innovation support programmes in particular, empirical studies outweigh theoretical contributions or, as suggested by Cerulli (2010, p. 424), we have "measurement without theory".

Chapter II focuses on the innovation process in SMEs, particularly on its advantages and limitations relative to innovation in large firms. The major constraints on enhancing their absorptive capacity are associated with their typically limited financial and human resources. In analysing SME internal resources, resource-based theory can also provide useful insights. In contrast, SME behavioural traits (e.g. smallness, absence of bureaucratic inertia), are usually recognized as the main advantages of SMEs in comparison to their larger counterparts. In addition, the literature provides several theoretical frameworks for conceptualizing SME innovation, such as portfolio/contingency models or taxonomies of SMEs based on their innovation activities.

In Chapter III, we continue the review of theoretical contributions in relation to the rationales for public innovation support, identifying two complementary frameworks: the neoclassical market-failure rationale; and the evolutionary system-failure rationale. Moreover, the evolution of policy in the domain of innovation revealed a large number of policy instruments applied in contemporaneous policy making. The second part of Chapter III provides an overview of evaluation methods and identities a dominance of matching estimators in empirical studies. In addition, considering the empirical evidence from all three streams of research - input, output and behavioural additionalities - the majority of studies report a positive treatment effect. However, the crucial limitations of the studies on the additionality effects of innovation support programmes are: (1) a very limited number of studies applying selection models and other quantitative methodologies that can take into account unobserved firm characteristics; and (2), a limited availability of longitudinal data, consequently severely restricted insights into the medium- and long-run effects of public intervention in the domain of innovation. In this thesis, the available data allows us to address the former but not the latter limitation.

The key research question in the thesis is the impact of innovation support measures on innovation output and on the innovative behaviour of SMEs. The effectiveness of public measures is assessed through empirical analysis of three different databases and by applying several evaluation methods. In Chapter IV, we investigated whether public measures in the domain of innovation positively effects innovation outputs in traditional manufacturing SMEs across seven EU regions in the United Kingdom, Germany, Italy, France, Spain, Portugal and the Netherlands. Innovation output is measured as the introduction of technological innovations (product and process), of non-technological innovations (organizational and marketing) and as the share of sales from new products and/or processes (i.e. innovative sales). The treatment effects are estimated by a binary endogenous switching model. Two robustness checks were conducted: a) besides estimating treatment parameters of a baseline (parsimonious) model, another set of results is reported for an augmented model; and b) matching estimators were applied using both baseline and augmented models. Based on the estimated average treatment on the treated (ATT) and the average treatment effects (ATE) we report two main findings, while focusing more on the second finding associated with the relationship between the ATT effect and the ATE. The first set of results refers to the estimated ATT effects, whereby its mean value in 20 baseline models is -0.09, suggesting that treatment assignment typically reduced the probability of innovation output by programme participants by 9 percentage points. This finding is consistent with that from 20 augmented models, where the mean value of the ATT effects is -0.18, indicating that treatment assignment typically reduced the probability of innovation output by programme participants by 18 percentage points.

As already noted, the second finding relates to the relationship between the ATT and the ATE effects. Namely, the ATT effect is systematically smaller than the ATE both in the baseline and in the augmented models. In addition, in the majority of cases, the ATT effects are negative while the ATEs are positive. This finding indicates a crowding out effect of innovation support programmes on participating SMEs, but also that an additional effect would have been attainable had support measures been randomly allocated among innovative SMEs (almost all firms in the sample report undertaking innovative activities and so qualify as innovative).

Chapter V investigated behavioural additionality in Spanish SMEs applying a range of matching estimators to the dataset from the Spanish Community Innovation

Survey (CIS) conducted in 2006. Behavioural additionality in our analysis refers to a particular category of network additionality, whereby the research question concerns the effect of public intervention on the probability of establishing and maintaining network relationships with suppliers, customers, competitors, government and Higher Education Institutions (HEIs). Furthermore, the treatment effects were estimated on two additional open innovation practices: outsourcing R&D; and acquiring other external knowledge (such as patents and know-how).

The empirical evidence suggests a positive, but heterogeneous impact of public support on open innovation in Spanish manufacturing SMEs. However, the results of sensitivity analysis indicate that many of the programme effects could be overestimated due to unobserved heterogeneity, which matching estimators cannot account for. Notably, the results for two cooperative partners - cooperation with suppliers and with HEIs - seem to be highly sensitive to hidden bias. We conclude that while hidden bias may be endemic in matching studies, there is no evidence that hidden bias is consistent across different studies of the effectiveness of public support on cooperation. A corollary is the usefulness of investigating the effects of public support for different types of cooperative partners separately, in which we depart from some previous studies (e.g. Fier et al., 2006; Busom and Fernández-Ribas, 2008; Spithoven et al., 2012, p. 171 and p. 181). Similar reasoning leads us also to the usefulness of investigating the effects of support from different levels of government separately (Busom and Fernández-Ribas, 2008).

In total, 18 treatment effects were estimated from the whole sample and the same number from the subsample of innovative SMEs. Five estimated effects in the whole sample are rather robust to selection bias; and six estimates in the subsample (perhaps due to being a more homogenous sample). In total, out of 36 treatment effects, only 11 are not likely to be overestimated. Finally, across both the whole sample and the subsample of innovative firms, five ATT effects are robust to hidden bias:

- For local/regional support, three effects on the following open innovation activities - aggregate cooperation, cooperation with government institutions, and outsourcing R&D;
- For national (government) support, two effects - on horizontal cooperation and cooperation with government institutions.

Overall, we find that public support most robustly increases SME cooperation with government institutions; only slightly less robust is that the largest treatment effects of public support - both regional (a robust finding) and federal (borderline robust) - are for outsourcing R&D activities. Our results suggest that, depending on the source of funding, SMEs are more likely to respond to public support by increasing either their cooperation with government institutions or their investment in extramural R&D than by establishing and maintaining cooperative networks.

A larger number of robust treatment parameters is reported for the subsample of innovative SMEs than for the whole sample. Moreover, the robust ATT effects are uniformly larger in the subsample than in the whole sample, suggesting that public support has a larger additionality effect on SMEs that undertake innovation, relative to those firms that do not innovate. The evidence is consistent to Penrose's (1959) argument that her theory of firm growth applies only to those firms that want to grow rather than to all firms; we find that innovation support is most effective when randomly allocated to firms that self-report as innovative in one form or another.

Finally, in Chapter VI, the hypotheses of both output and behavioural additionalities have been investigated using the MAPEER dataset of European SMEs, covering the period 2005-2010. The treatment effects are estimated by applying a binary endogenous switching model, similar to that in Chapter IV. In assessing the effectiveness of R&D policy on innovation output (i.e. output additionality), robust results are reported for two baseline models and two augmented models. In the former, both models are estimated for participation in national support programmes. A common finding in both models is that public intervention seem to have a crowding-out effect, demonstrated by a negative and statistically significant ATT effect. Estimated ATEs, however, are not consistent across two models. For less innovative firms (innovative sales more than 20%), the ATE effect is negative and even smaller than the ATT effect, suggesting that in this case allocating public funding randomly among the population relatively innovating SMEs would not worsen the adverse effect found for participating firms. Conversely, in highly innovative firms (innovative sales more than 40%), the estimated ATE effect is positive and statistically significant. Therefore, for this category of SMEs, public intervention in the form of randomly allocated funds would have a significant additional effect. Notwithstanding the problems with diagnostic testing, this finding is replicated across all but one model with diagnostic problems.

Another finding from the models without diagnostic problems points to perverse selection into public support. In three from four models, negative and statistically significant correlation coefficients between the error terms of the selection equation and the outcome equation in regime 1 (regime conducive to innovation) suggests a perverse selection on unobservables for participating firms.

Given that the estimated treatment effects in the augmented models are broadly consistent with those from the baseline models, the overall results – a prevailing pattern whereby ATT<ATE - seem to suggest that firms receiving public support are less likely to increase their innovation output as a consequence of treatment assignment than would be the case among firms selected from the sample at random. In this respect, the findings from the analysis of the MAPEER dataset are consistent with those reported in Chapter IV on the analysis of the GPrix survey. In both analyses, the evidence indicates that the ”picking-the-winner” strategy adopted by government agencies not only yields no additional effect but even gives rise to a crowding-out of private funding, i.e. the treatment effects are either zero or sometimes are even negative.

In this chapter, we also estimated programme effects on firms' innovative behaviour, specifically on networking and cooperation for innovation (i.e. behavioural additionality). Again, most parameters are imprecisely estimated, but four models report robust and consistent findings of a smaller ATT effect than ATE. Analysing each type of networking separately, the results suggest that a distribution of support measures via a lottery system would only marginally increase the probability of using online technology or knowledge brokers, but would have significantly increased the probability of informal networking with other firms as well as of participation in innovation networks. The largest potential effect of random distribution is implied by the results for informal networking with research organizations, for which the ATT effect is significantly negative and the ATE significantly positive. Finally, if we take into account the findings for each open innovation practice and from both baseline and augmented models, the dominant pattern is still of smaller ATT than ATE. Therefore, the overall results seem to indicate that, for most types of networking and cooperation for innovation, a random distribution of R&D support measures would have a more positive effect than using the current selection criteria.

Table 7.1. Comparison of the analyses conducted on the GPrix dataset and on the MAPEER dataset

	GPrix data	**MAPEER data**
Type of additionality studied	- Output additionality	- Output additionality - Behavioural additionality
Measures of innovation output	- Product innovation - Process innovation - Organisational innovation - Marketing innovation - Innovative sales	- Innovative sales
Source of funding	- Either national or international funding	- National funding - International funding - Either national or international funding
Main finding	- Systematically smaller ATT than ATE effect	- Systematically smaller ATT than ATE effect

Table 7.1 provides a comparison between the analysis conducted in Chapter IV on the GPrix dataset and the one conducted in Chapter VI on the MAPEER dataset. The main differences are associated with the type of additionality studied, the measures of innovation output employed and the source(s) of funding investigated. With respect to the type of additionality studies, the analysis of the MAPEER data is broader, encompassing the effectiveness of public measures in relation to output and behavioural additionality, while the analysis of the GPrix data focuses exclusively on output additionality. Regarding the measures of innovation output, the GPrix analysis is more comprehensive than the MAPEER analysis, by investigating five distinct measures: introduction of product innovation; introduction of process innovation; introduction of organisational innovation; introduction of marketing innovation; and innovative sales. In contrast, the MAPEER analysis employs a single measure of innovation output, that of innovative sales. Furthermore, the datasets differ regarding the sources of funding

that are separately investigated. The treatment assignment in the GPrix dataset is defined as firms' participation in either national or international innovation support measures, whereas in the MAPEER dataset, the distinction is made between national and international sources of funding, besides firms' participation in either type of funding. Finally, the similarity between the analyses conducted on the GPrix and on the MAPEER datasets is associated with the main findings reported in both analyses on the systematically smaller Treatment Effect on the Treated (ATT) than the Average Treatment Effect (ATE).

7.3 Policy implications

The main research question investigated in the thesis is whether public support enhances SME innovation. In other words, does public support have an additionality effect on innovation? The empirical studies focus on three distinct types of additionality: input, output and behavioural. Given the specific subject of this thesis, innovation in SMEs, we did not empirically test for input additionality, as SMEs usually conduct informal R&D or unmeasured innovation-related activities such as technical design, which implies that accurate data on their intramural and extramural R&D and innovation-related expenditures are scarce. Therefore, the focus of the thesis is on output and behavioural additionalities.

Output additionality is investigated in Chapters IV and VI. The major difference between analyses in these chapters is sector and country coverage. Namely, the dataset used in Chapter IV includes SMEs in traditional manufacturing sectors across seven EU regions, while the dataset used in Chapter VI is gathered from SMEs across manufacturing and service sectors in 28 European countries. Notwithstanding the differences in the industry and country coverage, findings from both empirical analyses are consistent – indicating that public support has a smaller additionality effect on innovation outputs in participating SMEs (the Average Treatment Effect on the Treated - ATT) relative to the effect it could have had if allocated to SMEs chosen at random from the respective samples (the Average Treatment Effect - ATE). Our main policy recommendation regarding output additionality is derived from the relationship between the ATT and ATE effects. However, a cautionary note should be taken into account, as noted in the concluding remarks in Chapters IV and VI. Namely, in the first stage of the selection process, a certain selection on observables (e.g. “due diligence” with respect to firm size and solvency) should be applied by government agencies. After this initial screening of the applicants, eligible SMEs then enter the second stage of the selection process, i.e. distribution of support measures through lottery.

Besides output additionality, another type of additionality – behavioural – was also a subject of quantitative evaluation in the thesis. Behavioural additionality was investigated using two distinct datasets: CIS2006 for Spanish SMEs; and the MAPEER dataset for SMEs across 28 European countries. The impact of innovation support programmes on behavioural additionality in Spanish SMEs was investigated in Chapter V. Taking the three sources of funding jointly (local/regional; federal government; and EU), the estimated ATT effects indicate that the largest impact of public support is found for cooperation with government institutions and for outsourcing R&D. In addition, the treatment parameters for other networking partners (customers, suppliers, competitors, consultants and HEIs) are rather small and the difference between them is not statistically significant. Moreover, the results of sensitivity analysis indicate that treatment effects might not be robust to unobserved heterogeneity. Given the limitations most researchers face in analysing the additionality effects of innovation related policies with respect to information on the selection process, the empirical findings for Spanish SMEs suggest the need for data on the selection process in order to control for unobservables related to the selection mechanism.

Finally, behavioural additionality was also estimated in Chapter VI, using the MAPEER sample of European SMEs. The overall results, similar to the conclusion on behavioural additionality reached in Chapter V, indicate that a random distribution of public support measures among innovative European SMEs could induce a larger additionality effect, relative to the current selection process by public agencies. Again, we should bear in mind that a distribution of support measures via lottery does not exclude due diligence checking on the part of public agencies, which should be performed as a first stage in the selection process – after which a random allocation of public instruments could be performed.

7.4 Contributions to knowledge

Our research has contributed to the current evaluation of public policy in several directions. First, we investigate output additionality in traditional manufacturing SMEs across Europe. No previous study explicitly focuses on additionality effects among traditional SMEs in traditional manufacturing sectors. In this analysis, we applied binary endogenous switching models, which is another contribution to knowledge, as this modelling, to our knowledge, has not been applied hitherto in the context of output additionality.

Second, we applied a range of matching estimators in Chapter V to investigate behavioural additionality in Spanish SMEs. Although the issue of behavioural additionality has been previously investigated for Spanish firms, our analysis contributes to the empirical literature by separately investigating three sources of funding. In addition, we conducted sensitivity analysis, as a recommended part of any analysis conducted by applying matching estimators. To our knowledge, only one study by Alecke et al. (2012), although in the context of input additionality, reports the results of sensitivity analysis.

Third, no study, irrespective of the type of additionality investigated, reports both the ATT effects and the ATEs. Analysis conducted in Chapters IV and VI estimates both treatment effects, in addition to estimating the Average Treatment effect of the Untreated (ATU) as well.

Fourth, empirical evidence presented in Chapter VI refers to both output and behavioural additionalities of European SMEs. To our knowledge, no previous studies cover such a large number of countries. Thus, our results can be taken as a general overview of the effectiveness of innovation policies on innovation performance among European SMEs.

Five, the range of empirical evidence from the thesis is consistent with Greene's (2009) argument, as noted in Section 3.6, on the inverse relationship between study quality and the size of estimated treatment effects on participating firms. Consistent with Greene’s hypothesis, the empirical analyses conducted in Chapters IV and VI employ endogenous switching models, that are more sophisticated than matching estimators, as the former control for both selection on observable and unobservable firm characteristics, whereas the latter are limited to selection on observed characteristics only. While the estimated treatment effects on participating firms are mostly negative when estimated by endogenous switching models (i.e. implying a crowding out effect of public funding), the estimated ATT effects from matching estimators reported in Chapter V are uniformly positive, suggesting an additional effect of innovation support measures.

Finally, policy implications drawn from the empirical analyses in the thesis about the random allocation of public support among innovative, or mostly innovative firms, are in line with Penrose's (1959) comment on the subject of her investigation, as noted in Section 4.5. Namely, Penrose excluded from her exposition firms that do not grow and/or do not want to grow, and developed her theory of firm growth by exclusively analysing those firms that do grow. In similar vein, the analysis in this thesis and its ensuing policy implications refer to innovating SMEs, as noted in Sections 4.5 and 6.5. Therefore, policy recommendations stemming from the empirical findings in the thesis are concerned with SMEs that undertake some type of innovation but could undertake more.

7.5 Limitations of the research

The major limitation of our research is the lack of longitudinal data. In cross-sectional analysis, we cannot model the dynamics of participation in public support programmes. The literature suggests that a successful record of previous participation increases the likelihood of applying for and receiving public funding in the future. Moreover, the effect of public support is likely to be distributed over the medium to long run (David et al., 2000; Lach, 2002; Busom and Fernández-Ribas, 2008; Cerulli, 2010; Zúñiga - Vicente et al., 2014), rather than to exhibit only a contemporaneous or short-run effect, which is the only impact captured in a cross-sectional setting.

Second, a few limitations stem from the applied econometric techniques. Regarding the binary endogenous switching models applied in Chapters IV and VI, there is no known way to test for the joint normality of the error terms, which is an underlying assumption in selection models. Furthermore, the matching estimators applied in Chapter V cannot take into account unobservable firm characteristics, which are likely to occur in the selection process. Although, following the best practice in the literature on matching, we conducted sensitivity analysis to provide some testing of the robustness of the estimated treatment effects, the analysis as such cannot answer the question as to whether potential unobserved heterogeneity influences the treatment assignment. In addition, the underlying assumption of matching estimators is that there are no spillover effects. This is a common limitation in any studies applying matching estimators. Cerulli (2010) notes that the issue of dealing with spillovers is foremost associated with problems of operationalizing spillovers, i.e. designing an appropriate measure of spillovers, as the literature on additionality in innovation policy does not provide any guidelines on how to measure and model spillover effects.

Third, a further limitation of our analysis is associated with the sample size permitted by the databases used in Chapters IV and VI. Namely, both datasets are too small for estimating individual country treatment effects. It would be of importance for policy makers and practitioners to compare the effectiveness of public interventions across countries. Yet sample size is one of the key limitations of empirical studies more generally. Moreover, besides the fact that very few studies include more than one country, comparison among studies is seriously hampered by the absence of a core (parsimonious) model and the corollary of differences in modelling strategies and applied evaluation models.

Fourth, as discussed in Chapter III, most studies do not contain information about the amount of subsidies. That is also a limitation of our research, preventing us from testing the hypothesis of a partial crowding out effect. Empirical evidence from the few studies with available levels of subsidies have indicated that partial crowding out could be pertinent to the treatment assignment.

Finally, the Community Innovation Survey (CIS) datasets are not specifically designed for the evaluation of innovation policy. Thus, no information on the selection process is available, which is a common and significant obstacle to evaluation studies (Cerulli, 2010).

7.6 Directions for future research

Limitations of our study discussed above can also provide avenues for future research. Availability of panel data would allow the modelling of dynamics in the innovation process which, in turn, would facilitate the estimation of the medium- and long-run effects of support measures. Furthermore, using longitudinal data would enable the application of evaluation methods that are capable of controlling for unobserved heterogeneity (such as Fixed Effects estimators, GMM estimators and conditional Difference-in-Difference estimators). Regarding the measurement of subsidies, the availability of levels of subsidies would enable the distinction between net (private, own) R&D effort and total R&D expenditure with the former being the adequate outcome variable for investigating input additionality (Cerulli, 2010). In addition, availability of the amount of subsidies would enable testing of the hypothesis of a partial crowding out effect (Cerulli, 2010; Zúñiga -Vicente et al., 2014).

An interesting avenue for future research, according to work by Antonioli and Marzucchi (2012), would be to investigate the causal relationships between input, output and behavioural additionality. We expect that the structural models, such as the one suggested by Garcia and Mohnen (2010), might provide some guidelines on how to incorporate all three types of additionality in one model, similar to the CDM model.

In Chapters V and VI, we investigated the treatment effects on firms' innovative behaviour (behavioural additionality). However, due to lack of data on other types of behavioural additionality, such as scale and scope additionality, follow-up and management additionality (Georghiou and Clarysse, 2006), our focus was specifically on network additionality. The other types of behavioural additionality are promising directions for future research, as no study has yet econometrically analysed these types of behavioural additionality.

Finally, as noted in Chapter III, most empirical studies focus on manufacturing sectors. The role of service innovation in firms' innovation performance is gaining attention (Dankbaar and Vissers, 2010) and is likely to be the subject of future studies (Zúñiga -Vicente et al., 2014).

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APPENDICES

Appendix I

Table A1.1. Empirical studies applying matching estimators - part I

Authors	Country	Dataset	Sample size	Sectors	Treatment variable	Outcome variable	Model specification
Czarnitzki and Fier (2002)	Germany	Pooled cross sectional data, Mannheim Innovation Panel - Services 1997-1999	1,084 firms, 210 treated	Service sectors	Binary	*Input additionality* - Innovation intensity (innovation expenditure over sales) - Innovation expenditure	- Firm size (log) - DV if firm is located in Eastern Germany - DV for continuous R&D activities - Lagged share of employees with a university degree in natural science and engineering (absorptive capacity) - Lagged share of employees in business administration - Population density of the district -Firm age (inverse) - Sectoral growth rates - DV for legal form - Time DV for 1998 and industry DVs
Almus and Czarnitzki (2003)	Eastern Germany	Pooled cross sectional data, Mannheim Innovation Panel (MIP) for 1995, 1997 and 1999	828 firms (625 treated and 303 untreated firms)	Manufacturing sectors	Binary	*Input additionality* - R&D intensity (ratio of R&D expenditure to sale)	- Firm size - Firm size squared - Firm age - Market competition - Sectoral and time DVs - Import ratio - Foreign competition (export related sales) - Concentration ratio - Capital intensity (tangible assets per

							employee) - DV for legal firm - Previous R&D experience (DV whether firm has R&D departments) - DV for belonging to a group
Aerts and Czarnitzki (2004)	Belgium (Flanders)	CIS3 (1998-2000) merged with annual account data and patent data (only 43 firms filed for patents)	776 firms (180 treated)	Manufacturing and selected service sectors	Binary	*Input additionality* - R&D expenditure - R&D intensity (R&D expenditure over turnover) *Output additionality* -DV for patenting firms - Number of patents per employee	- Firm size - Patent stock - Export quota (exports over turnover) - Capital intensity - Cash flow per employee - Debt per employee - Belonging to a group - DV for foreign parent company
Duguet (2004)	France	Pooled cross sectional data, BRN (fiscal files) and R&D surveys from 1985 to 1997	Between 1032 and 1672 firms	Manufacturing and service sectors	Binary	*Input additionality* - DV if firms increased R&D expenditure - Growth rate of R&D expenditure	- Lagged firm size (measured as sales) - Lagged private R&D to sales - Lagged debt to sales ratio - Past public support (DV for receiving support and a constructed average subsidy rate)
Czarnitzki and Hussinger (2004)	Germany	Pooled cross sectional data, merged the MIP and PROFI databases from 1992 to 2000	3,799 firms (588 treated)	Manufacturing sectors	Binary	*Input additionality* - Total R&D expenditure - Total R&D intensity - Private R&D expenditures (net of subsidies) - Private R&D intensity (private R&D expenditures over sales)	- Firm size (logarithm of the number of employees) - Patent stock per employee (lagged value) - DV for firms located in East Germany - Firm age (logarithm) - DV for belonging to a group - DV for firms belonging to a group with a foreign parent company - Export quota (exports over sales) - Import intensity at industry level - Hirschmann-Herfindahl Index (HHI) - DV for capital companies (firms with

							liability limiting legal form) - Time and twelve industry DVs
Heijs and Herrera (2004)	Spain	Business Strategy Survey (1998-2000)	681 firms, 243 treated firms	Manufacturing sectors	Binary	*Input additionality* - R&D intensity	- Firm size - Firm age - Firm ownership - Investment capacity - Innovation funding difficulty - Evolution of the main market - Evolution of market share (diversification) - Export propensity - Import propensity - Formality of innovative activity - Cooperative attitude - Technological export - Technological import - Regional and sectoral DVs
Kaiser (2004)	Denmark	Ministry of Economic and Business Affairs for two years separately 1999 and 2001	550 firms	Manufacturing and service sectors	Binary	*Input additionality* - R&D intensity (R&D expenditures over sales	- DV for holding at least one patent - DV for cooperation - DV for new or improved product - Share of high qualified employees - Export DV - Share of exports in Euros - Year DV for 1999 - Sectoral DVs
Lööf and Hesmati (2005)	Sweden	CIS3 1998-2000 merged with the register data	770 firms, 160 treated	Manufacturing and business services	Binary	*Input additionality* - R&D per employee	- Firm size - Firm size squared - Gross investment per employees - Capital stock per employee - Equity per employee - Debt per employee - Financial constraints

