CONTRIBUTIONS TO INVESTIGATING THE INNOVATION-PRODUCTIVITY-EXPORTING NEXUS: (I) THE DIRECTION AND STRENGTH OF THE RELATIONSHIPS; AND (II) THE USE OF TAX CREDITS TO PROMOTE RESEARCH AND DEVELOPMENT

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Abstract

The importance and benefits of productivity growth, innovation and technological progress, and international trade are long established and promotion of each of these is on the agendas of policy-makers. The links between productivity, innovation and exporting at the firm-level have been partially explored, yet the nature of this nexus is far from being understood. The literature suggests a multifaceted relationship between the three phenomena, and especially that the links between the phenomena tend to be multidirectional. Yet gaps in our understanding of the nature, timing and direction of the links between firm-level innovation, productivity and exporting can lead to less-than-optimal public policies targeting these three areas.

The first part of the thesis (Chapters 2-4) critically examines the literature to explore theoretically the broad topics of firm-level productivity, innovation and exporting. This theoretical exploration offers a comprehensive and holistic critical overview of these topics, and generates novel insights into the theoretical foundations and applicability of each concept in practice. Chapter 5 provides an overview of the theoretical understanding of the nexus between firm-level productivity, innovation and exporting, and a critical evaluation of previous studies that explored this nexus.

The first empirical chapter, Chapter 6, explores the nexus between firm-level productivity, innovation and exporting. This empirical investigation is built on the findings of the previous chapters, especially the suggested mutual endogeneity between firm-level productivity, innovation and exporting. The findings from the investigation, utilising a Spanish dataset of manufacturing firms in the period 2001 – 2016, provide strong support for Melitz's (2003) theoretical model suggesting that more productive firms are more likely to engage in exporting activities. However, the investigation suggests that the other links in the nexus tend to be absent or context-specific.

The final part of the thesis concentrates on the exploration of innovation policies and their success in promoting research and development (R&D) expenditures, in particular, R&D tax credits. Throughout the OECD, R&D tax credits are now the main policy designed to increase R&D expenditures, which are the longest-established indicator of innovation and, in turn, are the driver of innovation (according to the "new growth theory") and, hence, in turn, productivity and export growth (according to the literature and our findings in Chapter 6). Chapter 7 provides an in-depth exploration of different approaches to evaluating the effectiveness of R&D tax credits and assesses the plausibility of their underlying assumptions. Using the same dataset of Spanish manufacturing firms, Chapter

8 empirically investigates these different approaches. The results suggest that R&D tax credits are effective in increasing the R&D expenditures of firms. In this dataset, different approaches lead to similar levels of additionality.

These findings offer four main policy recommendations. First, the need for separate promotion mechanisms for increasing firm-level productivity, innovation and exporting. Second, helping firms to build their resources and capabilities can stimulate different aspects of the nexus. Third, R&D credits are an effective instrument in increasing firm-level R&D expenditures. Finally, this thesis suggests that, although different approaches yield similar results, caution should still be exercised in the choice of the approach used to evaluate the effectiveness of R&D tax credits.

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1. Introduction

The importance of innovation, productivity and international trade has been long recognised, at the level of both firms and countries. Additionally, the recent decades have pointed to the increasing importance of the three phenomena. Productivity growth in developed and developing countries has slowed down following the Global Financial Crisis of 2007 – 2009 (World Bank, 2020). The slowdown has been more prominent in some countries, such as the United Kingdom (National Institute of Economic and Social Research, 2022)[1]. The importance of innovation has been demonstrated historically and the recent years have even exacerbated the importance of innovation. For example, innovation was of pivotal importance for both countries and firms during the COVID-19 pandemic (Riom and Valero, 2020) and will be for tackling societal challenges such as climate change (Martin et al., 2020; European Commission, 2020). Additionally, some countries have pledged to increase their innovation spending – for example, the United Kingdom pledged to increase its spending into research and development (both public and private) to 2.4% of GDP by 2027 (HM Treasury, 2021). In the last few years, economic nationalism versus globalisation debates have also impacted views on the desirability of further rapid growth in international trade (De Bolle and Zettelmeyer, 2019).

An important point was made by the National Institute of Social and Economic Research (2022) regarding the UK's recent inferior productivity performance, attributing it, amongst other things, to "poor policy coordination" (p. 5) and emphasising the importance of "institutions working together" (p. 8). Building on the exploration of the links between firm-level innovation, productivity and exporting, this thesis will ultimately explore this premise to determine the importance of policy coordination and the extent to which it should be implemented.

1.1 Research questions and overview of the thesis

This thesis aims to thoroughly examine the topics of firm-level productivity, innovation and exporting. The scope of the project was initially much broader. Besides the current scope, it also involved the evaluation of the impact of R&D tax credits on innovation (measured by various innovation input and output variables), productivity and exporting. The literature review revealed too many unknowns to be comprehensively addressed

[1] The National Institute of Economic and Social Research (2022) notes that annual productivity growth (measured as growth in output per hour worked) in the three decades following the World War II was 3.6 per cent. In the three decades that followed, the growth decreased to 2.1 per cent. In the period 2007 – 2019, the growth decreased to 0.2 per cent.

within the scope of a PhD project. Although the literatures on innovation, productivity and exporting, and innovation policies are large, there remain quite substantial discrepancies between theory and evidence, between the different streams of empirical evidence and even, inconsistencies in theoretical foundations. Reviewing the literature on innovation, productivity and exporting – first separately and then jointly as a nexus – revealed knowledge gaps suggesting two priorities for empirical research. These two priorities were summarised in two broad research questions to be addressed in this research project:

1. What is the nature, the direction and the timing of the links between firm-level productivity, innovation and exporting?
2. Do R&D tax credits work in promoting R&D expenditures, taking into account the 'policy mix', as well as different evaluation approaches?

Additionally, each subsequent chapter, as outlined in Table 1.1 aims to address a range of questions that will contribute to answering the two broad research questions above.

Table 1-1. Overview of the chapters of the thesis and questions addressed by each chapter

Chapter	**Research questions addressed in the chapter**
Chapter 2 – Productivity	• How is productivity defined? • How is productivity measured and what are the implications of different measurements of productivity? • What are the determinants of productivity?
Chapter 3 – Innovation	• How is innovation defined? • Why is innovation important for economies and firms? • What are the different types of innovation and how is innovation different from research and development? • How is innovation measured? • What are the determinants of R&D and innovation?
Chapter 4 – Exporting	• How is exporting defined?

	• Why is international trade important for economies and firms? • What are the determinants of the propensity to and intensity of exporting and do the two sets of determinants differ?
Chapter 5 – The links between exporting, innovation and productivity	• What does the literature tell us about the productivity-innovation-exporting nexus? • What are the shared determinants of productivity, innovation, and exporting? • What should be the theoretical positioning of the empirical chapters?
Chapter 6 – Empirical investigation of the productivity-innovation-exporting nexus	• What is the theoretical motivation for the choice of panel VAR? • How does this research compare to the previous research covering the same/similar topics? • What are the main results of the empirical investigation in relation to the nature, direction and timings of the links in the productivity-innovation-exporting nexus? • What are the main limitations of the analysis?
Chapter 7 – Innovation policies	• What is the rationale for governments providing innovation support? • What are the main findings of the previous research about the effectiveness of single policy instruments (e.g. R&D tax credits, grants and subsidies and public procurement) on R&D expenditures, innovation outputs, exporting and productivity? • What are the main findings of the previous research about the effectiveness of the innovation 'policy mix' on R&D expenditures and innovation outputs?

	• What are different ways to evaluate the effectiveness of R&D tax credits on R&D expenditures and what are the potential theoretical implications of utilising different approaches and their assumptions?
Chapter 8 – Empirical evaluation of the effectiveness of R&D tax credits on R&D expenditures	• What are the main findings about the effectiveness of R&D tax credits on R&D expenditures? • How does this research compare to similar research on these topics? • Do different approaches to evaluating the effectiveness of R&D tax credits lead to different results and what implications does this have? • What are the main limitations of the empirical analysis?
Chapter 9 – Conclusions and policy implications	• What are the main findings of this research programme and what contribution to knowledge has been made? • What are the main policy implications of the research undertaken in this thesis? • What are the main limitations of the research undertaken in this thesis?

Chapter 2 elaborates on the different definitions of productivity and all the complexities regarding applying these theoretical constructs in practice. Total factor productivity, the concept of productivity much utilised in economic research, is the most encompassing measure of productivity available. However, as research on this topic (Atkin et al., 2019) strongly and incontestably reveals, measurement of total factor productivity requires extraordinary levels of detail in terms of data (e.g. details about product specifications) that are usually not available to researchers using even the largest and the most detailed secondary datasets. Furthermore, this chapter discusses different approaches that can be applied to measure productivity (e.g. index numbers and a range of parametric and non-parametric approaches). The details regarding the measurement of productivity in this research will be addressed in Chapter 6. The key takeaway from Chapter 2 is that productivity is not a conceptually clear concept, in the sense that the choice of different theoretical constructs of productivity (e.g. labour productivity versus total factor productivity, or even different types of total factor productivity), as well as different approaches to measure productivity, can have radically different policy-relevant implications. For example, if productivity is measured in quantity terms, product innovation will not influence productivity. Conversely, if productivity is measured in value terms, product innovation can substantially influence productivity.

Chapter 3 deals with the topic of innovation. The chapter starts by emphasising the importance of innovation both at the societal level, as well as at the firm-level. Innovation at the broader level contributes to: higher productivity; economic growth and development; and improved living standards, quality of life and well-being (Freeman and Soete, 1999; Fagerberg, 2006; Becker, 2013; OECD, 2018). At the firm-level, innovators tend to have a number of distinguishing characteristics compared to non-innovators. For example, compared to non-innovators, innovators: (i) tend to be more productive; (ii) are more likely to export; (iii) grow faster; (iv) pay higher salaries and (v) have greater presence in the sectors with higher R&D intensity and intra-industry trade (Bleaney and Wakelin, 2002; Caldera, 2010; Cassiman et al., 2010; Damijan et al., 2010; Movahedi et al., 2017). As innovation is not a field of enquiry of a single discipline, this chapter explores perspectives on innovation from: (1) mainstream economics, as the dominant economic paradigm; and (2) innovation studies, which, although an interdisciplinary field, are largely inspired by evolutionary economics. One of the conclusions drawn is that there is a need to bring the insights from the two approaches together in order to develop a fully coherent theory of innovation and to set rules and standards in devising definitions of concepts related to innovation and research on innovation. This chapter also explores different types of innovation, where the focus is placed on the types of innovation relevant for the later empirical chapters (e.g. product, process, organisational and marketing innovations). Additionally, this chapter explores the question of the differences between research and development (R&D) and innovation, which will be especially relevant in the context of the empirical chapters of this thesis. The chapter reiterates that R&D does not necessary precede innovation, nor lead to innovation when it occurs (OECD, 2018). Measurement of innovation is an additional topic explored in this chapter. The focus is placed on the measures of both innovation inputs (e.g. R&D expenditures, R&D intensity) and outputs (e.g. patents, innovation counts, innovative sales). The strengths and weaknesses of different measures are elaborated and these measures are contrasted and compared. Due to the richness of the dataset that will be used in the empirical chapters of the thesis—which will be elaborated later—these measures will be further contrasted and compared in the empirical analyses. Finally, the determinants of both R&D and innovation are discussed. As R&D and innovation share a large number of common determinants, their determinants are discussed together.

Chapter 4 deals with exporting. The chapter starts with the definition of exporting. Next, the chapter establishes the importance of exporting both at the national and at the firm level (Bernard et al., 2007; Krugman et al., 2012). The chapter also emphasises that while exporting typically leads to a better performance of firms (e.g. exporters tend to be larger, have higher productivity and higher productivity growth than non-exporters, etc.), it is costly for firms to engage in exporting activity (e.g. cost of tariff and non-tariff barriers, cost of market research, transport and distribution costs, etc.) (Vernon, 1966; Bleaney and Wakelin, 2002; Wagner, 2007; Bernard et al., 2007; Greenaway and Kneller, 2007; Wagner, 2008; Damijan et al., 2010; Caldera, 2010; Monreal-Perez et al., 2012; Álvarez et al., 2013; Movahedi et al., 2017). Finally, the chapter discusses the determinants of the propensity to export and the intensity of exporting. Considering that the recent empirical research suggests that the determinants of both the propensity to export and intensity of exporting largely overlap (Gashi et al., 2014), internal and external determinants of both are discussed together, rather than separately.

The literatures on exporting, innovation and productivity individually are large and, hence, they require being dealt with in separate chapters. There is a much smaller literature dealing explicitly with the links between (two out of three or all three of) exporting, innovation and productivity (e.g. Hirsch and Bijaoui, 1985; Wakelin, 1998; Basile, 2001; Bleaney and Wakelin, 2002; Aw et al., 2008; Caldera, 2010; Cassiman et al., 2010; Cassiman and Golovko, 2011; Becker and Egger, 2013; Gashi et al., 2014; Stojčić and Hashi, 2014; Atkin et al., 2017; Cassiman and Golovko, 2018; Stojčić et al., 2018a; Stojčić et al., 2018b). Besides an extensive exploration of the literature on the links between exporting, innovation and productivity, Chapter 5 brings together the discussions about the determinants of exporting, innovation and productivity from the three earlier chapters, identifying the extent to which the determinants of the three phenomena are shared. The chapter concludes that the research conducted on the links between exporting, innovation and productivity largely suffers from a ‘chicken-and-egg’ problem. While it confirms the existence of links between the three phenomena, it tells us very little about the ordering and timing of the same phenomena. Furthermore, the particular context (i.e. developing versus developed countries) might be relevant when exploring these links (e.g. Martins and Yang (2009) show that the link leading from exporting to productivity is more pronounced in the developing countries). Furthermore, the extensive exploration of the individual literatures on exporting, innovation and productivity revealed that the three phenomena share some common determinants, but also have many unique ones. Some of the shared determinants include: size of a firm; foreign ownership of a firm; and firms being engaged in importing activity.

Chapter 6 is the first empirical chapter and it builds on the theoretical foundations from Chapters 2-5. To allow for underlying endogeneity in the productivity-innovation-exporting nexus, a panel vector autoregression modelling strategy is utilised to explore the nature, direction and timing of the links between innovation, exporting and productivity (Abrigo and Love, 2016). The empirical investigation utilises the Survey on Business Strategies, Encuesta sobre Estrategias Empresariales (ESEE), which is a dataset of Spanish manufacturing firms that employ more than 10 employees. The same dataset will be utilised in Chapter 8. The rationale for choosing this particular dataset is its comprehensiveness, both in terms of the period covered and the range of variables related to innovation, productivity and exporting. The dataset offers seven different measures of innovation: R&D expenditures; number of product innovations introduced by a firm; patents registered by a firm in Spain; patents registered by a firm abroad; and dummy variables for process, marketing and organisational innovations. Additionally, the dataset allows calculation of both labour productivity and total factor productivity. Furthermore, the dataset allows for measuring exporting using the value of exports by a firm. The time period over which the dataset is used is 2001 – 2016, which allows for testing for the influences of the Global Financial Crisis on the nexus as there are an equal number of years before and after the Global Financial Crisis in the dataset. This chapter shows that, in line with Melitz (2003), a link leading from productivity to exporting is present regardless of the contexts, indicating that more productive firms are more likely to engage in exporting. Other links in the exporting-innovation-productivity nexus tend to be sporadic and context specific.

A particular feature of this analysis is the focus on short-run effects. Of course, there may be long-run equilibrium relationships between our variables of interest that, in principle, could be exploited by policy-makers. Nonetheless, policy institutions and their associated programmes can be subject to frequent churn and are thus often of too short a duration to realise their potential long-run impact. This is a well-known feature of economic policy making in the UK, for example. Consequently, a feature of this thesis is a focus on the potential short-run relationships between our variables of interest and thus the potential effectiveness of policies applied over short durations.

Chapter 7 discusses innovation policies. Economic theory suggests the existence of a market failure—a gap between private and social rates of return on R&D investment—that can be used to justify innovation policies, either direct or indirect (Hall and Van Reenen, 2000; Corchuelo and Martinez-Ros, 2010; Czarnitzki et al., 2011; Yang et al., 2012). R&D tax credits and R&D subsidies are commonly used innovation policies to promote R&D and innovation. A R&D tax credit is an indirect support instrument provided by governments. The aim of R&D tax credits is to boost R&D spending by lowering the after-tax costs of R&D for firms (Hall and Van Reenen, 2000). This chapter addresses the two very different approaches which are being used in the R&D tax credits evaluation literature: (1) that which uses either a dummy variable indicating that firms received R&D tax credits or the value of the credit granted to the firm; and (2) that which calculates the user-cost of R&D. The theoretical discussion of the features of these two distinct approaches sets the ground for an empirical comparison of the approaches using the ESEE dataset in Chapter 8. The importance of comparing and contrasting the two approaches is great (Gaillard-Ladinska et al., 2015; Connell, 2021), as the two approaches seem to lead to very different results, i.e. based on the narrative review, the estimated impact of R&D tax credits seems to be much larger when the user-cost approach is employed (Bloom et al., 2002; HMRC, 2010; Corchuelo and Martinez-Ros, 2010; Czarnitzki et al., 2011; Cappelen et al., 2012; Chiang et al., 2012; Yang et al., 2012; Foreman-Peck, 2013; Fowkes et al., 2015; Dechezleprêtre et al., 2016).

Chapter 8 investigates the effectiveness of R&D tax credits and the ‘policy mix’ on increasing R&D expenditures. The importance of the ‘policy mix’ has been emphasised in the literature (Flanagan et al., 2011; Petrin and Radičić, 2021). Four considerations guided the choice of this second investigation: (1) R&D expenditure is identified in the “new growth theory” as the driver of innovation (technical progress) and, hence, productivity growth; (2) in the innovation literature, R&D expenditures are the longest-established indicator of innovation (Smith, 2005); (3) the results of the literature review and the first empirical investigation suggest positive effects of innovation on productivity and, in particular, of productivity on exporting; and finally, (4) R&D tax credits are designed to increase R&D expenditures. Utilising a tobit modelling approach and the ESEE dataset, the chapter explores the impact of R&D tax credits on the propensity and intensity of R&D expenditures. Additionally, the chapter explores the effectiveness of the policy using two approaches: (1) that which uses either a dummy variable or the value of the credit granted to the firm; and (2) that which calculates the user-cost of R&D. The chapter shows that R&D tax credits encourage more firms to engage in research and development, but also increases the research and development efforts of those who previously engaged in these activities. Although there are differences in the literature between direct estimation and the user-cost approaches, our results are similar across the two approaches.

Chapter 9 offers conclusions and policy recommendations. The most important policy recommendation stem from the results presented in the empirical chapters and indicate the need for policy coordination, but separate support systems for productivity, innovation and exporting at the firm-level. Additionally, the conclusions point that some caution should still be exercised about the approach utilised to evaluate the effectiveness of the R&D tax credits policies.

2. Productivity

2.1 Introduction

Achieving higher productivity has been on the agenda of policy makers for a long time and is likely to stay there (e.g. HM Government, 2017). The performance of firms, as well as improvements in their performance, are often compared on the basis of productivity. Positive correlations between productivity and different indicators of success of a firm have been shown to exist, e.g. “profit, employment growth, export status, technology adoption, and mere survival” (Van Biesebroeck, 2008, p. 311). Productivity differences between firms are frequently substantial and persistent. While it would be hard to imagine a world in which those would disappear, it has been widely recognised that lowering the productivity gaps between different firms can lead to economy-wide benefits. Various activities of firms can lead to a rise in productivity, including innovation and exporting. This chapter aims to give an overview of what we already know about productivity, but also to cast light on inconsistencies and limitations in the analysis of productivity.

Mainstream economists define productivity as “the quantity of goods and services produced from each hour of a worker or factor of production’s time” (Mankiw and Taylor, 2014, p. 10). This definition clearly conveys that productivity is an efficiency in production concept expressed in purely quantitative terms. Furthermore, productivity, as portrayed above, is strictly a supply-side concept. However, this quantitative relationship is rarely observed as such. Concurrently, the management literature has developed and adopted a much broader definition of productivity. Porter, in his book *The Competitive Advantage of Nations*, defines productivity as “the value of the output produced by a unit of labour or capital” (1998, p. 6). The definition by Porter extends productivity beyond being a supply-side concept, recognising that productivity, in addition to incorporating technical efficiency, also depends on the quality and characteristics of the products. As Porter (1998) defines productivity in terms of value, the focus of the definition is also on the price of the product. Both an improvement in the quality and characteristics of products can lead to a hike in their prices.

Recent developments in productivity analysis, as will be discussed in more detail in the following sections, have led to a synergy of the two definitions contributing greatly to our understanding of productivity, its components and its determinants. The numerous problems faced when measuring total factor productivity, a concept widely used in mainstream economics, have been (at least partially) bridged by decomposing revenue-based productivity into different components. This chapter gives a comprehensive overview of the different approaches to decomposition of revenue-based productivity, their measurement requirements and limitations. The recent approaches to revenue-based productivity decomposition by Forlani et al. (2016) and Di Mauro et al. (2017) are discussed at length. Additionally, the research on the measurement of productivity is presented that contests the notion that measuring productivity by using revenue-based output and input measures is not acceptable or desirable. Finally, the determinants of the productivity of a firm are discussed. Following Syverson (2011), the determinants of productivity are divided into two broad groups: (1) internal; and (2) external determinants. Extensive discussion about the determinants of productivity is of particular importance to provide a platform for subsequent chapters and shed light on the common determinants of productivity, innovation and exporting.

This chapter is organised as follows. Section 2.2 gives a more detailed overview of both Porter's (1998) definition of productivity and the commonly used total factor productivity. Inconsistencies between the definition and practical application of total factor productivity are pointed out. Section 2.3 provides an overview of the recent research on productivity and especially, different approaches to the decomposition of revenue-based productivity. Section 2.4 provides an overview of the different internal and external determinants of productivity. Section 2.5 concludes.

2.2 Defining and measuring productivity

Porter (1998) observes productivity through competitive advantage, distinguishing between two types of competitive advantage: lower cost and product differentiation. Accordingly, both types of competitive advantage can lead to higher productivity of a firm in comparison with its competitors. Achieving a competitive advantage through lower costs assumes improvements in terms of the efficiency of the production process of a firm compared to the firm's competitors. In addition, it can involve designing and marketing a product more efficiently. A firm can achieve higher profits if it can produce its products at lower costs and, simultaneously, charge prices similar to the prices of its competitors. On the other hand, differentiation is about the uniqueness and superiority of a firm's products in terms of value compared to its competitors (i.e. the quality of the products, features of the product or after-sale service). Higher prices can be charged for differentiated products and, hence, by offering differentiated products in the market, a firm can achieve higher profitability compared to its competitors if it faces similar costs. According to Porter (1998), firms can utilise both types of competitive advantage simultaneously.

Mainstream economics offers a theoretically consistent approach to defining productivity. However, this definition is rarely fully operationalised as an empirical productivity measure. There are multiple ways to define productivity, which can be broadly grouped into the following two categories: (i) single-factor productivity, which represents a relationship between output and a single input (i.e. labour, capital, materials, etc.); and (ii) total factor productivity (TFP), a more complex measure that represents a relationship between output and a set of different inputs. The use of labour productivity or total factor productivity can lead to substantially different findings. For example, in the research on the productivity puzzle in the United Kingdom, Harris and Moffat (2017) found that when using labour productivity, a decrease in productivity was present in both manufacturing and services sectors in the period after 2008; while when using TFP, the decrease was observed only for services.

The most common single factor concept is labour productivity, defined within mainstream economics as physical output per labour input. Syverson (2011, p. 329-330) emphasises an important drawback of a single-factor productivity measures: "single-factor productivity levels are affected by the intensity of use of the excluded inputs". The second approach, total factor productivity, is not affected by the intensiveness of the use of the observable factor inputs. Total factor productivity can be presented by using one of the common variants of the production function:

$$Y_{it} = A_{it}F(K_{it}, L_{it}, M_{it}) \tag{2.1}$$

where Y_{it} is output of firm *i* in time *t*, $F(.)$ is a function of the inputs that are, in principle, observable (K_{it}, capital; L_{it}, labour; and M_{it}, intermediate materials). In this form of the production function, total factor productivity is A_{it}, an unobserved residual obtained when output quantity is regressed on the quantities of inputs used (Van Biesebroeck, 2008; Syverson, 2011). At first glance, measuring productivity seems straightforward. Van Biesebroeck (2008, p. 311) argues that there are at least six factors that determine the success of different methodologies in measuring productivity:

(i) Whether it is assumed that all firms share the same production technology and input trade-off;

(ii) Assumption on the functional form or alternatively, restrictions regarding "the deterministic portion of the production technology";

(iii) If the common technology is not imposed, an assumption about firm behaviour "to learn about the technological differences";

(iv) The assumption of common technology for all firms that enables econometric estimation, but leads to an issue of simultaneity bias, which will be discussed later in more detail;

(v) Structure that must be imposed on the "stochastic evolution of the unobserved productivity difference" in order to disentangle productivity from other unobservable elements that also influence output; and

(vi) Sensitivity to measurement error of different methodologies related to output or inputs.

Additional problems are encountered when measuring productivity that often limit the possibility to observe the quantitative relationship as desired. Instead of data on the actual quantities of output and some of the inputs (i.e. capital, materials); revenue-based data on i.e. deflated sales or value added may be used instead, whereas deflated values of inputs are sometimes used instead of the quantities of inputs (Van Beveren, 2012; Di Mauro et al., 2017).[2] This is a major departure from the theoretical derivation of total factor productivity conceived in physical terms.[3] Considering the basic definition of revenue (i.e. price times quantity), it can easily be deduced that price will play an important role in productivity measurement, and that using revenues instead of quantities of output may be appropriate if prices reflect different qualities of products. However, even if this were to be the case, a problem might arise due to the fact that firms are (often) exposed to different local market conditions. Price can reflect the market power that different firms possess, which can be only partially determined by the level of technical efficiency. Due to differences in market power across different producers, they can charge different mark-ups on their products and, hence, different prices.[4] Accordingly, quality and efficiency

[2] Atkin et al. (2019, p. 2) note that "in cases where these data [data on input and output quantities] are available, quantities are likely measured with substantial error since they cannot be easily read off accounting statements."

[3] De Loecker and Goldberg (2013) note that if firms are producing a homogeneous good and operating in industries with perfectly competitive input and output markets, the residual in the regression of sales on input expenditure would represent quantity-based productivity.

[4] It would be interesting to see whether globalisation has potentially led to an increase/decrease in this source of distortion in the measurement of TFP, as some evidence suggests that globalisation and increased

differences are not necessarily the only source of differences in mark-ups. Heterogeneity might additionally be reflected in differences in demand that firms face (i.e. across different firms and/or different locations). There might be a different demand conditions for firms' products, even when different producers are selling similar products (Forlani et al., 2016). Nonetheless, contrary to the dominant literature on the subject of revenue-based productivity, Atkin et al. (2019, p. 2) conclude that "if a firm's capabilities come from its ability to produce both quality and quantity, TFPR [revenue-based productivity] may be closer to the object of interest even though it confounds forces unrelated to productivity".[5]

Regarding factors of production, different measurement options are available for each and there is no definite answer on which one to use (Syverson, 2011; De Loecker and Goldberg, 2013). Different options for measuring labour inputs include the number of employees, the number of hours that employees worked, or quality adjusted labour measures (e.g. wage bills). Several measurements for capital inputs are used (e.g. establishment/book value of the capital stock of a firm). Furthermore, the inclusion of intangible capital and the quality of the inputs used raise additional questions in measuring the capital. Measurement problems are also faced when attempting to measure intermediate materials. Data on the quantity of intermediate materials used is often unavailable and, hence, data on expenditures is used instead. Another issue that arises is how to treat intermediate inputs in relation to the production function (i.e. whether to directly include intermediate inputs in the gross output production function or to subtract their value from the output).

2.2.1 Different approaches to measuring productivity

Total factor productivity accounts for several inputs used in the process of production. Input substitution possibilities are defined by a function such as the one defined in Equation (2.1). Van Biesebroeck (2008, p. 313) states that "each productivity measure is defined only with respect to that specific technology". Three approaches to measuring productivity can be distinguished: (i) index numbers; (ii) non-parametric approach (i.e. non-parametric frontier estimation – data envelopment analysis); and (iii) parametric approaches (i.e. stochastic frontiers, instrumental variables (GMM), semiparametric

concentration lead to an increase in mark-ups (e.g. Kaditi's 2012 investigation of firms that were part of the food-supply chain).

[5] The research by Atkin et al. (2019) will be discussed in more detail in the later sections.

estimation (i.e. Olley-Pakes)) (Van Biesebroeck, 2008). In the context of this thesis, distinguishing between different approaches to measuring productivity is of great importance. For example, Van Biesebroeck (2008) shows, as will be discussed in more detail in Section 2.4, that the empirical support for the link leading from exporting to productivity is dependent on the approach used to measure productivity.

The first approach – index numbers – offers a degree of flexibility when it comes to specification of production technology. No estimation of the production function is necessary to obtain the productivity measures using this approach. In this calculation "the first-order conditions for input choices imply that the factor price ratio, which is observable, equals the ratio of the marginal productivities of the factors" (Van Biesebroeck, 2008, p. 313). Furthermore, one of the advantages of using this approach is that it allows accounting for both multiple inputs and outputs. However, several non-trivial assumptions regarding firm market structure and firm behaviour underlie the estimation: perfect competition in output and input markets, and optimisation in the form of cost minimisation. As a disadvantage of the index number approach, Van Biesebroeck (2008, p. 314) notes: "Adjustments exist for regulated firms, non-competitive output markets, and temporary equilibrium, but these either involve estimating some structural parameters or are more data-intensive". The assumption of constant returns to scale does not necessarily have to be imposed, but if not information on scale economies is needed and Van Biesebroeck (2008, p. 313) notes, that in the case when it is not imposed, "estimating scale economies parametrically or information on the cost of capital suffices". Additionally, unlike some other approaches (i.e. parametric estimation approach), the index numbers approach does not allow for measurement error (Van Biesebroeck, 2008).

The second approach is data envelopment analysis, a nonparametric frontier estimation, which requires no assumptions regarding the form of production function or firm behaviour. The technology is heterogeneous across firms and is left unspecified. The definition of productivity used for the purposes of data envelopment analysis is "the ratio of a linear combination of outputs over a linear combination of inputs" (Van Biesebroeck, 2008, p. 314). The concept of domination is central to the data envelopment analysis and Van Biesebroeck (2008, p. 314) describes that "domination occurs when another firm, or a linear combination of other firms, produces more of all outputs using the same input aggregate, where inputs are aggregated using the same weights". If no such firm or combination of firms exists (i.e. if no domination takes place), then observations are 100% efficient. In the data envelopment analysis, each observation is assigned a linear programming problem. Data envelopment analysis suffers from several shortcomings – e.g. the firm is regarded as 100% efficient if: it has highest ratio of output to input for any combination of output and input; or in the case when variable returns to scale are imposed, it has "the lowest input or highest output level in absolute terms" (Van Biesebroeck, 2008, p. 314). Stochastic implementations are not most commonly used in practice. In the case when they are not used, outliers significantly impact the estimation. The presence of measurement error, even for just one firm, can impact all of the productivity estimates, as data envelopment analysis involves comparison of each observation with all the others (Van Biesebroeck, 2008).

The third approach involves parametric estimation, where the input trade-off and returns to scale are set to be the same for all firms. The functional form imposed allows for differences between firms to exist only with respect to productivity. As implied in the text above, estimates are less affected by measurement error when using parametric estimation methods due to the stochastic framework. The problems faced by using this approach will be discussed later in more detail. Van Biesebroeck (2008) discusses three estimators that address some of the problems that will be discussed below: (i) stochastic frontiers; (ii) instrumental variables (systems GMM); and (iii) a semiparametric estimator devised by Olley and Pakes (1996). In addition to these three, two other commonly applied estimators will be discussed: (i) semiparametric estimator devised by Levinsohn and Petrin (2003); and (ii) Wooldridge (2009).

The stochastic frontier method relies on separating the unobserved productivity component from the random error. This is achieved by imposing an assumption on the distribution of the unobserved productivity component. The second method – instrumental variables (systems GMM) – relies on using the method devised by Blundell and Bond (1998) for estimating the dynamic error component models. In this type of estimation, the productivity term is modelled in the way that separates it into two components: (i) a firm fixed effect; and (ii) an autoregressive component. Instrumental variables are relied upon for estimation. The advantages of using instrumental variables (systems GMM) are numerous: (i) there is a flexibility in generating instruments; (ii) it allows for different components of productivity; and importantly, (iii) as Van Biesebroeck (2008, p. 315) notes: "relative to the simple fixed-effects estimator, it also uses the information contained in the levels, which is likely to help with measurement error". However, to successfully apply this method, a long panel is needed and the method can suffer from the problem of weak instruments. When using the semiparametric estimator developed by Olley and Pakes (1996), productivity is modelled to follow a Markov process over which control variables exert no influence. Olley and Pakes' (1996) method uses investment "as a proxy variable for unobserved, time-varying productivity" (Wooldridge, 2009, p. 112). Olley and Pakes' method has the advantage that the only assumption imposed in relation to is that it follows a Markov process. The operationalization of Olley and Pakes' method involves two steps, both of which involve nonparametric approximations. This represents a potential weakness of the method. Levinsohn and Petrin's (2003) approach is a modification of Olley and Pakes' (1996) approach and uses intermediate inputs instead of investment as a proxy for productivity. This is done in order to "address the problem of lumpy investment" (Wooldridge, 2009, p. 112). Furthermore, Wooldridge (2009, p. 112) shows that "the moment conditions used by LP [Levinsohn and Petrin], as well as important extensions, can be easily implemented in a generalised method of moments (GMM) framework", instead of relying on a two-step approach.

In order to measure total factor productivity, a weighting system for different inputs must be put in place, so that, as a result, a single-dimensional input index can be constructed. When using a Cobb-Douglas production function,[6] Syverson (2011, p. 331) notes that "the inputs are aggregated by taking the exponent of each factor to its respective output elasticity". Therefore, when using a Cobb-Douglas production function,[7] total factor productivity can be presented as follows:

$$A_{it} = \frac{Y_{it}}{K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}} \tag{2.2}$$

Equation (2.2) implies that measurements of output elasticities $\alpha_x, x\epsilon\{K, L, M\}$ need to be obtained in order to obtain the estimates of total factor productivity. Output elasticities can be measured through a multiplicity of methods, as discussed previously.

[6] Although not considered in detail in the text, Syverson (2011, p. 331) points out that "it turns out this holds more generally as a first-order approximation to any production function".
[7] A Cobb-Douglas production function in the following form is used:

$$Y_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}$$

Estimating the production function is another method for estimation of the elasticities α_x. In the case of the Cobb-Douglas production function, estimations are based on the following equation:[8]

$$y_{it} = \alpha_0 + \alpha_K k_{it} + \alpha_L l_{it} + \alpha_M m_{it} + v_{it} + u_{it}^q \qquad (2.3)$$

where lower case letters denote logarithms of previously defined variables. Firm-level productivity for firm *i* in period *t*, ω_{it}, is defined as follows: $\omega_{it} = \alpha_0 + v_{it}$.[9] Finally, u_{it}^q is an independent and identically distributed (i.i.d.) term "representing unexpected deviations from the mean due to measurement error, unexpected delays or other external circumstances" (Van Beveren, 2012, p. 100).[10]

Van Beveren points to four methodological issues that arise when estimating Equation (2.3), which are caused by: (i) endogeneity of input choice/simultaneity bias; (ii) endogeneity of attrition/selection bias; (iii) omitted price bias; and (iv) problems which arise when firms produce more than one product (multi-product firms). The first issue, endogeneity of input choice/simultaneity bias, is well-known and widely discussed in the literature (Syverson, 2011; Van Beveren, 2012; De Loecker and Goldberg, 2013; Forlani et al., 2016). Endogeneity of input choice or simultaneity bias means that there is a

[8] The starting point in deriving Equation (2.3) is the following Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}$$

The same function can be expressed in the logarithmic form (logarithms are represented by the lowercase letters):

$$y_{it} = \alpha_0 + \alpha_K k_{it} + \alpha_L l_{it} + \alpha_M m_{it} + \varepsilon_{it}$$

Furthermore,

$$\ln(A_{it}) = \alpha_0 + \varepsilon_{it}$$

where α_0 is "the mean efficiency level across firms and over time", while ε_{it} "is the time- and producer-specific deviation from that mean, which can then be further decomposed into an observable (or at least predictable) and unobservable component" (Van Beveren, 2012, p. 100).

[9] The calculation of productivity, once Equation (2.3) is estimated, can be undertaken using the following:

$$\hat{\omega}_{it} = \hat{v}_{it} + \hat{\alpha}_0 = y_{it} - \hat{\alpha}_K k_{it} - \hat{\alpha}_L l_{it} - \hat{\alpha}_M m_{it}$$

Furthermore, unlogged productivity in levels is defined as the following:

$$\hat{\Omega}_{it} = \exp\,(\hat{\omega}_{it}).$$

[10] The expected value of i.i.d. error term is 0, $E[u_{it}^q] = 0$ (Van Biesebroeck, 2008).

correlation between unobserved productivity shocks and the inputs used in production. In practical terms, this means that different characteristics (including the productivity) of a firm govern its choice of inputs into its production. Different methods have been used to deal with the issue of simultaneity bias, inclusion of plant- or firm-level fixed effects being one of the possibilities for dealing with the bias. Use of instrumental variables entails another possibility. Furthermore, Olley and Pakes (1996) and Levinsohn and Petrin (2003) have devised semi-parametric estimators that deal with this problem (Biesebroeck, 2008; Van Beveren, 2012).

The second issue that arises is endogeneity of attrition or selection bias (Syverson, 2011; Van Beveren, 2012; De Loecker and Goldberg, 2013). Long, balanced panels were typically used for estimation purposes in empirical research, thereby ignoring firms that were entering and exiting the sample over the period. Even when using an unbalanced panel, selection bias will still remain an issue if the exit decisions of firms are ignored. [11] Van Beveren (2012, p. 102) suggests that: "Intuitively, the bias emerges because the firms' decisions on the allocation of inputs in a particular period are made *conditional on its survival*." Olley and Pakes' (1996) semi-parametric estimator deals with this issue of selection bias (Van Beveren, 2012).

The third issue that arises is omitted price bias (Klette and Griliches, 1996; Syverson, 2011; Van Beveren, 2012). Klette and Griliches (1996, p. 344) note that, when estimating production or cost functions, "the coefficients usually interpreted as the scale elasticity in such regressions more generally should be considered a mixture of both the scale elasticity and demand-side parameters". When estimating a production function, the common practice is to deflate revenue-based output measure and input expenditures using industry-level price indices.[12] Firm-level prices are rarely used due to the lack of their availability to the researchers. The input coefficients will be biased if input choice and firm-level price variation are correlated. Van Beveren (2012) illustrates the problem of the omitted output price bias using the following equation, where output in quantity terms is replaced by deflated sales, while it is assumed that inputs are available in quantity terms:

[11] Theoretical models (e.g. Melitz, 2003) establish that entry, growth and exit of firms depends on productivity. The tendency to exit is typically greater among the producers with lower individual productivity (Syverson, 2011).
[12] Omitted price bias is not an issue if data in quantity terms are used.

$$\tilde{r}_{it} = p_{it} + y_{it} - \bar{p}_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + (p_{it} - \bar{p}_{it}) + \omega_{it} + u_{it}^{q} \quad (2.4)$$

where $\tilde{r}_{it}$ is logarithm of deflated sales, p_{it} is the logarithm of firm-level prices, and $\bar{p}_{it}$ is the logarithm of industry-level price deflator. The other terms of the Equation (2.4) were defined previously. As stated earlier and demonstrated by Equation (2.4), the input coefficients will be biased if input choice and unobserved firm-level price differences are correlated. It is important to note that a case can be made for the inclusion of fixed effects (in this case, β_0 should be replaced by β_i) in Equation (2.4) (e.g. to capture known differences in TFP not captured by other variables, that tend to have long-lasting effects – i.e., firms with relatively high TFP retain this for long periods). However, the literature introducing the empirical approaches specifies pooled regressions without discussion of this issue (Olley and Pakes, 1996; Wooldridge, 2009; Rovigatti and Mollisi, 2018). Moreover, following these theoretical guidelines, the Stata estimator treats the data as a pooled cross-section, not allowing for fixed effects whether specified as group specific dummy variables or as a group specific component of the error term.

Van Beveren (2012, p. 102) further notes: "Assuming inputs and output are positively correlated and output and price are negatively correlated (as in a standard demand and supply framework), the correlation between (variable) inputs and firm-level prices will be negative, resulting in a negative bias for the coefficients on labour and materials." Omitted output price bias, which was demonstrated in Equation (2.4), occurs due to differences between industry-level price deflators and firm-level prices (i.e. which can arise due to the presence of imperfect competition).[13] Similar problem of omitted price bias occurs if data on quantities of inputs are unavailable and similar reasoning as in Equation (2.4) can be applied. Deflated values of inputs are used instead of quantities. If input markets are imperfectly competitive, then firms may be facing prices of inputs that are specific to them. The estimated factor elasticities will be biased due to unobserved firm-level price differences (Van Beveren, 2012). Although this never became a widespread practice among researchers, Klette and Griliches (1996, p. 352) deal with the problem by expressing omitted price variable "in terms of the firm's output growth relative to industry output, and eventually in terms of observables and parameters already present in the production (or cost) function".

[13] Dhyne et al. (2014) had access to the firm-specific prices and show that the estimated production function coefficients do not differ significantly when output is deflated using industry-level prices compared to the firm-level ones.

The fourth issue that arises is the case of firms producing more than one product – multi-product firms. Rather than being an isolated phenomenon, multi-product firms are widespread in firm-level datasets (Van Beveren, 2012; De Loecker and Goldberg, 2013).[14] However, even when data on the quantities of products is available, expressing quantities of all of the products produced by multi-product firm using the same measurement unit may not be appropriate or even feasible (Dhyne et al., 2014).[15] Even when the product-level output prices are available to the researchers, only firm-level – instead of product-level – input expenditures are generally available, which can pose a problem for estimation of the production function for multi-product firms (De Loecker and Goldberg, 2013). A solution can be sought by utilising one of the three approaches: "(a) eliminate multi-product firms from the sample and focus on single-product firms only; (b) aggregate product prices to the firm level and conduct the analysis at the firm level; (c) devise a mechanism for allocating firm input expenditures to individual products and conduct the analysis at the product level" (De Loecker and Goldberg, 2013, p. 9).[16] Furthermore, a bias can arise if different production technologies are used to produce the products by the firm or the firm faces different demand conditions for different products. Both are assumed to be identical across products in the production function framework (Van Beveren, 2012). Dhyne et al. (2014) devised an approach to deal with the measurement of productivity in multiproduct firms.[17] As presented by Dhyne et al. (2014, p. 15), this approach relies on the work of Diewert (1973), whose approach is based on the premise that "under mild regularity conditions there will exist a multi-product transformation function that relates the output of any good *g* to all the other goods a firm produces and to aggregate input use". Dhyne et al. (2014) aggregate all products produced

[14] For example, in the dataset of Belgian manufacturing firms used by Dhyne et al. (2014), 6,292 out of total 11,485 firms were multi-product firms (in at least one quarter during 1995-2007). Furthermore, the contribution of multi-product firms in the sample to total employment and total turnover is large, approximately between 70 and 75%.

[15] Dhyne et al. (2014) give an interesting example to illustrate this point: If a single firm produces two products: butter and guns, and they are both measured in terms of kilograms, it still would not be feasible to measure the production of this firm using the total weight of the products produced.

[16] Given the importance of multi-product firm (see footnote 14), it is arguable whether solution (a) does indeed represent a solution to the problem.

[17] In order to operationalise their approach, Dhyne et al. (2014) utilise different datasets, both at firm-product level and firm-level. At the firm-product level, the authors use the Belgian industrial production survey (PRODCOM survey) data (the information on production in PRODCOM survey is available both in monetary terms and quantities), as well as data on international trade (for "firm-level information on international transactions of goods, by product, classified according to the CN 8 digit product classification, and by country of destination for export or country of origin for imports" (Dhyne et al., 2014, p. 7). At the firm level, the authors use data available from: (i) the VAT declarations, for data on sales and purchases of firms; (ii) the Social Security declarations, for data on employment levels and wages; and (iii) the annual accounts.

by a firm, apart from product g, and estimate the following equation to obtain productivity:

$$q_{igt} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \gamma_{-g} r_{i(-g)t} + \omega_{igt} + \eta_{igt} \tag{2.5}$$

where q_{igt} is a logarithm of quantity of product g produced by firm *i* at time *t*; $r_{i(-g)t}$ is a logarithm of revenue of products produced by firm *i* at the time *t*, except for the product g;[18] and ω_{igt} is productivity of firm *i* of product g at the time *t*. Dhyne et al. (2014) assume that the productivity term, ω_{igt}, develops according to a first-order Markov process. Furthermore, that productivity, ω_{igt}, can be correlated with both inputs and a variable representing the output of other products, $r_{i(-g)t}$.

Table 2.1 shows the direction of bias that arises from all the above-mentioned issues.

Table 2-1. Summary of methodological issues in the estimation of total factor productivity

Origin of the bias	Definition	Direction of bias
Selection bias	Endogeneity of attrition: Correlation between ε_{it} and K_{it} (the quasi-fixed input), conditional on being in the data set	Downward bias in α_k
Simultaneity bias	Endogeneity of inputs: Correlation between ε_{it} and inputs x_{it} if firms' prior beliefs about ε_{it} influence its choice of inputs	Upward bias in α_l Upward bias in α_m Downward bias in α_k
Omitted price bias	Imperfect competition in input/output markets: Correlation between firm-level deviation of input/output price deflators and inputs x_{it}	Downward bias in α_l Downward bias in α_m Upward bias in α_k
Multi-product firms	Differences in production technologies across products produced by single firms	Undetermined

Source: Van Beveren (2012, p. 105)

2.3 New developments in productivity analysis

Particularly important research on the topic of productivity was undertaken by Atkin, Khandelwal and Osman. Atkin et al. (2019), in their paper *Measuring productivity: Lessons from tailored surveys and productivity benchmarking*, distinguish three different types of productivity: (i) quantity productivity, defined by the authors as: "the ability to produce quantity with a given set of inputs"; (ii) quality productivity, defined as: "the

[18] Revenues are deflated by a firm-specific price index.

ability to produce quality with a given set of inputs"; and (iii) capabilities, defined as: "the combination of the two, essentially a TFPQ [quantity-based productivity] measure using quality-adjusted quantities" (Atkin et al., 2019, p. 2-3). The data that Atkin et al. utilise comes from a survey conducted on a total of 219 rug producers and the detailed survey gathered information such as product specifications, as well as quantities and prices of both inputs and outputs of a production process. In order to obtain a measure that is, according to the authors, "closest to true productivity" (p. 3), a controlled laboratory was established in which different firms produced rugs "with identical specifications using identical material inputs and capital equipment". Additionally, the quality of the products was assessed by independent experts in both cases: (i) when the products were produced by a firm as a part of the regular activities; and (ii) when the products were produced in the controlled lab. The total of ten measures of productivity were produced by Atkin et al.: (i) survey-based, unadjusted quantity, unadjusted for product specifications; (ii) survey-based, specification-adjusted quantity productivity, adjusted for product specifications; (iii) survey-based, unadjusted quality productivity; (iv) survey-based, specification-adjusted quality productivity; (v) survey-based, unadjusted capability; (vi) survey-based, specification adjusted capability; (vii) revenue-based productivity; (viii) lab quantity productivity, based on the data from the controlled lab; (ix) lab quality productivity; and finally, (x) lab capabilities. By comparing these measures, the authors come to a set of very important conclusions that might change the tone of the productivity debate, considering that the authors are able to compare "ideal" measure of productivity closest to the theoretical construct to the ones commonly used in practice. Their first finding emphasises the importance of adjusting for product specifications when measuring productivity. This is demonstrated through comparison of the correlation between survey-based, unadjusted quantity productivity; survey-based, specification-adjusted quantity productivity and lab quantity productivity. The correlation between survey-based, specification-adjusted and lab quantity productivity is greater than between survey-based, unadjusted quantity productivity and lab quantity productivity. The second important finding is the existence of a strong negative correlation between survey-based, unadjusted quantity productivity and survey-based, unadjusted quality productivity. The authors describe this result as: "firms that make lower quality rugs produce more quickly" (p. 7). However, at the same time, survey-based, specification-adjusted quantity productivity and survey-based, specification-adjusted quality productivity are positively correlated, which the authors explain as: "more capable firms take longer to manufacture rugs only because they typically make varieties with more demanding specifications" (p. 7). The third important finding is that survey-based, unadjusted quantity productivity is negatively correlated with lab capabilities, whereas lab capabilities and revenue-based productivity are positively correlated. The authors interpret these findings as follows: "Although the relationship is weak, this reversal of slope relative to unadjusted TFPQ [quantity-based productivity] reveals that TFPR [revenue-based productivity] may be a more suitable proxy for a firm's capability than TFPQ if product specifications are unavailable." (p. 8). Furthermore, survey-based, specification adjusted quantity productivity is positively correlated with lab capabilities. Among all of the measures, lab capabilities are the most strongly correlated with survey-based, specification-adjusted capabilities. The fourth important finding of the paper is that differences in the dispersion of lab quantity productivity and survey-based, unadjusted quantity productivity are huge (i.e. lab quantity productivity is three times less dispersed compared to survey-based, unadjusted quantity productivity). The fifth significant finding of this paper is evidence of a large dispersion of quality productivity, which is present regardless of whether lab quality productivity, survey-based, unadjusted quality productivity or survey-based, specification-adjusted quality productivity are observed. Finally, the sixth important finding of the paper is evidence of a large dispersion in capabilities, which is greater than the dispersion in quantity productivity or quality productivity.

Although Atkin et al.'s (2019) insights are invaluable for our understanding of productivity measurement, the data requirements for obtaining all the measures of productivity presented above are very large and a vast amount of resources would have to be invested to investigate whether the patterns observed in Atkin et al. (2019) are universally present (i.e. for different products, industries, etc.). The following section will detail another method of bridging the gap between theory and practice in productivity analysis.

2.3.1 A consistent approach to definition and measurement

The recent economic literature has recognised the importance of decomposing estimated total factor productivity into several different components if measured by revenue-based data.[19] Table 2.2 gives a comprehensive overview of the studies that attempted to measure

[19] The concept of the decomposition of labour productivity changes is also present in the literature. However, in this case changes in labour productivity are decomposed into distinct components that are related to changes in total factor productivity and factor inputs (Harris and Moffat, 2017).

or calculate different components of revenue-based productivity, the datasets they employed and their main limitations.

Table 2-3. Overview of the studies that measured or calculated different components of revenue-based productivity

Paper	Components of revenue-based productivity	Data used	Limitations
Klette and Griliches (1996)	▪ Growth in industry output	▪ Plant-level data: Annual census data; ▪ Data on price deflators for gross production (at seller prices), materials, energy and capital (at buyer prices)	▪ Symmetric market sharing rule is imposed (Klette and Griliches, 1996); ▪ Industry output variable is also a proxy for other variables that are omitted (Klette and Griliches, 1996)
Foster et al. (2008)	▪ Quantity-based productivity; ▪ Producer-specific demand/Demand shocks	▪ Establishment-level data (annual value of shipments, shipments in physical units): Census of Manufactures	▪ Products aggregated together are quite dissimilar (Forlani et al., 2016); ▪ The identification in the approach is achieved by relying on the assumption that there is no correlation between demand shocks and quantity-based productivity (Forlani et al., 2016); ▪ Quantity data are necessary for operationalisation of the approach (Forlani et al., 2016); ▪ Firm specific log price coefficient is required in the regression due to the heterogeneity in mark-ups across firms (Forlani et al., 2016)
De Loecker and Warzynski (2012)	▪ Mark-ups[20]	▪ Firm-level, full firm accounts data for Slovenian manufacturers; ▪ Data on market entry and exit; ▪ Data on firm-level export status and export sales	▪ A restriction is put in place that allows prices to be set period by period (De Loecker and Warzynski, 2012); ▪ Labour is assumed to be a static input (De Loecker and Warzynski, 2012);[21] ▪ Input prices are assumed to be taken as given by firms (Forlani et al., 2016); ▪ Variable input does not face adjustment costs (De Loecker and Warzynski, 2012; Forlani et al., 2016); ▪ Mark-ups and demand shocks are proxied (Forlani et al., 2016)

[20] In this approach, mark-ups are computed after the production function is estimated.
[21] The approach, however, can accommodate for the dynamic nature of labour.

Forlani et al. (2016)	▪ Quantity-based productivity; ▪ Mark-ups; ▪ Demand-shock/Quality	▪ Firm-level production data (Belgian manufacturing firms; firm-year-product): Prodcom database—for the data on quantity and value of production sold; ▪ Annual firm accounts—for information on firms' inputs in value terms; ▪ Micro trade data (product-country-firm-month)—for information on export status of the firms	▪ It is assumed that everything that is produced is sold;[22] ▪ Focus on single product firms (Forlani et al., 2016); ▪ Input prices are assumed to be taken as given by firms (Forlani et al., 2016); ▪ Products aggregated together are quite dissimilar (Forlani et al., 2016); ▪ It is assumed that no adjustment costs are faced for material inputs (Forlani et al., 2016); ▪ Quantity data are necessary for operationalisation of the approach (Forlani et al., 2016); ▪ The approach developed by Forlani et al. (2016) can be applied to fewer different market structures compared to the other comparable approaches (e.g. De Loecker and Warzynski, 2012) (Forlani et al., 2016)
Di Mauro et al. (2017)	▪ Quantity-based productivity; ▪ Mark-ups; ▪ Demand-shock/Quality; ▪ Production scale	▪ Firm-level-based indicators (country-sector-year) on competitiveness: CompNet database; ▪ Data on quantity and value of production sold: Prodcom database	▪ As Di Mauro et al. (2017) closely follow Forlani et al. (2016) in part of their paper, all of the limitations listed under Forlani et al. (2016) apply as well; ▪ The variability over time in the number of firms N that produce product i is negligible ($N_{it} = N_i$); ▪ All products i belonging to industry j require the use of an identical ratio of labour and capital

[22] Although this is not explicitly stated, the same symbols are used for quantity produced and quantity sold.

Forlani et al. (2016) devised a setup that allows disentangling heterogeneity across single-product firms into: (1) quantity-based productivity; (2) demand shocks, which are also assumed to be a measure of quality;[23],[24] and (3) markups.[25] Such an approach is motivated by the arguments from the discussion on the limitations of measuring TFP from the previous section and the desire to improve its measurement. Furthermore, disentangling productivity into different components is valuable for further welfare or policy analysis. For example, in the context of welfare analysis, it can be valuable to analyse how market size expansion or increased trade integration affect mark-ups. In the context of policy analysis, separating quality from quantity-based productivity can inform policy-making and help to understand the source of competitiveness of an industry or a firm (Forlani et al., 2016). Di Mauro et al. (2017) extended Forlani et al. (2017)'s approach.

This section discussed how theoretical and practical considerations regarding TFP can be resolved. Next, we are going to discuss the determinants of productivity.

2.4 The determinants of productivity

The evidence points to the presence of substantial differences in productivity even among firms in narrowly defined industries (Van Reenen, 2011). These differences can be persistent (Syverson, 2011; Van Reenen, 2011). Achieving high productivity is of the utmost importance for firms, as the likelihood of their survival is dependent on it (Syverson, 2011).

A range of factors exert influence on productivity. Leibenstein (1966, p. 401) highlights this by stating: "Clearly there is more to the determination of output than the obviously observable inputs. The nature of the management, the environment in which it [firm] operates, and the incentives employed are significant." Different rationales can be applied when grouping these factors. In the following text, we utilise the grouping devised by

[23] Forlani et al. (2016, p. 3) emphasise that demand heterogeneity is modelled as: "… shocks shifting demand in a way that is complementary to heterogeneity in mark-ups and that can be interpreted as a measure of quality of a firm's products." Di Mauro et al. (2017) provide a hands-on example of how quantity is modelled in Forlani et al. (2016). For example, we can assume that the quality of product 1 is Λ_1, the quality of product 2 is Λ_2, and the product 2 is of greater quality than product 1. The exact relationship between quality of product 1 and the quality of product 2 is $\Lambda_2 = 2\Lambda_1$. In this case, consumption of n units of product 2 or twice as many ($2n$) units of product 1 makes the consumer equally satisfied.

[24] Although a convenient and wide-spread way to model quality, the groundedness of this approach in real-life is contestable.

[25] Although one can make assumptions about the direction of the links between these three components (i.e. improvements in quality can enable a firm to charge higher mark-ups), Equations (2.29), (2.30) and (2.31), below, will reveal the direction of the links as derived by Forlani et al. (2016).

Syverson (2011). Syverson (2011) recognises two groups of factors that have an impact on productivity: (1) factors that are internal to the firm, that can be tackled from within the firm itself to improve its productivity; and (2) factors that are external to the firm, such as e.g. certain aspects of the industry or market environment in which the firm operates.

2.4.1 Internal factors

When firms produce more than one product, their productivity across products typically differs. Dhyne et al. (2014) show that firms are most productive when producing their core product and productivity is lower for the non-core products (i.e. the 2^{nd} or 3^{rd} products that the firm produces).[26]

In the context of the current research, one of the most significant determinants of productivity is innovation. Porter (1990) recognises that innovation can lead to the creation of competitive advantage and that sustaining competitive advantage depends on continuous improvements. According to Porter, innovation can be one of the tools that firms use when competing with their competitors. Often firms are pressured to innovate, either by their competitors or buyers (i.e. end users, other firms). The discussion about the links between productivity and innovation is continued in Chapter 5.

The link between exporting, another focal point of this research, and productivity is both theoretically and empirically grounded. Syverson (2004) finds that productivity dispersion is larger within industries that are more involved in international trade. The literature describes the possible theoretical links between exporting and productivity through two concepts: (i) the self-selection hypothesis; and (ii) the learning-by-exporting hypothesis. Both concepts will be explained in more details in Chapters 4 and 5. In the context of the previous discussions from this chapter, it is important to note the results from the study by Van Biesebroeck (2008). Van Biesebroeck (2008) shows that the empirical support for learning-by-exporting largely depends on the approach utilised for productivity estimation. When using nonparametric estimation approaches – index number approach or data envelopment analysis – the author did not find support for learning-by-exporting. As explained in the earlier text, input elasticities are allowed to differ between firms when using nonparametric estimation approaches.

[26] The approach devised and used by Dhyne et al. (2014), as well as the data used, are described above.

Recent advancements in productivity analysis – discussed in the previous sections – have linked exporting and various components of revenue-based productivity. Forlani et al. (2016) reveal that there is not only a positive correlation between revenue-based total factor productivity and export status, but also a positive correlation between quantity-based total factor productivity and exporting status. By regressing export status on quantity-based productivity, demand shocks and mark-ups, Forlani et al. (2016) further show that: (1) demand heterogeneity has a more significant role in distinguishing between exporters and non-exporters than heterogeneities in terms of quantity-based productivity; (2) goods of a superior quality are sold by exporters compared to non-exporters;[27] and (3) mark-ups charged by exporters are lower than the mark-ups charged by non-exporters.

A significant internal factor influencing a firm's productivity is the talent and the practice of its management. The manager of a firm is the one responsible for organisation of the firm's processes (Syverson, 2011) and, in part, determines the productivity of a firm (Leibenstein, 1966). The recognition of this suggests that management matters for the productivity of a firm, which was also confirmed by empirical research. Bloom and Van Reenen (2010) point out that differences in quality of management and management practices partly explain the differences in the persistence of productivity.[28] This holds true both for the productivity at the firms' level and aggregate productivity. They recognise several factors that lead to differences in management practices, several of them that impact productivity through other channels as well (as will be discussed in more detail in the discussion of the external determinants of productivity). One of the factors is product market competition, i.e. firms facing greater competition tend to be better managed. Another factor is labour market regulations.[29] The relationship between ownership and management seems to play an important role as well, e.g. family owned and family managed firms, government-owned firms and firms managed by a founder

[27] Modelling of quality in Forlani et al. (2016) is explained in the previous section in more detail.
[28] Bloom and Van Reenen (2010) derived a series of conclusions about the quality of management from their detailed research comprising almost 6,000 interviews carried out with public and private firms employing between 100 and 5,000 employees that operate in the manufacturing sector in 17 countries. Besides the established link between the quality of management and productivity, some of their conclusions, from this and related studies, are that: (1) there are significant differences in management practices across firms and countries; (2) different firms and countries employ different management styles; (3) better management has a positive influence on the survival of firms; (4) better managed firms are (i) larger, (ii) have higher annual sales growth, and (iii) are more profitable; (7) management practices of a firm are influenced by the industry the firm is operating in; (8) the link between management and firm performance extends beyond manufacturing industries; (9) better managed firms are more energy efficient; and (10) have better work-life balance support.
[29] Three dimensions of management practices are: incentives, monitoring and targets. More rigorous labour market regulations are negatively correlated with one of these dimension: incentives.

seem to be particularly badly managed. Furthermore, foreign multinationals are typically better managed than domestic, non-exporting firms and this holds true regardless of the geographical locations in which multinationals operate. The findings show that multinationals are better managed than exporting, non-multinational, firms, whereas, in turn, exporting, non-multinational firms are better managed than domestic, non-exporting firms. Both managers' and workers' education seem to be correlated with better management.

The quality of inputs is another important determinant of productivity. Through the framework of the diamond of national advantage, Porter (1990) recognises the importance of factors of production in the creation of the competitive advantage of nations. His argument is not centred around the basic resources, as they are easily accessible by the firm, but resources that are specialised, superior and involve significant and continuous investment. Instead of creating an adverse impact, a lack of basic resources (i.e. labour shortages or limited availability of raw materials) within the nation might actually result in a beneficial impact on its firms, as it might raise the importance of innovation and continuous improvements. Superior labour (Leibenstein, 1966; Syverson, 2011) and capital inputs can positively influence productivity. The standard human capital literature assumes that several factors affect the quality of labour, such as: education, training, experience or the number of years spent at a firm. Furthermore, variations in the quality of capital can influence productivity, e.g. capital can differ in the amount of technological progress it embodies. Differences in the quality of intangible capital (i.e. firm's reputation, know-how, customer base, etc.) can also affect productivity differences (Syverson, 2011).

The so-called 'Solow paradox'[30] has spurred research on the link between information technology (IT) and productivity (Draca et al., 2006). Draca et al. (2006) provide a detailed overview of the studies testing the link between IT and productivity and conclude that most of the firm-level studies found a positive link between the two. At the same time, the spillover effect from IT to productivity has only weak supporting evidence. Furthermore, IT is found to be a determinant of productivity growth both in IT-producing and IT-using sectors (Draca et al., 2006; Syverson, 2011). Hikes in product prices, and as

[30] The 'Solow paradox', also called the 'productivity paradox', refers to the Solow's famous statement from 1987: "you can see the computer age everywhere but in the productivity statistics" (Rotman, 2018).

such, increases in productivity, can occur from product customisation achieved by IT (Syverson, 2011).

Although all the determinants discussed above encompass firm-level decisions, various strategic firm-level decisions directly influence productivity. Firm-level factors, including the organisational structure of production units, can also influence the productivity of a firm (Syverson, 2011). The size of a firm is related to its productivity. Forlani et al. (2016) show that there is a positive correlation both between revenue-based TFP and quantity-based TFP and the size of a firm. The age of a firm can also determine its productivity. Using a dataset of Chinese medium and large industrial firms for the period 1998 – 2007, Ding et al. (2016) find a higher TFP in younger firms and those firms with no political affiliation. Additionally, they find a lower TFP amongst state-owned firms. An interesting result in the context of this thesis is that they find that in most industries, neither exporting nor R&D have a strong impact on TFP.

Demand heterogeneity also has a role in explaining the differences in size between firms. Finally, Forlani et al. (2016, p. 25) find that "… larger firms typically sell higher quality goods and charge lower mark-ups". Siegel and Simons (2010) show that mergers and acquisitions (M&A) increase productivity of an acquired plant/firm through better matching of the skills of workers and managers and the firms and industries in need of those particular skills. The authors found that a decline in productivity before an M&A occurs is followed by an increase in productivity after an M&A occurs.[31] The productivity boost was shown to be higher for plants acquired in a partial acquisition, rather than a full acquisition.

2.4.2 External factors

Practices implemented by a single firm can have important and far-reaching consequences on the productivity of other firms. Agglomeration mechanisms, e.g. thick-input-market effects and knowledge-transfers, are often identified as drivers of these spillovers. Spillovers need not be tied to geographical proximity or common input markets, but are frequently specific to the same or similar industries (Syverson, 2011). For example, using UK plant-level data for the period 1984 – 2016, Harris et al. (2019) find that spatial proximity of similar and related firms does not necessarily positively

[31] Both output and employment decline after an M&A. Productivity increases still occur as the output decline is typically slower than the decline in employment (Siegel and Simons, 2010).

impact TFP. For some industries, a positive impact was found on larger manufacturing firms, as they were assumed to have larger absorptive capacity.

Although knowledge transfers are always present, their extent might differ. On the one hand, it does not seem logical that producers can retain all the details related to their production processes to themselves. However, on the other hand, differences in productivity between different producers are notable and persistent (Syverson, 2011).

As hinted in the discussion on the importance of innovation and exporting as the determinants of productivity, competition can also play a significant role in determining a firm's productivity. In 1966, Leibenstein introduced the concept of X-(in)efficiency, which emerges from the assumption, that in reality, not all firms are cost-minimisers. He argues that the gains that can be achieved from improving allocative efficiency by firms are small from the welfare point of view, but that improvements in X-efficiency can lead to substantial gains in output and welfare. Competitive pressures affect the degree of X-efficiency.

Syverson (2004, p. 543) shows that: "Factors that plausibly increase industry product substitutability are negatively correlated with within-industry productivity dispersion." Syverson (2011) recognises two distinct mechanisms through which competition can influence productivity within industries. Firstly, a Darwinian selection process affecting different producers where, as a result of competition, market shares are redistributed between firms towards more efficient producers; and, secondly, a within the firm mechanism, whereby competition induces firms to make investments in productivity. The second effect may also result in aggregate productivity growth. Van Reenen (2011) divides all of the effects of competition into two broader groups: (1) between firm effects, and (2) within firm effects. He recognises three between effects mechanisms in which productivity can be affected by the developments in competitive environment:[32] (1) reallocation, which leads to increases in aggregate productivity; (2) z scale effect, which leads to increase in the productivity of industry, and occur as a result of some firms producing more output than others;[33] and (3) "within firm" changes in productivity, where developments in competition can act on firms to undertake productivity enhancing investments.

[32] When describing a model used to explain between firm effects.
[33] If firms face the same marginal costs and fixed costs of entry.

Firms can face competitive pressures both from other firms operating in their domestic markets and from foreign firms. Porter (1990) emphasizes the importance of domestic rivalry for achieving the competitive advantage of nations, but recognises the significance of different types of rivalry as well. Domestic rivalry is specific in the sense that firms share the same conditions in terms of their local environment. The rivalry can enhance innovation across firms, with firms wanting to lower costs or deliver new or superior products or services to customers. Rivalry can extend beyond the mentioned and as noted by Porter (1990): "they [companies] compete not only for market share but also for people, for technical excellence, and perhaps most important, for "bragging rights"". If competitors are located nearby, the impact of competition may be amplified. Regarding foreign competitive pressures, Dhyne et al. (2014) show that greater foreign competition pushes firms to enhance their own productivity. However, foreign competitive pressures have a differential impact depending on the different products of firms. Dhyne et al. (2014, p. 28) show that "imports are positively related to productivity for the core product, but have a negative link for the lower ranked products". In the case of larger competitive pressures on the non-core products, firms have tendency to be less involved in producing those products (Dhyne et al., 2014).

Different institutional and environmental factors influence the productivity of firms. One such factor is the level of regulation in markets (Syverson, 2011). The flexibility of input markets influences competition, whereby more flexible input markets may positively influence productivity levels (Syverson, 2011). Scarpetta et al. (2002) show that strict product market regulations, as well as high hiring and firing costs, have a negative impact on productivity.

One of the factors contributing to productivity growth can be foreign direct investments. Using data for the United Kingdom for the period 1997-2008, Harris and Moffat (2013) showed that inward foreign-direct investment contributed to aggregate TFP growth. The authors note (p. 731): "At the aggregate level, productivity growth is mostly the result of a market selection process whereby high productivity continuing and entering plants gain market share at the expense of low productivity plants."

Government policies can also impact productivity of firms. Using UK manufacturing plant-level data for the period 1997 – 2014, Harris and Moffat (2020) explore the impact of subsidies aimed at reducing the price of the product (i.e. subsidies that are paid by the governments to firms per unit of good/service produced or imported) on TFP. They distinguish between low and high levels of subsidisation provided to firms, and find that low levels of subsidisation positively impact on TFP in food products, beverages and tobacco sectors. However, Harris and Moffat (2020) find that high-levels of subsidisation do not positively impact on the TFP of manufacturing firms.

Table 2-4. Summary of determinants of productivity and mechanisms through which they influence productivity

	Factor	**Mechanisms through which the factor influences productivity**
INTERNAL	**Innovation** (Porter, 1990; Syverson, 2011; Cassiman and Golovko, 2011; Movahedi et al., 2017)	▪ Product and process innovation
	Exporting (Syverson, 2004; Caldera, 2010; Damijan et al., 2010; Cassiman and Golovko, 2011; Forlani et al., 2016; Ding et al., 2016; Movahedi et al., 2017)	▪ Self-selection; ▪ Learning-by-exporting
	Management (Leibenstein, 1966; Bloom and Van Reenen, 2010; Syverson, 2011)	▪ Organisation of firms' processes; ▪ Differences in talent, quality and practices of management influence productivity
	Quality of inputs (Leibenstein, 1966; Porter, 1990; Syverson, 2011)	▪ Superior labour and capital (both tangible and intangible) inputs
	IT (Draca et al., 2006)	▪ Innovation; ▪ Spillovers
	Firm-level decisions (Siegel and Simons, 2010; Syverson, 2011; Forlani et al., 2016; Ding et al., 2016)	▪ Organisational structure of production unit; ▪ Size of a firm; ▪ Age; ▪ Mergers and acquisitions (M&A); ▪ Political affilitation
EXTERNAL	**Spillovers** (Syverson, 2011; Harris et al., 2019)	▪ Agglomeration mechanisms (e.g. knowledge-transfers)
	Competition (Porter, 1990; Syverson, 2011; Van Reenen, 2011; Harris and Moffat, 2013; Dhyne et al., 2014)	▪ Darwinian selection process – as a result of competition, market shares are redistributed between firms towards more efficient producers; ▪ Scale effect – increase in the productivity of industry; occurs as a result of some firms producing more output than others;[34] ▪ Within the firm mechanism – competition induces firms to make investments targeting increasing productivity
	Institutional and environmental factors (Scarpetta et al., 2002; Syverson, 2011; Harris and Moffat, 2020)	▪ Institutions; ▪ Regulations of markets; ▪ Government policies

[34] If firms face the same marginal costs and fixed costs of entry.

2.5 Conclusion

The concept of productivity has been a subject of research for decades, but it is still far from being conceptually clear. One of the aims of this chapter was to provide clarification of the concept of productivity. Different literatures offer different definitions of productivity, though recent developments in empirical work have successfully bridged this gap between different definitions of productivity, as well as between theoretical and empirical work.

Total factor productivity, the concept of productivity prevalently used in economics, is still the most encompassing measure available. The literature has pointed out numerous problems that surround its operationalisation in practice, such as: (i) selection bias; (ii) simultaneity bias; (iii) omitted price bias; and (iv) problem of multi-product firms. Contrary to this, new research (i.e. Atkin et al., 2019) shows that the emphasis placed on theoretical definition is ungrounded and the measure that is most often used in practice – revenue-based productivity – is closer to what we actually want to measure.

The productivity of firms is determined by numerous factors, which can be divided into two groups: (i) internal factors, and (ii) external factors. Internal factors are directly under the control of firms, whereas the external are not. Firms can influence their productivity through innovation, engaging in export activities, improving their management practices, using inputs of superior quality, adopting IT and through adopting a range of different firm-level decisions (i.e. mergers and acquisitions). On the other hand, productivity is influenced by: the extent of spillovers from which a firm can benefit, the extent and nature of competition that firm faces, and finally, different institutional and environmental factors. This chapter, along with the following two chapters, will serve as a platform and inform the last of the theoretical chapters – Chapter 5 as well as the empirical chapters.

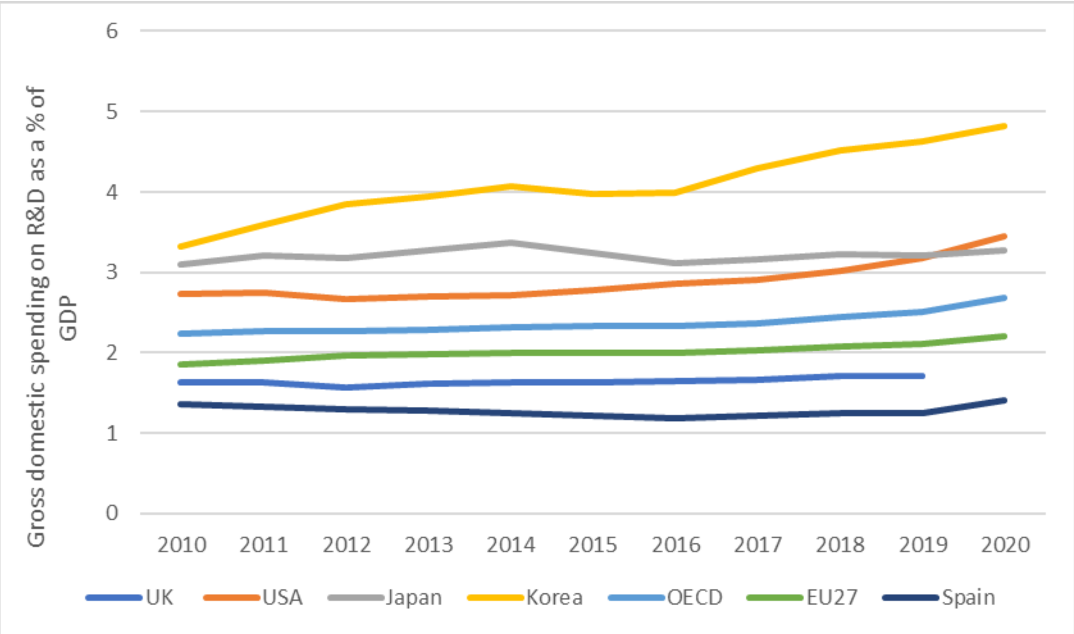
3. Innovation

3.1 Introduction

The progress of humankind in all spheres of life can be attributed to innovation(s). Economic progress was succinctly defined by Stamp (1933, p. 429) as “the orderly assimilation of innovation into the general standard of life”, emphasising that it is rooted in innovation. Innovation has been found to positively influence productivity, economic growth, living standards, quality of life and well-being (Freeman and Soete, 1999; Fagerberg, 2006; Becker, 2013; OECD, 2018). Furthermore, innovation is of great importance for firms. Simple data analyses in different studies have pointed to a set of common traits of innovative firms. Besides innovators being more productive than non-innovators, innovators appear to be more likely to export than non-innovators, grow faster than non-innovators, pay higher salaries than non-innovators and, finally, have a greater presence in the sectors with higher R&D intensity and intra-industry trade (Bleaney and Wakelin, 2002; Caldera, 2010; Cassiman et al., 2010; Damijan et al., 2010; Movahedi et al., 2017).