							- Skill constraints - Export - Foreign owned - Belonging to a group - Recurrent R&D - Demand pull R&D - 15 sectoral DVs
Hujer and Radic (2005)	Germany	IAB Establishment Panel (1997-2001)	2,714 firms, 492 treated	Manufacturing and service sectors	Binary	*Output additionality* - DV for the introduction of product innovation	- Competition intensity - Gini concentration - Export share - State of technology - DV for firms with a separate R&D department - Share of high qualified employees - Number of R&D cooperation - Firm size (the number of employees) - Share of one man businesses - Share of firms as partnerships - Share of private limited companies - Share of capital companies - Business development (Likert scale)
Fier et al. (2006)	Germany	Merged two waves of Mannheim Innovation Panel (MIP) data with PROFI, DPMA and CATI data, periods covered 1998-2000 and 2001-2003; additional data collected via telephone survey	659 firms, 142 treated	Manufacturing and selected service sectors	Binary	*Behavioural additionality* - DV for firms collaborating only with other businesses - DV for firms collaborating only with scientific institutions - DV for firms that collaborate with other businesses and scientific institutions	- Firm size (logarithm of turnover) - Firm age - Three DVs whether firms exhibit no, occasional or regular R&D activities - Patenting activities (lagged DV) - Export intensity - Regional DV for firms located in East Germany - Eight sectoral DVs and one year DVs

Czarnitzki and Licht (2006)	Germany (Western and Eastern separately)	Pooled cross sectional data, Mannheim Innovation Panel for 1994, 1996, 1998 and 2000 merged with data on patents application from the German Patent Office	1,967 for Eastern Germany (735 treated), 4,495 for Western Germany (638 treated)	Manufacturing and service sectors	Binary	*Input additionality* - R&D expenditures - Innovation expenditure (R&D and other inputs)	- Firm size (logarithm of the number of employees) - Herfindahl index of market concentration - Firm age - DV for export activity - Patent stock - DV for own R&D department - Credit rating - Firm ownership - Industry and time DVs
Aerts and Schmidt (2008)	Flanders (Belgium) and Germany	CIS 4 (2002-2004)	157 firms from Flanders and 484 firms from Germany	Manufacturing sector and computer services, R&D services and business-related services	Binary	*Input additionality* - R&D expenditure - R&D intensity (ratio of R&D expenditures over turnover)	- Firm size (natural logarithm of the number of employees) - Firms' patent stock (to control for the previous R&D activities) - DV for belonging to a group - DV for firms belonging to a group with a foreign parent company - Export quota (ratio of export over turnover) - DV for the firms from East Germany - Sectoral DVs - Interaction term between the industry DVs and the natural logarithm of the number of employees
Gonzáles, and Pazó (2008)	Spain	Business Strategy Survey (unbalanced panel of firms from 1990 to 1999)	9,455 observations from 2,214 firms	Manufacturing sectors	Binary	*Input additionality* - R&D intensity (R&D expenditure over sales)	- Firm size - Firm age - Capital growth - Export (DV) - Market power (DV) - Foreign capital (DV) - Technological sophistication (DV) - Industry, regional, time and size DVs
Busom and Fernandez -Ribas	Spain (Catalonia)	CIS 1999	624 firms, 180 treated	Manufacturing sectors	Binary	*Behavioural additionality* - DV for all types	- Firm size (number of employees) - DV =1 if at least one time-person is allocated to R&D over a longer period

(2008)						of cooperation - DV for customers/ suppliers partnerships - DV for public-private cooperation	- DV =1 if a firm applied for patents in Spain - DV = 1 if a firm applied for patents in Spain and abroad - Ratio of R&D researchers to non-R&D employees - Logarithm of average wage of R&D employees - DV= 1 if a foreign share in ownership is at least 50% - Export intensity (share of export in total sales) - Five industry DVs (based on the OECD classification of manufacturing firms according to technological intensity)
Cerulli and Potí (2008)	Italy	CIS3 (1998-2000) merged with balance sheet variables	5,672 firms (2,347 treated)	Manufacturing and service sectors	Binary	*Input additionality*: - R&D expenditures - R&D intensity (ratio of R&D expenditures to turnover) - R&D per employee *Output additionality* - Innovative turnover	- Firm size (number of employees) - Share of employees with a degree or university diploma - Share of turnover from export - Capital stock per employee - Cash flow per employee - Share of debt in total liabilities - Value of IPR and capitalized R&D expenditures per employee - Belonging to a foreign group - Firm age - Belonging to a group - Regional and sectoral DVs
Fernandez -Ribas and Shapira	Spain (Catalonia)	CIS3 period 1998-2000	930 firms	Manufacturing sectors	Binary	*Behavioural additionality* - DV =1 if a firm	- Firm size (three DVs for small, medium-sized and large firms) - Export intensity (exports over sales)

(2009)						cooperates with partners abroad; - DV=1 if a firm cooperates in joint R&D project with at least one partner from the EU - DV=1 if a firm cooperates in joint R&D project with at least one partner outside the EU	- DV=1 if a firm uses patents to protect innovation - DV=1 if a firm invests in machinery, equipment and other technological knowledge (patents, licences etc.) - DV=1 for firms with continuous R&D activities - Human capital (number of R&D researchers over a number of non-R&D employees - Five industry DVs (OECD classification)
Aschhoff (2009)	Germany	Pooled CIS dataset merged with a database with the grant size and patent application data, period 1994-2005	8,528 observations from 3.583 firms	Manufacturing and knowledge-intensive service sectors	Continuous	*Input additionality* - R&D expenditure *Output additionality* - Innovative sales from products new to the market	*Model specification for input additionality* - DV for the receipt of subsidy from EU schemes in previous 2 periods - DV for the receipt of subsidy at regional level in previous 2 periods - Logarithm of firm size - Logarithm of firm age - DV for continuous R&D investment - Shares of employees with a university degree - Patent stock - DV for belonging to national group - DV for belonging to national group - DV for East Germany - Sectoral and time DVs *Model specification for output additionality* - Counterfactual R&D expenditure - R&D induced by funding - R&D expenditures for firms with no

							grants - R&D expenditures of firms that received grants first time - R&D expenditures of frequent recipients - Logarithm of innovative sales - Logarithm of innovative sales squared - Logarithm of patent stock - DV for cooperation - DV for East Germany - Sectoral and time DVs
Herrera et al. (2010)	Spain	Pooled cross sectional data, Business Strategy Survey in 1999 and 2000	1,718 firms, 208 treated	Manufacturing sectors	Binary	*Input additionality* - R&D intensity (ratio of R&D expenditures to sales) *Output additionality* - Propensity to patenting (number of patents per employee)	- Lagged explanatory variables (previous R&D expenditure) - Firm size - Firm age - Regional and sectoral DVs - Firm's ownership - Innovation funding difficulty - Growing market DV - Market concentration (main market less than 10 competitors) - Export propensity
Marino et al. (2010)	Denmark	Pooled cross sectional data, Danish R&D statistics merged with IDA database, accounting database and CEBR database for the period 1997-2005	13,007 observations, 441 treated firms	Manufacturing and service sectors	Continuous and categorical	*Input additionality* - R&D expenditure (logarithm) - Growth rate of private R&D expenditure	- Logarithm of total assets over value added (proxy for capital intensity) - Logarithm of share of loans in total liabilities (indebtedness) - Share of export in sales - R&D intensity indicator - Public funding intensity (ratio of public funding to private R&D expenditure) - Share of highly-skilled employees

							- Share of vocational workers - DV for R&D department - DV for foreign ownership - DV for firms established less than 3 years ago - DV for co-patent (proxy for cooperation) - DVs for size, industry and year
Reinkowski et al. (2010)	Germany (Thuringia-East Germany)	GEFRA-Business Survey 2004 (2001-2003)	1,484 firms, 284 treated	Manufacturing and business oriented service sectors	Binary	*Input additionality* - Logarithm of R&D intensity (R&D expenditures over total turnover) *Output additionality* - DV for patent registration	- Logarithm of firm size (number of employees) - Logarithm of firm age - Logarithm of firm age square - Share of high-skilled employees - Regional sales - Share of sales in West Germany - DV for firms with R&D department
Marino and Parrota (2010)	Denmark	Danish R&D statistics merged with IDA database and accounting database 1997-2005 (pooled cross sectional data for two consecutive years)	268 observations	Manufacturing and service sectors	Continuous	*Input additionality* - Private R&D expenditures *Output additionality* - Number of patent applications *Behavioural additionality* - Share of R&D employees	- Total asset value - Indebtedness - R&D intensity - Public funding intensity - Share of highly-skilled employees - Export DV - Size, industry and time DVs
Carboni (2011)	Italy	Survey of Manufacturing Firms 2003 (2001-	1,235 firms	Manufacturing sectors	Binary	*Input additionality* - Private (internal and external) R&D	- Firm size (logarithm of the number of employees) - Firm size squared (logarithm)

		2003)				expenditures per employee - Internally financed R&D - Credit financed R&D	- Capital intensity - Share of researchers in total number of employees - DV for the innovation status - Ratio of debt over total debt - DV for credit constraints - DV if firm received support other than for R&D - Export DV - Fifteen sectoral DVs
Alecke et al. (2012)	East Germany	GEFRA Business Survey in 2003	1,267 firms, 284 treated firms (only SMEs in the sample)	Manufacturing and service sectors	Binary	*Input additionality* - R&D intensity (R&D expenditure relative to turnover) *Output additionality* - Patent application	- Firm size - Firm age - Capital intensity (tangible assets per employee) - Investment intensity (investment divided by sale) - Share of highly skilled workers in total number of employees - Export ratio - DV for firm's legal form - DV for belonging to a group - DV for R&D experience (absorptive capacity) - DV for own R&D department - Industry DVs
Marzucchi (2011)	Italy and Spain	CIS4 (2002-2004)	7,905 firms in Spain and 3,851 in Italy	Manufacturing sectors	Binary	*Input additionality* - Intramural R&D expenditure	- Turnover (logarithm) - DVs for firm size - DV for belonging to a group

	- Intramural R&D intensity (intramural R&D expenditure over turnover) *Output additionality* - DV for process innovation - Share of innovative sales due to products new to the market - Share of innovative sales due to products new to the firm - Sum of innovative sales - DV for patent application *Behavioural additionality* - DV for engagement in formal training programme - DV for cooperation with other firms - DV for cooperation with research organisations	- DV for affiliation with multinationals - Exporting - DV for engagement in R&D - DV for permanent engagement in R&D - DVs for lack of internal funding - DVs for difficulties in accessing external funding - DVs for the importance of the government sources of information - DVs for the importance of information from professional and industry associations - Sectoral DVs

						- DV for acquisition of information from other firms - DV for acquisition of information from universities or private research institutes	
Afcha Chavez (2011)	Spain	Business Strategy Survey for the period 1998-2005	1,136 firms (7,029 observations)	Manufacturing sectors	Binary	*Behavioural additionality* - DV=1 if firms cooperate with consumers or suppliers - DV =1 if firms cooperate with universities or technological centres	- Firm size (DV) - Firm age - Industry DVs - Percentage of foreign capital - DV = 1 if firms introduce product innovations - DV = 1 if firms introduce process innovations - Number of product innovations - Number of patents (in and outside of Spain) - DV = 1 if firms elaborate research indicators - Payments for licences - DV = 1 if firms employs engineers and graduates - DV = 1 if firms employs workers with experience in R&D activities - DV=1 if firms received regional subsidies - DV=1 if firms received national subsidies
Cerulli and Potí (2012)	Italy	Pooled CIS3 (1998-2000) and CIS4(2002-2004),	2,574 firms; longitudinal data 5,923	Manufacturing and service sectors	Binary	*Input additionality* - R&D expenditure - R&D intensity	- Firm size - Share of employees with a degree or university diploma

		(CIS4 merged with balance sheet data)	firms.			- R&D per employee	- Share of turnover from export - Capital stock per employee - Cash flow per employee - Chare of debt in total liabilities - Value of IPRs and capitalized expenditures per employee - DV for belonging to foreign group - DV for firm age (=1 of firm was founded between 1998-2000) - DV for belonging to a group - Regional and sectoral DVs
Czarnitzki and Lopes-Bento (2012)	Spain, Germany, Belgium (Flanders), Luxembourg and South Africa	CIS4, period 2002-2004 For Belgium, Germany and Luxembourg, CIS-harmonized survey for South Africa and PITEC dataset for Spain	805 firms from Flanders, 1,491 firms from Western Germany, 730 firms from Eastern Germany, 6,006 firms from Spain, 248 firms from Luxembourg and 510 firms from South Africa	Manufacturing and business related service sectors	Binary	*Input additionality* - Innovation intensity (ratio of total innovation expenditure to sales) - Internal R&D investment (ratio of internal R&D expenditures to sales)	- Firm age (natural logarithm) - Firm size (natural logarithm of the number of employees) - DV for belonging to a group - DV for the headquarter located in foreign territory - Capital stock (proxied by the lagged investment into tangible assets divided by the number of employees) - DV for permanent internal R&D activities - DV for exporting - Industry DVs
Herrera and Sánchez-González (2012)	Spain	Longitudinal PITEC (Panel of Technological Innovation) dataset (2003-2007)	4,713 firms (1,218 subsidized)	Manufacturing and service sectors	Binary	*Input additionality* - Private R&D intensity (ratio of internal R&D expenditures to turnover) *Output additionality* - Innovative sales	- Firm size (natural logarithm of the number of employees) - Firm age (DV whether the firm is newly created or not) - DV whether the firm is private without foreign capital - Exporting (ratio of exports over sales) - DV whether the firm undertakes continuous R&D activities - DV whether the firm received

						from products new to the firm - Innovative sales from products new to the market	subsidies in the previous period - Three DVs for industry categories (high-tech manufacturing, medium-tech manufacturing and high-tech service sectors) - Regional DVs
Antonioli et al. (2012)	Italia (Emilia-Romagna)	PRRIITT survey data merged with balance sheet data, period covered 2006-2008	408 firms, 99 treated	Manufacturing	Binary	*Behavioural additionality* - DV=1 if employees' competences are improved - DV=1 if training programmes were provided - DV=1 if training programmes for improving specialized competencies were provided - DV =1 if a firm cooperates with suppliers - DV =1 if a firm cooperates with customers - DV =1 if a firm cooperates with competitors	- Firm size (logarithm of the number of employees) - Expenditure per capita in intramural R&D and advertising - Cash flow per capita - Short-term debt index - Five sectoral DVs (according to Pavitt taxonomy) and ten regional DVs

						- DV =1 if a firm cooperates with firms in the same group within the region - DV =1 if a firm cooperates with firms in the same group outside the region	
Foreman-Peck (2013)	United Kingdom	CIS4, period 2002-2004 (only SMEs)	12,199 firms	Manufacturing and service sectors	Binary	*Output additionality* - Either product or process innovation, either new to the firm or to the market	- Share of graduates in the total number of employees - Number of graduated employees - Firm size (logarithm of turnover) - DVs for collaboration (with other firms in the group, with suppliers, with customers, with competitors and with universities) - Intramural R&D over turnover - Plant and machinery investment over turnover - Turnover (as a proxy for firm size) - Firm age - DV for belonging to a group - Exporting (foreign sales) - Sectoral and regional DVs
Czarnitzki and Lopes-Bento (2013)	Belgium (Flanders)	Pooled CIS4 (2002-2004), CIS5 (2004-2006), CIS6(2006-2008) merged with Belfirst database and ICAROS database	4,761 observations (292 treated firms)	Manufacturing and business related service sectors	Binary	*Input additionality* - Internal R&D intensity (internal R&D expenditures to sales) - Share of R&D employees	- Firm size (logarithm of the number of employees) - Firm size squared (logarithm of the number of employees squared) - DV for firms belonging to a group - DV for firms having headquarters on foreign territory - Firm age (logarithm) - Patent stock per employee - Exporting (export-to-sales ratio)

							- Labour productivity (sales per employee) - Number of IWT projects within the three preceding years - Industry and time DVs
Antonelli and Crespi (2013)	Italy	Merged MCC data from two waves (1998-2003); panel data	752 firms	Manufacturing sectors	Binary	*Input additionality* - R&D expenditure per employee - Private R&D expenditure per employee	- DV for past R&D subsidy - Firm size (lagged logarithm of the number of employees) - DV if firms engage in any innovative activities - Share of R&D employees in total number of employees - Export (lagged DV) - Fixed investment per employee (lagged logarithm) - DV for firms belonging to a group - Lagged DV for firms that were declined when applying for a loan - Share of employees with university degree (lagged value) - Industry DVs based on Pavitt taxonomy

Table A1.2. Empirical studies applying matching estimators - part II

Authors	Estimators	Pre-treatment variables	Balance variables (covariates only, PS only, covariates and PS)	Type of balancing test	Type of variance estimation	Robustness check	Results	Limitations
Czarnitzki and Fier (2002)	Nearest neighbour with Mahalanobis metric	Not clear	Propensity score with the population density of districts, in Mahalanobis metric industry DVs	Difference in mean before and after matching.	Bootstrapped SEs	No	Full crowding out can be rejected. ATT is 5.7 percentage points (p.p.) for innovation intensity and 1.6% p.p. for innovation expenditure.	- Bootstrapping is applied for estimating the variance. - Standardized bias not used as a balancing test. - No robustness check. - No sensitivity analysis.
Almus and Czarnitzki (2003)	Nearest neighbour matching with Mahalanobis metric and caliper	Not clear	Hybrid matching - propensity score and industry DVs	Difference in mean before and after matching, kernel density before and after matching	Bootstrapped SEs	No	Full crowding out can be rejected. ATT is 3.94 p.p.	- Bootstrapping is applied for estimating the variance. - Standardized bias not used as a balancing test. - No robustness check. - No sensitivity analysis.
Aerts and Czarnitzki (2004)	Nearest neighbour matching with	No	No	Difference in means after	Lechner - corrected SEs	OLS; subsample of innovative firms.	Crowding out is rejected in both the	- Small sample size - No robustness check applying other matching estimators

	Mahalanobis metric and with replacement			matching, kernel density			sample including non-innovating firms and in the subsample with only innovating firms. ATT for R&D intensity is 2.9% p.p. No effect on the patent application (no output additionality).	- No sensitivity analysis - Standardized bias not used as balancing test
Duguet (2004)	Nadaraya-Watson estimator (Gaussian kernel)	Yes	Not reported	Not reported	Bootstrapped SEs	Additional outcome variables: - DV for increase in R&D expenditure to sales ratio - growth rate of R&D expenditure to sales ratio	ATT statistically insignificant in 12 from 13 models; ATE statistically insignificant in 8 from 13 models.	- The study estimates ATT, ATE and ATU for each year separately. - No sensitivity analysis. - No robustness check applying other matching estimators.
Czarnitzki and Hussinger (2004)	Hybrid matching (NN matching with Mahalanobis metric)	Partly	Matching variables are propensity score and firm size. Mahalanobis metric based on industry	Difference in means after matching	Lechner (2001) SEs	Subsample of SMEs (firms with less than 500 employees)	Additionality found for all four outcome variables (ATT ranging from 0.90 to 1.15 %).	- No robustness check applying other matching estimators. - No sensitivity analysis. - Standardized bias not used as balancing test. - SMEs are defined as firms with less than 500 employees.

			and time DVs					
Heijs and Herrera (2004)	Nearest neighbour matching	Not reported	Not reported	Not reported	Bootstrapped SEs	4 model specifications; estimation for subsamples according to firm size.	Additionality reported as ATT is between 1.6 % and 2.1 %.	- Bootstrapping is applied for estimating the variance. Small firms are defines as having less than 200 employees, medium-sized firms as having 200-500 employees. - Very small sub-samples. - No sensitivity analysis. - No robustness check using other matching estimators.
Kaiser (2004)	Nearest neighbour, kernel matching and stratification matching	Not reported	Not reported	Not reported	Bootstrapped SEs.	IV approach; matching on subsamples of manufacturing and service sectors.	ATT insignificant, i.e. no additionality and no crowding out.	- Small sample size. - No sensitivity analysis for matching estimator. - The study does not report whether balancing test was conducted and what type.
Lööf and Hesmati (2005)	Nearest Neighbour and kernel matching	Not reported	Not reported	Difference in means after matching.	Not reported	Subsample of medium-sized and large firms.	Crowding out hypothesis can be rejected, but additionality is found only in firms with less than 50 employees.	- The study does not report type of variance estimation. - Small common support region (156 firms for kernel and 216 for NN matching). - No sensitivity analysis. - Standardized bias not used as balancing test.
Hujer and Radic (2005)	NN matching estimator	No	Propensity score only; exact matching on industrial sectors.	Standardized bias before and after matching.	Not reported	Kernel matching, multivariate probit, IV approach (simultaneous probit model), conditional difference-in-	Results change depending on the method applied; additionality found when methods controlling for	- No sensitivity analysis for matching estimators. - Type of variance estimation is not reported.

						difference estimator	observables are applied; when methods controlling for unobservables are applied, crowding out cannot be rejected.	
Fier et al. (2006)	NN matching with replacement and Mahalanobis metric	Not clear	Matching arguments in Mahalanobis metric: - propensity score - firm size - lagged patent DV - 3 DVs for regularity of R&D activities - firm age - 7 industry DVs - regional DV	Difference in means before and after matching	Lechner (2001)	Bivariate probit model for the continuing collaboration.	- Crowding out is found in the model where the outcome variable is collaboration with other businesses. Additionality reported in models where the outcome variables are collaboration with scientific institutions and cooperation with both competitors and scientific institutions. - The ATU effect is also estimated (it is negative and	- No sensitivity analysis for matching estimators - No robustness check applying other matching estimators - Standardized bias not used as balancing test.

							statistically significant for collaboration with both other businesses and scientific institutions).	
Czarnitzki and Licht (2006)	Nearest neighbour matching	Not clear	Propensity score, industry and year DVs	Difference in means after matching.	Not reported	Control group restricted to permanent R&D performers.	Crowding out effect can be rejected. Input additionality is reported for both measures of innovation Input.	- Type of variance estimation is not reported. - Standardized bias is not used as a balancing test. - No sensitivity analysis. - Difference-in-Difference (DiD) method could be applied on the pooled cross-sectional data.
Aerts and Schmidt (2008)	Nearest Neighbour matching with replacement	No	PS on control variables and exact matching on firm size variable and DV for Easter German firms	Difference in means before and after matching.	Lechner (2001)	- Only R&D active firms - Additional control variables	Crowding-out can be rejected in both the Flemish and the German case. Input additionality is found in both countries.	- No sensitivity analysis. - No robustness check using other matching estimators. - Standardized bias is not used as a balancing test.
Gonzáles and Pazó (2008)	Bias-adjusted Nearest Neighbour (NN) estimator	Yes	Propensity score, lagged outcome variable, lagged subsidy DV, sectoral, size and time DVs.	Difference in means before and after matching; kernel density	Abadie and Imbens - corrected standard errors	- For subsamples based on firm size and industry classification; - Two control groups: all non-	The ATT and ATU effects are statistically insignificant. Full crowding out can be rejected, but	- Difference-in-Difference (DiD) method could be applied because of availability of two-period data. - No sensitivity analysis. - Standardized bias not used as balancing test. - The dose-response model

						treated firms and just R&D performing firms.	no additionality is found except in small firms and those operating in low-technology sectors.	could be applied, as the amount of subsidy is available, to test for the partial crowding out effect.
Busom and Fernández-Ribas (2008)	Univariate and bivariate probit models	No	PS only	Difference in means after matching	Bootstrapped SEs	- Matching (kernel and stratification) - Hausman test for endogeneity	Behavioural additionality found for both public-private cooperation as well as customers/ suppliers partnerships	- Four covariates not balanced after matching (authors should either re-specify a probit model, use other matching estimators or both), but the authors report results with unbalanced covariates. - Type of kernel used in kernel matching is not reported. - The choice of bandwidth is not reported nor a robustness check with several bandwidths is conducted. - Standardized bias is not used as a balancing test. - No sensitivity analysis.
Cerulli and Potí (2008)	Nearest matching, stratification, three-nearest neighbours, kernel matching, radius matching	Partly	Not reported	Difference in means before and after matching; kernel density before and after matching	Not reported	- Heckman selection model; OLS - Subsamples based on firm size, industry and location	With regard to input additionality, full crowding out can be rejected, but not for low knowledge intensive services, small firms (10-19	- The study does not report what method for estimating variances is applied. - Standardized bias not used as balancing test. - No sensitivity analysis for matching estimators. - For kernel matching, robustness check could include different bandwidth.

							employees) and the automotive industry. No output additionality is reported (a statistically insignificant ATT effect).	
Fernández-Ribas and Shapira (2009)	NN matching (with and without weights); stratification and kernel matching	No	Not reported	Difference in mean after matching	Bootstrapped SEs (100 replications)	Bivariate probit models for three outcome variables (cooperation with partners abroad; cooperation in joint R&D project with at least one partner from the EU; cooperation in joint R&D project with at least one partner outside the EU)	The results are not robust (the statistically significant ATT effects are reported when stratification is used, and insignificant effects when other matching estimators are applied).	- Balancing test after matching is reported but it is not clear for which estimator. - The results are not robust (the statistically significant ATT effects are reported when stratification is used, and insignificant effects when other matching estimators are applied). - Type of kernel function is not reported. - The choice of bandwidth is not reported nor a robustness check with several bandwidths is conducted. - Standardized bias is not used as balancing test. - No sensitivity analysis. - Medium- sized firms are defined as having 50-285 employees (not in line with the European Commission regulation)
Aschhoff (2009)	NN matching with	Not defined for	Propensity score, firm	t-test on the mean	Lechner (2001)	Binary probit models	Full and partial	- Given the availability of the amounts of subsidies, a

	Mahalanobis metric	each covariate	size and patent stock included in Mahalanobis metric, exact matching for subsidy DVs and year DVs	differences after matching.		separately for each pair of subsidy category	crowding out can be rejected. Both input and additionalities are reported.	generalized propensity score (GDS) could be estimated and a dose-response method could be used. - No sensitivity analysis. - No robustness check applying other matching estimators. - Standardized bias is not used as a balancing test.
Herrera et al. (2010)	Nearest Neighbour (NN) matching estimator	Yes	Not reported	Difference in means before and after matching.	Bootstrapped SEs.	Robustness check based on firm size.	Input and output additionalities cannot be rejected, but the effect is larger for SMEs. Hence, the impact of public support is sensitive to firm size.	- No sensitivity analysis. - No robustness check applying other matching estimators. - Standardized bias is not used as a balancing test. - Bootstrapped SEs are not valid for NN matching.
Marino et al. (2010)	Generalized Propensity Score (GPS) method	Yes				Matching with categorical treatment variable; conditional difference in difference estimator.	Negative treatment effect for large amounts of subsidies (a partial crowding-out hypothesis cannot be rejected).	- No sensitivity analysis.
Reinkowski	Kernel	No	For	Difference	Bootstrapped	-Different	- Input	- Micro firms are defined as

et al. (2010)	matching		Mahalanobis metric matching propensity score, industry DVs and size DVs.	in means before and after matching	SEs (500 repetitions)	matching estimators: stratification, 5-NN with caliper and Mahalanobis metric matching; - Subsamples based on firm size - Subsample of permanent R&D performers	additionality is reported; a mean estimate for R&D intensity is 3.7 p.p. (the largest effect is found for micro firms). - Output additionality is reported: the ATT effect is 22 p.p. (but statistically insignificant effect for micro firms).	having between 1 and 20 employees (the CIS survey defines micro firms as having less than 10 employees). - Standardized bias is not used as a balancing test. - No sensitivity analysis. - Bootstrapping is not valid for NN matching.
Marino and Parrota (2010)	Generalized Propensity Score (GPS) method	Yes	Not reported	Not reported		No	Positive and decreasing effect for all three types of additionality. Also, for all three types of additionality, crowding out cannot be rejected for higher amounts of subsidy (a partial crowding-out hypothesis cannot be	- No sensitivity analysis.

							rejected).	
Carboni (2011)	NN matching with Mahalanobis metric with replacement	Yes	Not reported	Kernel density of the propensity score, difference in means after matching	Bootstrapped SEs	Subsample with only innovative firms; OLS regression	The ATT is separately estimated for grants, tax incentive and direct loans and input additionality is found for all three policy instruments.	- Standardized bias not used as balancing test. - No sensitivity analysis. - No robustness check applying other matching estimator. - Not clear why Generalized Propensity Score (GPS) was not applied as the amount of subsidy was available.
Alecke et al. (2012)	Kernel matching	No	Not reported	Difference in means before and after matching, pseudo-R^2.	Bootstrapped SEs.	Robustness check using stratification matching, k=5 nearest-neighbour matching, Mahalanobis metric distance matching. Also subsamples based on firm size and only for subsample of firms with permanent R&D activities.	Additionality is reported: - For input additionality, the ATT effect is on average 2.4 p.p. - For output additionality, the ATT effect is on average 20 p.p. - Results confirmed for subsamples based on firm size.	- Standardized bias is not used as a balancing test. - Bootstrapped SEs are not valid for NN matching. - For sensitivity analysis applying the Rosenbaum approach, the authors employed a user-written command *mhounds* in Stata statistical software. To our knowledge, that command can only be used for sensitivity analysis after NN matching without replacement and after stratification method.
Marzucchi (2011)	5- NN matching	Four pre-treatment covariates (turnover and 3 DVs for firm size)	Not reported	Not reported	Bootstrapped SEs (200 replications).	5-NN with caliper, kernel matching, trimming for kernel matching	Input additionality not found for regional policy; but found for national	National and regional policies analysed separately for both countries. - Balancing test not reported. - No sensitivity analysis. - Bootstrapped SEs not valid for NN matching.

							policy; heterogeneity in output and behavioural additionality depending on the their measures.	
Afcha Chavez (2011)	NN matching	Not clear	Not reported	Not reported	Not reported	Subsamples of - firms that did not cooperate in the previous years - firms that did cooperate in the previous years	- Behavioural additionality found for cooperation with universities or technological centres. - Statistically insignificant ATT effect is reported for vertical cooperation (with consumers and suppliers).	- Balancing test is not reported. - Variance estimation is not reported. - No robustness check using other matching estimators. - No sensitivity analysis.
Cerulli and Potí (2012)	Matching estimators, Control Function approach, Heckman selection model, Difference-in-difference estimator	Yes	Not reported	Before matching = difference in means t-test; no balancing test after matching.	Not reported	Yes, different evaluation methods	Additionality except for low knowledge-intensive services and very small firms (10-19 employees).	- Sample size varies significantly for each matching estimator as well as for other methods. - No balancing test after matching. - No sensitivity analysis.

Czarnitzki and Lopes-Bento (2012)	Nearest Neighbour (NN) matching estimator with replacement and with Mahalanobis metric	Partly	PS with additional matching arguments in two cases: firm age for Western Germany, two industry DVs and DV for the headquarter located in foreign territory for Flanders.	Difference in means t-test after matching.	Lechner-corrected SEs	OLS regression.	Input additionality found in each country.	- No sensitivity analysis. - No robustness check applying other matching estimators. - Standardized bias is not used as a balancing test.
Herrera and Sánchez-González (2012)	Bias-adjusted matching estimator	Pre-treatment outcome and treatment variables	PS	Difference in means t-test before and after matching.	Not reported.	No	- Input additionality found in SMEs. - Output additionality reported for small firms, but not for medium-sized firms.	- No sensitivity analysis. - No robustness check applying other matching estimators. - Standardized bias is not used as a balancing test.
Antonioli et al. (2012)	1:5 NN matching	Yes	Not reported	- Difference in means between treated and non-treated firms before and after matching; - Pseudo-R^2	Bootstrapped SEs (200 replications)	1:5 NN matching with 0.05 caliper; kernel matching with Epanechnikov kernel; 1% trimming for 1:5 NN matching	Behavioural additionality found for the improvement of workers' competencies ('cognitive capacity additionality')	- R&D activities are proxied by intramural R&D and advertising expenditures jointly. - Size and choice of bandwidth for kernel matching not reported. - Results of balancing tests are not reported. - Standardized bias is not used

				test - LR test of joint significance of covariates after matching			and for the cooperation with other firms in the group outside the region. - For other outcome variables, the ATTs effects are not statistically significant.	as a balancing test. - No sensitivity analysis.
Foreman-Peck (2013)	Nearest Neighbour (NN) matching estimator with caliper	Partly	Not reported	Yes, standardized bias before and after matching	Not reported	NN without caliper	Additionality reported as the ATT effects are between 20 and 30 %.	- Product and process innovations are treated jointly. - No sensitivity analysis. - No robustness check applying other matching estimators. - Variance estimator is not reported.
Czarnitzki and Lopes-Bento (2013)	NN matching with caliper and Mahalanobis metric	Partly	PS only; in robustness check PS and DV whether a firm received a subsidy from other sources	Difference in means between treated and non-treated firms before and after matching	Lechner (2001)	OLS regression for stability of treatment effect over time; OLS and kernel regression on the treatment effect on the number of supported projects; NN matching when other sources of funding are taken into	- Consistent results: - Input additionality is reported as the ATT effect is 3.73 p.p. when the outcome variable is R&D intensity and the effect is 9.57 p.p. when the outcome variable is R&D	- Robustness check: IV approach (it is questionable whether the instruments have a theoretical justification) - The size of caliper is not reported. - The choice of caliper size is not justified. - Standardized bias is not used as a balancing test. - No sensitivity analysis. - No robustness check applying other matching estimators.

						account; subsample of only innovative firms; IV approach (exclusion restrictions are lagged subsidy receipt and the average size of subsidy per project)	employment. - Treatment effects are stable over time. - Treatment effects are not affected by the receipt of support from other sources and by the receipt of grants repeatedly.	
Antonelli and Crespi (2013)	NN matching	Yes	Not reported	Not reported	Not reported	No	- Additionality found when the outcome variable is R&D per employee (the ATT effect is 2.59 p.p.). - The ATT effect is not significant when the outcome variable is private R&D.	- Balancing test is not reported. - The size of the common region is not reported. - Variance estimation is not reported. - No robustness check. - No sensitivity analysis.

Table A1.3. Empirical studies applying other evaluation methods - part I

Authors	Country	Dataset	Sample size	Sectors	Treatment variable	Outcome variable	Model specification
Busom (2000)	Spain	Cross-sectional data from 1988 provided by the Spanish Ministry of Industry	154 firms (75 participating firms)	Manufacturing and service sectors	Binary	*Input additionality* - R&D expenditure - R&D intensity (R&D expenditure over employees) - R&D personnel - R&D intensity with respect to R&D personnel (R&D personnel over employees)	- Firm size (number of employees) - Firm age - Public ownership (DV for firms that are partly publicly owned) - Foreign ownership (DV for firms that were participated with foreign capital) - Price determination (DV for the firm that declared to set prices and then adjusted production to sales) - Quantity determination (DV for the firm that declared to make production plans and then adjusted prices) - Regulated prices (DV for firms with regulated prices) - Monopoly (DV for the firm that declared behaving as such) - Strategic response (DV for the firm that declared it would increase own R&D in response to a rival's) - Importance of R&D in the short run (DV for the firm that declared R&D to be important in the short run)

							- Competitors as a source of ideas - Firm's own patents as a source of ideas - DV for the firms that report scientific and technical publications to be important - R&D cooperation (DV for the firm that cooperates on R&D with others) - DV for the firm conducting either basic or applied research - DV for the firm conducting development - DV for the firm reporting that R&D activities are oriented towards process innovation - DV for the firm reporting that R&D activities are oriented towards process innovation - Number of patents obtained by firm during the previous ten years - Export intensity (exports over sales) - Industry DVs
Lach (2002)	Israel	Panel data from the Surveys of Research and Development in Manufacturing (1991-1995)	Between 165-195 R&D performing firms per year (6-year longitudinal data)	Manufacturing sector	Continuous	*Input additionality* - R&D expenditure	- Firm size (natural logarithm of employment) - Sales (natural logarithm) - Industry and year DVs
Gonzáles et el. (2005)	Spain	Business Strategy Survey (unbalanced panel data from 1990-1999)	2,214 firms (9,455 observations)	Manufacturing sector	Continuous	*Input additionality* - R&D intensity (logarithm of R&D	- Firm size (DVs for five categories) - Firm age - Degree of technological sophistication

						expenditures over sales)	- Capital growth - Exporting (DV if the firm is exporter) - DV for firms with foreign capital - DV for firms with the market power - Time, regional and 17 industry DVs
Görg and Strobl (2007)	Ireland	Annual Business Survey (1999 - 2002) merged with Forbás annual database on grant payments	6,378 observations (5,422 non-participating)	Manufacturing sector	Continuous	*Input additionality* - R&D expenditure (natural logarithm)	Propensity score: - Firm size (lagged value) - Firm age (lagged value) - Export intensity (lagged value) - Domestic input use (lagged value) - Average wage (lagged value) - Labour productivity (lagged value) - Foreign ownership (lagged value) - DV for firms receiving R&D grant in the previous year
Aerts and Schmidt (2008)	Flanders (Belgium) and Germany	CIS 3 data (1998-2000) and CIS4 data (2002-2004) merged with patent application data	314 firms from Flanders and 968 firms from Germany	Manufacturing sector and computer services, R&D services and business-related services	Binary	*Input additionality* - R&D expenditure - Natural logarithm of R&D expenditure - R&D intensity (ratio of R&D expenditure over turnover) - Natural	- For propensity score: - Firm size (natural logarithm of the number of employees) - Firms' patent stock (to control for the previous R&D activities) - DV for belonging to a group - DV for firms belonging to a group with a foreign parent company

						logarithm of R&D intensity	- Export quota (ratio of export over turnover) - DV for the firms from East Germany - Sectoral DVs - Interaction term between the industry DVs and the natural logarithm of the number of employees - In OLS in differences: -Difference over time in funding -Difference over time in firm size (natural logarithm of the number of employees -Difference over time in patent stock -Difference over time in the export quota
Hussinger (2008)	Germany	Pooled cross-sectional dataset covering the period 1992-2000 (CIS merged with the BMBF project-level data on R&D funds and the patent database of the German Patent and Trade Mark Office)	3,744 observations (723 participating)	Manufacturing sector	Continuous	*Input additionality* - Private R&D expenditure divided by the number of employees *Output additionality* - Innovative sales from new products	-Firm size (number of employees) - Firm age - Market concentration (the firm's sales divided by the total industry sales on a 3-digit NACE level) - Patent stock per employee (proxy for the firm's past successful innovation activity) - Credit rating index - Export intensity (export sales divided by total sales) - DV for firms that belong to a firm group with a foreign parent

							company - DV for firms with limited liability - DV for firms located in Eastern Germany - Time and industry DVs
Gelabert et al. (2009)	Spain	CIS (2000-2005), unbalanced pooled cross-sectional data	5,045 observations	Manufacturing and service sectors	Continuous	*Input additionality* - R&D expenditure (natural logarithm)	- Firm size (natural logarithm of the number of employees - lagged value) - Financial constraints (importance of three financial factors in conducting innovation - lagged value) - Export intensity (ratio of exports over sales - lagged value) - Employees' qualifications (proportion of highly skilled employees - lagged value) - Year, regional and industry DVs
Garcia and Mohnen (2010)	Austria	CIS3 (1998-2000)	546 innovating firms	Manufacturing and service sectors	Binary	*Input additionality* - R&D intensity (R&D expenditure) *Output additionality* - Innovative sales from products new to the firm - Innovative sales from products new to the market	- Firm size (natural logarithm of the number of employees) - Competition (DV for those firms reporting that the international market is prevailing) - Cooperation (DV is the firm cooperates with other firms and institutions) - Human capital (the ratio of the number of workers with higher education divided by the total number of workers) - Appropriability (proxied by the perceived importance of economic risk as an obstacle to innovation)

							- Financial difficulties (the perceived difficulty in accessing finance as an obstacle to innovation) - Demand pull (importance of customers as a source of information) - Science push (importance of universities and public research institutes as sources of information) - DV for belonging to a group - DV for firms that belong to a firm group with a foreign parent company - Industry DVs (high-tech, low-tech and the wholesale industry)
Schneider and Veugelers (2010)	Germany (West German firms)	CIS4 (2002-2004)	1,715 firms	Manufacturing and service sectors	Binary	*Output additionality* - Innovative sales from new or substantially - Innovative sales from products new to the firm - Innovative sales from products new to the market	- Firm size (logarithm of employment) - Firm age (natural logarithm) - R&D intensity (intramural R&D expenditure over sales) - Importance of external sources of knowledge (termed basicness of R&D) - DV for belonging to a group - 14 sector DVs

Hewitt-Dundas and Roper (2010)	Ireland and Northern Ireland	Pooled data from three waves of the Irish Innovation Panel (IIP) data covering the period 1994-2002	1,571 observations from Ireland and 1,156 observations from Northern Ireland	Manufacturing sector	Binary	*Output additionality* - Innovative sales from new products - Innovative sales from new and improved products - Product innovation (DV=1 if the firm introduced product innovation)	- In-house R&D - Supply chain links - Non supply chain links - Plant size (the number of employees) - Plant size squared - Type of production (vintage, one-offs, small batches, large batches) - DV for the firm belonging to multi-plant group - DV for the externally owned plants - Workforce qualifications - Capital investment per employee - Five industry DVs
Catozzella and Vivarelli (2011)	Italy	CIS3 (1998-2000)	746 firms that introduced only product innovation (389 participating and 357 non-participating)	Manufacturing sector	Binary	*Input-output efficiency (innovative productivity)* - Ratio of innovative sales over total innovation expenditure	- Firm size (natural logarithm of the number of employees) - Growth rate in the number of employees - Export intensity (ratio of turnover from export over turnover) - Prevailing market coverage - DV for belonging to a group - DV for belonging to a group with a foreign headquarter - Industry DVs - Industry DVs based on Pavitt's taxonomy - Importance of sources of information (universities, research institutes and conferences) - Importance of market sources of

							information (customers, suppliers and competitors) - DV for cooperation for innovation with universities and research institutes - Motives for undertaking innovation (entering new markets; increasing production capacity; increasing production flexibility; lowering labour costs) - Importance of internal and financial barriers to innovation - DV for patenting activities - Sixteen DVs for innovative strategies (combination of four innovative inputs: internal R&D; external R&D; acquisition of machinery and equipment; acquisition of know-how) - DVs for introducing managerial and/or strategic and/or organizational innovation) - Evaluation of the innovative effect on product quality - DV for products new to the market
Klette and Møen (2012)	Norway	Panel R&D survey (1982-1995) merged with manufacturing statistics	192 business units (697 observations)	High-tech manufacturing industries (machinery, electrical equipment and technical instruments)	Continuous	*Input additionality* - R&D expenditure	- Sales - Sales squared - Total R&D subsidies - Cash flow (proxy for liquidity constraints)

Papa (2012)	Italy	CIS3 (1998-2000)	1,784 firms	Manufacturing and service sectors	Binary	*Input additionality* - R&D intensity (internal R&D expenditures divided by the turnover)	*Selection equation*: - Stock of knowledge capital (stock of R&D capital plus stock of patents divided by the number of employees) history of R&D investment and purchase of patents) - Export intensity (share of exports in total turnover) - Capital intensity (tangible assets divided by the number of employees) - DVs for financial difficulties (high, medium, low) - Cash flow per employees - Leverage ratio (financial expenditures as a percentage of revenues) - Firm size (natural logarithm of total employment) -DV for belonging to a group - DV for belonging to a group with a foreign headquarter - Regional and industry DVs *Outcome equation* - Capital intensity (tangible assets divided by the number of employees) - DVs for financial difficulties (high, medium, low) - Cash flow per employees - Leverage ratio (financial

							expenditures as a percentage of revenues) - Firm size (natural logarithm of total employment) -DV for belonging to a group DV for belonging to a group with a foreign headquarter - Regional and industry DVs - Objectives of innovation - Sources of information - Methods for protecting innovation
Bloch and Graversen (2012)	Denmark	R&D survey (1995-2005)	1,904 observations	Manufacturing and service sectors	Continuous	*Input additionality* - Private (net) R&D expenditures	- Lagged value of private R&D expenditures (logarithm) - Lagged value of R&D subsidies - Cooperation with other firms - Cooperation with public research institutes - Total sectoral funding budget (logarithm) - DV for R&D subsidy from foreign sources - DV for R&D subsidy from domestic sources - Firm size (DV) - Industry and time DVs
Spithoven et al. (2012)	Belgium	Panel data consisting of two waves: CIS3 (1998-2000) and CIS4 (2002-2004)	1,202 observations (601 firms)	Manufacturing and service sectors	Binary	*Behavioural additionality* - DV for cooperation with businesses (customers, suppliers and competitors) - DV for	- Firm size (logarithm of the number of employees) - R&D activity (DV) - Patenting activity (DV) - Incoming knowledge spillovers (importance of various sources of information) - Strategic appropriability of knowledge (importance of

	cooperation with public research institutions	mechanisms for protecting innovation) - Complexity of knowledge (importance of information obtained from public research institutions and professional conferences) - Higher education intensity of personnel (logarithm) - Export intensity (logarithm) - DV for domestic group membership - DV for foreign group membership - Importance of risk constraints - Importance of financial constraints - Industry DVs based on Pavitt's taxonomy

Table A1.4. Empirical studies applying other evaluation methods - part II

Authors	Estimator	Instruments	Robustness check	Type of additionality	Results	Limitations
Busom (2000)	Heckman selection model (both two-step and full-information *maximum-likelihood)*	No instrument	OLS estimation	Input additionality	- Overall results suggest additionality, but for 30% of participating firms, full crowding out effects cannot be rejected.	- No exclusion restrictions were used in the estimation of Heckman model. - OLS regression cannot be an appropriate robustness check, as it does not control for selection bias.
Lach (2002)	Fixed effects (FE) estimator and system GMM estimator	- Natural logarithm of exports - Lagged independent variables and the dependent variable	- OLS - Difference-in-Difference (DiD) estimator - Model specifications in first differences and in levels	Input additionality	- In the short run, no additionality nor crowding-out (using the DiD estimator) - In the long run, at the means of the data, an additional dollar of R&D subsidy increase company-financed R&D expenditures by 41 cents on average. - A positive and statistically significant treatment effect is found for small firms, but no effect is reported for large firms.	
Gonzáles et al. (2005)	Simultaneous equation model with thresholds estimated by Heckman procedure	- Subsidies expected in advance by firms	- Alternative model specifications	Input additionality	- Public subsidies have a positive, yet modest effect. - The estimated percentage increase in privately financed R&D expenditures is higher for the smallest	- Public support is treated as exogenous.

	(a partial maximum likelihood estimation - MLE instead of the two-step estimation)				firms. - The analysis also suggests that subsidies are distributed mainly to firms that would have performed innovative activities irrespective of such subsidies.	
Görg and Strobl (2007)	Conditional Difference-in-Difference (DiD) estimator (combination of matching with the Difference-in-Difference estimator) on pooled cross-sectional data	Not needed	- Difference-in-Difference (DiD) estimator - Alternative dependent variable (R&D expenditure per employee) - Plants divided into domestic and foreign	Input additionality	- The impact of R&D grants depends on the grant size and on the ownership of the plant. For domestic plants, large grants yield crowding-out effect, whereas small grants result in the additional effect (the hypothesis of a partial crowding out is supported). For foreign plants, insignificant treatment effects are reported, irrespective of the grant size.	- Pooled cross-sectional analysis, not a panel analysis, thus the estimator does not control for unobserved heterogeneity.
Aerts and Schmidt (2008)	Conditional Difference-in-Difference (DiD) estimator (combination of matching with the Difference-in-Difference estimator) on pooled cross-sectional data	Not needed	- Subsample of only R&D active firms - Additional control variables	Input additionality	Crowding-out can be rejected in both German and Flemish case. Input additionality reported for both countries.	- Pooled cross-sectional analysis, not a panel analysis, thus the estimator does not control for unobserved heterogeneity.