The percentage of GDP spent on R&D varies widely across countries, as shown in Figure 3.1. Among the selected groups of countries (the OECD and the EU) and countries (United States of America, United Kingdom, Spain, Korea and Japan), gross domestic spending on R&D has been fairly stable in the period 2010-2020 in all groups of countries/countries except for Korea. The percentage of GDP spent on R&D in 2020 in Korea was 4.81%, whereas in comparison, the EU27 and the OECD averages were 2.20% and 2.68%, respectively. Among selected countries, the lowest percentage of GDP spent on R&D was in Spain, amounting to just 1.41% in 2020.

Figure 3-1. Gross domestic spending on R&D in selected countries, 2010-2020 (as a percentage of GDP)



Source: OECD Data – Gross Domestic Spending on R&D (n.d.). Accessed from: https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm (accessed: 31st August 2022)

This chapter of the thesis contributes to the current debates among policymakers centred around innovation. For example, the Europe 2020 strategy set the target of investing 3.0% of the GDP of the European Union in R&D, which, as we can see in Figure 3.1, was not met Furthermore, one of the flagship initiatives of the Europe 2020 strategy is the Innovation Union. The Innovation Union is aimed to establish Europe's position as a "world-class science performer", tackle different obstacles to innovation (i.e. expensive patenting, etc.) and set a pathway for future collaborations between private and public sectors (European Commission, n.d.). Similarly, in the 2017 Industrial Strategy White Paper the Government pledged the intention for the United Kingdom to become "the most innovative country in the world" by 2030 (HM Government, 2017, p. 63). Different policies are to be put in place to achieve this ambitious goal, one of them being the intention to raise the level of R&D investment to 2.4% of GDP by 2027 and 3.0% in the longer term (HM Government, 2017).

Section 3.2 of this chapter will, besides providing a comprehensive overview of the definition of innovation, examine the different classifications of innovation. Section 3.3 will discuss how innovation occurs within firms, while Section 3.4 will provide an overview of the determinants of R&D and innovation. Section 3.5 of this chapter concludes and links this chapter to the remaining chapters of this thesis.

3.2 Theoretical foundations, the concept and the importance of innovation

3.2.1 Theoretical foundations and the definition of innovation

Historically, economists have been aware of the importance of R&D for economic progress; Adam Smith recognised that technological innovation was important for achieving economic progress.[35] One of the most significant figures in innovation thinking, whose contributions still influence and inspire scholars working in the field of

[35] Freeman and Soete (1999) note that there was an explosion of interest in innovation in the 1980s and 1990s. Kotsemir et al. (2013, p. 3) provide a detailed discussion of the developments of the concept of innovation from an evolutionary perspective, claiming that the period 1960s to 1990s was a "golden age in the study of innovation" in terms of the development of models and concepts related to innovation. The Google Ngram tool suggests that there has been almost continuous upsurge in the interest in innovation from the middle of 1940s onwards. Although an indicator, one should be aware that Google Ngram shows only the mentions of the term "Innovation + innovation" in Google Books published in the English language and not other pieces of written work that are perhaps even more commonly produced by scholars (e.g. journal articles) and/or other languages.

innovation, is Joseph Schumpeter (1883-1950).[36] To Schumpeter, innovation is "“new combinations” of existing resources" (Fagerberg, 2006, p. 6). Schumpeter contributed to the discussion about the distinction between *invention* and *innovation*.[37] The major point of departure between the two is in the application of a new idea (Freeman and Soete, 1999; Kotsemir et al., 2013). Invention can be defined as "an idea, a sketch or model for a new or improved device, product, process or system", while innovation is achieved "only with the first commercial transaction involving the new product, process system or device" (Freeman and Soete, 1999, p. 6).[38] Two important aspects are to be considered regarding the differences between invention and innovation: (i) the time dimension; and (ii) the actors involved in carrying out invention and innovation. With respect to the time dimension, there are no unique rules as to when invention and innovation occur in relation to one another. Invention and innovation could occur almost simultaneously, but it could also be that innovation follows invention with a significant time lag. Different actors might be responsible for inventions and innovations. While inventions can be carried out by a variety of different actors (e.g. universities), innovations are mostly carried out by firms (Fagerberg, 2006).

Freeman and Soete (1999, p. 2) illustrate the importance of innovation as a topic to be explored by economics by stating that "least of all can economists afford to ignore innovation". Exploration of innovation is not confined to a single stream within economics. Innovation is a subject of inquiry of: (i) mainstream economics (including neoclassical and post-neoclassical economics), and (ii) innovation studies, an interdisciplinary approach (Chaminade et al., 2018) bringing together "economic, management, organisational and policy studies of science, technology and innovation, with a view to providing useful inputs for decision-makers concerned with policies for, and the management of, science, technology and innovation" (Martin, 2016, p. 433).[39]

[36] Schumpeter's thinking on innovation occasionally changed in his writings from different periods. One notable example is that he assigned innovation predominantly to individual entrepreneurs in his earlier writings and to large oligopolistic firms in later ones (Fagerberg, 2006; Chaminade et al., 2018).
[37] The distinction between *invention* and *innovation* was recognised before Schumpeter (Kotsemir et al., 2013).
[38] Seemingly different definitions of innovation, as opposed to invention, are used in the innovation studies literature. For example, Fagerberg (2006) defines innovation as "first attempt to carry it [an idea for a new product or process] out into practice". However, the discussion following the definition suggests that Fagerberg did indeed think about a commercial application rather than just an application of a new idea.
[39] Firms and routines are at the centre of analysis of evolutionary economics. It is built on the premises of uncertainty and limited rationality of the economic agents who search for satisfactory solutions (Chaminade et al., 2018).

(Chaminade et al., 2018). The perspectives and the aims of these two approaches widely differ, as will be detailed below.

One could say that mainstream economics committed what Akerlof (2019) calls a "sin of omission" when it comes to innovation.[40] Innovation was explored mostly in the light of other topics (e.g. economic growth at a more aggregate level or productivity growth at a firm level) rather than independently or as a topic of central importance. Lazonick (2006, p. 30) succinctly noted that "over the past century, the theoretical efforts of economists have focused mainly on the optimising firm rather than the innovating firm". Furthermore, innovation studies scholars warned about orthodox economics' narrow view of innovation. For example, Edquist and Hommen (1999, p. 70) argued that the mainstream paradigm assigned no value to "product innovation and the structural character of interfirm relationships", while focusing on "process improvements achieved through 'learning by doing' in competitive markets where there are no fundamental differences among firms". Similarly, Fagerberg (2006) argued that economics focused only on certain aspects of innovation, such as product innovations and innovations related to methods of production. Their claims are only partially true. The central assumptions of the mainstream paradigm (i.e. optimisation, rationality, etc.) have been (to a varying extent) limiting exploration of innovation and innovation processes that occur in the real world (Chaminade et al., 2018). Furthermore, it appears that mainstream economists were often reluctant to use the term *innovation* and used terms such as *technical progress* or *industrial R&D* instead. On the other hand, at the more aggregate level, new growth theory has incorporated innovation into the model of economic growth. The aims of *industrial R&D*, as referred to by Grossman and Helpman (1990, p. 87), are: "cost reduction, product innovation, or quality improvements". Examined more thoroughly, the aims of *industrial R&D*, as defined above, largely coincide with the types of innovation and their aims as defined by OECD *Oslo Manual* that will be detailed later in this section (e.g. process innovation and organisational innovation can be aimed at reducing costs). While some mainstream theoretical models of innovation at the firm-level have acknowledged only innovation leading to cost reductions, other mainstream theoretical models have come a long way to depict other aims of innovation as well. One notable example of the former is the model by Aghion et al. (2018) that recognises only

[40] Akerlof (2019) defined the "sins of omission" of mainstream economics as important topics and problems that were ignored or underexplored because they could not be tackled in the preferred methodological manner (e.g. using mathematical models, methods of analysis).

innovation that leads to cost reduction, whereas an example of the latter is Acemoglu et al. (2018), which sees innovation in the context of product innovation and quality improvements. Additionally, although the process of innovation is not discussed in great detail at either a more aggregate or firm-level, different aspects of the innovation process are recognised and incorporated into the models, such as: spillovers in the economy, reverse engineering, and diffusion of innovation at an aggregate level (Grossman and Helpman, 1990; 1994); or the importance of prior knowledge for innovation at the firm-level (Acemoglu et al., 2018).

The other main approach to studying innovation is innovation studies. One of the innovation studies flagship concepts in relation to innovation is the concept of *systems of innovation* and, in particular, *national innovation systems*. The concept of national innovation systems, which will be discussed in more detail later, was influenced by evolutionary economics as an alternative to mainstream views on economic growth and international competitiveness (Chaminade et al., 2018). The strength of innovation studies is its detailed and thorough exploration of (the parts of) innovation processes predominantly within the business sector. However, the approach has failed to dedicate an equal amount of resources to exploration of innovation and innovation process within all sectors and subsectors of the economy. For example, Martin (2016) notes that empirical research has failed to explore innovation in the service sector to the same extent it was explored in the manufacturing sector. Furthermore, too little resources were dedicated to exploration of financial innovation; or tackling the problems that emerge when measuring innovation (to be discussed in more detail in the following section). Additionally, Gault (2018) emphasises a focus mostly on the business sector. Although an interdisciplinary field, innovation studies scholars fail to incorporate any insights about innovation from mainstream economics (e.g. insights on process innovation) and even consider their field as somewhat superior to mainstream economics (Martin, 2016).

Due to the different foci of the two separate streams (i.e. focus on innovation in the context of its links with other economic phenomena, such as e.g. productivity, versus a focus on the innovation process, such as e.g. systems approaches), the insights generated can be thought of as potentially complementary (OECD, 2005). Provision of strict definitions and useful generalisations (i.e. presenting complex real-life phenomenon such as innovation in simpler models) is one of the greatest strengths of the dominant economic paradigm. Additionally, and perhaps because of the aforementioned, it has had a prevailing influence on shaping innovation policies, as will be discussed in the penultimate section of this chapter. Innovation studies, on the other hand, have failed to uniformly define even their most important concepts, as will be indicated in the discussion below on national innovation systems. Furthermore, innovation studies (to a great extent) fail to make generalisations from the vast amount of research produced by the scholars within the field. Montalvo and Wehn (2018) note that Google Scholar returns approximately four million existent scholarly outputs when the word "innovation" is searched for, which indicates the necessity of making generalisations.

As indicated in the earlier discussion on different approaches to innovation, innovation has no unified definition even in the academic community.[41] However, one of the commonly used definitions of innovation is given in the *Oslo Manual: Guidelines for collecting and interpreting innovation data* (NESTA, 2009). Throughout this and the following chapters, the definition and the types of innovation from the 2005 edition of *Oslo Manual* will be used, although a more recent edition is available. This particular choice has been made to align the theoretical discussions on innovation presented in this chapter with the empirical investigations in the following chapters. Innovation 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" (OECD, 2005, p. 46). Three aspects of this definition need to be emphasised. The first aspect is the concept of novelty that is critical for the definition of innovation. This is emphasised by the construct that an innovation must be *a new or significantly improved* product, process, marketing or organisational method. A second aspect is the importance of the *implementation* of an innovation (Gault, 2018). The third aspect of the definition worth noting, although not explicitly stated in the definition, is that innovation has to be a new or significantly improved product, process, marketing organisational method *to the firm, to the market* or *to the world*. According to the OECD (2005), diffusion of innovation also constitutes innovation. This definition of innovation largely coincides with the definition of innovation used in most of the empirical research, as the *Oslo Manual* has been widely used in designing innovation surveys (NESTA, 2009). However, in some surveys this definition has been substantially broadened. For example, the definition of 'broad' and 'active' innovators

[41] This is even more exacerbated in everyday application of the term. Scholars have warned about potential dilution of the term *innovation* and the threat that the term *innovation* is moving away from a scientific concept to a buzzword (Kotsemir et al., 2013).

used in the Innovation Survey in the United Kingdom employs a definition that in one aspect substantially differs from the one provided above – it includes "innovation which is incomplete, reduced or abandoned" (Department for Business, Energy and Industrial Strategy, 2018, p. 9).

Measuring R&D and more broadly innovation and comparing it across firms, industries and countries represents a challenge, particularly for empirical researchers. Two types of measures are commonly used: (i) input measures (i.e. R&D expenditure,[42] R&D intensity); and (ii) output measures (i.e. patents, innovation counts, innovative sales[43]). Although both have been established, neither input measures, nor output measures necessarily capture all dimensions of innovation. There is no warranty that a firm that spends more on R&D will be more innovative in terms of output. Likewise, if a firm has more patents, it is not a warranty that those will necessarily be implemented and, hence, that a firm is more innovative. Innovative sales have an advantage of being an output measure – a measure of commercial realisation of innovation. However, the drawback of innovative sales is that they are revenue- and not a profit-oriented measure. An advantage of input measures is the ease of their comparability (i.e. if they are expressed in monetary terms) as opposed to some of the output measures (e.g. patents) (Becker, 2013; 2015). However, input measures – namely R&D expenditure or R&D intensity – can suffer from being measured inaccurately, which represents their significant drawback. This may occur due to two reasons: (i) firms may use different classifications for their R&D expenditures; and (ii) different definitions of R&D are used in different datasets. One caveat of using patents as a measure of innovation is that there can be significant variations in the propensity to patent across different industries or countries. For example, Sampat (2018), in a narrative review of empirical evidence on patents and innovation, concludes that: (i) sectoral differences are present in the extent to which patents affect the incentives to innovate (i.e. the effects are stronger in the pharmaceutical or chemical sectors than in others); (ii) the rationale for using patents differs across different fields, with patents being both an appropriability and strategic tool; and (iii) innovations are not always patented. Additionally, Sampat (2018) concludes that: (i) firms are using patent documents for information purposes; (ii) empirical studies offer mixed evidence on how

[42] Hall (2006, p. 1) notes that R&D expenditure are "one of the most widely used indicators of the innovative performance of firms, industries, and countries".
[43] Innovative sales are defined as "the proportion of sales due to product and process innovations" (Radičić et al., 2018, p. 11).

patents affect follow-on innovation; and (iii) stricter patent regulations do not lead to higher R&D for investments with high social value, but without large markets.

The measures of innovation we are using are often better reflections of technological innovations that were predominant several decades ago than of all innovation occurring nowadays.[44] That part of innovation not captured with the measures of innovation is sometimes referred to as 'dark innovation' (Martin, 2016). Furthermore, Martin (2016, p. 433) argues that the measures commonly used in empirical studies fail to account for innovation that is: "(i) incremental; (ii) not in the form of manufactured product innovations; (iii) involves little or no formal R&D; (iv) is not patented". However, in addition to the measures discussed above, empirical researchers often use survey data to capture innovation. Survey data potentially circumvents all the issues discussed by Martin (2016). However, survey data suffers from a number of drawbacks. It is subjective and hence, can be prone to measurement error (Cassiman and Veugelers, 2002). Potential dilution of the concept of *innovation* and lack of unified definition mentioned earlier can make this problem even more pronounced. Furthermore, survey data assigns equal value to all innovation (i.e. firms are usually asked only whether they introduced some specific type(s) of innovation). Additionally, measuring and econometrically assessing the impact of truly radical innovations in more general contexts, such as general-purpose technologies or technological revolutions, which will be mentioned in the section below, is challenging (Bloom et al., 2019).

Despite the differences between mainstream economics and innovation studies approaches in terms of their foci, they are probably most similar when it comes to empirical research. The differences seem to be apparent, but this does not universally apply, in two aspects: (i) the sophistication of techniques (i.e. scholars of mainstream economics are more likely to devise and test mathematical models using more sophisticated econometric models and techniques; whereas the extent and the sophistication of econometrics models and techniques varies widely within innovation studies); and (ii) choice of specific variables (i.e. innovation studies scholars are far more likely to use survey data, whereas mainstream economics scholars seem to be more keen on using other sources such as administrative datasets and patent measures). However, although aware of the limitations of the datasets they are using, empirical researchers are

[44] This is not to say that technological innovations are not prevalent nowadays, but rather that different non-technological innovations are also present.

bounded to working with the available datasets, both in terms their model specifications and choices of variables. Furthermore, neither of the approaches seems to have the answer on how to econometrically estimate the impact of the technological revolutions. On this note, Grossman and Helpman (1994, p. 32) note that the economic historians provide "perhaps the most convincing direct evidence in favour of viewing industrial innovation as the engine of growth".

3.3 Types of innovation

Innovation scholars have recognised that innovation can appear in different forms. Stamp (1933) recognised two types of innovation: (i) direct, and (ii) derivative. The former is defined as innovation "which creates new kinds of economic satisfactions", while the latter is defined as that "which accelerates or makes easier the production of existing economic goods" (Stamp, 1933, p. 429), which largely coincides with product and process innovation as discussed later. Furthermore, Schumpeter recognised five different types of innovation, which Fagerberg (2006, p. 6) grouped as follows: (i) "new products"; (ii) "new methods of production"; (iii) "new sources of supply"; (iv) "the exploitation of new markets"; and (v) "new ways to organise business". Nowadays, the most commonly used classifications of innovation are between: (i) technological and non-technological innovation; (ii) product, process, marketing and organisational innovation; (iii) functional and soft innovation; and (iv) radical and incremental innovation.[45],[46]

Technological innovation covers product and process innovation,[47] while non-technological innovation covers organisational and marketing innovation (Radičić et al., 2018) – both will be discussed in more detail below. The earliest edition of the *Oslo Manual* covered only technological product and process innovation in goods (NESTA, 2009). The establishment of the European Community Innovation Survey in the 1990s has led to the recognition of non-technological innovation (Radičić et al., 2018). The third edition of the *Oslo Manual* distinguishes four types of innovation: (i) product innovation,

[45] In the context of this thesis, it is important to note that none of the classifications of innovation used today recognises the exploitation of new markets by firms as innovation.
[46] These particular classifications of innovation will be discussed in more detail as they are of interest in the context of the subsequent chapters. This does not mean that other classifications of innovation are of a lesser importance, such as e.g. distinction between (i) dysfunctional, and (ii) frugal innovation, where dysfunctional innovation is described to benefit only a subgroup of customers who are able to afford it, and frugal innovation is available to all customers (Martin, 2016).
[47] It is recognised that the economic and social impacts of product versus process innovation may differ, i.e. product innovation typically leads to growth of employment and income, while the same need not to be necessarily true for process innovation (Fagerberg, 2006).

defined as “the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses” (OECD, 2005, p. 48); (ii) process innovation, defined as “the implementation of a new or significantly improved production or delivery method” (OECD, 2005, p. 49); (iii) marketing innovation, defined as “the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing” (OECD, 2005, p. 49);[48] and (iv) organisational innovation, defined as “the implementation of a new organisational method in the firm’s business practices, workplace organisation or external relations” (OECD, 2005, p. 51). The fourth edition of the *Oslo Manual* reduced the number of categories to only two: (i) product innovation, and (ii) business process innovation. The definition of product innovation in 2018 edition of the *Manual* has been broadened to include product design (excluding the design of the product packaging), which was previously classified as marketing innovation. Business process innovation encompasses both core and supporting activities of a firm and includes: (i) production of goods and services; (ii) distribution and logistics; (iii) marketing and sales; (iv) information and communication systems; (v) administration and management; and (vi) product and business process development. Although separate types of innovation have been distinguished, occurrence of one type of innovation does not preclude the other(s) from taking place, even concurrently (OECD, 2018) and different types of innovation may even be complementary to one another.

There has been a significant jump in the scope of the definition of innovation from the first edition of the *Oslo Manual* to the latest one. The broadened scope of the definition and the application of this definition in the process of gathering data on innovation has also broadened the scope of research conducted by empirical researchers. As the third classification of innovation – discussed below – suggests, there is a scope for further broadening of the definition. However, we have to beware that continuous broadening and changing of the scope of the definition of innovation in the *Oslo Manual* can have adverse effects on its usefulness and can potentially limit the ability of the researchers to investigate innovation and different types of innovation using long(er) time-series data.

The third classification of innovation distinguishes between: (i) functional, and (ii) soft innovation. Functional innovation can be understood as innovation that leads to

[48] However, it is important to note that marketing innovation does not include expansion to new markets.

functional changes of products or processes. Soft innovation is defined as "innovation in goods and services that primarily impacts upon sensory perception, aesthetic appeal or intellectual appeal rather than functional performance" (NESTA, 2009, p. 21). This type of innovation largely coincides with the concept of product differentiation.[49] As argued by NESTA (2009), soft innovation is not comprehensively covered in either the *Oslo* or the *Frascati Manual*.[50] For example, the definitions of product and process innovations by OECD (2005) do not cover soft innovation at all, as they are focused on functional changes in products and processes,[51] while it is only partially covered within the category of marketing innovation. The whole range of what are believed to be different innovative activities that are excluded in large part, but not solely, belong to the part of the economy that is referred to as "creative industries".[52] Examples of the excluded activities are: book writing and publishing; assembling a new theatre play; film writing, production and launching, etc. (NESTA, 2009). Soft innovation is not tied to a particular industrial sector or market. Additionally, it can occur both within products and processes, but is mostly associated with products. Furthermore, functional and soft innovation can be interdependent – one type of innovation can enable another, or both can be demand-led in the sense that demand for one type of innovation is dependent on the other. Two types of soft innovation are distinguished: (i) "innovation in products that are aesthetic or intellectual in nature" (i.e. introduction of new books, films, video games, fashion, etc.), and (ii) "aesthetic innovation in goods and services that are primarily functional in nature" (i.e. visual appearance of products) (NESTA, 2009, p. 21). While a distinction between functional and soft innovation is useful, it is recognised that a fine line between the two is sometimes very hard to determine (NESTA, 2009).

Typically, the fourth classification of innovation distinguishes between: (i) radical innovation, and (ii) incremental innovation. Incremental innovation represents a routine

[49] Differentiation can be summarized in the following: "Product variants are said to be differentiated when two or more goods or services are essentially or generically the same, but can be individually identified, through either their performance or aesthetic appeal, and are preferred differently by and between consumers on the grounds of those consumers' tastes or preferences." (NESTA, 2009, p. 23).

[50] The Frascati Manual sets the standards for recording research and experimental development (Hall, 2006; NESTA, 2009).

[51] The NESTA (2009) report was based on the third edition of the Oslo Manual. Considering that in the fourth edition, product design became part of product innovation, this does not necessarily hold true anymore.

[52] Creative industries are defined as "those industries which have their origin in individual creativity, skill and talent and which have a potential for wealth and job creation through the generation and exploitation of intellectual property" (Department for Digital, Culture, Media and Sport, 2001, p. 5). The creative industries constitute a large part of the economy of some countries – e.g. in the United Kingdom in 2016, the creative industries accounted for 5.3 per cent of the UK economy, contributing £91.8 billion to the gross value added (HM Government, 2018; Gkypali and Roper, 2018).

change or continuous improvement (Wan et al., 2005; OECD, 2005; Fagerberg, 2006). When it comes to radical innovation, the degree of "radicalness" of innovation can widely differ. Radical innovation can represent a substantial change compared to what is currently available (Wan et al., 2005; OECD, 2005). However, it can also lead to what are referred to as new general-purpose technologies or technological revolutions, which are sometimes recognised as a separate category in addition to incremental and radical innovations. Those are substantially different products or processes that have an economy-wide impact (Fagerberg, 2006; Mazzucato, 2018; Chaminade et al., 2018; Bloom et al., 2019).

3.3.1 The process of innovation within firms

Firm-level innovation is generally targeted at either increasing revenues or lowering the costs. The Global Innovation Survey conducted by the Boston Consulting Group (2015) over the period 2005-2015 showed that innovation in terms of product development was increasingly important as a strategic priority for firms. In 2015, 79% of firms placed it among their top three strategic priorities, compared to 66% of firms in 2005 (The Boston Consulting Group, 2015). Apart from the strategic importance of not only product but other types of innovations, innovation can enable firm to: (i) gain and utilise a first mover advantage; (ii) work towards closing or close an existent performance gap; (iii) increase its market share; and (iv) exploit competitive advantage in international market(s) (Azar and Ciabuschi, 2017).

Two prevalent theories of innovation process can be distinguished, which lead to different policy conclusions: (i) linear; and (ii) systems oriented. The significant departure between the two models is in their orientation. While the linear model of innovation is focused on the supply side of innovation, the systems-oriented approach takes into account the demand side perspective as well. The linear model of innovation was widely accepted from World War II onwards and sees innovation as a simple, single direction process that starts with basic scientific research,[53] proceeds with development and, finally, finishes with changes in production and marketing. Linear model implies that innovation is an ordered process (Kotsemir et al., 2013) and it is argued that this model is very simplistic and unrealistic representation of reality. In particular, (i) it does not account for feedbacks

[53] Hall (2006) argues that research and development consists of three activities: (i) basic research; (ii) applied research; and (iii) development. The difference between basic and applied research is in whether research is directed to a specific application, while development involves using research to create new products or processes.

and loops in the innovation process; and (ii) firms rarely start innovating with basic scientific research (Edquist and Hommen, 1999; Fagerberg, 2006; Chaminade et al., 2018).

The second theory of innovation process – systems-oriented theory – abolishes the notion that innovation is a product of individual actors only and acknowledges that different types of interactions between different actors occur in the process of innovation. A popular concept that emerged from systems-oriented theory is systems of innovation approaches. Systems of innovation are evolutionary systems emphasizing the importance of institutions and learning processes for innovation. Systems of innovation are often defined at different spatial levels and the most commonly used classifications are at the national, regional or local levels (Edquist and Hommen, 1999; Fagerberg, 2006); but also technological and sectoral systems of innovation have been recognised in the literature (Chaminade et al., 2018). The concept of national innovation system, the first one to emerge, was introduced when R&D, even among multinational firms, was mostly conducted within a single nation state (Martin, 2016). National innovation systems are not uniformly defined within the innovation studies literature, which distinguishes between narrow and broad definitions. Narrow definitions focus on the linkage and interaction between firms and research institutions. In addition, broad definitions focus on the interactions between users and producers and interactive learning processes that occur within firms. Furthermore, the focus of the narrow definition is on radical innovation, while the broad definition additionally encompasses incremental innovation and the diffusion of innovation. The national innovation system concept was aimed at influencing policies for economic growth and competitiveness (Chaminade et al., 2018). Its relevance and success in influencing innovation policies will be discussed in Section 3.4. Nowadays, we are witnessing the emergence of a global innovation system (Martin, 2016).

Research and (experimental) development (R&D) is often used as a synonym for innovation, while support for R&D is widely regarded as support for innovation (more on this in the later sections). However, R&D constitutes just one type of activity of a firm that can result in innovation and is "neither a sufficient nor necessary condition for either innovation activity or innovation to occur" (OECD, 2018, p. 54). The OECD's *Frascati Manual: Guidelines for collecting and reporting data on research and experimental development* from 2015 defines research and experimental development as "creative and systematic work undertaken in order to increase the stock of knowledge – including knowledge of humankind, culture and society – and to devise new applications of available knowledge" (OECD, 2015, p. 44). The key aspect of this definition is increasing knowledge, whether through creating new knowledge or new applications of knowledge that already exists. Conceptually, this substantially differs from the definition of innovation, which is aimed at implementation of new products, processes, organisational or marketing methods. Besides research and (experimental) development, OECD (2018, p. 35) recognises seven different types of activities that can lead to innovation by firms: (i) "engineering, design and other creative work activities"; (ii) "marketing and brand equity activities"; (iii) "intellectual property (IP) related activities; (iv) employee training activities"; (v) "software development and database activities"; (vi) "activities relating to the acquisition or lease of tangible assets"; (vii) "innovation management activities".

Firm can organise innovation activities in different ways. Some firms engage in innovation activities only on an ad hoc basis, while others make innovation a part of their business operations or define a specific innovation projects/programmes which have innovation as their goal (OECD, 2018). Furthermore, firms must have certain resources and capacities to engage in or excel at innovation. Firms interact with external actors continuously, hence their "absorptive capacity" – the capacity of firms to learn from those external actors – is of a great importance (Fagerberg, 2006). The resource-based theory of a firm is often discussed in the context of innovation. By resources, we mean all the factors that could potentially be either a strength or a weakness of a firm. Resource-based theory is based on the premise that possession of a valuable resource(s) can be a source of a number of benefits for that firm (e.g. entry barrier) (Wernerfelt, 1984, 1995; Lazonick, 2006).

3.4 The determinants of R&D and innovation

A vast amount of research has been produced to explore the determinants of R&D and innovation. This section will provide an overview of those determinants but, considering the size of the literature, this overview is by no means exhaustive. Furthermore, the focus, in the context of empirical investigations in the chapters to follow, is on the determinants in manufacturing firms. Following the classification of the determinants of productivity from the previous chapter, the determinants of R&D and innovation will also be grouped into: (i) internal; and (ii) external ones. Furthermore, to the extent possible, the determinants of product, process, marketing and organisational innovation will be discussed separately. The links between exporting and innovation are discussed at length in Chapter 5to avoid duplication.

3.4.1 Internal factors

Firm's internal characteristics are an important determinant of R&D spending of firms and innovation. Internal finance (i.e. cash flow) and sales appear to be of particular importance for funding R&D. Often firms need to rely on their internal funds to finance their R&D operations, as capital market imperfections (e.g. asymmetric information) impede their access to external funding. The link between R&D and internal finance is sensitive to firm age, firm size and countries, with young and small firms being more financially constrained (Becker, 2013). In an empirical investigation of manufacturing firms in Korea, Lee (2012) shows that R&D investment is positively influenced by: (i) past sales (defined as net sales over total sales);[54] (ii) availability of internal funds measured by the cash flow variable (defined as operating cash flow over total assets); (iii) debt finance (defined as total debt over total assets); (iv) ownership concentration (defined as shares held by controlling shareholders over total shares); and (v) foreign ownership (defined as shares held by foreign shareholders over total shares). Furthermore, Lee (2012) shows that the relationship is negative for low levels of equity, while it is positive for high levels of equity. Bhattacharya and Bloch (2004) find that the past profitability of a firm, signalling the availability of financial resources within a firm, is positively (but only weakly) linked to innovation for firms in low-technology industries.

Although suffering from the problem of a small, cross-section dataset on which empirical investigation is conducted,[55] the study of Wan et al. (2005) on the determinants of innovation in Singapore offers valuable insights into internal factors that determine the level of innovation of a firm.[56] Wan et al. (2005) find a positive and significant relationship between a higher degree of innovation and (i) a higher degree of decentralisation of decision-making within a firm, (ii) a higher degree of firm resources

[54] Lee (2012) provides no additional definitions of the variable *past sales*, although this definition lacks clarity.
[55] The total sample size was 71 firms. Furthermore, this represents only 7.1% of the designated sample size.
[56] The definition of innovation used by Wan et al. (2005, p. 262) is "a process that involves the generation, adoption, implementation and incorporation of new ideas, practices or artefacts within the organisation". Although the definition appears to broadly coincide with the definition of process innovation given above, the output measures used in the study encompass both product and process innovations (i.e. the number of new products and processes developed during a single year, percentage of sales attributed to the new products or processes).

dedicated to innovation (i.e. innovation funds), (iii) belief within a firm that innovation is an important determinant of the success of a firm, (iv) greater willingness to take risks by a firm, and (v) greater willingness to exchange ideas within a firm; while they find a positive but insignificant relationship between innovation and the frequency of internal communication within a firm. The authors point out, in the light of the findings indicated above, the importance of management in shaping the organisational culture that is supportive of innovation. Using 2013 data from 28 countries on approximately 18,000 workplaces with more than 10 employees, Franco and Landini (2022) explore the impact of workforce agility on innovation. They define workforce agility as "the capacity of an organisation to effectively and efficiently redeploy/redirect its workforce to value creating activities, especially innovation" (Franco and Landini, 2022, p. 3). They find a positive relationship between organisational agility and innovation, especially in the context of process innovation.

Radičić et al. (2018) explore innovation in traditional manufacturing industries[57] and show that a firm's established capacities for product innovation increase the likelihood of introducing product innovation and affect the level of marketing innovation of a firm. However, the established capacities for process innovation are shown to negatively affect subsequent product innovation, while established capacities for organisational innovation negatively affect subsequent introduction of process innovation. Similar to Wan et al. (2005), Radičić et al. (2018) show that dedicating more resources to innovation increases the likelihood of introducing process, organisational and marketing innovations. When measuring innovation performance by innovative sales, Radičić et al. (2018) show that greater total resources devoted to innovation, as well as existing innovation capacities for product innovation, exert a positive impact on innovative sales.

Most of the empirical research indicates that firm size is another determinant of innovation. Bhattacharya and Bloch (2004), using a dataset of small and medium manufacturing firms, find that firm size is important for innovation, i.e. the larger the firm size the greater the innovative activity of a firm. Additionally, the increase in innovative activity with firm size occurs at the decreasing rate and this holds true for small and

[57] Traditional manufacturing industries include: (i) manufacture of food products and beverages, (ii) textiles and textile products; (iii) leather and leather products; (iv) ceramics and other non-metallic mineral products; (v) mechanical/metallurgy; and (vi) automotive (for more detailed description, see Radičić et al., 2016; 2018).

medium enterprises in both high- and low-technology industries.[58] In the empirical investigation of a sample of SMEs, Radičić et al. (2018) find that the likelihood of introducing organisational innovation is greater among medium-sized firms in comparison with smaller firms. However, contrary to these findings regarding the link between firm size and innovation, Wan et al. (2005) found that neither the size of the firm, nor the type of the industry the firm belongs to (i.e. manufacturing, services) matters for innovation.

The study by Bhattacharya and Bloch (2004) offers additional interesting insights regarding the determinants of innovation. The growth of a firm is not significantly linked with future innovation, while R&D intensity is shown to have a positive impact on future innovation for all firms and high-technology firms, but not for low-technology firms.[59] The (industry variable) import share (i.e. ratio of imports to total sales) has a weak, but positive influence on innovation (Bhattacharya and Bloch, 2004). Furthermore, the structure of the firm may be an important determinant of innovation. Narula and Zanfei (2006, p. 319) claim that multinational enterprises have the ability to "carry out and control the global generation of innovation within its boundaries" and empirical research by Un (2011) and Kampik and Dachs (2011) point out (at least to the possibility) that subsidiaries of multinational firms are more innovative than domestic firms.

Absorptive capacity of the firm is of great importance for innovation but cannot be observed directly. In the literature, there are two main ways to proxy absorptive capacity: (i) by the firm's external relationships; and (ii) via the characteristics of the firm's employees. We consider these approaches in turn. Harris and Moffat (2011, p. 14-15) point to two types of knowledge that they claim are related to absorptive capacity: (i) internal, proxied by the

> "data on the impact on business performance of the implementation of new or significantly changed corporate strategies; advanced management techniques (e.g. knowledge management, Investors in People, JIT and Sigma 6); organisational structures (e.g. introduction of cross-functional teams, outsourcing of major business functions); and marketing concepts/strategies",

and (ii) external, proxied by

[58] This effect is drastically smaller for firms in low-technology industries compared to the firms in high-technology industries and the rate of effect decrease is smaller compared to high-technology industries.
[59] However, the authors indicate the results for R&D intensity may be unreliable (Bhattacharya and Bloch, 2004).

> "data on the relative importance of different sources of information used for innovation related activities and/or the types of cooperation partner on innovation activities".

Cooperation for innovation can occur in variety of forms – cooperation for innovation with: (i) suppliers; (ii) customers; (iii) competitors; (iv) higher education institutions, etc. – and can be beneficial as it allows different agents to: pool risks; share costs; be more time-efficient when it comes to innovation; commercialise their products within shorter time periods; and access different resources and knowledge (Radičić et al., 2018). Vernon (1966, p. 193) recognises that one country may invest more in product innovation compared to others due to "more effective communication between the potential market and the potential supplier of the market". Cassiman and Veugelers (2002), using a cross sectional dataset of Belgian innovating firms, show that: (i) higher incoming spillovers (a measure which indicates how important publicly available information sources are for innovation at the firm-level); and (ii) higher appropriability through strategic protection of products and processes (i.e. secrecy, complexity, or lead time) positively affect the probability of R&D cooperation. Furthermore, the size of a firm and a cost-sharing possibility positively influence the probability of R&D cooperation. Using a dataset comprised of SMEs in traditional manufacturing industries from seven European regions, Radičić et al. (2018) show that: (i) cooperation with competitors, higher education institutions and public sector institutions increases the likelihood of introducing product innovation; (ii) cooperation with public sector institutions increases the likelihood of introducing process innovation; (iii) cooperation with suppliers, private sector institutions and public sector institutions increases the likelihood of introducing organisational innovation; (iv) cooperation within an enterprise group increases the likelihood of introducing a marketing innovation; (v) breadth of cooperation, defined as the number of cooperative relationships, increases the likelihood of introducing product, process and organisational innovation and positively affects innovative sales; and, finally, (vi) cooperation with customers, higher education institutions and private sector institutions has a positive impact on sales related to product and process innovations. The second approach to absorptive capacity is via the link to employee characteristics (e.g. number of engineers, proportion of graduates, etc.). To anticipate, the models of innovation reported in this thesis use both approaches as suggested by Radicic et al. (2019).

Using German Community Innovation Survey data for 2018 for firms from both manufacturing and services sectors, Rammer et al. (2022) explored the impact of artificial intelligence (AI) on innovation performance of German firms. The authors confirm that AI positively influences innovation and returns on innovations, and that it is especially significant for radical innovations.

3.4.2 External factors

The degree of competition is an important external determinant of both R&D and innovation. Becker (2013) explains that there are two streams of theoretical arguments linking R&D and competition. The first line of argument applies to the incumbent firms, particularly those with higher market power. The argument suggests that a higher degree of competition lowers the incentives of firms to invest in R&D as rent-extracting possibilities from innovation are lower as the result of those investments. The second line of argument applicable more generally is that R&D can be used as a strategic tool of firms to fight their competitors and protect their market share (Becker, 2013). Bloom et al. (2019), in a narrative review of the effectiveness of different innovation policies, conjecture that the impact of competition on innovation can be positive and is non-linear. Bhattacharya and Bloch (2004) show that industry concentration[60] has a positive impact on future innovation for high-technology firms, but not low-technology firms. Similarly, Radičić et al. (2018) show that among SMEs in traditional manufacturing industries strong competitive pressures: (i) diminish the likelihood of introducing product and process innovations; (ii) do not affect the likelihood of introducing organisational and marketing innovations; and (iii) negatively affect innovative sales.

Another significant determinant of R&D is the location of a firm and the availability of human capital resources, such as: “geographical proximity to universities, membership of research joint ventures and cooperation with research centres, and the availability of highly qualified human capital” (Becker, 2013, p. 29). Furthermore, private R&D of domestic firms can also be positively affected by the proximity of foreign-owned multinational firms (Becker, 2013).[61]

Akcigit et al. (2018) looking at the impact of taxation on innovation in the 20th century in the United States of America show that there is a negative link between the corporate tax

[60] The four-firm concentration ratio is used as a measure of concentration.
[61] The great importance of agglomeration and spillovers for innovation is recognised. However, given that no data is available for exploration of agglomeration and spillovers in the empirical chapters of the thesis, discussion here was limited to acknowledging their importance.

rate and the number of: (i) patents; and (ii) patent citations.[62] Their research shows that a decrease in the corporate tax rate of one percentage point increases the number of patents produced by the firm in each year by 4-6% depending on model specification. Similarly, it increases the number of patent citations by 3.5-5%. Furthermore, a higher local corporate tax rate has a negative effect on the decision of a firm to locate a new R&D lab in a specific state. Finally, a further significant determinant of R&D and innovation is government support for innovation. Government support for innovation will be discussed in more details in Chapter 7. Summaries of the studies on the determinants of R&D and innovation presented in this section are provided in Table 3.1 and Table 3.2 below, respectively.

[62] Patent citations involve patents being cited in patent applications.

Table 3-1. The determinants of R&D

Author(s) (year)	Country	Industry and sector	Data type, sample period and data source	Main findings
Lee (2012)	▪ Korea	▪ Manufacturing firms	▪ Panel dataset of 424 firms for 1999-2008	▪ R&D is positively influenced by: 1 Past sales variable; 2 Availability of internal funds, measured by cash flows variable; 3 Debt finance; 4 Ownership concentration variable; 5 Foreign ownership variable; ▪ R&D investment of young firms is sensitive to fluctuations in cash flows; ▪ Cash flow positively affects R&D investment in non-*chaebol* firms, while it negatively affects R&D investment in *chaebol* firms; ▪ Equity financing and R&D investment: negative relationship is observed for low levels of equity, while the opposite holds true for high levels of equity
Becker (2013)	Narrative review of the determinants of R&D investment			▪ The main determinants of R&D investment are: ▪ Individual firm and industry characteristics; ▪ Competition in product markets; ▪ Government policies; ▪ Location and resource related factors; ▪ Spillovers from foreign R&D

Table 3-2. The determinants of innovation

Author(s) (year)	Country	Industry and sector	Data type, sample period and data source	Main findings
Cassiman and Veugelers (2002)	▪ Belgium	▪ Manufacturing firms	▪ Cross-sectional dataset from Community Innovation Survey	▪ Higher incoming spillovers and higher appropriability through strategic protection positively affect the probability of R&D cooperation;

Author(s) (year)	Country	Industry and sector	Data type, sample period and data source	Main findings
			conducted in 1993 covering 1990-1992	▪ Firm size positively impacts R&D cooperation (i.e. larger firms have a greater probability of cooperating); ▪ Cost-sharing has an important influence on the probability of cooperating in general
Bhattacharya and Bloch (2004)	▪ Australia	▪ Manufacturing SMEs	▪ Cross-sectional dataset from Confidentialised Unit Record File database from Business Longitudinal Survey of the Australian Bureau of Statistics for 1994-1998 (depending on the variable)	▪ Innovation is positively influenced by: ▪ Firms size (i.e. larger firms are more innovative), but the increase in innovative activity with firm size occurs at decreasing rate both in high- and low-technology firms; ▪ Past profitability in the case of low-technology firms; ▪ R&D intensity in the case of all firms and high-technology firms, but not among low-technology firms; ▪ Import share; ▪ Export orientation in the case of high-technology firms, but not for firms in low-technology industries; ▪ Industry concentration in the case of all firms and high-technology firms, but not low-technology firms
Wan et al. (2005)	▪ Singapore	▪ Manufacturing, construction, commerce, transportation and communication and other services firms	▪ Survey data on the most successful firms based on sales turnover in Singapore	▪ Innovation is positively influenced by: • A higher degree of decentralisation of decision-making within a firm; • A higher degree of firm resources dedicated to innovation (i.e. innovation funds); • Belief within a firm that innovation is an important determinant of the success of a firm; • Greater willingness to take risks by a firm; • Greater willingness to exchange ideas within a firm; ▪ Size or type of industry in which firms operate (i.e. manufacturing, services) do not influence innovation
Un (2011)	▪ Spain	▪ Manufacturing firms	▪ Panel dataset of 761 firms for 1990-2002	▪ Subsidiaries of foreign multinational firms are more product innovative compared to domestic firms, ceteris paribus; ▪ Subsidies of foreign multinational firms are more likely to produce product innovations out of R&D investments than domestic firms

Author(s) (year)	Country	Industry and sector	Data type, sample period and data source	Main findings
Radičić et al. (2018)	▪ Seven European regions: West Midlands (the UK), North Brabant (the Netherlands), Saxony-Anhalt (Germany), Limousin (France), Norte-Centro (Portugal), Comunidad Valenciana (Spain) and Emilia-Romagna (Italy)	▪ Traditional manufacturing SMEs	▪ Cross-sectional, survey dataset of 312 SMEs for 2005-2009	▪ Firm's established capacities for product innovation increase the likelihood of introducing product innovation and affect the marketing innovation of a firm; ▪ Established capacities for process innovation negatively affect subsequent product innovation; ▪ Established capacities for organisational innovation negatively affect subsequent introduction of process innovation; ▪ More resources dedicated to innovation increase the likelihood of introducing process, organisational and marketing innovations; ▪ More resources devoted to innovation and existent innovation capacities for product innovation positively influence innovative sales; ▪ Medium-sized firms are more likely to introduce organisational innovation as compared to smaller firms; ▪ Exporting is negatively linked to process innovation; ▪ Cooperation with competitors, higher education institutions and public sector institutions increases the likelihood of introducing product innovation; ▪ Cooperation with public sector institutions increases the likelihood of introducing process innovation; ▪ Cooperation with suppliers, private sector institutions and public sector institutions increases the likelihood of introducing organisational innovation; ▪ Cooperation within an enterprise group increases the likelihood of introducing marketing innovation; ▪ Breadth of cooperation increases the likelihood of introducing product, process and organisational innovation and positively affects innovative sales; ▪ Cooperation with customers, higher education institutions and private sector institutions has a positive impact on sales related to product and process innovation;

Author(s) (year)	Country	Industry and sector	Data type, sample period and data source	Main findings
				▪ Strong competitive pressures: ▪ Diminish the likelihood of introducing product and process innovations; ▪ Do not affect the likelihood of introducing organisational and marketing innovations; ▪ Negatively affect innovative sales
Akcigit et al. (2018)	▪ United States of America	▪ All inventors and firms	▪ Panel dataset, including: (i) historical patent data and inventor panel data from 1836 (including patent citations data from 1947 to 2010); (ii) R&D activities of US firms since 1921; and (iii) historical tax data (personal income tax database from 1900 to 2014 and corporate income tax database from 1900 to 2016)	▪ There is a negative link between corporate inventors and corporate tax (corporate inventors very elastic to corporate taxes); ▪ Decrease in corporate tax rate increases number of patents produced by the firm each year and the number of citations (i.e. depending on specification, a decrease in corporate tax rate by one percentage point increases patents by 4-6% and citations by 3.5-5%); ▪ Personal income tax rates have a non-linear impact on innovation of firms; ▪ High corporate tax rate negatively affects decision of a firm to locate a new R&D lab in a specific state

3.5 Conclusion

Innovation is of great importance for both countries and firms. As demonstrated in different parts of this chapter, innovation, especially transformative innovation, is a resource-intensive activity. Spending on innovation – both by governments and private sector – although widely different in different countries around the world, tends to be sizable. As discussed in the section on external determinants of R&D and innovation, the overall business environment that governments influence has important implications for innovation at the level of firms. Additionally, firms have to carefully plan and dedicate different internal resources to innovate.

Innovation is not the property of a single field of enquiry. Due to their different foci, diversity of insights about the importance of innovation and innovation processes are generated as a result of research produced in the two dominant approaches to innovation. However, the scholars from different fields investigating innovation tend to be (mostly) informed only by their own field and (mostly) fail to recognise the strengths and useful insights generated by the other. Bringing the two perspectives together can, besides improving our understanding of phenomena of utmost importance, help firms and governments to successfully create environments fostering innovation, organise the process of innovation and use innovation to strengthen the economies. Together with the previous and the following chapters, this chapter provides a theoretical basis for the empirical investigation of an interaction between complex firm-level phenomena – innovation, exporting and productivity – and how innovation policies affect them.

4. Exporting

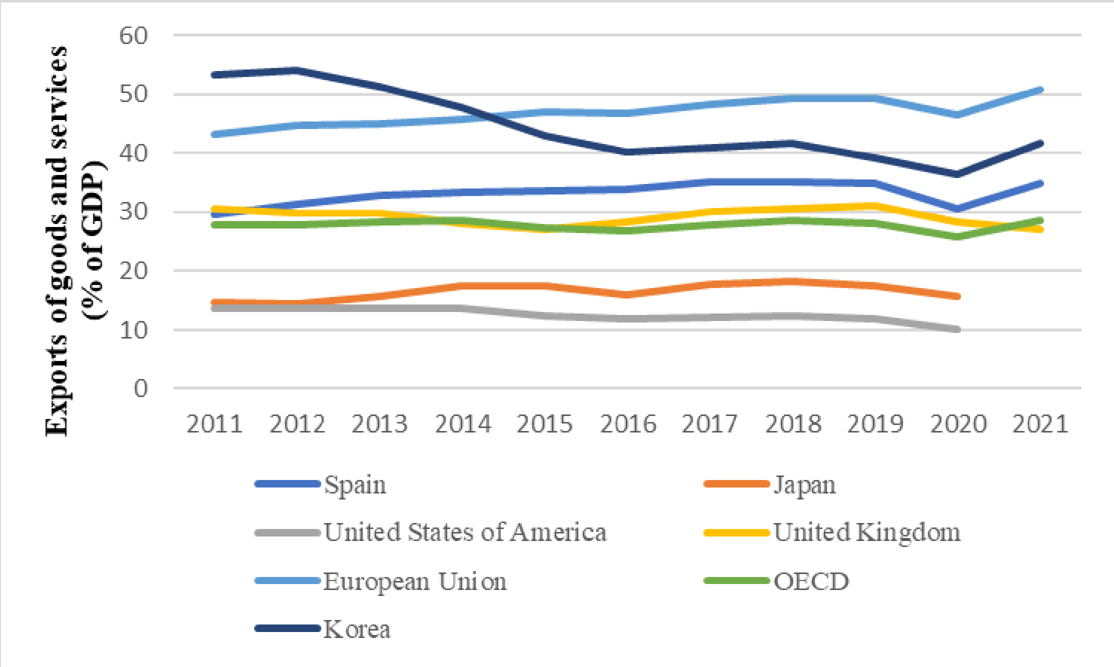
4.1 Introduction

The chapter on exporting is the final chapter exploring individually the focal topics of this research programme. Along with the previous two chapters, Chapter 4 sets the platform for Chapter 5 that will explore the literature on the productivity-innovation-exporting nexus, as well as provide a comprehensive overview of their shared and individual determinants. Additionally, this chapter provides a platform for the two empirical chapters of the thesis. Exporting at the more aggregate level will be explored only briefly in the introductory part of this chapter, while the remainder of the chapter will focus on exporting as a firm-level phenomenon in line with the aims of this thesis.

Exporting is a subject of exploration of both the macroeconomic and international trade literatures. The international trade literature has recognised that there are gains from engaging in international trade – e.g. more efficient use of available resources, specialisation, or benefits in terms of increased varieties available to customers – at an economy level. However, the literature also cautions that trade might not benefit all (e.g. due to income redistribution effects) (Bernard et al., 2007; Krugman et al., 2012). Greenaway and Kneller (2007, p. 156) state that "a large empirical literature points to a positive correlation [between export growth and output growth], even if the direction of causality is controversial". A body of literature shows that exporting positively affects economic growth within less developed countries. This result was shown to be robust both in times of rapid economic growth and in times of recession, when the magnitude of the effect was even larger (Balassa, 1985). A separate, but related, literature explores the link between export diversification and growth. Hesse (2008) using a sample of both developed and developing countries, shows that export diversification positively influences income per capita growth in developing countries. Additionally, Hesse (2008) shows that this effect might not hold for developed countries, which might benefit more from export specialisation. The reverse causation is supported by the Lederman et al. (2010) study covering 88 countries that uses GDP per capita as an explanatory variable for the amount of exports per capita of a country. The authors find support that "richer countries, with stronger and better institutions – including trade institutions – export more" (Lederman et al., 2010, p. 261).

Exports of goods and services as a percentage of GDP differs significantly across countries.[63] Figure 4.1 shows that the percentages have been varying over time, with all countries and groups of countries presented experiencing a decline in exports as a percentage of GDP in 2020. Exports of goods and services as a percentage of GDP were the highest in the European Union in 2021 (50.74%) among selected countries/groups of countries, while they were the lowest in the United States at 12.16% in 2020. Exports as % of GDP for Spain for the period 2011-2021 were consistently higher than the OECD average, but substantially lower than European Union average.

Figure 4-1. Exports of goods and services as a percentage of GDP for selected countries or groups of countries, 2011-2021



Source: The World Bank Data – Exports of goods and services (% of GDP) (n.d.). Accessed from: https://data.worldbank.org/indicator/ne.exp.gnfs.zs (Accessed: 2nd September 2022)

It is predominantly firms, rather than countries, that engage in trade. Relatively few firms engage in trade and the concentration of trade across firms is high. For example, Bernard et al. (2007) report that, in 2000, only approximately 4% of the firms operating in the United States of America engaged in exporting and, furthermore, that the majority of exporting activity was concentrated within a small segment of firms (i.e. 96% of the US exports was undertaken by only the top 10% of exporting firms). When examining only manufacturing firms in the United States of America in 2002, the authors find that only approximately 18% of firms were exporters, with the shares varying greatly across

[63] The coverage of countries and groups of countries in Figure 4.1 is the same as in the previous chapter.

different industries (Bernard et al., 2007). Exporting is associated with better performance of firms along different dimensions (e.g. productivity). However, it is also associated with significant costs for firms. Both benefits and costs will be described in more detail in Section 4.2. Section 4.3 discusses the internal and external determinants of exporting. Section 4.4 concludes.

4.2 The definition and the importance of exporting for firms

Mankiw and Taylor (2014, p. 606) define exports as "domestically produced goods and services that are sold abroad". Exporting is a frequently used internationalisation strategy by firms and, additionally, a growth strategy (Ayob and Freixanet, 2014). Vernon (1966), linking product cycle, international trade and international investments, describes exporting as a first step towards the internationalisation of a firm's activities, which is especially appropriate for products that lack standardisation. According to the author, only when a product is sufficiently standardised, may firms decide to set up a production facility abroad. The initial decision to produce a product in the country of origin may be due to: (i) considerations regarding the availability of input choices; (ii) low price elasticity of demand at the firm level; and (iii) the importance of communication with customers, suppliers and competitors. The decision to set up a production facility abroad depends on a plurality of factors (e.g. whether or not a firm has international patents, competition in the country of import, the degree of protectionism, etc.) (Vernon, 1966).

Exporting and foreign direct investment (FDI) can be thought of as substitute internationalisation strategies.[64] The choice of an internationalisation strategy is made by firms after evaluating: the size of the foreign market (i.e. larger foreign market may favour the choice of foreign production); and costs (i.e. exporting-related costs versus the costs of setting-up foreign production) (Greenaway and Kneller, 2007). Exporting is considered to be a more flexible strategy (Kotorri and Krasniqi, 2018) and to involve lower costs compared to FDI (i.e. fixed costs of FDI are larger than those of exporting, but FDI eliminates some of the variable costs, e.g. transportation costs) (Greenaway and Kneller, 2007). The appeal of exporting may depend on the size of a firm, as well as the degree of development of the country of origin of a firm. For example, the importance of

[64] This is not entirely true as multinational enterprises (MNEs) can be exporters as well (Greenaway and Kneller, 2007).

this strategy may be exacerbated when it comes to firms originating from smaller, developing and/or transition countries (Kotorri and Krasniqi, 2018).[65]

Theoretically, the well-established self-selection hypothesis suggests that more productive firms self-select to become exporters (Melitz, 2003). Self-selection occurs as a consequence of exporting being a costly activity so that only the more productive firms are able to cover the costs associated with exporting (Wagner, 2007; Van Biesebroeck, 2008). The costs associated with exporting may include, but are not limited to: (i) costs of tariffs and non-tariff trade barriers; (ii) costs of market research; (iii) costs associated with adjusting the firm's products to the foreign markets and production costs associated with that adjustment; (iv) transportation and distribution costs; (v) marketing costs; and (vi) human resources costs (e.g. the ability to manage foreign networks) (Vernon, 1966; Wagner, 2007; Álvarez et al., 2013). Some of the listed costs (e.g. those related to market research or adjusting the products to the foreign market) constitute sunk costs.[66] The size of these sunk costs, along with other firm characteristics, determine the choice of a firm to begin exporting activity (Greenaway and Kneller, 2007).[67]

Descriptive statistics and data analyses reveal numerous characteristics, which make exporters different from non-exporters. Compared to non-exporters, exporters are shown to be: (i) larger; (ii) more productive; (iii) often have higher productivity growth; (iv) more likely to innovate; (v) spend more on innovation; (vi) have more (major) innovations; (vii) are present in sectors with higher R&D intensity and if firms are not innovators, higher intra-industry trade; (viii) more frequently belong to industries that are more technology intensive; (ix) are more skill- and capital-intensive; and (x) pay higher wages (Bleaney and Wakelin, 2002; Bernard et al., 2007; Wagner, 2007; Greenaway and Kneller, 2007; Wagner, 2008; Damijan et al., 2010; Caldera, 2010; Monreal-Perez et al., 2012; Movahedi et al., 2017). Atkin et al. (2017), using a randomised controlled trial methodology and comparing mean outcomes between the treatment and control groups, show that the opportunity to export - created as part of the research design - leads to a significant average treatment effect (increases in profits). Using a sample of small rug

[65] Kotorri and Krasniqi (2018, p. 33) note that "in an open and small economy such as Kosovo, with a low level of economic development … accessing foreign markets remains the ultimate expansion strategy for ambitious SMEs".
[66] Greenaway and Kneller (2007, p. 156) note that "although the evidence base points unambiguously to the crucial role of sunk costs, little research has as yet focused on what these are…".
[67] Empirical research suggests that there is persistence of exporting activity among firms. In empirical investigations, the positive coefficient on the lagged export status of a firm "is usually interpreted as evidence of sunk-costs" (Greenaway and Kneller, 2007, p. 140).

manufacturers in Egypt, they show that the treated firms, who were given an opportunity to export rugs to high-income markets, reported 16-26% higher profits compared to the control group. Additionally, they show that firms improve the quality of their products as a consequence of engaging in exporting.[68]

4.3 The determinants of the propensity to export and the intensity of exporting

The following section discusses the determinants of: (i) the propensity to export; and (ii) the intensity of exporting. Similar to the convention adopted in previous chapters, the determinants will be divided into: (i) internal and (ii) external. The internal and external determinants of both propensity and intensity will be discussed together in order to avoid unnecessary duplication, following the empirical research that informs us that the determinants are largely overlapping (Gashi et al., 2014).[69] A summary of the discussion of the determinants of the propensity to export and intensity of exporting is provided in Table 4.1.

4.3.1 Internal determinants of propensity to export and intensity of exporting

Numerous studies have confirmed the validity of the self-selection hypothesis described earlier.[70] Wagner (2008) investigates the propensities to export of manufacturing plants in West and East Germany fourteen years after German re-unification. The rationale for this empirical investigation stems from the large differences in the number of exporting plants between West and East Germany – i.e. the percentages of exporting plants in all manufacturing plants are 65.53% and 46.25% f respectively. Wagner (2008) concludes that between 10 and 17% of the differences in propensities to export are due to: (i) the larger size of the plants in West Germany; and (ii) the greater labour productivity (measured as sales per employee) of West German plants. Similar results regarding the importance of firm size are obtained by Bleaney and Wakelin (2002), using a sample of UK manufacturing firms, who show that increase in a size of a firm increases the probability of exporting; Sjöholm (2003), using a sample of Indonesian manufacturing establishments, finds that size influences the propensity to export (i.e. larger

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[68] The study by Atkin et al. (2017) is particularly important in the context of the next chapter, where it will be discussed in more detail.

[69] Gashi et al. (2014, p. 410) point out that economic theory suggests that the determinants of both the propensity to export and the intensity of exporting will be the same, by stating: “The theory that export behaviour is determined essentially by the interplay of productivity levels and the fixed costs of exporting suggests that the same factors will affect both the firm’s propensity to export and, if it exports at all, the firm’s export intensity…”.

[70] More empirical evidence will be presented in the following chapter.

establishments have a greater likelihood of becoming exporters); and by Álvarez et al. (2013) for Chilean plants.[71] Furthermore, Gashi et al. (2014), using a sample of SMEs in transition countries, show that export behaviour (i.e. both the propensity to export and the intensity of exporting) is positively influenced by the size of a firm.

Contrary to the findings of Wagner (2008), Sjöholm (2003) finds that higher labour productivity (defined as value added per employee) does not increase the propensity to export. Bleaney and Wakelin (2002) find no support that lower unit labour costs, as a measure of efficiency, increase the probability of exporting. However, Kotorri and Krasniqi (2018), using a cross-sectional survey dataset on Kosovan SMEs, show that productivity is positively related to the export performance of firms (i.e. both the propensity to export and the intensity of exporting), i.e. more productive firms have better export performance.[72] Gashi et al. (2014) emphasise the importance of productivity-enhancing spillovers. Using the sample of SMEs in transition countries, they show that the three measures they utilise for productivity-enhancing spillovers positively affect both the propensity to export and the intensity of exporting: (i) sales to the MNEs; (ii) sales to large domestic firms; and (iii) imports of material inputs.[73] Similarly, Sjöholm (2003) shows that importing[74] positively affect a firm's propensity to export, while Kotorri and Krasniqi (2018) find a positive correlation between a firm's imports and export performance (in some specifications). However, Sjöholm (2003) does not find strong supporting evidence that spillovers[75] influence the propensity to export.

Empirical research generally shows that factors related to a firm's stock of human capital positively affect their export behaviour. Sjöholm (2003) shows that the workforce' level of skill, a variable measuring the level of education of employees, positively influences

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[71] As the dataset that Álvarez et al. (2013) are using has no information on firm size, in order to minimise the omitted variable bias, the authors used the total value of exports in the previous time period as a proxy for firm size. The authors argue that: (i) the profits from exporting are likely to be higher for larger firms; and (ii) entry costs are likely to be related to the size of the firm as well. However, it has to be emphasised that this is a very poor proxy for firm size.

[72] Productivity is measured using a subjective perception of managers on improvements in the performance of a firm over the previous three years and export performance is measured as a share of exports in total sales (Kotorri and Krasniqi, 2018). The authors do not offer either an extensive explanation for use of this measure, nor do they cite prior research using this measure. The measure of productivity utilised in this paper is poor as managers are asked to compare the performance of a firm in comparison with itself, rather than in comparison to the other firms in the market.

[73] *Sales to MNEs* are measured as the share of sales to MNEs that are located in the same country as the firm; *sales to large domestic firms* are measured as a share of sales to large domestic firms; and *imports* are defined as "imported material inputs as a share of total material inputs" (Gashi et al., 2014, p. 418).

[74] Imports are defined as imports of intermediate products by the establishment.

[75] Spillovers are measured byas "the foreign share of a district's gross output" (Sjöholm, 2003, p. 341).

the propensity of Indonesian manufacturing establishments to start exporting. Similarly, Gashi et al. (2014) show that a higher share of employees with completed university or higher education positively affects the export behaviour of SMEs in transition countries. Contrary to the above studies, Kotorri and Krasniqi (2018) find a negative correlation between the share of employees with completed higher education and export performance for Kosovan SMEs.[76] Additionally, Kotorri and Krasniqi (2018) find that export performance is linked with different managerial characteristics; namely it is: (i) negatively affected by the expectations of a manager that firm performance will improve in the future; (ii) positively related to the educational attainment of the manager (i.e. completed higher education of a manager is linked to better export performance); and (iii) positively related to the international experience of a manager.

Exporting tends to be a persistent activity and past experience of exporting may also matter for the future exporting activities of a firm. Álvarez et al. (2013) use a sample of Chilean exporters to test whether firms' past experience of exporting – embracing (i) the same product to a different market, (ii) different products to the same market or (iii) the same product-market pair – matters for new exports. The authors show that experience in exporting the same product to other market(s) increases the probability of exporting that product to a new market. Additionally, Álvarez et al. (2013) find that the experience of exporting a product in the past has a greater influence among smaller firms. The importance of having previous experience in exporting the same product is greater when it comes to: (i) heterogeneous products;[77] (ii) sectors with greater dependence on external finance; and (iii) simpler products. Furthermore, the authors find that a firm is less likely to introduce new products in new markets if it has more concentrated exports in terms of product-market pairs.[78] The square of own experience and the experience of others are significant as well.[79] The authors explain these findings as indicating diminishing returns

[76] The authors point to two explanations for this finding, both of which are specific to the Kosovo context. Their preferred explanation is that "workers are dissatisfied due to being overqualified and hence their qualifications do not contribute to the firm's performance" (Kotorri and Krasniqi, 2018, p. 41).
[77] Heterogeneous products are defined as "advertisement over sales for the sector" (Álvarez et al., 2013, p. 436). The authors argue that, at the sectoral level, greater product differentiation is positively linked to the resources spent on advertising.
[78] Concentration of exports is measured by the lagged value of the logarithm of the firm-level Herfindahl index, where the Herfindahl index (H_{it}) is defined as: $H_{it} = \sum_{pc}(\frac{V_{ipct}}{V_{it}})^2$, where pc represents a product-market pair; V_{ipct} is the value of the product-market pair that firm i exports at time t; and V_{it} is the total value that firm i exports at time t (Álvarez et al., 2013).
[79] The only variable that was not significant is the variable measuring the experience of other exporters for different products in the same market.

to experience, for the own experience variable; and a congestion effect of different firms exporting the same product, for the experience of other exporters.

A range of other determinants has been shown to influence either the propensity to export or the intensity of exporting. Basile (2001), for a sample of Italian manufacturing firms, shows that higher labour costs per unit of product, which measure cost competitiveness, negatively affect the propensity to export. Networks can have an important influence on exporting. On the one hand, Gashi et al. (2014) show that membership of a business association positively influences both the propensity to export and the intensity of exporting of SMEs in transition countries. On the other hand, Sjöholm (2003) examines the importance of foreign networks on the propensity to export of Indonesian manufacturing establishments with more than 20 employees and finds that foreign ownership, and especially larger percentages of foreign ownership, increased the propensity to export among Indonesian establishments. Gashi et al. (2014) show that the export behaviour of a firm is positively influenced by: (i) the greater foreign ownership of a firm; (ii) the greater the share of goods in total sales; (iii) being engaged in production compared to trade or service activities; (iv) availability of credit/finance; and (v) the greater the domestic market share the firm has.[80] Basile (2001) shows that being a part of a business group increases the propensity to export among Italian manufacturers with more than 10 employees. Additionally, Basile (2001) shows that the probability of exporting is greater among firms belonging to a: (i) 'traditional' sector, (ii) 'scale intensive' sector, and (iii) 'specialised supplier' sector; compared to a 'science based' sector. Positive links are also found for firms belonging to a: (i) 'traditional' sector, and (ii) 'specialised supplier' sector; and export intensity. The age of a firm can influence the propensity of a firm to start exporting, as shown by Sjöholm (2003) who finds that younger establishments in Indonesia were more likely to start exporting, while in Gashi et al. (2014), the age variable is mostly insignificant. Furthermore, Kotorri and Krasniqi (2018) find a positive link between adopting quality standards and export performance.[81]

[80] *Foreign ownership* is measured by "the percentage share of the firm's assets owned by foreign shareholder(s)"; *availability of credit/finance* is captured using a "dummy for companies who have a credit line or a loan from a financial institution"; and *domestic market share* is captured using a "dummy for companies with more than 5% of total domestic market sales" (Gashi et al., 2014, p. 418).

[81] Adoption of quality standards is measured as having obtained quality certification (Kotorri and Krasniqi, 2018).

4.3.2 External determinants of propensity to export and intensity of exporting

The broader environment within which firms operate can shape their export decisions (Greenaway and Kneller, 2007). Lederman et al. (2010), as already briefly discussed in the introductory part, showed that the amount of export per capita at the country level is: (i) positively influenced by its GDP per capita; and (ii) negatively influenced by the extent of the barriers imposed by other countries.[82] Álvarez et al. (2013) find that the probability of a new product-market pair is positively affected by the experience of other exporters (i.e. increase in the value of the same product exported by other firms to the same market; increase in the value of same products exported by other firms to different markets; and, increase in the value of different products by other exporters to the same market). The location of the firm can influence exporting. Sjöholm (2003) finds that Indonesian establishments that were located in districts that exported more had a greater propensity to start exporting. Contrary to the finding of Sjöholm (2003), Gashi et al. (2014) find no evidence that location[83] of a firm, as one of the measures used to determine productivity-enhancing spillovers, affects either the propensity or intensity to export.

Increasing demand is often at the heart of many export promotion policies (Atkin et al., 2017). The existence and work of export promotion agencies can influence exports both at the more aggregate level and at the firm level.[84] The aim of export promotion agencies and programmes is to support firms in their search for new external markets (Lederman et al., 2010; Ayob and Freixanet, 2014). The scope of services offered by export promotion agencies differs significantly across countries and regions and, additionally, this scope can differ depending on whether the agencies are established in developed or developing countries (Ayob and Freixanet, 2014). Lederman et al. (2010, p. 257-258) list four categories of services offered by export promotion agencies: (i) "country image building (advertising, promotional events, but also advocacy)"; (ii) "export support services (exporter training, technical assistance, capacity building, including regulatory compliance, information on trade finance, logistics, customs, packaging, pricing)"; (iii) "marketing (trade fairs, exporter and importer missions, follow-up services offered by representatives abroad)" and (iv) "market research and publications (general, sector, and firm level information, such as market surveys, on-line information on export markets,

[82] The extent of barriers is captured by "an index of market access restrictions imposed by the rest of the world on exports of country…" (Lederman et al., 2010, p. 260).
[83] Location is captured by a "dummy for firms located in the capital city" (Gashi et al., 2014, p. 418).
[84] Export promotion agencies have often been criticised. A discussion of these critiques is beyond the scope of this chapter. For such a discussion, see Lederman et al. (2010).

publications encouraging firms to export, importer and exporter contact databases)". In addition to various non-financial assistance services, export promotion programmes can involve financial assistance to firms as well (Ayob and Freixanet, 2014).

Lederman et al. (2010) conducted a survey of export promotion agencies around the world to determine their impact on exports at the aggregate level. Their results suggest that export promotion agencies have a positive impact on national exports on average, i.e. exports per capita in a country are positively affected by the budget of the export promotion agency in the same country,[85] and export promotion agencies appear to be most effective: (i) in the presence of greater trade barriers; and (ii) when a greater proportion of exports from a country consists of heterogeneous goods. Additionally, the authors find a positive correlation between exports and a single strong export promotion agency, instead of several smaller ones. Ayob and Freixanet (2014) find that awareness of exporting promotion programmes among Malaysian SMEs is generally high.[86] When comparing the level of awareness of different export programmes between exporters and non-exporters, the authors find that exporters have significantly higher awareness of four out of nine programmes, namely: (i) international trade information/publications; (ii) tax incentives; (iii) export infrastructure facilities;[87] and (iv) export advisory services. In contrast, the frequency of use of the programmes is low, although significantly higher for exporters compared to non-exporters for six out of nine programmes, namely: (i) export information and online resource centre; (ii) export courses/training; (iii) sponsored international trade fairs/shows; (iv) credit consultation and financial advisory; (v) international trade information/publications; and (vi) tax incentives. The perception of the usefulness of the programmes is high and the programmes are perceived to be more useful by exporters than by non-exporters. Ayob and Freixanet (2014) find that, among Malaysian SMEs, international trade shows and the provision of trade information/publication are the most useful programmes. The perception of usefulness of programmes between exporters and non-exporters differs for two out of the nine programmes: (i) non-exporters have a significantly higher perception of the benefits of the provision of export infrastructure facilities than exporters;[88] while (ii) exporters have

[85] Diminishing returns to scale are also present.
[86] Although different across different programmes.
[87] According to the authors, *export infrastructure facilities* programme "provides SMEs with access to industrial infrastructure facilities related to export activities" (Ayob and Freixanet, 2014, p. 41)..
[88] The results table (Table 6 in Ayob and Freixanet, 2014) indicates that there is a significant difference between exporters and non-exporters when it comes to perceptions of the usefulness of export infrastructure facilities. However, the authors note in the text that the difference is in regard to export information services.

benefitted from tax incentives significantly more compared to non-exporters. Furthermore, the perception of usefulness of the programmes among exporters is increasing over time. Finally, Ayob and Freixanet (2014) find that there is generally a positive relationship between export experience and the frequency of use and perception of usefulness of the programmes.

Table 4.1 provides an overview of the studies discussed in this section.

Table 4-1. Overview of the studies on determinants of exporting

Author(s) (year)	Country	Industry and sector	Data type, sample period and data source	Main findings
Sjöholm (2003)	▪ Indonesia	▪ Manufacturing establishments with more than 20 employees	▪ Panel dataset for the period 1994-1997	▪ The propensity to start exporting is positively influenced by: ▪ Foreign ownership (estimated marginal effects show that propensity to export increases by 12% with foreign ownership), where establishments with less than 5% of foreign ownership were more likely to start exporting than domestic establishments; and establishments with predominant foreign ownership were more likely to become exporters than establishments with minority foreign ownership; ▪ Imports of intermediate products by establishments (estimated marginal effects show that propensity to export increases by imports of intermediate products by 4%); ▪ Size of the establishment; ▪ Being located in a district that has more exports; ▪ Quality of exports (measured by skill – defined in the text above – and R&D); ▪ Age of the establishment negatively influences the propensity to export
Wagner (2008)	▪ Germany	▪ Manufacturing plants (in firms with more than 20 employees)	▪ Cross-sectional dataset from 2004	▪ The differences in the propensity to export between plants in West and East Germany are in part due to: ▪ Differences in the size of the plants (i.e. plants in the West Germany are larger than those in East Germany); ▪ Differences in labour productivity (i.e. plants in West Germany are more productive than their counterparts in East Germany)

Author(s) (year)	Country	Industry and sector	Data type, sample period and data source	Main findings
Álvarez et al. (2013)	▪ Chile	▪ All exporting firms	▪ Panel dataset covering all Chilean exporters during the period 1991-2001	▪ The experience in exporting the same product to other market(s) increases the probability of exporting the same product to a new market; ▪ The experience of exporting a product in the past has a greater influence among the smaller firms; ▪ The importance of having previous experience in exporting a product is greater when it comes to: (i) heterogeneous products; (ii) sectors with greater dependence on external finance; and (iii) simpler products; ▪ The experience in exporting other product(s) to a particular market increases the probability of exporting new products to that market; ▪ The probability of exporting of a new product-market pair is positively affected by the experience of other exporters; ▪ A firm is less likely to introduce new products in new markets if it has more concentrated exports
Ayob and Freixanet (2014)	▪ Malaysia	▪ Manufacturing SMEs	▪ Cross-sectional dataset covering 284 SMEs (both exporters and non-exporters)	▪ There is generally a positive relationship between export experience and frequency of use and perception of usefulness of the export promotion programmes
Gashi et al. (2014)	▪ Dataset covering firms in 31 transition countries[89]	▪ SMEs	▪ Cross-sectional dataset; ▪ Pooled cross-sectional dataset; ▪ Panel dataset; ▪ All three from Business Environment and Enterprise Performance	▪ Export behaviour is positively influenced by: ▪ Human capital related factors, i.e. the greater the share of employees with completed university or higher education, the greater the expected share of exports in firm's sales; ▪ Recent introduction of product or process innovation, i.e. firms that recently introduced product or process

[89] This country count is not precisely true for all periods, as the list of countries in Gashi et al. (2014) includes: Yugoslavia (for 2002 data); Serbia and Montenegro (for 2005); and Serbia, Montenegro and Kosovo (for 2008/2009).

Author(s) (year)	Country	Industry and sector	Data type, sample period and data source	Main findings
			Surveys (BEEPS) covering period 2002-2009	innovation export up to 3% of their output more than firms without innovation; ▪ Sales to MNEs and large domestic firms; ▪ Higher share of imported material input; ▪ Size of a firm; ▪ Foreign ownership; ▪ Production firms engage more in exporting compared to trade and service firms; ▪ Availability of finance/credit; ▪ Membership in business associations; ▪ Greater share of domestic market
Kotorri and Krasniqi (2018)	▪ Kosovo	▪ Trade, services and manufacturing SMEs	▪ Cross-sectional dataset from the survey of 500 Kosovan SMEs in 2013	▪ Export performance is positively affected by: ▪ Productivity; ▪ Higher education of a manager; ▪ International experience of a manager; ▪ Adoption of quality standards; ▪ Larger imports; ▪ Export performance is negative affected by: ▪ Expectations about the future performance of a firm; ▪ Share of employees with higher education

4.4 Conclusion

The research is conclusive that exporting can have positive effects both at the national and firm levels. It is a frequently used internationalisation and growth strategy of firms and it is associated with better performance of firms, in spite of the costs of engaging in this activity. The determinants of exporting have been the subject of inquiry by empirical researchers, which show that exporting is influenced by a range of both internal (i.e. management, foreign networks, etc.) and external (i.e. institutions, export promotion programmes, etc.) determinants. This chapter concludes an overview of the three key variables explored in this thesis – innovation, exporting and productivity – and sets a platform for comparison of the determinants of the three concepts that will be a subject of the following chapter, as well as for the empirical chapters of this thesis.