Hussinger (2008)	Heckman selection model and semiparametric selection models (three models developed by Cosslett, 1991; by Newey, 1999; and by Robinson, 1988)	- Interaction term of the patent stock and past publicly funded projects - DV for capital companies - DV for foreign parent companies - Credit rating index	- OLS regression	- Input additionality - Output additionality	- Empirical results reject crowding-out effects on both innovation input and innovation output.	
Gelabert et al. (2009)	Instrumental Variable (IV) estimation of the Fixed Effects (FE) model	The budget dedicated to R&D policies, across geographical regions and sectors.	- Additional control variables - Tobit model estimated by the Instrumental Variable (IV) approach of the Fixed Effects (FE) model - Matching estimation (bias-adjusted matching estimator)	Input additionality	- A significant negative interaction between public support and appropriability mechanisms (i.e. a negative moderating role of appropriability). - Crowding-out effect is found for those firms reporting the highest levels of appropriability.	- GMM estimator could be used as a robustness check to control for a dynamics of R&D investment - Given the availability of the amount of subsidy, a dose-response function could be used instead of matching estimators applicable on binary treatment variable.
Garcia and Mohnen (2010)	System of simultaneous equations (simultaneous bivariate probit model and simultaneous bivariate tobit	Sources of information	No	- Input additionality - Output additionality	- The ATE effects are positive and statistically significant on both innovation input and output. Only government support is found to have a positive additional effect; the EU funding has no effect when the impact of government	- The model estimates the ATE effects, but not the ATT effects. - No robustness check.

	model)				support is taken into account.	
Schneider and Veugelers (2010)	Instrumental Variable (IV) approach	- The share of subsidized firms in the region where the firm is established - The share of subsidized firms per industry (at the NACE 2-digit level)	- Reestimating the model applying an alternative definition of young, innovative firms	Output additionality	- The study reports a negative and statistically significant ATE effect.	- The ATT effects are not estimated, only the ATE effects. - Using an endogenous binary switching model would enable the estimation of the ATT effect as well as serving as a robustness check.
Hewitt-Dundas and Roper (2010)	Instrumental Variable (IV) approach	- DV (=1 if the firm received support for process development; zero otherwise) - DV (=1 if the firm received support for R&D; zero otherwise) - DV (=1 if the firm received support for capital investment; zero otherwise)	- Subsample of only indigenously owned plants	Output additionality	- In whole sample, the ATE effects are positive but not statistically significant for Ireland, but are statistically significant for Northern Ireland. - In the subsample of indigenously owned plants, in both countries, the ATE effects are positive and statistically significant.	- The ATT effects are not estimated, only the ATE effects. - No robustness check; instead of or as robustness check, the authors could apply the endogenous binary switching model.
Catozzella and Vivarelli (2011)	Bivariate endogenous switching model	Not reported	No	Input-output efficiency	Crowding-out effect, as the ATT effect is negative and statistically significant at the 1 per cent level.	- It is not clear if the authors did not include instrumental variables in their model, or whether they include them without reported them. - Double inclusion of industry DVs in the model (26 industry DVs together with the categorization of industries following Pavitt's taxonomy). - Problem with diagnostics

						test (correlation coefficient is equal to one). - No robustness check applying other methods or alternative model specifications.
Klette and Møen (2012)	Fixed Effects (FE) estimator, Difference-in-Difference (DiD) estimator	Not needed	- FE estimation with loglog model specification (both dependent variable and R&D subsidies are in natural logarithms) - Model specification with DVs for small and large firms - Model specification with separate sources of funding	Input additionality	No effect, i.e. neither crowding out nor additionality is reported.	- Year dummies are not included in the model. - Firm size is not controlled for in the original model, but it is included as a robustness check.
Papa (2012)	Endogenous switching type II-tobit model	Export intensity	- OLS regression - Heckman selection model - Heckman treatment model	Input additionality	No effect, i.e. neither crowding out nor additionality is reported; insignificant ATT and ATE effects.	It is questionable if export intensity is a valid exclusion restriction.
Bloch and Graversen (2012)	System GMM estimator	Lagged R&D subsidies and lagged private R&D expenditure	- OLS regression - 2SLS regression	Input additionality	Partial and full crowding out effects can be rejected. Input additionality reported; additionality effect of 0.12 per cent.	- Highly unbalanced panel data (a large number of firms only have two consecutive observations). - Limited use of instruments.

Spithoven et al. (2012)	Bivariate probit model	Lagged values of independent variables	- NN Mahalanobis matching with replacement	Behavioural additionality	Behavioural additionality is reported.	- When applying a bivariate probit model, the ATE effect is estimated, not ATT effect.

Appendix II

Table A2.1. Variable definition

Variable	Definition
Innovation output	DV= 1 if innovation takes place; =0 if innovation does not take place
Participation	DV=1 if the firm participated in one or more support programmes; = 0 if it did not
Size	Number of employees in 2009
MPower	DV = 1 if the firm responded "Very strong" to the question "How would you judge the competition in your main market(s)"; otherwise 0
Export	The percentage of the firm's turnover accounted for by exports
Industry	Industry dummy variables (the omitted category is "Other")
Country	Country dummy variables (the omitted category is the UK)
Quasi firm fixed effects (QFFE)	
Resources devoted by the firm to innovation compared to the present	DV = 1 if the response was "Fewer"; = 0 if "About the same" or "More"
The firm's capabilities relative to other firms in their industry with respect to product innovation	DV = 1 for "Above average" and "Leading"; = 0 for "Average" and "Lagging"
The firm's capabilities relative to other firms in their industry with respect to process innovation	DV = 1 for "Above average" and "Leading"; = 0 for "Average" and "Lagging"
The firm's capabilities relative to other firms in their industry with respect to organisational innovation	DV = 1 for "Above average" and "Leading"; = 0 for "Average" and "Lagging"
The firm's capabilities relative to other firms in their industry with respect to marketing innovation	DV = 1 for "Above average" and "Leading"; = 0 for "Average" and "Lagging"
Collaboration	DV =1 if the firm responded "Yes" to the question "From 2005 to 2009 did your enterprise co-operate on any of your innovation activities with other enterprises or institutions?"; otherwise 0
Obstacle	DV = 1 if the response was "Very high importance" to the question "What are the specific needs for SMEs to enable them to participate in innovation support programmes?"and 0 otherwise ("No importance", "Low importance", "Important" or "High importance").

Table A2.2. Variable descriptions with means and standard deviations (SD) for participants and non-participants

Variable	Variable in the dataset	Participants	Non-participants
Product innovation in goods	Product_innovation_goods_yes	0.83 (0.38)	0.61 (0.49)
Product innovation in services	Product_innovation_services_yes	0.58 (0.50)	0.42 (0.49)
Product innovation - combined	Product_innovation	0.93 (0.26)	0.73 (0.45)
Process innovation - processes for manufacturing goods or providing services	Q8_1_2	0.86 (0.35)	0.61 (0.49)
Process innovation - logistics, delivery or distribution processes	Q8_2_2	0.38 (0.49)	0.34 (0.48)
Process innovation - support processes (e.g. maintenance, purchasing, accounting etc.)	Q8_3_2	0.64 (0.48)	0.58 (0.50)
Process innovation - combined	Process_innovation_total	0.91 (0.29)	0.76 (0.43)
Organisational innovation - new business practices for organising procedures	Q9_1_2	0.58 (0.49)	0.48 (0.50)
Organisational innovation - new methods of organising work responsibilities and decision making	Q9_2_2	0.47 (0.50)	0.40 (0.49)
Organisational innovation - new methods of organising external relations with other firms or public institutions	Q9_3_2	0.52 (0.50)	0.29 (0.46)
Organisational innovation - combined	Organizational_innovation	0.78 (0.41)	0.63 (0.48)
Marketing innovation - changes to aesthetic design or packaging	Q10_1_2	0.47 (0.50)	0.33 (0.47)
Marketing innovation - new media or techniques for product promotion	Q10_2_2	0.47 (0.50)	0.35 (0.48)
Marketing innovation - new methods for sales channels	Q10_3_2	0.43 (0.50)	0.22 (0.42)
Marketing innovation - new methods of pricing goods or services	Q10_4_2	0.29 (0.46)	0.23 (0.42)
Marketing innovation - combined	Marketing_innovation	0.74 (0.50)	0.55 (0.50)
Innovative sales > 5 %	Q17_4	0.86 (0.34)	0.71 (0.46)
Innovative sales > 10 %	Q17_3	0.65 (0.48)	0.57 (0.50)
Innovative sales > 15 %	Q17_1	0.54 (0.50)	0.45 (0.50)
Innovative sales > 25 %	Q17_2	0.36 (0.48)	0.26 (0.44)
Any type of innovation	TOTAL	0.99 (0.08)	0.90 (0.30)

Number of employees in 2009	Q2_2009	34.56 (46.78)	34.54 (45.98)
Number of employees in micro firms (less than 10 employees)		4.73 (2.14)	4.16 (2.22)
Number of employees in small firms (less than 50 employees and more than 10)		22.51 (9.57)	23.13 (9.60)
Number of employees in medium - sized firms (less than 250 employees and more than 50)		110.23 (50.19)	104.77 (51.50)
Market power (strength of competition)	Q4t_5	0.22 (0.42)	0.25 (0.43)
Leather industry	Q3t_1	0.02 (0.15)	0.06 (0.23)
Ceramics	Q3t_2	0.10 (0.30)	0.06 (0.24)
Textiles	Q3t_3	0.10 (0.30)	0.14 (0.35)
Mechanical/Metallurgy	Q3t_4	0.34 (0.48)	0.25 (0.44)
Automotive	Q3t_5	0.09 (0.28)	0.12 (0.33)
Food products	Q3t_6	0.14 (0.35)	0.15 (0.36)
Other sectors	Q3t_7	0.20 (0.40)	0.21 (0.41)
Resources invested in innovative activities five years ago	Q12t_1	0.52 (0.50)	0.29 (0.45)
Innovative capacities for product innovation in 2005 (above average and leading)	Prodin_2005	0.31 (0.47)	0.24 (0.43)
Innovative capacities for process innovation in 2005 (above average and leading)	Procin_2005	0.27 (0.44)	0.17 (0.38)
Innovative capacities for marketing innovation in 2005 (lagging)	Q16_3t_1	0.34 (0.48)	0.35 (0.48)
Innovative capacities for organizational innovation in 2005 (lagging)	Q16_4t_1	0.27 (0.45)	0.29 (0.46)
Export	Q5_export	22.65 (30.37)	16.91 (28.58)
Collaboration [111]	Q18_yes	0.84 (0.37)	0.33 (0.47)
Administrative needs - simple application procedure (very high importance)	Q31_1t_5	0.41 (0.49)	0.32 (0.47)
Administrative needs - short time-to-contract periods (very high importance)	Q31_2t_5	0.17 (0.38)	0.16 (0.37)
Administrative needs - short application-to-funding periods (very high importance)	Q31_3t_5	0.32 (0.47)	0.21 (0.41)
Administrative needs - simple reporting requirements (very high importance)	Q31_4t_5	0.28 (0.45)	0.17 (0.37)

[111] Collaboration is not included in the baseline model, but is included in the augmented model. This dummy variable has a value of 1 if a firm collaborates on innovation activities with other firms or institutions.

Administrative needs - transparent proposal evaluation procedures (very high importance)	Q31_5t_5	0.27 (0.45)	0.18 (0.37)
Administrative needs - adequate assistance/guidance during project by programme officer (very high importance)	Q31_6t_5	0.30 (0.46)	0.21 (0.41)
Financial needs - high funding rates (very high importance)	Q31_7t_5	0.23 (0.42)	0.24 (0.43)
Financial needs - limited requirements to get loans (very high importance)	Q31_8t_5	0.17 (0.38)	0.14 (0.35)
Financial needs - availability of additional financing opportunities (very high importance)	Q31_9t_5	0.15 (0.36)	0.14 (0.34)
SME (internal needs) - adequate in-house knowledge on project management (very high importance)	Q31_10t_5	0.21 (0.41)	0.12 (0.33)
SME (internal needs) - adequate networks of potential partners (very high importance)	Q31_11t_5	0.10 (0.30)	0.06 (0.23)
SME (internal needs) - compliance of programme aims to SMEs interests (very high importance)	Q31_12t_5	0.21 (0.41)	0.16 (0.36)
SME (internal needs) - strong acknowledgement of need to participate in innovation programmes (very high importance)	Q31_13t_5	0.20 (0.40)	0.12 (0.32)
SME (internal needs) - easy access to information about available programmes (very high importance)	Q31_14t_5	0.24 (0.43)	0.22 (0.41)
External needs - adequate marketing of/ information about programmes (very high importance)	Q31_15t_5	0.24 (0.43)	0.17 (0.38)
External needs - adequate external assistance/guidance during project (very high importance)	Q31_16t_5	0.25 (0.43)	0.15 (0.36)
External needs - adequate external assistance/guidance after project (very high importance)	Q31_17t_5	0.17 (0.38)	0.10 (0.30)
External needs - appropriate general economic conditions (very high importance)	Q31_18t_5	0.19 (0.39)	0.20 (0.40)

Table A2.3. Number of participating and non-participating firms by country[112]

Country	Number of firms	Number of participating firms	Number of non-participating firms	Mean (standard deviation)
Germany	38	25	13	0.66 (0.48)
Spain	53	34	19	0.64 (0.48)
Italy	46	18	28	0.39 (0.49)
Netherlands	31	12	19	0.39 (0.49)
Portugal	19	9	10	0.47 (0.51)
France	34	16	18	0.47 (0.51)
United Kingdom	91	31	60	0.34 (0.48)
TOTAL	**312**	**145**	**167**	

[112] Data in Table A2.3 are for SMEs only (312 firms in total). There are 21 large firms in the sample.

Table A2.4 Innovative firms that received support in each category of innovation

Variable	Number of innovative firms	Percentage of innovative firms	Number of innovative firms that received support	Percentage of innovative firms that received support
Product innovation in goods	224	67.27 %	117	52.23 %
Product innovation in services	148	44.44 %	75	50.68 %
Product innovation - combined	269	80.78 %	136	50.56 %
Process innovation - processes for manufacturing goods or providing services	234	70.27 %	124	52.99 %
Process innovation - logistics, delivery or distribution processes	107	32.13 %	59	55.14 %
Process innovation - support processes (e.g. maintenance, purchasing, accounting etc.)	190	57.06 %	87	45.79 %
Process innovation - combined	271	81.38 %	132	48.71 %
Organisational innovation - new business practices for organising procedures	171	51.35 %	85	49.71 %
Organisational innovation - new methods of organising work responsibilities and decision making	142	42.64 %	68	47.89 %
Organisational innovation - new methods of organising external relations with other firms or public institutions	124	37.24 %	75	60.48 %
Organisational innovation - combined	231	69.37 %	118	51.08 %
Marketing innovation - changes to aesthetic design or packaging	130	39.04 %	67	51.54 %
Marketing innovation - new media or techniques for product promotion	129	38.74 %	67	51.94 %
Marketing innovation - new methods for sales channels	103	30.93 %	62	60.19 %
Marketing innovation - new methods of pricing goods or services	83	24.92 %	43	46.24 %
Marketing innovation - combined	211	63.36 %	109	51.66 %
Innovative sales > 5%	246	73.87 %	127	51.63 %
Innovative sales > 10%	191	57.36 %	96	50.26 %
Innovative sales > 15%	154	46.25 %	79	51.30 %
Innovative sales > 25%	97	29.13 %	53	54.64 %

Table A2.5. Results for baseline model - combined categories of product and process innovations

Variable in the dataset	Product innovation - combined						Process innovation - combined					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	SE[a]	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Q2_2009	0.042	0.052	0.001	0.003	-0.001	0.002	0.007	0.005	0.006**	0.003	-0.001	0.002
Q4t_5	-5.164***	0.707	-0.714	0.447	-0.090	0.265	-0.115	0.419	-0.519**	0.261	0.095	0.202
Q3t_1	2.913	1.825	-0.771	0.529	0.012	0.494	7.257***	0.847	-0.665	0.511	-0.182	0.478
Q3t_2	14.541***	1.947	1.008	0.714	-0.224	0.466	0.570	0.694	0.443	0.516	0.034	0.372
Q3t_3	14.800***	1.164	0.246	0.504	-0.127	0.356	-0.079	0.553	0.392	0.417	-0.108	0.296
Q3t_4	9.223***	1.269	0.684	0.484	0.286	0.291	0.373	0.478	0.237	0.344	0.360	0.237
Q3t_5	9.852***	1.190	0.340	0.524	-0.081	0.357	0.462	0.629	0.060	0.410	-0.008	0.320
Q3t_6	12.382***	1.763	0.544	0.521	-0.553*	0.373	7.404***	0.742	0.473	0.358	-0.580*	0.328
Netherlands												
Portugal												
France												
Germany					0.721**	0.296						
Spain					1.427***	0.257					1.437***	0.267
Q12t_1	-0.623	1.301	0.877***	0.288	0.703***	0.179	-0.344	0.423	0.974***	0.250	0.688***	0.173
Prodin_2005	9.046***	0.792	1.175**	0.536	-0.173	0.254	0.159	0.439	-0.066	0.370	-0.127	0.241
Procin_2005	8.858***	0.792	-0.499	0.543	0.377	0.260	0.945*	0.525	0.511	0.380	0.400	0.253
Q16_3t_1	-0.540	1.155	-0.021	0.306	0.082	0.238	0.727	0.551	-0.190	0.308	0.075	0.219
Q16_4t_1	-4.023***	1.463	-0.549*	0.309	-0.080	0.247	-0.331	0.429	-0.334	0.286	-0.093	0.227
Q5_export	0.117 **	0.058	0.003	0.005	0.003	0.003	-0.008	0.005	-0.002	0.004	0.005*	0.003
Q18_yes												
Q31_3t_5												
Q31_7t_5												
Q31_10t_5												
Q31_17t_5					0.783 **	0.380						
Q31_18t_5					-0.332	0.281						

Log likelihood	-205.85905					-248.48591				
No of obs.	242					261				
rho1	-0.999 (0.005)					-0.406 (0.588)				
rho0	0.871 (0.417)					0.999 (0.002)				
Wald test	p = 0.0232					p=0.0183				

Notes: [a] SE denotes standard error.

Table A2.6. Results for baseline model - combined categories of organisational and marketing innovations

Variable in the dataset	Organisational innovation - combined						Marketing innovation - combined					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	SE[a]	Coeff.	SE	Coeff.	SE	Coeff	SE	Coeff	SE	Coeff	SE
Q2_2009	0.009**	0.004	0.008**	0.004	-0.000	0.001	0.001	0.003	-0.002	0.003	-0.003	0.003
Q4t_5	-0.511*	0.289	-0.094	0.272	-0.019	0.205	-0.704**	0.329	-0.269	0.290	0.484*	0.261
Q3t_1	6.827***	0.417	-0.597	0.540	-0.1505	0.462	0.243	0.776	-0.201	0.693	0.194	0.686
Q3t_2	-0.075	0.546	1.124*	0.625	0.013	0.387	6.740***	1.825	7.238***	0.419	-0.503	0.410
Q3t_3	0.415	0.477	0.535	0.428	-0.174	0.321	7.721***	2.049	0.899*	0.465	-0.342	0.395
Q3t_4	0.185	0.370	0.276	0.340	0.494**	0.242	-0.096	0.367	0.132	0.361	0.224	0.298
Q3t_5	0.569	0.599	0.465	0.379	0.051	0.331	-0.221	0.489	-0.015	0.432	-0.246	0.386
Q3t_6	-0.230	0.387	-0.017	0.326	-0.622*	0.333		0.513	0.725	0.461	-1.054***	0.369
France												
Spain					1.464***	0.279	0.954*	0.520	-0.737	0.473	1.708***	0.311
Netherlands												
Italy												
Portugal	0.360	0.582	6.682***	0.497	-0.141	0.370						
Q12t_1	0.141	0.318	0.851***	0.270	0.725***	0.183	0.816***	0.262	0.472	0.304	0.835***	0.213
Prodin_2005							-0.473	0.365	0.723**	0.368	-0.466*	0.275
Procin_2005							0.226	0.402	-0.055	0.404	0.301	0.285
Q16_3t_1	-0.056	0.267	-0.074	0.314	-0.017	0.209	-0.783**	0.343	-0.844**	0.355	-0.081	0.270
Q16_4t_1	-0.145	0.269	-0.739**	0.328	-0.014	0.219	0.247	0.396	0.051	0.367	0.067	0.277
Q5_export	0.001	0.004	0.005	0.005	0.005	0.003	-0.001	0.005	0.004	0.006	0.004	0.004
Q31_3t_5					-0.908***	0.241						
Q31_7t_5											-0.597**	0.236
Q31_10t_5												
Q31_17t_5											0.898***	0.315
Q31_18t_5												
Log likelihood	-247.31131						-219.12568					
No of obs.	255						241					
rho1	-0.642 (0.330)						0.809 (0.187)					

rho0	0.728 (0.260)					-0.071 (0.353)				
Wald test	p = 0.0488					p=0.0651				

Notes: [a] SE denotes standard error.