5. The links between productivity, innovation and exporting

5.1 Introduction

One of the aims of this thesis is to provide new insights into the understanding of the links between innovation, exporting and productivity. The three focal topics were reviewed independently in the preceding chapters, focusing on the importance of each individual topic and their determinants. Separate, large bodies of literature examine these three topics, while only a small literature examines the links between innovation, exporting and productivity. This chapter aims to bring together the discussions from the previous three chapters and thoroughly examine the literature that unpacks the links between innovation, exporting and productivity. In doing so, it develops new insights into the links between innovation, exporting and productivity, identifies some gaps in the literature, and establishes that these variables must be treated as mutually endogenous (this insight is the platform for the empirical investigation in the following chapter). Exporting will be treated as an activity separate from innovation. Both Schumpeter, as indicated in Chapter 3, and some of his earlier critics (e.g. Shaw Solo, 1951) treat opening new markets as a form of innovation. However, although exporting is used as a proxy for opening new markets, exporting represents only one type of opening of new markets. Given that exporting can be a relatively poor proxy for opening new markets (e.g. the small number of exporters in the United States of America, according to the figures presented in the *Introduction* of Chapter 4, may be the consequence of the size and the structure of the US market) and that the recent literature is consistent in treating exporting and innovation as separate activities, they will be treated separately in this and the following empirical chapters.

Innovation, exporting and productivity are all related to a firm's dynamism. Dynamism of a firm can be thought of as the ability of a firm to have an active role in the environment in which it operates: i.e. to proactively shape the environment in which it operates; to respond to any changes in its external environment; and to make all the necessary internal adjustments in order to respond to challenges. In the context of this thesis, on the one hand, both innovation and exporting are, at least partially, responses of a firm to the wider environment in which it operates. On the other hand, productivity growth can be thought of as a measure of the dynamism of a firm. As we will see in Section 5.3, and particularly in Table 5.2, these three phenomena share some common determinants, but also have an even greater number of unique determinants. However: (i) although all three phenomena are related to business dynamism, this does not necessarily mean that firms will equally excel in all three; and (ii) the shared determinants may not impact all these three firm-level phenomena to the same degree or with the same timing. Complex, strong relationships between different phenomena are present in different areas of economics. From Chapter 3, we have learned that technological progress and innovation are related to economic growth and this is postulated by, on one side, neoclassical and endogenous theories of economic growth, and on the other side, evolutionary theories of growth (Dosi and Nelson, 1994). Economic growth, as an area of research, suffers from some similar problems as the examination of the productivity-innovation-exporting nexus. Although the theoretical foundations in the economic growth literature are substantially stronger, empirical research dominates the research on economic growth, especially when it comes to generating new insights (Acemoglu, 2012), and a consensus about the particular model and the determinants of economic growth are not universally agreed on (Gjika, 2018). In many respects, the level of productivity of a firm resembles the level of economic development of a country, as both constitute measures that are outcomes of a wide range of different activities and influences. Acemoglu (2012, p. 546), regarding economic development, notes: "… economic development […] is highly multi-faceted […]. It is not just about growth of aggregate output, but also about the fundamental transformation of an economy, ranging from its sectoral structure, to its demographic and geographic makeup, and perhaps more importantly, to its entire social and institutional fabric." As in the relationship between economic growth and its determinants (e.g. physical capital stock, human capital, technological progress, etc. (Trajkova, 2013)), the links in productivity-innovation-exporting, nexus can be circular, rather than linear.

This chapter is structured as follows. Section 5.2 provides an overview of the literature that explores the links between innovation, exporting and productivity. Section 5.3 brings together the discussion about the determinants of innovation, exporting and productivity from this and the previous three chapters. Section 5.4 draws upon the discussions from the earlier chapters to clearly illustrate the theoretical positioning of the empirical chapters of the thesis. Section 5.5 discusses and compares ideal and feasible datasets in terms of data requirements for the exploration of the productivity-innovation-exporting nexus. Section 5.6 concludes.

5.2 The links between innovation, exporting and productivity

The direction of the causal relationship between internationalisation, including exporting, and productivity has been described as 'controversial' (Greenaway and Kneller, 2007, p. 135). Differences in productivity between exporters and non-exporters can be explained by two theoretically-consistent, non-mutually exclusive hypotheses: (i) the 'self-selection' hypothesis; and (ii) the 'learning' or 'learning-by-exporting' hypothesis (Wagner, 2007).[90] The importance of productivity and sunk costs for exporting is recognised in the influential paper by Melitz (2003).[91] At the core of Melitz's theoretical model is heterogeneity between firms based on their productivity and it is assumed that the most productive firms export, while the least productive firms cease to exist.[92] Similarly, Greenaway and Kneller (2007, p. 135) observe: "It has become something of a stylised fact that *ex-ante* productivity determines the choice of whether or not to export." As explained at more length in the previous chapter, self-selection occurs due to the costs associated with exporting. In a narrative survey of the research exploring the link between exporting and productivity, covering the period 1995-2006, Wagner (2007) concludes that the self-selection hypothesis has been generally proven to hold true. Some authors recognise the possibility that firms intentionally enhance their productivity prior to engaging into exporting activity. Movahedi et al. (2017) test the hypothesis of "conscious self-selection" into exporting through productivity-enhancing investment in innovation using a cross-sectional dataset and on a sample of 86 manufacturing SMEs from Lower Normandy (France). The authors consider exporting to be a process, with distinct design and implementation phases, where an intention to export is transformed into capabilities and willingness to

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[90] Some authors refer to the hypothesis as 'learning-by-exporting', where they distinguish that learning-by-exporting can emerge as a consequence of several different mechanisms (i.e. learning-by-doing or knowledge transfers) (Atkin et al., 2017). In contrast, other authors refer to all the learning that occurs as a consequence of exporting as 'learning', while they define 'learning-by-exporting' just as knowledge transfers (i.e. that occur through the interaction with foreign competitors and/or customers).
[91] Theoretical models on firm dynamics generally do not discuss why the initial differences in productivity exist (Movahedi et al., 2017).
[92] Melitz's model is more informative for the movements in industry-level productivity and, hence, will not be described further. Average industry productivity increases as a consequence of some firms engaging in export markets due to the exit of the least productive firms, as well as reallocation of market shares towards more productive firms.

export and, finally, exporting. To test their hypothesis, Movahedi et al. (2017) utilise a CDM model – a three-step model, where the estimation involves a combination of logit models in the first and final steps, and a linear regression model in the second step. The first stage involves the link between innovation inputs and the probability of innovation; the second stage the link between innovation and productivity; and, finally, in the third stage, the link between productivity and willingness to export. Innovation output, exporting and productivity variables are treated as endogenous. The authors conduct their investigation on a sample of non-exporting firms, where the willingness to export of firms is compared.[93],[94] The hypothesised relationship is unidirectional, leading from innovation output to productivity and, finally, willingness to export.[95] Movahedi et al. (2017) find support for "conscious self-selection", stating that "the SMEs invest *ex ante* in innovation by mobilising R&D and inventiveness, human resources and their own financial resources, to improve their productivity and to export *ex post*" (Movahedi et al., 2017, p. 17).

Three channels have been recognised through which learning can occur from engaging into exporting activity: (i) knowledge transfers from foreign competitors or customers about processes or products that can lead to cost savings and/or quality improvements; (ii) increases in scale; and (iii) due to the increased competition firms face, firms may find it necessary to increase the efficiency of their production or to innovate (Greenaway and Kneller, 2007). Learning-by-exporting represents a challenge for empirical researchers, as will be discussed later. The empirical literature on learning that occurs as a consequence of exporting has been described as "voluminous" (Atkin et al., 2017, p. 558), but the hypothesis has not been systematically proven and the results can be described as mixed (Wagner, 2007; Aw et al., 2008; Atkin et al., 2017).[96] In the meta-analysis of 33 studies that tested the learning-by-exporting hypothesis, Martins and Yang (2009) show that the impact of exporting on productivity is more pronounced in developing compared to developed countries. Additionally, the results from Martins and Yang (2009) suggest that the impact of learning-by-exporting is the

[93] This excludes the possibility of learning-by-exporting.
[94] The study by Movahedi et al. (2017) utilises survey data. In the survey, non-exporting firms are asked to declare their willingness to export.
[95] The specification by Movahedi et al. (2017) ignores the possibility of a simultaneous relationship between the three phenomena.
[96] Wagner (2007) reviews the literature from 1995-2006 and concludes that the literature reports mixed results.

highest in the first year that a firm starts exporting. Furthermore, the authors investigate whether the choice of sample heterogeneity (i.e. reliance on only matched samples) has implications for the results. They find that the corresponding learning-by-exporting effect is lower when the study includes only matched firms. An important finding from Martins and Yang (2009) in the context of this thesis, although not consistent across all model specifications, is that the studies that use productivity variables other than total factor productivity as a dependent variable, exhibit larger positive effects of exporting on productivity.[97]

In Chapter 2, we learned from the study by Van Biesebroeck (2008) that support for the existence of learning-by-exporting can depend on the approach used to estimate productivity (i.e. non-parametric versus parametric). Furthermore, Atkin et al. (2017) point out the practical difficulties of detecting learning-by-exporting, when a production function approach to productivity estimation is applied. First, considering that firms generally self-select into export markets, it is hard to attribute productivity to either selection or learning. Second, using commonly applied revenue-based total factor productivity poses problems. In line with the discussion in Chapter 2, revenue-based total factor productivity can capture various influences of exporting, such as: changes in mark-ups, the product mix, product quality, and exchange rate changes. Adjusting for prices and use of quantity-based productivity with the typically available datasets may help to circumvent the problem of changing mark-ups and potentially of exchange rate changes, but not the other two (Atkin et al., 2017).

Novel insights on learning-by-exporting were generated by Atkin et al. (2017), who use a randomised controlled trial on several hundred rug manufacturers in Egypt. The rug manufacturers were randomly assigned into exporting to high-income markets to uncover learning-by-exporting.[98] As described in the previous chapter, Atkin et al. (2017) find that exporting leads to significant increases in profits. Furthermore, they show that higher prices at least partially drive the increase in profits. The authors show that the treatment firms (i.e. firms that were provided with the opportunity to export),

[97] An interesting finding in Martin and Yang (2009) is that the explored literature does not appear to suffer from publication bias.

[98] Atkin et al. (2017) warn the readers that generalisations from their study should be precluded, as the sample is comprised of small firms that usually have just one full-time employee and whose production is not automated.

compared to control firms (i.e. those that were not given the opportunity to export), experienced a decline in total output when unadjusted for product specifications.[99] Furthermore, treatment firms increase their labour input use, while no changes were found in capital usage or intermediate inputs.[100] Additionally, Atkin et al. (2017) investigate whether there were disparities in quality between firms in the treatment and control groups and find substantial differences. Namely, when measured on a scale ranging from one to five, treatment firms have 0.79 points higher quality on average. Labour productivity (measured as output per hour), as well as total factor productivity, when unadjusted for product specifications, substantially decline in treatment compared to control firms. However, the opportunity to export leads to a rise in both productivity measures when adjusted for product specifications and quality. Furthermore, Atkin et al. (2017) show that both productivity and quality increase with time. When firms were asked to produce the rugs according to standard specifications in a controlled lab facility, the authors confirm that the treatment firms indeed produce products of higher quality and do not require more time to produce those products. Reviewing the evidence on the discussions that firms had with an intermediary firm that was coordinating the exporting activities, the authors conclude that increases in quality are partially driven by knowledge transfers, particularly concerning market requirements. The authors conclude that the rise in quality and productivity when adjusted for product specifications signals learning-by-exporting.

As already depicted through the discussion above, the links between productivity, innovation and exporting[101] have been explored in different contexts (e.g. countries, groups of firms – i.e. SMEs versus all firms – etc.). Some of the links were more explored than others, as will be discussed in more detail at the end of this section. To pre-empt the later discussion, Freel et al. (2019, p. 2), for example, note that "ample empirical evidence" is available on the links between innovation and exporting, but "the extent to which exporting induces innovation in firms" (Freel et al., 2019, p. 2) is less explored. Some of the authors point to the importance of the choice of specific

[99] Atkin et al. (2017, p. 582) note that the findings regarding the reduction in output as a consequence of opportunity to export are not consistent with either international trade models, theory on the scale effects or "exporting simply being a generic demand shock".
[100] The authors conjecture that the fact that the output declines, while the inputs remain unchanged, points to higher quality production as the higher quality rugs require more material inputs.
[101] Either between two out of these three phenomena or all three

variables when exploring the links between innovation, exporting and productivity. Movahedi et al. (2017) note that the choice between innovation input versus innovation output variables matters when exploring the link between innovation and propensity to export, indicating that the studies using innovation input measures (e.g. R&D) fail to show a significant link.[102] In the light of the discussion from Chapter 2, the definition of productivity will matter in empirical investigation of the links between innovation, exporting and productivity. For example, certain types of innovation contribute less, if at all, to improvements in quantity-based productivity, yet have an influence on firm revenues. Syverson (2011, p. 345) points out that improvements in product quality as a result of innovation can constitute an improvement in productivity, if productivity is defined as "units of quality delivered per unit input". Cassiman et al. (2010) note that product innovation is likely to influence variations in demand, while process innovation is likely to influence quantity-based productivity. Furthermore, the authors (p. 372) conjecture that: "As a result product innovation is expected to affect measured productivity more and, consequently, entry into exporting."

Hughes (1986) hypothesises a simultaneous, two-way relationship between exporting and innovation. The author suggests that engaging in exporting can stimulate R&D if differences exist in the nature of demand between the domestic and the export market(s). Exporting enhances the ability of a firm to capture rents related to innovation and, hence, can have a positive impact on R&D. Although exporting, licensing and foreign direct investment can all help to capture the rents, Hughes (1986, p. 389) argues: "… success in export markets may inform firms about the viability of current R&D, while licensing and FDI represent returns to past R&D". Hughes (1986) examines the link between exporting and R&D at an industry-level and hypothesises that trade occurs if there is a difference between R&D spending within the same industry, but across different countries. Additionally, the author points out the importance of both innovation and scale economies for trade.[103] Using UK manufacturing data at an industry-level and estimating a simultaneous system of two structural equations, Hughes (1986) provides empirical support for the hypothesis of a simultaneous

[102] No explanation is provided by the authors regarding this finding.
[103] The importance of innovation and scale economics is emphasized particularly in the following excerpt (Hughes, 1986, p. 387): "The trade resulting from an innovation will be impermanent, unless there is a continuing sequence of innovations, or there are associated scale economies. If there are scale economies and product differentiation then countries with the same level of R&D may trade."

relationship between exporting and the technology level of an industry. The author also shows that the export levels are affected by both: (i) the technology gap across countries, measured by R&D; and (ii) the level of technology.[104] The first firm-level empirical study examining the link between R&D intensity and export performance was done by Hirsch and Bijaoui (1985). Using a sample of 111 Israeli firms from 1977-1981 and the means of descriptive statistics, the authors show that the ratio of exports to total sales of the sample of innovative firms[105] was greater than that of all firms operating in their respective industries in both 1975 and 1981. Using linear ordinary least squares, the authors examine the link between R&D intensity and export performance within the sample of innovators. [106] As formulated by Hirsch and Bijaoui (1985), R&D is assumed to affect export performance with a lag of four years.[107] The authors find that R&D intensity positively influences export performance.

Basile (2001) devises a short-run microeconomic model that links export behaviour (including both propensity to export and intensity of exporting) and product innovation. In the model, firms have to, non-simultaneously, decide on: (i) the level of product innovation; (ii) the level of output firms will produce; and (iii) the markets they will serve. The authors hypothesise that if the return to product innovation is higher in the foreign than in the domestic market, firms will export and have higher export intensity. Exogenous factors such as exchange rate shocks are expected to influence the relationship between innovation and exporting. Basile's (2001) empirical investigation of a sample of Italian manufacturing firms utilises Cragg's specification of the tobit model. The results show that the propensity to export is greater among firms that

[104] Considering that the study by Hughes (1986) uses industry-level, and not firm-level data, the results will not be discussed in greater detail.

[105] The sample consists of 111 firms that conduct civilian R&D and that have received a research grant, with all large firms and a random sample of SMEs being included in the final sample.

[106] R&D intensity is defined as "the ratio of employees engaged in research and development in 1977 to total employment", while export performance is defined as "rate of change in exports during the 1979-1981 over the 1975-1977 period" (Hirsch and Bijaoui, 1985, p. 244). Hirsch and Bijaoui (1985) note that the proxy they use for R&D intensity suffers from several problems, and hence possibly understates the value of investments in innovation because it does not account for: (i) past R&D investments, due to the lack of data; (ii) the influence of the R&D contracts awarded to other firms; (iii) purchase of know-how (i.e. through licensing, etc.); and (iv) the contribution of investments in equipment bought for the purposes of conducting R&D.

[107] Hirsch and Bijaoui (1985, pp. 244-245) note: "… some time must elapse before an investment in an R&D project yields tangible results in the form of new products or new processes." Furthermore, they note that, in examining this link, it would be desirable to account for the "cumulative effects of past R&D investments".

introduce either product and/or process innovations.[108] Furthermore, the results imply that employing R&D strategies (i.e. product innovation with/without process innovation through R&D investments, process innovations through R&D investments) increases propensity to export among Italian manufacturers. The results for the intensity of exporting are not consistently significant for any of the variables of interest.

Wakelin (1998) utilises UK data to explore the impact of innovation on export behaviour, encompassing both the probability to export and the intensity of export. Descriptive statistics in Wakelin (1998) reveal an interesting pattern: (i) non-innovators export more than innovators when small in size, on average;[109] and (ii) innovators that are large in size are typically not currently exporting. When testing for the model specification, Wakelin (1998) concludes that innovators and non-innovators should be explored separately. In a pooled sample of both small and large firms, the author shows that the probability of exporting is positively influenced by the number of innovations that a firm has. Furthermore, Wakelin (1998) shows that the probability of exporting is positively influenced by: (i) sector-level production of innovations[110] for both innovators and non-innovators; and (ii) sector-level R&D expenditure[111] for the non-innovators.[112] The author also shows that the intensity of exporting is negatively influenced by: (i) sector-level R&D expenditure;[113] and (ii) for the non-innovators, sector-level use of innovations.[114] ,[115]

[108] Product innovations are measured through R&D activity, while process innovations are measured as "investments in new capital equipment" (Basile, 2001, p. 1193).
[109] The author suggests that this might be due to the established position of small innovative firms in their domestic markets.
[110] The sector-level production of innovation is measured as "the number of innovations produced in the sector for 1979-1983, from the survey, excluding each firm's individual innovations, scaled by the number of enterprises in the sector" (Wakelin, 1998, p. 833).
[111] Sector-level R&D expenditure is measured as "the expenditure on R&D in the sector scaled by the number of enterprises in the sector" (Wakelin, 1998, p. 833). Wakelin notes that sector-level R%D expenditure can indicate the level of competition in the sector, as well as potential spillovers among firms in the sector.
[112] The author explains the second finding as the influence of spillovers from R&D expenditures to non-innovative firms.
[113] The author notes that "the R&D expenditure of other firms seems to indicate rivalry between firms in terms of competition" (Wakelin, 1998, p. 839).
[114] Sector-level use of innovations is measured as "the number of innovations used in the sector from 1979 to 1983, taken from the SPRU survey, scaled by the number of enterprises in the sector" (Wakelin, 1998, p. 833).
[115] The author explains the second finding as reflecting the absence of spillovers from innovation to exporting.

Bleaney and Wakelin (2002, p. 11) offer novel insights about the link between exporting and innovation, recognising that there are differences in the determinants of exporting depending on whether firms innovate or not. They recognise the possibility of the existence of links between exporting, innovation and productivity; and note: "Any positive correlation between these two variables [exporting and productivity] may in fact simply reflect the effects of a third factor: innovative activity." Similarly, Cassiman et al. (2010) note: "In the empirical setting, omitting an innovation variable from the analysis may lead to the overestimation of the productivity-exports association." Bleaney and Wakelin (2002) investigate these links in a sample of UK manufacturing firms. Testing for the differences in the mean, they show that the propensity to export is greater for innovating firms compared to those that are not. Furthermore, the authors investigate whether there are differences in the determinants of the probability of exporting between innovating and non-innovating firms. They show that although size is an important determinant for both groups of firms, the effect is substantially lower for non-innovating firms. While an increase in a firm's average wage[116] reduces the probability of exporting among innovators, it increases the probability of exporting among non-innovators. An increase in capital intensity[117] also decreases the probability of exporting among innovators, while the effect is insignificant among non-innovators. Bleaney and Wakelin (2002, p. 11) conclude: "… for innovating firms, exporting is led by innovative activity and firm size, whereas for non-innovating firms, a higher export probability is associated with greater efficiency (as measured by lower unit labour costs) …". In a separate estimation exercise, which includes sector variables in addition to firm variables, Bleaney and Wakelin (2002) show that an increase in sector-level R&D increases the probability of exporting for both innovators and non-innovators, with the effect being larger for non-innovators. Furthermore, an increase in capital intensity decreases the probability of exporting for non-innovators, while the effect is insignificant for innovators. Additionally, Bleaney and Wakelin (2002) show that an increase in intra-industry trade[118] leads to an increase in the probability of exporting for both innovators and non-innovators, with the effect

[116] Bleaney and Wakelin (2002, p. 7) note that their average wage variable will capture the effect of the educational level of the employees and "the extent to which efficiency differences are reflected in wage rather than profit differentials".
[117] The nature of the capital intensity variable is not elaborated in further detail.
[118] Measured by the Grubel-Lloyd index.

being substantially larger for innovators. Among innovators, a larger number of major innovations increases the probability of exporting.

Aw et al. (2008) devise a theoretical model, which brings together investment in R&D, physical capital, the decision to export and productivity.[119] In the model, firms have different levels of productivity and productivity affects the return to the aforementioned types of investment. Aw et al. (2008, p. 451) also note: "In turn, these investments have feedback effects that can alter the path of future productivity for the firm". Each firm produces a differentiated product.[120] The authors postulate that firms' productivity will be responsive to investment in R&D. Furthermore, Aw et al. (2008) postulate that each firm operating in the domestic market makes three different and dynamic decisions in each year: (i) exporting decision; (ii) choice of the level of R&D; and (iii) investment in physical capital. Using data on Taiwanese manufacturing firms from four industries – (i) consumer electronics, (ii) telecommunications equipment, (iii) computers and storage equipment, and (iv) electronics parts and components – Aw et al. (2008) estimate separate equations for (i) exports, (ii) R&D, and (iii) investment in physical capital. In the export equation, the authors show that the probability of exporting in the current period is positively correlated with: (i) R&D in the previous period; and exporting in the previous period. Furthermore, investments in R&D in the current period are positively correlated with being engaged in: (i) exporting in the previous period; and (ii) R&D in the previous period. The estimates from the investment in physical capital equation will not be discussed in detail, as they are beyond the scope of this chapter. However, the conjecture made by Aw et al. (2008) regarding these results is highly relevant for this chapter. Aw et al. (2008) find that investment in physical capital is: (i) negatively related to past exporting; and (ii) positively related to past R&D. Aw et al. (2008, p. 454) suggest that the combination of these two results "may suggest that R&D and physical investment are substitute pathways for investment spending, and that exporting firms channel their investment spending into R&D, possibly to raise product quality, rather than the physical plant".

[119] Aw et al. (2008) note that alternative assumptions can heavily influence the nature of the model, e.g.: choice of whether to treat R&D investment as a sunk or a variable cost; whether investment in R&D leads to creation of a stock of knowledge; etc.
[120] Aw et al. (2008, p. 452) note that productivity "can also be interpreted as a measure of product quality".

Becker and Egger (2013) investigate the impact of product and process innovation on export behaviour by using a sample of German firms. Using a variety of matching estimators, they find that firms' propensity to export[121] is: (i) positively influenced by product innovation; (ii) positively influenced by a combination of product and process innovation; and (iii) not positively influenced by process innovation alone. An interesting additional finding from Becker and Egger (2013) is that the impact of product innovations on the propensity to export is greater when process innovations had already been implemented, but that the propensity to export does not increase if process innovations had been implemented following the product innovations. The authors further investigate the impact of product and process innovation on the intensive margin of exporting, defined as "the fraction of exports in total plant sales" (Becker and Egger, 2013, p. 351). They show that process innovations are of greater importance for the intensive, compared to the extensive, margin of exporting and have a positive impact on the intensive margin of exporting.[122] A similar empirical investigation was conducted by Gashi et al. (2014), who explore the impact of product or process innovation as a productivity-enhancing factor in the context of SMEs in transition countries. Gashi et al. (2014) find that firms having recently introduced product or process innovation[123] exported 3% more of their output compared to firms without innovation. Stojčić and Hashi (2014) use a firm-level Community Innovation Survey dataset covering firms from 12 European countries[124] to estimate a CDM model with the following stages: (i) decision of a firm to engage in innovation; (ii) decision of a firm on the amount of innovation expenditures; (iii) link between innovation expenditure and innovation output; and (iv) the impact of innovation output on productivity. The first two stages are estimated using the tobit model and Heckman procedure; the third stage using a bivariate probit model; and finally, the fourth stage, using ordinary least squares. Stojčić and Hashi (2014) emphasise their novel choice of measure of innovation output, as well as their way of labelling a firm as an innovator. The authors measure innovation output through introduction of product and process

[121] The authors refer to the propensity to export as the *extensive margin* (Becker and Egger, 2013).

[122] Generally, and consistent with the explanations by Becker and Egger (2013), the intensive margin of exporting involves exporting existing product lines, while extensive margin of exporting involves new product lines.

[123] The introduction of product or process innovation is captured through a "dummy for firms which introduced new products or upgraded existing products or introduced new technology over the last 36 months" (Gashi et al., 2014, p. 418).

[124] The twelve countries are: Bulgaria, Romania, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Slovak Republic, Greece, Spain, Portugal and Norway.

innovation, while they label a firm as an innovator if it invested in innovation.[125] The results from the first stage of the CDM model estimated by Stojčić and Hashi (2014) show that both the propensity to innovate of firms and the amount of financial resources they invest in innovation is greater if they: (i) are exporters; and (ii) previously engaged in innovation.[126] However, in estimating the third stage of their model, Stojčić and Hashi (2014) show that: (i) being an exporter is negatively related to engaging in process innovations, and combined product and process innovations; and (ii) previous experience in innovation is positively linked to engaging in product innovations, and negatively linked to engaging in process innovations as well as to product and process innovations combined. The fourth stage reveals that productivity is positively influenced by: (i) process innovations, (ii) product and process innovations combined, (iii) organisational innovations, (iv) being an exporter, and (v) having a previous innovation/patenting experience; while it is negatively influenced by: (i) product innovations, and (ii) marketing innovations. Considering that productivity in Stojčić and Hashi (2014, p. 143) is defined as "turnover per employee (natural logarithm)", the results from the last stage regarding the impact of product and marketing innovations are contrary to expectations.[127]

Several studies have explored the Spanish dataset that will be used in the following three chapters of this thesis. Caldera (2010) first builds a theoretical model linking innovation, productivity and exporting.[128] Caldera (2010) examines the exporting-innovation link using ESEE data for the period 1991-2002. By graphically comparing the productivity distributions, Caldera (2010) shows that innovators are more

[125] Stojčić and Hashi (2014, p. 128) note: "… it is assumed that all firms invest some amount of innovation effort but not all of them report it". Innovation expenditure, as defined by Stojčić and Hashi (2014, p. 131), includes R&D expenditures, but also "expenditure on machinery, equipment, software, patents, know-how and training of staff for innovation activities".
[126] Previous innovation experience is measured through the variable *patenting experience* defined as "dummy – 1 if the firm introduced patent in three years prior to the survey" (Stojčić and Hashi, 2014, p. 143).
[127] It is expected that both marketing and product innovations actually increase turnover and hence, productivity.
[128] As development of a theoretical model linking innovation, productivity and exporting is not a part of this thesis, exhaustive reviews of the existing theoretical models will not be provided. The theoretical models developed so far are mostly very restrictive and do not depict the true nature of innovation. For example, the outcome of Caldera's theoretical model is that the investment in innovation leads only to lower marginal costs. Other features of this theoretical model are that it predicts that the firms that engage in innovation are also more likely to engage in exporting than those that do not innovate. The direction of the link predicted by the model is that productivity leads to innovation, and in turn, innovation leads to exporting.

productive than non-innovators, and similarly, that exporters are more productive than non-exporters.[129] Furthermore, the author shows that innovating exporters tend to have the highest productivity, while firms that engage into neither of the activities tend to have the lowest productivity. Caldera (2010) shows that the productivity distributions of non-exporting innovators and non-innovating exporters overlap. Using different econometric techniques, Caldera (2010) shows that the probability of exporting is greater amongst innovators, where innovation is captured or measured by a R&D dummy variable, R&D intensity, a process innovation dummy variable and a product innovation dummy variable. The effect of introducing product innovation on the future probability of exporting is stronger than that of introducing process innovation (respectively, 2-16% compared to 1-8%, depending on the econometric specification). Furthermore, the probability of exporting is greater for more productive firms, as measured by total factor productivity.

The ESEE dataset is also used by Cassiman et al. (2010) and Cassiman and Golovko (2018). The focus of both of these studies is only on a subset of firms – namely, small and medium sized enterprises – which, along with the methods employed to investigate the links between innovation, exporting and productivity, represents the largest difference between these studies and the first empirical chapter of this thesis. Cassiman et al. (2010) focus on a subsample of SMEs within the period 1990-1998. The authors employ a one-year lag for the product and process innovation variables they use in their investigation. Cassiman et al. (2010) use the Kolmogorov-Smirnov equality-of-distributions test to examine differences in productivity distributions for different groups of firms (i.e. exporters, non-exporters, etc.). The authors show that: (i) exporters, (ii) innovators more generally, and (iii) product innovators are more productive than (i) non-exporters (for the first case), and (ii) non-innovators (for the other two), respectively. However, they find no difference between the productivity of process innovators and non-innovators. The authors compare productivity distributions of exporters and non-exporters, when they engage in: (i) product innovation, (ii) process innovation, (iii) innovation in general, and (iv) no innovation. Non-innovating exporters are more productive than non-innovating non-exporters. The productivity

[129] Caldera (2010) defines firms as innovators if their R&D expenditures are positive and as exporters if their export sales are positive.

difference between exporters and non-exporters exists even when both groups of firms are innovators; however, this difference is smaller. In the case when both exporting and non-exporting firms are product innovators, the Kolmogorov-Smirnov tests show that the differences in productivity distributions are not significant. By calculating transition probabilities, Cassiman et al. (2010) show that product innovation increases the likelihood of a firm becoming an exporter. Furthermore, the likelihood that the firm will stop exporting is smaller if it is a product innovator. Cassiman and Golovko (2018) examine the link between importing, exporting, the propensity to innovate in product/process, and productivity for a sample of Spanish manufacturing SMEs[130] for the period 1991-2009. In their analysis, Cassiman and Golovko (2018) examine decisions of exporting and innovation in comparison to the decision of firms to engage in importing. By using a random effects linear probability model and comparing the group of 'strict' importers[131] to firms that do not engage in importing, they show that the probability of product innovation among firms increases one year prior to becoming an importer, but that becoming an importer also increases product innovation in the same year when the firm becomes an importer. The probability of process innovation increases both two years and one year prior to starting to import, but also in the year when importing begins. Importing affects the propensity to export in the year that a firm becomes an importer, but continues to affect exporting for three years afterwards. The authors estimate a separate model to capture the influence of imports, exports and innovation, where the values of these three variables are taken from the year before, on productivity. The results show that exporting, importing, process innovation and product innovation, but only when combined with importing, in the year before increase productivity in the subsequent year. The authors conclude that the "results indicate that imports and innovations seem to precede the entry of firms into the export markets" (Cassiman and Golovko, 2018, p. 29).

Figure 5.1 below provides a brief summary of the empirical research on the links between innovation, exporting and productivity discussed previously in this section. We can see that all the links, but one (i.e. the link leading from productivity to innovation), have been explored and found to be significant. As already emphasised

[130] SMEs are defined as firms that employed less than 200 employees in 1991.
[131] 'Strict' importers are firms that, after starting to import, continue to import.

earlier in this section, some of the links have been explored more frequently than others. On the one hand, in line with the conjecture by Freel et al. (2019), we observe that the link leading from exporting to innovation has been far less explored than the reverse link. On the other hand, the link leading from innovation to exporting appears to be the most frequently explored.

Figure 5-1. Summary of the empirical research on the links between innovation, exporting and productivity

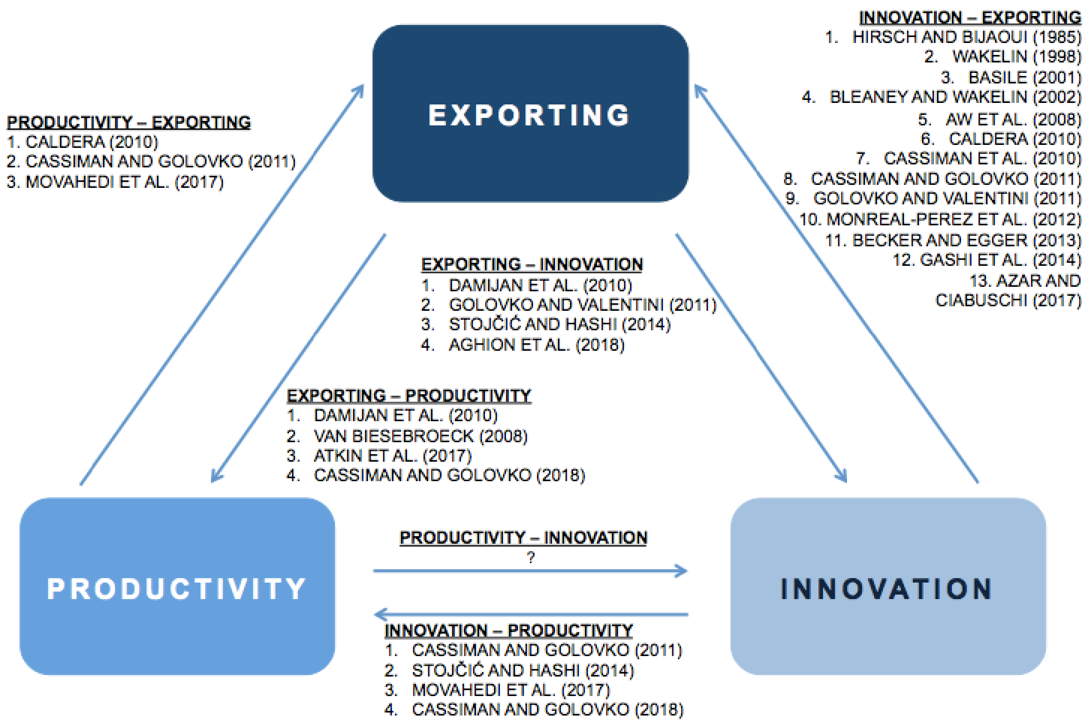


Table 5.1 provides an overview and a summary of the main results of the studies discussed in this section.

Table 5-1. The overview of the studies linking innovation, exporting and productivity

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
Hirsch and Bijaoui (1985)	▪ Israel; ▪ Firm-level dataset covering 111 firms active in performing civilian R&D[132] during the period 1977-1981 or a sub-period, and that were recipients of research grants; ▪ Large firms were all included in the sample, whereas were randomly excluded from the sample	▪ Panel dataset	▪ To examine the correlation between proprietary knowledge and export performance	▪ Ordinary least squares	▪ Export performance is positively influenced by: ▪ R&D intensity; ▪ Size of a firm; ▪ Other firms' characteristics
Wakelin (1998)	▪ United Kingdom; ▪ Firm-level dataset covering 320 manufacturing firms for a period 1988-1992	▪ Pooled cross-sectional dataset	▪ To investigate how innovation impacts export behaviour (i.e. "the probability of a firm exporting", "the propensity to export of the exporting firms" (Wakelin, 1998, p. 829)	▪ Restricted model—single censored tobit model (both the decision about whether or not to export and how much to export are included in the same model);	▪ The probability of exporting is: ▪ Positively influenced by: (i) size; (ii) firm innovation; (iii) average salary for the non-innovators; (iv) unit labour costs for the innovators; (v) sector-level production of innovations; and (vi) sector-level R&D expenditure for the non-innovators;

[132] Some firms that performed defence R&D were also the part of the sample.

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
				▪ Unrestricted model—Model estimated in two stages where the first stage involves a probit model used for the decision of whether or not to engage in exporting and which utilises full sample, and the second stage which utilises truncated estimation procedure and only the data on exporters	▪ Negatively influenced by: (i) unit labour costs for the non-innovators; ▪ Intensity of exporting is: ▪ Positively influenced by: (i) capital intensity; (ii) average wage; and (iii) unit labour costs for the innovators; ▪ Negatively influenced by: (i) size squared for innovators; (ii) unit labour costs for the non-innovators; (iii) sector R&D expenditure; and (iv) sector-level use of innovations for the non-innovators
Basile (2001)	▪ Italy; ▪ Firm-level data covering manufacturing with more than 10 employees; ▪ Data collected in 1992 (covering the period 1989-1991); in 1995 (covering the period 1992-	▪ Cross-sectional dataset; ▪ Panel dataset	▪ To investigate the link between exporting and innovation of Italian firms in three different periods: 1. 1991 – period of fixed exchange rate for Italian currency; 2. 1994 – period of exit of Italian currency from the Exchange	▪ Cragg's specification of the tobit model	▪ The propensity to export is positively influenced by: ▪ Product and/or process innovations; ▪ Use of R&D strategies (i.e. product innovation with/without process innovation through R&D investments, process innovations through R&D investments)

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
	1994); and in 1998 (covering the period 1995-1997)		Rate Mechanism and its devaluation; 3. 1997 – return of Italian currency to the Exchange Rate Mechanism and its appreciation		
Bleaney and Wakelin (2002)	▪ United Kingdom covering the period 1988 – 1992; ▪ Focus on manufacturing firms	▪ Panel dataset	▪ To investigate the link between exporting and efficiency	▪ Probit model	▪ Size positively influences the probability of exporting, however, the effect is substantially lower for non-innovating firms; ▪ The increase in average wage reduces the probability of exporting among innovators and increases the probability of exporting among non-innovators; ▪ Increase in sector-level R&D increases the probability of exporting for both innovators and non-innovators, however, the effect is larger for non-innovators; ▪ Increase in intra-industry trade increases the probability of exporting for both innovators and non-innovators, however, the effect is substantially larger for innovators; ▪ Among innovators, larger number of major innovations increases the probability of exporting

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
Aw et al. (2008)	▪ Taiwan; ▪ Firm-level dataset covering the period 2000-2004 for firms operating in the following industries: consumer electronics, telecommunications equipment, computers and storage equipment, and electronics parts and components	▪ Panel dataset	▪ To develop a structural model depicting joint export-investment decision and put the theoretical equations to the empirical test	▪ Probit; ▪ Tobit	▪ Probability of exporting in the current period is: ▪ Positively and significantly correlated with: (i) log revenue share in the current period; (ii) export dummy from the previous period; (iii) R&D dummy from the previous period; and ▪ Negatively and significantly correlated with: (i) capital stock in the current period; ▪ Investment in R&D in the current period is: ▪ Positively and significantly correlated with: (i) log revenue share in the current period; (ii) export dummy in the previous period; (iii) capital stock in the current period; and (iv) R&D dummy in the previous period
Caldera (2010)	▪ Spain; ▪ Firm-level dataset covering Spanish manufacturing firms over the period 1991-2002	▪ Panel dataset	▪ To examine the exporting-innovation link at the firm-level	▪ Random effects probit model; ▪ Probit (robust standard errors clustered at the firm-level); ▪ Linear probability model (robust standard errors	▪ Probability of exporting is positively influenced by: ▪ Product and process innovations; ▪ Firm size; ▪ Age; ▪ Foreign ownership; ▪ Total factor productivity; ▪ Past exporting

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
				clustered at the firm-level); ▪ Fixed effects model; ▪ Instrumental variables; ▪ GMM Arellano-Bond estimator	
Becker and Egger (2013)	▪ Germany	▪ Panel dataset	▪ To investigate the impact of product and process innovation on export propensity	▪ Propensity score matching; ▪ Radius matching; ▪ Nearest-neighbour matching; ▪ Kernel matching	▪ The propensity to export is positively influenced by: ▪ Product innovation; ▪ The combination of product and process innovation; ▪ Product innovations have greater influence on the propensity to export if process innovations had already been implemented. However, if process innovations had been implemented after the product innovations, the propensity to export does not increase; ▪ Process innovations positively influence intensive margin of exporting
Gashi et al. (2014)	▪ Transition countries, covering the period 2002-2009; ▪ Focus on SMEs	▪ Cross-section datasets; ▪ Pooled cross-section dataset;	▪ To investigate the determinants of export behaviour (both propensity to export and intensity of	▪ Tobit	▪ The percentage of output exported is 3% larger for firms that introduced product or process innovation compared to the firms that did not

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
		▪ Panel dataset	exporting) of SMEs in transition countries		
Stojčić and Hashi (2014)	▪ European countries (Bulgaria, Romania, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Slovak Republic, Greece, Spain, Portugal, Norway); ▪ Sixth Community Innovation Survey conducted in the period 2004-2006	▪ Cross-section dataset	▪ To examine innovation-productivity link across 12 European countries	▪ CDM model: 1. Tobit model and Heckman procedure, for the first two stages of the CDM model: (1) firm's decision to innovate, and (2) firm's decision on the amount of innovation expenditure; 2. Bivariate probit model, for the third stage of the CDM model linking innovation expenditure and innovation output; and 3. OLS for the fourth stage of the CDM	▪ Propensity to innovate is: ▪ Positively influenced by: (i) firm size, (ii) being a part of a group of firms; (iii) being an exporter; (iv) having patent(s); (v) organisational innovation; (vi) marketing innovation; and (vii) factors hampering innovation (i.e. cost, knowledge, market factors); ▪ Negatively influenced by: (i) other factors hampering innovation; (ii) being part of trade or service industries; and (iii) being located in a new EU member state in Central and Eastern Europe; ▪ The amount of financial resources that a firm invests in innovation is: ▪ Positively influenced by: (i) firm size; (ii) being a part of a group of firms; (iii) having patent(s); (iv) organisational innovation; (v) marketing innovation; (vi) factors hampering innovation (i.e. cost and knowledge factors);

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
				model: the impact of innovation output on productivity	▪ Negatively influenced by: (i) belonging in trade and service industries; and being located in Central and Eastern European country; ▪ Product innovations are: ▪ Positively and significantly influenced by: (i) innovation input; (ii) patenting experience; (iii) previously abandoned and ongoing innovations; (iv) market factors hampering innovations; (v) belonging to service sector; and (vi) being located in CEEC country; ▪ Negative and significantly influenced by: (i) firm size; (ii) being part of a group; (iii) cost and knowledge factors hampering innovations; and (iv) belonging to a trade sector; ▪ Process innovations are: ▪ Positively and significantly influenced by: (i) innovation input; (ii) firm size; (iii) previously abandoned and ongoing innovations; (iv) other factors hampering

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
					innovations; and (v) belonging to a trade sector; ▪ Negatively and significantly influenced by: (i) being part of a group; (ii) being an exporter; (iii) having patent(s); (iv) market factors hampering innovations; (v) belonging to a service sector; and (vi) being located in CEEC country; ▪ Both product and process innovations combined are: ▪ Positively and significantly influenced by: (i) innovation input; (ii) firm size; (iii) previously abandoned and ongoing innovations; (iv) other factors hampering innovations; (v) belonging to a CEEC country; ▪ Negatively and significantly influenced by: (i) being a part of a group; (ii) being an exporter; (iii) having patent(s); (iv) cost and knowledge factors hampering innovations; and (v) belonging to a service sector; ▪ Productivity is:

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
					▪ Positively and significantly influenced by: (i) process innovations only; (ii) product and process innovations combined; (iii) being a part of a group; (iv) being an exporter; (v) having patent(s); (vi) organisational innovations; (vii) market and other factors hampering innovations; and (viii) belonging to trade sector; ▪ Negatively and significantly affected by: (i) product innovations; (ii) firm size; (iii) marketing innovations; (iv) cost and knowledge factors hampering innovations; (v) belonging to a service sector; and (vi) being located in CEEC country
Atkin et al. (2017)	▪ Egypt, covering the period 2011-2014; ▪ Focus on microfirms	▪ Panel dataset	▪ To investigate the impact of exporting on productivity and profits of firms	▪ Randomised control trial (intent-to treat; treatment-on-the treated specifications)	▪ Output and productivity unadjusted for product specifications decline as a result of opportunity to export; ▪ Quality and specifications-adjusted productivity increase as a consequence of opportunity to export

Author (year)	Country/Period	Type of dataset	The aim of the study	Econometric technique	Main results in the context of the links between innovation, exporting and productivity
Movahedi et al. (2017)	▪ France (Lower Normandy); ▪ Focus on manufacturing SMEs; ▪ Data referring to the period 2006-2008	▪ Cross-sectional dataset	▪ To investigate the "conscious self-selection" hypothesis (i.e. firm-level investments in order to increase productivity), with the emphasis on the importance of innovation	▪ CDM sequential model based on three-steps: 1. Logit model (impact of inputs of innovation on probability to innovate); 2. Linear regression model (impact of innovation on productivity); 3. Logit model (impact of productivity on the willingness to export)	▪ Firms invest in innovation in order to improve their productivity and as a consequence of improved productivity, engage into exporting activity
Cassiman and Golovko (2018)	▪ Spain, covering the period 1991-2009; ▪ Focus on SMEs	▪ Panel dataset	To investigate the dynamic relationship between firm's imports, exports, innovation and productivity	▪ Random effects linear probability model	▪ Importing induces product and process innovation, and exporting; ▪ Exporting, importing, process innovation and product innovation, but only when combined with importing, in the year before, increase productivity in the subsequent year

5.3 The determinants of R&D, innovation, propensity to export, intensity of exporting and productivity

The determinants of productivity, R&D and innovation, and the propensity to and intensity of exporting were individually reviewed in Chapters 2, 3 and 4. The literature points to the possibility of the same determinants driving, for example, both innovation and exporting – e.g. Becker and Egger (2013, p. 332) note that "the processes determining exporting and innovation – in particular, product and process innovations – are correlated". Table 5.2 provides a concise summary of the current knowledge concerning the determinants of R&D (as we have argued in Chapter 3, sometimes treated as an input to innovation and sometimes as a measure of innovation), innovation, productivity, and the propensity to export and intensity of exporting. The table reveals the extent to which the determinants are common. Only direct influences are shown in Table 5.2; however, it would be reasonable to assume that some of the determinants might have indirect influences on R&D, innovation, productivity, propensity of exporting and/or intensity of exporting. Furthermore, although an extensive survey of the literature has been carried out, due to the size of the literatures exploring productivity, innovation and exporting, as indicated in Chapter 3, there is a possibility that some determinants are not identified in Table 5.2.

As can be deduced from Table 5.2, some of the determinants are shared among four or more phenomena, such as: (i) size of a firm, which is related to productivity, R&D, propensity to export and intensity of exporting; and (ii) imports, which are related to productivity, innovation, propensity to export and intensity of exporting. There are also a number of determinants that influence more than one out of: (i) productivity; (ii) R&D and innovation; and (iii) propensity to export and intensity of exporting. Innovation, as a more general category, influences productivity, the propensity to export and intensity of exporting; while R&D intensity influences intensity of exporting. Productivity and innovation are both affected by: (i) the organisational structure of a firm and production units; and (ii) exporting. Finally, competition, and innovation policy affect productivity, R&D and innovation. The available literature so far provides evidence on some determinants (e.g. firms' ownership, attitudes, and decentralisation of decision making) that are linked to only one of our variables of interest.

Although productivity, propensity to export, intensity of exporting, R&D and innovation share some common determinants, this does not necessarily mean that the influence of those determinants is exactly the same. For example, the strength of the links may differ significantly, as well as their timing.

Table 5-2. The determinants of productivity, R&D, innovation, propensity to export and intensity of exporting

Legend:

Symbol	Description
+	Research predominantly suggests that the effect is positive
−	Research predominantly suggests that the effect is negative
X	Research predominantly suggests that the effect is not significant
?	Research predominantly suggests that the effect is not consistently either positive, negative or significant at all
blank cell	The link has not been investigated
() under the symbol	Number of reviewed studies that explored the particular variable

Firm-level determinants		Quantity-based productivity	Value-based productivity (including labour productivity and total factor productivity)	R&D	Innovation	Propensity to export	Intensity of exporting	Data availability in the ESEE dataset
Productivity	Labour productivity					+ (1)		✓
	Total factor productivity							✓
	Unit labour costs					? (2)	? (1)	
Innovation and innovation-related characteristics	Innovation inputs				+ (1)			✓
	Previous innovation experience		+ (1)		? (1)			
	Innovation outputs		? (2)			? (2)	x (1)	✓
	Previously abandoned and ongoing innovations				+ (1)			
	Organisational resources dedicated to innovation				+ (1)			

Firm-level determinants		Quantity-based productivity	Value-based productivity (including labour productivity and total factor productivity)	R&D	Innovation	Propensity to export	Intensity of exporting	Data availability in the ESEE dataset
	R&D (measured as dummy variable)			+ (1)		+ (1)		✓
	R&D intensity				? (1)		+ (1)	✓
	Factors hampering innovations – Cost factors		- (1)		? (1)			
	Factors hampering innovations – Knowledge factors		- (1)		? (1)			
	Factors hampering innovations – Market factors		+ (1)		? (1)			
	Factors hampering innovations – Other factors		+ (1)		? (1)			

Firm-level determinants		Quantity-based productivity	Value-based productivity (including labour productivity and total factor productivity)	R&D	Innovation	Propensity to export	Intensity of exporting	Data availability in the ESEE dataset
Firm characteristics and firm-level decisions	Size		? (2)		? (3)	? (4)	? (3)	✓
	Size squared				- (1)	- (2)	? (1)	✓
	Age (including experience)					x (1)	x (1)	✓
	Firm legal structure					x (1)	x (1)	
	Quality standards adopted by a firm					+ (1)	+ (1)	
	Capital stock		+ (1)	+ (1)				✓
	Capital intensity					? (2)	+ (1)	✓

Firm-level determinants		Quantity-based productivity	Value-based productivity (including labour productivity and total factor productivity)	R&D	Innovation	Propensity to export	Intensity of exporting	Data availability in the ESEE dataset
	Foreign ownership (including foreign capital)		+ (1)					✓
	Belonging to a business group		+ (1)		- (1)			✓
	Firm activity/Type of industry firm belongs to[133]		? (1)		? (2)	+ (1)		✓
	Location of a firm[134]		- (1)		? (1)			✓
	Growth of a firm (including past growth of a firm)				x (1)	? (1)	? (1)	✓

[133] Firm activity relates to: (i) belonging to trade, manufacturing or service sectors; or (ii) belonging to high-technology, medium-technology and low-technology industries.
[134] Location relates to the geographical location of a firm.

Firm-level determinants		Quantity-based productivity	Value-based productivity (including labour productivity and total factor productivity)	R&D	Innovation	Propensity to export	Intensity of exporting	Data availability in the ESEE dataset
	Expectations of a manager about future firm performance					x (1)	x (1)	
	Frequency of internal communication				? (1)			
	Degree of decentralisation of decision-making within a firm				+ (1)			
	Attitude within a firm about the importance of innovation for firm's success				+ (1)			
	Attitude towards risk-taking				+ (1)			

Firm-level determinants		Quantity-based productivity	Value-based productivity (including labour productivity and total factor productivity)	R&D	Innovation	Propensity to export	Intensity of exporting	Data availability in the ESEE dataset
	Attitude towards exchanging ideas within a firm				+ (1)			
	Firm's other characteristics						+ (1)	
Finance-related characteristics	Profitability				? (1)			✓
	Revenue share			+ (1)		+ (1)		
Trade	Exporting		+ (2)	+ (1)	? (1)	+[135] (1)		✓
	Importing (including importing of material inputs)		+ (1)			? (1)	? (1)	✓

[135] This means that exporting in the previous period is positively related to the propensity to export in the current period.

Firm-level determinants		Quantity-based productivity	Value-based productivity (including labour productivity and total factor productivity)	R&D	Innovation	Propensity to export	Intensity of exporting	Data availability in the ESEE dataset
Human-capital related characteristics, not related to management	Educational attainment of employees					? (1)	? (1)	✓
	Training undertaken by a firm					x (1)	x (1)	
	Human-capital intensity (i.e. average wage)					? (2)	+ (1)	
Management of a firm	Existence of professional management within a firm					x (1)	x (1)	
	Educational attainment of a manager					+ (1)	+ (1)	
	International experience of a manager					+ (1)	+ (1)	
	Age of a manager					x (1)	x (1)	

Firm-level determinants		Quantity-based productivity	Value-based productivity (including labour productivity and total factor productivity)	R&D	Innovation	Propensity to export	Intensity of exporting	Data availability in the ESEE dataset
	Age of a manager squared					x (1)	x (1)	
Sector- and industry-level variables	Intra-industry trade					? (1)		
	Number of innovations used in the sector					x (1)	? (1)	
	Number of innovations produced in the sector					+ (1)	? (1)	
	Sectoral-level R&D expenditures					? (2)	- (1)	
	Sectoral-level capital intensity					? (1)		
	Sectoral-level average wage					x (1)		
	Industry-level exports				? (1)			

Firm-level determinants		Quantity-based productivity	Value-based productivity (including labour productivity and total factor productivity)	R&D	Innovation	Propensity to export	Intensity of exporting	Data availability in the ESEE dataset
	Industry-level imports				+ (1)			
	Industry concentration				? (1)			
	Agglomeration					? (1)	? (1)	
Environment-related characteristics	Corruption					x (1)	x (1)	

5.4 Theoretical positioning of the empirical chapters

Hirsch and Bijaoui (1985, p. 238) note "the analysis of real economic and other social phenomena shows them to be consistent at times with different, and even conflicting theories". In this light, as already discussed in Chapter 3, the analysis of innovation even within economics can be undertaken within two streams of economics: (i) orthodox, mainstream economics; or (ii) heterodox, evolutionary economics. Both streams of economic sciences are heavily influenced by other fields: physics, in the case of the former; and evolutionary biology (Dosi and Nelson, 1994), in the case of the latter. The theoretical sides of these two streams have a number of points of departure. For example, one of the important points of departure, according to Dosi and Nelson (1994), is about how actors, ranging from individuals to firms, make their decisions. On the one hand, mainstream economics relies on the presumption of rationality of different actors. Evolutionary economics, on the other hand, is concerned with how a plurality of factors, as well as interactions between those factors, lead to particular decisions. Furthermore, it is worth noting that, at least in some respects, the two streams have come closer together. For example, some of the features claimed to be characteristic of evolutionary economics – e.g. the existence of feedback loops – have been recognised both in theoretical models[136] (e.g. Aw et al., 2008) and in empirical studies within the mainstream tradition. In terms of model specifications in empirical investigations, the differences between the two streams can be negligible.[137]

Having these differences in mind, it is worth reiterating the purpose of this thesis. The wider aim of the thesis is to contribute to evidence-based policy making. Establishing robust relationships, if those exist, is of particular value in the context of policy making. This thesis explores the productivity-innovation-exporting nexus with the aim of establishing the direction and timing of the links between the three phenomena.

[136] One of the criticisms of theoretical models in the neoclassical tradition is the lack of reality in relation to certain assumptions (i.e. the assumption of representative agents, etc.). While it is true that some theoretical models tend to more realistic than the others, it has to be recognised that all theoretical models need to involve a certain level of abstraction. In relation to this, Attanasio et al. (2017) write: "Critics complain that economists' models are not realistic and make absurd assumptions. The London Tube map is not realistic and makes absurd assumptions. If it did not it would be illegible. And useless. The map is useful precisely because it abstracts from unnecessary details to show you the way. This is what economic models are for, they help us to find our way through complex data in a complex world."

[137] Within the mainstream economics tradition, it is common that theoretical models, after being developed, are subjected to rigorous econometric testing. However, it is worth noting that there is a point of departure regarding how phenomena should be investigated within the evolutionary economics tradition. While some scholars within this tradition rely on econometric investigations, others are rather sceptical about the use of econometrics altogether and largely rely on narrative evidence (e.g. case studies).

Furthermore, this thesis contributes to the exploration of the influence that innovation policy (i.e. R&D tax credits) has on R&D expenditures, innovation, productivity and exporting. In this light, there are a few things worth noting. First, mainstream economics has proven to be particularly useful and influential in terms of policy making. An ability to determine law-like relations, make useful generalisations,[138] as well as the preciseness and consistency of its definitions have been its particular strengths. Second, the previous literature has already systematically shown that some law-like relations between the phenomena examined in this thesis exist, e.g. more productive firms become exporters. Third, tax credits – the policy instrument that will be the particular focus of the investigation in Chapter 8 – has emerged from the orthodox tradition. Fourth, while underlying influences – internal and external determinants – of productivity, innovation and exporting are heavily investigated in this thesis theoretically, they are not the focus of the thesis per se. The main aim of these extensive accounts in this and previous chapters is to inform and enrich the empirical investigations in the following three chapters. The literature review in Chapter 3 was informed by both streams of economics, taking into account the extent of the influence and the significance of contributions of evolutionary economics in the area of innovation research. The topics in Chapters 2 and 4 were mainly[139] explored through the lens of the dominant economic paradigm, as the influences of other streams of economics on these two topics are less substantial. Hence, the empirical investigations will be informed by both streams of economics, especially in the context of innovation. However, overall, the aims of the investigations in the following three chapters are better aligned with the approach and tools of mainstream economics.

5.5 Data requirements for the investigation of the productivity-innovation-exporting nexus

Two general conclusions can be reached regarding data requirements from the discussions in Chapters 2 to 4 as well as from Section 5.2 of this chapter. The first conclusion relates to the appropriateness of using either cross-sectional or pooled cross-sectional data in the investigations of the links between productivity, innovation and exporting, and ultimately even innovation policy evaluations. Baltagi (2008) points to several benefits of using panel data compared to either cross-sectional or time-series data that are relevant in the context of this thesis. According to Baltagi (2008), panel data:

1. can control for the heterogeneity of individuals, firms or countries;

[138] This is not to say that it is impossible to make generalisations in the context of evolutionary economics.
[139] The concept of productivity in Chapter 2 is also discussed from the perspective of management theory.

2. provide "*more informative data, more variability, less collinearity among the variables, more degrees of freedom and more efficiency*" (p. 7);
3. facilitate examination of the "dynamics of adjustment" — this type of data enables tracking individuals over a period of time and examining the changes that happen;
4. examine phenomena that cannot be detected using any other type of data; and
5. "allow us to *construct and test more complicated behavioural models than purely cross-section or time-series data*".

Related to point 5 and very relevant in the context of this thesis, Baltagi (2008, p. 8) notes that "technical efficiency is better studied and modelled with panels". Additionally, Gujarati (2011, p. 280) notes that "…technological change can be better studied by panel data than by pure cross-sectional or pure time series data". The rationale for the conjectures made by Baltagi and Gujarati indicated in the previous sentences can be found in points one and three of the list above.

The second argument relates to the measurement of different phenomena. Empirical researchers often use observational data readily available to them in some form (i.e. commercial datasets, datasets available from different governmental or international agencies, etc.). Measurement of different phenomena in empirical research, as established in the previous chapters and Chapter 2 in particular, often do not correspond to the ideal theoretical constructs, but are rather constrained by the availability of data. While measuring exporting is generally less controversial, the same cannot be said about productivity and innovation. Chapter 2 conveys that to measure productivity, researchers would ideally not only need data on quantities of outputs and inputs used in production, but also data on the quality of products and product specifications. In Chapter 3, we have seen that, although a variety of measures of innovation are employed in the empirical studies, they are far from ideal – e.g. measures based on the data on R&D miss out innovation that does not occur through R&D, measures that purely count innovations undertaken by firms tell us nothing about the radicalness or quality of those innovations, and measures such as patents exclude large number of firms that do not patent, etc. The most encompassing measure of innovation would account not only for the number of innovations, but also for their quality and degree of their radicalness. The study by Atkin et al. (2017; 2019) puts forward the interesting possibility of using experimental, instead of observational, data for investigating the links between exporting, innovation and productivity. By using randomised controlled trials (RCTs), researchers have greater freedom in designing their studies and gathering data, and can get closer to the ideal data requirements. This is not to say that satisfactory data cannot be obtained using observational data, or that experimental data comes without limitations. For example, Deaton and Cartwright (2018) discuss in detail how RCTs might not always be the most appropriate methodology for exploring certain phenomena(s) and why the results of RCTs should be taken with caution. It should be noted that gathering and using experimental data has a number of challenges. For example, gathering experimental data at the firm-level is extremely difficult and may not be feasible in the context of developed countries or most industries. Additionally, due to financial and time constraints, as well as potential ethical implications, conducting an RCT is not feasible for many empirical researchers. Bearing in mind this discussion, using experimental data in this research programme is not feasible. Hence, the empirical chapters that follow will utilise observational data. However, as was already briefly discussed in Section 5.3 (and presented in Table 5.2) and as will be discussed in detail in the following chapter, the observational data that will be used in the empirical investigations in this thesis is extremely rich and allows the utilising of various concepts discussed in this and previous chapters (e.g. different measures of innovation and productivity), as well as (to a great extent) bridging the gap between theoretical constructs and their empirical applications.

5.6 Conclusion

This chapter explores the small body of literature that investigates the links between two out of three, or all three, phenomena of interest: innovation; exporting; and productivity. Some of the links have been subject to many empirical investigations, while the only unexplored link is the one leading from productivity to innovation. Although these studies offer novel and useful insights (e.g. the importance of quality, importing, etc.) about the links between innovation, exporting and productivity, the research suffers from a “chicken-and-egg” problem. The research suggests and confirms that various links exist, but it is not possible to make precise generalisations about the orderings of these phenomena. Moreover, empirical research has suggested that particular context(s) might have a substantial influence on some of the links (e.g. the learning-by-exporting hypothesis and the developed vs. developing countries context) and that timing can be of the utmost importance (e.g. the timing of the R&D-exporting link in Hirsch and Bijaoui, 1985).

The three phenomena – innovation, exporting and productivity – share some common determinants, such as size or importing. Considering that all three are firm-level phenomena, the commonality of the determinants was expected. The discussion in this chapter, as well as the summary of the determinants of innovation, exporting and productivity will serve to inform and shape the empirical investigation of the links between innovation, exporting and productivity in the next chapter.

6. Empirical investigation of the productivity-innovation-exporting nexus

6.1 Introduction

Chapters 2 to 5 explore the focal topics of this thesis (i.e. productivity, innovation and exporting) individually, as well as the nexus between these three firm-level phenomena. Additionally, these chapters explore the extent to which these phenomena co-determine each other, as well as both their internal and external determinants. This chapter is the first empirical chapter, which will, building on the previous four theoretical chapters, address one of the focal research questions of this thesis: the direction, timing and the strength of the links between productivity, innovation and exporting. The findings from this chapter will inform Chapters 7 and 8, the two other empirical chapters, as well as the chapter offering policy recommendations, shaping the strategy for addressing the other research questions.

Chapter 6 builds on several important conclusions from the previous chapters. First, the previous chapters – Chapter 5 in particular – strongly convey that links between productivity, innovation and exporting exist. A large number of empirical studies show the existence of the links leading from: (i) innovation to exporting; and (ii) productivity to exporting (i.e. the so-called self-selection hypothesis). A smaller number of empirical studies suggest the existence of the other links as well (i.e. links leading from: innovation to productivity; exporting to innovation; and exporting to productivity), while only the link from productivity to innovation is not supported by the empirical literature. Second, we have learned that some of the links might be context specific. For example, the evidence suggests that the link from exporting to productivity is more pronounced in a developing country context. Third, the measures used for different phenomena, as well as the methods used to obtain those measures, matter (e.g., see the discussion in Chapter 2 on productivity measurement). Decisions regarding these choices matter not only in the context of exploring the productivity-innovation-exporting nexus, but also for determining policies that promote each of the three phenomena. This is of particular importance in the context of innovation and productivity. Fourth, productivity, innovation and exporting share a small number of common determinants but have a greater number of unique determinants. As already emphasised, productivity, innovation and exporting, at least to a certain extent, co-determine each other. According to the literature, factors such as the firm size, or whether a firm is engaged in importing have influence on all three phenomena. The influence can be direct or moderating. This notion will be explored further in the empirical analysis.

Although the productivity-innovation-exporting nexus has been explored in the literature, this literature has a number of shortcomings. As emphasised previously, its theoretical foundations are relatively weak and underdeveloped compared to most other areas of economics. Rather than being guided by theory, empirical research seems to have been largely guided by the research questions different authors explored, as well as the prior empirical literature.[140, 141] Hence, it seems that some links were left relatively unexplored, precluded by the absence of relevant theory. Previous empirical studies focused on particular links, typically without taking into account the wider context of the links between phenomena.

This chapter aims to empirically explore the nexus by a using a novel approach in these types of empirical investigations. We start by utilising a vector error correction model, which estimates short-run contemporaneous relationships conditional on a long-run equilibrium relationships. This approach yields interesting results but is not fully informative about potential relationships about our variables of interest. To address all the potential interactions between our variables of interest – innovation, productivity and exporting – we then progress to estimate panel vector autoregression (VAR) models. The choice of this approach is based on the findings from the previous chapters, reflecting the state of both theory and the empirical literature, leaving as open as possible the number and direction of the causal relationships among the variables under consideration. Section 6.2 describes the dataset and provides descriptive statistics. Section 6.3 discusses the theoretical foundations of the econometric techniques employed in this chapter. Section 6.4 discusses the results and Section 6.5 concludes.

6.2 Dataset description and summary statistics

6.2.1 Description of the dataset

The Survey on Business Strategies, *Encuesta sobre Estrategias Empresariales (ESEE)*, will be used for the purposes of empirical investigation in this and the following two

[140] There is nothing wrong with empirical research being (substantially) richer than its theoretical foundations and by empirical research being guided by particular research questions per se.
[141] Empirical explorations can lead to the development of theories. For example, one of the most widely known relationships in economics – the relationship between inflation and unemployment, which came to be known as the Phillips curve – emerged from empirical explorations.

chapters. The Survey emerged as a result of an agreement between the Ministry of Industry of the Kingdom of Spain and the SEPI Foundation, and is a product of the SEPI Foundation. The ESEE is conducted among manufacturing firms with 10 or more employees across Spain on a yearly basis. Firms that exit the sample are replaced by new firms, while the same sampling procedure is preserved throughout the whole period the survey is available (1990 – 2016) (Radičić and Pinto, 2019). All firms with 200 or more employees are surveyed, while multistage random sampling is applied to the firms that have between 10 and 200 employees (Foundation SEPI, n.d.; Radičić and Pinto, 2019). The Survey encompasses questions related to the strategic decisions of firms (e.g., prices or R&D expenditures) and their environment. While some of the questions in the survey involve reporting data based on self-assessment, others require firms to report accounting data based on their profit and loss statements and balance sheets. As indicated in Table 5.2 in the previous chapter, the ESEE is suitable for the empirical investigations in this thesis as it contains a number of variables of interest (e.g., determinants of innovation, exporting and productivity). The particular appeal of the ESEE for this chapter is that it contains numerous measures of innovation, ranging from R&D expenditures to the number of product innovations and patents registered both in Spain and elsewhere. Furthermore, the dataset allows for construction of both labour productivity and total factor productivity measures. Unlike some of the previous applications of this dataset in the investigations of the productivity-innovation-exporting nexus (Cassiman et al., 2010; Cassiman and Golovko, 2018), which focused only on a subset of firms, this empirical investigation will look at firms of all sizes. Furthermore, firms will be divided into subsamples based on a number of relevant characteristics, as will be discussed in more detail in the section below. Additionally, the advantage of the specific timeframe for which the dataset (2001-2016)[142] is available in this thesis is that it covers an almost equal number of years prior to and after the latest global financial crisis, which allows us to take into account any impact that the crisis may have had on the productivity-innovation-exporting nexus.

[142] As mentioned earlier, the ESEE is collected for the period 1990-2016, while the dataset used in this thesis is from 2001 onwards. It has to be emphasised that not all the variables in the dataset are available from 2001 onwards (e.g. variables on marketing and organisational innovations are available only from 2007 onwards). The available length of the dataset – 16 years – is deemed to be sufficient for this empirical investigation and is longer than the datasets used in most of the comparable empirical investigations. The decision on the final length of the dataset was made taking into account the above considerations, as well as the cost of extending the dataset back to 1991.

The dataset was examined thoroughly prior to its use in the following empirical investigations. Only minimal data cleaning was necessary, apart from exclusion of observations with negative values of value added, resulting in 175 observations being deleted. The final dataset is an unbalanced panel with 93,265 observations from 5,840 firms over the period 2001-2016.

No weighting variable is available in the dataset, which precludes us from applying weights in the empirical analysis. However, Gashi et al. (2010, p. 430) cite Wooldridge (2002), Purdon and Pickering (2001), and Cameron and Trivedi (2005) to the effect that if “if the model is correctly specified there should not be a difference between weighted and unweighted regression coefficients”.

6.2.2 Choice of deflators

The choice of deflators was given careful consideration. Besides availability, the final decision on the preferred choice of deflator was made having in mind the key variables being explored in this research. The options available for deflators can be broadly grouped in the following three categories: (i) the Consumer Price Index (CPI); (ii) industry-specific price indices; and (iii) firm-specific price indices constructed using available ESEE data. The discussion in Chapter 2 suggests that firm-specific price indices are superior to the other two choices. However, due to the large number of missing observations in the ESEE, this option was explored but is not preferred. CPI and industry-specific price indices were both considered further and were used to estimate the preferred model specification. Data on deflators was taken from the OECD.[143] The availability of industry-specific price indices was also limited – e.g., industry specific indices were available for value added, while only more general producer price indices were available for capital variables. No differences in the results emerged and correlations between variables deflated by CPI and industry-specific price indices were high. For example, the correlation between value added deflated by industry-specific price indices and CPI is 0.9868. The CPI was chosen as the preferred deflator. The main reason, besides availability, for this choice is that CPI removes only economy-wide inflation, while industry specific indices can remove changes in prices that occurred due to factors other

[143] Value added was deflated either by industry-specific price indices or the CPI. General producer price indices or CPI were used to deflate the value of exports and R&D expenditure variables. General capital deflators were used to deflate intangible fixed assets, tangible fixed assets and purchases of tangible fixed assets.

than economy-wide inflation (e.g., changes in prices caused by product innovation) (Padley and Pugh, 2000).

6.2.3 Total factor productivity estimations

Total factor productivity can be estimated using a variety of methods, as discussed in Chapter 2. Total factor productivity in this chapter was estimated using the Olley and Pakes (OP) (1996), Levinsohn and Petrin (LP) (2003), and Wooldridge (2009) methods and was implemented using the *prodest* command in Stata.[144] Some reasons that underlie the decision to use a value added specification when estimating TFP could also extend to the choice of OP TFP estimation method as a preferred method. Hall et al. (2009) note several reasons why value added specifications are preferred with firm-level data: (i) the degree of vertical integration will significantly influence the materials-output ratio of firms; (ii) adjustment costs of stocking of materials would need to be taken into account when modeling demand for inputs; and (iii) a high quality of the data on materials might not be accessible. These reasons, especially (ii) and (iii) apply for the choice of OP over LP's specification. OP uses investment as a productivity proxy, whereas LP use intermediate inputs instead. Gandhi et al. (2017, p. 8) discuss some concerns about the use of value-added specifications. They note: "Regardless of the motivation for value added, the objects from a value-added specification, particularly productivity, will be fundamentally different than those from gross output." Additionally, they find that the pattern of productivity heterogeneity is different compared to whether the production function is specified as a gross output production function or value-added specification (Gandhi et al., 2017).

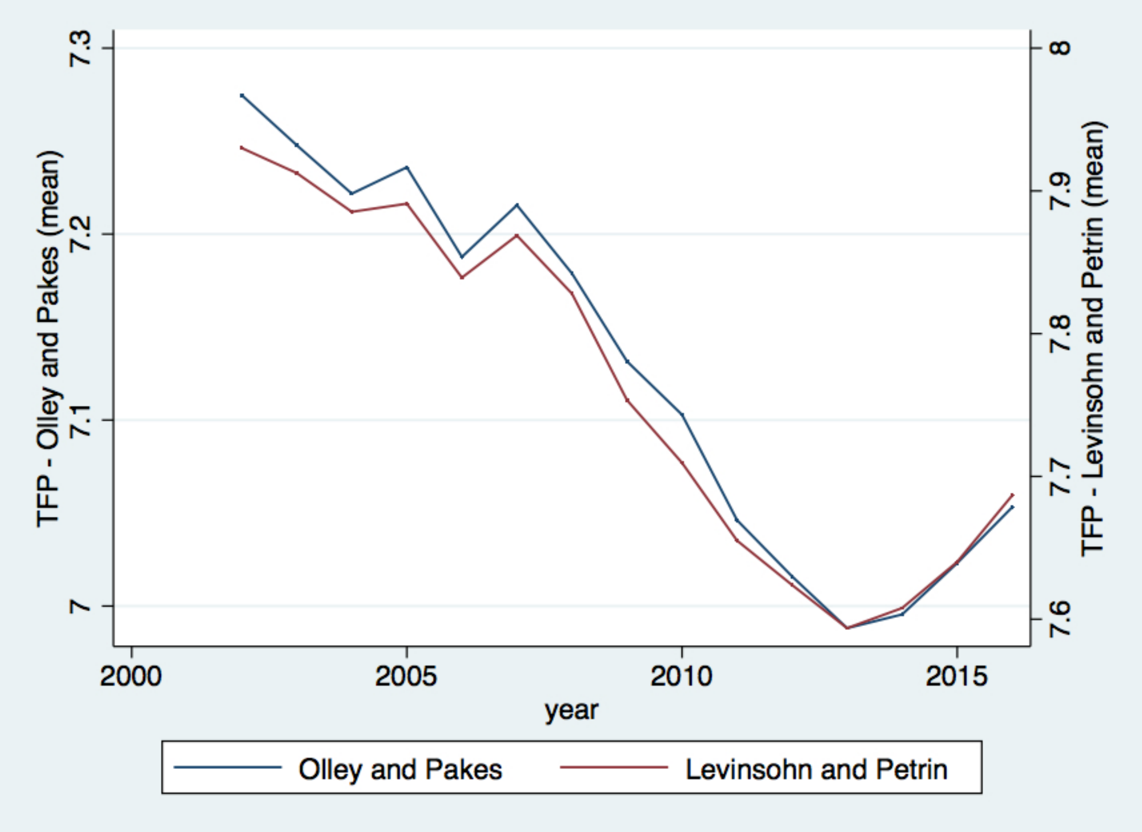
As we can see in Figure 6.1, the estimates using both methods are fairly similar and are following the same trajectory. Wooldridge's estimation procedure (not detailed here) produces similar results when the simple TFP specification is used; however, with the richer specification that is preferred, the results are different compared to the other two methods and fail on the grounds of diagnostic tests.

The final specification for estimating TFP in this chapter is richer compared to the specifications commonly used in the literature (TFP estimates are presented in Appendix 12). The decisions on the inclusion of components detailed in further text are based on

[144] The *prodest* command was chosen as it allows implementation of different TFP estimation methods.

the discussions in Chapters 2-5. The specification uses value added as a measure of output; the number of hours worked as a labour input variable (free variable); purchases of tangible fixed assets as an investment variable – productivity proxy; tangible fixed assets (land and buildings excluded), intangible fixed assets and age of a firm as state variables; and, finally, capacity utilization and the proportion of engineers and graduates as control variables.

Figure 6-1. Comparison of mean TFP using the OP and the LP methods



6.2.4 Description of the variables and summary statistics

The contemporaneous correlation coefficients between different variables measuring innovation, exporting and productivity are presented in Table 5.1a. It is interesting to note that the correlations between different innovation variables are mostly low, apart from the correlations between patents registered in Spain and patents registered abroad.[145] However, one has to take into account that the variables presented below correspond to different stages of the innovation process. R&D expenditures are a measure of innovation input. Patents can be regarded as an intermediate measure of innovation, where firms have been successful in developing a new technology; however, the innovation was not necessarily introduced in the market or put into use. The number of product innovations measures innovation outputs. The fact that different measures represent different stages of the innovation process might be an explanation for the low correlation between these different variables. Furthermore, it is noteworthy that the correlation between real R&D expenditures and the number of patents registered outside of Spain is larger than the correlation between R&D expenditures and number of patents registered in Spain. Patents

[145] Statistical significance of correlation coefficients was tested using the *pwcorr* command in Stata. All correlation coefficients are statistically significant at 5% level.

registered outside of Spain might be patents of higher quality, as discussed in Chapter 3, and linked with more radical innovations, which could explain the larger correlation with R&D expenditures.

Given the possibility that the phenomena are not linked contemporaneously, Table 6.1b explores correlations between twice lagged real R&D expenditures, once lagged patents registered in Spain and abroad, and the current number of product innovations, real value of exports and total factor productivity. In the context of the empirical investigation that will follow in this chapter, it is important to note from Table 6.1b that when lags are introduced, correlations increase, albeit only slightly, between a number of variables – e.g. correlations increase between R&D expenditures, number of patents registered abroad, value of exports and TFP.

Table 6-1a. Contemporaneous correlations between number of product innovations, real R&D expenditures, patents registered in Spain, patents registered abroad and value of exports (all of the variables divided by number of hours worked in thousands and deflated by CPI if deflation was required) and total factor productivity

(Number of observations = 24,481)

	R&D expenditures	Patents registered in Spain	Patents registered outside of Spain	Number of product innovations	TFP	Value of exports
R&D expenditures	1.0000					
Patents registered in Spain	0.1642	1.0000				
Patents registered outside of Spain	0.2530	0.4952	1.0000			
Number of product innovations	0.1815	0.1557	0.1064	1.0000		
TFP	0.0941	0.0254	0.0272	0.0892	1.0000	
Value of exports	0.1478	0.0134	0.0521	0.0413	0.0675	1.0000

Table 6-1b. ***Lagged correlations between real R&D expenditures (lagged twice), patents registered in Spain (lagged once), patents registered abroad (lagged once), number of product innovations and value of exports (all of the variables divided by number of hours worked in thousands and deflated by CPI if deflation was required) and total factor productivity***

(Number of observations = 19,679)

	R&D expenditures	Patents registered in Spain	Patents registered outside of Spain	Number of product innovations	TFP	Value of exports
R&D expenditures	1.0000					
Patents registered in Spain	0.1511	1.0000				
Patents registered outside of Spain	0.2635	0.4873	1.0000			
Number of product innovations	0.1504	0.1227	0.0898	1.0000		
TFP	0.1038	0.0263	0.0282	0.0893	1.0000	
Value of exports	0.1503	0.0141	0.0528	0.0379	0.0731	1.0000

Summary statistics, as well as definitions of the variables used in this chapter are presented in Table 6.2. Key variables such as measures of innovation – R&D expenditures, patents and number of product innovations – and measure of exporting – value of exports – have been divided by the total effective hours worked in thousands of hours to account for differences in firm size for the purposes of this empirical investigation. All variable transformations are detailed in Table 6.2. Additionally, Table 6.2 indicates which variables are used for the purposes of estimations.

Table 6-2. Summary statistics and definition of the variables[146]

Variable	Variable description	Variable code	No. of Obs.	Mean	SD	Min	Max
Value added	Sum of sales, variation in stocks and other management income, minus the purchases and external services Measured in Euros, deflated by CPI	VA2015prices	28,338	1.72e+07	6.54e+07	154.079	3.71e+09
Logarithm of value added[x]	Logarithm of value added measured in Euros and deflated by CPI	lnVA	28,338	14.868	1.838	5.037	22.033
R&D expenditures	Total R&D expenditures in one year Measured in Euros, deflated by CPI	GTID2015prices	28,241	1,150,528	1.26e+07	0	5.16e+08
R&D expenditures divided by hours worked	R&D expenditures measured in Euros and deflated by CPI divided by total effective hours worked in thousands hours	GTID_NWH	28,199	875.158	2,831.534	0	70,084.38
R&D expenditures in differences[+]	Differenced R&D expenditures divided by hours worked	GTID_diff	23,860	-6.828	1,620.475	-63,925.01	64,131.86
R&D expenditures in differences divided by 100[+]	R&D expenditures in differences divided by 100	GTID_diffR	23,860	-.068	16.205	-639.250	641.319
Number of product innovations	Number of product innovations	NIP	28,051	1.445	11.404	0	900
Number of product innovations divided by hours worked	Number of product innovations divided by total effective hours worked in thousands of hours	NIP_NWH	28,034	0.013	.134	0	6.667

[146] * next to the name of the variable in *Variable* column indicates that the variable was used to divide the sample;
x next to the name of the variable in *Variable* column indicates that the variable was used to estimate TFP;
+ next to the name of the variable in *Variable* column indicates that the variable was used for panel VAR estimations.

Number of product innovations - categorical⁺	Categorical variable indicating the number of product innovations divided by hours worked	NIP_C	28,034	.456	1.077	0	4
Number of patents registered in Spain	Number of patents filed in Spain in a year	PATESP	28,328	.166	2.448	0	288
Number of patents registered in Spain divided by hours worked	Number of patents registered in Spain divided by total effective hours worked in thousands hours	PATESP_NWH	28,319	.001	.013	0	.804
Number of patents registered in Spain – categorical⁺	Categorical variable indicating the number of patents divided registered in Spain divided by hours worked	PATESP_C	28,319	.119	.585	0	4
Number of patents registered abroad	Number of patents filed outside of Spain in a year	PATEXT	28,341	.266	4.895	0	308
Number of patents registered abroad divided by hours worked	Number of patents registered abroad divided by total effective hours worked in thousands of hours	PATEXT_NWH	28,336	0.000	0.006	0	.316
Number of patents registered abroad – categorical⁺	Categorical variable indicating number of patents registered abroad divided by hours worked	PATEXT_C	28,336	.082	.489	0	4
Process innovations⁺	Dummy variable indicating whether a firm had undertaken process innovation in a year	IPR_dum	28,355	.323	.468	0	1
Organisational innovations⁺	Dummy variable indicating whether a firm had undertaken organisational innovation in a year (organisation of workforce, external relationship management)	IMO_dum	18,252	.218	.413	0	1
Marketing innovations⁺	Dummy variable indicating whether a firm had undertaken marketing innovation in a year (product design, packaging, product placement, promotion, price)	ICO_dum	18,252	.192	.394	0	1

Labour productivity+	Value added deflated by CPI divided by number of hours worked	LP2015prices	28,247	31 944.37	34 089.5	2.691	2 239 598
Total factor productivity	Estimated using the Olley and Pakes procedure	TFP_18	24,822	7.133	.943	-1.928	10.399
Total factor productivity+	Differenced total factor productivity	TFP_18diff	21,241	-.035	.541	-8.894	9.303
Value of exports	Value of exports Measured in Euros, deflated by CPI	VEXPOR2015prices	28,321	3.25e+07	2.44e+08	0	8.52e+09
Value of exports divided by hours worked	Value of exports measured in Euros and deflated by CPI divided by total effective hours worked in thousands of hours	VEXPOR_NWH	28,240	34,083.08	85,798.49	0	3,412,149
Value of exports in differences+	Differenced value of exports divided by hours worked	VEXPOR_diff	23,917	1,156.564	39,898.32	-1,413,511	2,154,190
Value of exports in differences divided by 1000+	Differenced value of exports divided by hours worked divided by 1,000	VEXPOR_diffR	23,917	1.157	39.898	-1.413,511	2.154,19
Indicator variable for high R&D performers*	Dummy variable indicating whether firms spent more than average for all firms on R&D expenditures in any given year	HighRD_F	93,265	.087	.281	0	1
Indicator for high exporters*	Dummy variable indicating whether exports as a percentage of total sales were above average for all firms in any given year	HighPX_F	93,265	.304	.460	0	1
Tangible fixed assets	Tangible fixed assets with land and buildings excluded [147] Measured in Euros, deflated by general capital deflator	RIMVA2015prices	28,295	3.81e+07	1.76e+08	11.742	3.91e+09
Logarithm of tangible fixed assets^{x}	Logarithm of tangible fixed assets measured in Euros and deflated by general capital deflator	lnRIMVA	28,295	15.159	2.189	2.463	22.086
Purchases tangible fixed assets	Purchases of tangible fixed assets made in a year Measured in Euros, deflated by general capital deflator	CIM2015prices	28,354	2 571 371	1.76e+07	0	8.86e+08

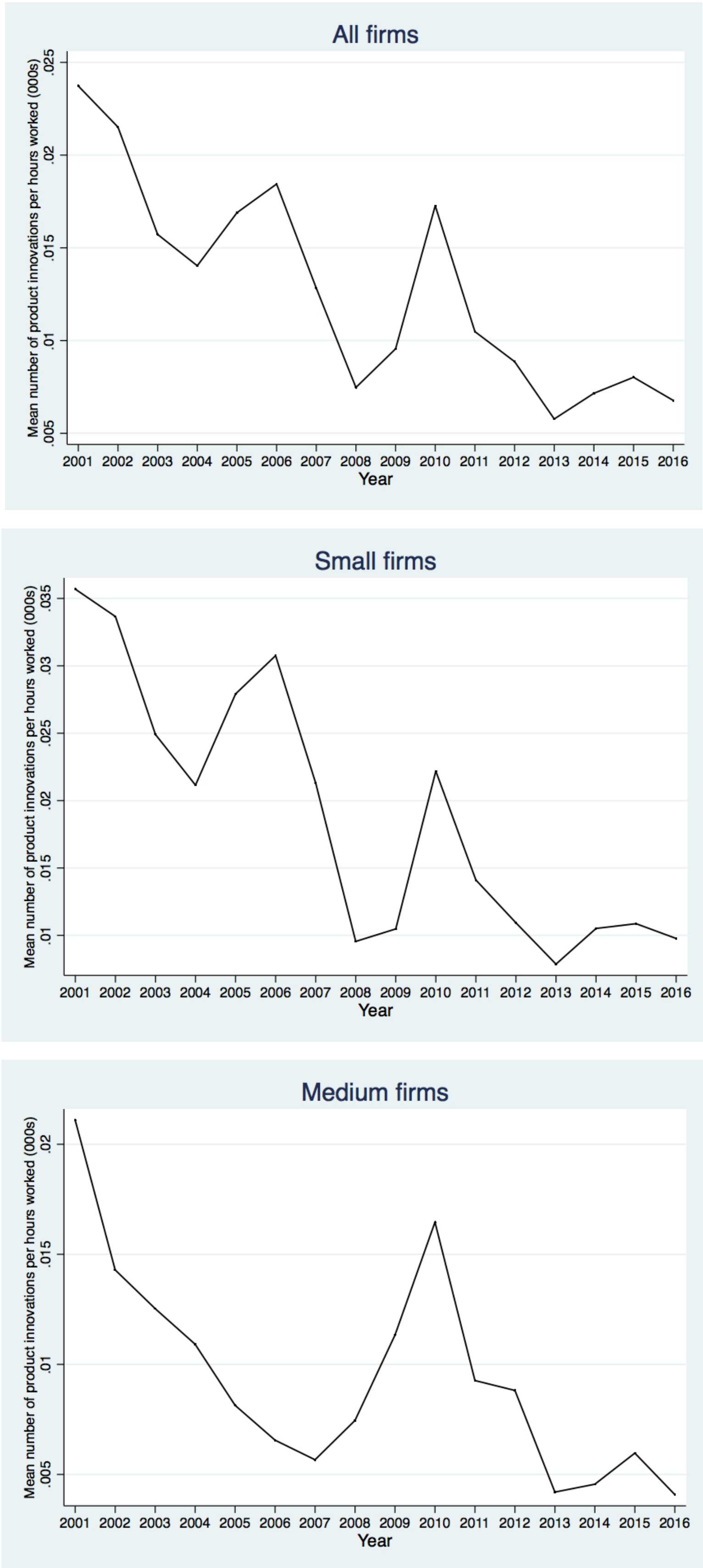
[147] Due to the large number of zero values for different firms for land and buildings, these were not included in the measure.

Logarithm of purchases tangible fixed assets[x]	Logarithm of purchases of tangible fixed assets measured in Euros and deflated by general capital deflator	lnCIM	28,354	9.669	5.612	0	20.602
Intangible fixed assets	Intangible fixed assets Measured in Euros, deflated by general capital deflator	INM2015prices	28,350	2.18e+07	3.40e+08	0	2.47e+10
Logarithm intangible fixed assets[x]	Logarithm of intangible fixed assets measured in Euros and deflated by general capital deflator	lnIMN	28,350	11.009	5.264	-.019	23.931
Age of a firm[x]	Age is defined as = (year – year firm was founded) + 1	Age	45,558	30.043	19.719	-1	182
Capacity utilization[x]	Average of utilization of firm's standard production capacity Measured in percentages	UC	28,214	78.186	17.246	3	100
Highly educated workforce[x]	Proportion of engineers and graduates in firm's total workforce	PIL	28,045	6.315	8.567	0	100
Firm's main activity[x]	Firm's main activity divided into 20 categories	NACECLIO	28,355	10.039	5.426	1	20
Number of hours worked	Total effective hours worked Measured in thousands of hours	HETN	28,264	375.1	1,180.809	2	24 877
Logarithm number of hours worked[x]	Logarithm of number of hours worked	lnHETN	28,264	4.720	1.439	.693	10.122
Cooperation for innovation with universities*	Dummy variable indicating whether a firm collaborated with universities or technological centres	COOP_Unis	93,265	.069	.253	0	1
Cooperation for innovation with other firms*	Dummy variable indicating whether a firm collaborated with customers, competitors or suppliers	COOP_Firms	93,265	.072	.259	0	1
Dynamism of the market*	Categorical variable indicating whether the market expanded, contracted or stayed the same	DMER1N	28,355	2.108	.697	1	3

Next, we will look at the charts of the means of the variables of interest across all firms and their developments during the period 2001-2016, as well as the means of the variables divided by the number of hours worked in thousands for the same period for small, medium-sized and large firms.[148,149] Firm size is, as was seen in the previous chapters, important in the context of the discussion of the three phenomena of interest and their links. Besides interest in the trends of these variables, there are two additional reasons for presenting these charts, both of which are related to the later empirical investigation. The first reason is to conduct a visual inspection of the variables for their stationarity.[150] The Global Financial Crisis (GFC) significantly impacted economies and firms. Theoretically, the behaviour of R&D and innovation can be both procyclical and countercyclical (Roper and Turner, 2020). Accordingly, the second reason is the visual inspection of the charts for the potential impact of the GFC on the variables of interest. This is to check whether there is a potential structural break in the data. Figure 6.2 shows the mean number of product innovations per hours worked in thousands for all firms across years and the mean number of product innovations per hours worked in thousands for small, medium-size and large firms separately. The charts suggest that there was a drastic reduction in the number of product innovations over time. Furthermore, this downward trend started before the GFC. A similar downward trend is observed in the charts showing the number of product innovations per number of hours worked in thousands for firms of different sizes. Particularly noticeable are huge declines in the number of product innovations per number of hours worked for small firms (in 2008) and for medium-sized firms (in 2007). The charts suggest that this variable is not stationary.

[148] Productivity variables, as they already take into account firm size, were not additionally divided by the number of hours worked.
[149] Small firms are firms with less than 50 employees, medium-sized firms between 50 and less than 250 employees, and large firms 250 or more employees.
[150] Formal tests of stationarity of time series – unit root tests – were done prior to the empirical analysis and will be discussed later.

Figure 6-2. Mean number of product innovations divided by number of hours worked in thousands for all firms; small firms; medium firms; and large firms (2001-2016)



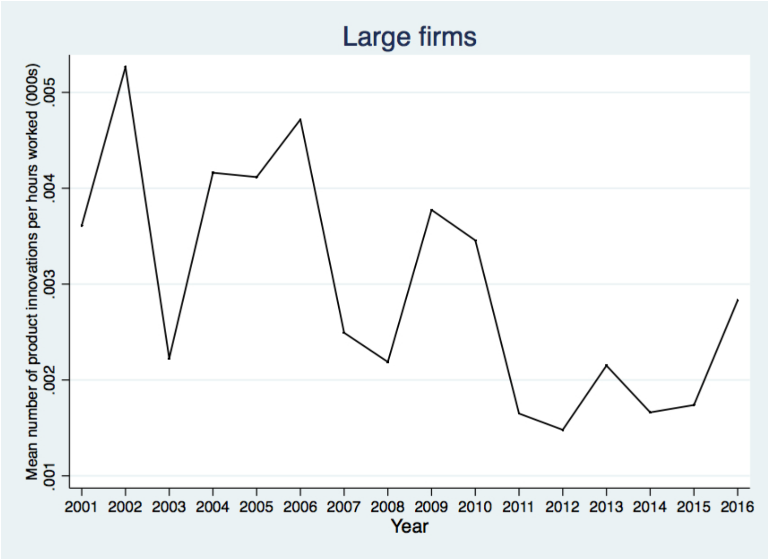


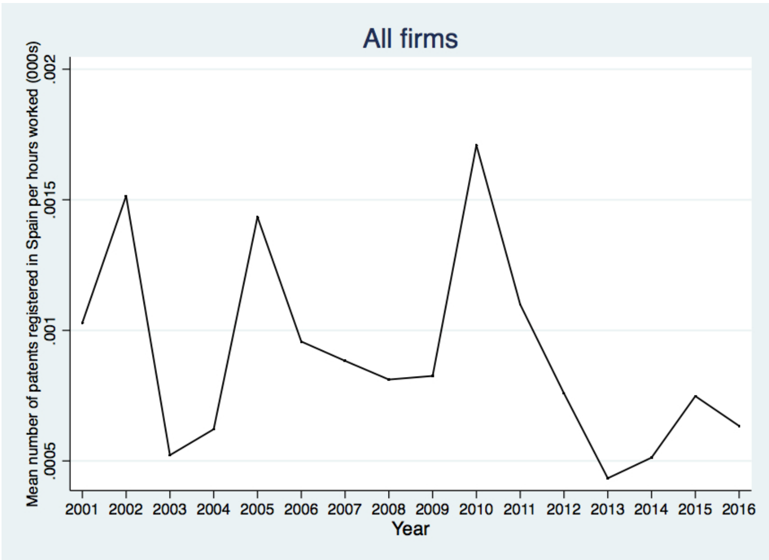
Figure 6.3 presents the mean total real R&D expenditures in Euros per hours worked in thousands for the period 2001-2016 for all firms, small, medium-sized and large firms. The procyclical nature of R&D investments is visible in the top left chart – there was a decrease in R&D expenditures in 2008, followed by an increase after the GFC. The trend depicted of real R&D expenditures in the whole sample is mostly consistent with Roper's (2020) recent analysis.[151] In the analysis of business R&D expenditures for Spain, Roper (2020) shows that the level of R&D expenditures in the years following the crisis (up to and including 2017) was lower than it was in 2008. This was true for the majority of industries across both manufacturing and services sectors. The charts showing mean total R&D expenditures per number of hours worked in thousands for small, medium and large firms depict slightly contrasting trends for these three groups of firms, suggesting that the influence of the size of the firm should be explored in the further analysis. These charts also suggest non-stationarity of the variable. Additionally, contrasting the trends presented in Figure 5.2 for the number of product innovations and those in Figure 5.3 for R&D expenditures suggests that there might be diminishing returns to R&D. The phenomena of diminishing returns to R&D has been documented, e.g. Bloom et al. (2019).

[151] The chart depicting this is not presented in the text.

Figure 6-3. Mean real total R&D expenditures per hours worked in thousands for all firms; small firms; medium firms; and large firms (Euros; 2001-2016)

Figure 6.4 shows the mean number of patents registered in Spain per number of hours worked in thousands for the period 2001-2016 for all firms, small, medium-sized and large firms during the same period. The mean number of patents registered in Spain reached its peak in 2010 and experienced a sharp decline until 2013, when it started increasing again. The chart presenting the mean number of patents registered in Spain per number of hours worked in thousands for different firm sizes are more volatile. Particularly noticeable are a huge decline of patents per number of hours worked for small firms in 2003, a sharp increase for medium-sized firms in 2010 and a sharp increase for large firms in 2016. At the first glance, these variables do not appear to be stationary.

Figure 6-4. Mean number of patents registered in Spain per hours worked in thousands for all firms; small firms; medium firms; and large firms (2001-2016)



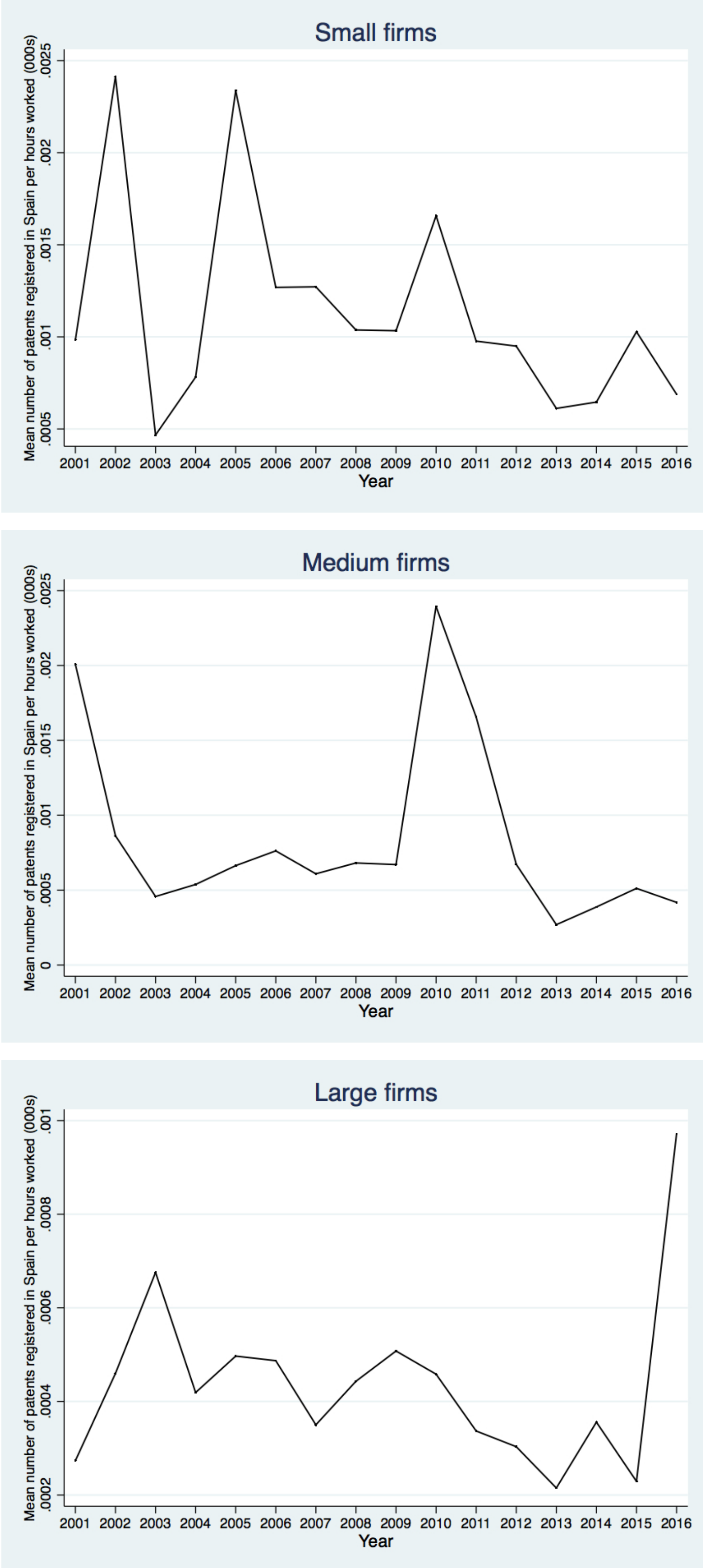
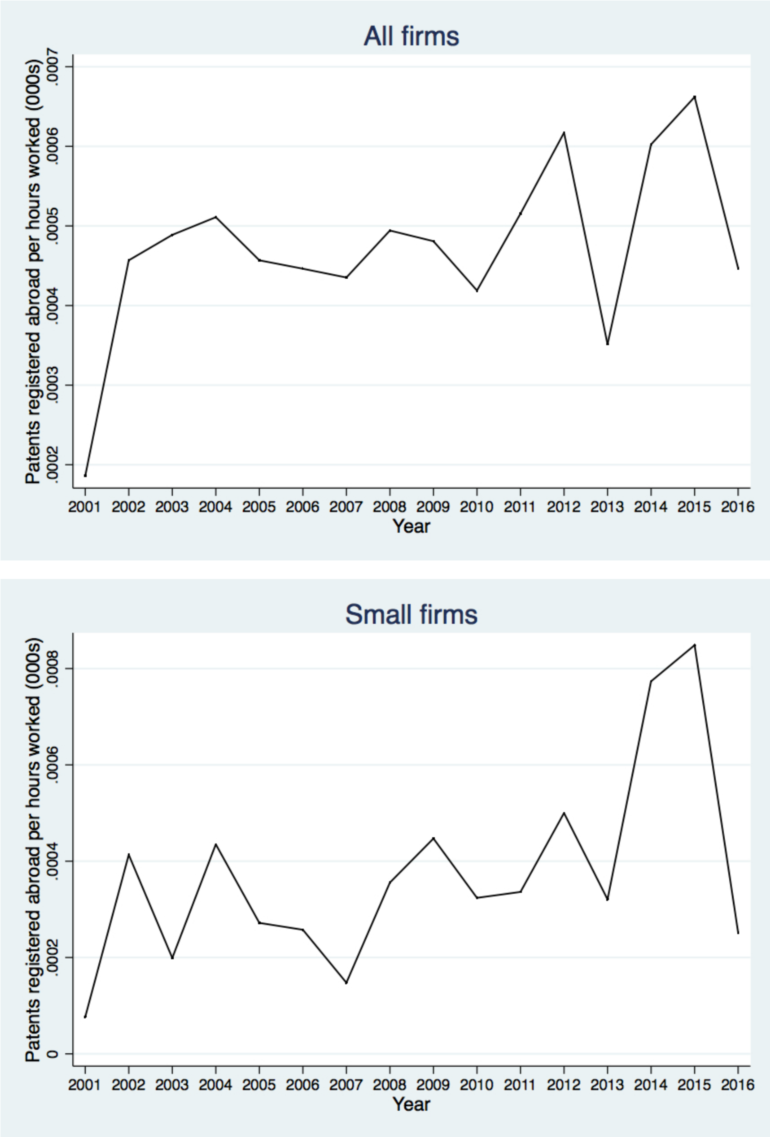
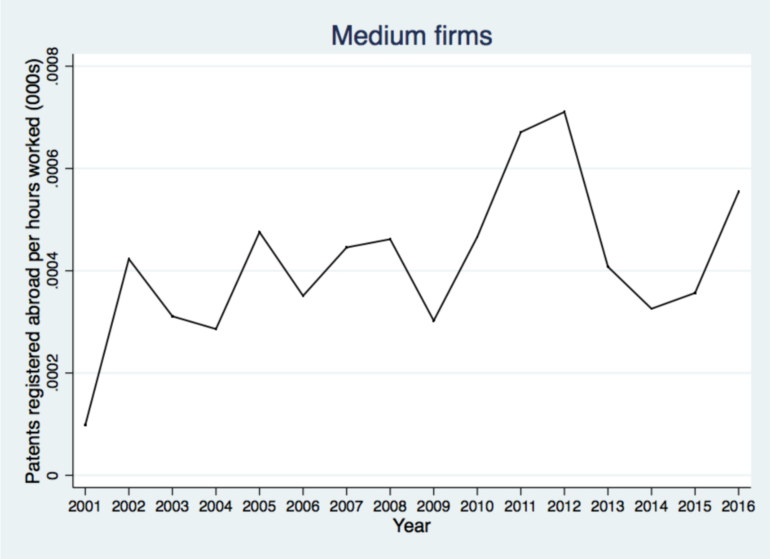


Figure 6.5 shows the mean number of patents per number of hours worked in thousands for all firms, small, medium and large firms. The mean number of patents registered

outside of Spain was very volatile over the observed period, with sharp declines in 2010 and 2013, followed by recoveries, and in 2016. Volatility also characterises the mean number of patents registered outside of Spain per number of hours worked for all firm sizes.

Figure 6-5 Mean number of patents registered outside of Spain per hours worked in thousands for all firms; small firms; medium firms; and large firms (2001-2016)





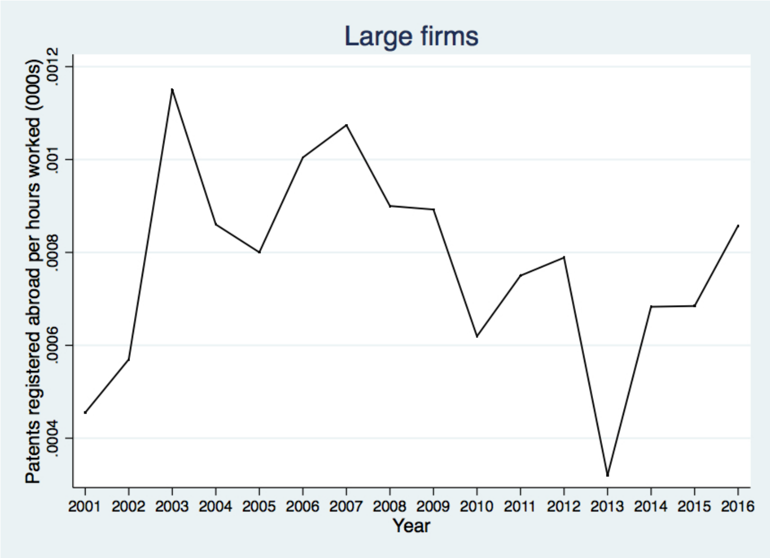
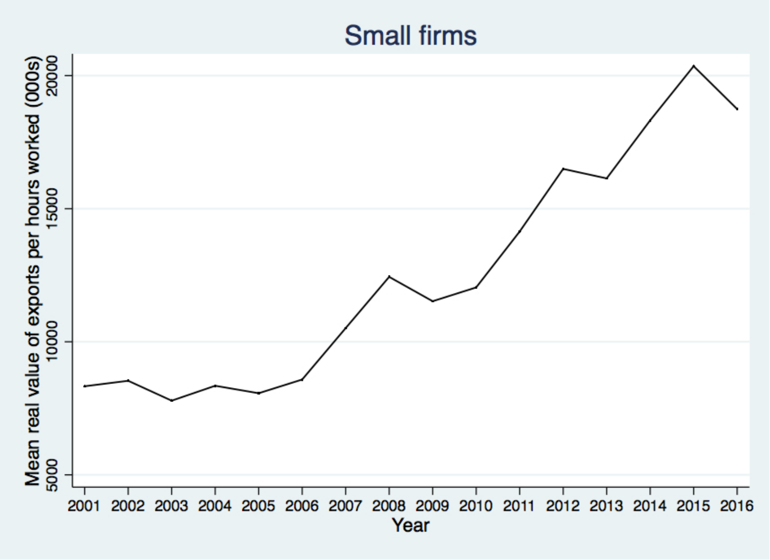
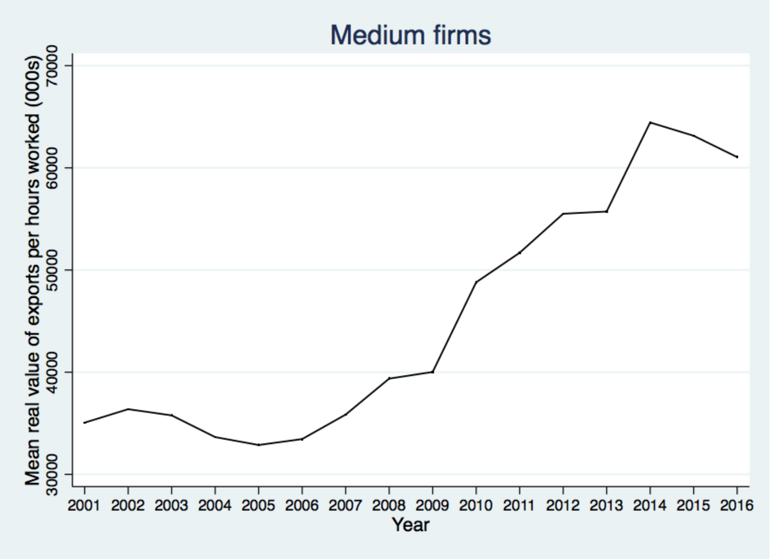


Figure 6.6 shows the mean real value of exports in Euros per hours worked in thousands for all firms for the period 2001-2016, as well as small, medium-sized and large firms separately for the same period. The mean value of exports per hours worked declined in 2009. The decline was followed by a recovery, but it was on a decline again from 2014 onwards. The mean value of exports per number of hours worked (000s) has an upward trend for medium and large firms until 2014 and for small firms until 2015. A particularly sharp increase in the mean value of exports per number of hours worked (000s) is noticeable for large firms in the period 2009-2012.

Figure 6-6. Mean real value of exports per hours worked in thousands for all firms; small firms; medium firms; and large firms (2001-2016)





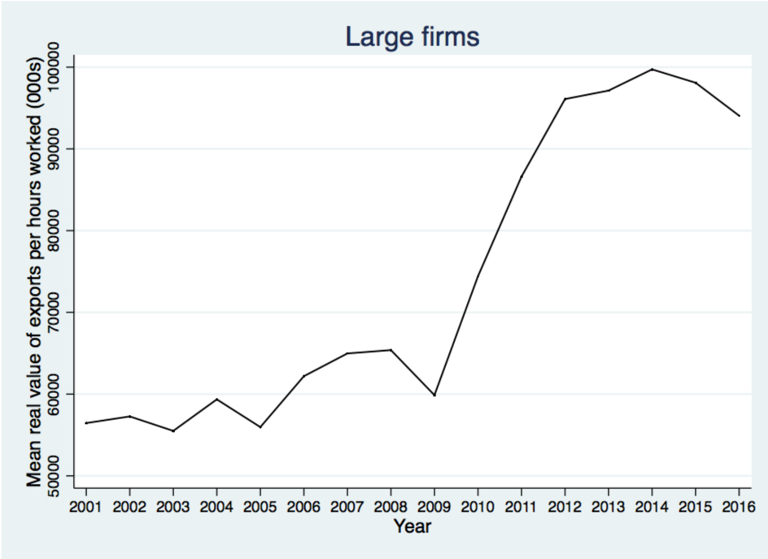
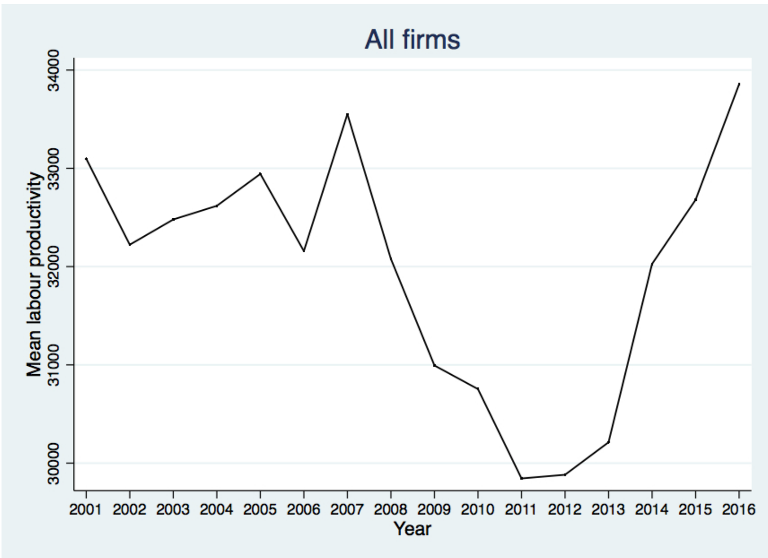


Figure 6.7 shows the mean of labour productivity (real value of output per hour worked) for the period 2001-2016. The mean was declining from 2007 onwards, reaching its lowest level in 2011. The decline was followed by a recovery, and in 2016 the mean labour productivity was the highest over the whole period. A similar pattern is observed for small, medium-sized and large firms. Labour productivity, at a glance, does not appear to be a stationary variable.

Figure 6-7. Mean labour productivity for all firms; small firms; medium firms; and large firms (Euros/number of hours worked, 2001-2016)



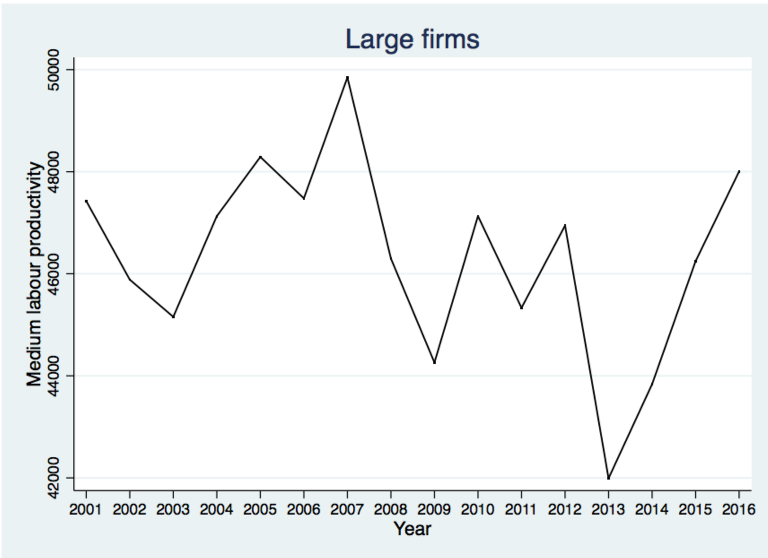
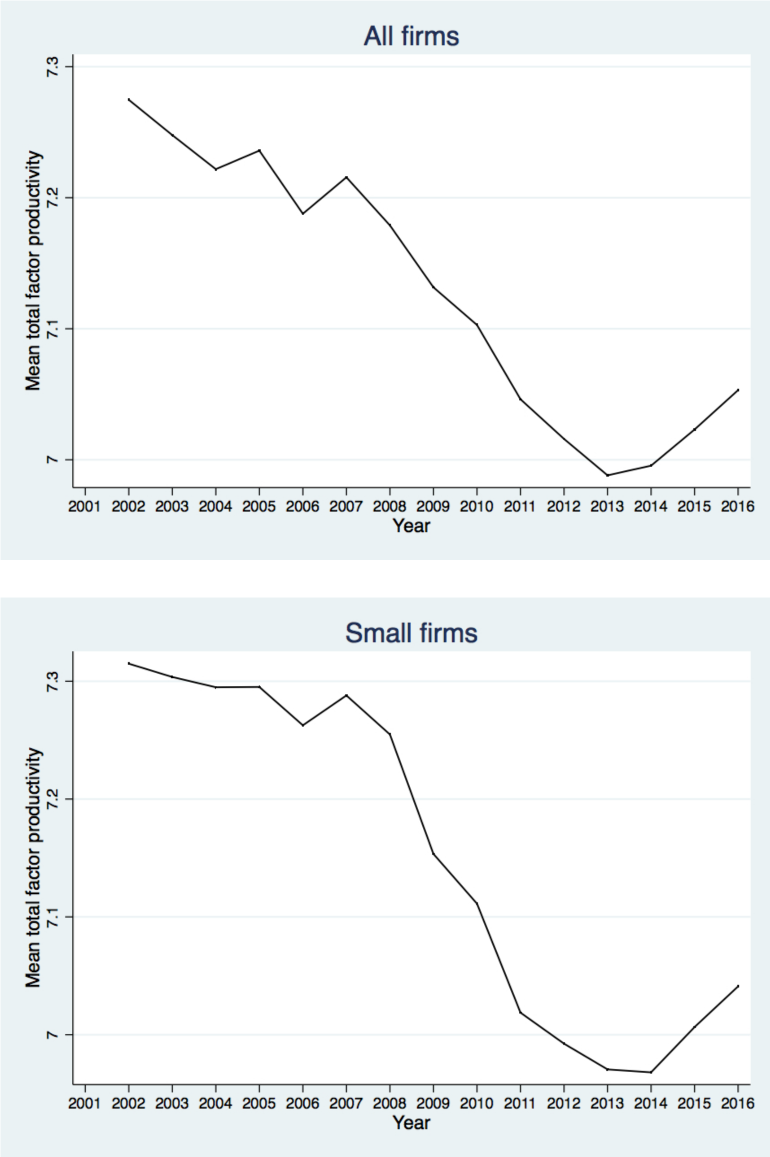
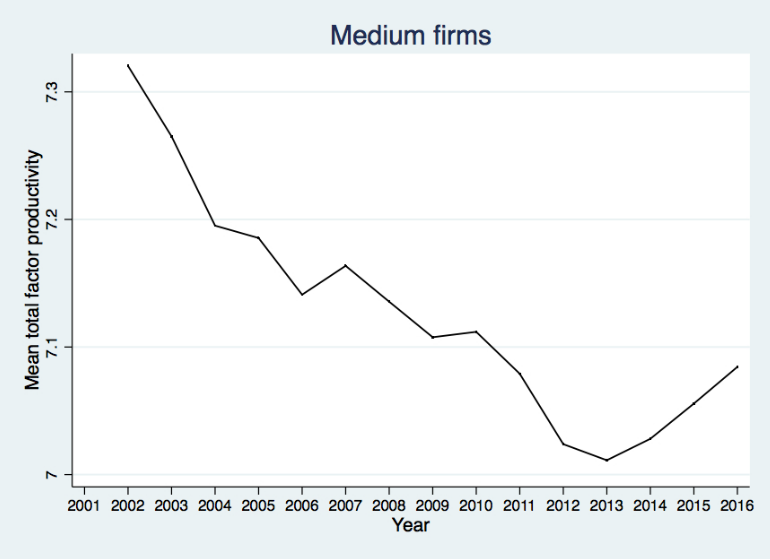


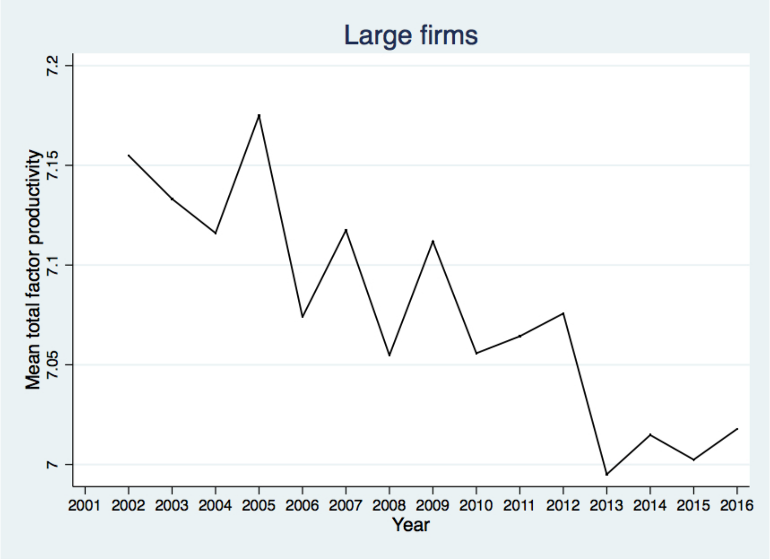
Figure 6.8 shows mean total factor productivity for all firms for the period 2001-2016. TFP for all firms, as well as for firms of different sizes, exhibits a downward trend until 2013 when it started following an upward trajectory. Furthermore, TFP is yet to reach its

level prior to the GFC. Similar patterns of TFP trajectories are observed in the work of Comin et al. (2020) that used a different dataset and methodology to the ones used here and explored TFP growth rates for Spain for the period 1995-2005.

Figure 6-8. Mean total factor productivity for all firms; small firms; medium firms; and large firms (2001-2016)







6.3 Theoretical foundations and empirical application of the vector-error correction and vector autoregressive models

There is no single estimation approach that allows for the full system estimation of vector-error correction models (VECMs) using panel data. The VECM approach comes from time-series modelling and allows the estimation of short-run relationships between variables conditional on their long-run equilibrium relationships (if any) together with the speed of adjustment towards long-run equilibrium. However, although the VECM approach can also be applied to panel-data (assuming sufficient time-series depth), the current state of the art is limited to single equation rather than full systems estimation.

In this section, we begin with the VECM approach. Then, to explore the full set of relationships between our variables of interest as a system, we use vector autoregression analysis (VAR). Compared to the VECM approach, the VAR approach is limited in two respects: (i) no distinction is made between short-run and long-run equilibrium relationships; and (ii) there is no information on contemporaneous relationships.

6.3.1. Vector-error correction models

VECM can be applied to panel data but within the limitations of single equation analysis (Blackburne and Frank, 2007). Among our variables of interest, we choose productivity as our dependent variable, because productivity is the outcome of a firm's aggregate activities, which, in our model, are captured by innovation and exporting. Hence, the estimated model is:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} X_{i,t-j} + \mu_i + \epsilon_{it} \tag{6.1}$$

To estimate this model, we applied the pooled mean group (pmg) approach (Blackburne and Frank, 2007). The resulting estimates are as follows.

Table 6-3 Results from pooled mean group approach (no. of observations = 5,011)

D.TFP_18	**Coefficient**	**Std. err.**	**z**	**P>|z|**	**[95% confidence intervals]**	
__ec						
GTID2015prices	6.26e-08	6.29e-09	9.95	0.000	5.03e-08	7.49e-08
VEXPOR2015prices	2.32e-09	1.79e-10	12.94	0.000	1.97e-09	2.67e-09
SR						
__ec	-.631	.029	-21.79	0.000	-.688	-.574
TFP_18						
LD.	-.028	.023	-1.23	0.220	-.073	.017
GTID2015prices						
D1.	2.30e-06	2.09e-06	1.10	0.272	-1.80e-06	6.41e-06
LD.	-2.05e-06	1.48e-06	-1.38	0.168	-4.96e-06	8.62e-07
VEXPOR2015prices						
D1.	1.65e-06	1.95e-06	0.85	0.396	-2.16e-06	5.47e-06
LD.	-5.28e-08	3.27e-07	-0.16	0.872	-6.94e-07	5.89e-07
_cons	4.390	.197	22.31	0.000	4.004	44.775

These estimates provide two-fold support for a long-run equilibrium relationship between each of innovation and exports and productivity. First, the cointegrating vector reveals that both innovation and exports are positively related to productivity with high levels of statistical significance. (The positive relationship between innovation and productivity replicates previous studies.) Second, in accord with the Granger representation theory, the estimates reveal a strongly significant error-correction mechanism whereby this equilibrium tends to be maintained over time. Moreover, these estimates each have an economically sensible quantitative interpretation. Increased expenditures of 1,000,000 Euros on innovation will typically, ceteris paribus, lead to an increase in a firm's TFP of 0.06 (mean value of 7.133, hence an increase of approximately 0.8%), while a similar increase in the value of exports will typically, ceteris paribus, lead to an increase in firm's productivity of 0.002 (mean value of 7.133, hence an increase of approximately 0.03%). A long-run equilibrium relationship requires corresponding error-correction to reduce disequilibrium, which in our model proceeds at a rate of 63% per annum. Turning to the short-run relationships, none of these are statistically significant.

Although this is not a systems estimator, we did try to gain insight into other potential relationships by estimating corresponding models with innovation or productivity as the dependent variables. Unfortunately, these alternative models would not compute, because the estimator lacked feasible initial values. Consequently, to gain insight into all the potential relationships between our three variables of interest, we turn to VAR analysis.

Some previous studies, as explored in Chapter 5, have identified contemporaneous links between phenomena. The same is not done in this chapter, taking into account that not necessarily all (if any) links will be contemporaneous. In most instances, it takes time for companies to reach decisions, especially complex decisions such as those around innovation, exporting and improving productivity (e.g. if a company successfully innovates or raises productivity, then before this can have an impact on exporting, the firm will have to make decisions regarding e.g. product adjustments to meet consumer preferences and regulatory requirements in each export market, briefing and training of local agents, marketing strategies, logistical arrangements, etc.). Strong theory underpins only one of the relationships – between productivity and exporting – and the theoretical considerations do not assume contemporaneous relationships between the two phenomena (Melitz, 2003).

In addition to theoretical reasons why contemporaneous relationships are unlikely, the pooled mean group estimates reported above likewise suggest an absence of contemporaneous relationships. First, the positive effects of innovation and exporting on productivity are long-run and small. Second, the short-run relationships lack statistical significance, so these estimates provide no evidence of short-run relationships. On these grounds, we have arguments for VAR estimation in which the relationships under investigation are lagged and which therefore exclude contemporaneous relationships.

6.3.2. Vector autoregressive (VAR) models

Vector autoregressive (VAR) models emerged from macroeconomics. The models were developed as an alternative method to multivariate simultaneous equation models (Abrigo and Love, 2016). Within macroeconomics, the choice between: (i) 'general-to-specific', 'reality-first', or vector autoregressive approaches, versus (ii) 'specific-to-general', 'theory-first', or dynamic stochastic general equilibrium (DSGE) models, for the investigation of inter-related phenomena within systems represents a philosophical question. The first approach puts the data in the forefront of the analysis, as the data is relatively unconstrained by a particular theory to be tested beyond the choice of variables. However, even in this approach, theory has its role and guides the analysis. As Hoover et al. (2008, p. 252) succinctly state, analysis that is not guided by a theory at all is 'hopeless' and "without some prior conceptual notion we would never find a starting place for any investigation". The second approach requires development and calibration of a sophisticated theoretical model, which can then be tested using data (Colander, 2009; Juselius, 2009).[152]

In this Chapter, the choice of using VAR models was not guided by the philosophical debates referenced above, as much as by the peculiarity of the research problem at hand and the potential of VAR models to shed new light on the productivity-innovation-exporting nexus. Formalising a theory that describes the links between productivity, innovation and exporting would be welcome; but, considering that there are still many unknowns surrounding them and their interrelationships, as discussed in Chapters 2-5, it would initially be more informative to fully understand what is going on in the real world. Considering that the literature has clearly shown that links between productivity, innovation and exporting exist (see Figure 5.2), however these links were to be framed in any newly established theory, only testing would show whether such theoretical framing holds true. Hence, further theorising in the absence of more complete information about

[152] Interestingly, Juselius (2009, p. 16) notes "the 'reality first' approach indicates that many widely used theory models are empirically inadequate". Colander (2009) advances similar arguments.

the nature of these links has only limited power to further disentangle the links between productivity, innovation and exporting.

More generally, the vector autoregression (VAR) approach "sees the world as a highly complex dynamic system" (Hoover et al., 2008, p. 252). The VAR approach in the panel data context allows examination of productivity, innovation and exporting as inter-related phenomena, in line with what the literature has previously established. Within the VAR system, the variables are usually considered to be endogenous (Abrigo and Love, 2016). The impact of exogenous shocks on the VAR system can also be examined if identifying restrictions are imposed that are grounded either in theory or in statistical procedures.

Abrigo and Love (2016, p. 779) represent 'a k-variate homogeneous panel VAR of order p with panel-specific fixed effects' using a system of linear equations (Equation (6.2)):

$$\Upsilon_{it} = \Upsilon_{it-1}\mathrm{A}_1 + \Upsilon_{it-2}\mathrm{A}_2 + \cdots + \Upsilon_{it-p+1}\mathrm{A}_{p-1} + \Upsilon_{it-p}\mathrm{A}_p + \mathrm{X}_{it}\mathrm{B} + u_i + e_{it} \quad (6.2)$$

where Abrigo and Love (2016, p. 779) define Υ_{it} as a '$(1 \times k)$ vector of dependent variables', X_{it} as a '$(1 \times l)$ vector of exogenous covariates', u_i as '$(1 \times k)$ vectors of dependent variable-specific panel fixed-effects' and e_{it} as 'idiosyncratic errors'. Furthermore, i and t are defined as $i \in \{1,2 \ldots, N\}$ and $t \in \{1,2, \ldots, T_i\}$. In the panel VAR as specified above, the parameters of interest are the $(k \times k)$ matrices $\mathrm{A}_1, \mathrm{A}_2, \ldots, \mathrm{A}_{p-1}, \mathrm{A}_p$, as well as the $(l \times k)$ matrix B. As assumed by Abrigo and Love (2016, p. 779), the data generating process is the same for all cross-sectional units, while "systematic cross-sectional heterogeneity is modelled as panel-specific fixed effects". The focus of the empirical investigation in this chapter will be on the links between the endogenous variables, rather than links between different endogenous and exogenous variables.

Testing variables for stationarity is important in VAR analyses. This is done with unit root tests, where the presence of a unit root indicates that the moment conditions are "completely irrelevant" and points to the problem of weak instruments of the GMM estimators (Abrigo and Love, 2016, p. 781). Prior to advancing the empirical investigation, unit root tests were conducted on the continuous variables included in the investigation: real value of R&D expenditures per hours worked, real value of exports per hours worked, labour productivity and total factor productivity. Since the dataset used is unbalanced, the appropriate unit root tests are either the Im-Pesaran-Shin or Fisher-type tests (Stata, n.d.). Although theoretically possible, practically it was impossible to run the Im-Pesaran-Shin unit root test with this dataset. Hence, the Fisher-type test was implemented.

The null hypothesis for the Fisher-type test is that all panels (time-series observations on a single variable for each firm separately) contain a unit root, while the alternative hypothesis assumes stationarity of at least one panel. When implementing the test, a drift term was included and one lag was used.[153] The tests were implemented using the *xtunitroot fisher* (Stata, n.d.) command in Stata. The results of the Fisher-type test are presented in Appendix 1. Although the test results strongly reject the null hypothesis that all panels contain a unit root, the results should be taken with a degree of caution considering that the alternative hypothesis states that at least one panel is stationary. Additionally, the PP type tests and some of the Fisher-type tests could not be computed for a substantial number of panels for all of the variables, because in some panels the time span was too short. It is very important to note that average time periods for which test is computed is approximately seven. This might be too short for the test to be powerful; e.g. Campbell and Perron (1991, p. 13) note "for tests of the unit root hypothesis versus stationary alternatives the power depends very little on the number of observations per se but is rather influenced in an important way by the span of the data". Considering that the graphs presented above suggest that the variables overall are not stationary, that Fisher-type does not reject the possibility that the majority of the panels are non-stationary, and the short span of data, the dataset was reduced to a balanced panel and additional unit root tests were run. Those tests showed mixed results regarding the stationarity of the variables. These results, as well as computational problems with implementing estimations in levels, led to the decision to difference the data. Additionally, differencing the variables is not only important to deal with the issues of non-stationarity, but also to address the particular problem of weak instruments (Abrigo and Love, 2016). It is worthwhile to note that previous empirical investigations that used the ESEE (e.g., Caldera, 2010; Cassiman et al., 2010; Cassiman and Golovko, 2011; Cassiman and

[153] Alternative specifications of the testing equation were used – i.e. different lag orders of the differences variable and different deterministic components (i.e. constant and/or time trend) – but did not yield substantially different results from those reported.

Golovko, 2018) did not conduct unit root tests or discuss stationarity of the data, which might cast doubt over the reliability of the results obtained.[154]

An elaborate overview of the empirical investigations conducted is presented in Figure 6.9a and Figure 6.9b. A total of 451 separate models were estimated. While the structure of the estimated models is similar, as will be elaborated in more details in the further text, particular importance was placed on different contexts or dimensions or heterogeneity that might impact the productivity-innovation-exporting nexus. As such, this empirical investigation will enhance understanding as to whether these links are context-specific or represent "law-like" relationships that hold true regardless.[155] Additionally, this analysis will elaborate on the moderating effects in the productivity-innovation-exporting nexus. Explorations were initially done using labour productivity as the productivity variable and, due to practical considerations and the results obtained, some of contexts were not further explored using TFP as a productivity variable. The following dimensions were explored using labour productivity:

1. Sectors in which firms operate;
2. Importance of the GFC, by dividing the full period into the periods 2001-2008 and 2009-2016;
3. Size of the firm;
4. R&D performance (high vs. low R&D performers);
5. Export performance (high vs. low exporters);
6. Cooperation with universities;
7. Cooperation with other firms; and
8. State of the market (expansionary, recessionary or stable market).[156]

State of the market was explored only with labour productivity and *Sectors in which firms operate* was explored only with labour productivity and R&D expenditures as the innovation variable. Large number of estimations were unstable (the importance of stability will be explored later) and, overall, there did not appear to be sectoral influences on the productivity-innovation-exporting nexus. The importance of the GFC was explored only with labour productivity. No systematic influences of the GFC on the productivity-innovation-exporting nexus were found. While the GFC is an obvious

[154] In all of the papers, dummy variables were used as exporting and innovation variables, apart from Caldera (2010) who also used R&D intensity as an innovation variable in addition to dummy variables. All of the mentioned papers used shorter spans of data. Additionally, some of the papers focused only on SMEs.
[155] The concepts and the possibility of existence were discussed in Chapter 5.
[156] State of the market was explored only when labour productivity was used as a productivity variable.

candidate when considering potential causes of structural breaks, this finding is consistent with the graphical presentations of our key variables in Section 6.3, which do not reveal systematic changes in trends coincident with the GFC. The graphs for product innovation, R&D spending and patents show the shock impact of the GFC but do not much affect their general trends throughout the sample period, while much the same can observed for exports. Visual inspection does not lead to such clear conclusions in the case of labour productivity but is more clear in the case of TFP. Although Spain is not included in the cross-country study of TFP slowdown of Fernald and Inklaar (2022, p. 5), they conclude that: “Our preferred story – and what we consider to be the leading story – for the US TFP growth slowdown is a slowing trend that predated the Great Recession … the UK and EU-5 slowdowns in the 2000s are largely the expected result of a frontier slowdown.” It is reasonable to assume that – consistent with neoclassical growth theory – the role of convergence in productivity slowdown in Europe may apply also to Spain. In their survey covering the US, UK, Germany, France and Japan, Goldin et al. (2021), although sceptical of the convergence story, nonetheless attribute no role at all to the GFC in TFP slowdown and only a partial role to the slowdown in capital deepening.

For each of 451 models, the following procedure was followed. First, panel VAR estimates were obtained and the stability of the model was checked. Next, impulse response functions and cumulative response functions were obtained for every model. In addition, when impulse response functions appeared to be of borderline significance, they were additionally individually explored. Considering that the same procedure and steps were followed for each model estimation, the significance, meaning and interpretation of each step is illustrated on the example in the following text: empirical exploration of all firms for the period 2001-2016.

Figure 6-9a. Estimates conducted using labour productivity as the productivity variable

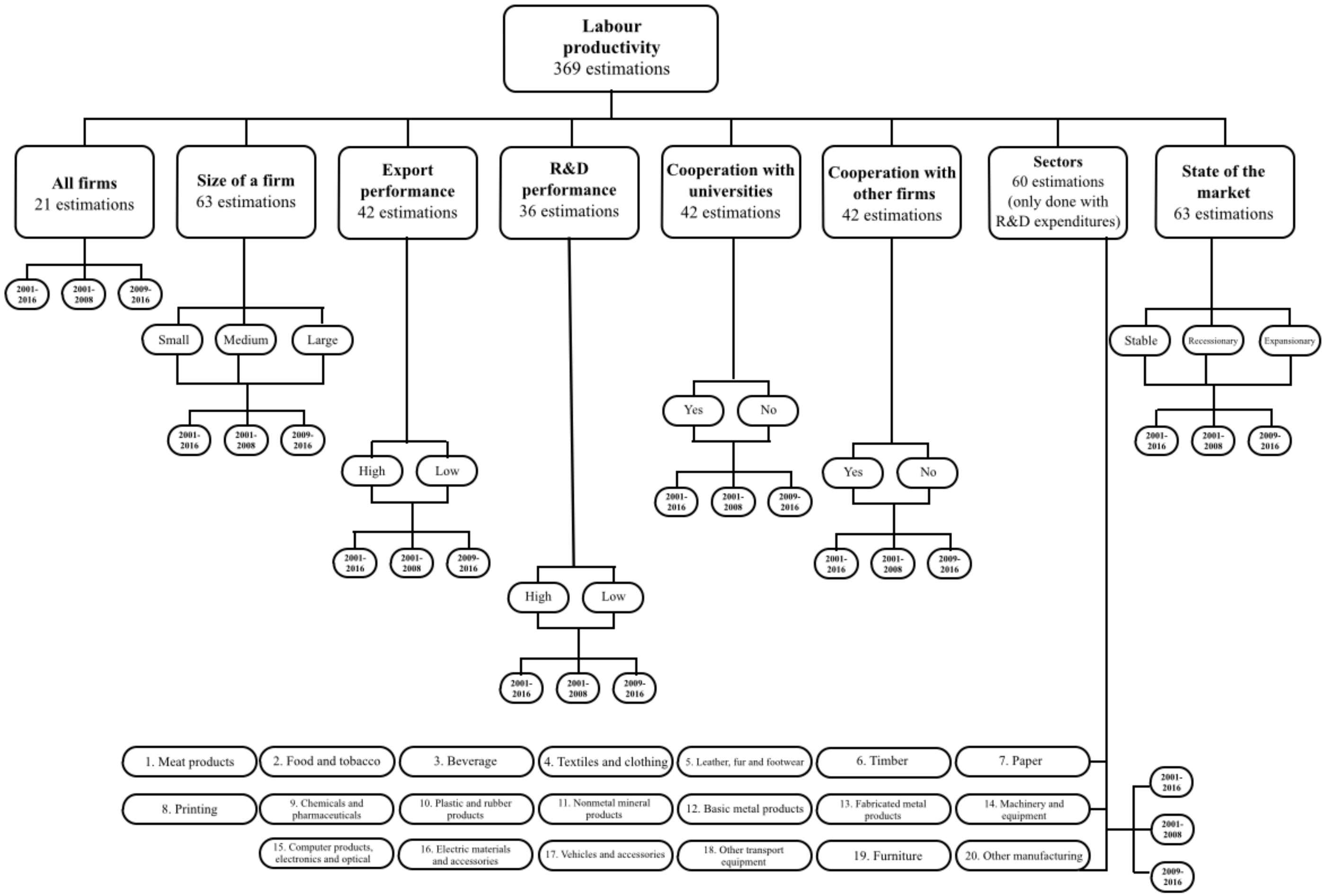
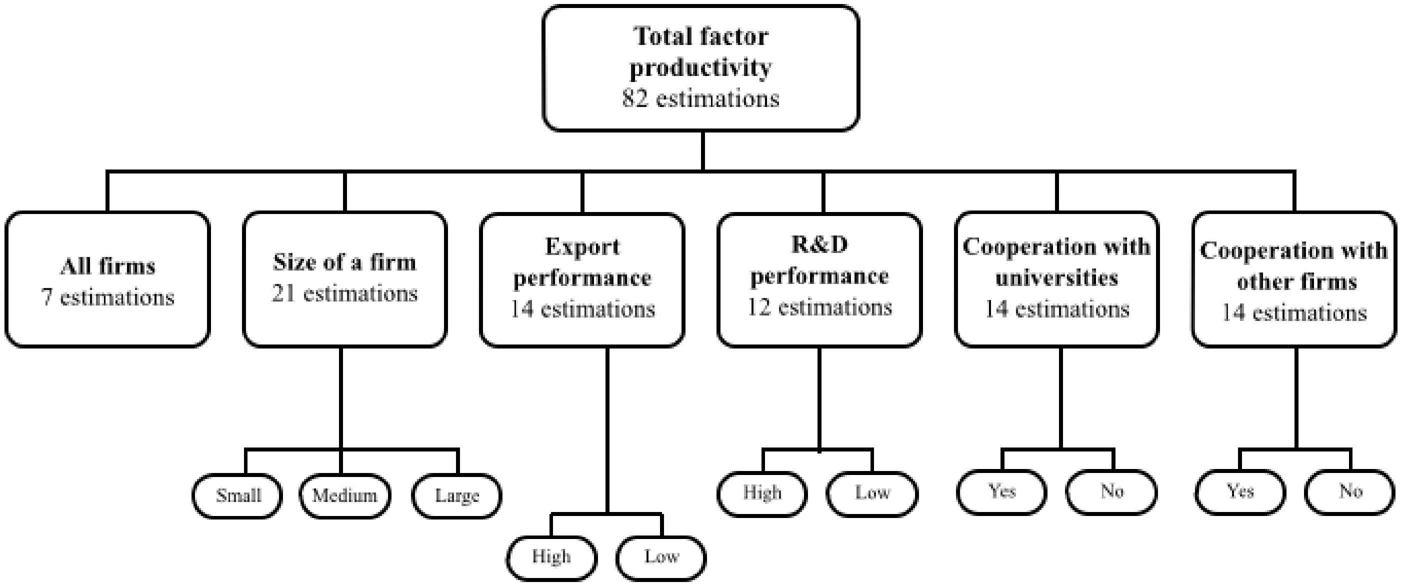


Figure 6-9b. Estimates conducted using TFP as the productivity variable



The lag order of the VAR specification and moment condition were considered, following Abrigo and Love's (2016) emphasis of their importance. The choice of lag orders was determined investigating the appropriate lag order follows Abrigo and Love (2016, p. 782) using the differenced variables. The coefficient of determination, defined as "the proportion of variation explained by the panel VAR model", was examined for a number of panel VAR specifications. An example is given in Figure 6.10, following a panel VAR specification used in the further analysis exploring the links between differenced R&D expenditures per hours worked, differenced TFP and differenced real value of exports per hours worked for all firms. The coefficient of determination is obtained by implementing the *pvarsoc* command after panel VAR estimations. For illustrative purposes, in the example below the maximum lag order specified is four. In this example we can see that the first lag explains 51.6% of variation, two lags 62.1%, three lags 64.4% and four lags 69.5%. Hence, two lags are chosen in the final specification of the estimated model given that we are using annual data and the costs of estimating additional parameters in the VAR (i.e., loss of degrees of freedom, multicollinearity and increased computational difficulties).

Figure 6-10 Coefficient of determination after panel VAR exploring the links between differenced R&D expenditures per hours worked, differenced TFP and differenced real value of exports per hours worked for all firms (2001-2016)

Lags	**CD**
1	.516
2	.621
3	.644
4	.695

The stability of the model is another important consideration when estimating panel VAR models. Stable models indicate that impulse-response functions (IRFs) and forecast-error variance decompositions (FEVDs) are meaningful. The stability of each estimated model will be reported together with the results. Stability is checked by implementation of the *pvarstable* command after each panel VAR estimation.

The Stata syntax for the final model estimated in generic form is:[157]

[157] "Innovation variable", "Productivity variable" and "Exporting variable" are used to denote all variables as detailed in the earlier parts of the chapter.

pvar "innovation variable" "productivity variable" "exporting variable", lags(2) vce(cluster Col1) overid td

where:

lags(2) indicates that the lag order included in the model is 2;

vce(cluster Col1) indicates that cluster-robust standard errors at the firm-level are reported;

overid indicates that the Hansen *J* statistic of overidentifying restrictions will be included as part of the estimations;[158]

td indicates that cross-sectional means are removed from each variable before the model is estimated.[159]

The full procedure and results will be explained in detail for one example – the exploration of the links between differenced TFP, differenced R&D expenditures per hours worked and differenced value of exports per hours worked using the full sample. After the presentation of this example, only results will be discussed. Due to the extremely large number of estimations, it is not feasible to discuss the estimation procedure and all of its components for each estimation separately. Figure 6.11 shows the coefficients obtained after panel VAR GMM estimation. The Hansen *J* statistic, as we can see at the bottom of Figure 6.11, is not reported as the model is just identified. Abrigo and Love (2016) do not provide further comments on panel VAR coefficients in their seminal paper and the same practice will be followed here.

Figure 6-11. Panel VAR output results for the link between differenced TFP (TFP_18diff), differenced R&D expenditures per hours worked (GTID_diffR) and differenced real value of exports per hours worked (VEXPOR_diffR)

[158] However, as the model is just identified, the statistic cannot be reported.

[159] Abrigo and Love (2016, p. 785) note that "this could be used to remove common time fixed effects from all the variables prior to any other transformation".

GMM Estimation

Final GMM Criterion Q(b) = **9.49e-35**
Initial weight matrix: **Identity**
GMM weight matrix: **Robust**

No. of obs = **12644**
No. of panels = **2182**
Ave. no. of T = **5.795**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GTID_diffR						
GTID_diffR						
L1.	-.3336005	.0733671	-4.55	0.000	-.4773973	-.1898036
L2.	-.1718424	.0379999	-4.52	0.000	-.2463209	-.0973639
TFP_18diff						
L1.	.309512	.3968569	0.78	0.435	-.4683131	1.087337
L2.	.4501615	.2923657	1.54	0.124	-.1228648	1.023188
VEXPOR_diffR						
L1.	-.0110229	.0085307	-1.29	0.196	-.0277428	.0056971
L2.	-.0053924	.0076057	-0.71	0.478	-.0202993	.0095145

```
TFP_18diff     |
  GTID_diffR   |
          L1.  |  -.0000458   .0002525    -0.18   0.856    -.0005408    .0004492
          L2.  |   .0002035    .000277     0.73   0.463    -.0003394    .0007464
               |
  TFP_18diff   |
          L1.  |  -.4186306   .0234196   -17.88   0.000    -.4645321   -.3727291
          L2.  |  -.1573881   .0178666    -8.81   0.000    -.1924059   -.1223702
               |
VEXPOR_diffR   |
          L1.  |  -.0001641    .000287    -0.57   0.567    -.0007266    .0003984
          L2.  |  -.0004984   .0002549    -1.96   0.051    -.0009979    1.09e-06
-------------------------------------------------------------------------------
VEXPOR_diffR   |
  GTID_diffR   |
          L1.  |   .0815062   .0420173     1.94   0.052    -.0008462    .1638585
          L2.  |   .0909743   .0773349     1.18   0.239    -.0605993    .2425479
               |
  TFP_18diff   |
          L1.  |   1.868478   1.217174     1.54   0.125    -.5171395    4.254096
          L2.  |   .1951241   1.212311     0.16   0.872    -2.180961    2.571209
               |
VEXPOR_diffR   |
          L1.  |  -.4389107   .1271819    -3.45   0.001    -.6881827   -.1896387
          L2.  |  -.3739308   .1719055    -2.18   0.030    -.7108593   -.0370023
-------------------------------------------------------------------------------
Instruments : l(1/2).(GTID_diffR TFP_18diff VEXPOR_diffR)


Test of overidentifying restriction:
  Hansen's J chi2(0) = 1.200e-30 (p =      .)
```

Next, we will examine Granger causality. Besides theoretical considerations, Granger causality can be used to inform the ordering of the variables in the panel VAR model. Granger causality, according to Abrigo and Love (2016, p. 792) informs us about "whether past values of a variable, say, *x*, are useful in predicting the values of another variable *y*, conditional on past values of *y*, that is, whether *x* "Granger-causes" *y*". Granger causality is explored using the Stata command *pvargranger*. Figure 6.12 presents Granger causality for the example model. The null hypothesis, as stated at the top of Figure 6.12, suggests the absence of Granger causality between two variables. In our case, we cannot reject the null hypothesis for any of the variable pairs at the conventional 5% significance level. However, at the 10% or close to the 10% level, exporting Granger causes TFP (p-value 0.092), while innovation and TFP both Granger cause exporting (p-values 0.123 and 0.118, respectively; and 0.08 jointly). From this, we can conclude that neither exporting or productivity affect innovation, that exporting affects productivity, and that both innovation and productivity affect exporting. This provides support to the ordering of the variables when estimating impulse response functions and cumulative impulse response functions that will be elaborated in more detail later.

Figure 6-12. Granger causality results

```
panel VAR-Granger causality Wald test
  Ho: Excluded variable does not Granger-cause Equation variable
  Ha: Excluded variable Granger-causes Equation variable
```

Equation \ Excluded	chi2	df	Prob > chi2
GTID_diffR			
TFP_18diff	**2.378**	**2**	**0.304**
VEXPOR_diffR	**1.746**	**2**	**0.418**
ALL	**3.762**	**4**	**0.439**
TFP_18diff			
GTID_diffR	**1.127**	**2**	**0.569**
VEXPOR_diffR	**4.782**	**2**	**0.092**
ALL	**5.771**	**4**	**0.217**
VEXPOR_diffR			
GTID_diffR	**4.188**	**2**	**0.123**
TFP_18diff	**4.273**	**2**	**0.118**
ALL	**8.347**	**4**	**0.080**

The stability of the model is explored next. Figure 6.13 shows the results for the stability of the model in our case. Tabular results confirm that all moduli are less than one, hence, confirming the model's stability. This is also apparent from Figure 6.14.

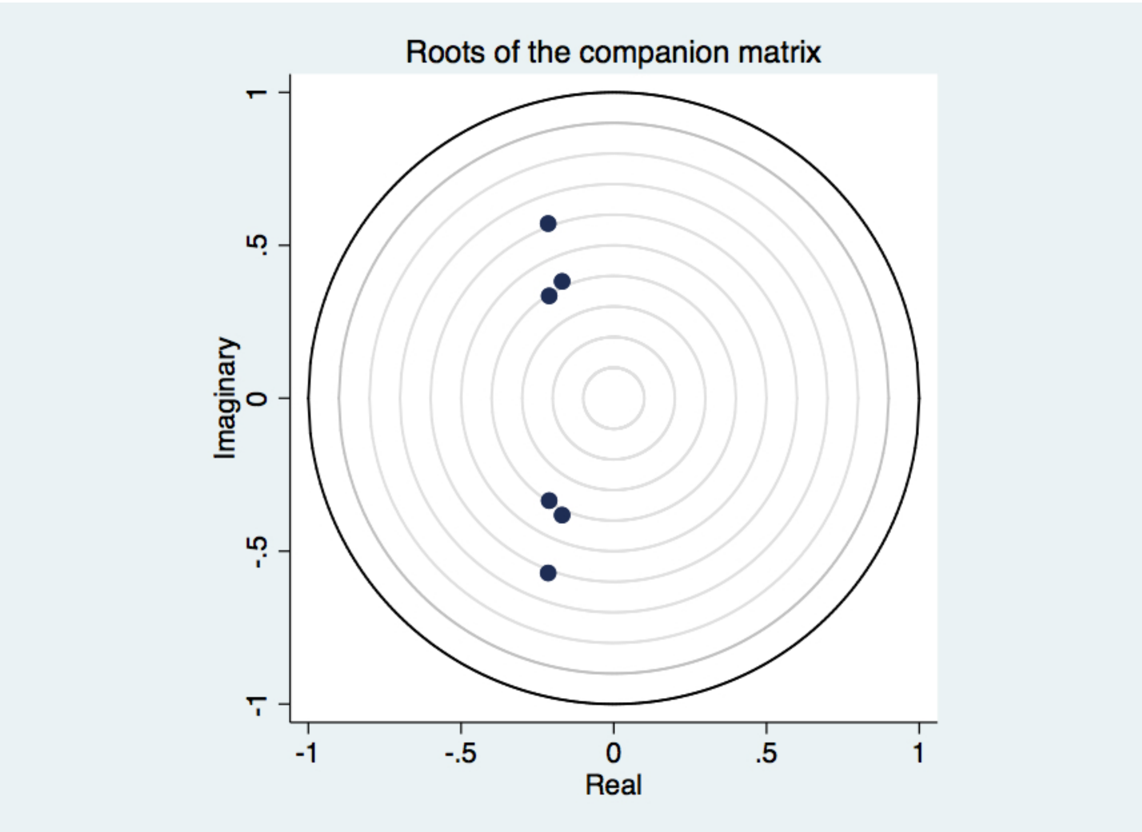
Figure 6-13. Stability of the model in tabular form

```
Eigenvalue stability condition
```

Eigenvalue Real	Eigenvalue Imaginary	Modulus
-.2150015	-.5712397	.6103609
-.2150015	.5712397	.6103609
-.169183	-.3820572	.4178404
-.169183	.3820572	.4178404
-.2113865	-.3347223	.3958829
-.2113865	.3347223	.3958829

```
All the eigenvalues lie inside the unit circle.
pVAR satisfies stability condition.
```

Figure 6-14. Stability of the model in graphical form



Impulse response functions (IRFs), the results of most interest to us, are explored next. Calculated IRFs are highly dependent on the ordering of the variables (Abrigo and Love, 2016). Abrigo and Love (2016, p. 794) note "the ordering constrains the timing of the response: shocks on variables that come earlier in the ordering will affect subsequent variables contemporaneously, while shocks on variables that come later in the ordering will affect only the previous variables with a lag of one period". IRFs are calculated using the *pvarirf* command.