Appendix III

Table A3.1. Variable definition, mean and standard deviation of dependent and independent variables

Variable	Variable definition	Mean	Standard deviation
FUNLOC	DV=1 if a firm received local/regional support; 0 otherwise;	0.231	0.422
FUNGMT	DV=1 if a firm received government support; 0 otherwise;	0.164	0.370
FUNEU	DV=1 if a firm received EU support; 0 otherwise;	0.023	0.149
COOPERATION	DV=1 if a firm cooperates with suppliers, customers, competitors, consultants, universities and government; 0 otherwise;	0.222	0.416
COOP_CUSTOMERS	DV=1 if a firm cooperates with customers; 0 otherwise;	0.061	0.240
COOP_SUPPLIERS	DV=1 if a firm cooperates with suppliers; 0 otherwise;	0.107	0.309
COOP_COMPETITORS	DV=1 if a firm cooperates with competitors; 0 otherwise;	0.036	0.187
COOP_CONSULTANTS	DV=1 if a firm cooperates with consultants, commercial labs or private R&D institutes; 0 otherwise;	0.057	0.232
COOP_HEI	DV=1 if a firm cooperates with universities or other Higher Education Institutions (HEI); 0 otherwise;	0.070	0.255
COOP_GOVERNMENT	DV=1 if a firm cooperates with government or public research institutes; 0 otherwise;	0.088	0.284
OUTSOURCING_RD	DV=1 if a firm conducts extramural R&D; 0 otherwise;	0.247	0.431
EXTERNAL_KNOWLEDGE	DV=1 if a firm purchases or licenses patents, know -how and other types of knowledge from other firms; 0 otherwise;	0.025	0.157
SMALL_FIRMS	DV=1 if a firm has between 10 and 50 employees;	0.638	0.481
BARRIER3	Importance of too high innovation costs as a barrier to innovation (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	1.842	1.090
BARRIER4	Importance of lack of qualified personnel as a barrier to innovation (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	1.441	1.006
BARRIER7	Importance of difficulties in finding cooperative partners as a barrier to innovation (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	0.996	1.041
PROPAT	DV=1 if a firm applied for a patent; zero otherwise;	0.113	0.316
CONTINOUS_RD	DV=1 if a firm continuously perform R&D activities during 2004-2006; 0 otherwise;	0.345	0.475
GP	DV=1 if a firm belongs to enterprise group; zero otherwise;	0.258	0.438
EXPORT	DV=1 if a firm is exporter; zero otherwise;	0.686	0.464
INCOMING1	Importance of following sources of information: conferences, trade fairs and exhibitions (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	1.051	1.041

INCOMING2	Importance of following sources of information: scientific journals and publications (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	0.861	0.930
INCOMING3	Importance of following sources of information: professional and industry associations (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	0.688	0.867
INFO_INTERNAL	Importance of the information generated within the firm or enterprise group (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	2.135	1.006
INFO_CUSTOMERS	Importance of customers as a source of information (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	1.363	1.145
INFO_SUPPLIERS	Importance of suppliers as a source of information (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	1.541	1.102
INFO_COMPETITORS	Importance of competitors as a source of information (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	1.059	1.034
INFO_CONSULTANTS	Importance of consultants as a source of information (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	0.791	0.977
INFO_HEI	Importance of HEIs as a source of information (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	0.515	0.851
INFO_GOVERNMENT	Importance of government as a source of information (score between 0- no importance; 1 - low importance; 2 -medium importance; and 3 -high importance);	0.348	0.667
INDUSTRY1	DV=1 if a firm operates in sectors 20 or 21; 0 otherwise;	0.053	0.224
INDUSTRY2	DV=1 if a firm operates in sector 22; 0 otherwise;	0.041	0.198
INDUSTRY3	DV=1 if a firm operates in sector 27; 0 otherwise;	0.024	0.153
INDUSTRY4	DV=1 if a firm operates in sector 28; 0 otherwise;	0.132	0.339
INDUSTRY5	DV=1 if a firm operates in sectors 15 or 16; 0 otherwise;	0.129	0.336
INDUSTRY6	DV=1 if a firm operates in sectors 17 or 18; 0 otherwise;	0.053	0.224
INDUSTRY7	DV=1 if a firm operates in sector 19; 0 otherwise;	0.017	0.129
INDUSTRY8	DV=1 if a firm operates in sectors 23 or 24; 0 otherwise; (base category)	0.096	0.294
INDUSTRY9	DV=1 if a firm operates in sector 25; 0 otherwise;	0.061	0.240
INDUSTRY10	DV=1 if a firm operates in sector 26; 0 otherwise;	0.068	0.252
INDUSTRY11	DV=1 if a firm operates in sector 29; 0 otherwise;	0.116	0.320
INDUSTRY12	DV=1 if a firm operates in sectors 30, 31,32 or 33; 0 otherwise;	0.094	0.291
INDUSTRY13	DV=1 if a firm operates in sectors 34 or 35; 0 otherwise;	0.046	0.209
INDUSTRY14	DV=1 if a firm operates in sectors 36 or 37; 0 otherwise;	0.071	0.257

Table A3.2. NACE classification of economic activity - Rev. 1.1

Economic activity - Section D: Manufacturing	
15	Manufacture of food products and beverages
16	Manufacture of tobacco products
17	Manufacture of textiles
18	Manufacture of wearing apparel, dressing and dyeing of fur
19	Tanning and dressing of leather, manufacture of luggage, handbags, saddlery, harness and footwear
20	Manufacture of wood and products of wood and cork, except furniture, manufacture of articles of straw and plaiting materials
21	Manufacture of pulp, paper and paper products
22	Publishing, printing and reproduction of recorded media
23	Manufacture of coke, refined petroleum products and nuclear fuel
24	Manufacture of chemicals and chemical products
25	Manufacture of rubber and plastic products
26	Manufacture of other non-metallic mineral products
27	Manufacture of basic metals
28	Manufacture of fabricated metal products, except machinery and equipment
29	Manufacture of machinery and equipment n.e.c.5

30	Manufacture of electrical and optical equipment
31	Manufacture of electrical machinery and apparatus n.e.c.5
32	Manufacture of radio, television and communication equipment and apparatus
33	Manufacture of medical, precision and optical instruments, watches and clocks
34	Manufacture of motor vehicles, trailers and semi-trailers
35	Manufacture of other transport equipment
36	Manufacture of furniture, manufacturing n.e.c.5
37	Recycling

Table A3.3. Correlation matrix for barriers to innovation (Stata output)

	barrier1	barrier2	barrier3	barrier4	barrier5	barrier6	barrier7
barrier1	1.0000						
barrier2	0.7200	1.0000					
barrier3	0.6088	0.6145	1.0000				
barrier4	0.4296	0.3962	0.4281	1.0000			
barrier5	0.4135	0.4214	0.4249	0.6751	1.0000		
barrier6	0.4068	0.4274	0.4089	0.5736	0.7263	1.0000	
barrier7	0.3971	0.4395	0.3551	0.4299	0.4835	0.5323	1.0000

Table A3.4. Cooperation and programme participation in local or regional and government programmes (N=8,022)

	Cooperation		Outsourcing R&D		Acquisition of other external knowledge	
Local or regional support	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**
Yes	711 (8.9 %)	1,071 (13.4 %)	809 (10.1 %)	1,045 (13.0 %)	63 (0.8 %)	1,791 (22.3 %)
No	1,143 (14.2 %)	5,097 (63.5 %)	1,171 (14.6 %)	4,997 (62.3 %)	141 (1.8 %)	6,027 (75.1 %)
Government (national) support						
Yes	493 (6.1 %)	819 (10.2 %)	570 (7.1 %)	742 (9.2 %)	54 (0.7 %)	1,258 (15.7 %)
No	1,289 (16.1 %)	5,421 (67.6 %)	1,410 (17.6 %)	5,300 (66.1 %)	150 (1.9 %)	6,560 (81.7 %)
EU support						
Yes	90 (1.1 %)	92 (1.2 %)	82 (1.0 %)	1,898 (23.7 %)	6 (0.1 %)	176 (2.2 %)
No	1,692 (21.1 %)	6,148 (76.6 %)	100 (1.2 %)	5,942 (74.1 %)	198 (2.5 %)	7,642 (95.2 %)

Note: For each stream of funding and each type of open innovation (cooperation, outsourcing R&D and acquisition of other external knowledge), the sum of percentages adds to 100 percent.

Table A3.5. Type of cooperation and participation (subsample of cooperating firms)

Type of cooperation	Local or regional support		Government support		EU support	
	Participating firms (N=711)	Non-participating firms (N=1,071)	Participating firms (N=493)	Non-participating firms (N=1,289)	Participating firms (N=90)	Non-participating firms (N=1,692)
Customers (N=493)	225	268	155	338	40	453
Suppliers (N=859)	302	557	221	638	46	813
Competitors (290)	119	171	109	181	29	261
Consultants (N=456)	203	253	151	305	35	421
HEI (N=562)	256	306	217	345	46	516
Government (N=708)	378	330	265	443	57	651

Table A3.6. Probit estimates with marginal effects for three types of funding

	Local/regional support		Government support		EU support	
Covariates	**Coefficients (SEs)**	**Marginal effects (SEs)**	**Coefficients (SEs)**	**Marginal effects (SEs)**	**Coefficients (SEs)**	**Marginal effects (SEs)**
gp	-0.001 (0.039)	-0.000 (0.011)	0.020 (0.042)	0.005 (0.010)	-0.058 (0.078)	-0.003 (0.004)
sm	0.198*** (0.076)	0.056*** (0.021)	-0.267*** (0.081)	-0.060*** (0.018)	0.021 (0.149)	0.001 (0.008)
export	0.029 (0.038)	0.008 (0.011)	0.082* (0.043)	0.019* (0.010)	0.074 (0.080)	0.004 (0.004)
info_internal	0.031 (0.039)	0.009 (0.011)	0.114** (0.045)	0.026** (0.010)	0.024 (0.085)	0.001 (0.004)
info_suppliers	-0.031 (0.029)	-0.009 (0.008)	0.037 (0.031)	0.008 (0.007)	0.022 (0.058)	0.001 (0.003)
info_customers	0.021 (0.019)	0.006 (0.005)	0.008 (0.021)	0.002 (0.005)	-0.013 (0.039)	-0.001 (0.002)
info_competitors	-0.030 (0.020)	-0.008 (0.006)	-0.010 (0.022)	-0.002 (0.005)	0.027 (0.041)	0.001 (0.002)
info_consultants	0.137*** (0.019)	0.039*** (0.005)	0.109*** (0.021)	0.025*** (0.005)	-0.028 (0.040)	-0.001 (0.002)
info_HEI	0.118*** (0.023)	0.033*** (0.007)	0.158*** (0.025)	0.036*** (0.006)	0.084* (0.043)	0.004* (0.002)
info_government	0.071** (0.031)	0.020** (0.009)	0.033 (0.033)	0.007 (0.007)	0.153*** (0.055)	0.008*** (0.003)
incoming1	0.032 (0.022)	0.009 (0.006)	0.004 (0.024)	0.001 (0.005)	-0.022 (0.045)	-0.001 (0.002)
incoming2	-0.035 (0.026)	-0.010 (0.007)	-0.026 (0.029)	-0.006 (0.006)	0.042 (0.052)	0.002 (0.003)
incoming3	-0.027 (0.025)	-0.008 (0.007)	-0.056** (0.028)	-0.013** (0.006)	-0.035 (0.051)	-0.002 (0.003)
barrier3	0.030* (0.017)	0.009* (0.005)	0.012 (0.019)	0.003 (0.004)	0.008 (0.035)	0.000 (0.002)

barrier4	0.040**	0.011**	-0.008	-0.002	0.013	0.001
	(0.019)	(0.005)	(0.021)	(0.005)	(0.039)	(0.002)
barrier7	0.023	0.007	0.063***	0.014***	0.042	0.002
	(0.018)	(0.005)	(0.019)	(0.004)	(0.035)	(0.002)
propat	0.236***	0.067***	0.187***	0.042***	0.303***	0.015***
	(0.049)	(0.014)	(0.052)	(0.012)	(0.086)	(0.004)
continous_RD	0.328***	0.092***	0.421***	0.095***	0.191**	0.010**
	(0.038)	(0.011)	(0.041)	(0.009)	(0.077)	(0.004)
0b.info_suppliers#1.sm	-0.017		0.181		0.100	
	(0.102)		(0.111)		(0.209)	
1. info_suppliers #0b.sm	0.028		-0.055		0.018	
	(0.072)		(0.079)		(0.144)	
1. info_suppliers #1.sm	-0.052		0.152*		-0.038	
	(0.084)		(0.091)		(0.175)	
2. info_suppliers #0b.sm	-0.035		-0.129*		0.022	
	(0.063)		(0.066)		(0.119)	
2. info_suppliers #1.sm	-0.033		0.138**		0.079	
	(0.061)		(0.068)		(0.125)	
3o. info_suppliers #0b.sm	0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)	
3o. info_suppliers #1o.sm	0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)	
0b.info_internal#1.sm	0.039		0.459***		0.069	
	(0.134)		(0.155)		(0.294)	
1. info_internal #0b.sm	-0.041		-0.004		0.242	
	(0.103)		(0.120)		(0.209)	
1. info_internal #1.sm	-0.372***		0.160		-0.072	
	(0.100)		(0.112)		(0.214)	
2. info_internal #0b.sm	0.071		-0.002		0.092	
	(0.068)		(0.075)		(0.136)	
2. info_internal #1.sm	-0.055		0.092		-0.134	
	(0.062)		(0.070)		(0.135)	
3o. info_internal #0b.sm	0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)	
3o. info_internal #1o.sm	0.000		0.000		0.000	

	(0.000)		(0.000)		(0.000)	
Constant	-1.398***		-1.869***		-2.657***	
	(0.136)		(0.159)		(0.309)	
1. info_suppliers		-0.012		-0.000		-0.002
		(0.015)		(0.013)		(0.005)
2. info_suppliers		-0.024*		-0.000		0.002
		(0.014)		(0.012)		(0.005)
3. info_suppliers		-0.023		0.001		0.000
		(0.015)		(0.013)		(0.006)
1.sm		0.030***		-0.004		-0.002
		(0.010)		(0.009)		(0.004)
1. info_internal		-0.062***		-0.018		0.002
		(0.019)		(0.017)		(0.008)
2. info_internal		0.008		-0.003		-0.002
		(0.019)		(0.017)		(0.007)
3. info_internal		0.020		0.010		0.001
		(0.018)		(0.016)		(0.007)
Industry DVs		Included		Included		Included
No. of observations	8,022	8,022	8,022	8,022	8,022	8,022

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

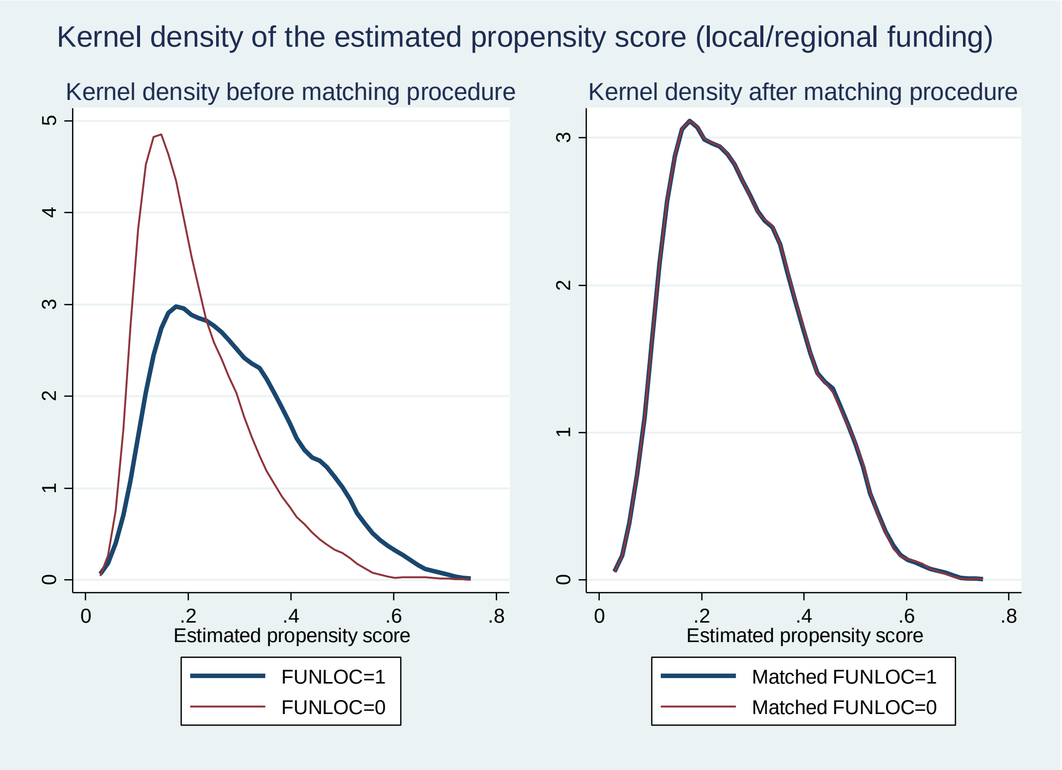
Table A3.7. Average Treatment Effects (ATTs) for the whole sample - kernel matching estimates with confidence intervals

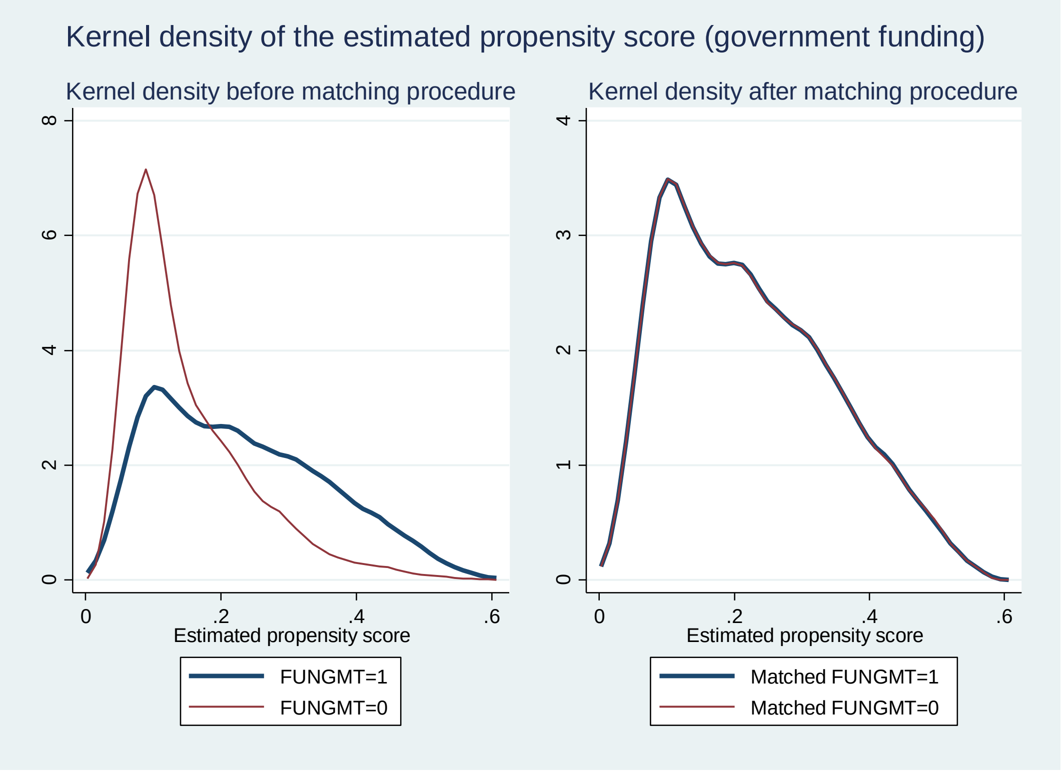
Dependent variable	Local/regional support		Government support		EU support	
	Kernel matching (Epanechnikov kernel, bw=0.06) ATT (bootstrapped SEs)	95% confidence intervals	Kernel matching (Epanechnikov kernel, bw=0.06) ATT (bootstrapped SEs)	95% confidence intervals	Kernel matching (Epanechnikov kernel, bw=0.001) ATT (bootstrapped SEs)	95% confidence intervals
Aggregate cooperation	0.141*** (0.014)	[0.113 0.169]	0.085*** (0.014)	[0.056 0.113]	0.170*** (0.035)	[0.100 0.239]
Cooperation with customers	0.053*** (0.009)	[0.036 0.070]	0.029*** (0.010)	[0.009 0.050]	0.129*** (0.030)	[0.069 0.188]
Cooperation with suppliers	0.039*** (0.010)	[0.019 0.059]	0.026** (0.013)	[0.001 0.051]	0.106*** (0.034)	[0.040 0.172]
Cooperation with competitors	0.027*** (0.007)	[0.013 0.040]	0.045*** (0.008)	[0.029 0.061]	0.106*** (0.027)	[0.052 0.161]
Cooperation with consultants	0.037*** (0.009)	[0.018 0.055]	0.028*** (0.010)	[0.008 0.047]	0.087*** (0.030)	[0.029 0.146]
Cooperation with HEI	0.042*** (0.010)	[0.023 0.061]	0.047*** (0.011)	[0.025 0.069]	0.107*** (0.034)	[0.040 0.174]
Cooperation with government	0.118*** (0.012)	[0.094 0.141]	0.084*** (0.012)	[0.061 0.107]	0.169*** (0.036)	[0.098 0.240]
Outsourcing R&D	0.168*** (0.013)	[0.142 0.194]	0.122*** (0.013)	[0.097 0.148]	0.096** (0.038)	[0.022 0.171]
Acquisition of other external knowledge	0.007 (0.005)	[-0.004 0.017]	0.012* (0.006)	[0.000 0.024]	0.000 (0.016)	[-0.032 0.032]

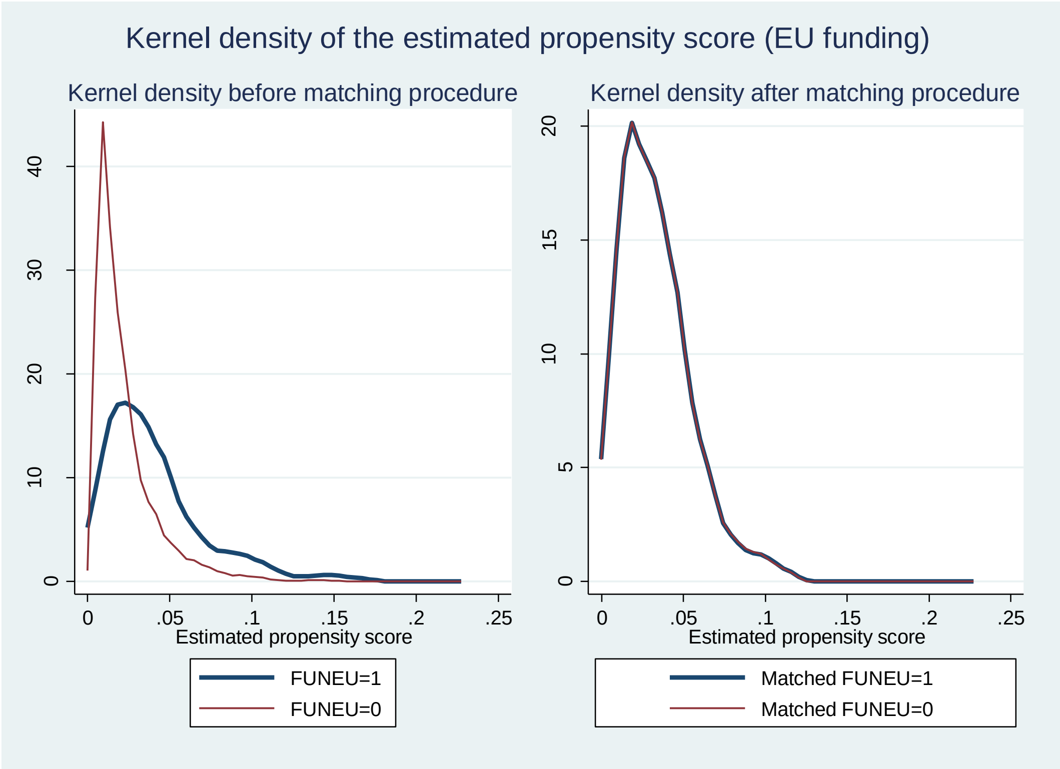
Table A3.8. Regions of common support for matching estimators with the estimated propensity score

Estimator	Local support		Government support		EU support	
	Common support	Common support (percentage of total sample)	Common support	Common support (percentage of total sample	Common support	Common support (percentage of total sample
NN matching without replacement and with caliper	7,963	99.26 %	8,014	99.90 %	8,022	100 %
NN matching with Mahalanobis metric and caliper	7,952	99.13 %	7,984	99.53 %	8,000	99.73 %
Kernel matching	8,022	100 %	8,021	99.99 %	8,021	99.99 %

Figure A3.1. Kernel density of the estimated propensity scores before and after matching for each source of funding (first raw for local/regional funding; second raw for national funding and third raw for EU funding)







Kernel density of the estimated propensity score (EU funding)
Kernel density before matching procedure
Kernel density after matching procedure
0
10
20
30
40
0
5
10
15
20
0
.05
.1
.15
.2
.25
Estimated propensity score
FUNEU=1
FUNEU=0
Matched FUNEU=1
Matched FUNEU=0

Table A3.9. Stata output of *mhbounds* command (outcome variable- *cooperation with suppliers*; treatment variable - *government support*)

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	1.51354	1.51354	.065071	.065071
1.05	1.06286	1.96534	.143922	.024687
1.1	.633235	2.39651	.26329	.008276
1.15	.222907	2.80924	.411804	.002483
1.2	.061488	3.20519	.475485	.000675
1.25	.438155	3.58581	.330637	.000168
1.3	.800152	3.95235	.211811	.000039
1.35	1.14866	4.30594	.125348	8.3e-06
1.4	1.48473	4.64755	.068807	1.7e-06
1.45	1.8093	4.97808	.035203	3.2e-07
1.5	2.12318	5.2983	.016869	5.8e-08
1.55	2.42713	5.60892	.007609	1.0e-08
1.6	2.72182	5.91057	.003246	1.7e-09
1.65	3.00785	6.20383	.001316	2.8e-10
1.7	3.28577	6.48922	.000509	4.3e-11
1.75	3.55608	6.76721	.000188	6.6e-12
1.8	3.81922	7.03823	.000067	9.7e-13
1.85	4.07562	7.30268	.000023	1.4e-13
1.9	4.32564	7.56092	7.6e-06	2.0e-14
1.95	4.56965	7.81328	2.4e-06	2.8e-15
2	4.80796	8.06007	7.6e-07	3.3e-16

Table A3.10. Probit estimates with marginal effects for the subsample of innovative firms