The ordering of choice in this empirical investigation, based on discussions from Chapters 2-5, as well as further consideration of the three phenomena, is the following: innovation – productivity – exporting. It is noted that the ordering does affect the results (e.g. Appendix 3 represents how the results reported in Figures 6.17 and 6.18 change as the result of changes in ordering). As explained in the discussion on Granger causality, neither exporting nor TFP appear to have a contemporaneous effect on innovation, justifying the choice of innovation as the initial variable. Exploration of correlation coefficients at the very beginning also supports this ordering, as correlation coefficients increased after lags on innovation variables were introduced. Next, according to Granger causality, productivity does affect exporting and vice versa. Accordingly, because Granger causation suggests, contemporaneous causation in both directions, our ordering of these two variables is strongly based on the available theory – i.e. Melitz (2003) – suggesting that productivity has a strong impact on whether firms export or not, while the reverse effect is less strongly supported for developed economies (Martins and Yang, 2009) and it may be highest within a year of beginning exports (Martins and Yang, 2009) nonetheless takes effect over time (Atkin et al., 2017)). Accordingly, our ordering suggests that shocks to innovation can affect productivity or exporting contemporaneously, while shocks to exporting can only affect innovation or productivity with a one-period lag.

Figure 6.15 presents simple IRFs, while Figure 6.16 presents cumulative IRFs. It is important to acknowledge that some of the relationships reported are not statistically significant. Simple IRFs show that a shock to the change in TFP has a significantly positive effect on the change in difference in TFP in period 0, negative in period 1, positive in period 3 and negative in period 4. Overall, the cumulative effect is positive and significant. A shock to the change in R&D expenditure divided by the number of hours worked leads to an increase in difference in R&D expenditures divided by number of hours worked in period 0, decline in period 1 and an increase in period 3. The cumulative effect is positive. An increase in the change in exporting divided by the number of hours worked leads to an increase in the difference in exporting divided by the number of hours worked in period 0 and decline in period 1. Overall, the cumulative effect is positive.

Turning to the links between the variables, a positive shock in change in productivity divided by the number of hours worked leads to an increase in difference in exporting divided by the number of hours worked in period 0, and a positive shock in innovation divided by number of hours worked leads to an increase in difference in exporting divided by number of hours worked in period 1. Cumulative effects in both cases are positive. We now interpret both of these results quantitatively:

- In the first case, a change in the difference of TFP by one standard deviation represents an increase in TFP of approximately 7.6% (i.e. the standard deviation of the change in TFP scaled against the mean level – standard deviation of the change in TFP = 0.541; mean level of TFP = 7.133);
- This impulse leads to an increase in the change of exports by 2,500 Euros per 1,000 hours worked by the end of period 4. For the typical firm, the change in exports is 2,500 Euros per 1,000 hours worked multiplied by the average number of hours worked in thousands (375.1) leads to a change in exports of 937,750 Euros;
- This change in exports represents approximately a 2.9% increase in exports for a typical firm (i.e. change in exports scaled against the mean level of value of exports – mean level of value of exports = 32.5 million);
- The impulse of one standard deviation of R&D expenditures per 1,000 hours worked represents approximately a doubling of R&D expenditures. The resulting change in exports is 100 Euros per 1,000 hours worked by the end of period 4. For a typical firm, the change in exports of 100 Euros per 1,000 hours worked leads to a change in exports of approximately 37,510 Euros. Scaled against the mean level, this represents a 0.1% increase in the value of exports.

Figure 6-15. Simple IRFs

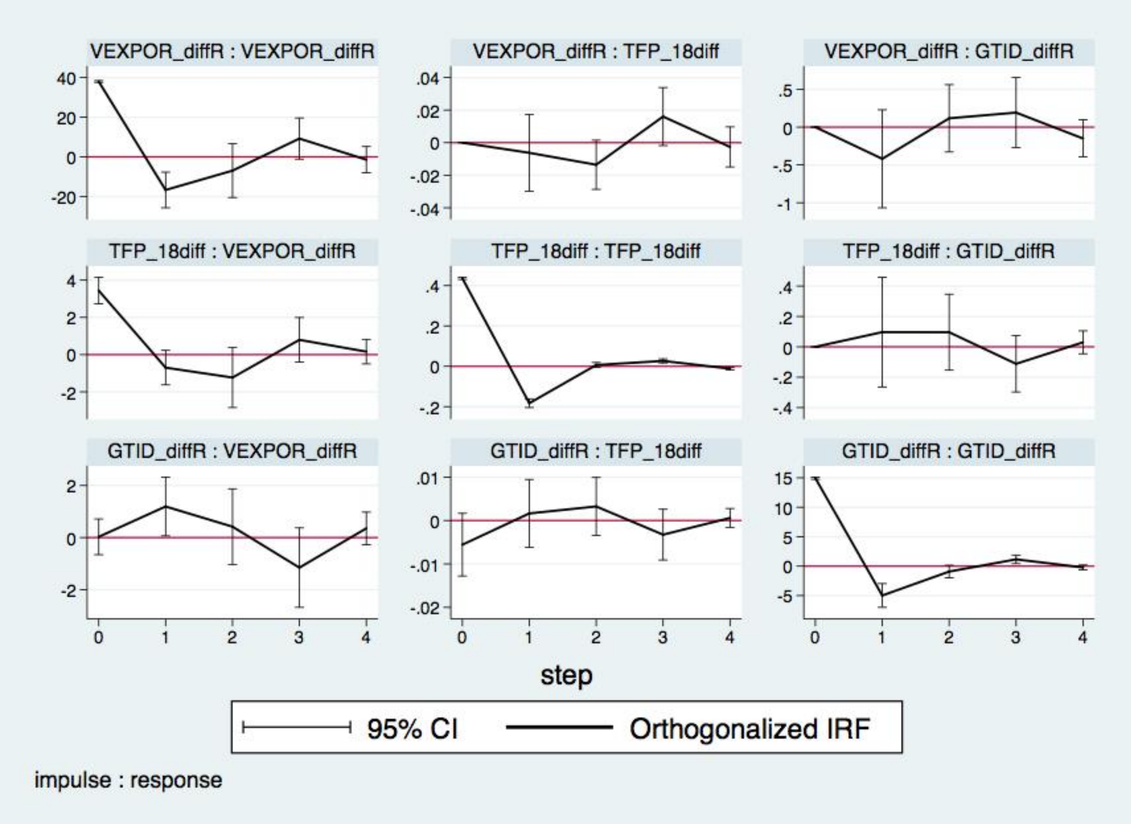
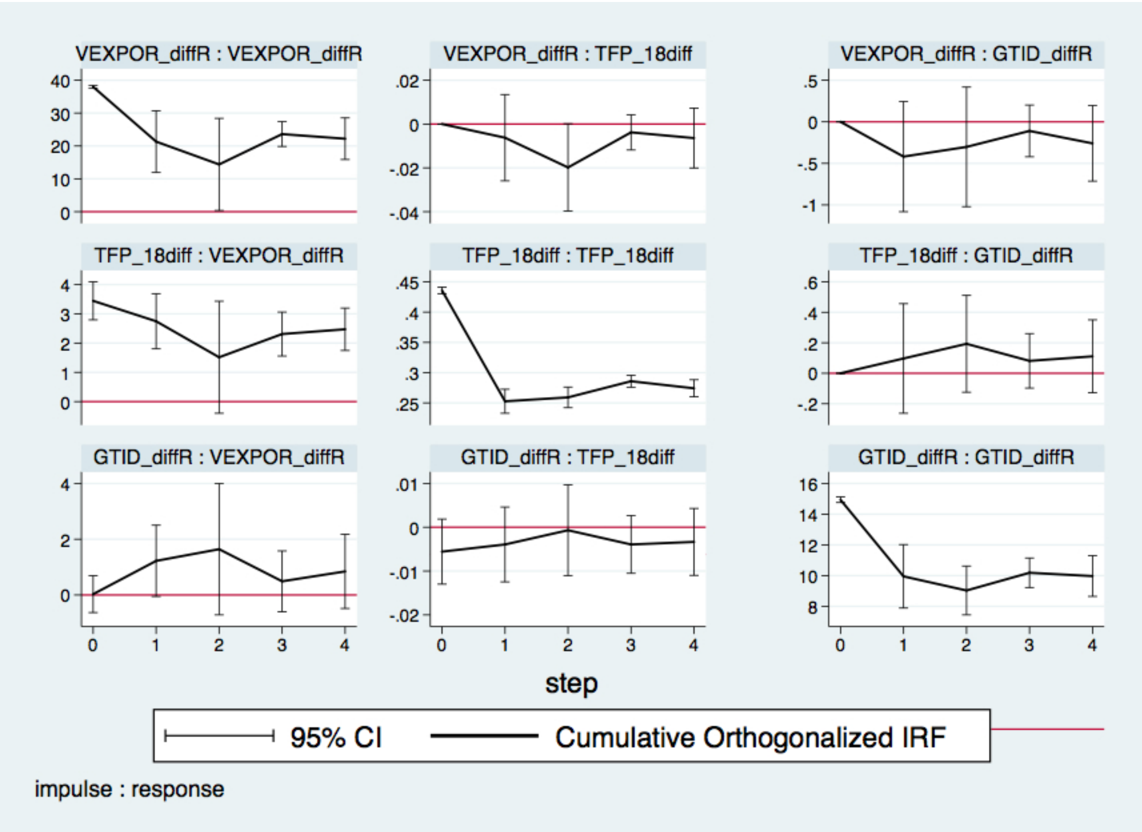


Figure 6-16. Cumulative IRFs



Finally, forecast-error variance decompositions (FEVDs) can be obtained using the Stata command *pvarfevd*. However, in the context of the interpretation of the results, they provide little value added, hence, will not be elaborated on. Additionally, FEVDs are obtained without standard error bands.

6.4 Results

Results based on the preferred model specification explained above and different sample restrictions are presented in Tables 6.3 – Tables 6.14. Full set of IRFs and cumulative IRFs on which aforementioned tables are based are presented in Appendix 2 in the following order:

- Appendix 2.1 (Figure A2.1.1 to Figure A2.1.14) matches Table 6.4;
- Appendix 2.2 (Figure A2.2.1 to Figure A2.2.14) matches Table 6.5;
- Appendix 2.3 (Figure A2.3.1 to Figure A2.3.14) matches Table 6.6;
- Appendix 2.4 (Figure A2.4.1 to Figure A2.4.14) matches Table 6.7;
- Appendix 2.5 (Figure A2.5.1 to Figure A2.5.12) matches Table 6.8;
- Appendix 2.6 (Figure A2.6.1 to Figure A2.6.12) matches Table 6.9;
- Appendix 2.7 (Figure A2.7.1 to Figure A2.7.14) matches Table 6.10;
- Appendix 2.8 (Figure A2.8.1 to Figure A2.8.14) matches Table 6.11;
- Appendix 2.9 (Figure A2.9.1 to Figure A2.9.14) matches Table 6.12;
- Appendix 2.10 (Figure A2.10.1 to Figure A2.10.14) matches Table 6.13;
- Appendix 2.11 (Figure A2.11.1 to Figure A2.11.14) matches Table 6.14; and
- Appendix 2.12 (Figure A2.12.1 to Figure A2.12.14) matches Table 6.15.

The results based on labour productivity are summarised in the tables in Appendix 4, but will not be discussed in detail, as labour productivity is not our preferred productivity measure. Individual IRF and cumulative IRF figures will not be included for labour productivity estimates, as they involve 492 individual figures. These figures are available upon request. All of the tables, presented in the main text and appendices, contain information on the sample period, the number of observations used in estimations, and the stability of the model. The main part of the tables is the summary of simple and cumulative IRFs and their statistical significance.

The main results that emerged from this empirical investigation hold regardless of the choice of productivity or innovation variables or whether full or restricted samples are used. Before we proceed with the discussion of the productivity-innovation-exporting nexus, there are two important takeaway points from Tables 6.4 – 6.15. First, the estimated TFP models are all stable, meaning that IRFs and cumulative IRFs can be interpreted as discussed in the example in the previous section. Second, the effects of shocks to the variables on themselves – i.e. the impact of productivity on productivity, of innovation on innovation and of exporting on exporting – are generally cumulatively positive. This finding is broadly consistent with the literature discussed in Chapter 5. For example, Aw et al. (2008) find that both R&D and exporting are correlated with engagement in the same activities in the previous period, while Stojčić and Hashi (2014) show a positive link from previous engagement in innovation activities to propensity to innovate.

Table 6-4. The links between innovation, exporting and productivity for the whole sample*

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	12,644	12,743	12,746	12,488	8,406	8,406	12,756
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Productivity—Innovation							
Innovation—Productivity							
Exporting—Productivity					Period 3 (+) *Cumulative (-, NAS)*	Period 3 (+) *Cumulative (-, NAS)*	
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting	Period 1 (+) *Cumulative (+, NAS)*						
Exporting—Innovation							

*NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

***Table 6-5. The links between innovation, exporting and productivity for small firms*, ***

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	6,329	6,338	6,338	6,295	4,286	4,286	6,339
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+/-, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+/-, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*
Productivity—Innovation	Period 3 (-) *Cumulative (+, NAS)*						
Innovation—Productivity			Period 0 (+) *Cumulative (+, NAS)*	Period 1 (-) *Cumulative (+/-, NAS)*			
Exporting—Productivity	Period 2 (-) *Cumulative (+/-, NAS)*				Period 2 (-) *Cumulative (+/-, NAS)*	Period 2 (-) *Cumulative (+/-, NAS)*	
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting							
Exporting—Innovation							

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Small firms are those that employ fewer than 50 employees.

Table 6-6. The links between innovation, exporting and productivity for medium firms, ***

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	3,823	3,886	3,886	3,786	2,680	2,680	3,890
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Productivity—Innovation							
Innovation—Productivity			Period 1 (-) *Cumulative (+/-, NAS)*				
Exporting—Productivity					Period 1 (-) *Cumulative (-, NAS)*		
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*
Innovation—Exporting							
Exporting—Innovation	Period 2 (+) *Cumulative (+/-, NAS)*					Period 1 (+) *Cumulative (+, NAS)*	

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Medium firms employ from 50 to 249 employees.

Table 6-7. The links between innovation, exporting and productivity for large firms, ***

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	2 492	2 519	2 522	3 786	2 680	2 680	3 890
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Productivity—Innovation							
Innovation—Productivity			Period 1 (+) *Cumulative (+/-, NAS)*		Period 0 (+) *Cumulative (+, NAS)*		
Exporting—Productivity					Period 1 (-) *Cumulative (-, NAS)*		
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*
Innovation—Exporting							
Exporting—Innovation						Period 1 (+) *Cumulative (+, NAS)*	

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Large firms employ more than and including 250 employees.

Table 6-8. The links between innovation, exporting and productivity for high R&D performers, ***

Innovation variable	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	2,243	2,246	2,132	1,437	1,437	2,253
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable
Links between:						
Productivity—Productivity	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Productivity—Innovation						
Innovation—Productivity						Period 0 (+), Period 1 (+) *Cumulative (+, NAS)*
Exporting—Productivity						
Productivity—Exporting	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting						
Exporting—Innovation			Period 1 (-) *Cumulative (-, NAS)*			

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** High R&D performers are firms that invested more than average of all the firms in the sample in any year.

Table 6-9. The links between innovation, exporting and productivity for low R&D performers, ***

Innovation variable	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	10,500	10,500	10,356	6,969	6,969	10,503
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable
Links between:						
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), *Period 3 (+)* *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*
Productivity—Innovation						
Innovation—Productivity		Period 0 (+) *Cumulative (+, NAS)*	Period 1 (-), Period 3 (-) *Cumulative (-, NAS)*			
Exporting—Productivity	Period 2 (-) *Cumulative (-, NAS)*			Period 3 (+) *Cumulative (-, NAS)*	Period 3 (+) *Cumulative (-, NAS)*	Period 2 (-) *Cumulative (-, NAS)*
Productivity—Exporting	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 2 (-) *Cumulative (+/-, NAS)*	Period 0 (+), Period 2 (-) *Cumulative (+/-, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*
Innovation—Exporting				Period 2 (+) *Cumulative (+/-, NAS)*		
Exporting—Innovation						

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Low R&D performers are remaining firms that were not classified as high R&D perfomers (high R&D performers are firms that invested more than average of all the firms in the sample in any year).

Table 6-10. The links between innovation, exporting and productivity for high exporters*,**

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	6,447	6,518	6,518	6,334	4,300	4,300	6,528
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Productivity—Innovation							Period 1 (+) *Cumulative (+, NAS)*
Innovation—Productivity		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*				
Exporting—Productivity							
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting							
Exporting—Innovation							

*NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

**High exporters are firms that exported more than average of all the firms in the sample in any year.

Table 6-11. The links between innovation, exporting and productivity for low exporters*, *

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	6,197	6,225	6,228	6,154	4,106	4,106	6,228
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*
Productivity—Innovation							
Innovation—Productivity	Period 2 (+) *Cumulative (+, NAS)*			Period 1 (-) *Cumulative (-, NAS)*			
Exporting—Productivity	Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*
Productivity—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting					Period 0 (+) *Cumulative (+)*		
Exporting—Innovation					Period 1 (-) *Cumulative (-, NAS)*		

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Low exporters are the remaining firms that were not classified as high exporters (high exporters are firms that exported more than average of all the firms in the sample in any year).

Table 6-12. The links between innovation, exporting and productivity for firms that engaged in cooperation with other firms, ***

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	3,910	3,973	3,977	3,802	2,588	2,588	3,984
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation							Period 1 (+) *Cumulative (+, NAS)*
Innovation—Productivity					Period 0 (+) *Cumulative (+, NAS)*		Period 2 (+) *Cumulative (+, NAS)*
Exporting—Productivity							
Productivity—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Innovation—Exporting							
Exporting—Innovation							Period 1 (+) *Cumulative (+, NAS)*

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Firms that engaged in cooperation with other firms are firms that engaged in cooperation with customers, competitors or suppliers any time within the last three years.

Table 6-13. The links between innovation, exporting and productivity for firms that did not engage in cooperation with other firms, ***

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	10,292	10,355	10,355	10,231	6,922	6,922	10,360
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation							
Innovation—Productivity							
Exporting—Productivity							
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting			Period 2 (-) *Cumulative (+, NAS)*	Period 1 (+) *Cumulative (+/-, NAS)*			
Exporting—Innovation	Period 1 (-) *Cumulative (-, NAS)*						

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Firms that did not engage in cooperation with other firms are firms that did not engage in cooperation with customers, competitors or suppliers any time within the last three years.

***Table 6-14. The links between innovation, exporting and productivity for firms that engaged in cooperation with universities*, ***

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	3,841	3,893	3,890	3,733	2,608	2,608	3,900
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumultive (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Productivity—Innovation				Period 1 (+) *Cumulative (+, NAS)*			
Innovation—Productivity		Period 0 (+) *Cumulative (+, NAS)*			Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+)*
Exporting—Productivity							
Productivity—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Innovation—Exporting							
Exporting—Innovation							

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Firms that engaged in cooperation with universities are firms that engaged in cooperation with universities or technological centres any time within the last three years.

Table 6-15. The links between innovation, exporting and productivity for firms that did not engage in cooperation with universities, ***

Innovation variable	**R&D expenditures**	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Time period	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016	2001-2016
Number of observations	10,353	10,412	10,418	10,271	6,852	6,852	10,418
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:							
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation							
Innovation—Productivity				Period 1 (-) *Cumulative (-, NAS)*			
Exporting—Productivity							
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting	Period 0 (+) *Cumulative (+, NAS)*						
Exporting—Innovation	Period 3 (+) *Cumulative (-, NAS)*			Period 1 (-) *Cumulative (-, NAS)*			

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Firms that did not engage in cooperation with universities are firms that did not engage in cooperation with universities or technological centres any time within the last three years.

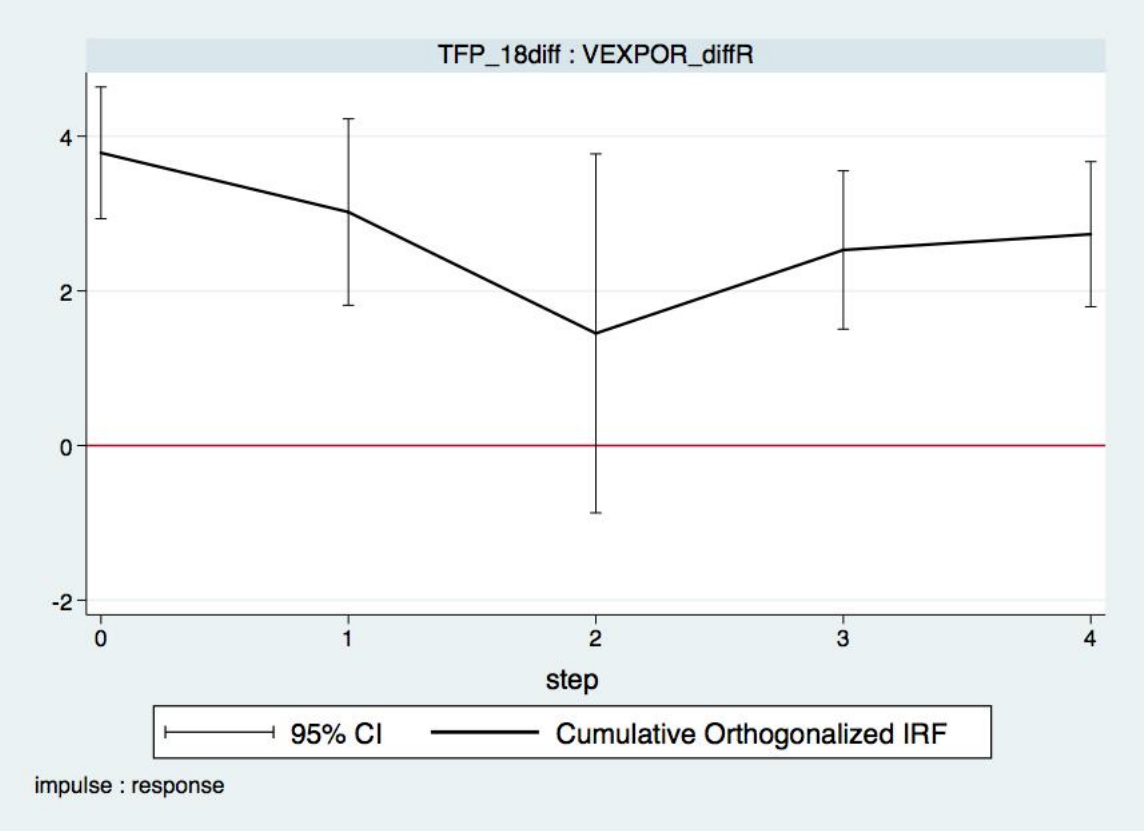
Tables 6.16 – 6.21 summarise the findings on the links between productivity, innovation and exporting. These tables contain the same information as Tables 6.4 – 6.15, but are reorganised for easier readability. Besides indicating (i) the context (i.e. subsample) in which a link is found, and (ii) the innovation measure used, the tables below present the statistical significance of IRFs and cumulative IRFs. Additionally, the tables are colour coded for easier readability – green represents a positive cumulative effect, red represents a negative cumulative effect, blue represents a mixed cumulative effect, while white represents no statistically significant link.

6.4.2 The link from productivity to exporting

Table 6.16 summarises the results of the link leading from productivity to exporting. This link is present in every estimation conducted and is typically positive, except in the context of small firms and low R&D performers, when marketing or organisational innovation are used as measures of innovation. This finding is in line with the seminal theoretical model devised by Melitz (2003) – discussed in Chapter 5 – suggesting that more productive firms engage in exporting. Additionally, the results from Table 6.16 confirm Greenaway and Kneller's (2007) observation that this link may be regarded as a stylised fact.

We quantitatively interpret one result from Table 6.16 as an illustrative example. The interpretation of the similar backwards link – from exporting to productivity – will be discussed in the following section, to compare and contrast the magnitude of the effects. The chosen link is the link when estimations are done for all firms and when organisation innovation was used as a measure of innovation. The cumulative effect is presented in Figure 6.17.

Figure 6-17. Cumulative IRF from productivity to exporting (organisational innovation used as a measure of innovation; all firms; 2001-2016)



As we can see from the Figure 6.17, by the end of period four, a positive shock of a standard deviation of the change in TFP (which, as detailed above, constitutes an increase in TFP of 7.6%) leads to an increase in difference in exporting per 1,000 hours worked of approximately 3,000 Euros per 1,000 hours worked. For a typical Spanish firm,[160] this leads to an increase in the value of exports of 1,125,300 Euros. Scaled against the mean level of value of exports, this represents 3.5% of the mean.

6.4.3 The link from exporting to productivity

Table 6.17 summarises the results on the link leading from exporting to productivity. This link is not systematically proven, but is context specific. Although the literature allows for the possibility of mixed findings on the link from exporting to productivity (Wagner, 2007; Aw et al., 2008; Atkin et al., 2017), it is striking that all the statistically significant results reported in Table 6.17 are negative. One interesting finding to note is the contrast between high and low R&D performers and high and low exporters. While this link is

[160] This result embraces both propensity and intensity of exporting. As discussed throughout Chapter 4, the literature suggests that underlying determinants of both are the same.

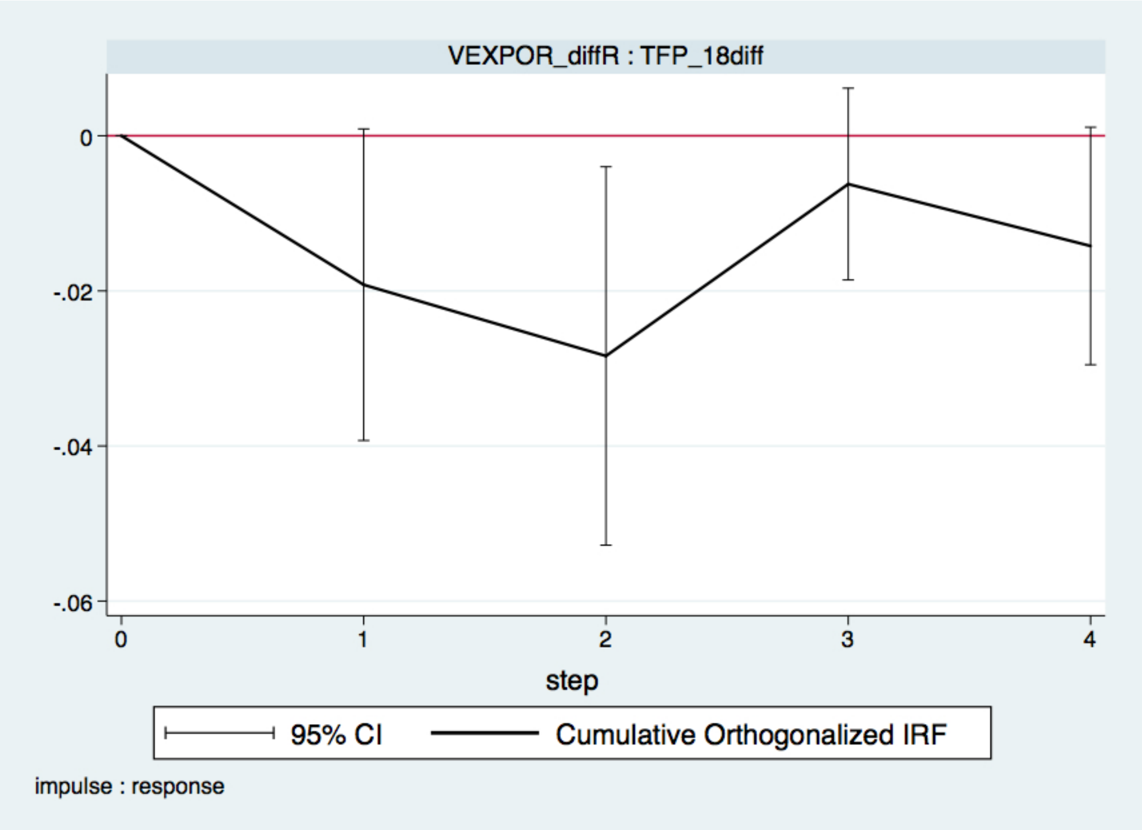
cumulatively negative for low exporters, it does not hold at all for high exporters. Informed by resource-based theories of the firm, we can conjecture that for low exporters the managerial effort directed at increasing exports is more likely to incur a substantial opportunity cost in terms of less effort devoted to productivity-enhancing measures, while increases in exports may be accomplished at lower cost by firms that are already high exporters and thus further up the relevant learning curve. Similar is true for high versus low R&D performers. Additionally, the negative link holds most prevalently in the context of organisational and marketing innovations. Here we may conjecture that both of these types of innovation may be required for a firm to increase exports, and thus may be particularly good contexts for highlighting the competing claims on resources of exporting and productivity-enhancing activities. The results in general suggest that there might be a trade-off between exporting and innovation activities for firms. Firms are in possession of limited resources and both innovation and exporting are costly and time-consuming activities, as discussed in Chapters 3 and 4. Although we cannot claim this within any degree of certainty, as the analysis does not explore underlying determinants of the variables of interest, the results might indicate that firms engage in both productivity-enhancing and exporting activities, but that these are constrained by the same resource base and are thus – at least to some extent – substitutes. This is especially true for small firms, which tend to be more resource constrained. For small firms, mixed results are obtained, partially supporting the claim.

We further conjecture that the evidence of a predominantly negative or weak influence of exports on productivity may reflect the limited time series depth in the available dataset. Starting with 16 years, we use up five years by (i) differencing our variables, (ii) allowing for two lags of each variable in the VAR, and (iii) the minimum feasible instrumentation (one and two lags of each differenced variable). In the context of our unbalanced dataset (in the full sample, the mean time-series depth is 5.8) it is thus not an option to add further lags.[161] However, as we noted earlier, Atkin (2017) finds that exports induce positive productivity effects over time. If so, then it is possible that two lags in the VAR is not sufficient to capture longer-run positive effects of exporting on productivity. This possibility carries a policy corollary, which we discuss later.

[161] Moreover, attempts to do so resulted in models that would not converge to a solution.

We are going to quantitatively interpret one result from Table 6.17 as an illustrative example. For comparative purposes, the chosen link, as in previous section, is the one when estimations are done for all firms and when organisation innovation was used as a measure of innovation. The cumulative effect is presented in Figure 6.18.

Figure 6-18. Cumulative IRF from exporting to productivity (organisational innovation used as a measure of innovation; all firms; 2001-2016)



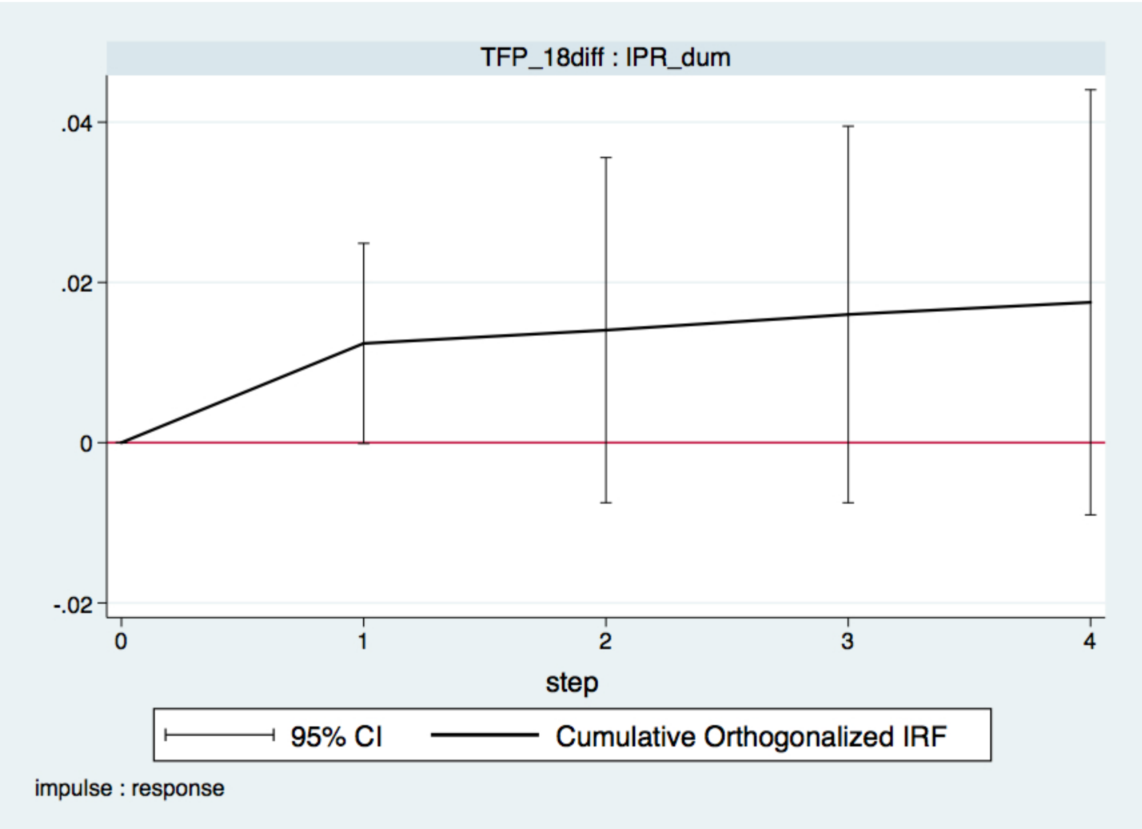
By the end of period four, the decrease in difference of TFP would be approximately -0.01 as a result of a standard deviation positive change to the difference of the value of exports per 1,000 hours worked. For a typical firm, this would results in an increase in the value of exports per 1,000 worked (scaled against the mean level) of 117.1%. The resulting decrease in TFP is 0.01 (or 0.14% of the mean level of TFP). What we can conclude from interpretations in this and the previous section is that a relatively large increase in TFP can lead to substantial increase in value of exports, whereas that enormous increase in value of exports leads to small decrease in TFP.

6.4.4 The link from productivity to innovation

Table 6.18 summarises results on the link from productivity to innovation, which is the only link that was not found in the literature discussed in Chapter 5. Correspondingly, the occurrence of this link in this dataset is episodic – it appears very rarely (in four from 84 estimates), although there is some evidence that it appears in the context of process innovation, small firms and firms that cooperate with other firms or universities. The positive link is expected on resource grounds – i.e. more productive firms can be expected to have lower resource constraints for investment in innovation. This might explain the small firm results (see Table 6.18).

One result from Table 6.18 will be interpreted as an illustrative example, although it has to be noted that the link is not statistically significant. The interpretation of the similar backwards link – from innovation to productivity – will be discussed in the following section, to compare and contrast the magnitude of the effects. The chosen link is the link when estimations are done for firms that cooperated with other firms and when process innovation was used as a measure of innovation. The cumulative effect is presented in Figure 6.19.

Figure 6-19. Cumulative IRF from productivity to innovation (process innovation used as a measure of innovation; firms that cooperated with other firms; 2001-2016)



The increase in TFP of approximately 7.6% (as discussed earlier) leads to an increase in process innovation of close to 0.02 (2 percentage point) or approximately 6.2% of the mean of process innovation dummy. This leads us to conclusion that large increase in TFP would potentially lead to a negligible increase in process innovations.

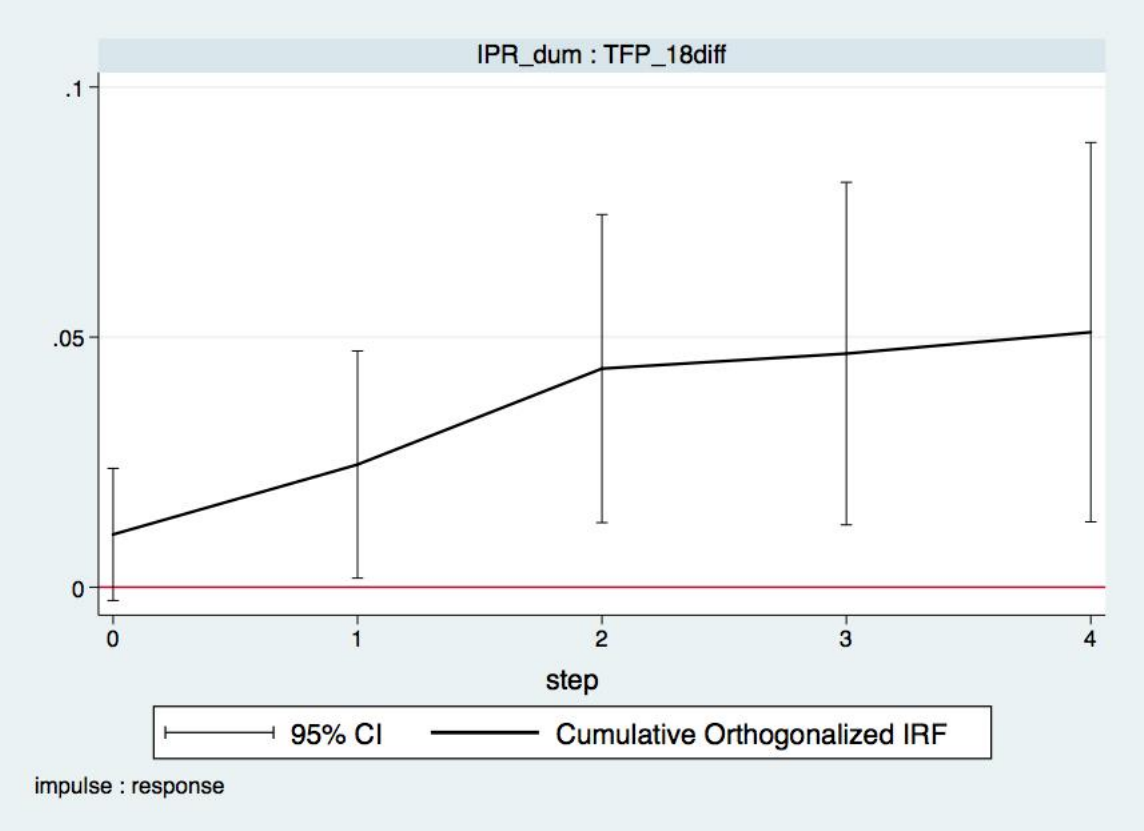
6.4.5 The link from innovation to productivity

Table 6.19 summarises the results on the links leading from innovation to productivity. The link shows up as significant in specific contexts and as both positive and negative. When the number of product innovations is used as the innovation measure, the link is negative for low R&D performers, low exporters and firms with no cooperation with universities and mixed for small firms. Low R&D performance and no cooperation with universities might indicate incremental rather than radical innovations. Therefore, one conjecture from this finding might be that incremental innovations do not uniformly lead to an increase in productivity. Conversely, positive or mixed effects of innovation on productivity reported for firms of all sizes registering patents outside Spain suggest that radical innovation does indeed increase productivity.

Additionally, interesting findings occur in the context of process and organisational innovation. For large firms and those that cooperate with other firms or universities, organisational innovation has a positive impact on productivity. Furthermore, for high R&D performers, as well as for firms that cooperate with other firms or universities, process innovation increases productivity. As both process and organisational innovation are related to an increase in the efficiency of production or the internal structures of firms, this finding is expected, especially when using TFP as the productivity measure.

One result from Table 6.19 will be interpreted as an illustrative example. The link that will be interpreted is when estimations are done for firms that cooperated with other firms and when process innovation was used as a measure of innovation. The cumulative effect is presented in Figure 6.20.

Figure 6-20. Cumulative IRF from innovation to productivity (process innovation used as a measure of innovation; firms that cooperated with other firms; 2001-2016)



The results suggest that a large increase in process innovation leads to an almost negligible increase in TFP. A positive shock of a standard deviation in process innovation, which approximately represents an increase in process innovation by approximately 145%, leads to an increase in TFP of approximately 0.05. For a typical firm, this represents a 0.7% increase in TFP (scaled against the mean value of TFP).

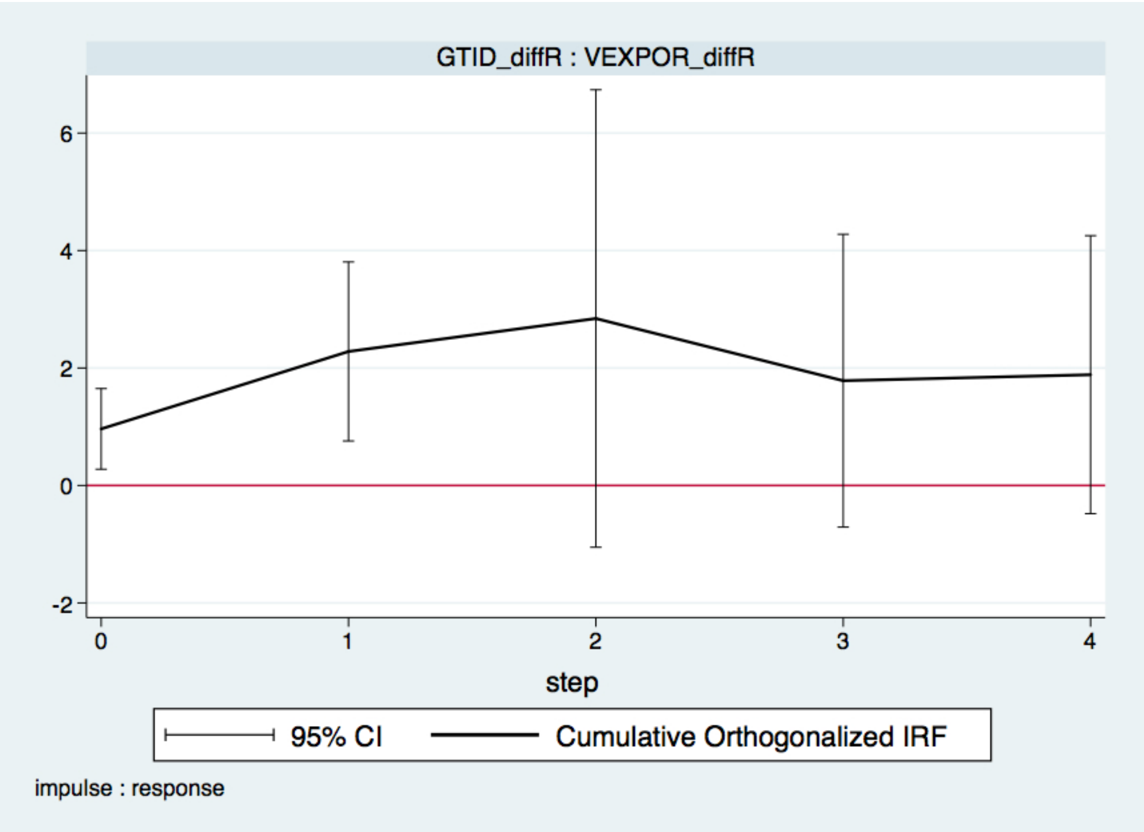
6.4.6 The link from innovation to exporting

The summary of the results on the link from innovation to exporting is presented in Table 6.20. Although the incidence of significant results is sporadic (six from 82 estimates) and the signs mixed (three positive and three negative), there is some limited evidence that radical innovation (associated with R&D expenditures and patents) leads to an increase in exporting. In the whole sample estimates, the cumulative effect of R&D expenditures on exporting is positive. This finding is in line with Caldera (2010). Similarly, cumulative effect of patents registered abroad for firms that do not engage in cooperation with other firms is positive. Unlike Basile (2001), Caldera (2010) or Becker and Egger (2013), there are no indications that product[162] or process innovations lead to an increase in exporting.

We have already conjectured that lack of a systematic positive effect of exports on productivity in our data might reflect the inability of our two-lag VAR to capture longer-run effects. The same conjecture may be made – perhaps even more strongly – in relation to the lack of a systematic positive influence of innovation on exporting. We have already recorded the observation of Hirsch and Bijaoui (1985) that R&D may affect export performance with a lag of four years. If so, then this effect may be – at least to some extent – beyond the range of our two-lag VAR.

We quantitatively interpret the link from innovation to exporting for firms that did not cooperate with universities and when R&D expenditures is chosen as a measure of innovation presented in Figure 6.21. It is noted that not link is not always statistically significant.

Figure 6-21. Cumulative IRF from innovation to exporting (R&D expenditures used as a measure of innovation; firms that did not cooperate with universities; 2001-2016)



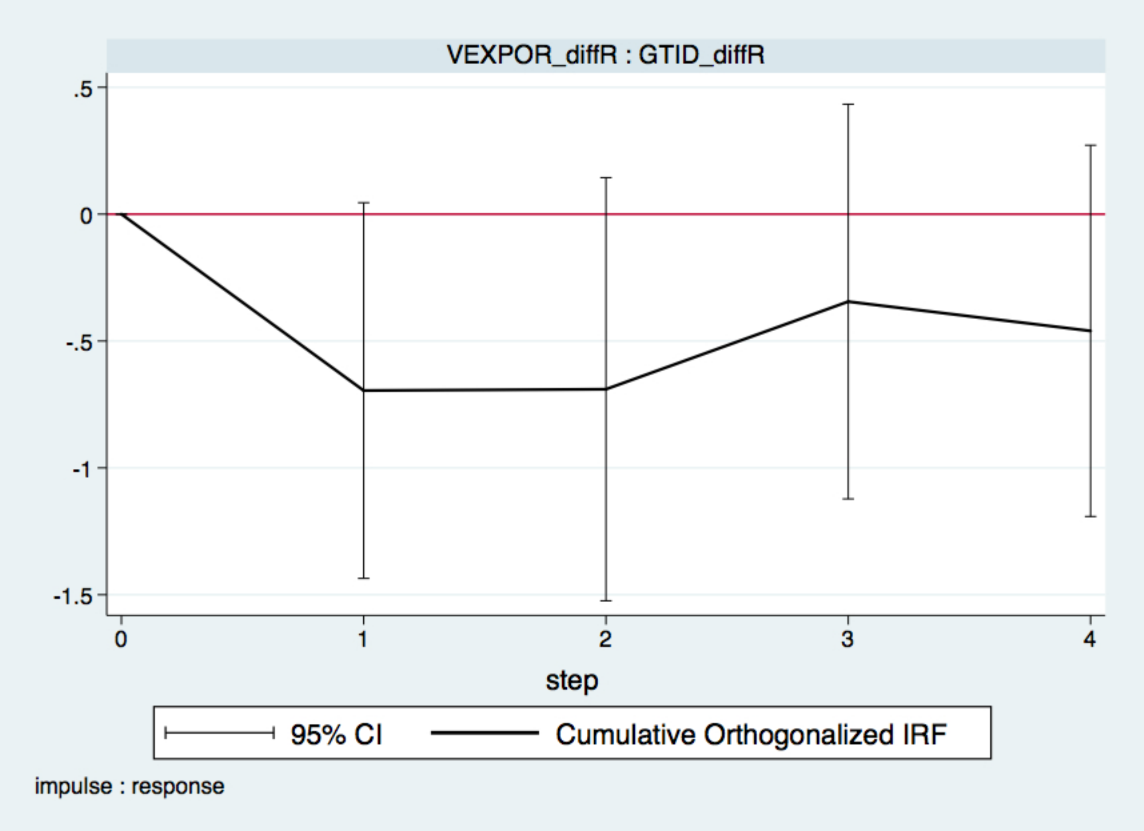
[162] The only significant result for product innovation is mixed.

A change in R&D expenditures of approximately 185% (scaled against the mean of R&D expenditures per 1,000 hours worked) leads to an increase in difference of value of exports by approximately 2,000 Euros per 1,000 hours worked by the end of period four. For a typical firm, this constitutes an increase in the value of exports of 750,200 Euros, which represents 2.3% of the mean value of exports. To achieve substantial increase in exports, a substantial increase in R&D expenditures is needed.

6.4.7 The link from exporting to innovation

Finally, Table 6.21 presents the summary of the results on the link from exporting to innovation. As for the link from innovation to exporting, the incidence of significant results is sporadic and the signs mixed. However, exporting tends to negatively affect R&D expenditures (for firms that do not engage in cooperation with firms or universities) and product innovations (for high R&D performers and firms that do not engage in cooperation with universities). These negative results suggest a trade-off for firms between innovation and exporting activities, perhaps due to the limited resources that firms possess and the nature of these activities. Conversely, exporting tends to lead to increase in marketing innovations (for medium and large firms). This finding is intuitive, as to be able to successfully sell their products, firms must engage in marketing activities and new markets might necessitate new marketing approaches.

Figure 6-22. Cumulative IRF from exporting to innovation (R&D expenditures used as a measure of innovation; firms that did not cooperate with universities; 2001-2016)



Quantitative interpretation of Figure 6.22 is provided below. An increase in the difference of value of exports per 1,000 hours worked of approximately 117% (scaled against the mean level value of exports) leads to a decrease in difference of R&D expenditure per 1,000 hours worked of 50 Euros per 1,000 hours worked. For a typical firm in the sample, this constitutes a decrease in R&D expenditures of 18,755 Euros, which represents 1,6% of the mean of R&D expenditures in the sample. Very large increase in the value of exports leads to a negligible decrease in R&D expenditures.

Table 6-16. The link from productivity to exporting

	R&D expenditures	Patents registered in Spain	Patents registered outside of Spain	Number of product innovations	Organisational innovations	Marketing innovations	Process innovations
Whole sample	Period 0 (+) *Cumulative (+, NAS)*	18Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Small firms	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Medium firms	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*
Large firms	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*
High R&D performers	***Not examined***	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Low R&D performers	***Not examined***	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 2 (-) *Cumulative (+/-, NAS)*	Period 0 (+), Period 2 (-) *Cumulative (+/-, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*
High exporters	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Low exporters	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Cooperation with firms	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
No cooperation with firms	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Cooperation with universities	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
No cooperation with universities	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*

Table 6-17. The link from exporting to productivity

	R&D expenditures	Patents registered in Spain	Patents registered outside of Spain	Number of product innovations	Organisational innovations	Marketing innovations	Process innovations
Whole sample					Period 3 (+) *Cumulative (-, NAS)*	Period 3 (+) *Cumulative (-, NAS)*	
Small firms	Period 2 (-) *Cumulative (+/-, NAS)*				Period 2 (-) *Cumulative (+/-, NAS)*	Period 2 (-) *Cumulative (+/-, NAS)*	
Medium firms					Period 1 (-) *Cumulative (-, NAS)*		
Large firms					Period 1 (-) *Cumulative (-, NAS)*		
High R&D performers	***Not examined***						
Low R&D performers	***Not examined***	Period 2 (-) *Cumulative (-, NAS)*			Period 3 (+) *Cumulative (-, NAS)*	Period 3 (+) *Cumulative (-, NAS)*	Period 2 (-) *Cumulative (-, NAS)*
High exporters							
Low exporters	Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+) *Cumulative (-, NAS)*	Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*
Cooperation with firms							
No cooperation with firms							
Cooperation with universities							
No cooperation with universities							

Table 6-18. The link from productivity to innovation

	R&D expenditures	Patents registered in Spain	Patents registered outside of Spain	Number of product innovations	Organisational innovations	Marketing innovations	Process innovations
Whole sample							
Small firms	Period 3 (-) *Cumulative (+, NAS)*						
Medium firms							
Large firms							
High R&D performers							
Low R&D performers							
High exporters							Period 1 (+) *Cumulative (+, NAS)*
Low exporters							
Cooperation with firms							Period 1 (+) *Cumulative (+, NAS)*
No cooperation with firms							
Cooperation with universities				Period 1 (+) *Cumulative (+, NAS)*			
No cooperation with universities							

Table 6-19. The link between innovation and productivity

	R&D expenditures	Patents registered in Spain	Patents registered outside of Spain	Number of product innovations	Organisational innovations	Marketing innovations	Process innovations
Whole sample							
Small firms			Period 0 (+) *Cumulative (+, NAS)*	Period 1 (-) *Cumulative (+/-, NAS)*			
Medium firms			Period 1 (-) *Cumulative (+/-, NAS)*				
Large firms			Period 1 (+) *Cumulative (+/-, NAS)*		Period 0 (+) *Cumulative (+, NAS)*		
High R&D performers	***Not examined***						Period 0 (+), Period 1 (+) *Cumulative (+, NAS)*
Low R&D performers	***Not examined***		Period 0 (+) *Cumulative (+, NAS)*	Period 1 (-), Period 3 (-) *Cumulative (-, NAS)*			
High exporters		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*				
Low exporters	Period 2 (+) *Cumulative (+, NAS)*			Period 1 (-) *Cumulative (-, NAS)*			
Cooperation with firms					Period 0 (+) *Cumulative (+, NAS)*		Period 2 (+) *Cumulative (+, NAS)*
No cooperation with firms							
Cooperation with universities		Period 0 (+) *Cumulative (+, NAS)*			Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+)*
No cooperation with universities				Period 1 (-) *Cumulative (-, NAS)*			

Table 6-20. The link from innovation to exporting

	R&D expenditures	**Patents registered in Spain**	**Patents registered outside of Spain**	**Number of product innovations**	**Organisational innovations**	**Marketing innovations**	**Process innovations**
Whole sample	Period 1 (+) *Cumulative (+, NAS)*						
Small firms							
Medium firms							
Large firms							
High R&D performers	***Not examined***						
Low R&D performers	***Not examined***				Period 2 (+) *Cumulative (+/-, NAS)*		
High exporters							
Low exporters					Period 0 (+) *Cumulative (+)*		
Cooperation with firms							
No cooperation with firms			Period 2 (-) *Cumulative (+, NAS)*	Period 1 (+) *Cumulative (+/-, NAS)*			
Cooperation with universities							
No cooperation with universities	Period 0 (+) *Cumulative (+, NAS)*						

Table 6-21. The link from exporting to innovation

	R&D expenditures	Patents registered in Spain	Patents registered outside of Spain	Number of product innovations	Organisational innovations	Marketing innovations	Process innovations
Whole sample							
Small firms							
Medium firms	Period 2 (+) *Cumulative (+/-, NAS)*					Period 1 (+) *Cumulative (+, NAS)*	
Large firms						Period 1 (+) *Cumulative (+, NAS)*	
High R&D performers	***Not examined***			Period 1 (-) *Cumulative (-, NAS)*			
Low R&D performers	***Not examined***						
High exporters							
Low exporters					Period 1 (-) *Cumulative (-, NAS)*		
Cooperation with firms							Period 1 (+) *Cumulative (+, NAS)*
No cooperation with firms	Period 1 (-) *Cumulative (-, NAS)*						
Cooperation with universities							
No cooperation with universities	Period 3 (+) *Cumulative (-, NAS)*			Period 1 (-) *Cumulative (-, NAS)*			

6.5 Conclusion

This chapter offers the most comprehensive exploration of the productivity-innovation-exporting nexus done so far. Compared to the studies in the literature, this chapter:

- Treats all three variables as endogenous, taking into account the possibility that they all might affect each another;
- Carefully considers not only the direction, but also the strength and the timings of the links;
- Utilises a longer dataset and, compared to at least some previous studies, a more comprehensive dataset (i.e., it does not focus on a subset of SMEs or large firms);
- Explores whether events such as the GFC impact the nature of the links as well as potential sectoral heterogeneities;
- Explores the extent to which the links are context specific by using different subsamples;
- Thoroughly considers and contrasts choices of deflators for the variables used;
- Utilises numerous measures of innovation; and
- Utilises both labour productivity and TFP as measures of productivity.

This chapter suggests that the choice of the deflators – between CPI and industry specific indices – is a minor issue in empirical investigations, considering large correlations between variables deflated using both. Additionally, the chapter suggests that for the strongest and most prevalent link in the productivity – innovation – exporting nexus, the choice between innovation input and innovation output, or different productivity measures is not important as the findings hold regardless.

Figure 5.1 from the previous chapter presents the state of the literature with regards to the productivity-innovation-exporting nexus. The literature suggests that all the links are present, apart from the link leading from productivity to innovation. The empirical literature suggests that the strongest link should the one leading from innovation to exporting, while the theoretical literature suggests that it should be the one leading from productivity to exporting. Figure 6.23 summarises the findings from the empirical investigation in this chapter in a similar fashion as Figure 6.1 summarises findings from the literature. The thickness of the arrows in Figure 6.23a/b indicates the strength of the links between productivity, innovation and exporting, while the number of positive, negative and mixed results is reported on the arrow. The total empirical investigations summarised in Figure 6.23a is 312 (including both labour productivity and TFP estimates) and in Figure 6.23b 82 (only TFP estimates).[163] It is important to emphasise that for the results, not only statistical significance, but also economic substance was taken into account. Besides the influence of each of the variables on itself, the most prevalent link that holds true regardless of the context is the one leading **from productivity to exporting**. This offers strong empirical support to the Melitz (2003) theoretical model. Also, this result offers strong support for economic reasoning that "law-like" relationships do occur in social contexts, as this link holds regardless of the context in which it was investigated. The findings of this chapter are in sharp contrast to the empirical literature exploring the productivity-innovation-exporting nexus, as the link leading **from innovation to exporting** is relatively less well supported, although this link predominantly positive as expected. Additionally, all other links, apart from the one leading from productivity to exporting are highly context specific. Another important finding emerges here in relation to the discussion in Chapter 5 related to the systems-approach and the existence of feedback effects. This empirical investigation clearly shows that feedback effects are not guaranteed and if they occur, are often negative. The results from this chapter suggest that moderating effects – and indeed all of the moderating explored with TFP estimates – have a significant role in productivity-innovation-exporting nexus.

[163] Sectoral and state of the market investigations, as well as estimations where there was no observations were excluded.

Figure 6-23a. Summary of findings for both labour productivity and TFP estimates (statistically significant estimates)

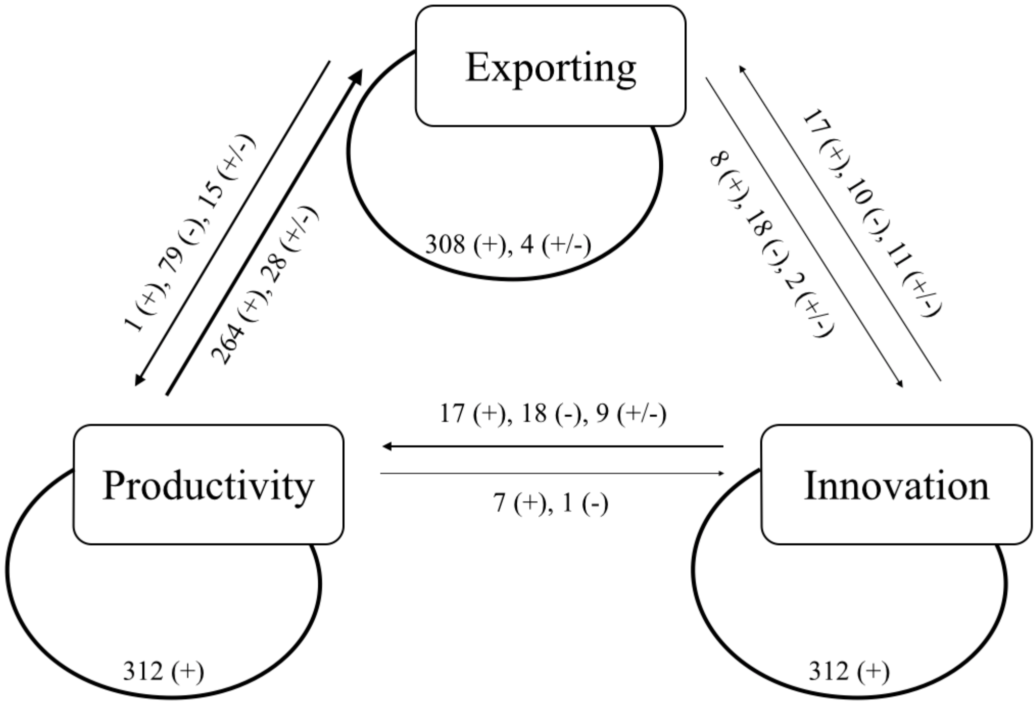
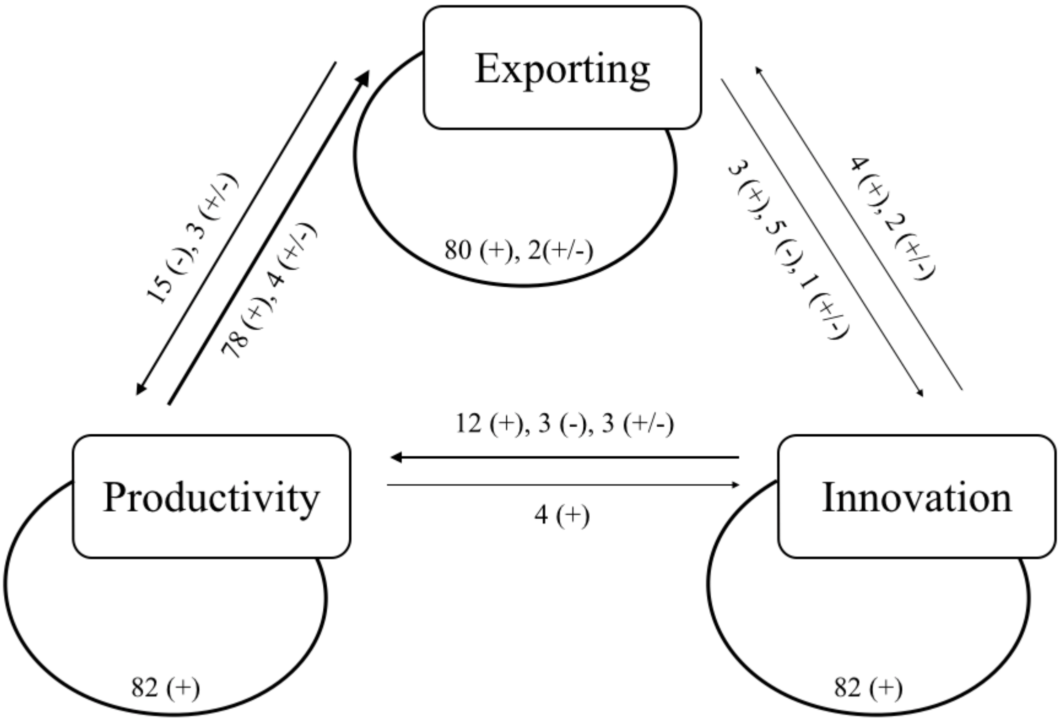


Figure 6-23b. Summary of findings for TFP estimates (statistically significant estimates)



A limitation of this study has already been acknowledged while discussing the findings reported in this Chapter. This is the possibility that two of the links – i.e., **from exports to productivity** and **from innovation to exporting** – may be underrepresented in our findings, because each of them may be subject to longer lags than can be detected by our two-lag (differenced) VAR. Indeed, the same consideration may also apply to the link **from innovation to productivity**, which although mainly positive where it does appear is likewise underrepresented in our findings. Hirsch and Bijaoui (1985, pp. 244-245) note that: "… some time must elapse before an investment in an R&D project yields tangible results in the form of new products or new processes." Accordingly, "some time" is required before innovation activity may influence productivity and/or exports. Allowing for uncertainty regarding how much time is needed to test these conjectured longer-run effects, to investigate these conjectured longer-run effects with panel VAR models will require a dataset with a considerably extended time dimension.

7. Innovation policies

7.1 Introduction

This chapter explores innovation policies and different approaches to the evaluation of innovation policies. It builds on the discussions from Chapter 3 on innovation and will serve as the basis for the empirical investigation in Chapter 8 that will examine the effectiveness of R&D tax credits and compare the prevalent approaches to the evaluation of R&D tax credits.

Both theory and evidence suggest presence of underinvestment in R&D in comparison to socially optimal levels. Public support provided for business R&D is usually justified by differences between the private and social rate of return on R&D investments (Jones and Williams, 1999; Hall and Van Reenen, 2000; Corchuelo and Martinez-Ros, 2010; Czarnitzki et al., 2011; Yang et al., 2012). Among the OECD economies, tax credits are an increasingly important – and, in some countries, the dominant – policy instrument for promoting business R&D (OECD, 2019). In the UK, for example, according to the latest statistics, the annual cost of R&D tax credits was £3.5 billion for 2016-2017 (HMRC, 2018). Evaluating the effectiveness of R&D tax credits is thus a challenge of prime importance.

Section 7.2 discusses the rationale and aims of government support for innovation. Section 7.3 examines approaches to the evaluation of R&D tax credits. Section 7.4 concludes.

7.2 The rationale for and aims of government support for innovation

The provision of support for innovation aims to motivate firms to start investing or increase their investments in innovation inputs. Consequently, this investment into innovation inputs can translate into increased capabilities of the firm, innovation outputs and better overall performance of a firm (Becker, 2019). Becker (2019) identifies four distinct mechanisms through which policy can lead to an increase in R&D, innovation and economic performance:

1. The provision of financial support to the firms increases their liquidity and the available resources allocated to innovation. Furthermore, Becker (2019)

suggests that this relationship may be of an inverted U-shaped form as an abundance of resources can make firms less prone to take risks;

2. Besides decreasing the amount of financial resources needed for the investment in R&D and innovation at the firms' end, public support for R&D and innovation also leads to the de-risking of the investment regarding "technologies involved and commercial profitability" (p. 2);
3. The support for R&D and innovation can act as a market-making mechanism initially triggered to address social or economic challenges, as will be discussed in more detail below;
4. The support can unlock access to knowledge for firms, which was unavailable to the firms beforehand.

The dominant economic paradigm argues that private R&D has the characteristics of a public good – being non-excludable in the absence of institutional constraints and to a certain extent non-rivalrous (Hall, 2006; NESTA, 2009; Becker, 2013; WWCLEG, 2015; Becker, 2019). Positive externalities arise when the private and social rates of return to R&D differ (NESTA, 2009; Becker, 2013) and, in the case of R&D, social rates of return tend to be higher than private rates of return due to knowledge spillovers – firms are unable to appropriate all the benefits that result from their investment (Jones and Williams, 1998; Becker, 2019; Bloom et al., 2019). Jones and Williams (1998) construct a theoretical model and using estimates from previous empirical research to operationalise their model, they show that there is likely to be considerable underinvestment in R&D compared to the socially optimal levels – the actual level being two to four times lower than the socially optimal level. Knowledge spillovers are one of the market failures on the basis of which government support for innovation is argued. The second market failure is asymmetric information that results from secrecy around R&D and innovation projects that firms wish to retain when searching for funding for their projects (Bloom et al., 2019). However, Bloom et al. (2019, p. 168) conjecture that the second market failure might not be a sufficient reason to justify the use of innovation policies by governments, as "governments often have worse information about project quality than either firms or investors, so designing appropriate policy interventions is difficult". Furthermore, supporting strategic aims – i.e. for the purposes of international comparisons among countries or achieving proficiency in different sectors, technologies or locations – can serve as a justification for public support for R&D (NESTA, 2009; Becker, 2019).

In the systems of innovation approach, policy is not necessarily about fixing market failures, but "partly a question of supporting interactions in a system that identify existing technical and economic opportunities or create new ones" (Edquist and Hommen, 1999). There are different definitions of national innovation systems, as discussed in Chapter 3, and the design of support depends on the exact definition involved (Chaminade et al., 2018). Chaminade et al. (2018) distinguish between: (i) reactive policies, whose primary aim is fixing systemic failures and keeping the path of innovations unchanged; and (ii) proactive policies, aimed at shifting innovation in certain, new direction(s). Recent thinking on innovation policy is in line with proactive policies and is led by Mazzucato (2018) who argues that governments that aim to shape the markets and innovation directions need to move away from fixing market and institutional failures (Kattel and Mazzucato, 2018). Mazzucato argues for mission-oriented policies, where governments are envisaged to be the leading actors in directing innovations. The argument for such an approach is based on the premise that historically governments were successful in leading truly radical innovations (platform-based technologies or technological revolutions, as explained in the earlier text) (Chaminade et al, 2018).[164]

Innovation policies can be classified into two broad categories according to their orientation: (i) supply-side orientated policies, which include R&D tax incentives and subsidies; and (ii) demand-side oriented policies, which include public technology procurement (Edquist and Hommen, 1999). The two most commonly used innovation policies are R&D tax credits and R&D subsidies. R&D subsidies are a direct policy, where funds are assigned by policy makers for specific innovative projects of their choice. R&D tax credits are an indirect innovation policy that are aimed at boosting R&D expenditures through lowering after-tax costs of R&D for firms (Hall and Van Reenen, 2000). R&D tax credits are non-discretionary and – subject to eligibility – universal (WWCLEG, 2015; Dechezlepretre et al., 2016). Projects with the largest

[164] Some examples of government-sponsored R&D are "jet engines, radar, nuclear power, the Global Positioning System (GPS), and the internet" (Bloom et al., 2019, p. 166).

returns for an individual firm are supported by R&D tax credits, whereas those with the largest social returns tend to receive subsidies (Hall and Van Reenen, 2000; WWCLEG, 2015). Policy inefficiencies are likely to be lower for R&D tax credits compared to R&D subsidies, as subsidies “are highly dependent on the information available to the policy makers that manage the R&D programme and the strategic priorities set by these” (Castellacci and Lie, 2015, p. 820). The effectiveness of the two policies differs too. While the impact of tax credits can be seen in the short run, the impact of subsidies is generally observable only in the medium to long run (Becker, 2013).

7.3 Approaches to evaluation of innovation policies

The literature dealing with the evaluation of the effectiveness of R&D tax credits on business R&D, innovation and economic performance outcomes can be divided into two streams, according to the approach to evaluation used:

1. **Approach 1 (Additionality approach)**. The literature that applies standard policy-evaluation instruments and in order to account for R&D tax credits uses a dummy variable to indicate whether the firm has taken advantage of a R&D tax credit or not. Alternatively, the value of the credit granted to the firm can be used. The datasets used when applying this approach include both firms that received the R&D tax credit and those that did not. A representative model for Approach 1 is provided by Yang et al. (2012):[165]

$$R_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 X_{it} + \beta_3 Z_{i,t-1} + f_i + \varepsilon_{it} \qquad (7.1)$$

where R_{it} represents R&D expenditure of firm *i* at time *t*; T_{it} the remit of taxation by R&D tax credits for firm *i* at time *t*; X_{it} are control variables for firm *i* at time *t* (i.e. age of a firm); $Z_{i,t-1}$ are control variables for firm *i* at time *t-1* (i.e. profitability of a firm, size of a firm, capital intensity of a firm, exports of a firm);[166] f_i are the time invariant fixed effects for firm *i*; and ε_{it} is the error term for firm *i* at time *t*. In

[165] The original notation from Yang et al. (2012) was changed to enable easier comparability between representative models for Approach 1 and Approach 2.
[166] Some of the explanatory variables are lagged in order to deal with their potential endogeneity.

the literature, the model is estimated both as static and dynamic (Dimos et al., 2022). Estimated as a log-log-linear model,[167] the coefficient β_1 is a direct estimate of the constant elasticity of R&D expenditure with respect to R&D tax credit received by firm i. The estimated elasticity and the mean values of R&D expenditures and tax credits are used to calculate the additionality ratio (Yang et al., 2012).

2. **Approach 2 (User-cost approach)**. The literature that applies standard policy-evaluation instruments and in order to account for R&D tax credits calculates the user-cost of R&D. A representative model in Approach 2 is provided by Fowkes et al. (2015):[168]

$$R_{it} = \beta_1 R_{i,t-1} + \beta_2 C_{it} + \beta_3 X_{it} + f_i + \varepsilon_{it} \tag{7.2}$$

where $R_{i,t-1}$ is the R&D expenditure of firm *i* at time *t-1*; C_{it} the user-cost of R&D for firm *i* at time *t*, X_{it} are control variables for firm *i* at time *t* (e.g. lagged R&D, turnover, liquidity ratio, real interest rate, etc.); f_i are the fixed effects for firm *i* (e.g. availability of scientists, ability of managers employed by a firm, wider macroeconomic factors); and ε_{it} is the error term for firm *i* at time *t*. Due to the large variations in their R_{it} variable, Fowkes et al. (2015) estimated a double-logarithmic linear model, in which the coefficient β_2 is "the short-run elasticity of R&D investment with respect to the user cost of R&D" (Fowkes et al., 2015, p. 38). The calculated additionality ratio (defined by Fowkes et al. (2015, p. 45) as: "the additional spending on R&D from an increase in the tax credit over the additional cost in foregone tax revenue") requires a series of supplementary calculations, which will be described in more details below.

Studies applying Approach 2 use datasets consisting only of firms that claimed R&D tax credits. This can lead to overestimation of the effectiveness of R&D tax credits (Kohler et al., 2012).

[167] Yang et al. (2012) specify the following variables in logarithmic terms: R_{it}, T_{it}, and some of the variables contained in $X_{i,t-1}$ (i.e. size of a firm, capital intensity of a firm and exports of a firm).

[168] The original notation from Fowkes et al. (2015) was changed to enable easier comparability between representative models for Approach 1 and Approach 2.

Some discussion of why one approach may be preferred over the other does appear in the literature, but infrequently and – even when undertaken – is far from exhaustive, to the best of our knowledge. Hall and Van Reenen (2000) suggest that the advantages of Approach 2 compared to Approach 1 are two-fold: better grounding in economic theory; and that the direct response to the price of R&D is estimated. However, their second criticism towards Approach 1 is only valid when a tax credit dummy variable, rather than the value of R&D tax credits is used. Yet, the user-cost approach can suffer from problems, ranging from relabelling other expenses as R&D to relying only on time variation for estimation (Hall and Van Reenen, 2000; Connell, 2021). The same paper also discusses Approach 1 when using dummy variable for R&D tax credit. The relative simplicity of this approach is listed on the advantages side, while imprecision and the inability to separately identify the credit dummy and the time dummies is listed on the disadvantages side (Hall and Van Reenen, 2000).

Comparison of findings in the literature are sometimes not straightforward even when the same approach is applied, due to different foci of the studies (e.g. examination of the impact of R&D tax credits on innovation outcomes rather than R&D expenditures). The studies using Approach 2 tend to report high additionality ratios (Connell, 2021), as will be discussed later. For example, Yang et al. (2012) evaluated the effectiveness of Taiwanese R&D tax credit policy using Approach 1 and found that a dollar of tax foregone leads to 0.094 dollars of additional R&D expenditure, while HMRC (2010), Fowkes et al. (2015) and Dechezlepretre et al. (2016) evaluated the effectiveness of the UK R&D tax credits policy using Approach 2 and reported that one pound of tax revenue spent on R&D tax credits generates between 0.41 and 3.37 pounds of additional R&D expenditures. The results using Approach 1 are generally not reported in terms of additionality ratios. However, it can be noted that the results obtained using Approach 1 vary greatly across different studies.

Table 7.1 provides a summary of findings from the studies applying different approach to evaluation of the effectiveness of R&D tax credits.

Table 7-1. Summary of findings of the previous studies regarding the effectiveness of R&D tax credits

Paper	Dataset used	Methods used	Results
APPROACH 1: NON USER-COST APPROACH			
Corchuelo, M., Martinez-Ros, E. (2010) 'Who benefits from R&D tax policy?', ***Cuadernos de Economía y Dirección de la Empresa*****, 13(45), pp. 145-170.**	▪ Spanish Business Strategy Survey for 2002 (some variables measured for the period 1998 to 2002)	▪ Matching estimators (nearest neighbour, Kernel-based matching) ▪ Heckman's two-step selection model	▪ Sample average of treatment effect on treated firms of tax incentives on R&D technological effort (R&D spending over sales) are significant and range from 0.67 to 0.87 depending on whether a full sample is used or sub-samples of large firms or SMEs; ▪ The coefficients on the log of B-index[169] variable in *t-1* period (used "to obtain the elasticity of R&D effort due to the tax benefit" (Corchuelo and Martinez-Ros, 2010, p. 159)) obtained in the second step of Heckman selection model where the dependent variable is log of R&D technological effort for the firms that know about the tax incentives range from -0.43 and -0.78, depending on the sample used, when significant;

[169] B-index variable represents "the firm's minimum profit expected to obtain from investing in R&D, allowing for tax incentives" (Corchuelo and Martinez-Ros, 2010, p. 156).

Paper	Dataset used	Methods used	Results
			▪ The coefficients on the log of B-index variable in *t-1* period obtained in the second step of Heckman selection model, where dependent variable is log of R&D technological effort for the firms that conduct R&D and know about the tax incentives, range from -0.49 and -0.89, depending on the sample used, when significant.[170]
Czarnitzki, D., Hanel, P., and Rosa, J. (2011) 'Evaluating the impact of R&D tax credits on innovation: A microeconometric study on Canadian firms', *Research Policy*, 40(2), pp. 217-229.	▪ Canadian 1999 Survey of Innovation – manufacturing firms	▪ Matching (nearest neighbour)	▪ Introduction of world-first and Canada-first innovations are affected by R&D tax credits scheme; ▪ 17% and 40% of the firms that received the credit introduced world-first and Canada-first innovation, while in the case of not receiving the credit, the percentages would be 5% and 22% respectively; ▪ Comparable results are obtained when looking at the sample of innovators only.

[170] Although the reported signs on the coefficients when using different methods are not the same, the authors report the results as similar.

Paper	Dataset used	Methods used	Results
Cappelen, A., Raknerud, A., and Rybalka, M. (2012) 'The effects of R&D tax credits on patenting and innovations', *Research Policy*, 41(2), pp. 334-345.	▪ Norwegian micro data – firms included in 2001 and 2004 CIS (CIS 3 and CIS 4); ▪ Tax Register; ▪ The Register of Employers and Employees; ▪ The National Education Database	▪ Probit ▪ Logit	▪ The coefficients of the impact of R&D tax credits scheme (dummy variable) on patenting applications range from 0.24 to 1.10 in different specifications, but are insignificant; ▪ The coefficients of the impact of R&D tax credit scheme (dummy variable) on introduction of a new products for the firm range from 1.48 to 1.68 in different specifications, but are not always significant; ▪ The coefficients of the impact of R&D tax credit scheme (dummy variable) on introduction of a new products for the market range from 1.10 to 1.51 in different specifications, but are not always significant; ▪ The coefficients of the impact of R&D tax credit scheme (dummy variable) on introduction of new production processes range from 1.27 to 1.88 in different specifications, but are not always significant.
Chiang, S., Lee, P., and Anandarajan, A. (2012) 'The effect of R&D tax credit	▪ Firms' annual reports for electronics firms listed on	▪ Regression analysis (no further details	▪ The coefficients in the regressions of R&D tax credit (defined as ratio of R&D tax credit to sales) on R&D investment

Paper	Dataset used	Methods used	Results
on innovation: A life cycle analysis', *Innovation: Management, Policy and Practice*, 14(4), pp. 510-523.	the Taiwan Stock Exchange or Taiwan's Over-the-Counter Market from 2002-2007; ▪ Taiwan Economic Journal database; ▪ The Market Observation Post System	provided in the paper)	(defined as the change in R&D from year *t-1* to year *t* divided by total assets at the beginning of year *t*) range from 0.0868 to 0.7237 in different specifications.
Yang, C., Huang, C., and Hou, T. (2012) 'Tax incentives and R&D activity: Firm-level evidence from Taiwan', *Research Policy*, 41(9), pp. 1578-1588.	▪ Panel dataset of manufacturing firms listed on the Taiwan Stock Exchange over the period 2001-2005 – large and medium enterprises	▪ Non-parametric propensity score matching ▪ Panel instrumental variable and GMM techniques	▪ Instrumental variable approach: ○ The estimated elasticity of R&D expenditures with respect to tax credits is 0.302 for all firms and 0.370 for electronics firms; ▪ GMM: ○ 0.08% growth on R&D expenditure growth results from 1% growth in tax credits. This effect is more pronounced for electronics firms;

Paper	Dataset used	Methods used	Results
			▪ 0.094 dollars (0.120 for electronics firms) of extra R&D expenditure results from one dollar of tax foregone.
Foreman-Peck, J. (2013) 'Effectiveness and efficiency of SME innovation policy', *Small Business Economics*, 41(1), pp. 55-70.	▪ Fourth Community Innovation Survey for UK for 2002-2004	▪ Matching (nearest neighbour) ▪ Probit ▪ Instrumental variable approach ▪ OLS	▪ Impact of state aid on innovation by SMEs: ○ The results show that the effects of tax credits are not significantly different from non-tax credit innovation aid (0.296 compared to 0.298, respectively) for unweighted estimates. The difference is slightly larger for weighted estimates (0.303 for tax credit and 0.274 for non-tax credit innovation aid); ○ The coefficient for tax credits in probit estimates is 0.1872, while the coefficient for the other UK state aid is 0.2291; ▪ The calculated return to the state aid in terms of GDP is £1,180 million per annum in 2002 prices, while the costs of SME innovation policy were £320 million per annum.

Paper	Dataset used	Methods used	Results
Lenihan et al. (2022) 'R&D Grant and Tax Credit Support for Foreign-Owned Subsidiaries: Does It Pay Off?', *ZEW Discussion Paper No. 22-003.*	▪ Panel dataset for Ireland (2007 – 2016)	▪ Propensity Score Matching	▪ Positive influence of domestic R&D tax credits is found for both domestic firms and foreign owned firms; ▪ Lenihan et al. (2022) find the treatment effect of €0.677 million for foreign-owned treated firms.
APPROACH 2: USER-COST APPROACH			
Bloom, N., Griffith, R., and Van Reenen, J. (2002) 'Do R&D tax credits work? Evidence from a panel of countries 1979-1997', *Journal of Public Economics*, 85(1), pp. 1-31.	▪ Annual "Doing business…" guides by Price Waterhouse – for details on the tax system; ▪ ANBERD – data on business enterprise R&D; ▪ MSTI; ▪ OECD STAN – information on value-added	▪ OLS ▪ Instrumental variable approach	▪ The elasticity of R&D user cost with respect to R&D is slightly above -0.1 and the long-run elasticity of user-cost on R&D spending is approximately -1.
HMRC (2010) *An evaluation of research and development tax credits*	▪ HMRC data – R&D tax credit claims; ▪ Company accounts data	▪ Arellano-Bond estimator	▪ Between £0.41 and £3.37 of R&D investment results from £1.0 of tax revenue spent on tax credits.

Paper	Dataset used	Methods used	Results
		▪ Blundell-Bond estimator	
Fowkes, R., Sousa, J., and Duncan, N. (2015) 'Evaluation of research and development tax credit', *HMRC Working Paper 17.*	▪ Company Tax Returns (CT600) – the data on R&D expenditure; ▪ Financial Analysis Made Easy (FAME) – the data on turnover, profits, number of employees and liquidity ratio; ▪ ONS's Inter-Departmental Business Register (IDBR) survey and data provided by firms to Companies House – in order to assign firms to SIC 2007 sector	▪ OLS ▪ FE estimator ▪ Arellano-Bond estimator	▪ The estimated elasticity of user-cost with respect to R&D expenditure ranges from -1.09 to -1.96 (with lower estimates produced when proxy for credit conditions is included); ▪ The calculated additionality ratios equal 2.35 for large firms, 1.88 for SMEs that are making enhanced deduction claim and 1.53 for SMEs that are making credit claim.

Paper	Dataset used	Methods used	Results
Dechezlepretre, A., Einio, E., Martin, R., Nguyen, K., and Van Reenen, J. (2016) 'Do tax incentives for research increase firm innovation? An RD design for R&D', *CEP Discussion Paper No 1413*.	▪ HMRC Corporate Tax Returns (CT600) and the extension, Research and Development Tax Credits (RDTC) dataset between 2006 and 2011; ▪ Bureau Van Dijk's FAME dataset; ▪ PATSTAT	▪ Regression discontinuity design	▪ The results show that R&D tax credits: o Leads to the causal annual effect on R&D of £138,500 per firm; o Leads to the average increase in patenting of 0.073 patents per year per firm; o Did not cause a decrease in innovation quality; o Stimulated £1.7 of R&D per every £1.0 of the subsidy; o Led to positive effects on TFP, sales and employment; ▪ R&D tax-price elasticity ("the percentage increase in R&D capital with respect to the percentage increase in the tax-adjusted user-cost of R&D capital" (Dechezlepretre et al., 2016, p. 17)) of R&D is 2.6. The authors further note: "The estimated R&D tax-price elasticity of 2.6 implies that a firm entering the SME scheme as a result of the new threshold increases its R&D by 84% of its pre-policy level in the tax

Paper	Dataset used	Methods used	Results
			deduction case, and 109% of its pre-policy R&D in the payable tax credit case" (Dechezlepretre et al., 2016, p. 20).
Scott and Glinert (2020) 'Evaluation of the Research and Development Expenditure Credit (RDEC)', *HMRC Working Paper 20*.	▪ Administrative data from corporate tax returns for the UK from 2010/2011 – 2017/2018	▪ Ordinary least squares, ▪ Fixed effects, ▪ Arrelano-Bond	▪ The preferred model estimates result in additionality ratio between 2.4 – 2.7.

7.3.1 Conceptualisation of the user-cost of R&D

Creedy and Gemmell (2017, p. 201) point out that "user cost relates to the rental, the rate of return to capital, that arises in a profit maximising situation in which further investment in capital produces no additional profit". The formula for the user-cost of R&D is based on Hall and Jorgenson's (1967) paper *Tax policy and investment behaviour* (Bloom et al., 2002). Underlying Equation (7.3) is the neoclassical theory of optimal capital accumulation, from which Hall and Jorgenson (1967) derived a formula for the implicit rental value of capital services under static expectations.[171] The formula is:

$$c = q(r + \delta)\frac{(1 - k)(1 - uz)}{(1 - u)} \tag{7.3}$$

where c represents the cost of capital services; q the price of capital goods; r the discount rate; δ the rate of replacement; k the tax credit rate; u the tax rate on business income; and finally, z "the present value of the depreciation deduction on one dollar's investment (after the tax credit)" (Hall and Jorgenson, 1967, p. 393). From Equation (7.3), it can be observed that the cost of capital services will be higher the higher the price of capital goods, the discount rate and the rate of replacement. Furthermore, the cost of capital services is dependent on the tax credit rate, the tax rate on business income and the value of depreciation deductions. Equation (7.3) was later reiterated as a user-cost of R&D formula.

Following Hall and Jorgenson, different authors extended the concept and derived their variants of the cost of capital. King (1974, p.25) introduces three different methods of financing, including "retaining profits, issuing new shares, and borrowing". However, the optimal investment policy in King (1974) assumes perfect certainty and that there are no transaction costs. Auerbach (1979) incorporates different costs of capital depending on the methods of financing of a firm. King and Fullerton (1983, p. 6) recognise that the cost of capital depends "upon the asset and industry composition of the investment, the form of finance used for the project, and the saver who is providing the funds". However, they impose strong assumptions in their derivation of the cost of capital function (i.e. perfect certainty). Devereux and Pearson (1995) extend the concept of the cost of capital to transnational investments.

[171] For more details on the derivation of the formula, see pages 392-393 of Hall and Jorgenson (1967).

Several concerns arise regarding the overall applicability of the user-cost approach. Firstly, recent research points out that, although the cost of capital affects investment rates, its impact is only small and differs during different time periods (Melolinna et al., 2018).[172] Firm-level uncertainty, on the other hand, greatly affects investment (Melolinna et al., 2018). Secondly, the applicability of the same formula for R&D should not be taken for granted. Individual elements contained in the formula are likely to be significant for innovation, but not all; e.g. see Akcigit et al. (2018) for a comprehensive overview of the impact of corporate taxes on innovation.[173] Broadly, both investment in capital and investment in R&D are forward-looking with uncertain returns. Yet, how similar are these types of investment? The major distinction between them is that investment in capital typically has a fairly certain outcome, whereas the same cannot be said about an investment in R&D (Becker, 2013; Kattel and Mazzucato, 2018). Thirdly, Hall and Jorgenson's (1967) original formula is based on the premise of static expectations. Yet, R&D and innovation are aimed at reinventing the whole systems and established practices, both at the firm and economy-wide levels; require commitments in terms of resources and continuity (Becker, 2013); and frequently come with significant adjustment costs (Fowkes et al., 2015). Although this might be less true for incremental innovation compared to radical innovation, the applicability of the static expectations premise in the case of R&D in general is highly questionable. Due to the large uncertainties related to R&D and innovation, it is plausible to assume that firms do form expectations about the future; analyse the environment thoroughly and constantly; and shape governmental policies in different ways. Furthermore, it is plausible to assume that firms will not base their decisions solely on what happened in the past, but, rather, will do their best to anticipate whatever the future may bring. Unlike Hall and Jorgenson's (1967) seminal work, the user-cost of R&D approach is based on rational expectations. However, as will be discussed in the following section, the manner in which rational expectations are introduced might be just as inappropriate as the use of static expectations.

One of the earliest papers to apply the user-cost-based approach to R&D is Hall (1992). The author applies an investment model "to estimate the tax price responsiveness of R&D

[172] Melolinna et al. (2018) find that the impact of the cost of capital was greater before the Global Financial Crisis compared to after the crisis.

[173] Akcigit et al. (2018) also review the impact of personal taxes on innovation. King and Fullerton (1983, p. 2) point out that "the incentives to invest depend upon the combined weight of personal and corporate taxes".

spending" (Hall, 1992, p. 12) and treats R&D in the same manner as investment in physical capital. Although Hall (1992) does not apply Hall and Jorgenson's (1967) formula discussed above, the author does apply an investment model and points out the importance of including adjustment costs of R&D in such a model, which – although sometimes conceptually discussed – are widely ignored in the models to be discussed below. Adjustment costs of R&D are in essence very different from adjustment costs of capital. A large portion of R&D costs comprises of R&D personnel costs (Hall, 1992; Hall and Van Reenen, 2000). Furthermore, Bloom (2007, p. 1) derives a theoretical model showing the difference between adjustment costs of capital and adjustment costs of R&D and points out: "Investment in the capital stock typically incurs *stock* adjustment costs from changing the capital stock, while R&D investment in the knowledge stock typically incurs *flow* adjustment costs from changing the flow rate of the knowledge stock."

7.3.2 Operationalisation of the user-cost approach

There are different variants of the user-cost of R&D formulas that are used in the literature. The first variant of the user-cost of R&D formula is presented in Hall and Van Reenen (2000) and Bloom et al. (2002). Bloom et al. (2002) use the formula for the country-level, rather than firm-level calculations. Many assumptions are imposed in order to obtain the formula for the user-cost of R&D. Both papers lead to the same user-cost of R&D formula, but the assumptions are formulated in a slightly different way. Although some of these assumptions are simplifications, others cannot be easily accepted, as will be discussed in more detail later in this section. The key assumptions made are presented in Table 7.2.

Table 7-2. Assumptions imposed by Hall and Van Reenen (2000) and Bloom et al. (2002) to obtain the user-cost of R&D formula

Assumptions imposed by Hall and Van Reenen (2000)	**Assumptions imposed by Bloom et al. (2002)**
▪ Profit-maximising firm; ▪ The returns on R&D investment not gained immediately; ▪ In period 1: R&D stock rises by 1 unit; in period 2: the unit is disposed of;	▪ Profit-maximising firm; ▪ The returns on R&D investment not gained immediately – in period 1: investment in R&D; in period 2: returns on investment are realised;

▪ Retained earnings as a method of financing an investment; ▪ Perfect foresight; ▪ No tax exhaustion; ▪ 10% constant real interest rate assumed in derivation of tax component.	▪ Retained earnings as a method of financing; ▪ Exemption of payment of personal taxes for shareholder; ▪ Tax changes not foreseen by a firm.

The resulting formula in both studies is the following:

$$\rho_{jt} = \frac{1 - \left(A_{jt}^{d} + A_{jt}^{c}\right)}{1 - \tau_t}\left(r_t + \delta_j\right) \quad (7.4)$$

where ρ_{jt} is the user-cost of an investment in R&D for asset j in period t; A_{jt}^{d} is the net present value[174] of depreciation allowances for asset j in period t;[175] A_{jt}^{c} is the net present value of tax credit for asset j in period t;[176] τ_t is the tax on revenue that is earned from

[174] Although the authors in the papers refer to the parts of the formula as values, these are actually rates, which is implied both in their explanations and by Equation (7.4).

[175] Bloom et al. (2002) distinguish between depreciation allowances on a straight-line basis or declining balance basis while Hall and Van Reenen (2000) only note depreciation allowances on a declining balance basis. If depreciation allowances are given on a straight-line basis, then the net present value of depreciation allowances is equal to:

$$A_{jt}^{d} = \tau_t \phi_t$$

where ϕ_t is the rate of depreciation allowances at time *t*.

If depreciation allowances are given on declining balance basis, then the net present value of depreciation allowances is given by the following formula:

$$A_{jt}^{d} = \frac{\tau_t \phi_t (1 + r_t)}{(\phi_t + \tau_t)}$$

[176] The net present value of a tax credit depends on whether a volume based tax credit or incremental tax credit is implemented. In the case of volume based tax credits, the net present value of a tax credit is the same as the statutory credit rate (τ_t^{c}):

$$A_{jt}^{c} = \tau_t^{c}$$

An incremental tax credit with a base defined as a *k*-period moving average is assumed. The implication of the incremental credit of this kind is given by Bloom et al. (2002) stating that the following two assumptions are crucial for calculation of the value of the credit: (i) expectations about future R&D growth by a firm; and (ii) no tax exhaustion. In this case, the net present value of a tax credit is given by the following formula:

R&D investment in period t; r_t is the real interest rate at period t; and δ_j is the rate of economic depreciation of asset j.[177] It is assumed that three types of assets are used in R&D: current expenditure; buildings; and plant and machinery (Hall and Van Reenen, 2000; Bloom et al., 2002). The fraction in the formula is also referred to as "the tax component of the user-cost of R&D" (Hall and Van Reenen, 2000, p. 468). From Equation (7.4), it can be observed that the higher the net present value of the tax credit and the net present value of depreciation allowances, the lower the user-cost of an investment in R&D. Furthermore, the lower the depreciation rate and real interest rate, the lower the user-cost of an investment in R&D.

Finally, the domestic user-cost of R&D for a country is the sum of the weighted user-costs for individual assets and is given in Equation (7.5) below.

$$\rho_t^d = \sum_{j=1}^{3} w_j \rho_{jt}^d \tag{7.5}$$

where w_j represent weights for the three types of assets. The following weights derived by Cameron (1994) based on the analysis of UK data on R&D expenditures have been used: 0.90 (current expenditure); 0.064 (plant and machinery); and 0.036 (buildings) (Hall and Van Reenen, 2000; Bloom et al., 2002).

Two particularly problematic assumptions are imposed to derive this variant of the formula for the user-cost of R&D: (i) firms are assumed to have perfect foresight (Hall and Van Reenen, 2000); and (ii) firms do not anticipate tax changes (Bloom et al., 2002). The assumption of perfect foresight is generally unrealistic and its applicability in the context of R&D is completely ungrounded. If firms really do have perfect foresight, there would be no failed R&D projects, while in reality this is certainly not the case (Baker et

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$$A_{jt}^c = \tau_t^c(B_t - \frac{1}{k}\sum_{i=1}^{k}(1+r_t)^{-i}B_{t+1})$$

where B_{t+1} is "an indicator which takes the value 1 if R&D expenditure is above its incremental R&D base in period t and zero otherwise" (Hall and Van Reenen, 2000, p. 468; Bloom et al., 2002, p. 5-6). Some versions of this formula explicitly introduce the inflation rate – e.g. in Griffith et al. (2001).

[177] The concepts of accounting and economic depreciation differ. For a comprehensive overview of accounting and economic depreciation and how they relate to each other, see Kim and Moore (1988).

al., 1986). Perfect foresight would wipe away the uncertainty of R&D; in particular, the financing of R&D project by firms would not be problematic.

When it comes to tax changes, these are often discussed, their potential impact evaluated, and sometimes even announced well before they are introduced. Due to that, firms can often prepare themselves for the tax change that might occur and adjust their behaviour accordingly. In relation to this, King (1974, p. 21) states: “In recent years governments have often announced tax changes in advance, and increasing attention is being paid to the use of announcements of future tax changes as a policy tool in its own right. These announcement effects can have a significant impact on investment behaviour.”

The user-cost formula that we will adopt in this thesis is explained in detail by Scott and Glinert (2020).
To obtain the formula for the user-cost of capital, several steps are followed:

1. The first step involves obtaining the unit cost of capital without tax, which is equal to the unit price of capital (*p*), multiplied by the sum of real interest rate (r) and capital depreciation rate (δ). The user-cost approach treats investment in capital and investment in R&D as substitutes. Hence, if a firm decides to invest in capital instead of R&D, it would be receiving interest and be subject to depreciation (Scott and Glinert, 2020).

$$Pre - tax\ unit\ cost\ of\ capital = p \times (r + \delta) \qquad (7.8)$$

2. The second step involves post-tax unit cost of capital (t in Equation (7.9) stands for tax). Investment into capital reduces the amount of firm’s profits, as well as corporate tax liability (Scott and Glinert, 2020).

$$Post - tax\ unit\ cost\ of\ capital = p \times (1 - t) \times (r + \delta) \qquad (7.9)$$

3. Post-tax unit cost of capital with an R&D subsidy for a profitable company takes the following form (s is the R&D tax credit rate):

$$Post - tax\ unit\ cost\ of\ capital = p \times (1 - t) \times (1 - s) \times (r + \delta) \quad (7.10)$$

4. Scott and Glinert (2020) assume that post tax income for a profitable company takes the following form, where MPK is the marginal product of capital:

$$Post - tax\ income = MPK \times (1 - t) \quad (7.11)$$

5. In equilibrium, we assume that unit cost of capital is equal to post-tax income

$$p \times (1 - t) \times (r + \delta) = MPK \times (1 - t) \quad (7.12)$$

6. This gives us the formula for user-cost of capital for profitable firms[178]:

$$(1 - s) \times (r + \delta) = \frac{MPK}{p} \quad (7.13)$$

To calculate the additionality ratio, we assume an increase in R&D tax credit rate by 1 percentage point. Following the increase, we calculate the increase in R&D expenditures, as well as exchequer cost. A practical demonstration of additionality ratio calculations is included in Chapter 8, following the user-cost estimations.

7.3.3 Measuring the financial cost of capital

The problem of measuring the financial cost of capital applies specifically to the second variant of the user-cost formula presented above (the real interest rate used in first variant is readily calculated from observable nominal interest rates and inflation rates). While some studies applying the user-cost approach to evaluation have used approximations for the value of the financial cost of capital; e.g. in the evaluation by Fowkes et al. (2015, p. 41), it is stated that "in line with Harris et al. (2006), we assume a rate of 10 per cent per annum as an approximation"; others apply different approaches to its measurement.

[178] The sample in Chapter 8 will be restricted to profitable firms only. To explore the user-cost of capital formula for unprofitable companies, consult Scott and Glinert (2020).

Using a constant rate as an approximation can pose a problem, as the cost may differ across a variety of dimensions: different firms; different projects; and/or different sources of funds (Thomson, 2010); and different time periods. As alternatives to assuming the financial cost of capital, commonly used approaches to measure the cost are utilising either the return on assets (ROA) measure or the capital asset pricing model (CAPM).

The rationale for applying the ROA measure for the cost is given by Thomson (2010, p. 270): "averaged over the business cycle, the return actually generated by the company's assets should be correlated to the return required by investors". The general formula presented in Equation (7.14) is used to calculate return on assets (ROA):

$$ROA_{it} = \frac{profit_{it} + interest_{it}}{assets_{it}} \tag{7.14}$$

The definitions of profit slightly differ across different studies: e.g. "the profits are recorded before tax and the assets are the total quoted company assets" (HMRC, 2010, p. 39); or "profit is measured before tax and extra-ordinary items, and the denominator is the book value of total assets" (Thomson, 2010, p. 270). A problem arises when applying this approach, as R&D is not capitalised in firms' financial statements. This leads to the underestimation of the denominator in Equation (7.14) if firms invest heavily in R&D. The formula in Equation (7.14) is adjusted to deal with this problem, by adding annual R&D expenditure to the numerator of Equation (7.14) and an imputed R&D stock[179] to the denominator of the same equation. The ROA approach benefits from two main advantages: its simplicity; and that the calculation is possible using the financial data of firms. Thomson (2010) lists, on the negative side, that the data on past profitability of a firm can convey different information about a firm, such as its technological advantages or demand prospects.

The second approach to calculating the cost is the application of the capital asset pricing model (CAPM). The cost of equity formula given in Equation (7.15) is applied:

$$R_{it} = R_f + \beta_i\big(E(R_m) - R_f\big) \tag{7.15}$$

[179] A perpetual inventory method is used.

where R_{it} is the rate of return on asset i; R_f is the risk-free rate of return;[180] β_i is the covariance between the asset returns and the market returns; $E(R_m)$ is the expected return on the market; and the term $\left(E(R_m) - R_f\right)$ as a whole is the risk premium. The main advantage of using this approach to the cost measurement is its better theoretical groundedness (Thomson, 2010). Yet, Thomson (2010) notes several disadvantages, such as: application only to publicly listed firms; the assumption of investors holding efficient and diversified portfolios rooted in CAPM; and setting the price for equity for investments is often done using CAPM.

7.3.4 Depreciation rates used

The problem of measuring depreciation rates applies to both variants of the formula. For Variant 1 of the user-cost of R&D formula, Hall and Van Reenen (2000) and Bloom et al. (2002) applied the following economic depreciation rates for the assets used in R&D: 30% for current expenditure on R&D, 3.61% for buildings and 12.64% for plant and machinery.[181]

Commonly, in studies using Variant 2, a depreciation rate of 15 per cent is applied (HMRC, 2010; Thomson, 2010; Fowkes et al., 2015; Dechezlepretre et al., 2016). Where noted, it is emphasised that the choice of the rates is in line with previous studies. Although using the same depreciation rates over different time periods is convenient, recent research has shown that this might not be a good representation of reality. Li and Hall (2018, p. 16) note that "the main drivers of R&D depreciation rates are the industry's pace of technological progress and the degree of market competition". Also, it is pointed out that the depreciation of R&D is strongly related to its contribution to the firm's profit. Their estimates of depreciation rates show that different industries face different depreciation rates, as well as that the rates are, overall, higher than 15% (Li and Hall, 2018).

7.3.5 The implications of different assumptions imposed for evaluation of the effectiveness of R&D tax credits

Different factors can lead to an under-estimation of the user-cost of R&D and thus potentially, to an overestimation of the effectiveness of R&D tax credits. The calculated

[180] Thomson (2010, p. 271) uses "implied annual return on 5-year treasury bonds".
[181] Again, here one should be aware of the difference between economic and accounting depreciation rates.

user-cost of R&D will be lower the lower are: (i) the real rate of return/financial cost of capital; and (ii) the rate of depreciation used. Numerous problems are encountered when calculating the financial cost of capital and underestimation of the financial cost of capital is a possibility. Furthermore, it is plausible to assume that the commonly used depreciation rate is lower than the actual depreciation rate, which consequently leads to a lower calculated user-cost of R&D. However, it should be noted that if keeping both the real rate of return/financial cost of capital and depreciation rate constant over the time period over which the evaluation is undertaken[182] - while examining the change in user-cost of R&D resulting from: (i) introduction of R&D tax credits, or (ii) changes in R&D tax credits policy - the levels of the calculated user-cost of R&D will be different, but the relative changes in the user-cost of R&D will be the same. Hence, this should have no impact on the evaluated effectiveness of R&D tax credits.

7.4 Conclusion

Hall and Jorgenson's (1967) seminal work on the user-cost of capital has been extended over the years and has been applied in the context of R&D. Calculating the user-cost of R&D is just one way of evaluating the effectiveness of R&D tax credits. The studies applying Approach 1 and Approach 2 generally lack comparability, due to their different foci. Where comparisons can be made, different results are observed. To the best of our knowledge, however, remarkably no study has used both approaches on the same dataset to compare the results, which is what will be done in Chapter 8 of this thesis.

Extending the concept of user-cost of capital to R&D is convenient, as both constitute investments. However, there are numerous problems in doing so. R&D investments are highly uncertain, more so than investments in capital. Adjustment costs, although significant in the case of R&D, are largely ignored in the derivation of the user-cost of R&D. The assumption of the perfect foresight applied in the user-cost of R&D setting is an unlikely representation of reality. Finally, when applying the user-cost of R&D approach, problems arise when measuring the financial cost of capital and choosing the depreciation rate(s). One question that naturally arises is how accurate is the calculated user-cost of R&D; conversely, whether, and if so, to what extent, measurement error is present? Given that the literature does not answer this question, or – as yet – even ask it,

[182] Other elements of the user-cost of R&D formula(s), other than the part of the formula that accounts for R&D tax credit, should be kept constant as well.

we conclude that, contrary to common practice, the user-cost approach should no longer be relied upon as the sole approach to evaluating the effectiveness of R&D tax credits.

The commonly identified disadvantages of Approach 1 – imprecision and the inability to separately identify the credit dummy and the time dummies – apply only when a dummy variable is used to account for R&D tax credits. Yet, this is no longer an issue when the value of the R&D tax credit is used, as is the case in more recent studies (e.g. Yang et al., 2012). Taking this into account, as well as the critique of the user-cost of R&D presented in this paper, more resources should be dedicated to comparison of the two approaches, as well as to more detailed investigation of the application of Approach 1.

8. Empirical evaluation of the effectiveness of R&D tax credits on R&D expenditures

8.1 Introduction

The aim of this Chapter is to explore the effectiveness of innovation policies. A particular focus is placed on the effectiveness of R&D tax credits. The reason for this focus is that there appears to be a large variation in the estimated impact of this policy in the evaluation literature, as was explored in Chapter 7. The empirical investigation will also take into account R&D subsidies. This chapter will take into account two important aspects of the R&D expenditures – R&D tax credits nexus that are commonly overlooked in this type of evaluation study: (i) the issue of self-selection into participation in R&D tax credits schemes by firms; and (ii) potential endogeneity between R&D expenditure and R&D tax credits as a consequence of firms' expectations in relation to tax credits. The novelty in the examination of the impact of R&D tax credits on R&D expenditures will first of all lie in: (i) the examination of both the propensity and intensity effects of R&D tax credits on R&D expenditures; while (ii) taking into account potential differences between within firm (i.e. time-series) and between effects (i.e. cross-sectional variation between firms). There follows the main contribution of this chapter, (iii) the comparison of the two different approaches used in the literature to evaluate the effectiveness of tax credits. These two approaches – focussed, respectively, on the direct measurement of additionality and the indirect measurement of additionality via the prior calculation of user-cost – can result in substantially different results for policy effectiveness. The reasons for this divergence were explored theoretically in Chapter 7, while this Chapter will empirically investigate any differences.

The ESEE dataset, covering Spanish manufacturing firms with over 10 employees over the period 2001-2016, will be utilised for the purposes of the empirical investigation.[183] The ESEE has previously been used to investigate the effectiveness of R&D tax credits as an innovation policy (Labeaga, Martinez-Ros and Mohnen, 2014; Busom et al., 2017). However, as indicated above, the main aim of this chapter goes beyond just investigating the effectiveness of innovation policies. In addition, the time span of the dataset used in the chapter is substantially longer than that in previous similar empirical investigations.

[183] A more detailed description of the dataset was provided in Chapter 6. In the interest of space, the description will not be repeated here.

This chapter is structured as follows. Investigation 1 examines the impact of R&D tax credits on R&D expenditures using the full sample (Section 8.2). Investigation 2 compares the additionality and user-cost approaches to the evaluation of R&D tax credits on R&D expenditures in a necessarily smaller sample (Section 8.3). Section 8.4 concludes.

8.2 Investigation 1: The investigation of the impact of R&D tax credits on R&D expenditures using the additionality approach

8.2.1 Model specification

The determinants of firms' participation in R&D tax credits and R&D subsidies programme are of great interest for policy makers, as participation is a necessary prerequisite for the success of any programme. Busom et al. (2017), who used the ESEE for the period 2001-2008, found that firms that were previously participants of both support programmes were more likely to participate in succeeding programme(s) than similar non-participating firms. State dependence might be a reflection of the learning that a firm undergoes (for both instruments) and the reputation that they might enjoy with the public funding agencies (for subsidies). Busom et al. (2017) do not find any support for cross-programme interactions – i.e. if a firm benefited from one type of policy support this does not mean that it will obtain another type of policy support in the next year. Additionally, Busom et al. (2017) explore the factors that drive participation in each of the programmes. Some determinants are identified as shared in regards to participation in both subsidy and tax credits programmes, such as the size of a firm; belonging to a high-tech industry; previous involvement in R&D activities; and human capital.[184] Participation in a subsidy programme is additionally impacted by firms' productivity levels, while participation in the tax credits programme is affected by whether firms engage in diversification[185] and whether they are innovative exporters.[186]

Busom et al. (2017) use a dynamic random effects probit model to explore programme participation. The approach taken in this chapter will be different. The first investigation will utilise a dynamic tobit model with random effects (Wooldridge, 2005),estimated on the whole sample of firms – i.e. regardless of whether or not they conduct R&D – so as to estimate the effects of tax credits on both their propensity to engage in R&D and their

[184] Human capital is proxied by Busom et al. (2017) as a dummy variable indicating whether a firm employs higher education graduates.
[185] Diversification is measured using a dummy variable of whether or not a firm produced a single product line in the previous period (Busom et al., 2017).
[186] Innovative exporters are defined by Busom et al. (2017) as firms that introduced a product innovation and exported in the previous period.

intensity of R&D once they conduct any R&D. Tobit deals with the self-selection issue discussed in the *Introduction*, because the estimations are performed on the entire sample including the firms that do not perform any R&D. Tobit was the preferred model as theoretically, as discussed in Chapters 3 and 5, because there are similar determinants of undertaking R&D expenditures (propensity) and the response of R&D expenditure to R&D tax credits (intensity). Accordingly, this part of the investigation explores not only programme participation but also the effectiveness of the credits obtained.

In addition to self-selection, there is a potential endogeneity between R&D expenditures and R&D tax credits. This issue was not explored in the previous literature; however, it is considered in this empirical investigation. Following on from the discussion presented in the previous chapter, we have concluded that R&D tax credits are a relatively stable policy and are, unlike R&D subsidies, granted to all eligible firms automatically (i.e. policy makers are not involved in the decision of which firms are granted R&D tax credits). Therefore, in advance of performing any R&D expenditures ($t-1$), firms can anticipate that they will receive this type of innovation support at $t+1$ if their R&D expenditures at t fulfil the specified criteria for R&D tax credits to be granted. This can lead to the issue of simultaneity. Actual firm R&D expenditures in period t can be planned in the period $t-1$, as to an extent R&D tax credits can be anticipated in period $t-1$. However, R&D tax credits are received by the firm only in period $t+1$. Consequently, actual R&D in period t influences both the anticipated tax credits in $t-1$ and the actual tax credits in period $t+1$. Theoretically, there should be no influence of current R&D expenditures on current level of R&D tax credits. Hence, by using current levels of R&D expenditures and R&D tax credits, the problem can be avoided or at least attenuated.

Endogeneity between R&D expenditures and R&D tax credits is explored following the two-step procedure described in Wooldridge (2001). The first step of this procedure involves running a simple OLS regression with R&D expenditures as the dependent variable. Residuals from this regression are saved and included in a second-step tobit regression with R&D tax credits as the dependent variable. The statistical insignificance of the residual term in the second regression suggests that endogeneity would not pose a problem in this empirical investigation (Appendix 6)

The nature of the ESEE dataset, in particular patterns of missing values (Appendix 5), was thoroughly explored prior to empirical investigation. Although the ESEE has been used extensively, to the best of our knowledge, the nature of data “missingness” has not been thoroughly or routinely explored in previous empirical investigations. As evidenced and discussed in Appendix 5, the level of missingness does not exceed 10% of all observations per variable and should not pose a problem for empirical investigation. This yields a sample for estimation of 22,908 observations from 3,313 firms (giving an average number of observations of 6.9 years, which although unbalanced is nonetheless appropriate for a wide-N, short-T dynamic estimator).

For the additionality approach to evaluation of the effectiveness of R&D tax credits, part of the post-estimation will explore (regression results are presented in Appendix 7)[187]: (i) propensity effects (Table 8.4), (ii) intensity effects (Table 8.5), and (iii) the combined intensity and propensity effects (Appendix 7). To anticipate, the consistency in (i) the signs, (ii) direction, and (iii) relative magnitudes of these effects suggests that tobit provides sensible results. Propensity effects indicate how successful R&D tax credits would be in converting non-R&D performers into performers. Intensity effects indicate by how much R&D tax credits raise R&D expenditures for R&D performers. The overall effects combine the propensity and intensity effects.

The estimated model was of the following form:

$$lnR\&D\ expenditures_{it} = \alpha_0 + \beta R\&D\ expenditures_{it-1} + \gamma R\&Dtaxcredits_{it} + \delta X_{it} + (u_i + \varepsilon_{it}) \quad (8.1)$$

Where *i* indexes firms, t indexes years and $(u_i + \varepsilon_{it})$ is the composed random effects error term, with u_i capturing firm-specific unobservable, time-invariant effects, and ε_{it} being the usual idiosyncratic error. X_{it} is a set of control variables, including 20 industry dummy variables, size of the firm, total employment in R&D, and indicators for whether the firm cooperated with suppliers, competitors, customers, and universities or technological centres. Additionally, following good practice (Petrin and Radičić, 2021), the investigation controls for other innovation policies available to Spanish firms, such as the value of R&D subsidies and the value of R&D tax credits for technological innovation. Due to the persistence of investments in R&D by the companies that conduct R&D and innovation, as demonstrated in Chapter 6, as well as findings of Busom et al. (2017),[188] a dynamic specification of the model is used. In the literature that directly estimates the additionality effects of tax credits, in excess of 80 per cent of estimates have been

[187] The regression results of a model with a dummy variable included were presented in Appendix 9. It is noted that inclusion of the dummy variable does make a difference when it comes to estimated regression coefficients. The postestimation in this chapter was based on the results with dummy variable excluded.

[188] Labeaga, Martinez-Ros and Mohnen (2014, p. 6) note "R&D is not an activity to conduct with discontinuity since investment in knowledge, for instance, skilled workers and new technological equipment that entail sunk costs are difficult to amortise in a short period of time."

generated by estimating static models (Dimos et al., 2022), typically with no supporting diagnostic tests. Yet history matters. Path dependency is common in firm behaviour, including the performance of R&D and the receipt of R&D credits by Spanish manufacturing firms (Busom, at al., 2017). Accordingly, exclusion of the lagged dependent variable would certainly entail model misspecification in our case and puts something of a question mark over much of the extant evaluation literature. For this reason, R&D flow variables were used to measure both lagged and current levels of R&D.

Following Wooldridge (2005), the initial value of the dependent variable was included among the control variables. Three-way interactions were also introduced between R&D tax credit variable R&D subsidies and industry dummies. One of the novelties of this empirical investigation is the examination of within and between effects of the variables of interest. Bell and Jones (2013, p. 5) make a strong case that between and within group effects should be examined, stating that “models which control out, rather than explicitly model, context and heterogeneity offer overly simplistic and impoverished results which can lead to misleading interpretations”. Within group variation is specified as deviations of actual observations from the within group averages. Between group variations are defined asaverages of the variable across the years (Bell and Jones, 2015, pp. 141-142) Following a long-established distinction in econometric literature, the between estimates based on cross-section variation may be interpreted as long-run effect, while the between estimates based on time-series variation may be interpreted as short-run effect (Koutsoyiannis, 1977; Kennedy, 1985). This distinction carries over into modern panel econometrics (Baltagi, 2005). [189] In the light of the features of the model discussed above, we do not adopt, in addition, the standard procedure to calculating long run effects. In this model, applied to full sample estimates discussed below, the short versus long-run distinction is captured by within and between effects respectively.[190]

8.2.2 Descriptive statistics

Table 8.1 presents descriptive statistics for the full sample variables used in this part of the empirical investigation.

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[189] In relating within variation to short-run effects and between variation to long-run effects, we follow Baltagi (2005, p 200-201): “Applied studies using panel data find that the Between estimator (which is based on the cross-sectional component of the data) tends to give long-run estimates while the Within estimator (which is based on the time-series component of the data) tends to give short-run estimates. This agrees with the folk wisdom that cross-sectional studies tend to yield long-run responses while time-series studies tend to yield short-run responses ….”

[190] The three-way interactions were included for both within and between R&D tax credits and R&D subsidies variables. There is no within and between distinction for the industry dummies.

Table 8-1. Descriptive statistics for the full sample

Variable	Description	Number of observations	Mean	Standard Deviation	Min	Max
lagGTID	Lagged value of logarithm of R&D expenditure (Euros, deflated by CPI) + 1 lagGTID ≡ Lag(lnGTIDnew2) = lag(ln(GTID2015 prices + 1))	26,318	4.446	6.159	0	20.062
TFP2	Within variation of total factor productivity variable[191]	24,822	1.04e-09	.442	-7.875	3.074
VEXPOR2	Within variation of value of exporting (in 1,000,000 Euros, deflated by CPI)	28,321	4.84e-08	74.565	-2439.91	3647.41
DEDID2	Within variation value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI)	28,355	2.88e-10	.643	-10.431	41.006
Subsidies2	Within variation of R&D subsidies provided by different levels of government combined (in 1,000,000 Euros, deflated by CPI)	28,341	-7.58e-10	1.764	-49.791	126.172
PERTOT2	Within variation of total employment (in 10,000 employees)	28,355	2.89e-11	.013	-.551	.332
DEDIT2	Within variation of value of tax deductions for technological innovations applied to the company income tax (in Euros, deflated by CPI)	28,355	1.94e-09	9.883	-135.691	830.063
CUCT2	Within variation of dummy variable indicating whether a firm cooperated with universities and/or technological centres (0 = No, 1 = Yes)	28,355	-1.06e-09	.233	-.938	.938
CTCO2	Within variation of dummy variable indicating whether a firm cooperated with competitors (0 = No, 1 = Yes)	28,355	-2.04e-10	.110	-.875	.938
CTCL2	Within variation of dummy variable indicating whether a firm cooperated with customers (0 = No, 1 = Yes)	28,355	-7.90e-10	.214	-.938	.938

[191] Details on how TFP variable is constructed is provided in Chapter 6.

CTPR2	Within variation of dummy variable indicating whether a firm cooperated with suppliers (0 = No, 1 = Yes)	28,355	-1.04e-09	.232	-.938	.938
PERSOC2	Within variation of dummy variable indicating whether a firm belongs to a corporate group (0 = Yes, 1 = No)	54,335	-4.27e-10	.148	-.938	.938
EMPIDT2	Within variation of total employment in R&D	49,361	-1.92e-08	16.500	-788.938	752.063
lnGTIDnew2_IN	Initial value of lnGTIDnew2 = ln(GTID2015 prices + 1) GTID2015prices are R&D expenditure (in 1,000,000 Euros, deflated by CPI)	67,096	4.314	6.025	0	19.275
TFP_MI	Between variation of total factor productivity variable	55,198	7.144	.846	3.203	9.633
VEXPORnew_MI	Between variation of value of exporting (in 1,000,000 Euros, deflated by CPI)	67,160	22.013	171.095	0	5328.882
PERTOTnew_MI	Between variation of total employment (in 10,000)	67,192	.0178	.056	.0003	1.159
DEDIDnew_MI	Between variation value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI)	67,192	.0590	.457	0	10.431
Subsidies_MI	Between variation of R&D subsidies provided by different levels of government combined (in 1,000,000 Euros, deflated by CPI)	67,160	.126	2.489	0	143.631
DEDITnew_MI	Between variation of value of tax deductions for technological innovations applied to the company income tax (in Euros, deflated by CPI)	67,192	.508	4.387	0	135.691
EMPIDT_MI	Between variation of total employment in R&D	66,054	5.426	44.397	0	1573.938
CUCT_MI	Between variation of dummy variable indicating whether a firm cooperated with universities and/or technological centres (0 = No, 1 = Yes)	67,192	.209	.356	0	1
CTCL_MI	Between variation of dummy variable indicating whether a firm cooperated with customers (0 = No, 1 = Yes)	67,192	.1525	.311	0	1

CTCO_MI	Between variation of dummy variable indicating whether a firm cooperated with competitors (0 = No, 1 = Yes)	67,192	.022	.115	0	1
CTPR_MI	Between variation of dummy variable indicating whether a firm cooperated with suppliers (0 = No, 1 = Yes)	67,192	.187	.336	0	1
PERSOC_MI	Between variation of dummy variable indicating whether a firm belongs to a corporate group (0 = Yes, 1 = No)	63,224	.653	.454	0	1

8.2.3 Results

The regression results are presented in Appendix 7. As it is marginal effects that are of interest, only marginal effects are presented and discussed in this section.

The regression results (Appendix 7) show that the dynamic specification based on Wooldridge (2005) is supported by the sign, size and statistical significance of the lagged dependent variable (0.65 – between zero and one, as expected – with p=0.000) as well as by the estimated effect of the initial condition (0.41 with p=0.000). In combination, these estimates tell us that the history of firms' R&D spending matters for current R&D spending.

We now turn to the estimated marginal effects (Tables 8.2 – 8.3 and 8.4 – 8.5), which are of most interest. First, the effects of R&D tax credits and R&D subsidies tend to be similar (i.e. the confidence intervals are overlapping). Second, the long-run effects (i.e. the between estimates) for both R&D tax credits and R&D subsidies tend to be larger than the short-run effects (i.e. the within estimates). This is consistent with the evaluation literature on R&D tax credits (Hall and Van Reenen, 2000). Third, overall the effects tend to be relatively small, which is also consistent with the literature (Dimos et al., 2022).

Propensity effects are calculated as $Pr\ (y > 0)$, as we are interested in how effective R&D tax credits are in encouraging R&D non-performers to become R&D performers. Propensity effects for tax credits and subsidies are presented in Table 8.2, while propensity effects for all independent variables are presented in Table 8.4. A distinction can be made between short-term and long-term effects. The short-term effects being represented by the within variation (i.e. variation within a single firm over a number of years), while the long-term effects are represented by the between variation (i.e. variation between different firms) estimates.

- The short-term propensity effect (within effect) or probability of observing positive R&D expenditures increases by 124.2 percentage points for the firm that receives 1,000,000 Euros more in R&D tax credits (DEDID2).[192] However, the mean tax credit in the sample is €83,704, so that for firms not undertaking R&D

[192] We rescale a one unit change in R&D tax credits by a factor of 100, from 1 million to 10,000 euros. Hence, we have to rescale the estimated short-run marginal effect from 1.24 to 0.0124. So a rescaled one unit change in R&D gives rise to a rescaled change in the probability of enacting R&D of 0.0124. For example, if the probability of enacting R&D is 0.35 (the sample proportion of firms with positive R&D expenditures) before the one unit change then the probability after the one unit change becomes 0.3624 or a change of 1.24 percentage points.

a more realistic marginal increase would be, say, €10,000, which would yield an increased probability of undertaking R&D of 1.242 percentage points. In contrast, the results indicate that, when we take two firms with identical sets of characteristics, the long-term propensity effect (between effect) of observing positive R&D expenditures increases by 482 percentage points for the firm that receives €1,000,000 more in R&D tax credits (DEDIDnew_MI). Following the argument on the within effect, a marginal increase in tax credits by €10,000 would raise the probability of engaging in R&D by 4.822 percentage points. Therefore, we characterise the propensity effects of R&D tax credits as small but non-trivial from a policy perspective. To induce firms into conducting R&D or undertaking innovation efforts, R&D tax credits may need to be flanked by a range of other public policies – for example, to enhance firms' willingness and ability to cooperate more closely with customers and suppliers as well as with universities and technological centres (both the within and the between effects of these cooperation variables are estimated to be positive and statistically significant in the results reported in Table 8.4).

- The short-term effect of subsidies is comparable to that of tax credits, where a €10,000more received in subsidies increases the probability of observing positive R&D expenditures by 0.765 percentage points (Subsidies2). On the other hand, the long-term effect of subsidies appears to be substantially larger, standing at 2.509 percentage points for an additional €10,000 received (Subsidies_MI).

These findings suggest that R&D tax credits and R&D subsidies are similarly effective methods for turning R&D non-performers into performers. Although the effects of both instruments are small, the finding of similar effectiveness – even after allowing for different within and between effects – is in line with a recent meta-regression study of their relative effectiveness (Dimos et al., 2022).

Table 8-2. Propensity effects for R&D tax credits and R&D subsidies

Variable	**Description**	**ey/dx**	**Delta-method standard errors**	**z**	**P > |z|**	**95% confidence interval**	
DEDIDnew_MI	Value of tax deductions for R&D applied to company income tax (in million Euros, deflated by CPI) – between variation	4.822	1.440	3.35	0.001	1.999	7.644

DEDID2	Value of tax deductions for R&D applied to company income tax (in million Euros, deflated by CPI) – within variation	1.242	0.394	3.16	0.002	0.470	2.013
Subsidies_MI	R&D subsidies provided by governments at all levels (in million Euros, deflated by CPI) – between variation	2.509	0.794	3.16	0.002	0.953	4.064
Subsidies2	R&D subsidies provided by governments at all levels (in million Euros, deflated by CPI) – within variation	0.765	0.179	4.27	0.000	0.414	1.116

Other marginal propensity effects are presented in Table 8.4. Engaging in exporting activities does not seem to contribute to an increased probability of observing positive R&D expenditures either in the short- or in the long-run. This might suggest a trade-off between the two activities – innovation and exporting – both in the short- and in the long-run. As both exporting and innovation are resource-intensive activities, firms may decide to focus on one due to limited resources. Long-run variations in productivity between firms exhibits a significant positive influence on whether firms will engage in R&D (TFP_MI), whereas the short-term effect is insignificant. More productive firms are more likely to be R&D performers. This effect shows that long-run differences in productivity between a firm and their competitors is what matters, rather than relative improvements in productivity performance of a firm over time. In the long run, belonging to a corporate group negatively impacts the propensity of a firm to invest in R&D (PERSOC_MI). The quantitative effect is substantial – belonging to a corporate group reduces the propensity of firm engaging in R&D by 39 percentage points. This may be due to firms belonging to corporate group operating in different locations and conducting their R&D at a single location inside or outside of Spain.

Cooperation with universities and technological centres, customers and suppliers all positively influence the propensity of a firm to engage in R&D, with cooperation with suppliers offering the most substantial contribution, increasing the propensity of engagement in R&D by a firm by 95.3 percentage points in the short run (CTPR2) and 101.9 percentage points in the long run (CTPR_MI). The significant results when it comes to cooperation with universities and technological centres are expected as firms would often cooperate with universities/technological centres specifically for innovation purposes.

Table 8.3 presents the intensity effects for R&D tax credits and R&D subsidies, while Table 8.5 presents all intensity effects. The intensity effects are calculated as $E\ (y \mid a < y < b)$, where the effects are conditional on firms having positive R&D expenditures.[193] In terms of the significance, sign and relative magnitude of the between and within effects, the intensity results are comparable to the propensity effects. The intensity effects confirm that an additional €10,000 €in R&D tax credits leads to an increase in R&D expenditures of 0.837 % in the long run (DEDID_MI). The short-run effects are smaller, standing at 0.288% (DEDID2) in response to an additional €10,000 of tax credits. This is in line with the observation made by Hall and Van Reenen (2000), who suggest that the effect of R&D tax credits increases over time. When it comes to subsidies, an increase in €10,000in subsidies leads to an increase in intensity of R&D expenditures conducted by a firm of 0.169 % in the short run (Subsidies2) and 0.508 % in the long run (Subsidies_MI). The results suggest that R&D tax credits might be more successful at increasing the intensity of R&D expenditures of firms compared to subsidies.

Table 8-3. Intensity effects for R&D tax credits and R&D subsidies

Variable	Description	ey/dx	Delta-method standard errors	z	P > |z|	95% confidence interval	
DEDIDnew_MI	Value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI) – between variation	0.837	0.260	3.22	0.001	0.328	1.346
DEDID2	Value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI) – within variation	0.288	0.083	3.46	0.001	0.124	0.0451
Subsidies_MI	R&D subsidies provided by governments at all levels (in 1,000,000 Euros, deflated by CPI) – between variation	0.508	0.171	2.96	0.003	0.172	0.843

[193] In our model, the expected value (*E*) of the dependent variable (*y*) is the expected value of the log of R&D expenditure, so that the change in the dependent variable brought about by a small change in the value of R&D tax credits can be interpreted as an approximate percentage change.

Subsidies2	R&D subsidies provided by governments at all levels (in 1,000,000 Euros, deflated by CPI) – within variation	0.169	0.039	4.33	0.000	0.009	0.246

To obtain a representative long-run additionality measure for the regression sample, we calculate the constant elasticity of R&D spending with respect to tax credits at their respective mean values. The constant elasticity decomposes as follows:

$$\frac{\%\Delta R\&D}{\%\Delta TC} = \frac{\Delta R\&D}{\Delta TC} \times \frac{TC}{R\&D} \qquad (8.2)$$

- The second term on the right-hand side is obtained by dividing the mean R&D tax credit (DEDIDnew_MI; €0.2379515) by the mean R&D expenditures (GTID2015prices; €3,492,025) and that equals to 0.00000006814;
- By assuming a one unit increase in R&D tax credits (€1,000,000) and given that our estimated marginal effect is equal to 84%, we obtain an increase in R&D expenditures at the mean of €2,933,301 (= €3,492,025*0.84). This gives a first term on the right-hand side, i.e. the ratio of absolute change in R&D expenditures to absolute change in R&D tax credits of 2,933,301 (=€2,933,301/1). This is the additionality ratio – an additional €1,000,000 of R&D tax credits yields €2,933,301 of R&D expenditures at the mean values or €1 of additional R&D tax credits leads to €2.93 of R&D expenditures;
- The elasticity on the left-hand side is obtained by multiplying 2,933,301 (ΔR&D/ΔTC) and 0.00000006814 (TC/R&D), which gives the value of 0.2.[194] Of course, we should take into account also the lower within effect, particularly considering that the typical calculations in the literature are based on estimates that are, essentially, weighted averages of within and between effects.

These findings are important for the interpretation of the results of our second investigation reported below.

[194] The extreme size of the numbers reflects scaling effect. As a check on the calculation, we can derive the elasticity by multiplying the semi-elasticity with the sample average value of R&D tax credits: 0.84 * 0.2379515 = 0.2.

Table in Appendix 8 presents combined propensity and intensity effects. Combined effects tend to be in line with the intensity effects, although slightly smaller due to the inclusion of non-R&D performers into calculations of the effects. Moreover, it is the intensity effect that are directly comparable to the user-cost and additionality estimates reported in our next investigation. Therefore, the combined effects will not be commented on separately.

Table 8-4. Investigation 1 - Propensity effects derived from tobit estimation of R&D expenditures

Variable	Description	ey/dx	Delta-method standard errors	z	P > |z|	95% confidence interval	
lagGTID	Lagged value of dependent variable	.149	.004	34.08	0.000	.141	.158
lnGTIDnew2_IN	Initial condition	.094	.005	19.26	0.000	.084	.104
DEDIDnew_MI	Value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI) – between variation	4.822	1.440	3.35	0.001	2.000	7.644
DEDID2	Value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI) – within variation	1.242	.394	3.16	0.002	.470	2.013
DEDITnew_MI	Value of tax deductions for technological innovations applied to the company income tax (in Euros, deflated by CPI) – between variation	.004	.006	0.62	0.534	-.008	.016
DEDIT2	Value of tax deductions for technological innovations applied to	.001	.0008	1.44	0.151	-.0004	.003

	the company income tax (in Euros, deflated by CPI) – within variation						
Subsidies_MI	R&D subsidies provided by governments at all levels (in 1,000,000 Euros, deflated by CPI) – between variation	2.509	.794	3.16	0.002	.953	4.064
Subsidies2	R&D subsidies provided by governments at all levels (in 1,000,000 Euros, deflated by CPI) – within variation	.765	.179	4.27	0.000	.414	1.116
VEXPORnew_MI	Exporting – between variation	-.0001	.0002	-0.65	0.516	-.0006	.0003
VEXPOR2	Exporting – within variation	-.00009	.00009	-0.98	0.325	-.0003	.00009
TFP_MI	Total factor productivity – between variation	.094	.041	2.29	0.022	.0135	.175
TFP2	Total factor productivity – within variation	-.034	.023	-1.48	0.140	-.079	.011
PERSOC_MI	Dummy variable indicating whether a firm belongs to a corporate group (0 = Yes, 1 = No) – between variation	-.393	.051	-7.77	0.000	-.493	-.294

PERSOC2	Dummy variable indicating whether a firm belongs to a corporate group (0 = Yes, 1 = No) – within variation	.035	.045	0.77	0.443	-.054	.124
CUCT_MI	Dummy variable indicating whether a firm cooperated with universities and/or technological centres (0 = No, 1 = Yes) – between variation	.558	.072	7.74	0.000	.417	.699
CUCT2	Dummy variable indicating whether a firm cooperated with universities and/or technological centres (0 = No, 1 = Yes) – within variation	.344	.034	10.20	0.000	.278	.410
CTCL_MI	Dummy variable indicating whether a firm cooperated with customers (0 = No, 1 = Yes) – between variation	.430	.091	4.73	0.000	.252	.608
CTCL2	Dummy variable indicating whether a firm cooperated with	.589	.038	15.46	0.000	.514	.663

	customers (0 = No, 1 = Yes) – within variation						
CTPR_MI	Dummy variable indicating whether a firm cooperated with suppliers (0 = No, 1 = Yes) – between variation	1.019	.094	10.89	0.000	.836	1.202
CTPR2	Dummy variable indicating whether a firm cooperated with suppliers (0 = No, 1 = Yes) – within variation	.953	.037	25.84	0.000	.881	1.026
CTCO_MI	Dummy variable indicating whether a firm cooperated with competitors (0 = No, 1 = Yes) – between variation	-.238	.182	-1.31	0.191	-.594	.119
CTCO2	Dummy variable indicating whether a firm cooperated with competitors (0 = No, 1 = Yes) – within variation	-.009	.062	-0.15	0.880	-.130	.111
PERTOTnew_MI	Total employment – between variation	.677	.707	0.96	0.338	-.708	2.062
PERTOT2	Total employment – within variation	2.366	.696	3.40	0.001	1.002	3.729

EMPIDT_MI	Total employment in R&D – between variation	-.00007	.0012	-0.06	0.951	-.002	.002
EMPIDT2	Total employment in R&D – within variation	.0003	.0004	0.90	0.369	-.0004	.001

Note:A description of variables is provided in the Descriptive statistics section. All variables with the extension “_MI” represent between variation, whereas all variables with extension “2” represent within variation.

Table 8-5. Investigation 1 - Intensity effects derived from tobit estimation of R&D expenditures

Variable	**Description**	**ey/dx**	**Delta-method standard errors**	**z**	**P > |z|**	**95% confidence interval**	
lagGTID	Lagged value of dependent variable	.045	.001	39.06	0.000	.042	.047
lnGTIDnew2_IN	Initial condition	.028	.001	20.68	0.000	.025	.031
DEDIDnew_MI	Value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI) – between variation	.837	.260	3.22	0.001	.328	1.346
DEDID2	Value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI) – within variation	.288	.083	3.46	0.001	.124	.450
DEDITnew_MI	Value of tax deductions for technological innovations applied to the company income tax (in Euros, deflated by CPI) – between variation	.001	.002	0.62	0.534	-.002	.005
DEDIT2	Value of tax deductions for technological innovations applied to	.0003	.0002	1.44	0.151	-.0001	.0008

	the company income tax (in Euros, deflated by CPI) – within variation						
Subsidies_MI	R&D subsidies provided by governments at all levels (in 1,000,000 Euros, deflated by CPI) – between variation	.508	.171	2.96	0.003	.172	.843
Subsidies2	R&D subsidies provided by governments at all levels (in 1,000,000 Euros, deflated by CPI) – within variation	.169	.039	4.33	0.000	.093	.246
VEXPORnew_MI	Exporting – between variation	-.00004	.00007	-0.65	0.516	-.0002	.00009
VEXPOR2	Exporting – within variation	-.00003	.00003	-0.98	0.325	-.00008	.00003
TFP_MI	Total factor productivity – between variation	.0282	.012	2.29	0.022	.004	.052
TFP2	Total factor productivity – within variation	-.01	.007	-1.48	0.140	-.024	.003
PERSOC_MI	Dummy variable indicating whether a firm belongs to a corporate group (0 =	-.118	.0149	-7.87	0.000	-.147	-.088

	Yes, 1 = No) – between variation						
PERSOC2	Dummy variable indicating whether a firm belongs to a corporate group (0 = Yes, 1 = No) – within variation	.010	.014	0.77	0.443	-.016	.037
CUCT_MI	Dummy variable indicating whether a firm cooperated with universities and/or technological centres (0 = No, 1 = Yes) – between variation	.167	.021	7.81	0.000	.125	.209
CUCT2	Dummy variable indicating whether a firm cooperated with universities and/or technological centres (0 = No, 1 = Yes) – within variation	.103	.01	10.28	0.000	.083	.122
CTCL_MI	Dummy variable indicating whether a firm cooperated with customers (0 = No, 1 = Yes) – between variation	.128	.027	4.74	0.000	.075	.181
CTCL2	Dummy variable indicating whether a	.176	.011	15.71	0.000	.154	.198

	firm cooperated with customers (0 = No, 1 = Yes) – within variation						
CTPR_MI	Dummy variable indicating whether a firm cooperated with suppliers (0 = No, 1 = Yes) – between variation	.304	.028	11.07	0.000	.251	.358
CTPR2	Dummy variable indicating whether a firm cooperated with suppliers (0 = No, 1 = Yes) – within variation	.285	.011	27.08	0.000	.264	.305
CTCO_MI	Dummy variable indicating whether a firm cooperated with competitors (0 = No, 1 = Yes) – between variation	-.071	.054	-1.31	0.191	-.178	.035
CTCO2	Dummy variable indicating whether a firm cooperated with competitors (0 = No, 1 = Yes) – within variation	-.003	.018	-0.15	0.880	-.039	.033
PERTOTnew_MI	Total employment – between variation	.202	.211	0.96	0.338	-.211	.616
PERTOT2	Total employment – within variation	.707	.208	3.40	0.001	.300	1.114

EMPIDT_MI	Total employment in R&D – between variation	-.00002	.0004	-0.06	0.951	-.0008	.0007
EMPIDT2	Total employment in R&D – within variation	.0001	.0001	0.90	0.369	-.0001	.0003

Note:A description of variables is provided in the *Descriptive statistics* section. All variables with the extension "_MI" represent between variation, whereas all variables with extension "2" represent within variation.

8.3 Investigation 2: Comparison of the user-cost and additionality approaches

The second empirical investigation of this chapter compares user-cost and additionality approaches using the same sample, and to the extent possible, the same model specification. In accord with the practice in the user-cost literature, the following restrictions are placed on the full sample: (i) value of user-cost is positive, (ii) profit value is positive, and (iii) value of tax credits is positive. The resulting sample consists of 2,555 observations, with average number of years being 3.5 years. The restrictions placed on the sample are in line with other user-cost studies. The model used in investigation 2 is presented in Equation 8.3) and is similar to the one used in investigation 1 with several important differences. First, due to computational difficulties, most likely reflecting the greatly reduced sample size and correspondingly increased imbalance of the data, between and within effects could not be distinguished and the model could not be specified with interaction effects. Second, due to restrictions placed on the sample by the standard user-cost approach, a tobit model is no longer the appropriate modeling strategy. Because only firms that perform R&D and have received R&D tax credits are included in the sample, a dynamic linear model with random effects is estimated instead (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998; see also Roodman, 2009, who is the author of xtabond2 for Stata, the programme used to obtain the estimated reported in this second investigation). The much reduced sample is dictated by the user-cost approach, and for comparability is used also for the additionality approach.

$$lnR\&D\ expenditures_{it} = \alpha_0 + \beta R\&D\ expenditures_{it-1} + \gamma UserCost_{it} + \delta X_{it} + (u_i + \varepsilon_{it}) \quad (8.3)$$

More detailed description of the terms included in Equation (8.3) is given after Equation (8.1). The independent variable of interest in these estimations is the user-cost of R&D, while the independent variable of interest in the additionality estimations is the value of R&D tax credits received. The additionality effect for the user-cost estimations was calculated following the procedure detailed by Scott and Glinert (2020).

8.3.1 Additionality using the user-cost approach

The user-cost included in the estimations is based on the following formula (Scott and Glinert, 2020), which is discussed in more detail in Chapter 7:

$$(1 - s) \times (r + \delta)$$

where s is the tax credit rate, r is the real interest rate, and δ is the capital depreciation rate. Following previous user-cost studies, the interest rate r is set at 10%, while the capital depreciation rate δ is set at 15%. Considering the complexity of Spanish innovation policy – a mix of incremental and volume-based schemes, as well as the availability of the regional R&D tax credits – deciding upon the appropriate tax credit rate was not straightforward. We resolved this difficulty by calculating the R&D tax credit rate from the data. Labeaga, Martinez-Ros and Mohnen (2014, p. 12-13) recognise two types of user-cost: (i) effective user cost – "measured on the basis of claimed tax deductions"; and (ii) legal user cost – "based on eligible tax deductions according to legislation". While a majority of user-cost studies (e.g. Fowkes et al., 2015; Scott and Glinert, 2020) utilise the legal user cost in their evaluation studies, this investigation will utilise the effective user cost. Labeaga, Martinez-Ros and Mohnen (2014, p. 31) find that: "… the impact of the legal user cost on R&D expenses is higher than the impact of the effective user cost as measured by the long-run elasticities. This finding has a policy implication, since many firms entitled to receiving R&D tax credits do not use or do not even know the tax incentive programme." The effective user cost in this investigation is calculated at the industry level, assuming heterogeneities in innovation efforts at the industry level. The R&D tax credit rate at the industry level is calculated from the data as industry-level average of the firm-level ratios of R&D tax credits to R&D expenditures over the entire period, yielding one value per industry.

Table 8.6 presents the results of user-cost estimations (also Appendix 10). The coefficient on the user-cost of R&D (UC_industry) is the coefficient of interest in the table. To avoid a specification problem, our variable of interest is treated as endogenous. When treated as exogenous, the UC estimate is positive, which is a clear warning that there is a specification problem. Yet, when adequately instrumented (as demonstrated by the autocorrelation and Hansen tests), the UC effect appears with the right sign, although without statistical significance. Although our variable of interest proves to be statistically insignificant, it is established practice to proceed with user-cost calculations based on statistically insignificant estimates in the user-cost regression.

Table 8-6. User-cost estimates

Variable	Coefficient	Corrected standard errors	z	P > |z|	95% confidence intervals	
l.lnGTIDnew2	0.963	0.139	6.92	0.000	0.691	1.236
TFP_18	0.114	0.223	0.51	0.610	-.323	0.550
VEXPOR2015prices	1.91e-10	4.53e-10	0.42	0.673	-6.97e-10	1.08e-09
UC_industry	-12.384	22.516	-0.55	0.582	-56.514	31.756
Subsidies	0.022	0.035	0.63	0.526	-0.046	0.090
PERTOT	-0.0002	0.0003	-0.66	0.511	-0.0009	0.0004
DEDIT2015prices	3.91e-07	5.41e-07	0.72	0.470	-6.69e-07	1.45e-06
EMPIDT	-0.002	0.001	-1.19	0.233	-0.004	0.001
CUCT	0.756	0.415	1.82	0.069	-0.059	1.570
CTCO	0.066	0.358	0.18	0.855	-0.636	0.768
CTCL	-0.400	0.255	-1.57	0.116	-0.899	0.099
CTPR	-0.426	0.293	-1.45	0.146	-1.001	0.149
PERSOC	-0.996	0.457	-2.18	0.029	-1.892	-0.100
lnGTIDnew2_IN	0.473	0.164	2.89	0.004	0.152	0.794
_cons	0.564	6.430	0.09	0.930	-12.038	13.167
Year dummies	*Included*					
Industry dummies	*Included*					

Our user-cost variable is constant (time-invariant) at the industry level, which has a two-fold corollary: (i) because the estimated coefficient on the user-cost variable measures between-group effects – based on the cross-section component of the data – it may be regarded as the long-run equilibrium effect (Baltagi, 2005, p. 200); and (ii) it would therefore be mistaken to further multiply the user-cost estimate (by 1 – the estimated coefficient on the lagged dependent variable) to obtain the long-run effect (for this procedure, see Baltagi, 2005, p. 157-58).

Calculating the additionality ratio follows the procedure that was detailed, from a theoretical perspective in Chapter 7, and is presented in Table 8.7. The *Before* column assumes the R&D tax credits rate that was currently applicable, while the *After* columns assumes an increase in the R&D tax credit rate of 1 percentage point. The user-cost of capital in the *Before* column is the mean of the restricted sample *UC_industry* variable (0.213), which is the effective user-cost calculated from the data utilising the formula.

$$(1 - s) \times (r + \delta)$$

As explained in the previous paragraph, we assume an increase in *s* of 1 percentage point in the *After* column, whilst *r* and δ remain unchanged. For ease of calculation, we assume that a firm is spending €100 on R&D expenditure (R&D expenditure *Before* column). With the increase in R&D tax credit rate, in the *After* column, R&D expenditures increase to €105.3. This is obtained as detailed in Table 8.7. The exchequer cost is obtained as the multiplication of R&D expenditures and R&D tax credit rate used in the respective columns with (1 - corporate tax rate). The corporate tax rate in Spain is 25% and remains the same in the *Before* and *After* columns.

Table 8-7. Additionality ratio derivation

UC_industry	**BEFORE**	**AFTER**
Implied user cost elasticity	= 0.213 * -12.384 = -2.638	
User cost of capital	0.213 (s = 0.154) (calculated from the data)	= (1- 0.164)*(0.15 + 0.10) = 0.209
R&D expenditure	100	= 100 + (100*(-2.638))*(0.209/0.213 – 1)=105.278
Exchequer cost	= (100*0.148)*(1-0.25) = 11.613	= (105.278*0.164)*(1-0.25) = 13.015
Additionality ratio	= (105.278-100)/(13.015-11.613) = 3.763	

So, according to these calculations, the additionality ratio is €3.763. In other words, every Euro of tax credits gives rise to nearly €4 of additional R&D spending. In comparison, this estimate is falls between the lower and upper estimates reported by Scott and Glinert (2020).[195] Moreover, while quantitative comparison is not possible, these findings are qualitatively consistent with the positive additionality effects reported by Lenihan et al. (2022).

[195] "The additionality ratios derived from OLS models range between 6.88 and 7.04. For FE, the results are between 2.39 and 2.72 and for AB they are between 1.86 and 2.63" (Scott and Glinert, 2020, p. 16).

8.3.2 Additionality ratio estimates using direct estimation (i.e. the additionality approach)

Table 8.8 presents additionality estimations using the restricted sample (also Appendix 11). The coefficient of interest here is the coefficient on R&D tax credits (lnDEDID), which, following the testing procedure reported in our first investigation, we continue to treat as exogenous. The coefficient estimate is 0.36 and statistically significant at the one percent level, suggesting that for a 1 percent increase in R&D tax credits, the resulting increase in R&D expenditures is 0.36%. We can compare the results of this empirical investigations to the full sample investigation (Investigation 1). As the estimates in Table 8.8 are an average of between and within effects, the estimated coefficient should ideally lie in between the estimates that we obtained in the full sample investigation, which is the case here.

The coefficient on lagged dependent variable is 0.425, which lies in the range between 0 and 1. Additionally, the coefficient is highly significant (p=0.000), thereby justifying the choice of the dynamic specification. The model specification is satisfactory in terms of all the standard diagnostic tests.

Table 8-8. Investigation 2 - Additionality approach regression estimates

Variable	**Coefficient**	**Corrected standard errors**	**z**	**P > |z|**	**95% confidence intervals**	
l.lnGTIDnew2	0.425	0.113	3.78	0.000	0.205	0.646
TFP_18	-0.159	0.117	-1.36	0.173	-0.388	0.070
VEXPOR2015prices	-8.39e-12	1.59e-10	-0.05	0.958	-3.20e-10	3.03e-10
lnDEDID	0.356	0.092	3.89	0.000	0.177	0.536
Subsidies	0.018	0.010	1.90	0.057	-0.001	0.037
PERTOT	0.00004	0.00009	0.44	0.656	-0.0001	0.0002
DEDIT2015prices	1.05e-07	2.27e-07	0.47	0.642	-3.39e-07	5.50e-07
EMPIDT	0.0005	0.0004	1.17	0.240	-0.0003	0.001
CUCT	-0.280	0.183	-1.53	0.127	-0.639	0.079
CTCO	-0.204	0.143	-1.42	0.155	-0.485	0.077
CTCL	-0.191	0.087	-2.19	0.028	-0.362	-0.020
CTPR	-0.478	0.174	-2.74	0.006	-0.821	-0.136
PERSOC	0.214	0.191	1.12	0.261	-0.159	0.588
lnGTIDnew2_IN	0.0007	0.088	0.01	0.994	-0.172	0.173
_cons	6.610	1.773	3.73	0.000	3.136	10.085
Year dummies	*Included*					

Industry dummies	*Included*

To obtain a representative additionality measure, we calculate the constant elasticity of R&D spending with respect to tax credits at their respective mean values using the Equation (8.2).

- The second term on the right-hand side is obtained by dividing the mean R&D tax credit (€606,489.3) by the mean R&D expenditures (€3,898,985) and that equals to 0.156;
- To obtain the long-run coefficient, we adopt the standard procedure of dividing the short-run coefficient (lnDEDID) by (1 – the coefficient on the lagged dependent variable(l.lnGTIDnew2)), which gives us the long-run coefficient 0.62 (p=0.000);
- To obtain additionality ratio (first term on the right-hand side), we divide the long-run elasticity by the second term on the right-hand side (0.62/0.156). This gives us the additionality ratio of €3.974.

8.4 Conclusion

This chapter investigated the impact of innovation policies – R&D tax credits in particular – on innovation. The novelty of the chapter lies: (i) in a comparison of the different approaches to evaluation of the effectiveness of R&D tax credits, (ii) in distinguishing between the effect of R&D tax credits on both the propensity and intensity of R&D expenditures, and (iii) in distinguishing between short and long-term effects. The chapter leads to several important findings. This empirical investigation shows that the effects of R&D tax credits and R&D subsidies tend to be similar (Investigation 1). These results hold for both full and restricted samples. The long-run effects of both policies tend to be larger than their short-run effects, meaning that the policy effectiveness increases over time (in both investigations).

When it comes to the different approaches to evaluation of the effectiveness of R&D tax credits (Investigation 2), this chapter finds that, contrary to the theoretical considerations discussed in Chapter 6, the two approaches lead to similar estimated policy effectiveness (Table 8.9).

Table 8-9. Comparison of additionality ratios

Investigation	Approach to evaluation used	Additionality ratio
Investigation 1	Additionality approach	€2.93
Investigation 2	User-cost approach	€3.76
Investigation 2	Additionality approach	€3.97

The validity of this main finding is supported by two features of the research design implemented in this chapter.