	Local/regional support		Government support		EU support	
Covariates	**Coefficients (SEs)**	**Marginal effects (SEs)**	**Coefficients (SEs)**	**Marginal effects (SEs)**	**Coefficients (SEs)**	**Marginal effects (SEs)**
Gp	0.009 (0.050)	0.003 (0.017)	0.050 (0.052)	0.014 (0.015)	-0.089 (0.095)	-0.006 (0.007)
Sm	0.170* (0.102)	0.057* (0.034)	-0.356*** (0.106)	-0.103*** (0.031)	0.020 (0.198)	0.001 (0.014)
Export	0.041 (0.058)	0.014 (0.019)	0.005 (0.062)	0.001 (0.018)	0.034 (0.116)	0.002 (0.008)
info_internal	0.014 (0.071)	0.005 (0.024)	0.169** (0.083)	0.049** (0.024)	0.056 (0.159)	0.004 (0.011)
info_suppliers	-0.083** (0.039)	-0.028** (0.013)	-0.039 (0.041)	-0.011 (0.012)	-0.068 (0.075)	-0.005 (0.005)
info_customers	0.027 (0.026)	0.009 (0.009)	0.025 (0.027)	0.007 (0.008)	-0.006 (0.051)	-0.000 (0.004)
info_competitors	-0.054** (0.027)	-0.018** (0.009)	-0.024 (0.029)	-0.007 (0.008)	0.014 (0.053)	0.001 (0.004)
info_consultants	0.128*** (0.025)	0.043*** (0.008)	0.122*** (0.027)	0.035*** (0.008)	-0.051 (0.051)	-0.004 (0.004)
info_HEI	0.108*** (0.028)	0.036*** (0.009)	0.179*** (0.029)	0.052*** (0.008)	0.091* (0.050)	0.006* (0.003)
info_government	0.132*** (0.037)	0.044*** (0.012)	0.056 (0.038)	0.016 (0.011)	0.233*** (0.062)	0.016*** (0.004)
incoming1	0.002 (0.030)	0.001 (0.010)	-0.010 (0.032)	-0.003 (0.009)	-0.001 (0.058)	-0.000 (0.004)
incoming2	-0.013 (0.034)	-0.004 (0.011)	-0.010 (0.036)	-0.003 (0.010)	0.033 (0.065)	0.002 (0.004)
incoming3	-0.050 (0.033)	-0.017 (0.011)	-0.059* (0.035)	-0.017* (0.010)	-0.026 (0.063)	-0.002 (0.004)
barrier3	0.019 (0.024)	0.006 (0.008)	-0.031 (0.025)	-0.009 (0.007)	-0.015 (0.046)	-0.001 (0.003)

barrier4	0.030 (0.026)	0.010 (0.009)	-0.009 (0.028)	-0.003 (0.008)	0.032 (0.051)	0.002 (0.004)
barrier7	0.070*** (0.024)	0.024*** (0.008)	0.124*** (0.025)	0.036*** (0.007)	0.089* (0.046)	0.006* (0.003)
Propat	0.256*** (0.056)	0.086*** (0.019)	0.215*** (0.059)	0.062*** (0.017)	0.255*** (0.098)	0.018*** (0.007)
continous_RD	0.085* (0.051)	0.028* (0.017)	0.202*** (0.056)	0.059*** (0.016)	0.040 (0.101)	0.003 (0.007)
0b.info_suppliers#1.sm	-0.104 (0.144)		0.160 (0.152)		0.066 (0.277)	
1. info_suppliers #0b.sm	-0.097 (0.094)		-0.202** (0.099)		-0.013 (0.171)	
1. info_suppliers #1.sm	-0.108 (0.114)		0.038 (0.121)		-0.172 (0.230)	
2. info_suppliers #0b.sm	-0.102 (0.079)		-0.202** (0.081)		-0.045 (0.149)	
2. info_suppliers #1.sm	-0.114 (0.086)		0.066 (0.093)		0.065 (0.170)	
3o. info_suppliers #0b.sm	0.000 (0.000)		0.000 (0.000)		0.000 (0.000)	
3o. info_suppliers #1o.sm	0.000 (0.000)		0.000 (0.000)		0.000 (0.000)	
0b.info_internal#1.sm	-0.095 (0.263)		0.636** (0.297)		-0.081 (0.585)	
1. info_internal #0b.sm	0.132 (0.179)		0.165 (0.206)		0.413 (0.364)	
1. info_internal #1.sm	-0.211 (0.177)		0.561*** (0.197)		0.257 (0.366)	
2. info_internal #0b.sm	-0.016 (0.100)		0.056 (0.111)		0.084 (0.209)	
2. info_internal #1.sm	-0.070 (0.096)		0.168 (0.108)		-0.233 (0.211)	
3o. info_internal #0b.sm	0.000 (0.000)		0.000 (0.000)		0.000 (0.000)	

3o. info_internal #1o.sm	0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)	
Constant	-1.020***		-1.593***		-2.539***	
	(0.235)		(0.273)		(0.533)	
1. info_suppliers		-0.043*		-0.059***		-0.015
		(0.024)		(0.023)		(0.011)
2. info_suppliers		-0.073***		-0.066***		-0.012
		(0.023)		(0.022)		(0.011)
3. info_suppliers		-0.064**		-0.062**		-0.018
		(0.026)		(0.025)		(0.012)
1.sm		0.033**		-0.027*		-0.004
		(0.016)		(0.014)		(0.006)
1. info_internal		0.001		0.051		0.031*
		(0.047)		(0.042)		(0.019)
2. info_internal		0.012		0.019		0.004
		(0.043)		(0.038)		(0.015)
3. info_internal		0.033		0.034		0.013
		(0.042)		(0.037)		(0.015)
Industry DVs		Included		Included		Included
No. of observations	3,861	3,861	3,861	3,861	3,808	3,808

Note: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table A3.11. Balancing tests for the subsample of innovative firms

Matching estimator	Local/regional support				Government support				EU support			
	Pseudo-R^2	LR test	Mean bias	t-test	Pseudo-R^2	LR test	Mean bias	t-test	Pseudo-R^2	LR test	Mean bias	t-test
NN matching without replacement and caliper	0.003	1.000	1.6	Yes	0.007	0.993	2.5	Yes	0.029	1.000	5.2	Yes
NN matching with Mahalanobis metric and caliper	0.003	1.000	1.2	Yes	0.005	0.999	1.6	Yes	0.034	1.000	3.7	Yes
Kernel matching Epanechnikov kernel, bw=0.06 (0.001 for EU support)	0.000	1.000	0.8	Yes	0.001	1.000	1.0	Yes	0.003	1.000	1.7	Yes

Table A3.12. Average Treatment Effects (ATTs) for the subsample of Spanish SMEs - kernel matching estimates with confidence intervals

Dependent variable	Local/regional support		Government support		EU support	
	Kernel matching (Epanechnikov kernel, bw=0.06) ATT (bootstrapped SEs)	95% confidence intervals	Kernel matching (Epanechnikov kernel, bw=0.06) ATT (bootstrapped SEs)	95% confidence intervals	Kernel matching (Epanechnikov kernel, bw=0.001) ATT (bootstrapped SEs)	95% confidence intervals
Aggregate cooperation	0.177*** (0.017)	[0.143 0.211]	0.108*** (0.020)	[0.070 0.147]	0.215*** (0.050)	[0.116 0.314]
Cooperation with customers	0.071*** (0.013)	[0.045 0.098]	0.038*** (0.014)	[0.010 0.066]	0.148*** (0.045)	[0.058 0.237]
Cooperation with suppliers	0.058*** (0.016)	[0.028 0.089]	0.036** (0.017)	[0.002 0.070]	0.129** (0.051)	[0.029 0.230]
Cooperation with competitors	0.033*** (0.009)	[0.016 0.050]	0.063*** (0.010)	[0.043 0.083]	0.140*** (0.036)	[0.070 0.210]
Cooperation with consultants	0.043*** (0.014)	[0.015 0.070]	0.035** (0.016)	[0.004 0.066]	0.090** (0.042)	[0.008 0.172]
Cooperation with HEI	0.058*** (0.013)	[0.032 0.084]	0.057*** (0.017)	[0.024 0.090]	0.122*** (0.044)	[0.035 0.209]
Cooperation with government	0.152*** (0.016)	[0.121 0.183]	0.109*** (0.018)	[0.073 0.144]	0.189*** (0.048)	[0.094 0.283]

Outsourcing R&D	0.202*** (0.016)	[0.170 0.235]	0.154*** (0.021)	[0.114 0.195]	0.097* (0.051)	[-0.003 0.197]
Acquisition of other external knowledge	0.011* (0.006)	[-0.001 0.023]	0.011 (0.008)	[-0.006 0.027]	-0.001 (0.019)	[-0.038 0.036]

Appendix IV

Table A4.1. Variable definition and descriptive statistics

Variable	Variable name in the database	Variable construction	Mean (standard deviation)
Treatment variables			
Participation in national support measures	National_support	DV=1 if the firm participated in national/regional R&D programmes in the last five years; zero otherwise	0.529 (0.500)
Participation in international support measures	Internat_support	DV=1 if the firm participated in international R&D programmes in the last five years; zero otherwise	0.274 (0.447)
Participation in either national or international support measures	Joint_support	DV=1 if the firm participated in either national/regional R&D programmes or international programmes in the last five years; zero otherwise	0.599 (0.491)
Output dependent variables			
Innovative sales more than 10% - proportion of sales is above 10% from new or substantially improved products of processes introduced since 2005	Q14_morethan10	DV =1 if the share is above 10% ; zero otherwise	0.672 (0.470)
Innovative sales more than 20% - proportion of sales is above 20% from new or substantially improved products of processes introduced since 2005	Q14_morethan20	DV =1 if the share is above 20%; zero otherwise	0.572 (0.495)
Innovative sales more than 30% - proportion of sales is above 30% from new or substantially improved products of processes introduced since 2005	Q14_morethan30	DV =1 if the share is above 30%; zero otherwise	0.467 (0.499)
Innovative sales more than 40% - proportion of sales is above 40% from new or substantially improved products of processes introduced since 2005	Q14_morethan40	DV =1 if the share is above 40%; zero otherwise	0.397 (0.490)
Innovative sales more than 50% - proportion of sales is above 50 % from new or substantially improved products of processes introduced since 2005	Q14_morethan50	DV =1 if the share is above 50%; zero otherwise	0.347 (0.476)
Use of online technology or knowledge brokers/intermediaries	Q23_1	DV=1 if the response was "Apply" or "Apply extensively"; =0 if "Don't apply at all", "Don't apply" or "Neutral" to the question "Do you have a specific approach towards acquiring external knowledge - Use of online technology or knowledge	0.323 (0.468)

		brokers/intermediaries"	
Informal networking with other firms	Q23_2	DV=1 if the response was "Apply" or "Apply extensively"; =0 if "Don't apply at all", "Don't apply" or "Neutral" to the question "Do you have a specific approach towards acquiring external knowledge - Informal networking with other firms"	0.623 (0.485)
Informal networking with research organizations	Q23_3	DV=1 if the response was "Apply" or "Apply extensively"; =0 if "Don't apply at all", "Don't apply" or "Neutral" to the question "Do you have a specific approach towards acquiring external knowledge - Informal networking with research organizations"	0.527 (0.500)
Strategic alliances with other firms	Q23_4	DV=1 if the response was "Apply" or "Apply extensively"; =0 if "Don't apply at all", "Don't apply" or "Neutral" to the question "Do you have a specific approach towards acquiring external knowledge - Strategic alliances with other firms"	0.457 (0.498)
Non-equity alliances with other firms	Q23_5	DV=1 if the response was "Apply" or "Apply extensively"; =0 if "Don't apply at all", "Don't apply" or "Neutral" to the question "Do you have a specific approach towards acquiring external knowledge - Non-equity alliances with other firms"	0.255 (0.436)
Participation in innovation networks, S&T parks, clusters etc.	Q23_6	DV=1 if the response was "Apply" or "Apply extensively"; =0 if "Don't apply at all", "Don't apply" or "Neutral" to the question "Do you have a specific approach towards acquiring external knowledge - Participation in innovation networks, S&T parks, clusters etc."	0.399 (0.490)
Close involvement of end users/customers in idea generation/concept development	Q23_7	DV=1 if the response was "Apply" or "Apply extensively"; =0 if "Don't apply at all", "Don't apply" or "Neutral" to the question "Do you have a specific approach towards acquiring external knowledge - Close involvement of end users/customers in idea generation/concept development"	0.583 (0.494)
Control variables in baseline model			
Annual R&D expenditures as % of total expenditure (including both intramural and extramural R&D activities; purchase of patents and know-how; training in R&D; and market introduction of innovation	RD_expenditure	=1 if the share is 0-10 %; =2 if the share is 11-20%; =3 if the share is 21-50 %; =4 if the share is >50%	2.020 (1.121)
Geographic markets where firms sell goods or services	Export	DV=1 if firms engage in exporting activities; zero otherwise	0.662 (0.473)
How would you judge the competition in your main market(s)	Competition	DV = 1 if the firm responded "Very strong"; otherwise 0	0.628 (0.484)
R&D department	RD_department	DV=1 if firms have a separate R&D department; zero otherwise	0.397 (0.490)

Micro firms	Micro_firms	DV=1 if firms have less than 10 employees; zero otherwise	0.493 (0.500)
Small firms	Small_firms	DV=1 if firms have more than then 10 but less than 50 employees; zero otherwise	0.317 (0.466)
Medium-sized firms	Medium_firms	DV=1 if firms have more than then 50 but less than 250 employees; zero otherwise	0.190 (0.393)
High tech firms	High_tech	DV=1 if firm report to be operating in high technology industries; zero otherwise	0.198 (0.399)
Medium high tech firms	Medium_high	DV=1 if firm report to be operating in medium high technology industries; zero otherwise	0.136 (0.343)
Medium low tech firms	Medium_low	DV=1 if firm report to be operating in medium low technology industries; zero otherwise	0.122 (0.327)
Low tech firms	Low_tech	DV=1 if firm report to be operating in low technology industries; zero otherwise	0.147 (0.354)
Information and Communication Technology (ICT) firms	ICT	DV=1 if firm report to be operating in ICT industries; zero otherwise	0.202 (0.402)
Firms in service sectors	Service	DV=1 if firm report to be operating in service sectors; zero otherwise	0.195 (0.397)
'Innovation leaders', i.e. countries whose performance is well above the EU27 average	Leaders	DV=1 if countries are Denmark, Finland, Germany and Sweden; zero otherwise	0.191 (0.394)
'Innovation followers', i.e. countries whose performance is close to that of the EU27 average	Followers	DV=1 if countries are Austria, Belgium, Cyprus, Estonia, France, Ireland, Luxembourg, Netherlands, Slovenia and the United Kingdom; zero otherwise (base category)	0.287 (0.453)
'Moderate innovators', i.e. countries whose performance is below that of the EU27 average	Moderate	DV=1 if countries are Czech Republic, Greece, Hungary, Italy, Malta, Poland, Portugal, Slovakia and Spain; zero otherwise	0.372 (0.484)
'Modest innovators', i.e. countries whose performance is well below that of the EU27 average	Modest	DV=1 if countries are Bulgaria, Latvia, Lithuania, Romania and Bosnia and Herzegovina; zero otherwise	0.149 (0.367)
Additional control variables in augmented model			
Resources devoted by the firm to innovation compared to the present	Q19_fewer	DV = 1 if the response was "Fewer"; = 0 if "About the same" or "More"	0.432 (0.496)
The firm's research and innovation record relative to other firms in their industry in 2005	Q18a_leading	DV = 1 for "Leading"; = 0 for "Average" and "Lagging"	0.233 (0.423)
Location of the firm in technology park/area	Tech_park	DV=1 if firms are located in a technology park/area; zero otherwise	0.267 (0.443)
Integration of a cluster/technology platform	Tech_platform	DV=1 if firms integrate a cluster/technology platform; zero otherwise	0.232

			(0.422)
Developed R&D and innovation strategy for the next five years	RD_strategy	DV=1 if firms have developed R&D and innovation strategy for the next five years; zero otherwise	0.490 (0.500)
Exclusion restrictions (barriers to participation)			
Administrative needs - simple application procedure	Q53a5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Simple application procedures" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.547 (0.498)
Administrative needs - short time-to-contract periods	Q53b5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Short time-to-contract periods" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.402 (0.491)
Administrative needs - short time-to-funding periods	Q53c5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Short time-to-funding periods" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.438 (0.497)
Administrative needs - short proposal evaluation periods	Q53d5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Short proposal evaluation periods" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.365 (0.482)
Administrative needs - transparent proposal evaluation procedures	Q53e5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Transparent proposal evaluation procedures" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.429 (0.495)
Administrative needs - adequate assistance/guidance during project by Project officer	Q53f5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Adequate assistance/guidance during project by Project officer " and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.361 (0.481)
Administrative needs - simple reporting requirements	Q53g5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in	0.441 (0.497)

		R&D programmes? - Simple reporting requirements" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	
Financial needs - high funding rates	Q54a5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - High funding rates" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.418 (0.494)
Financial needs - limited requirements to get loans	Q54b5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Limited requirements to get loans" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.278 (0.448)
Financial needs - availability of additional financing opportunities	Q54c5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Availability of additional financing opportunities" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.258 (0.438)
SME (internal needs) - adequate in-house knowledge on project management	Q55a5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Adequate in-house knowledge on project management" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.250 (0.433)
SME (internal needs) - adequate networks of potential partners	Q55b5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Adequate networks of potential partners" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.251 (0.434)
SME (internal needs) - compliance of programme aims to SMEs interests	Q55c5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Compliance of programme aims to SMEs interests" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.417 (0.493)
SME (internal needs) - easy access to information about available programmes	Q55d5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Easy access to information about available programmes" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.338 (0.473)
SME (internal needs) - strong acknowledgement of need to participate in innovation programmes	Q55e5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in	0.231 (0.422)

		R&D programmes? - Strong acknowledgement of need to participate in innovation programmes" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	
External needs - adequate marketing of/ information about programmes	Q56a5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Adequate marketing of/ information about programmes" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.245 (0.431)
External needs - adequate external assistance/guidance during project	Q56b5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Adequate external assistance/guidance during project" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.297 (0.457)
External needs - adequate external assistance/guidance after project	Q56c5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Adequate external assistance/guidance after project" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.210 (0.408)
External needs - appropriate technological conditions	Q56d5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Appropriate technological conditions" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.200 (0.400)
External needs - appropriate market conditions	Q56e5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Appropriate market conditions" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.262 (0.440)
External needs - appropriate general economic conditions	Q56f5	DV = 1 if the response was "Most important" to the question "Which would you say are the specific needs for SMEs in order to participate in R&D programmes? - Appropriate general economic conditions" and 0 otherwise ("Not important at all", "Not important", "Neutral" or "Important")	0.251 (0.434)

Table A4.2. NACE Rev. 1.1 classification of manufacturing industries based on technology intensity

	NACE rev. 1.1
High-technology intensive industries	
Aircraft and spacecraft	353
Pharmaceuticals	2423
Office, accounting and computing machinery	30
Radio, TV and communications equipment	32
Medical, precision and optical instruments	33
Medium high-technology intensive industries	
Electrical machinery and apparatus, n.e.c	31
Motor vehicles, trailers and semi-trailers	34
Chemicals, excluding pharmaceuticals	24 excluding 2423
Railroad equipment and transport equipment, n.e.c	352+354+355
Machinery and equipment, n.e.c	29
Medium low-technology intensive industries	
Building and repairing of ships and boats	351
Rubber and plastics products	25
Coke, refined petroleum products and nuclear fuel	23
Other non-metallic mineral products	26
Basic metals and fabricated metal products	27-28
Low-technology intensive industries	
Manufacturing, n.e.c.; Recycling	36-37
Wood, pulp, paper, paper products, printing and publishing	20-22
Food products, beverages and tobacco	15-16
Textiles, textile products, leather and footwear	17-19

Source: OECD (2006)

Table A4.3. Stata output for Table 6.1 - baseline model for the outcome variable *Q14_morethan20%* and the treatment variable *National_support*

```
Switching probit model                          Number of obs   =        597
                                                Wald chi2(19)   =     119.44
Log likelihood = -697.94464                     Prob > chi2     =     0.0000

------------------------------------------------------------------------------
                 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
National_support |
  RD_expenditure |   .2646175   .0593114     4.46   0.000     .1483694    .3808657
          Export |   .2235557   .1248314     1.79   0.073    -.0211094    .4682208
     Competition |  -.2064032   .1162027    -1.78   0.076    -.4341562    .0213499
   RD_department |   .4647884   .1271939     3.65   0.000      .215493    .7140838
     Small_firms |   .5019668    .132002     3.80   0.000     .2432477    .7606858
    Medium_firms |   .3399108    .168609     2.02   0.044     .0094432    .6703783
             ICT |   -.039245   .1784199    -0.22   0.826    -.3889415    .3104516
       High_tech |   .3935551   .1891262     2.08   0.037     .0228745    .7642357
Medium_high_tech |   .2800859   .2055375     1.36   0.173    -.1227602     .682932
        Low_tech |   .1757023   .1914237     0.92   0.359    -.1994811    .5508858
 Medium_low_tech |  -.0756874   .2004708    -0.38   0.706    -.4686029     .317228
          Modest |   .4758848   .1907526     2.49   0.013     .1020166    .8497529
        Moderate |   .5044922   .1379337     3.66   0.000     .2341471    .7748372
         Leaders |  -.1128448   .1714396    -0.66   0.510    -.4488602    .2231707
           Q53a5 |   .2157107   .1176571     1.83   0.067     -.014893    .4463145
           Q53e5 |  -.2379858   .1089085    -2.19   0.029    -.4514426   -.024529
           Q53f5 |   -.212693   .1239695    -1.72   0.086    -.4556688    .0302828
           Q53g5 |   .3024794   .1310898     2.31   0.021     .0455481    .5594107
           Q56a5 |  -.2370802   .1260118    -1.88   0.060    -.4840589    .0098984
           _cons |  -1.287014    .223033    -5.77   0.000     -1.72415   -.8498771
-----------------+------------------------------------------------------------
Q14_morethan20_1 |
  RD_expenditure |    .346018   .0631558     5.48   0.000     .2222349    .4698011
          Export |    .343929   .1457299     2.36   0.018     .0583037    .6295543
```

```
     Competition |  -.0919527   .1258373    -0.73   0.465    -.3385894    .1546839
   RD_department |   .4152879   .1366268     3.04   0.002     .1475043    .6830716
     Small_firms |   .1992147    .150196     1.33   0.185     -.095164    .4935934
    Medium_firms |   .2186404   .1885824     1.16   0.246    -.1509742    .5882551
             ICT |     .18193   .2066791     0.88   0.379    -.2231535    .5870135
       High_tech |   .0823958   .2033589     0.41   0.685    -.3161803    .4809719
Medium_high_tech |   .3870964   .2204663     1.76   0.079    -.0450095    .8192024
        Low_tech |    .117047   .2163464     0.54   0.588    -.3069842    .5410782
 Medium_low_tech |  -.0720578   .2298733    -0.31   0.754    -.5226012    .3784856
          Modest |   .5868417   .2205092     2.66   0.008     .1546515    1.019032
        Moderate |   .2735386   .1551746     1.76   0.078    -.0305981    .5776752
         Leaders |   .0498003   .1890688     0.26   0.792    -.3207678    .4203684
           _cons |  -1.896981   .2611918    -7.26   0.000    -2.408907   -1.385054
-----------------+----------------------------------------------------------------
Q14_morethan20_0 |
  RD_expenditure |   .3617256   .0850035     4.26   0.000     .1951218    .5283295
          Export |    .405946   .1596679     2.54   0.011     .0930027    .7188893
     Competition |   .1494808   .1808904     0.83   0.409    -.2050579    .5040195
   RD_department |   .6386812   .1916454     3.33   0.001     .2630632    1.014299
     Small_firms |  -.2791534    .271756    -1.03   0.304    -.8117853    .2534785
    Medium_firms |  -.1187781   .2429793    -0.49   0.625    -.5950088    .3574526
             ICT |  -.0002391   .2232277    -0.00   0.999    -.4377573    .4372791
       High_tech |    .060269    .286801     0.21   0.834    -.5018507    .6223886
Medium_high_tech |   .3158726   .3029902     1.04   0.297    -.2779773    .9097226
        Low_tech |   .0698013   .2398128     0.29   0.771    -.4002231    .5398257
 Medium_low_tech |   .0302486    .259805     0.12   0.907    -.4789599     .539457
          Modest |   .7203163   .2574969     2.80   0.005     .2156316    1.225001
        Moderate |   .2458776   .2003216     1.23   0.220    -.1467455    .6385007
         Leaders |   .0077079    .227163     0.03   0.973    -.4375233    .4529392
           _cons |  -.8141757   .3109352    -2.62   0.009    -1.423597    -.204754
-----------------+----------------------------------------------------------------
        /athrho1 |   1.687197   .6919129                      .3310726    3.043321
        /athrho0 |   .6673332   .6008183                      -.510249    1.844915
-----------------+----------------------------------------------------------------
            rho1 |   .9337893   .0885909                      .3194842    .9954643
```

```
         rho0 |   .5832229   .3964505                    -.4701392    .9512648
----------------------------------------------------------------------------------
LR test of indep. eqns. (rho1=rho0=0):chi2(2) =     6.05  Prob > chi2 = 0.0485
------------------------------------------------------------------------------


Bootstrap results                               Number of obs      =       315
                                                Replications       =      1000


      command:  summarize tt, detail
        _bs_1:  r(mean)


------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.2334671   .0056808   -41.10   0.000    -.2446012    -.222333
------------------------------------------------------------------------------


Bootstrap results                               Number of obs      =       282
                                                Replications       =      1000


      command:  summarize tu, detail
        _bs_1:  r(mean)
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.4897803   .0104284   -46.97   0.000    -.5102196    -.469341
------------------------------------------------------------------------------
```

```
Bootstrap results                               Number of obs      =       597
                                                Replications       =      1000

      command:  summarize te, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.3556805   .0036413   -97.68   0.000    -.3628174   -.3485436
------------------------------------------------------------------------------
```