1. Comparison of the two additionality ratios estimated using the direct additionality approach: i.e. (i) *Investigation 1* – calculated from the fully-specified model (Equation (8.1) applied to the full sample; and (ii) *Investigation 2* – from direct estimation of the reduced model (Equation (8.3)) applied to the reduced and highly unbalanced sample. The consistency of the estimated additionality effects across the two investigations suggests that the additionality effects estimated in *Investigation 2* are not an artefact either of the (reduced) model or of the (reduced) sample.
2. In *Investigation 2*, the two additionality estimates – from the user-cost approach and the directly estimated additionality approach – are obtained from the same (reduced) model applied to the same (reduced) sample, where the reduction in sample size is dictated by the user-cost approach.

These results are reassuring for researchers and policy makers alike. In this case, the two standard approaches to evaluating the effectiveness of tax credits yield similar estimates.

9. Conclusions and policy recommendations

9.1 Conclusions and contributions to knowledge

The thesis explored several complex topics, including the productivity – innovation – exporting nexus, and the role and the effectiveness of innovation policies, focusing on R&D tax credits as one of the two most significant policies used to promote innovation. The two broad research questions that were intended to be answered in this thesis – as detailed in the Introduction – were:

1. What are the nature, the direction and the timing of the links between firm-level productivity, innovation and exporting?
2. Do R&D tax credits work in promoting R&D expenditures, taking into account the ‘policy mix’, as well as different evaluation approaches?

The first four theoretical chapters contributed to our understanding of productivity, innovation and exporting, as well as casting light on the productivity – innovation – exporting nexus. The second chapter of the thesis discussed productivity and sought to provide points of clarification of the definition and measurement of productivity. The contribution of this chapter lies in pointing to the need to make an informed choice when it comes to utilising different productivity measurements. Significant discrepancies exist between theoretical definitions and practical productivity measurements, especially in relation to total factor productivity. We identified the following practical difficulties when measuring TFP: (i) both inputs and outputs are rarely measured in the quantity-form typically specified by theory; (ii) there are a number of different measures of both inputs and outputs and no straightforward criteria for choosing between them; and (iii) there is no universal choice on the specification of production function used in TFP estimates. Most importantly, given that applied studies rarely have access to quantity data, instead overwhelmingly performing TFP calculations on value data, there is the difficulty of partitioning price changes into, for example, those representing quality-improvements and demand effects, and changes in mark-ups supported by market power on the supply-side. Consequently, product innovation is not specifically captured by TFP in its theoretical form, and is rarely captured in applied studies (some recent exceptions are explored in Chapter 2). Finally, Chapter 2 identifies a range of internal and external determinants of productivity, such as firm’s management, competition, etc.

The third chapter explored the topic of innovation. This chapter discussed the importance of innovation, both for countries (e.g. in terms of economic growth or well-being) and firms (e.g. in allowing firms to establish a competitive advantage). The chapter also discussed the theoretical positioning of the thesis, as innovation is explored from the perspective of neoclassical economics, as well as evolutionary economics. This discussion partially informs the first empirical chapter, which explores the productivity – innovation – exporting nexus as a system. Additionally, the discussion on measures of innovation (i.e. innovation inputs, intermediate measures, and innovation outputs) leads to an additional avenue of inquiry, as the first empirical analysis utilises different innovation measures. Finally, the chapter discusses the determinants of innovation, such as R&D intensity and firm size.

The fourth chapter explores the topic of exporting, and its advantages and disadvantages for firms. The chapter discusses to what extent are the determinants of the propensity and intensity of exporting shared, and sets the scene for the fifth and sixth chapters. The fifth chapter provides a thorough overview of the literature on the productivity – innovation – exporting nexus, as well as the determinants of productivity, innovation and exporting. The literature suggests a "chicken and egg problem", where links in the nexus tend to go in all directions, without a clear indication of which comes first (see Figure 5.1). In this chapter, the main contribution is to survey the literature to establish the extent and robustness of the evidence for each of the six links in the productivity – innovation – exporting nexus. This gives a benchmark against which to compare the findings in our own empirical study reported in Chapter 6. (To anticipate, some but not all of these links are supported.) Additionally, the discussion in this chapter identifies the common determinants of innovation, exporting and productivity (e.g. size of the firm and whether it is importing), but concludes that most of the determinants of productivity, innovation and exporting are not shared. This literature review established the importance of using panel data for the investigation of the productivity – innovation – exporting nexus, as the effects in the literature do not appear to be contemporaneous. This informed the design of the empirical investigation in this research.

The sixth chapter empirically investigated the productivity – innovation – exporting nexus using Spanish data on manufacturing firms that employ over 10 employees. The dataset is chosen because, unusually, it provides a large quantity of data on a large number of firms over an extended period of time. The empirical investigation differs from previous investigations using the same dataset by way of: (i) using a much longer sample; (ii) applying a novel methodology to allow all three of our variables of interest to be endogenous; and (iii) by undertaking the most comprehensive investigation of the firm-level productivity – innovation – exporting nexus to date. Uniquely, we report a very large number of regressions, not only to generate an extensive evidence base but also to avoid selective reporting of findings, a practice identified by the extensive literature on publication bias as inflating estimates reported in quantitative literatures across the social and life sciences (see for example Bruns et al., 2019). The investigation shows that the link leading from productivity to exporting is the most frequently present one, in line with Melitz (2003). Additionally, the findings suggest that the timings of the links matter and that feedback effects are neither guaranteed nor always present. In the case of the links from innovation to productivity and from innovation to exporting, the evidence is sparse but, where present, mainly suggests positive relationships. However, we conjecture that the relative weakness of the evidence for these relationships might reflect the inability of our model to capture influences taking effect over four years or more. This limitation of our model – i.e. specification with two lags of each differenced variable – is imposed by the depths of the time-series in the available data.

The seventh chapter investigates innovation policies and in particular, R&D tax credits. While reviewing the literature, it has become apparent that the estimated effects of R&D tax credits varied quite substantially depending upon the methodological and empirical strategies adopted (i.e. some of the reported effects were 2 – 3 times higher than others). This led to a deeper exploration of two dominant approaches to the evaluation of R&D tax credits: the evaluation (additionality) approach; and the user-cost approach. The theoretical underpinnings of both approaches were analysed. In brief, the user-cost approach is commonly used and preferred in the economic literature due to its strong foundations in economic theory, while, at the same time, it relies on a substantial number of assumptions that are not necessarily realistic (e.g. regarding depreciation rates). The additionality approach, common in the innovation literature, is simpler to apply, and the criticisms related to this approach are based on the variant that uses a dummy variable to indicate that a firm received a tax credit, rather than on the variant that utilises the value of R&D tax credits received.

The eighth chapter, which is the second empirical chapter, evaluates the impact of R&D tax credits on the propensity and intensity of R&D expenditures of firms. Using Spanish manufacturing data and a tobit modelling strategy, the research is the first to undertake an empirical investigation that looks both at the propensity and at the intensity of firms' R&D expenditure to R&D tax credits. In addition, the main contribution of this chapter is to compare the effects of R&D tax credits when estimated by the additionality and user-cost approaches. However, although these approaches to estimating the effects of R&D

tax credits are very different, they are implemented using the same sample and, apart from the variable of interest in the two approaches – user-cost and value of R&D tax credits respectively – the same model. In both cases, the findings suggest that R&D tax credits do lead to increased R&D expenditure at the firm-level. Moreover, although the user-cost estimate is somewhat larger than the additionality approach estimate, they are closer than suggested by the range of estimates reported in the respective literatures.

9.2 Policy recommendations

There are four main policy recommendations that result from this research programme. The first policy recommendation stems from the findings from the first four theoretical chapters, as well as the first empirical chapter. We have learned that a number of the determinants of productivity, innovation and exporting are unique to each of the three phenomena. Only a small number of the determinants of innovation, productivity and exporting tend to be shared. The first empirical chapter revealed that the links in the productivity-innovation-exporting nexus are neither guaranteed nor universal. The exploration of the short-term relationships between innovation, exporting and productivity is important from the perspective of public policy. Short-termism is common in public policy making – e.g. Department for Levelling Up, Housing and Communities (2022), Coyle and Muhtar (2021) or Jones (2019) for examples from the UK. Policies often tend not to be in place for long enough to exploit long-term relationships and gain the benefits of cumulative causation. Instead, the focus on the short-run relationships – indeed, deliberately excluding more complex exploration of the long-run equilibrium relationships – is designed to investigate what can be achieved by institutions and policies of short duration. Our findings suggest that the effectiveness – and, hence, value for money – of policies subject to short-term churn is likely to be limited compared to the effectiveness of policies sustained over time. The only short-run link that is consistently estimated, irrespective of particular contexts, is the link leading from productivity to exporting. The other short-run links are highly contextual. This finding – together with systematic evidence of strong persistence in each of innovation, productivity and export – suggests that promoting one segment of the nexus will not necessarily positively influence the other two parts in the short-run. This does not mean that some policy coordination is not beneficial, or even necessary; in particular, the joint promotion of productivity and exporting. However, our results indicate that separate instruments still need to exist when it comes to institutions and policies capable of only short-run promotion of firm-level productivity, innovation and exporting. Although we are able to report some evidence of long-run equilibrium relationships between our variables of interest, we conjecture that for policy makers to exploit these relationships requires a consistent and integrated commitment over longer periods than are analysed in this thesis.

The second policy recommendation, stemming from the findings from Chapters 2 – 6, emphasises the importance of building firms' resources and capabilities. Engaging in innovation and exporting and increasing firm's productivity are all resource-intensive activities. In particular, they make competing claims on managerial time and energy. This may help to explain some of the negative effects revealed in Chapter 6 (for example, while predominantly positive, in some contexts, the effects of innovation on productivity are negative). Policies that relax resource constraints, especially those that increase the quantity and quality of managerial resources, are needed to help firms to develop across a broad front embracing innovation, productivity and exporting. Detailing precisely what resources and capabilities are needed is beyond the scope of this thesis. This would require qualitative research which is currently lacking in this area. We conjecture that the time constraint on managerial effort may be particularly binding in the context of policies and programmes subject to short-term churn.

The third policy recommendation comes from the findings from the second empirical chapter. Consistent with the findings in the literature, the empirical chapter confirms that R&D tax credits are effective in increasing both the propensity and intensity of R&D expenditures. Evidence of such effectiveness does not establish value for money. However, rigorous cost-benefit analyses of R&D support are largely absent from the literature and such analysis is beyond the scope of this thesis.

Finally, the fourth policy recommendation stems from the results that suggest that a degree of caution should be exercised when choosing the approach to evaluate the effectiveness of R&D tax credits as a policy. Although in our study, the two approaches yield similar estimates, the estimates tend to be less similar in the literature as a whole. The best practice would be to use both approaches and compare the results.

9.3 Limitations and directions for future research

Several other important findings from the research that can inform future research stem from findings from Chapter 6. The use of innovation measures (i.e. R&D expenditures, number of product innovations, etc.) appeared to be a consideration of lesser importance, as the choice of the measures did not impact our findings. Additionally, the choice of deflators did not lead to any differences in the findings.

One of the main limitations of this research programme is its focus on Spain and the extensive use of Spanish data. The results may not apply to all countries, only to those countries with broadly similar levels of development. Although the dataset is comprehensive and ranges over a long period of time, it does have several limitations: (i) the ESEE dataset utilised for the empirical work is restricted to manufacturing firms that employ over 10 employees and thus (ii) excludes microenterprises as well as (iii) firms in the services and creative industries. However, this limitation yields a relatively homogeneous dataset, which helps to explain why our findings do not systematically vary by subsectors. At the very beginning of the research project, considerations were made to explore productivity and innovation in the service sector of the economy and the creative industries. This is an important research agenda, as the nature of these sectors of the economy (i.e. products in these sectors, value creation processes) is substantially different compared to the manufacturing industries.

One of the limitations of Chapter 6 is the use of a panel VAR modelling strategy. Panel VAR allowed for exploration of the productivity – innovation – exporting nexus and treating all three as endogenous. However, it cannot allow for a thorough exploration of the determinants of each of the three phenomena.

When it comes to the empirical exploration of Chapter 8, the main limitation again comes from the nature of the data. The complexities of the Spanish R&D tax credits system have been impossible to account for completely while applying the user-cost approach, and the application of the user-cost approach in most previous cases has been undertaken in environments with less complex systems. The initial research project idea was to explore the impact of R&D tax credits on productivity and exporting too. Due to various complexities, this proved to be an impossible task within the scope of this PhD research; however, it suggests an agenda for future research.

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APPENDICES

Appendix 1: Unit root tests for the empirical investigation in Chapter 6

Figure A1.1 Unit root tests

```
Fisher-type unit-root test for GTID_NWH
Based on augmented Dickey-Fuller tests
-----------------------------------------------
Ho: All panels contain unit roots          Number of panels       =   4201
Ha: At least one panel is stationary       Avg. number of periods =   6.71

AR parameter: Panel-specific               Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Included                     ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(2048) P      6295.8754       0.0000
 Inverse normal            Z       -47.1475       0.0000
 Inverse logit t(5124)     L*      -50.5091       0.0000
 Modified inv. chi-squared Pm       66.3731       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

Fisher-type unit-root test for LP2015prices
Based on augmented Dickey-Fuller tests
-----------------------------------------------
Ho: All panels contain unit roots          Number of panels       =   4201
Ha: At least one panel is stationary       Avg. number of periods =   6.72

AR parameter: Panel-specific               Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Included                     ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(4194) P       1.20e+04       0.0000
 Inverse normal            Z       -65.1944       0.0000
 Inverse logit t(10489)    L*      -67.2716       0.0000
 Modified inv. chi-squared Pm       84.8419       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Fisher-type unit-root test for **TFP_18**
Based on augmented Dickey-Fuller tests

Ho: All panels contain unit roots — Number of panels = **3460**
Ha: At least one panel is stationary — Avg. number of periods = **7.17**

AR parameter: **Panel-specific** — Asymptotics: **T -> Infinity**
Panel means: **Included**
Time trend: **Not included**
Drift term: **Included** — ADF regressions: **1** lag

		Statistic	p-value
Inverse chi-squared(**4016**)	P	**1.05e+04**	**0.0000**
Inverse normal	Z	**-57.6397**	**0.0000**
Inverse logit t(**10044**)	L*	**-58.8916**	**0.0000**
Modified inv. chi-squared	Pm	**72.3804**	**0.0000**

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Fisher-type unit-root test for **VEXPOR_NWH**
Based on augmented Dickey-Fuller tests

Ho: All panels contain unit roots — Number of panels = **4200**
Ha: At least one panel is stationary — Avg. number of periods = **6.72**

AR parameter: **Panel-specific** — Asymptotics: **T -> Infinity**
Panel means: **Included**
Time trend: **Not included**
Drift term: **Included** — ADF regressions: **1** lag

		Statistic	p-value
Inverse chi-squared(**3140**)	P	**8404.1024**	**0.0000**
Inverse normal	Z	**-48.4489**	**0.0000**
Inverse logit t(**7854**)	L*	**-51.5245**	**0.0000**
Modified inv. chi-squared	Pm	**66.4270**	**0.0000**

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Figure A1.2 Unit root tests conducted using xtbunitroot

```
. xtbunitroot VEXPOR2015prices, known(8) trend
Karavias and Tzavalis (2014) panel unit root test for VEXPOR2015prices
------------------------------------------------------------------------------
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
------------------------------------------------------------------------------
Number of panels:                  5840     Avrge number of periods:  5.54
Number of breaks:                  1
Cross-section dependence:          No       Linear time trend:       Yes
Cross-section heteroskedasticity:  No       Normal errors:           No
------------------------------------------------------------------------------
                    Statistic   Asymtotic critical-value        p-value
------------------------------------------------------------------------------
 Z-statistic               .               -1.6449                    .
------------------------------------------------------------------------------
Result: the null is not rejected
Significance level of test:   .05
```

```
. xtbunitroot GTID2015prices, known(8) trend
(aravias and Tzavalis (2014) panel unit root test for GTID2015prices
------------------------------------------------------------------------------
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
------------------------------------------------------------------------------
Number of panels:                  5840     Avrge number of periods:  5.52
Number of breaks:                  1
Cross-section dependence:          No       Linear time trend:       Yes
Cross-section heteroskedasticity:  No       Normal errors:           No
------------------------------------------------------------------------------
                    Statistic   Asymtotic critical-value        p-value
------------------------------------------------------------------------------
 Z-statistic         -7.0333           -1.6449                0.0000
------------------------------------------------------------------------------
Result: the null is rejected
Known break date(s):   2008
Significance level of test:   .05
```

```
. xtbunitroot TFP_18, known(8) trend
Karavias and Tzavalis (2014) panel unit root test for TFP_18
------------------------------------------------------------------------------
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
------------------------------------------------------------------------------
Number of panels:                  5840.2   Avrge number of periods:  4.95
Number of breaks:                  1
Cross-section dependence:          No       Linear time trend:       Yes
Cross-section heteroskedasticity:  No       Normal errors:           No
------------------------------------------------------------------------------
                    Statistic   Asymtotic critical-value        p-value
------------------------------------------------------------------------------
 Z-statistic         44.1460           -1.6449                1.0000
------------------------------------------------------------------------------
Result: the null is not rejected
Significance level of test:   .05
```