Table A4.4. Stata output for Table 6.1 - baseline model for the outcome variable *Q14_morethan40%* and the treatment variable *National_support*

```
Switching probit model                          Number of obs   =        612
                                                Wald chi2(15)   =     115.41
Log likelihood = -721.29217                     Prob > chi2     =     0.0000

------------------------------------------------------------------------------
                 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
National_support |
  RD_expenditure |   .2735851   .0572094     4.78   0.000     .1614567    .3857134
          Export |   .1714215   .1220202     1.40   0.160    -.0677337    .4105768
     Competition |   -.237637   .1153998    -2.06   0.039    -.4638165   -.0114575
   RD_department |   .4829465   .1223066     3.95   0.000     .2432299    .7226632
     Small_firms |   .4903477   .1274722     3.85   0.000     .2405067    .7401886
    Medium_firms |   .3454308   .1645576     2.10   0.036     .0229038    .6679577
             ICT |  -.0455824   .1743819    -0.26   0.794    -.3873646    .2961997
       High_tech |    .301633    .187032     1.61   0.107     -.064943    .6682091
Medium_high_tech |   .2225728   .2010144     1.11   0.268    -.1714083    .6165539
        Low_tech |   .0671398   .1866492     0.36   0.719     -.298686    .4329656
 Medium_low_tech |  -.1344887   .1972035    -0.68   0.495    -.5210004    .2520231
          Modest |   .3959503   .1838538     2.15   0.031     .0356034    .7562972
        Moderate |   .5080168   .1336173     3.80   0.000     .2461317    .7699019
         Leaders |  -.0288846   .1663791    -0.17   0.862    -.3549815    .2972124
           Q53g5 |   .2740484   .0941252     2.91   0.004     .0895665    .4585303
           _cons |  -1.316507   .2145036    -6.14   0.000    -1.736927    -.896088
-----------------+------------------------------------------------------------
Q14_morethan40_1 |
  RD_expenditure |   .0886667   .0739853     1.20   0.231    -.0563417    .2336752
          Export |  -.1882039   .1393569    -1.35   0.177    -.4613384    .0849307
     Competition |   .1109837   .1261839     0.88   0.379    -.1363322    .3582997
   RD_department |  -.1254016   .1370118    -0.92   0.360    -.3939398    .1431367
     Small_firms |  -.4066888   .1399103    -2.91   0.004    -.6809079   -.1324696
    Medium_firms |  -.4723349   .1805906    -2.62   0.009    -.8262859   -.1183838
```

```
             ICT |   .0294822   .1923967     0.15   0.878    -.3476084    .4065729
       High_tech |   -.320637   .1962342    -1.63   0.102    -.7052489    .0639748
Medium_high_tech |  -.0751825      .2125    -0.35   0.723    -.4916749      .34131
        Low_tech |  -.0209486   .2081187    -0.10   0.920    -.4288539    .3869566
 Medium_low_tech |   .1138601   .2214582     0.51   0.607      -.32019    .5479102
          Modest |  -.1071327   .2084677    -0.51   0.607    -.5157218    .3014564
        Moderate |  -.4108789   .1456441    -2.82   0.005    -.6963361   -.1254216
         Leaders |   .0333677   .1931892     0.17   0.863    -.3452763    .4120116
           _cons |   .9453939   .2964098     3.19   0.001     .3644414    1.526346
-----------------+----------------------------------------------------------------
Q14_morethan40_0 |
  RD_expenditure |   .3654562   .0876016     4.17   0.000     .1937602    .5371523
          Export |    .248826    .168426     1.48   0.140    -.0812828    .5789349
     Competition |  -.1572825   .1706072    -0.92   0.357    -.4916665    .1771014
   RD_department |   .6890709   .1897445     3.63   0.000     .3171786    1.060963
     Small_firms |  -.2182538   .2996306    -0.73   0.466    -.8055191    .3690115
    Medium_firms |  -.2067101   .2862564    -0.72   0.470    -.7677623    .3543421
             ICT |  -.0641866   .2317244    -0.28   0.782     -.518358    .3899848
       High_tech |  -.0551824   .3092865    -0.18   0.858    -.6613728     .551008
Medium_high_tech |   .3137696   .3022539     1.04   0.299    -.2786372    .9061763
        Low_tech |   .0452621   .2500072     0.18   0.856    -.4447429    .5352671
 Medium_low_tech |  -.0849428   .2701049    -0.31   0.753    -.6143387    .4444532
          Modest |   .3715238   .2628781     1.41   0.158    -.1437078    .8867554
        Moderate |   .2540792   .2428569     1.05   0.295    -.2219116    .7300699
         Leaders |   .0650137   .2281119     0.29   0.776    -.3820774    .5121049
           _cons |  -.9554895   .3283776    -2.91   0.004    -1.599098   -.3118813
-----------------+----------------------------------------------------------------
        /athrho1 |  -1.831274   .8695893                      -3.535638     -.12691
        /athrho0 |   .5850282   .6721294                      -.7323213    1.902378
-----------------+----------------------------------------------------------------
            rho1 |  -.9499505   .0848667                      -.9983031    -.126233
            rho0 |   .5263104   .4859478                      -.6244834    .9564405
----------------------------------------------------------------------------------
LR test of indep. eqns. (rho1=rho0=0):chi2(2) =     5.98  Prob > chi2 = 0.0503
------------------------------------------------------------------------------
```

```
Bootstrap results                               Number of obs      =       324
                                                Replications       =      1000

      command:  summarize tt, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.3040444   .0070293   -43.25   0.000    -.3178216   -.2902671
------------------------------------------------------------------------------

Bootstrap results                               Number of obs      =       288
                                                Replications       =      1000

      command:  summarize tu, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |    .629136   .0107892    58.31   0.000     .6079896    .6502824
------------------------------------------------------------------------------
```

```
Bootstrap results                               Number of obs      =       612
                                                Replications       =      1000

      command:  summarize te, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |   .1368257   .0112801    12.13   0.000     .1147171    .1589343
------------------------------------------------------------------------------
```

Table A4.5. Stata output for Table 6.2 - augmented model for the outcome variable *Q14_morethan40%* and the treatment variable *Internat_support*

```
Switching probit model                          Number of obs   =        624

                                                Wald chi2(21)   =     117.09

Log likelihood = -663.89873                     Prob > chi2     =     0.0000


-----------------------------------------------------------------------------------

                 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-----------------+-----------------------------------------------------------------

Internat_support |

  RD_expenditure |   .3491512   .0653462     5.34   0.000     .2210749    .4772274

          Export |   .3526477    .141691     2.49   0.013     .0749385     .630357

     Competition |   .1267265   .1248973     1.01   0.310    -.1180677    .3715206

    Q18a_leading |   .3066738    .140851     2.18   0.029     .0306109    .5827367

       Q19_fewer |   .1809797   .1248265     1.45   0.147    -.0636759    .4256352

     RD_strategy |   .2963741   .1280303     2.31   0.021     .0454393    .5473089

   RD_department |  -.1673414   .1362374    -1.23   0.219    -.4343618    .0996789

     Small_firms |   .5136904   .1431559     3.59   0.000       .23311    .7942709

    Medium_firms |   .6718022   .1777692     3.78   0.000     .3233808    1.020223

             ICT |  -.0198283    .187715    -0.11   0.916    -.3877428    .3480863

       High_tech |  -.0935011   .2031972    -0.46   0.645    -.4917602    .3047581

Medium_high_tech |  -.1483543   .2165703    -0.69   0.493    -.5728243    .2761158

        Low_tech |  -.2262283   .2129451    -1.06   0.288    -.6435931    .1911364

 Medium_low_tech |  -.4694872   .2292838    -2.05   0.041    -.9188753   -.0200991

          Modest |  -.1868683   .2077297    -0.90   0.368    -.5940111    .2202745

        Moderate |   .1108529   .1456749     0.76   0.447    -.1746646    .3963704

         Leaders |  -.3334775   .1866958    -1.79   0.074    -.6993944    .0324395

       Tech_park |   -.141118   .1599095    -0.88   0.378    -.4545347    .1722988

   Tech_platform |   .0347479   .1409338     0.25   0.805    -.2414772    .3109731

           Q55b5 |   .5212036    .128062     4.07   0.000     .2702066    .7722005

           Q56a5 |  -.4997463    .143608    -3.48   0.001    -.7812129   -.2182798

           _cons |  -2.052897   .2517218    -8.16   0.000    -2.546263   -1.559532

-----------------+-----------------------------------------------------------------
```

```
Q14_morethan40_1 |
  RD_expenditure |    .047133   .1532311     0.31   0.758    -.2531943    .3474604
          Export |  -.2235249   .2290942    -0.98   0.329    -.6725413    .2254915
     Competition |  -.1732342   .1908881    -0.91   0.364     -.547368    .2008995
    Q18a_leading |  -.1471074   .2003813    -0.73   0.463    -.5398475    .2456326
       Q19_fewer |  -.1080795   .1846711    -0.59   0.558    -.4700283    .2538692
     RD_strategy |  -.3132276   .1900999    -1.65   0.099    -.6858165    .0593613
   RD_department |   .2123574    .191232     1.11   0.267    -.1624505    .5871652
     Small_firms |  -.4219925   .2164268    -1.95   0.051    -.8461813    .0021963
    Medium_firms |  -.4654328   .2757956    -1.69   0.091    -1.005982    .0751167
             ICT |   .0615903   .2722617     0.23   0.821    -.4720327    .5952134
       High_tech |  -.0424594   .2936038    -0.14   0.885    -.6179123    .5329935
Medium_high_tech |   .1998354   .3170256     0.63   0.528    -.4215233    .8211942
        Low_tech |   .2131995   .3404051     0.63   0.531    -.4539822    .8803812
 Medium_low_tech |   .3935369   .3576047     1.10   0.271    -.3073555    1.094429
          Modest |   .5700692    .328062     1.74   0.082    -.0729206    1.213059
        Moderate |  -.0114928   .2103991    -0.05   0.956    -.4238675     .400882
         Leaders |   .1790547   .3150626     0.57   0.570    -.4384567    .7965661
       Tech_park |   .1016392   .2306607     0.44   0.659    -.3504475    .5537258
   Tech_platform |   .2121153   .2036228     1.04   0.298     -.186978    .6112086
           _cons |   .9178207   .7875828     1.17   0.244    -.6258133    2.461455
-----------------+----------------------------------------------------------------
Q14_morethan40_0 |
  RD_expenditure |    .386054   .0795109     4.86   0.000     .2302155    .5418924
          Export |   .2090658   .1481454     1.41   0.158    -.0812938    .4994253
     Competition |   .0268414   .1334029     0.20   0.841    -.2346235    .2883062
    Q18a_leading |   .2540219   .1684102     1.51   0.131     -.076056    .5840998
       Q19_fewer |  -.0205102   .1380436    -0.15   0.882    -.2910707    .2500504
     RD_strategy |   .4917788   .1386527     3.55   0.000     .2200245    .7635332
   RD_department |   .2010859   .1648323     1.22   0.222    -.1219795    .5241513
     Small_firms |  -.0568396   .1761437    -0.32   0.747    -.4020749    .2883957
    Medium_firms |  -.4353591   .2467777    -1.76   0.078    -.9190345    .0483164
             ICT |  -.0779422   .2075382    -0.38   0.707    -.4847096    .3288252
       High_tech |  -.2857327   .2285777    -1.25   0.211    -.7337369    .1622714
Medium_high_tech |   .1497814   .2380142     0.63   0.529    -.3167178    .6162806
```

```
        Low_tech |   .0740077   .2165841     0.34   0.733    -.3504893    .4985046
 Medium_low_tech |  -.1346611   .2375916    -0.57   0.571    -.6003321    .3310098
          Modest |   .1530738   .2148786     0.71   0.476    -.2680804    .5742281
        Moderate |  -.0250267   .1636905    -0.15   0.878    -.3458542    .2958009
         Leaders |    -.27131   .2059826    -1.32   0.188    -.6750284    .1324084
       Tech_park |   .3191547   .1836126     1.74   0.082    -.0407194    .6790287
   Tech_platform |   .1238816   .1691092     0.73   0.464    -.2075663    .4553295
           _cons |  -1.170287   .2455098    -4.77   0.000    -1.651478   -.6890969
-----------------+----------------------------------------------------------------
       /athrho1 |   -.918442   .5302138                       -1.957642     .120758
       /athrho0 |   .6458152   .4274645                       -.1919997     1.48363
-----------------+----------------------------------------------------------------
            rho1 |  -.7251595   .2513975                       -.9609095    .1201744
            rho0 |   .5688461    .289143                       -.1896747    .9021459
----------------------------------------------------------------------------------
LR test of indep. eqns. (rho1=rho0=0):chi2(2) =     5.65  Prob > chi2 = 0.0592
------------------------------------------------------------------------------
Bootstrap results                                Number of obs      =       180
                                                 Replications       =      1000
      command:  summarize tt, detail
        _bs_1:  r(mean)
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.3831744   .0122615   -31.25   0.000    -.4072066   -.3591422
------------------------------------------------------------------------------
```

```
Bootstrap results                               Number of obs      =       444
                                                Replications       =      1000

      command:  summarize tu, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |    .461435   .0093012    49.61   0.000      .443205    .4796651
------------------------------------------------------------------------------


Bootstrap results                               Number of obs      =       624
                                                Replications       =      1000

      command:  summarize te, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |   .2194848   .0108486    20.23   0.000     .1982219    .2407477
------------------------------------------------------------------------------
```

Table A4.6. Stata output for Table 6.2 - augmented model for the outcome variable *Q14_morethan50%* and the treatment variable *Joint_support*

```
Switching probit model                          Number of obs   =        602

                                                Wald chi2(23)   =     158.34

Log likelihood =  -628.1716                     Prob > chi2     =     0.0000


------------------------------------------------------------------------------

                 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-----------------+------------------------------------------------------------

Joint_support    |

  RD_expenditure |    .355184    .0663936     5.35   0.000     .2250549    .4853131

          Export |   .3085777    .1334842     2.31   0.021     .0469536    .5702019

     Competition |  -.2722651    .1245337    -2.19   0.029    -.5163467   -.0281835

    Q18a_leading |   .1438989    .1546474     0.93   0.352    -.1592044    .4470022

       Q19_fewer |   .3734633     .124342     3.00   0.003     .1297575    .6171692

     RD_strategy |    .468996    .1297098     3.62   0.000     .2147695    .7232226

   RD_department |   .2094246    .1391138     1.51   0.132    -.0632335    .4820826

     Small_firms |   .5534443    .1439967     3.84   0.000     .2712159    .8356727

    Medium_firms |   .5036274    .1807023     2.79   0.005     .1494574    .8577975

             ICT |    .028164    .1864929     0.15   0.880    -.3373553    .3936834

       High_tech |   .4052328    .2098795     1.93   0.054    -.0061236    .8165891

Medium_high_tech |   .4111893     .226508     1.82   0.069    -.0327582    .8551369

        Low_tech |   .2255347    .2007286     1.12   0.261    -.1678862    .6189556

 Medium_low_tech |  -.2151206    .2137201    -1.01   0.314    -.6340044    .2037632

          Modest |   .4496696    .2030164     2.21   0.027     .0517648    .8475744

        Moderate |   .5323983    .1491423     3.57   0.000     .2400848    .8247117

         Leaders |  -.0900976    .1861106    -0.48   0.628    -.4548677    .2746725

       Tech_park |  -.1132943    .1631936    -0.69   0.488    -.4331478    .2065592

   Tech_platform |    .119652    .1524095     0.79   0.432    -.1790652    .4183691

           Q53b5 |   -.287023    .1263085    -2.27   0.023    -.5345832   -.0394628

           Q53g5 |    .357096    .1224175     2.92   0.004     .1171621    .5970298

           Q55c5 |   .3009728    .1288445     2.34   0.019     .0484422    .5535034

           Q56a5 |  -.3887055    .1521572    -2.55   0.011    -.6869281   -.0904828

           _cons |  -1.687793    .2455388    -6.87   0.000     -2.16904   -1.206546
```

```
-----------------+----------------------------------------------------------------
Q14_morethan50_1 |
  RD_expenditure |   .0555302   .1057651     0.53   0.600    -.1517655    .2628259
          Export |   .0629472    .194133     0.32   0.746    -.3175465    .4434409
     Competition |   .0743911   .1403597     0.53   0.596    -.2007089    .3494911
    Q18a_leading |   .0944682   .1596583     0.59   0.554    -.2184564    .4073928
       Q19_fewer |  -.2048094    .139796    -1.47   0.143    -.4788046    .0691858
     RD_strategy |  -.1431674   .1767955    -0.81   0.418    -.4896803    .2033455
   RD_department |   .1521474   .1488583     1.02   0.307    -.1396095    .4439044
     Small_firms |  -.4344586   .1618373    -2.68   0.007     -.751654   -.1172633
    Medium_firms |  -.5715042   .2010274    -2.84   0.004    -.9655107   -.1774976
             ICT |  -.1513048   .2116591    -0.71   0.475     -.566149    .2635395
       High_tech |  -.4607625   .2206516    -2.09   0.037    -.8932317   -.0282933
Medium_high_tech |  -.1140379   .2420838    -0.47   0.638    -.5885135    .3604377
        Low_tech |  -.2595168   .2413972    -1.08   0.282    -.7326468    .2136131
 Medium_low_tech |  -.1602041   .2646693    -0.61   0.545    -.6789465    .3585383
          Modest |   .2366982   .2567071     0.92   0.356    -.2664386    .7398349
        Moderate |  -.1607928    .178082    -0.90   0.367    -.5098271    .1882416
         Leaders |  -.0767525    .214736    -0.36   0.721    -.4976273    .3441223
       Tech_park |   .4002539   .1744354     2.29   0.022     .0583668     .742141
   Tech_platform |   .0473125   .1555783     0.30   0.761    -.2576153    .3522404
           _cons |   .3719841   .6724082     0.55   0.580    -.9459118     1.68988
-----------------+----------------------------------------------------------------
Q14_morethan50_0 |
  RD_expenditure |   .5447352   .1127241     4.83   0.000     .3237999    .7656705
          Export |   .1993034   .1840047     1.08   0.279    -.1613392     .559946
     Competition |  -.3670411    .175223    -2.09   0.036    -.7104718   -.0236103
    Q18a_leading |     .13946   .2236681     0.62   0.533    -.2989214    .5778415
       Q19_fewer |   .0613523    .206463     0.30   0.766    -.3433078    .4660123
     RD_strategy |   .8578264   .1876549     4.57   0.000     .4900295    1.225623
   RD_department |   .2824083   .2087873     1.35   0.176    -.1268073    .6916239
     Small_firms |  -.0381934   .2947653    -0.13   0.897    -.6159228    .5395361
    Medium_firms |  -.1328357   .3416227    -0.39   0.697    -.8024038    .5367325
             ICT |  -.2665599     .27573    -0.97   0.334    -.8069808    .2738609
       High_tech |   .0065277   .3178512     0.02   0.984    -.6164491    .6295045
```

```
Medium_high_tech |   .1357715   .3313479     0.41   0.682    -.5136584    .7852014
        Low_tech |  -.1750808   .2865985    -0.61   0.541    -.7368035    .3866418
 Medium_low_tech |  -.1670091    .281587    -0.59   0.553    -.7189094    .3848912
          Modest |   .1900722   .3120866     0.61   0.543    -.4216063    .8017508
        Moderate |   .3582731   .2229192     1.61   0.108    -.0786405    .7951867
         Leaders |  -.0581687   .2532893    -0.23   0.818    -.5546066    .4382693
       Tech_park |    .006911   .2323564     0.03   0.976    -.4484992    .4623212
   Tech_platform |   .3045352   .2456054     1.24   0.215    -.1768426    .7859129
           _cons |  -1.119524   .3035633    -3.69   0.000    -1.714497   -.5245508
-----------------+----------------------------------------------------------------
        /athrho1 |  -.9068903   .6009153                      -2.084663    .2708821
        /athrho0 |   1.125264   .6402638                      -.1296302    2.380158
-----------------+----------------------------------------------------------------
            rho1 |  -.7196363   .2897154                      -.9695455    .2644455
            rho0 |   .8093921    .220817                      -.1289089    .9830196
----------------------------------------------------------------------------------
LR test of indep. eqns. (rho1=rho0=0):chi2(2) =     7.12  Prob > chi2 = 0.0285
------------------------------------------------------------------------------


Bootstrap results                               Number of obs      =       365
                                                Replications       =      1000

      command:  summarize tt, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.4959366   .0083709   -59.25   0.000    -.5123433     -.47953
------------------------------------------------------------------------------
```

```
Bootstrap results                               Number of obs      =       237
                                                Replications       =      1000

      command:  summarize tu, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |   .4604012   .0130887    35.18   0.000     .4347478    .4860547
---------------------------------------------------------------------------

Bootstrap results                               Number of obs      =       602
                                                Replications       =      1000

      command:  summarize te, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.1157419   .0122628    -9.44   0.000    -.1397766   -.0917071
------------------------------------------------------------------------------
```

Table A4.7. Stata output for Table 6.3 - baseline model for the outcome variable *Q23_1* and the treatment variable *Joint_support*

```
Switching probit model                          Number of obs   =        598

                                                Wald chi2(18)   =     138.70

Log likelihood = -666.98421                     Prob > chi2     =     0.0000


------------------------------------------------------------------------------------

                 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-----------------+------------------------------------------------------------------

Joint_support    |

   RD_expenditure |   .4023882   .0622332     6.47   0.000     .2804133     .524363

          Export |   .3162801   .1295052     2.44   0.015     .0624546    .5701056

     Competition |  -.1687623    .122106    -1.38   0.167    -.4080856    .0705611

    RD_department |   .3844571   .1302937     2.95   0.003     .1290861    .6398281

     Small_firms |   .5672606   .1372714     4.13   0.000     .2982137    .8363075

    Medium_firms |   .3970851   .1734926     2.29   0.022     .0570459    .7371244

             ICT |  -.0692418   .1783929    -0.39   0.698    -.4188854    .2804018

       High_tech |    .189973   .1979808     0.96   0.337    -.1980622    .5780082

Medium_high_tech |   .2452408   .2190782     1.12   0.263    -.1841446    .6746261

        Low_tech |   .1080715   .1928645     0.56   0.575    -.2699359    .4860788

 Medium_low_tech |  -.2957482   .2014461    -1.47   0.142    -.6905753    .0990788

          Modest |   .3167507   .1935402     1.64   0.102    -.0625812    .6960826

        Moderate |   .4938691   .1416781     3.49   0.000      .216185    .7715531

         Leaders |  -.0582706   .1716074    -0.34   0.734    -.3946149    .2780738

          Q53c5 |  -.2517281   .1154632    -2.18   0.029    -.4780318   -.0254245

          Q53g5 |   .3208134   .1168995     2.74   0.006     .0916947    .5499322

          Q55c5 |   .3614343   .1584656     2.28   0.023     .0508474    .6720211

          Q55d5 |  -.4571667   .1225155    -3.73   0.000    -.6972927   -.2170407

          _cons |  -1.288582   .2306264    -5.59   0.000    -1.740602   -.8365631

-----------------+------------------------------------------------------------------

Q23_1_1          |

   RD_expenditure |   .0851899   .0649049     1.31   0.189    -.0420213    .2124012

          Export |   .0094327   .1516238     0.06   0.950    -.2877446    .3066099

     Competition |  -.2059021   .1290565    -1.60   0.111    -.4588483     .047044

    RD_department |   .2895985   .1369649     2.11   0.034     .0211522    .5580449
```

```
     Small_firms |   .4540225   .1456601     3.12   0.002      .168534    .7395109
    Medium_firms |   .1448184   .1922793     0.75   0.451    -.2320421    .5216789
             ICT |   .0140528   .2011687     0.07   0.944    -.3802306    .4083363
       High_tech |  -.0112318   .2088194    -0.05   0.957    -.4205103    .3980466
Medium_high_tech |  -.1648184   .2367467    -0.70   0.486    -.6288334    .2991966
        Low_tech |  -.3133731   .2370909    -1.32   0.186    -.7780627    .1513164
 Medium_low_tech |   .0600089   .2253631     0.27   0.790    -.3816946    .5017125
          Modest |   .3228147   .2040886     1.58   0.114    -.0771916     .722821
        Moderate |  -.1533604     .15535    -0.99   0.324    -.4578408      .15112
         Leaders |  -.2200543   .1951255    -1.13   0.259    -.6024932    .1623847
           _cons |  -1.197048   .2687563    -4.45   0.000      -1.7238    -.670295
-----------------+----------------------------------------------------------------
Q23_1_0          |
  RD_expenditure |   .2766361   .1268177     2.18   0.029     .0280779    .5251943
          Export |   .0497023   .2024189     0.25   0.806    -.3470315    .4464362
     Competition |  -.3095753    .172229    -1.80   0.072     -.647138    .0279873
   RD_department |   .1622151   .2314285     0.70   0.483    -.2913765    .6158068
     Small_firms |  -.2410169    .351767    -0.69   0.493    -.9304675    .4484338
    Medium_firms |   .2723129   .2658652     1.02   0.306    -.2487734    .7933992
             ICT |   .2575467   .2519692     1.02   0.307    -.2363038    .7513973
       High_tech |   .0486738   .3108626     0.16   0.876    -.5606057    .6579533
Medium_high_tech |   .0219306   .3415109     0.06   0.949    -.6474186    .6912797
        Low_tech |   .2287352   .2574231     0.89   0.374    -.2758047    .7332751
 Medium_low_tech |    .052549    .301095     0.17   0.861    -.5375865    .6426844
          Modest |   .5602818   .2755073     2.03   0.042     .0202974    1.100266
        Moderate |   .0362866   .2690757     0.13   0.893    -.4910921    .5636652
         Leaders |  -.1772315   .2322465    -0.76   0.445    -.6324263    .2779634
           _cons |  -.3043646   .2700044    -1.13   0.260    -.8335635    .2248343
-----------------+----------------------------------------------------------------
        /athrho1 |   1.892975   1.411668                      -.873844    4.659794
        /athrho0 |   .7741112    .714261                     -.6258146    2.174037
-----------------+----------------------------------------------------------------
            rho1 |    .955632   .1224869                     -.7033219    .9998207
            rho0 |   .6493137   .4131226                     -.5551635    .9744668
----------------------------------------------------------------------------------
```

```
LR test of indep. eqns. (rho1=rho0=0):chi2(2) =     4.88  Prob > chi2 = 0.0871
------------------------------------------------------------------------------

Bootstrap results                               Number of obs      =       366
                                                Replications       =      1000

      command:  summarize tt, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.4720295   .0087238   -54.11   0.000    -.4891279   -.4549311
------------------------------------------------------------------------------

Bootstrap results                               Number of obs      =       232
                                                Replications       =      1000

      command:  summarize tu, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.3467678   .0095554   -36.29   0.000    -.3654961   -.3280396
------------------------------------------------------------------------------
```

```
Bootstrap results                               Number of obs      =       598
                                                Replications       =      1000

      command:  summarize te, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.4244067   .0063083   -67.28   0.000    -.4367708   -.4120426
------------------------------------------------------------------------------
```

Table A4.8. Stata output for Table 6.3 - baseline model for the outcome variable *Q23_6* and the treatment variable *Joint_support*

```
Switching probit model                          Number of obs   =        577
                                                Wald chi2(18)   =     130.83
Log likelihood = -644.71303                     Prob > chi2     =     0.0000

------------------------------------------------------------------------------------
                 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------------
Joint_support    |
  RD_expenditure |   .4179928   .0634109     6.59   0.000     .2937096    .5422759
          Export |   .3423679   .1301345     2.63   0.009     .0873089    .5974269
     Competition |  -.2326028   .1241418    -1.87   0.061    -.4759163    .0107107
   RD_department |   .2913064   .1332152     2.19   0.029     .0302094    .5524033
     Small_firms |   .5403833    .141264     3.83   0.000      .263511    .8172556
    Medium_firms |   .4796263   .1784899     2.69   0.007     .1297925    .8294601
             ICT |   .0323735    .182168     0.18   0.859    -.3246692    .3894162
       High_tech |   .3173909   .2008284     1.58   0.114    -.0762255    .7110073
Medium_high_tech |   .3282488   .2209116     1.49   0.137    -.1047301    .7612276
        Low_tech |    .165151   .2009095     0.82   0.411    -.2286245    .5589264
 Medium_low_tech |  -.2040352   .2073444    -0.98   0.325    -.6104227    .2023523
          Modest |   .4426506   .2155912     2.05   0.040     .0200997    .8652015
        Moderate |   .4994668   .1458614     3.42   0.001     .2135837    .7853499
         Leaders |  -.0555439   .1769111    -0.31   0.754    -.4022833    .2911954
           Q53b5 |  -.2444728   .1037882    -2.36   0.018    -.4478938   -.0410517
           Q53g5 |   .3786616   .1203169     3.15   0.002     .1428448    .6144784
           Q55c5 |   .3090084   .1110643     2.78   0.005     .0913263    .5266904
           Q56a5 |  -.3258325   .1404133    -2.32   0.020    -.6010375   -.0506275
           _cons |   -1.46233   .2402939    -6.09   0.000    -1.933297   -.9913624
-----------------+------------------------------------------------------------------
Q23_6_1          |
  RD_expenditure |   .2005571   .0936151     2.14   0.032      .017075    .3840393
          Export |  -.1704701   .1935586    -0.88   0.378    -.5498381    .2088978
```

```
     Competition |  -.0788345   .1430504    -0.55   0.582    -.3592081    .2015391
   RD_department |   .3532084    .149582     2.36   0.018     .0600331    .6463837
     Small_firms |   .1532957   .1924196     0.80   0.426    -.2238397    .5304311
    Medium_firms |  -.0734568   .2318925    -0.32   0.751    -.5279577    .3810442
             ICT |  -.2162229   .2274922    -0.95   0.342    -.6620994    .2296535
       High_tech |  -.2521107   .2401332    -1.05   0.294    -.7227632    .2185418
Medium_high_tech |  -.2796096   .2649524    -1.06   0.291    -.7989067    .2396875
        Low_tech |  -.7447902   .2830952    -2.63   0.009    -1.299647   -.1899339
 Medium_low_tech |  -.5826691   .2632264    -2.21   0.027    -1.098583   -.0667548
          Modest |   .0964796   .2669759     0.36   0.718    -.4267834    .6197427
        Moderate |  -.2989473   .2177364    -1.37   0.170    -.7257028    .1278082
         Leaders |     -.0175   .2113534    -0.08   0.934    -.4317451    .3967451
           _cons |  -.3374209   .6775352    -0.50   0.618    -1.665366    .9905238
-----------------+----------------------------------------------------------------
Q23_6_0          |
  RD_expenditure |   .4034728   .0758774     5.32   0.000     .2547558    .5521898
          Export |   .3967221    .146468     2.71   0.007       .10965    .6837942
     Competition |    -.18566   .1436984    -1.29   0.196    -.4673036    .0959837
   RD_department |   .1789886   .1596804     1.12   0.262    -.1339793    .4919564
     Small_firms |   .2034678   .1849749     1.10   0.271    -.1590763     .566012
    Medium_firms |   .2653111   .2147409     1.24   0.217    -.1555733    .6861956
             ICT |   .2322743   .2069687     1.12   0.262    -.1733769    .6379255
       High_tech |    .384815   .2356484     1.63   0.102    -.0770474    .8466774
Medium_high_tech |    .232634   .2644574     0.88   0.379     -.285693    .7509611
        Low_tech |   .1235955   .2262041     0.55   0.585    -.3197564    .5669474
 Medium_low_tech |   .2373193   .2359898     1.01   0.315    -.2252123    .6998509
          Modest |  -.1551297   .2862212    -0.54   0.588     -.716113    .4058536
        Moderate |   .1368658   .1716165     0.80   0.425    -.1994963    .4732279
         Leaders |  -.1571784   .1983884    -0.79   0.428    -.5460125    .2316557
           _cons |  -.8375964   .2439047    -3.43   0.001    -1.315641    -.359552
-----------------+----------------------------------------------------------------
        /athrho1 |   .5797442   .5436356                      -.4857619     1.64525
        /athrho0 |   2.024101   .7302064                       .5929227    3.455279
-----------------+----------------------------------------------------------------
            rho1 |   .5224795   .3952313                      -.4508462     .928203
```

```
        rho0 |   .9656914   .0492453                      .5319944    .9980076
-----------------------------------------------------------------------------------
LR test of indep. eqns. (rho1=rho0=0):chi2(2) =    15.36  Prob > chi2 = 0.0005
------------------------------------------------------------------------------


Bootstrap results                               Number of obs      =       353
                                                Replications       =      1000


      command:  summarize tt, detail
        _bs_1:  r(mean)


------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.4493254   .0085394   -52.62   0.000    -.4660623   -.4325885
------------------------------------------------------------------------------


Bootstrap results                               Number of obs      =       224
                                                Replications       =      1000


      command:  summarize tu, detail
        _bs_1:  r(mean)


------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.0608236   .0119489    -5.09   0.000     -.084243   -.0374043
------------------------------------------------------------------------------
```

```
Bootstrap results                               Number of obs      =       224
                                                Replications       =      1000

      command:  summarize tu, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.0608236   .0119489    -5.09   0.000     -.084243   -.0374043
------------------------------------------------------------------------------

Bootstrap results                               Number of obs      =       577
                                                Replications       =      1000

      command:  summarize te, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.2987056   .0077219   -38.68   0.000    -.3138402    -.283571
------------------------------------------------------------------------------
```

Table A4.9. Stata output for Table 6.4 - augmented model for the outcome variable *Q23_2* and the treatment variable *Joint_support*

```
Switching probit model                          Number of obs   =        604
                                                Wald chi2(22)   =     150.25
Log likelihood = -676.32083                     Prob > chi2     =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Joint_suppor						
RD_expenditure	.3243455	.0683323	4.75	0.000	.1904166	.4582744
Export	.2948207	.1300574	2.27	0.023	.0399128	.5497286
Competition	-.2253083	.1238869	-1.82	0.069	-.4681221	.0175055
Q18a_leading	.1551269	.1545522	1.00	0.316	-.1477899	.4580437
Q19_fewer	.3044536	.1235001	2.47	0.014	.0623978	.5465093
RD_strategy	.552151	.1269405	4.35	0.000	.3033523	.8009497
RD_department	.1492198	.141375	1.06	0.291	-.12787	.4263096
Small_firms	.4992139	.1431531	3.49	0.000	.218639	.7797889
Medium_firms	.4216671	.179332	2.35	0.019	.0701828	.7731514
ICT	.0473918	.1827905	0.26	0.795	-.3108709	.4056546
High_tech	.370667	.2072853	1.79	0.074	-.0356047	.7769387
Medium_high_tech	.3688219	.2216799	1.66	0.096	-.0656627	.8033066
Low_tech	.1360297	.19946	0.68	0.495	-.2549047	.5269641
Medium_low_tech	-.2032574	.2094989	-0.97	0.332	-.6138678	.2073529
Modest	.5133501	.2023728	2.54	0.011	.1167068	.9099935
Moderate	.4619303	.1501008	3.08	0.002	.1677381	.7561224
Leaders	.0161465	.1806874	0.09	0.929	-.3379943	.3702872
Tech_park	-.1772437	.1640304	-1.08	0.280	-.4987375	.14425
Tech_platform	.1235845	.1516613	0.81	0.415	-.1736662	.4208352
Q55c5	.4136141	.1229113	3.37	0.001	.1727123	.6545159
Q55d5	-.2253611	.1362632	-1.65	0.098	-.4924321	.0417099
Q56a5	-.2748658	.146415	-1.88	0.060	-.561834	.0121023
_cons	-1.498753	.2399268	-6.25	0.000	-1.969001	-1.028505

```
-----------------+----------------------------------------------------------------
Q23_2_1          |
   RD_expenditure |  -.1146259   .0934631    -1.23   0.220    -.2978102    .0685585
           Export |    .143377   .1812148     0.79   0.429    -.2117975    .4985516
      Competition |   .0654689   .1471379     0.44   0.656    -.2229162    .3538539
     Q18a_leading |   .0026068   .1659371     0.02   0.987    -.3226239    .3278375
        Q19_fewer |  -.0677489   .1514936    -0.45   0.655    -.3646709     .229173
      RD_strategy |   .0891092    .195839     0.46   0.649    -.2947283    .4729467
    RD_department |    .052712   .1582894     0.33   0.739    -.2575296    .3629536
      Small_firms |  -.3050111    .174744    -1.75   0.081    -.6475031    .0374809
     Medium_firms |  -.0784341   .2270372    -0.35   0.730    -.5234188    .3665506
              ICT |  -.1505408   .2323142    -0.65   0.517    -.6058682    .3047867
        High_tech |  -.4938215   .2359489    -2.09   0.036    -.9562728   -.0313702
 Medium_high_tech |   -.234673   .2594254    -0.90   0.366    -.7431376    .2737915
         Low_tech |  -.6015496   .2682998    -2.24   0.025    -1.127408   -.0756917
  Medium_low_tech |  -.2006664   .2808967    -0.71   0.475    -.7512139    .3498811
           Modest |   .0938063   .2603461     0.36   0.719    -.4164626    .6040753
         Moderate |  -.3853272   .1787705    -2.16   0.031    -.7357109   -.0349434
          Leaders |   .2462013   .2296375     1.07   0.284    -.2038799    .6962824
        Tech_park |  -.0057519   .1885108    -0.03   0.976    -.3752263    .3637225
    Tech_platform |   .1402939   .1633064     0.86   0.390    -.1797807    .4603685
            _cons |   1.305263   .5872564     2.22   0.026     .1542619    2.456265
-----------------+----------------------------------------------------------------
Q23_2_0          |
   RD_expenditure |   .3169084   .0936955     3.38   0.001     .1332687    .5005482
           Export |   .3930375   .1542647     2.55   0.011     .0906842    .6953907
      Competition |  -.2008154   .1561013    -1.29   0.198    -.5067683    .1051376
     Q18a_leading |  -.0364249   .2035004    -0.18   0.858    -.4352784    .3624285
        Q19_fewer |   .4512608   .1551932     2.91   0.004     .1470877    .7554339
      RD_strategy |   .5029505   .1698264     2.96   0.003      .170097    .8358041
    RD_department |  -.0977077   .2076477    -0.47   0.638    -.5046898    .3092744
      Small_firms |   .2278657   .2025463     1.13   0.261    -.1691178    .6248491
     Medium_firms |   .0249529   .2421843     0.10   0.918    -.4497196    .4996255
              ICT |  -.0645677   .2300422    -0.28   0.779    -.5154422    .3863068
        High_tech |    .053467   .2867535     0.19   0.852    -.5085595    .6154935
```

```
Medium_high_tech |   .2985144   .2936297     1.02   0.309    -.2769893    .8740181
        Low_tech |    .090796   .2354015     0.39   0.700    -.3705824    .5521745
 Medium_low_tech |  -.1921831   .2420155    -0.79   0.427    -.6665249    .2821586
          Modest |  -.0588996   .2939675    -0.20   0.841    -.6350653     .517266
        Moderate |   .1000584   .1945565     0.51   0.607    -.2812654    .4813821
         Leaders |   .1412201   .2343816     0.60   0.547    -.3181593    .6005995
       Tech_park |   -.270172   .2137697    -1.26   0.206     -.689153    .1488089
   Tech_platform |  -.1699784   .2173597    -0.78   0.434    -.5959957    .2560388
           _cons |  -.2362018   .2654915    -0.89   0.374    -.7565554    .2841519
-----------------+----------------------------------------------------------------
        /athrho1 |  -.6360061   .6355906                      -1.881741    .6097285
        /athrho0 |   1.302486   .8292339                      -.3227824    2.927755
-----------------+----------------------------------------------------------------
            rho1 |   -.562174   .4347188                      -.9546467    .5439359
            rho0 |   .8623618   .2125593                      -.3120206    .9942882
----------------------------------------------------------------------------------
LR test of indep. eqns. (rho1=rho0=0):chi2(2) =     4.63  Prob > chi2 = 0.0989
------------------------------------------------------------------------------


Bootstrap results                               Number of obs      =       371
                                                Replications       =      1000


      command:  summarize tt, detail
        _bs_1:  r(mean)
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.2918618   .0066112   -44.15   0.000    -.3048196    -.278904
------------------------------------------------------------------------------
```

```
Bootstrap results                               Number of obs      =       233
                                                Replications       =      1000

      command:  summarize tu, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |   .3722927   .0100356    37.10   0.000     .3526232    .3919623
------------------------------------------------------------------------------

Bootstrap results                               Number of obs      =       604
                                                Replications       =      1000

      command:  summarize te, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.0357252   .0081513    -4.38   0.000    -.0517013    -.019749
------------------------------------------------------------------------------
```

Table A4.10. Stata output for Table 6.4 - augmented model for the outcome variable *Q23_3* and the treatment variable *Joint_support*

```
Switching probit model                          Number of obs   =        578
                                                Wald chi2(22)   =     142.59
Log likelihood = -607.43866                     Prob > chi2     =     0.0000

------------------------------------------------------------------------------------
                 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------------
Joint_support    |
  RD_expenditure |   .3417879   .0692895     4.93   0.000       .205983    .4775929
          Export |    .266443   .1329128     2.00   0.045      .0059386    .5269473
     Competition |  -.2652909   .1269666    -2.09   0.037     -.5141409   -.016441
     Q18a_leading |   .2316789   .1566021     1.48   0.139     -.0752555    .5386133
       Q19_fewer |   .3125734   .1256326     2.49   0.013      .0663381    .5588087
     RD_strategy |   .5364487   .1291308     4.15   0.000      .2833569    .7895405
   RD_department |   .1242236   .1408402     0.88   0.378     -.1518181    .4002653
     Small_firms |   .4562178   .1440898     3.17   0.002       .173807    .7386285
    Medium_firms |    .534912   .1846305     2.90   0.004      .1730428    .8967812
             ICT |   .0472154   .1858316     0.25   0.799     -.3170078    .4114386
       High_tech |   .4767469   .2060542     2.31   0.021      .0728882    .8806056
Medium_high_tech |   .3758283   .2210987     1.70   0.089     -.0575172    .8091738
        Low_tech |   .2430647   .2040055     1.19   0.233     -.1567787     .642908
 Medium_low_tech |  -.2712546   .2159783    -1.26   0.209     -.6945642     .152055
          Modest |   .4146353   .2108519     1.97   0.049      .0013731    .8278974
        Moderate |   .4846074   .1496192     3.24   0.001      .1913592    .7778556
         Leaders |  -.0854493   .1841625    -0.46   0.643     -.4464013    .2755027
       Tech_park |  -.1441577   .1642813    -0.88   0.380     -.4661432    .1778277
   Tech_platform |   .1603142   .1516987     1.06   0.291     -.1370098    .4576383
           Q55c5 |    .420945   .1246492     3.38   0.001       .176637     .665253
           Q56a5 |   -.386883   .1430864    -2.70   0.007     -.6673271   -.1064388
           Q56f5 |  -.2341166   .1395317    -1.68   0.093     -.5075937    .0393606
           _cons |   -1.54467   .2498276    -6.18   0.000     -2.034323   -1.055017
```

Q23_3_1						
RD_expenditure	-.1288209	.0773016	-1.67	0.096	-.2803292	.0226873
Export	-.0868916	.1610728	-0.54	0.590	-.4025885	.2288053
Competition	.0788903	.1389763	0.57	0.570	-.1934982	.3512788
Q18a_leading	.2959351	.1740422	1.70	0.089	-.0451813	.6370515
Q19_fewer	-.0449016	.1418667	-0.32	0.752	-.3229553	.233152
RD_strategy	.2385325	.1803882	1.32	0.186	-.1150218	.5920869
RD_department	.0548179	.154492	0.35	0.723	-.247981	.3576167
Small_firms	-.2088661	.1664433	-1.25	0.210	-.5350889	.1173567
Medium_firms	-.1789026	.2069615	-0.86	0.387	-.5845397	.2267345
ICT	.0957315	.2179717	0.44	0.661	-.3314851	.5229482
High_tech	.0444805	.2220933	0.20	0.841	-.3908145	.4797754
Medium_high_tech	.2056013	.2558846	0.80	0.422	-.2959234	.707126
Low_tech	-.2425587	.2400981	-1.01	0.312	-.7131422	.2280249
Medium_low_tech	.4497663	.2848144	1.58	0.114	-.1084596	1.007992
Modest	-.3886988	.2340141	-1.66	0.097	-.847358	.0699604
Moderate	-.5258618	.1684994	-3.12	0.002	-.8561146	-.195609
Leaders	.3276496	.2334967	1.40	0.161	-.1299955	.7852947
Tech_park	-.0819434	.1843429	-0.44	0.657	-.4432488	.279362
Tech_platform	.2023092	.1630361	1.24	0.215	-.1172356	.521854
_cons	1.086654	.4494527	2.42	0.016	.2057433	1.967566
Q23_3_0						
RD_expenditure	.3169339	.1164655	2.72	0.007	.0886657	.5452022
Export	.5700203	.1971953	2.89	0.004	.1835246	.9565161
Competition	-.2321881	.2006206	-1.16	0.247	-.6253974	.1610211
Q18a_leading	.3075895	.2404881	1.28	0.201	-.1637584	.7789375
Q19_fewer	.3400346	.1977107	1.72	0.085	-.0474712	.7275404
RD_strategy	.7618029	.2033866	3.75	0.000	.3631725	1.160433
RD_department	-.0852969	.2456516	-0.35	0.728	-.5667652	.3961715
Small_firms	.2564167	.2462558	1.04	0.298	-.2262359	.7390693
Medium_firms	-.3322843	.381537	-0.87	0.384	-1.080083	.4155146
ICT	-.1747011	.2765155	-0.63	0.528	-.7166615	.3672593
High_tech	-.3167812	.3778849	-0.84	0.402	-1.057422	.4238597

```
Medium_high_tech |   .1754269   .3551558     0.49   0.621    -.5206657    .8715195
        Low_tech |  -.3283876   .3270428    -1.00   0.315    -.9693798    .3126045
 Medium_low_tech |  -.0095596   .3149503    -0.03   0.976    -.6268508    .6077315
          Modest |  -.4063202   .3990595    -1.02   0.309    -1.188463    .3758221
        Moderate |    -.15476   .2761672    -0.56   0.575    -.6960378    .3865178
         Leaders |  -.1737512   .2720493    -0.64   0.523     -.706958    .3594557
       Tech_park |   .0634203    .260379     0.24   0.808    -.4469131    .5737536
   Tech_platform |   .4610982   .2617026     1.76   0.078    -.0518294    .9740258
           _cons |  -1.023305   .3472542    -2.95   0.003    -1.703911   -.3426995
-----------------+----------------------------------------------------------------
        /athrho1 |  -1.228435     .79307                     -2.782823     .325954
        /athrho0 |   .6615821   .5557983                     -.4277626    1.750927
-----------------+----------------------------------------------------------------
            rho1 |  -.8421247   .2306454                      -.992375    .3148806
            rho0 |   .5794153   .3692045                     -.4034498    .9414809
----------------------------------------------------------------------------------
LR test of indep. eqns. (rho1=rho0=0):chi2(2) =     5.14  Prob > chi2 = 0.0766
------------------------------------------------------------------------------


Bootstrap results                               Number of obs      =       353
                                                Replications       =      1000


      command:  summarize tt, detail
        _bs_1:  r(mean)
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |  -.1187854   .0090855   -13.07   0.000    -.1365927   -.1009781
------------------------------------------------------------------------------
```

```
Bootstrap results                               Number of obs      =       225
                                                Replications       =      1000

      command:  summarize tu, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |   .6281265   .0129744    48.41   0.000     .6026971    .6535559
------------------------------------------------------------------------------

Bootstrap results                               Number of obs      =       578
                                                Replications       =      1000

      command:  summarize te, detail
        _bs_1:  r(mean)

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _bs_1 |   .1740734   .0108255    16.08   0.000     .1528559    .1952909
------------------------------------------------------------------------------
```