```
. xtbunitroot LP2015prices, known(8) trend
Karavias and Tzavalis (2014) panel unit root test for LP2015prices
------------------------------------------------------------------------------
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
------------------------------------------------------------------------------
Number of panels:                  5840     Avrge number of periods:  5.53
Number of breaks:                  1
Cross-section dependence:          No       Linear time trend:       Yes
Cross-section heteroskedasticity:  No       Normal errors:           No
------------------------------------------------------------------------------
                    Statistic   Asymtotic critical-value        p-value
------------------------------------------------------------------------------
 Z-statistic         -7.3224           -1.6449                0.0000
------------------------------------------------------------------------------
Result: the null is rejected
Known break date(s):   2008
Significance level of test:   .05
```

Appendix 2: IRFs and cumulative IRFs for the TFP estimations in empirical investigation in Chapter 6

Appendix A2.1: IRFs and cumulative IRFs for whole sample estimations

Figure A2.1.1 IRFs; R&D expenditures

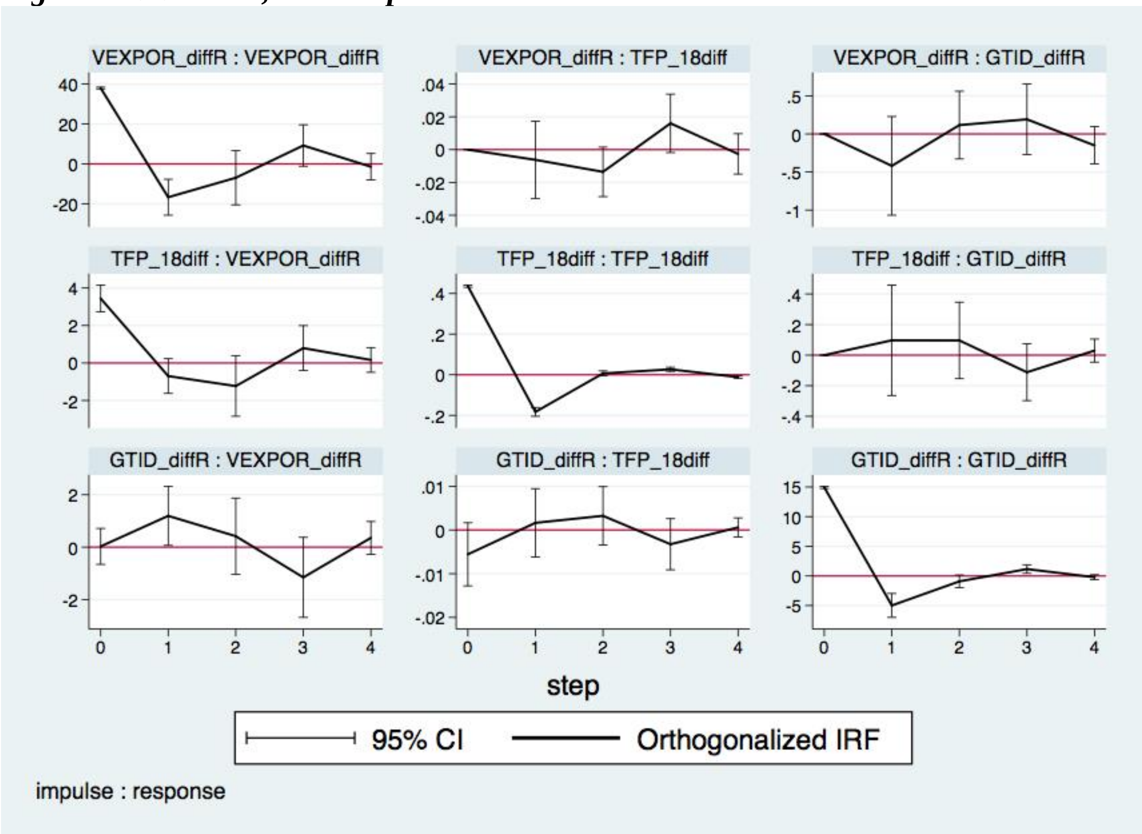


Figure A2.1.2 Cumulative IRFs; R&D expenditures

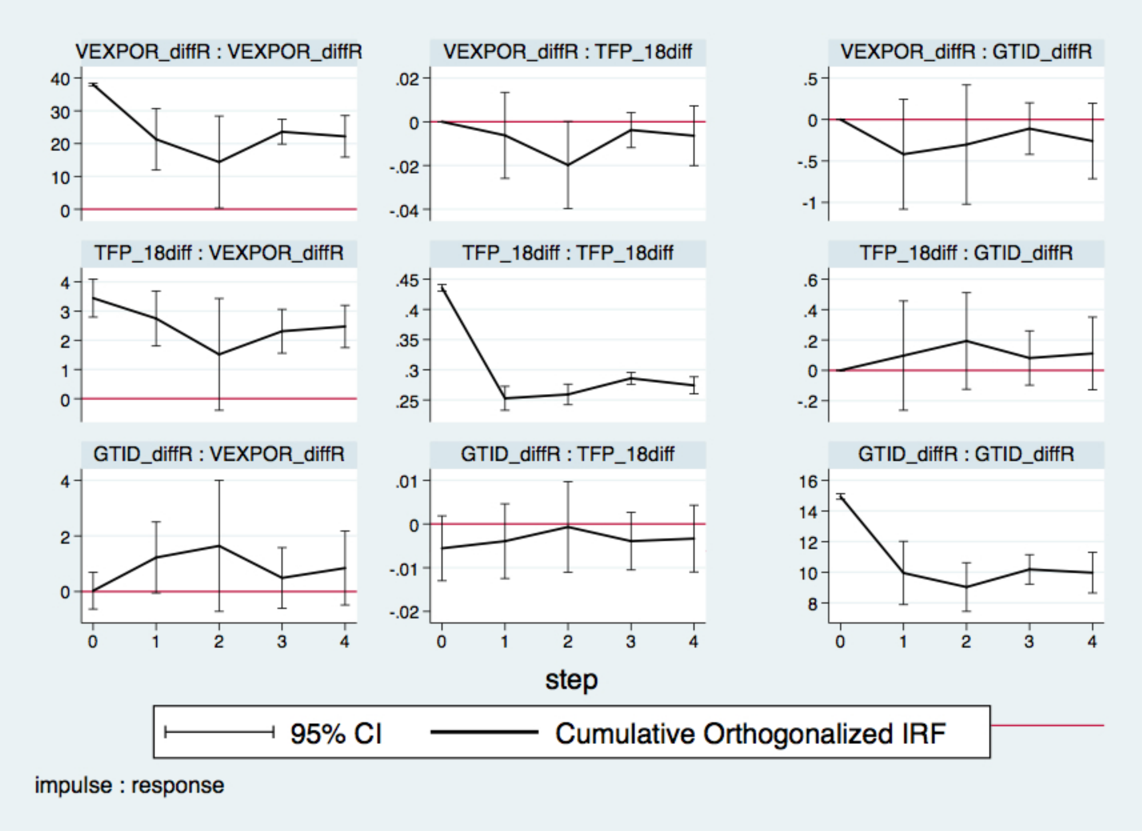


Figure A2.1.3 IRFs, patents registered in Spain

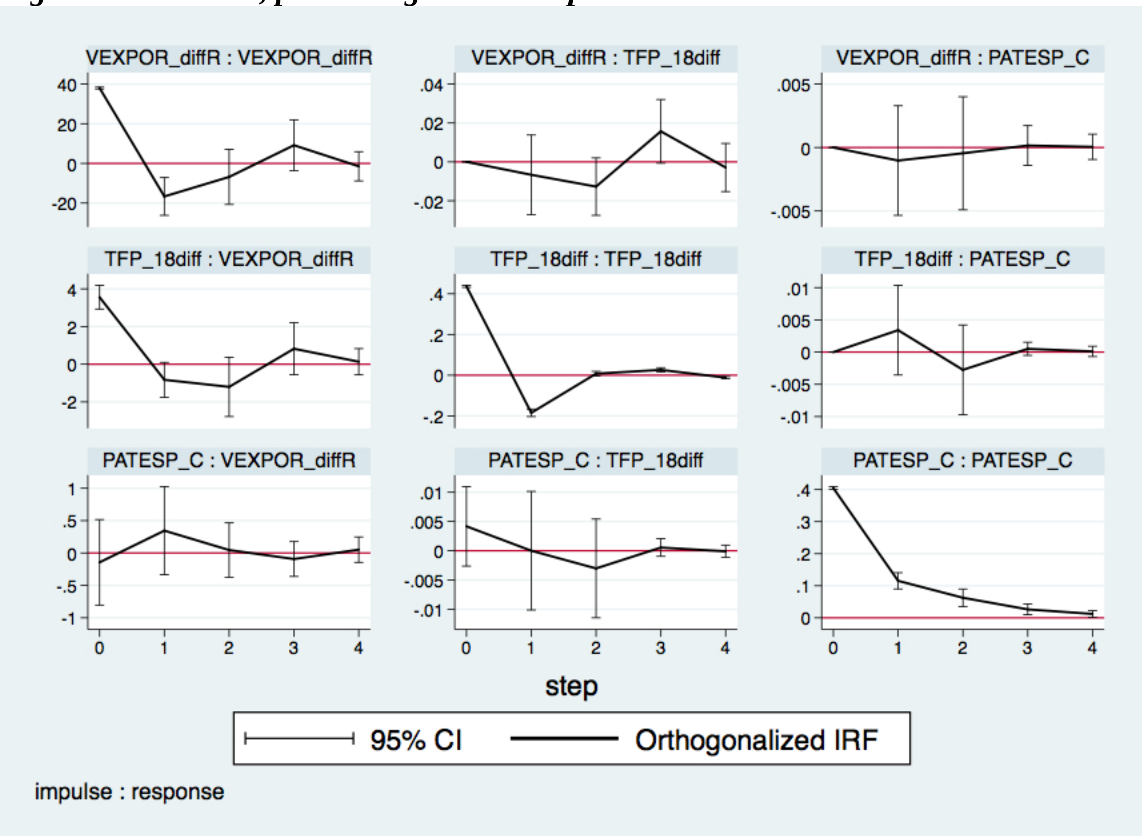


Figure A2.1.4 Cumulative IRFs, patents registered in Spain

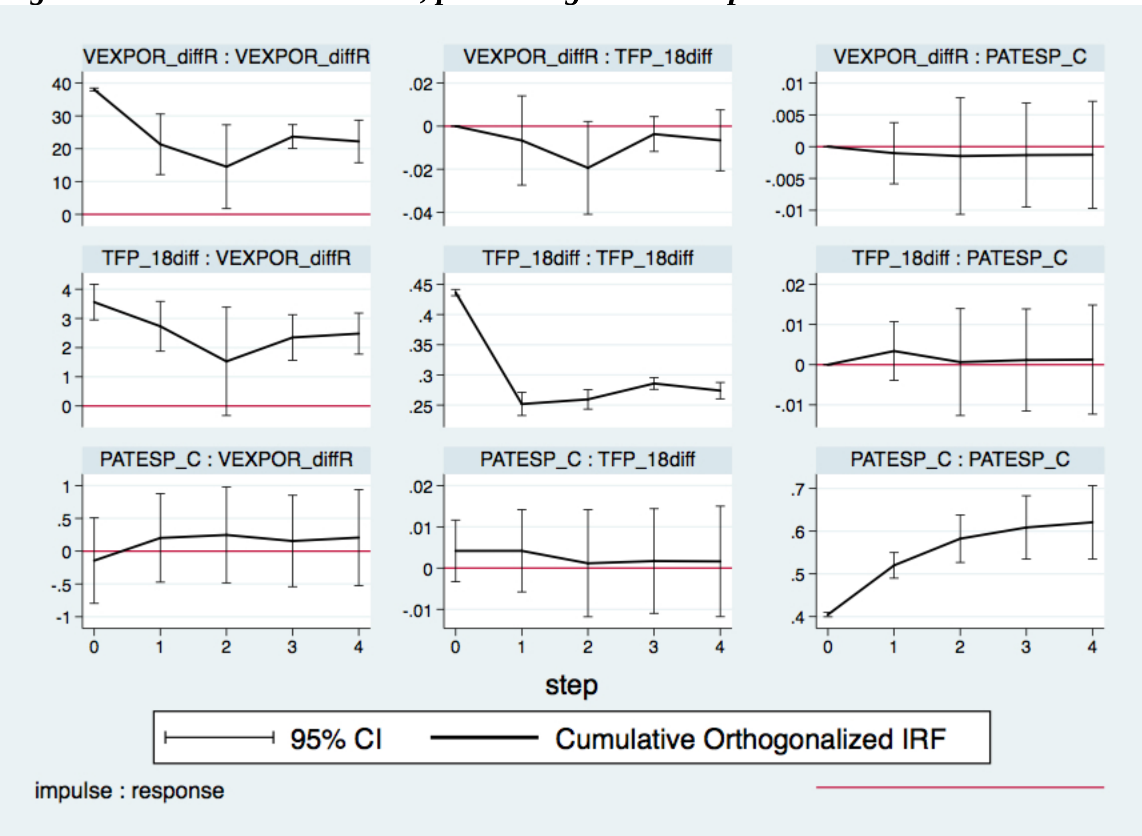


Figure A2.1.5 IRFs, Patents registered abroad

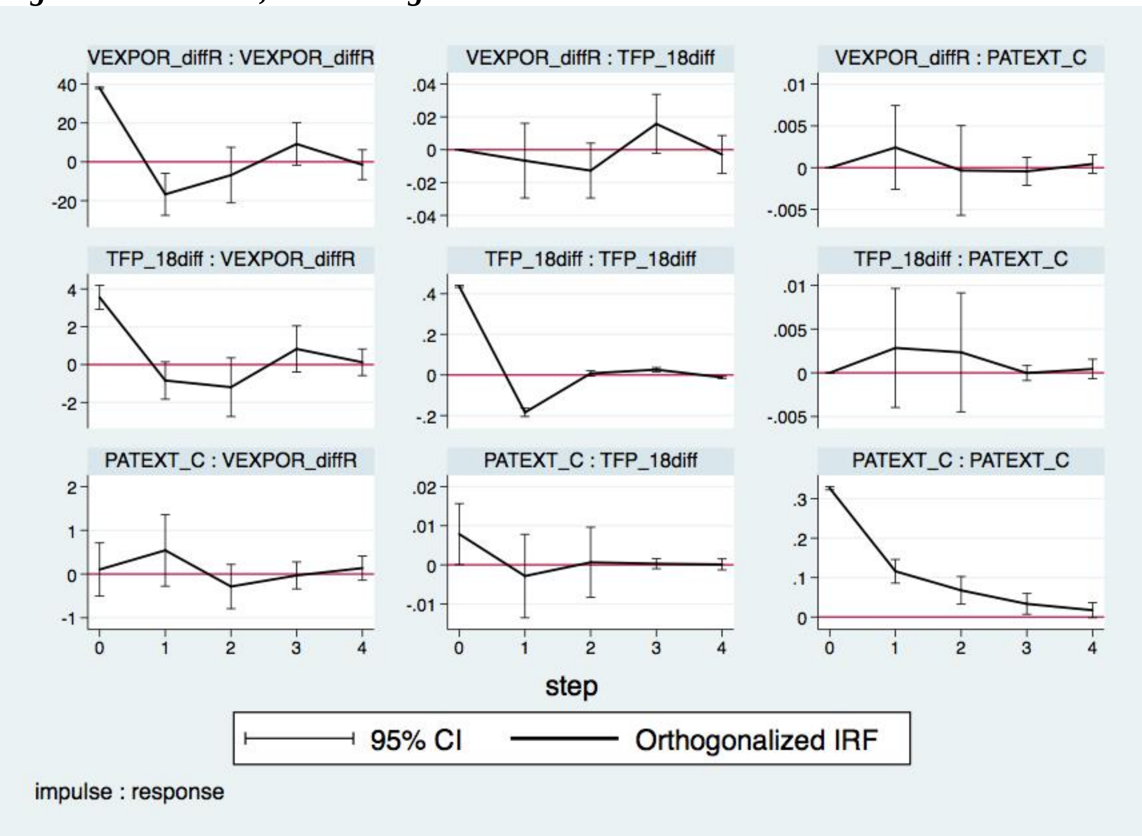


Figure A2.1.6 Cumulative IRFs, Patents registered abroad

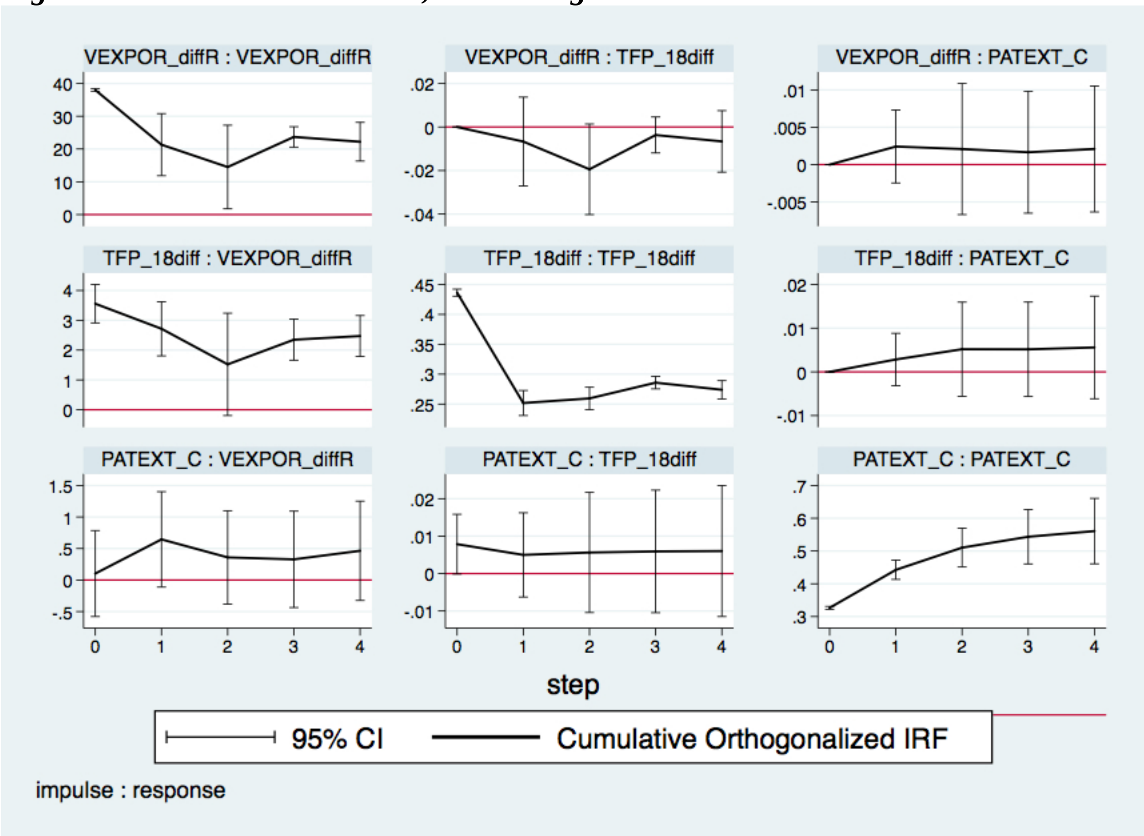


Figure A2.1.7 IRFs, Number of product innovations

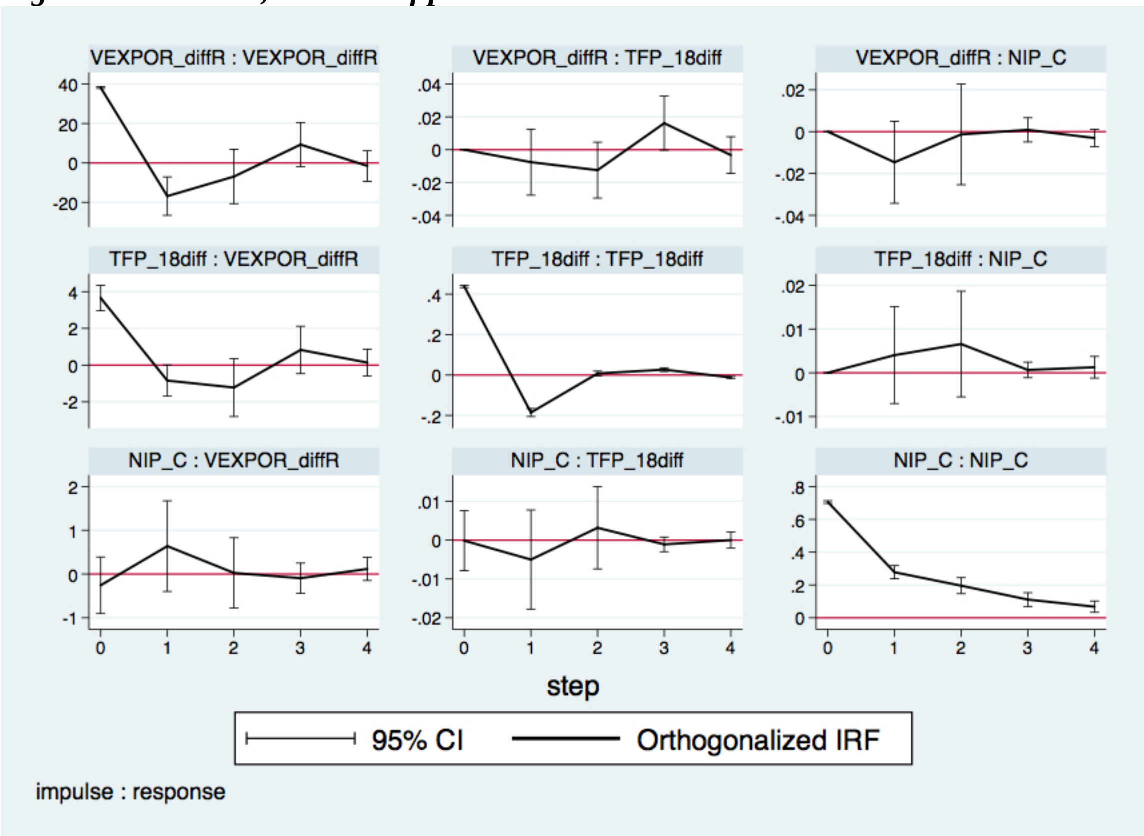


Figure A2.1.8 Cumulative IRFs, Number of product innovations

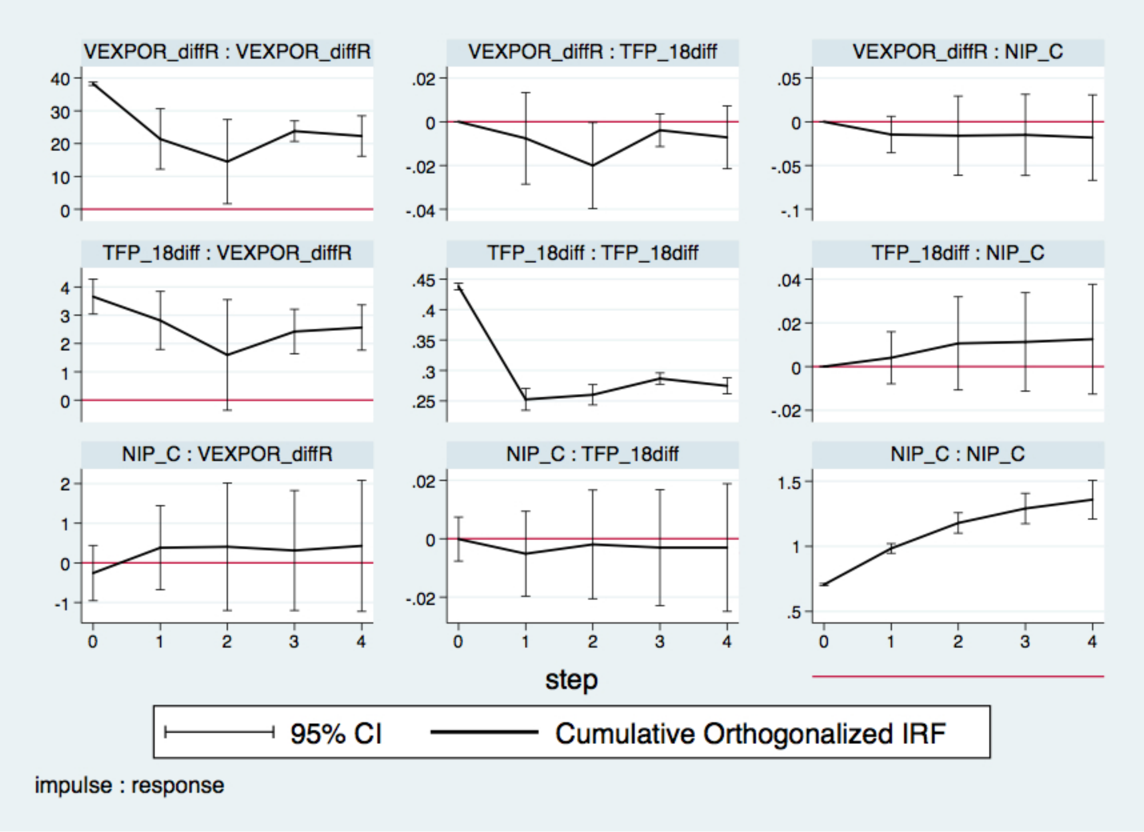


Figure A2.1.9 IRFs, Organisational innovations

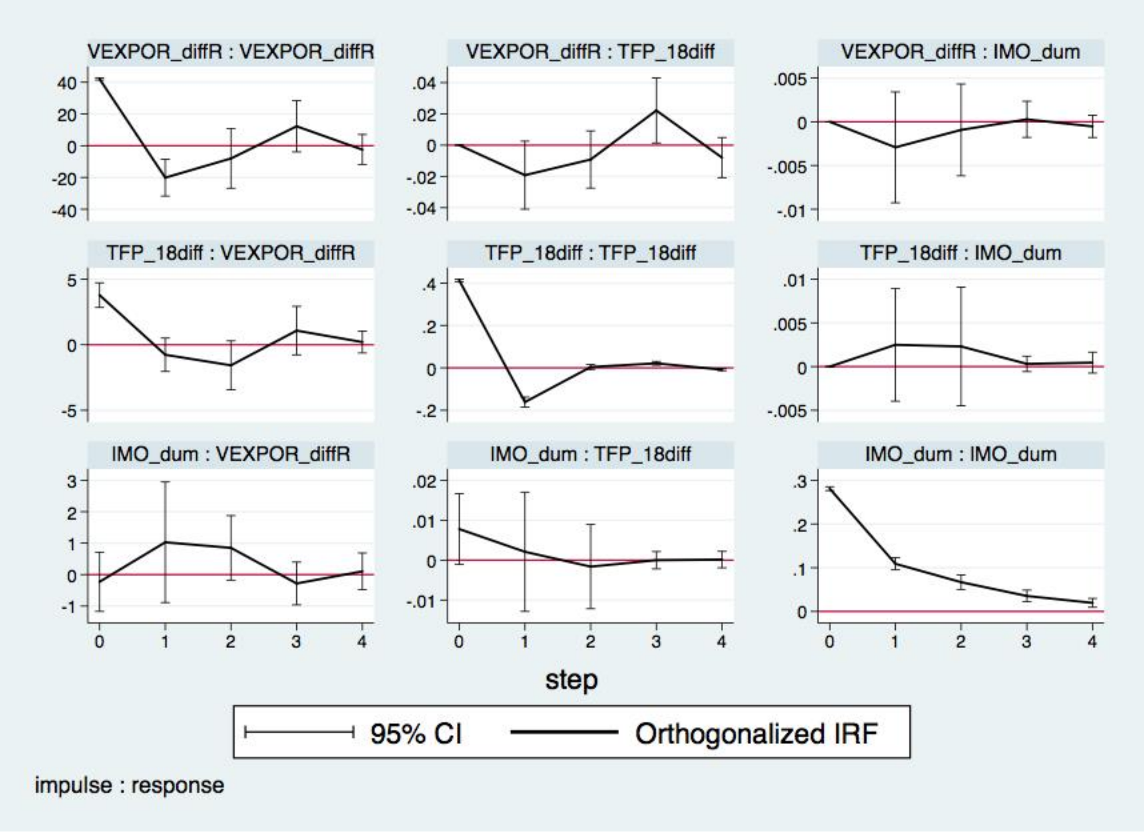


Figure A2.1.10 Cumulative IRFs, Organisational innovations

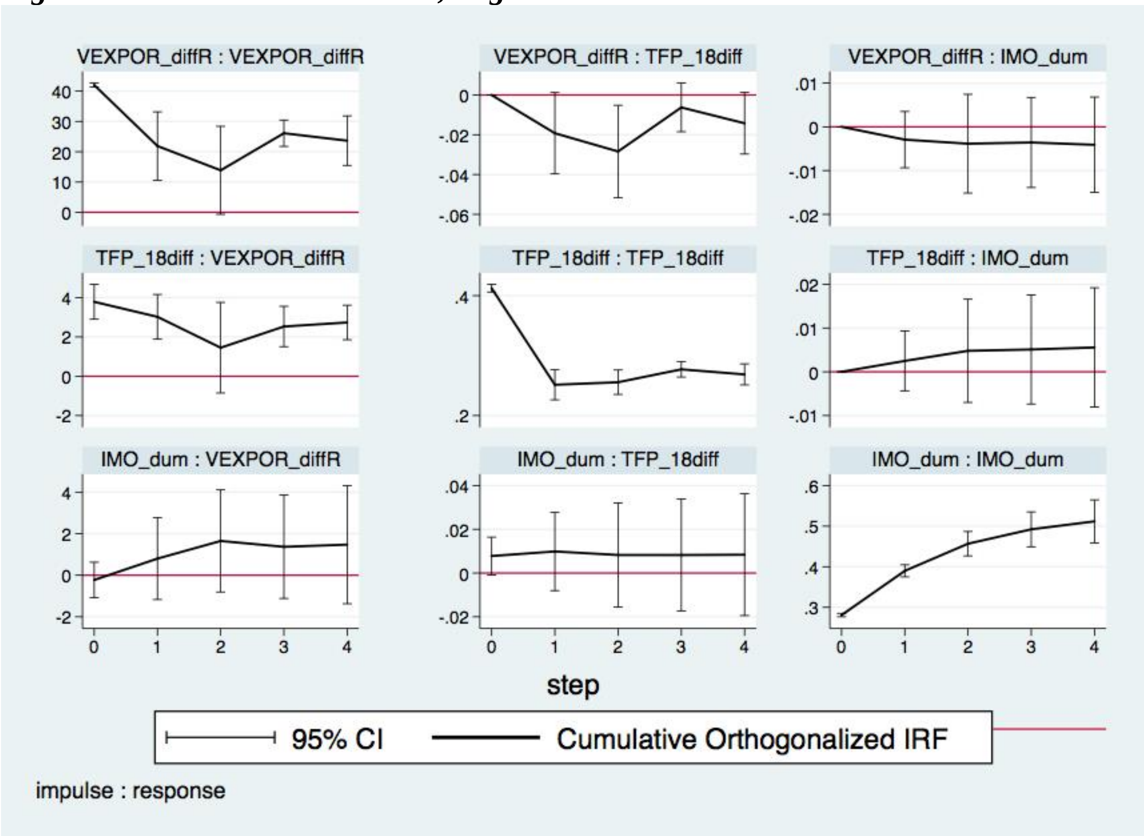


Figure A2.1.11 IRFs, Marketing innovations

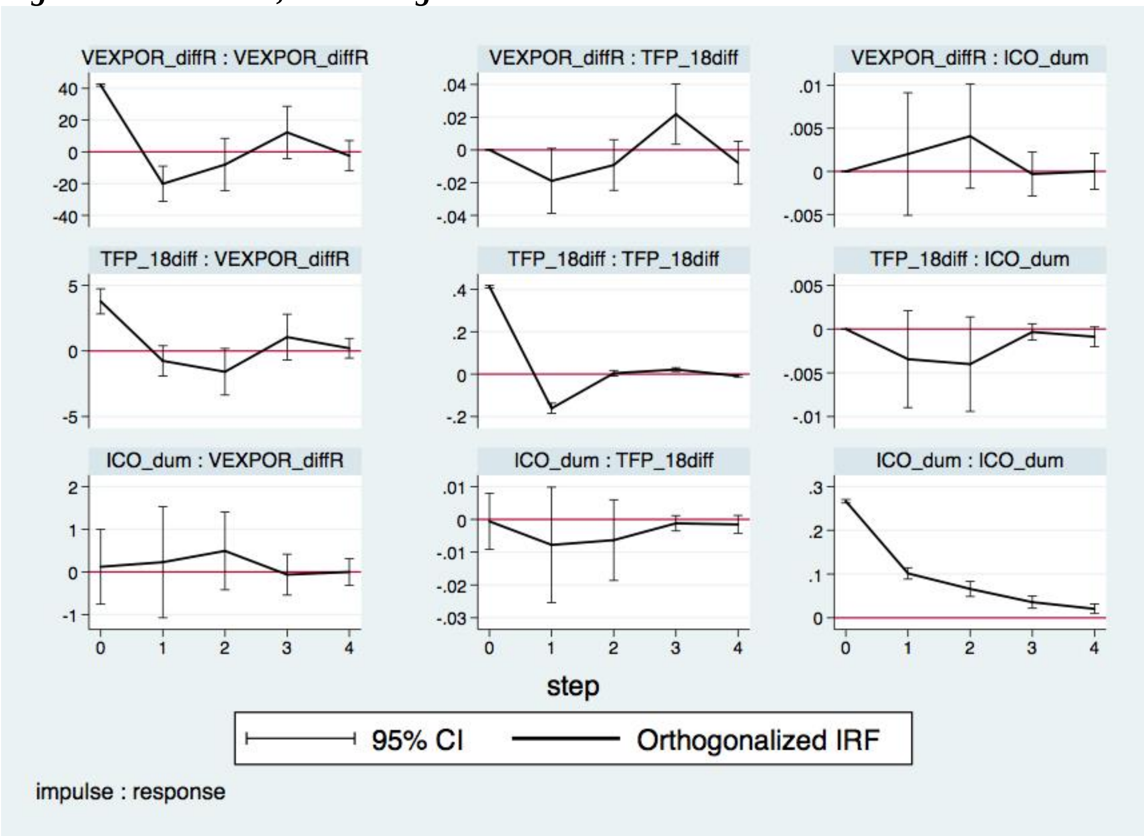


Figure A2.1.12 Cumulative IRFs, Marketing innovations

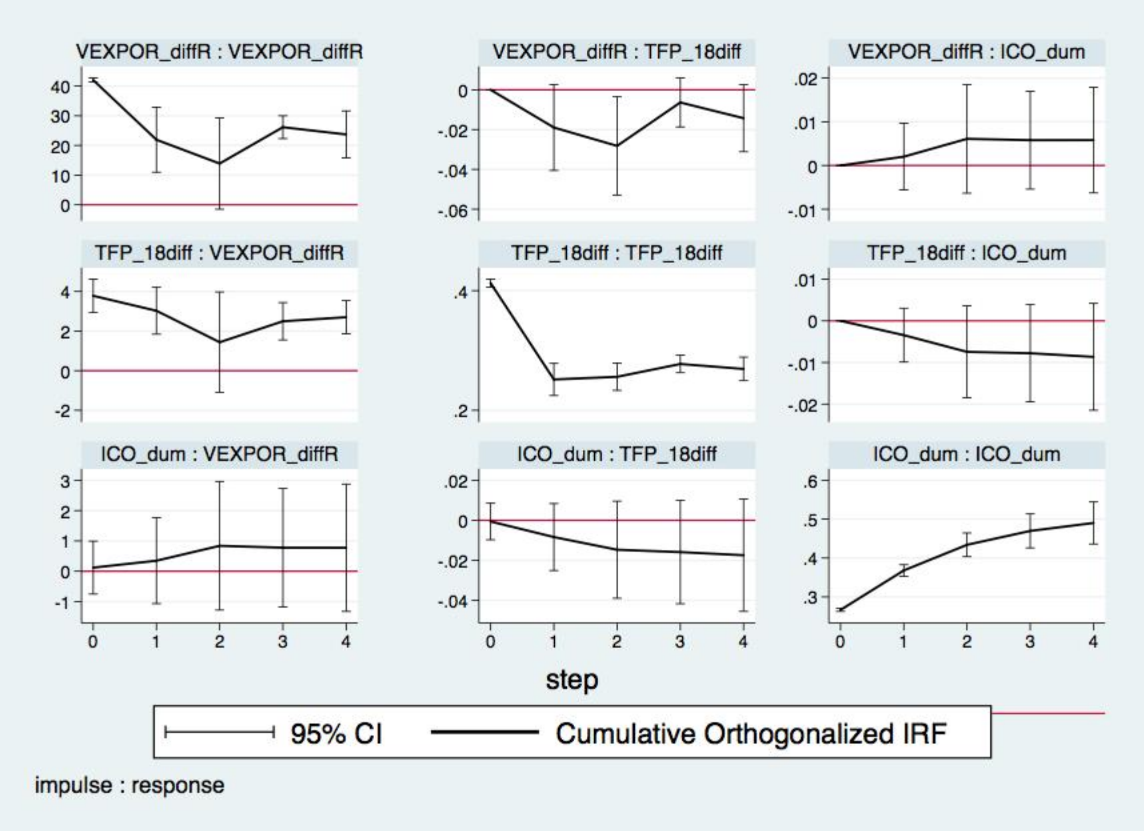


Figure A2.1.13 IRFs, Process innovations

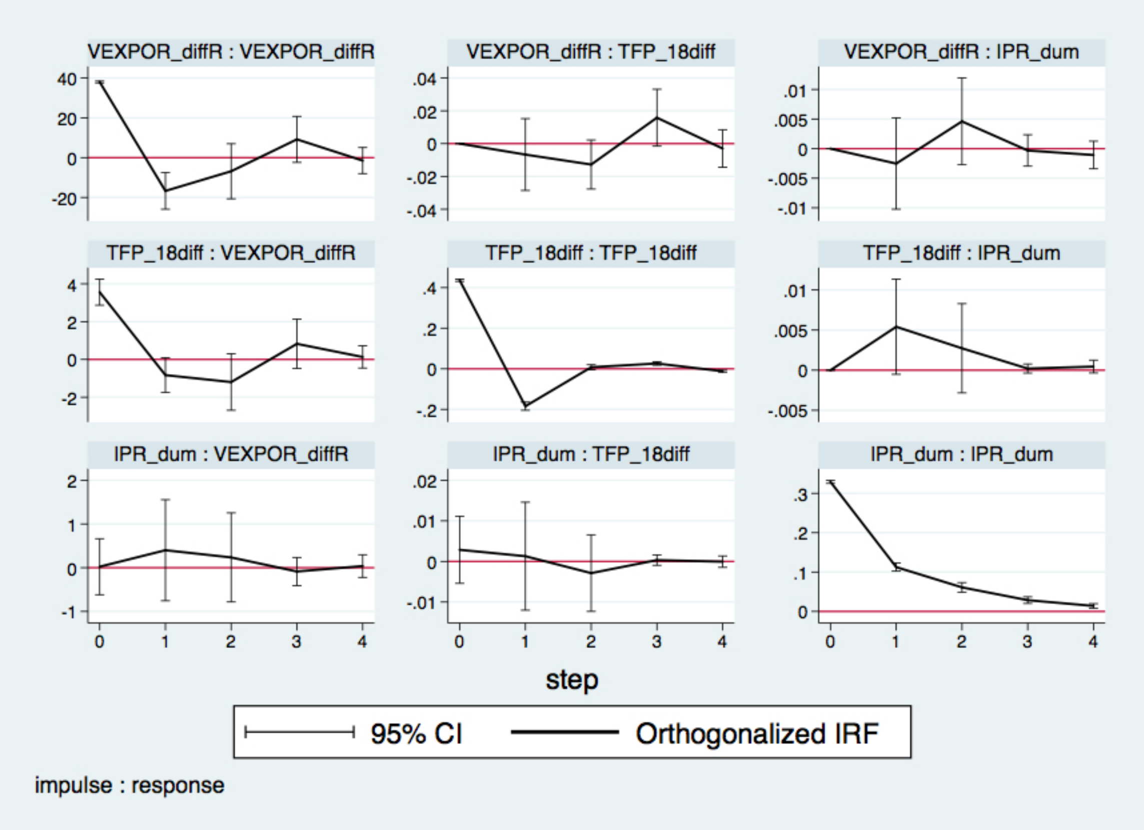
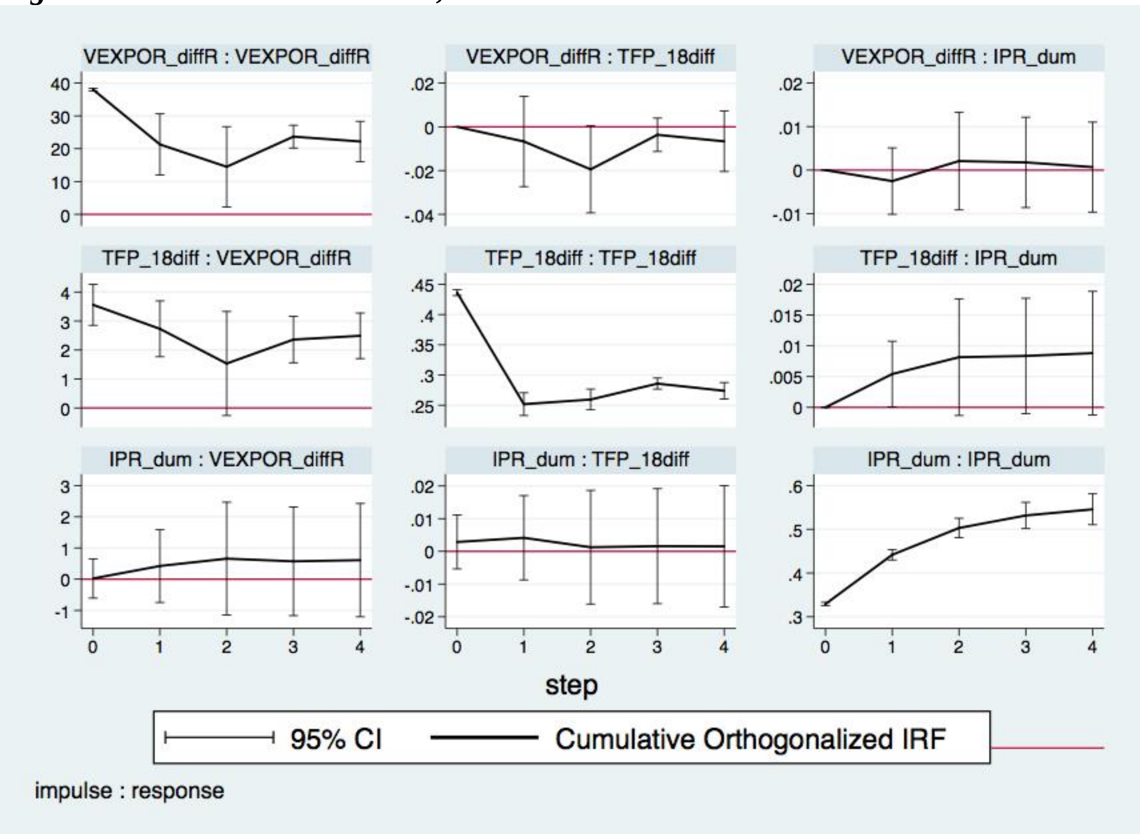


Figure A2.1.14 Cumulative IRFs, Process innovations



Appendix A2.2: IRFs and cumulative IRFs for small firms subsample

Figure A2.2.1 IRFs, R&D expenditures

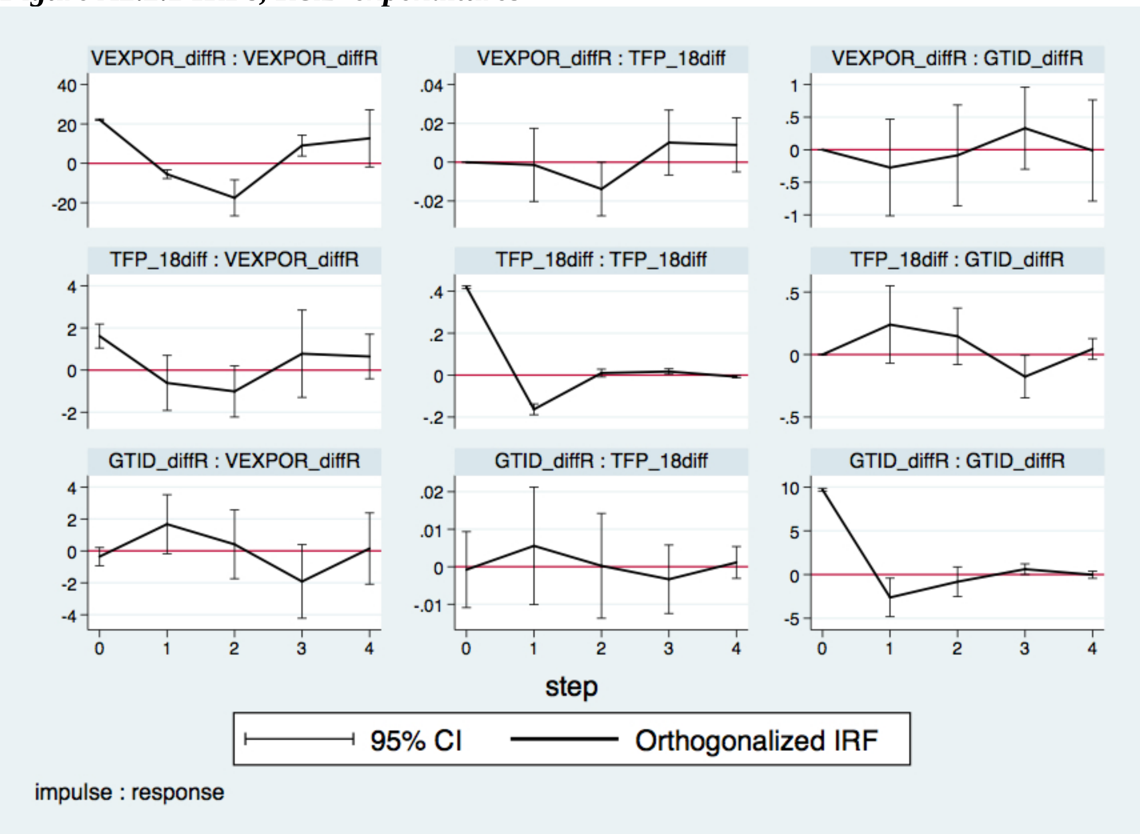


Figure A2.2.2 Cumulative IRFs, R&D expenditures

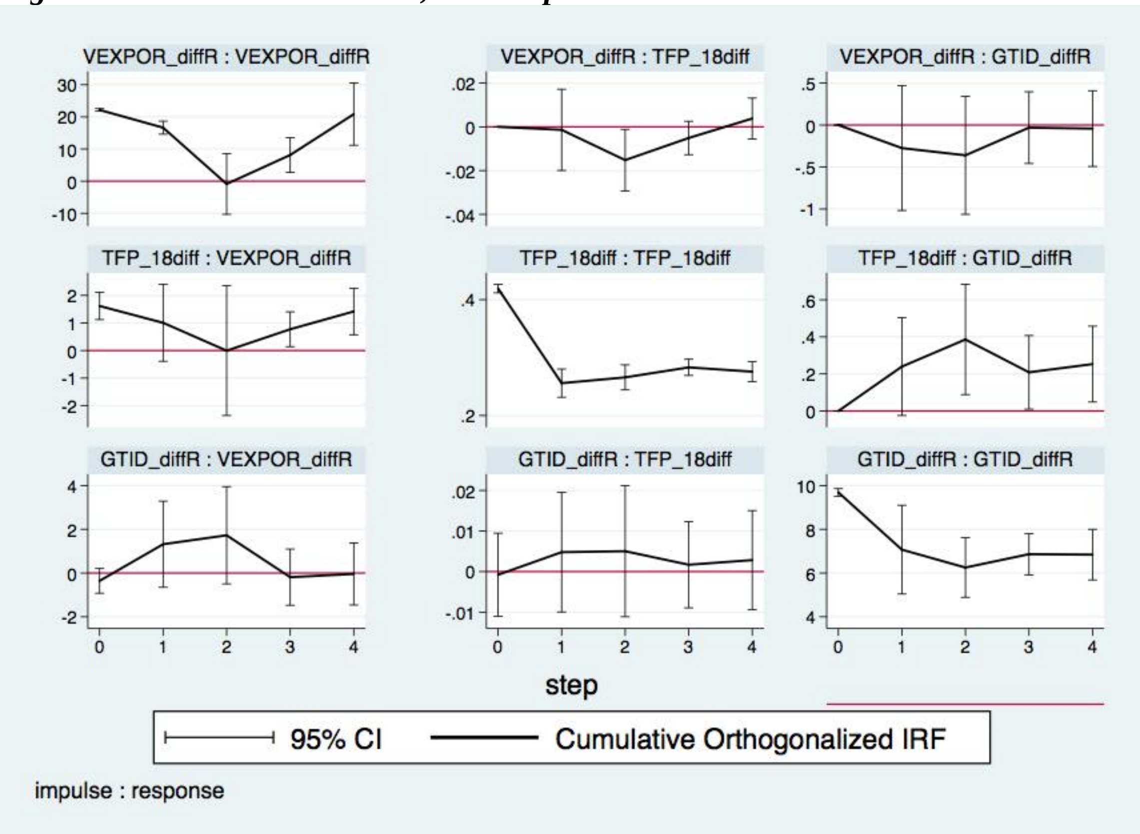


Figure A2.2.3 IRFs, patents registered in Spain

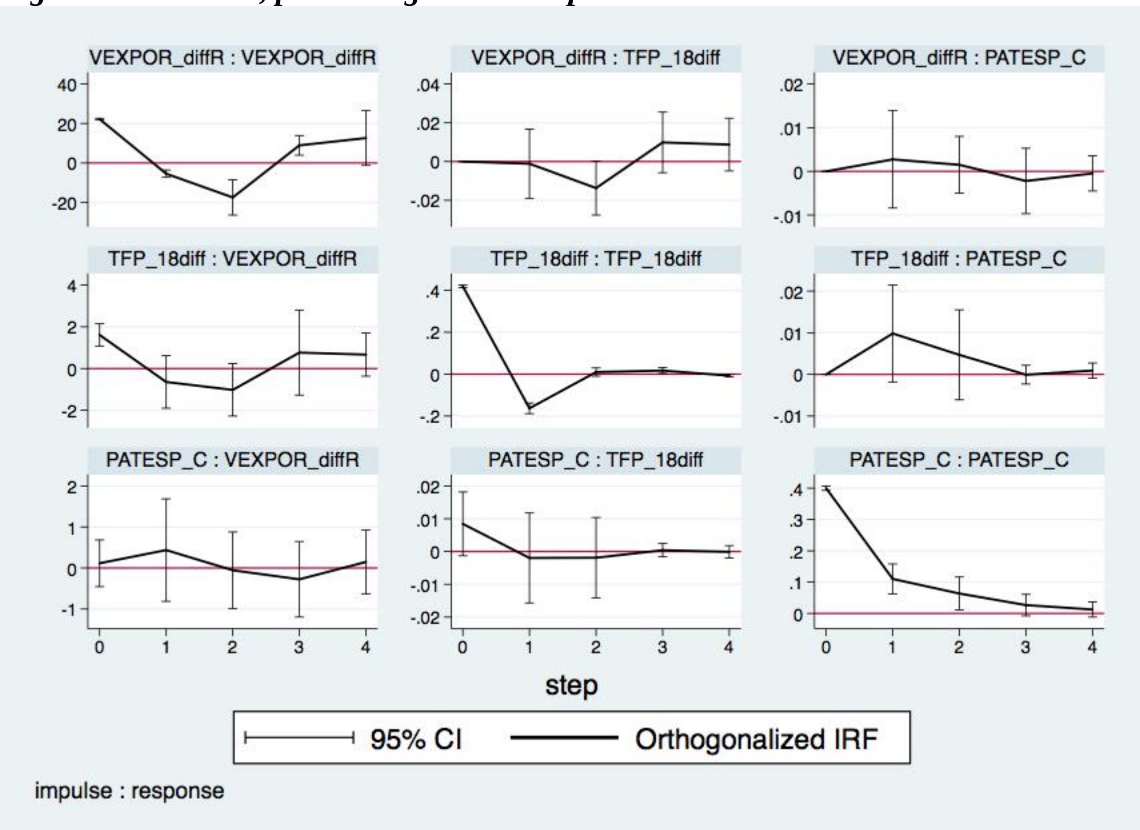


Figure A2.2.4 Cumulative IRFs, patents registered in Spain

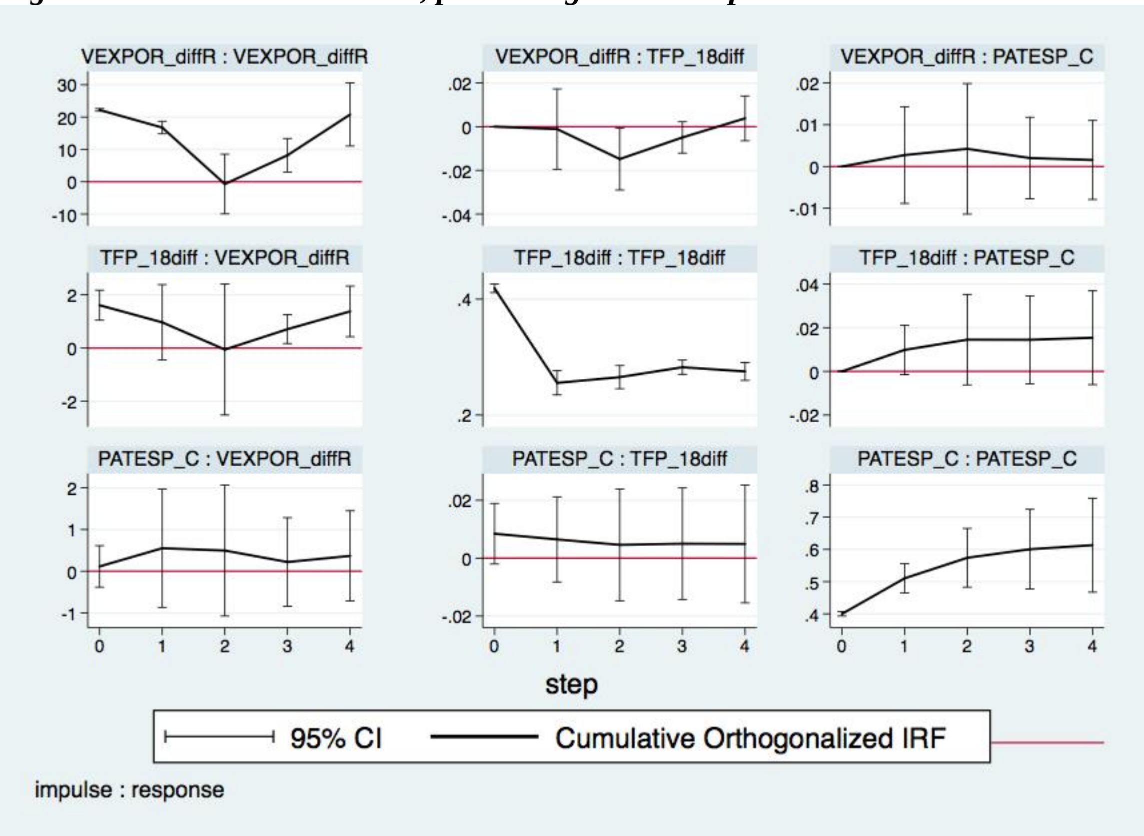


Figure A2.2.5 IRFs, patents registered abroad

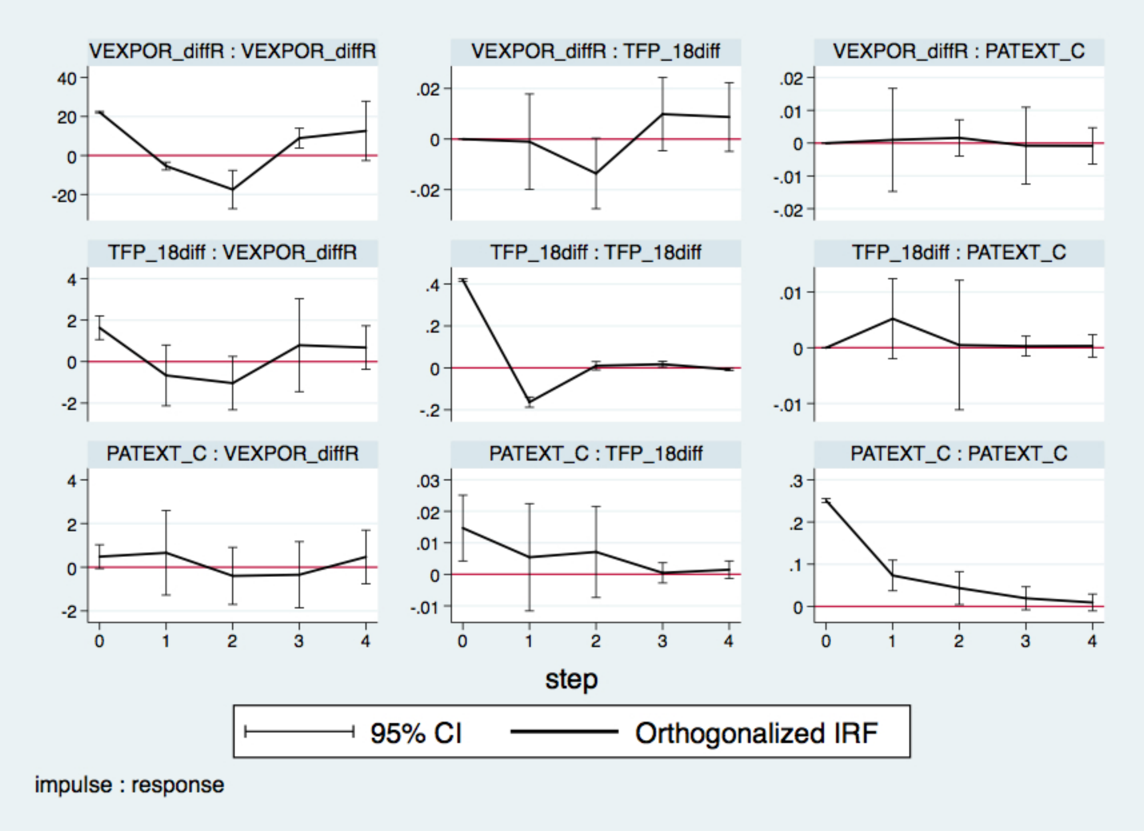


Figure A2.2.6 Cumulative IRFs, patents registered abroad

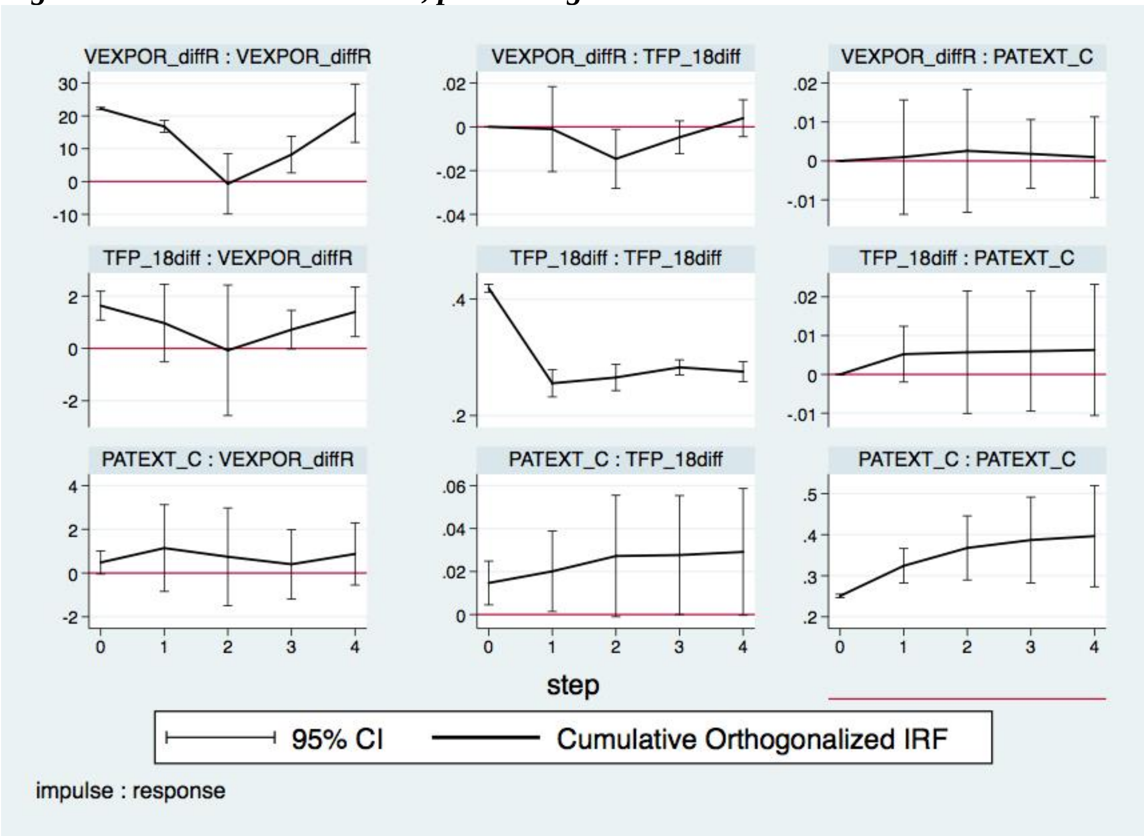


Figure A2.2.7 IRFs, Number of product innovations

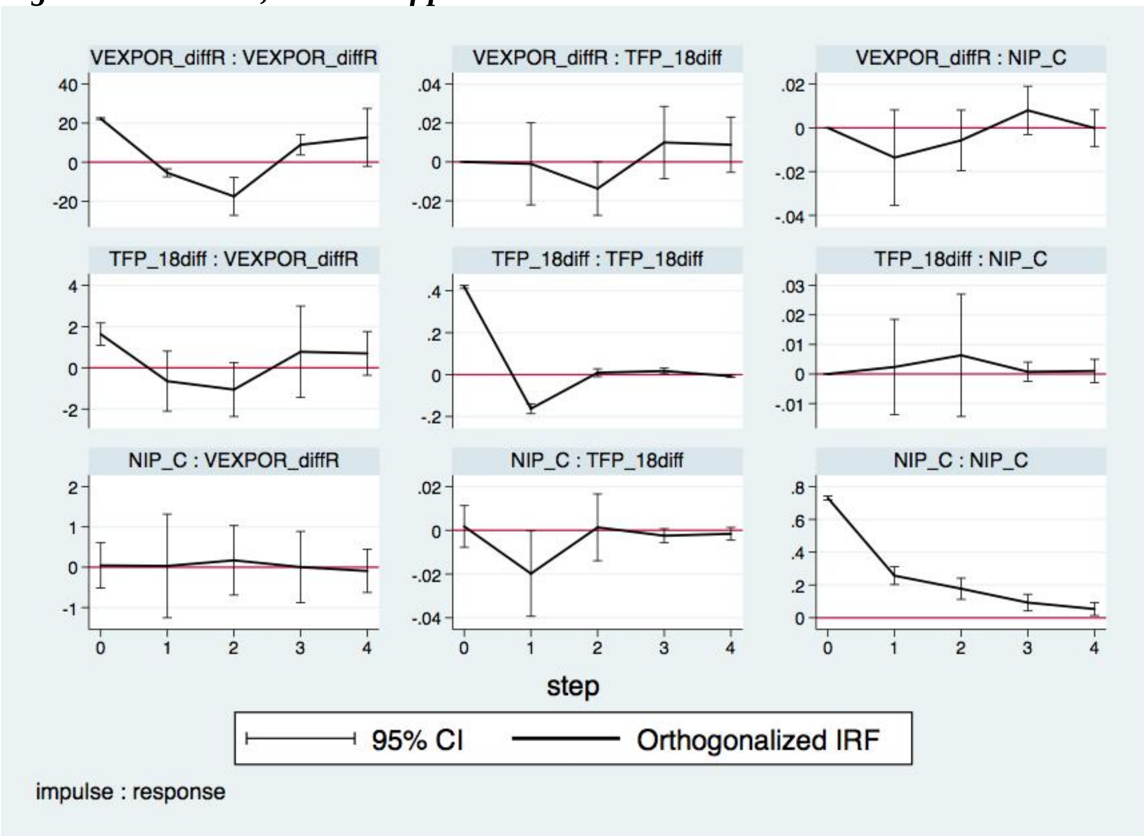


Figure A2.2.8 Cumulative IRFs, Number of product innovations

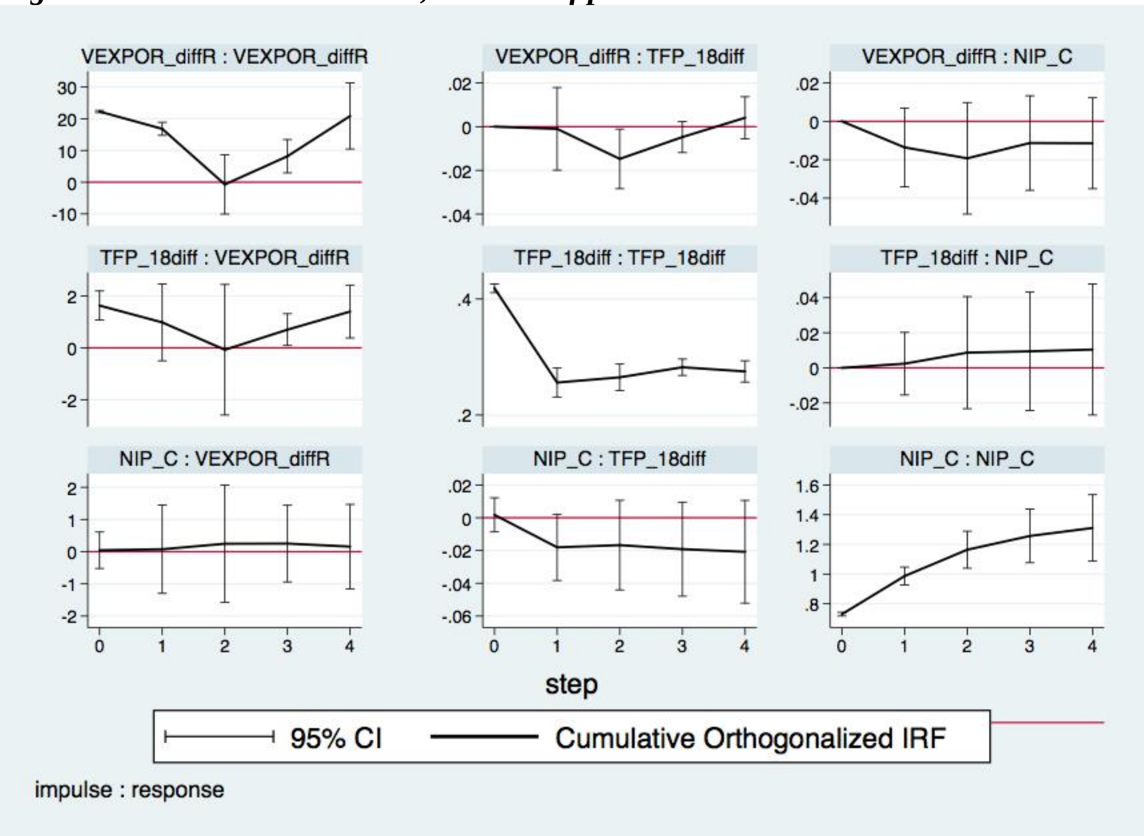


Figure A2.2.9 IRFs, Organisational innovations

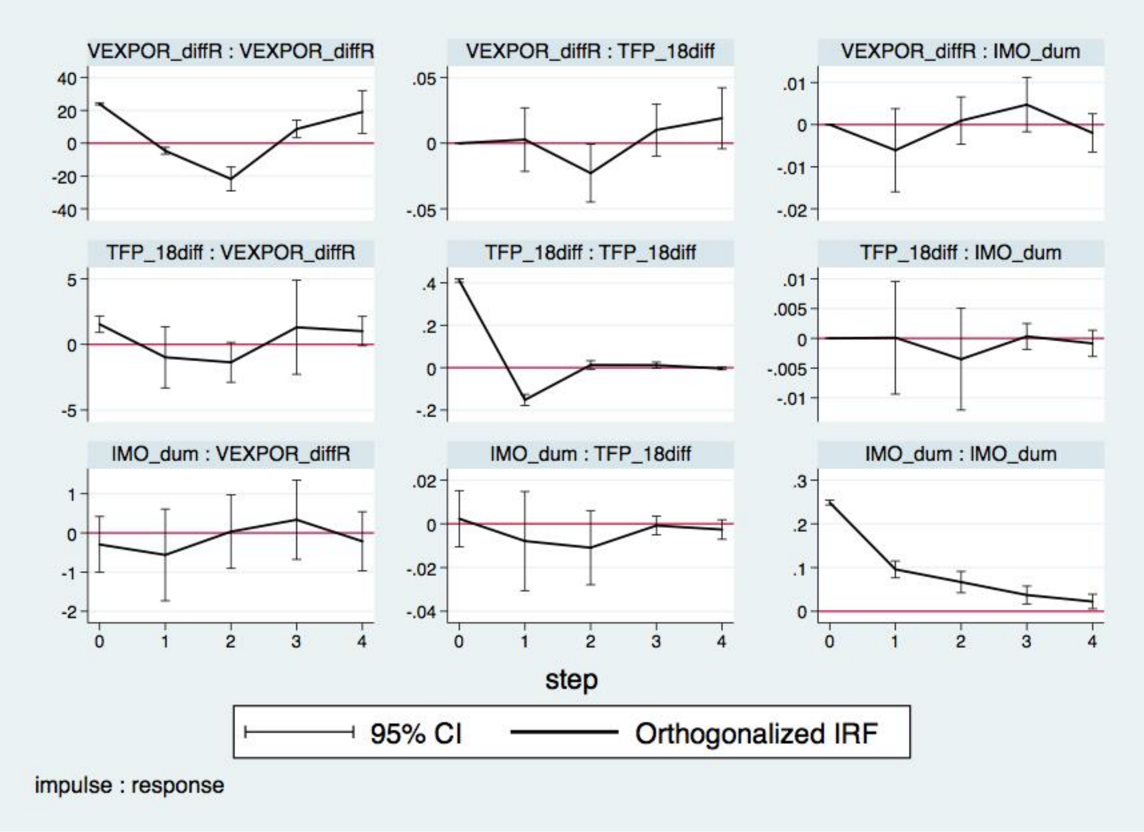


Figure A2.2.10 Cumulative IRFs, Organisational innovations

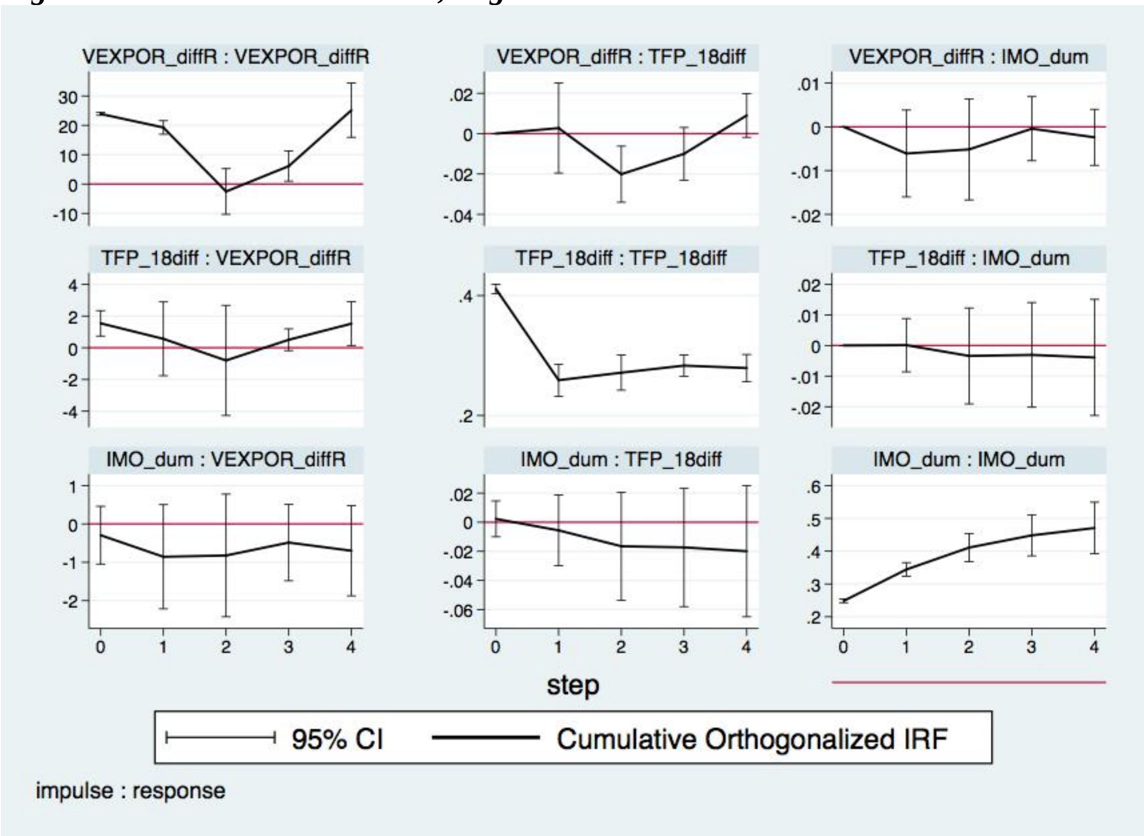


Figure A2.2.11 IRFs, Marketing innovations

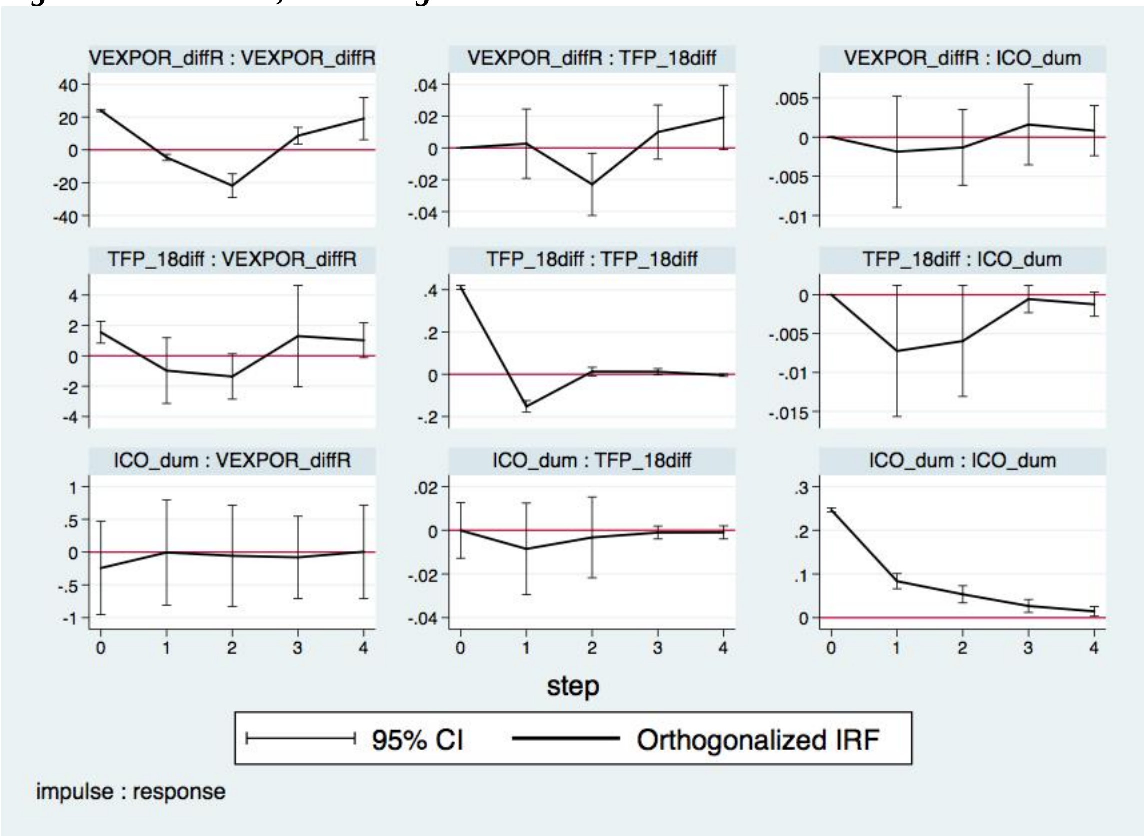


Figure A2.2.12 Cumulative IRFs, Marketing innovations

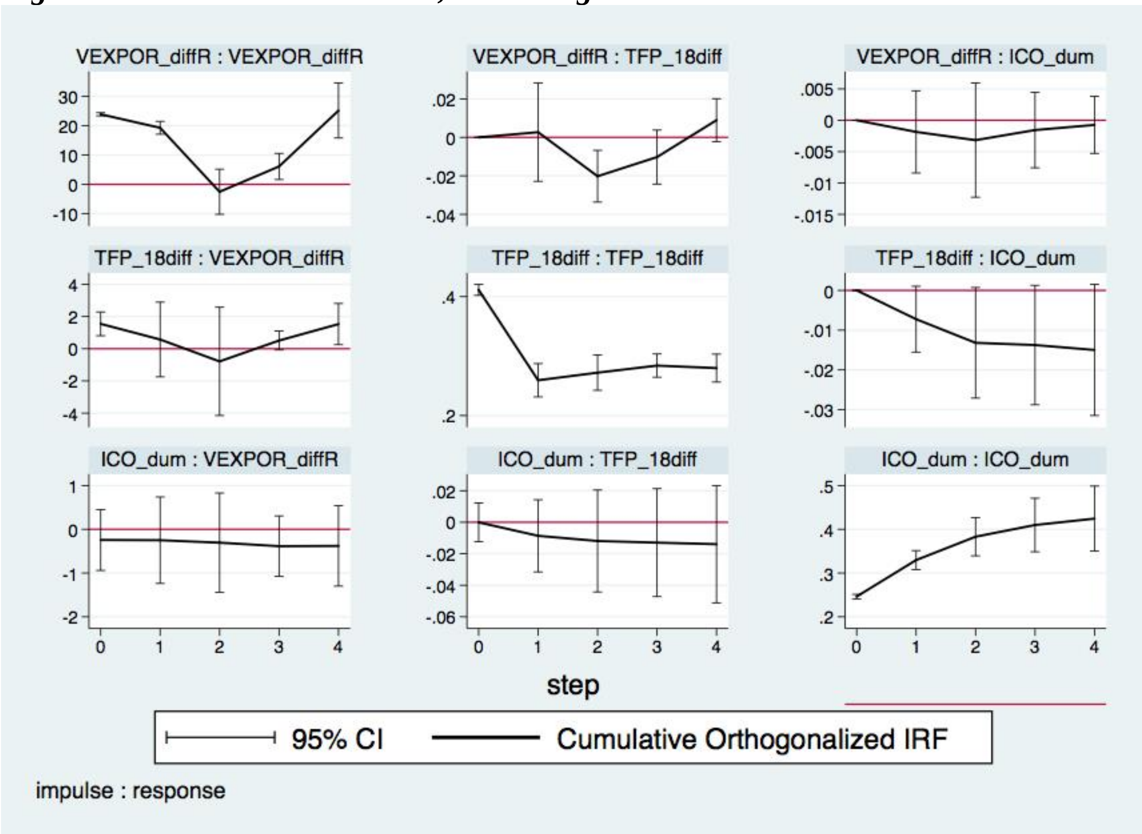


Figure A2.2.13 IRFs, Process innovations

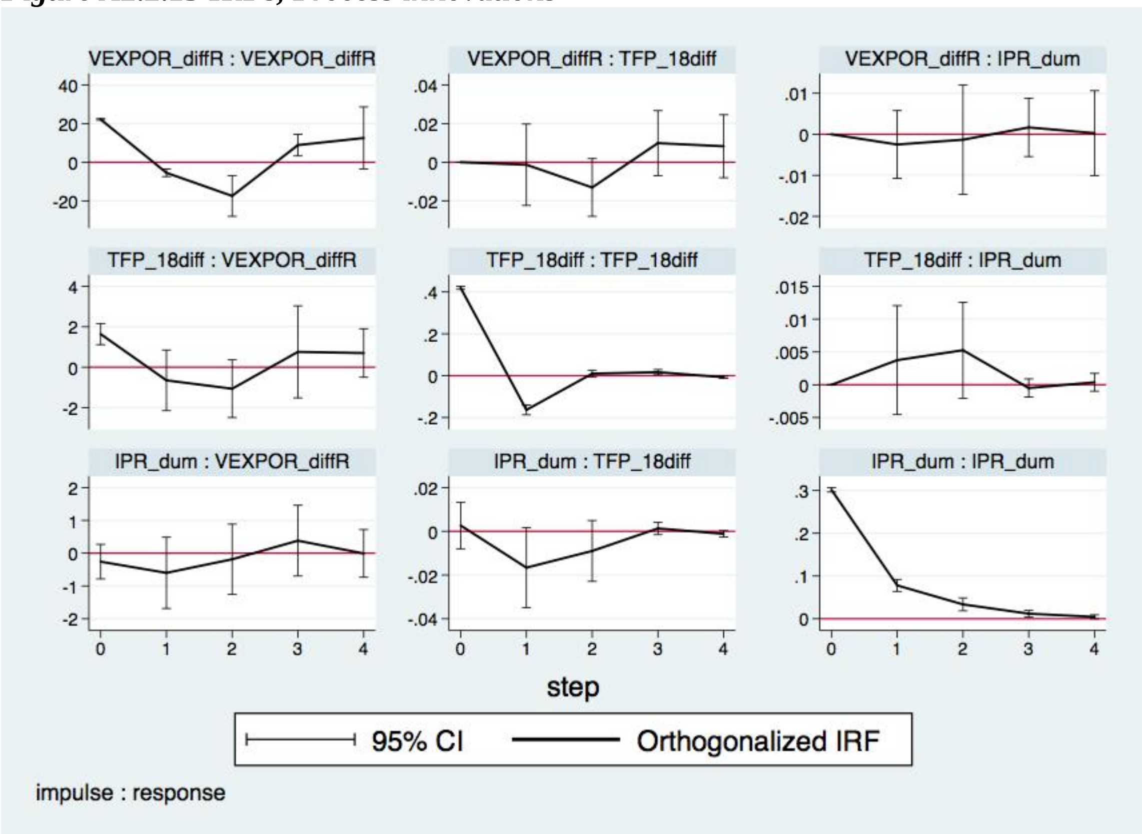
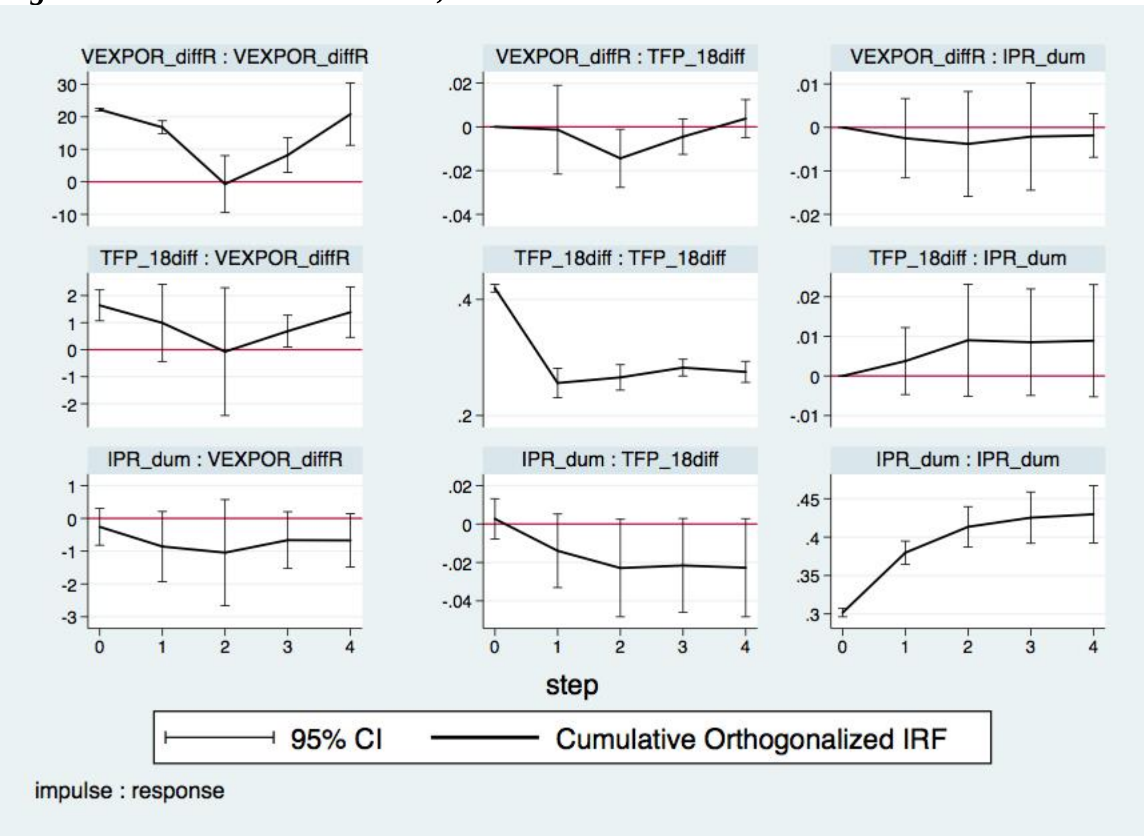


Figure A2.2.14 Cumulative IRFs, Process innovations



Appendix A2.3: IRFs and cumulative IRFs for medium firms subsample

Figure A2.3.1 IRFs, R&D expenditures

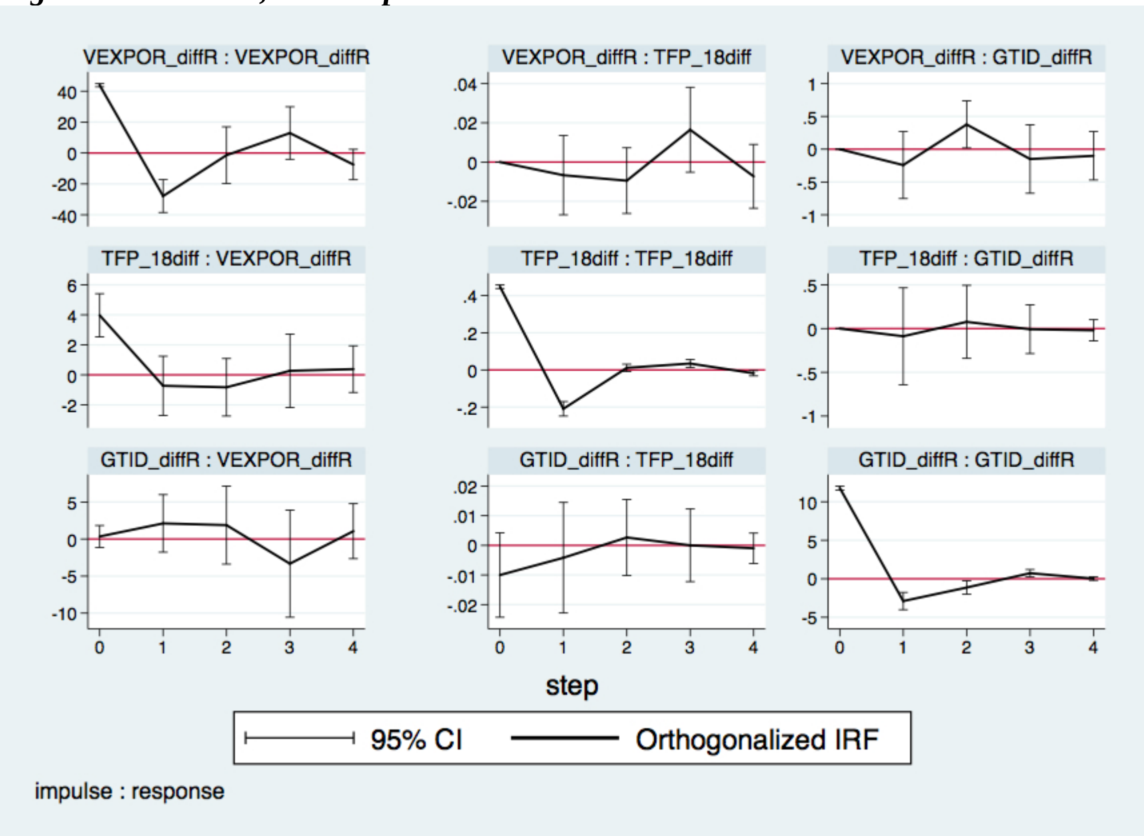


Figure A2.3.2 Cumulative IRFs, R&D expenditures

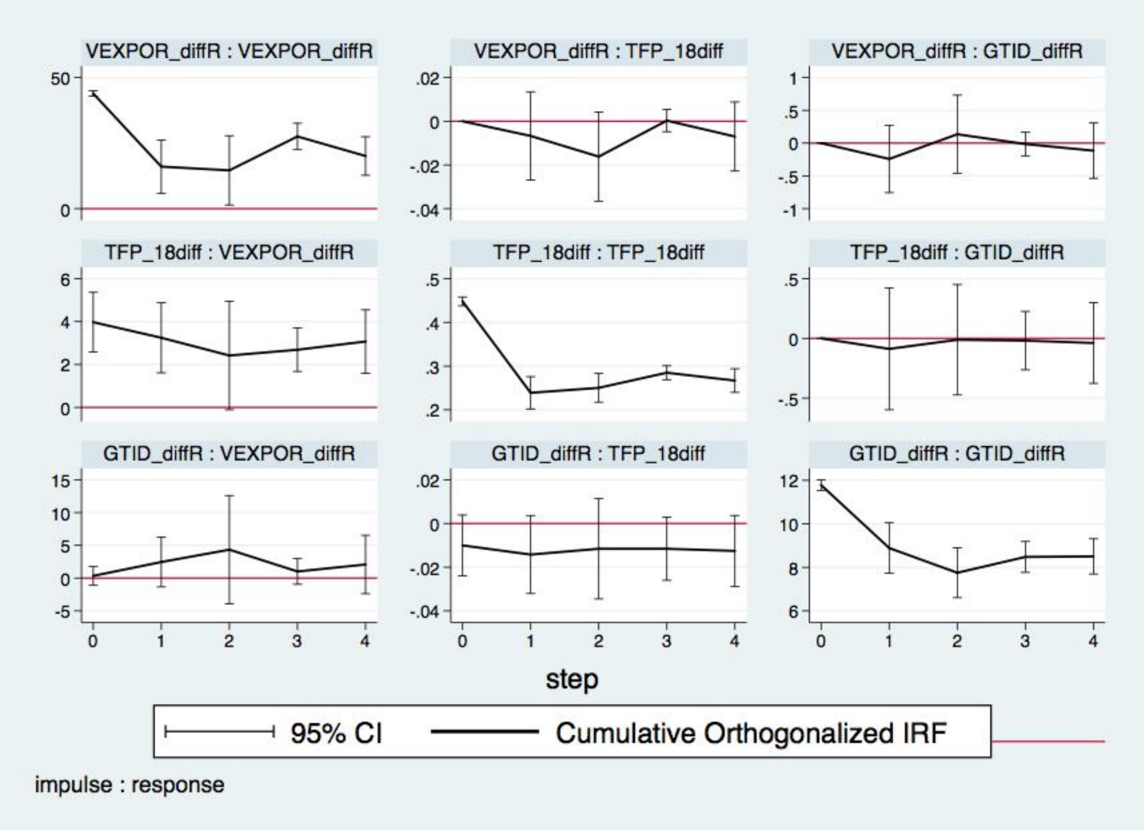


Figure A2.3.3 IRFs, patents registered in Spain

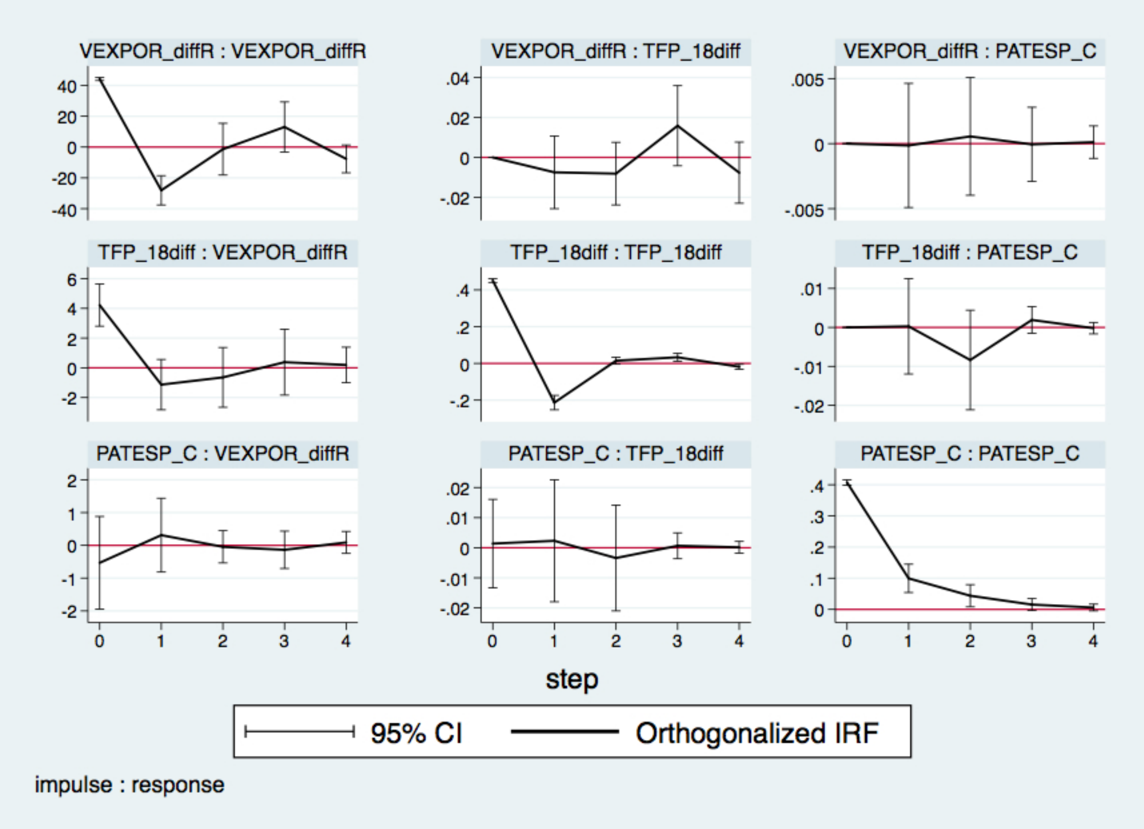


Figure A2.3.4 Cumulative IRFs, patents registered in Spain

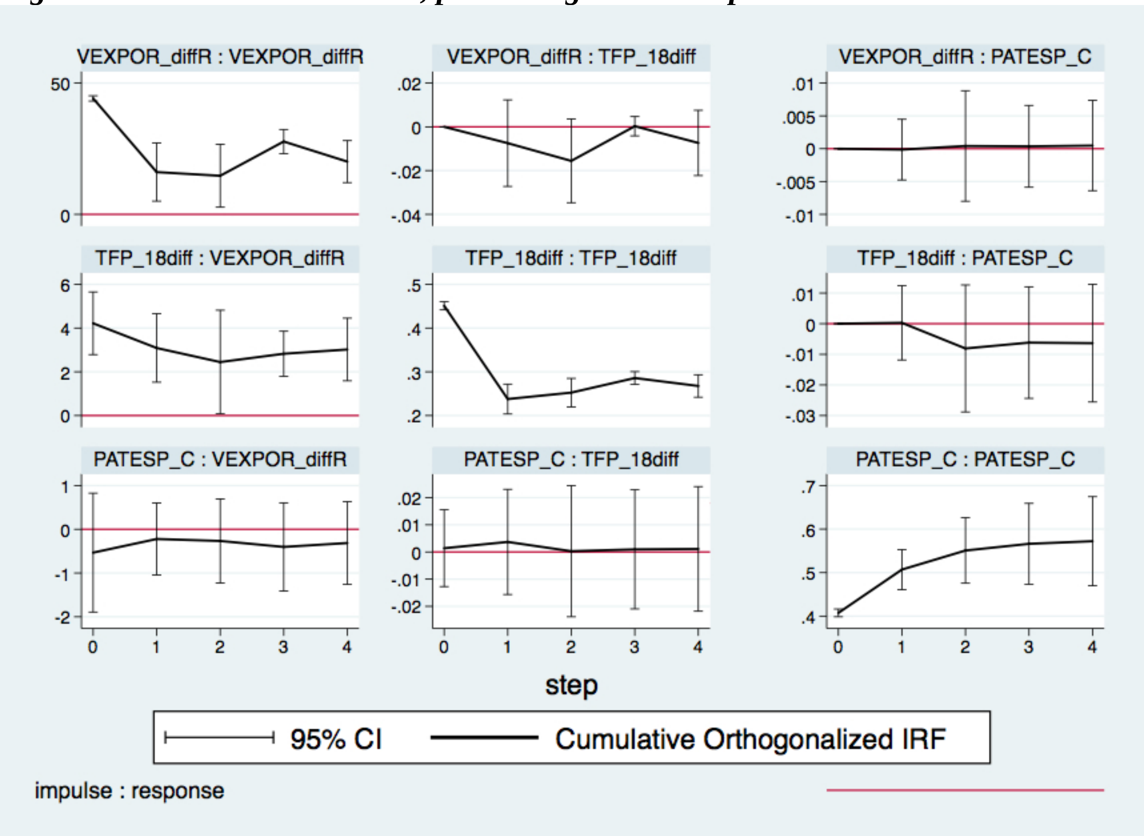


Figure A2.3.5 IRFs, patents registered abroad

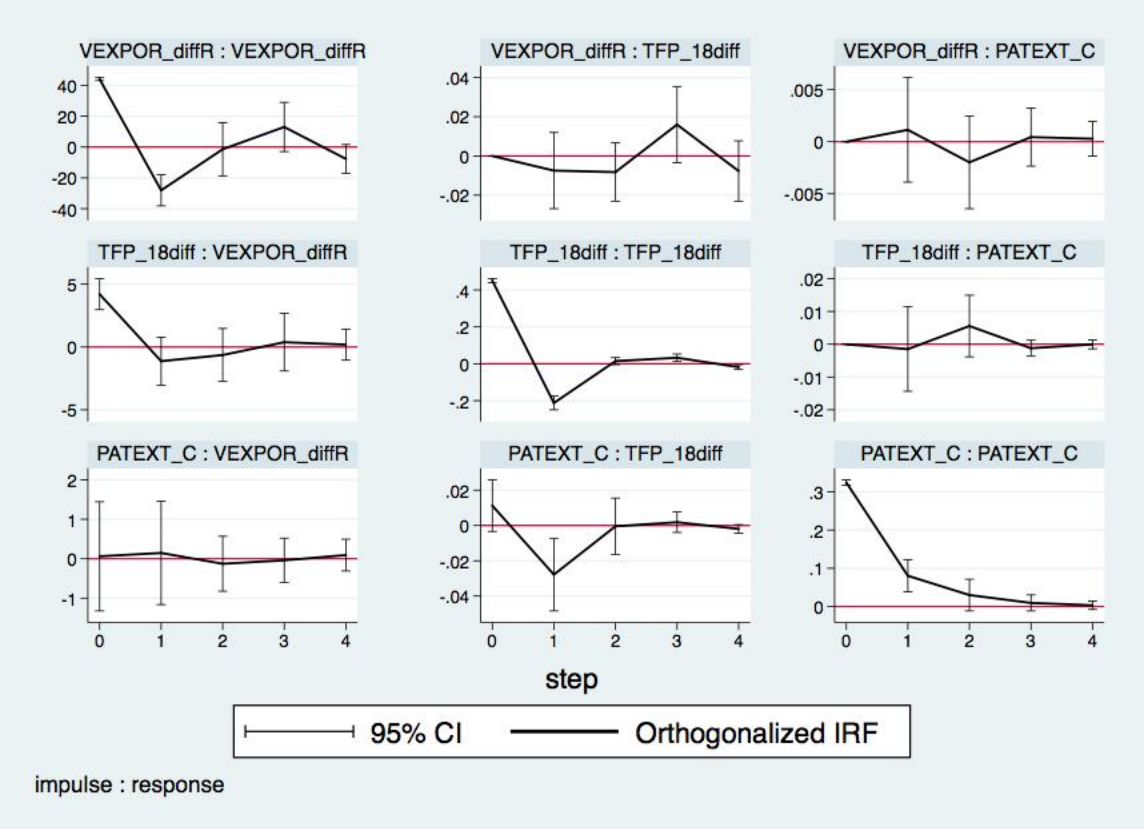


Figure A2.3.6 Cumulative IRFs, patents registered abroad

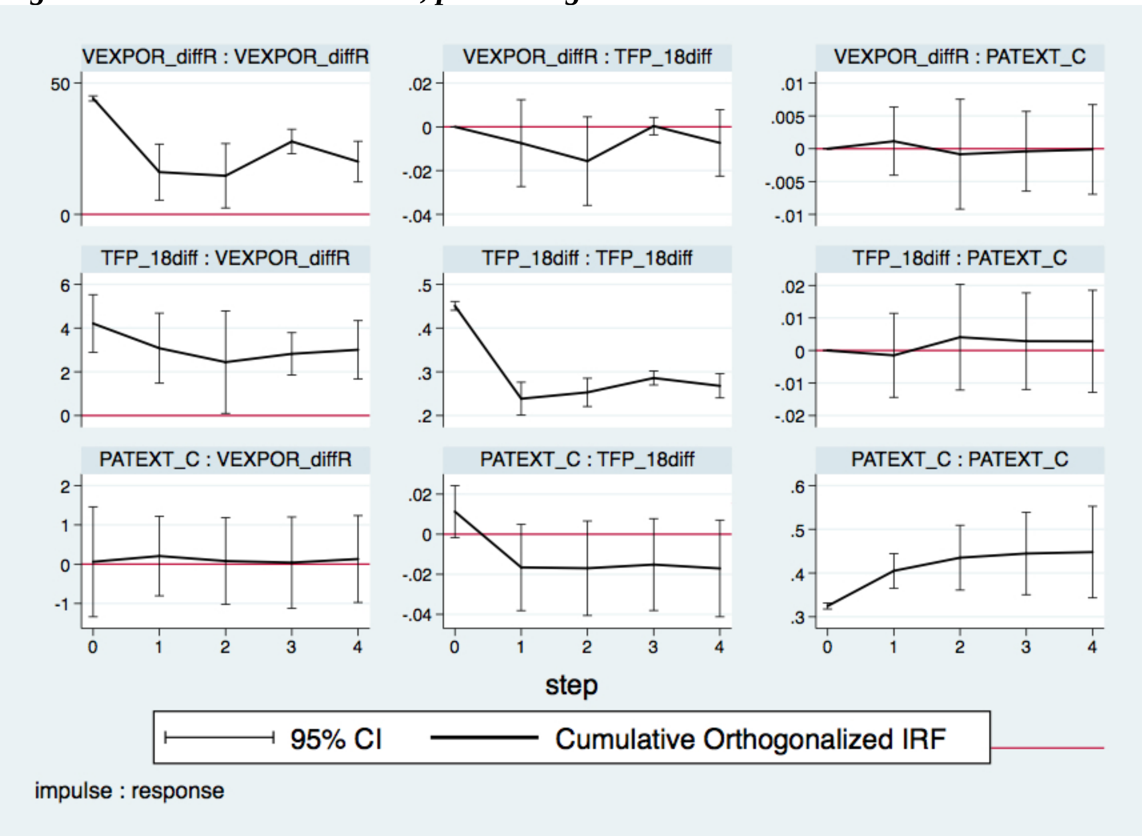


Figure A2.3.7 IRFs, Number of product innovations

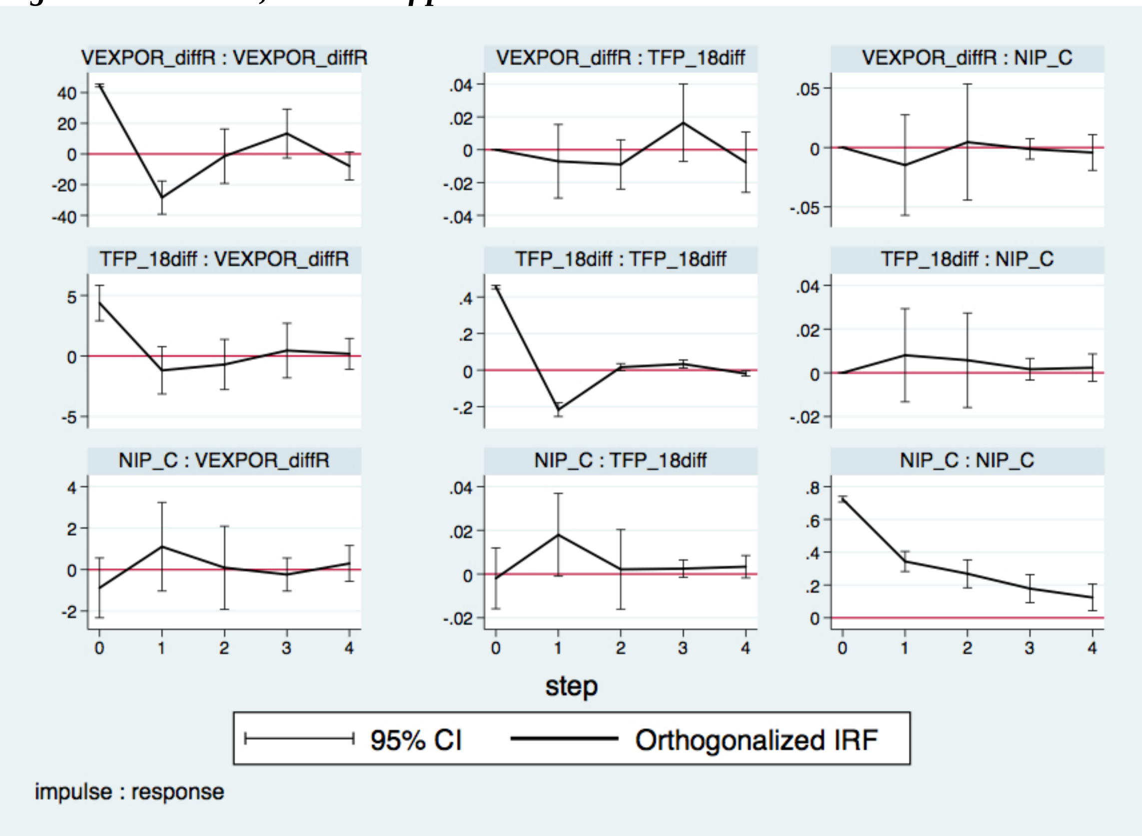


Figure A2.3.8 Cumulative IRFs, Number of product innovations

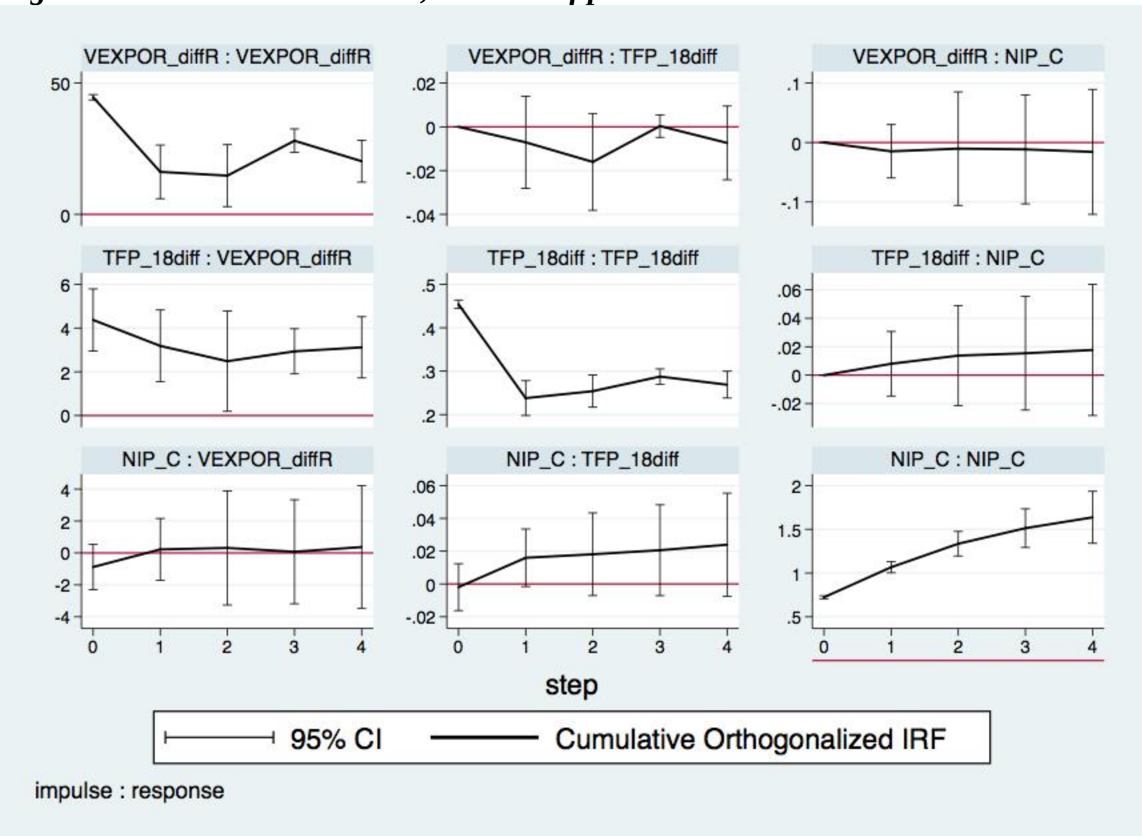


Figure A2.3.9 IRFs, Organisational innovations

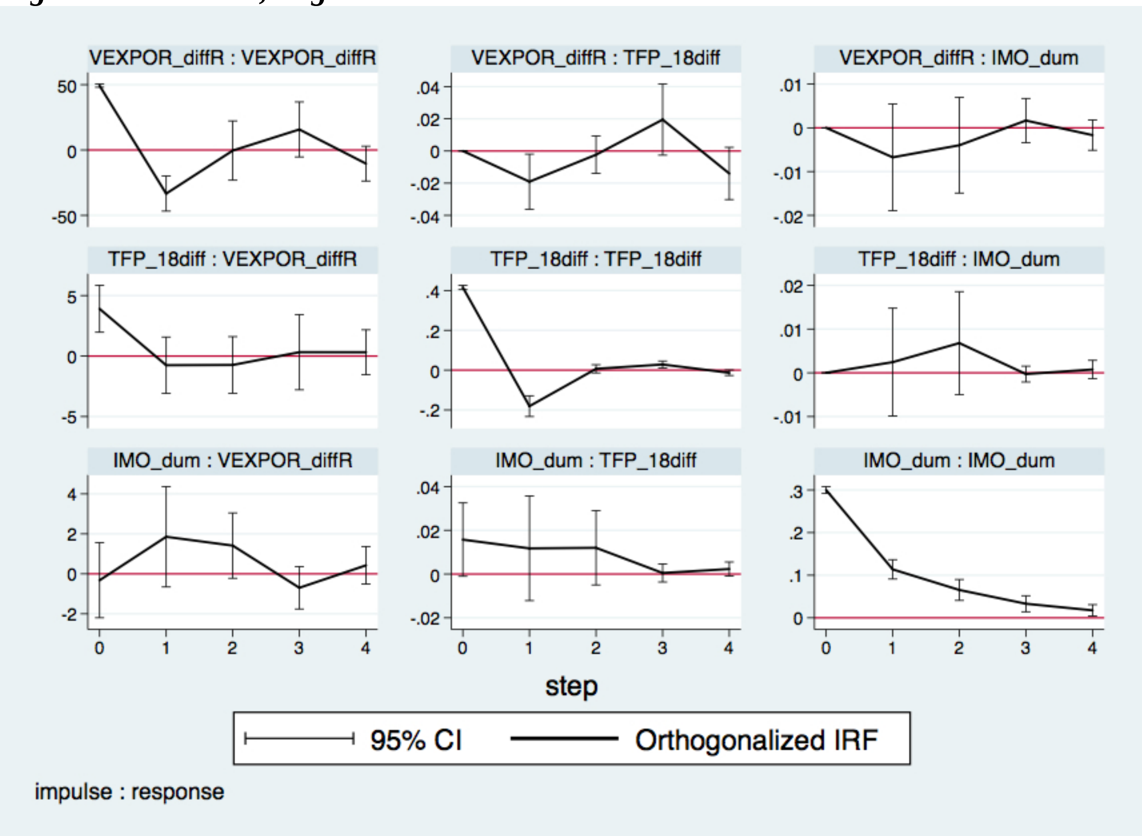


Figure A2.3.10 Cumulative IRFs, Organisational innovations

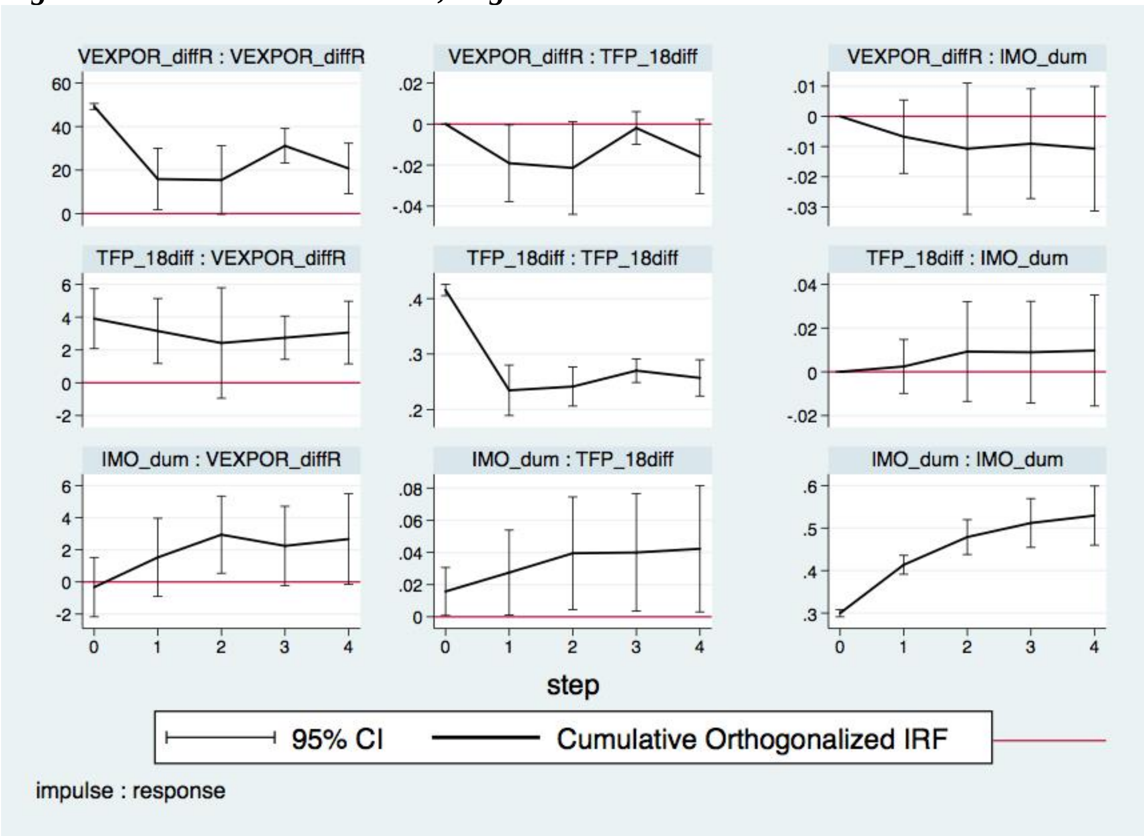


Figure A2.3.11 IRFs, Marketing innovations

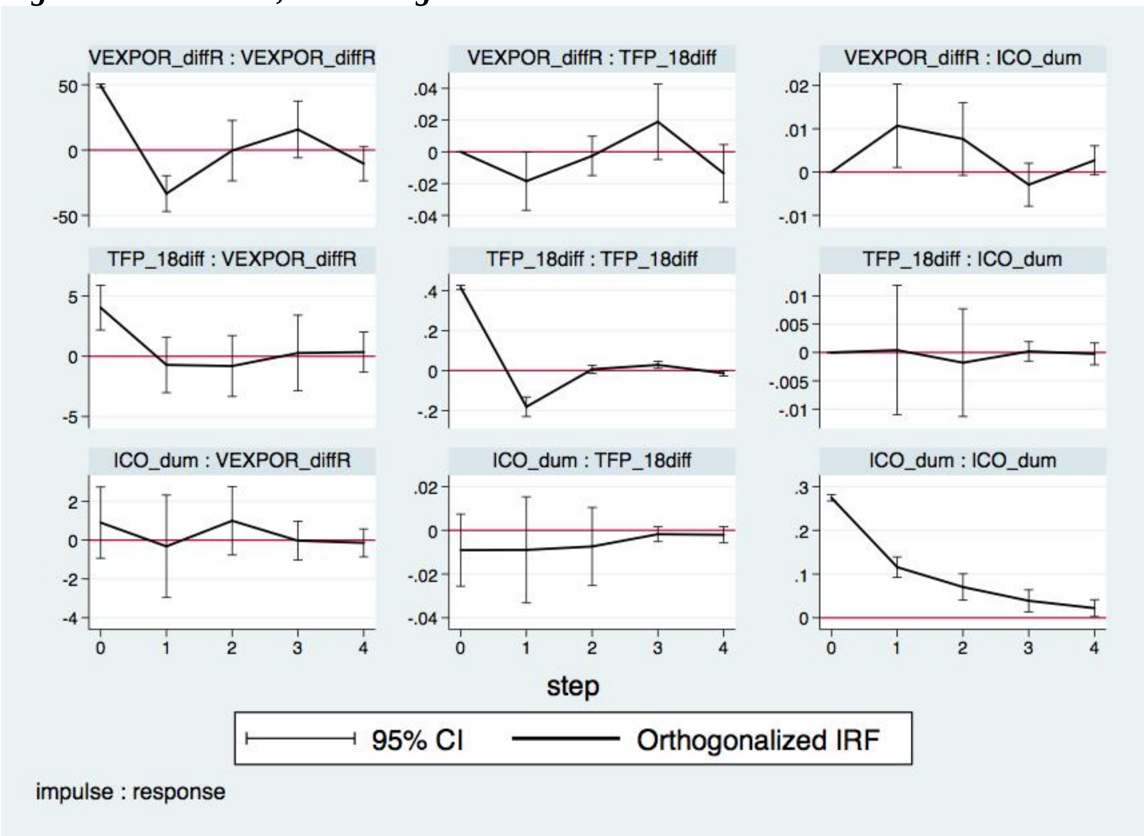


Figure A2.3.12 Cumulative IRFs, Marketing innovations

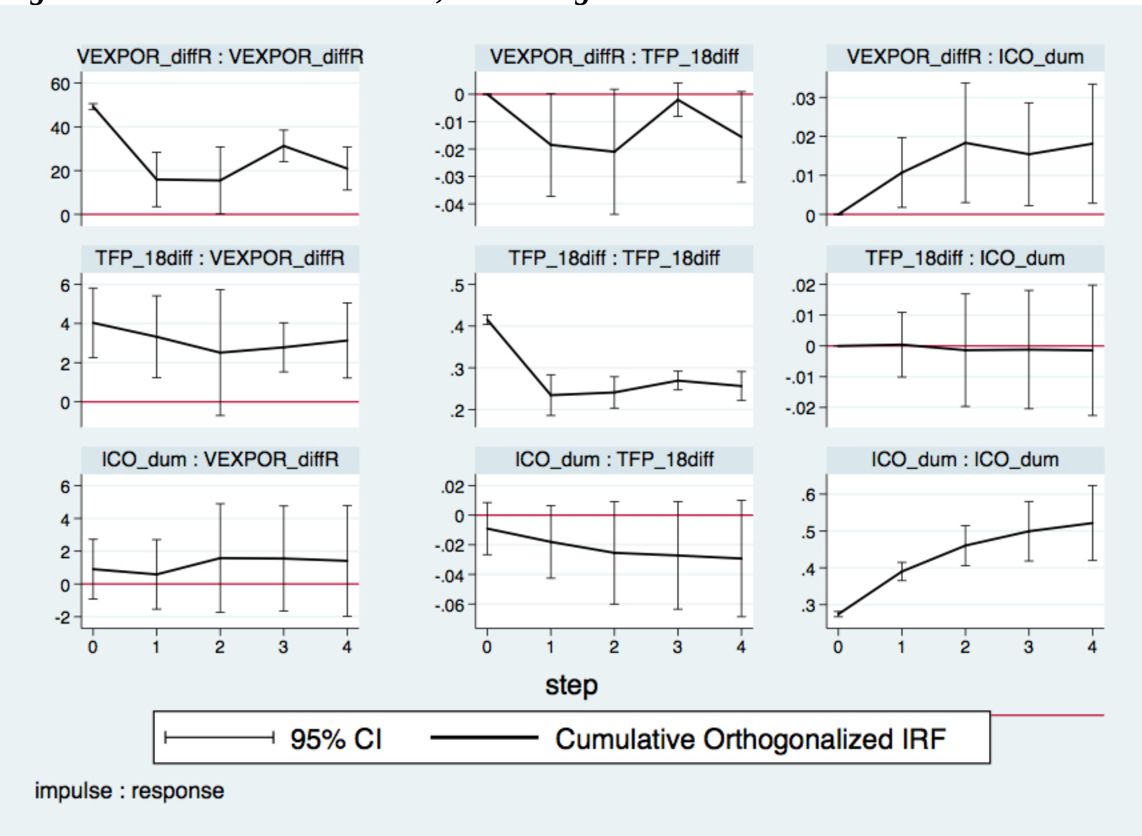


Figure A2.3.13 IRFs, Process innovations

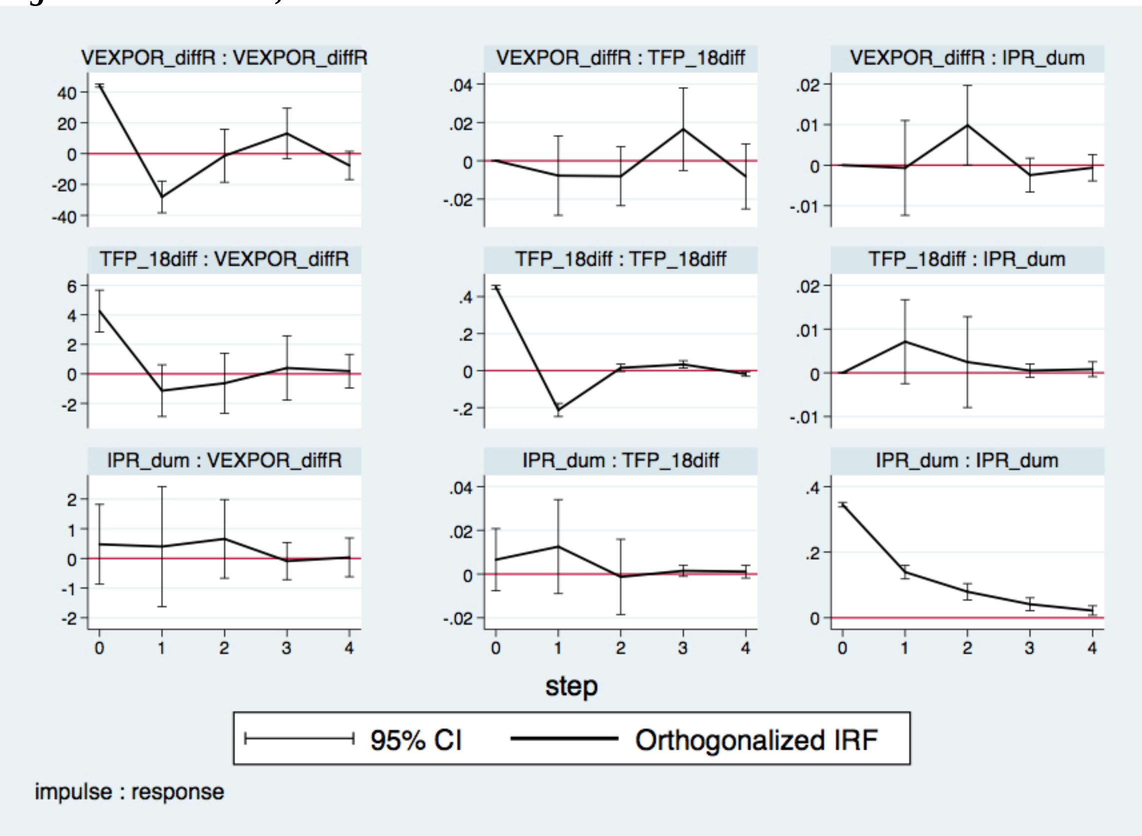
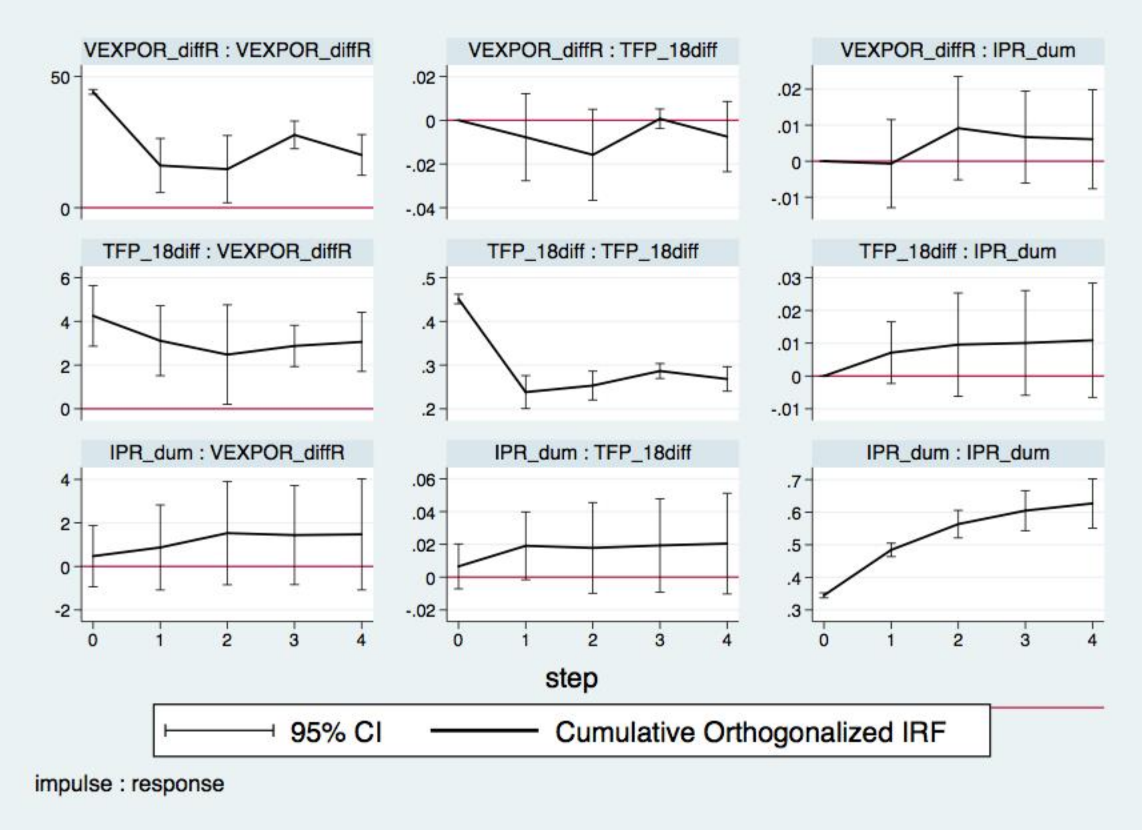


Figure A2.3.14 Cumulative IRFs, Process innovations



Appendix A2.4: IRFs and cumulative IRFs for large firms subsample
Figure A2.4.1 IRFs, R&D expenditures

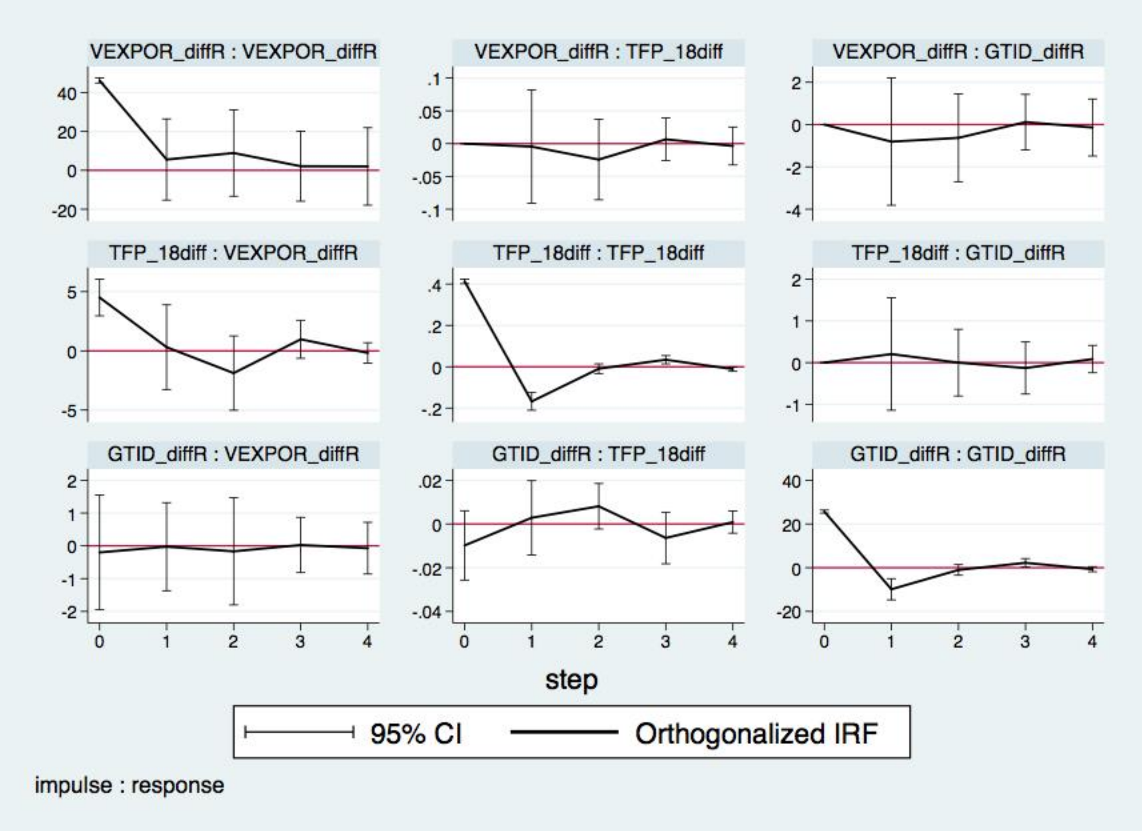


Figure A2.4.2 Cumulative IRFs, R&D expenditures

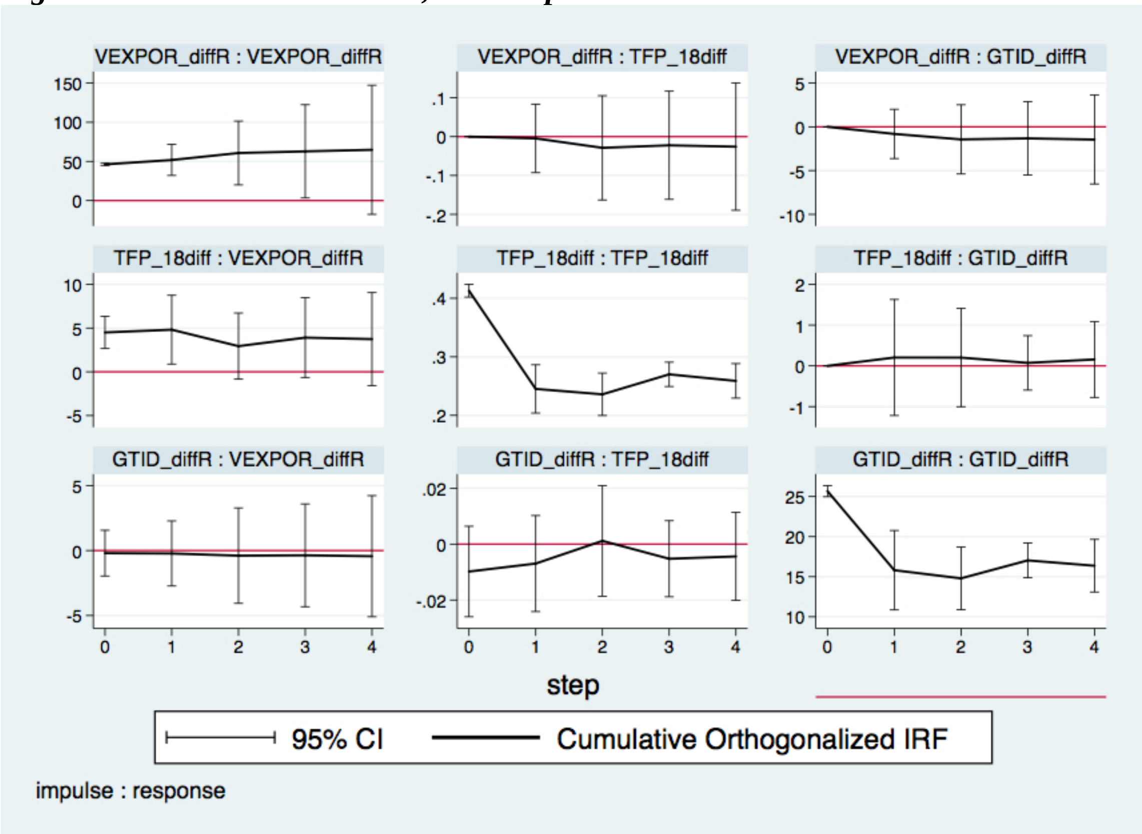


Figure A2.4.3 IRFs, Patents registered in Spain

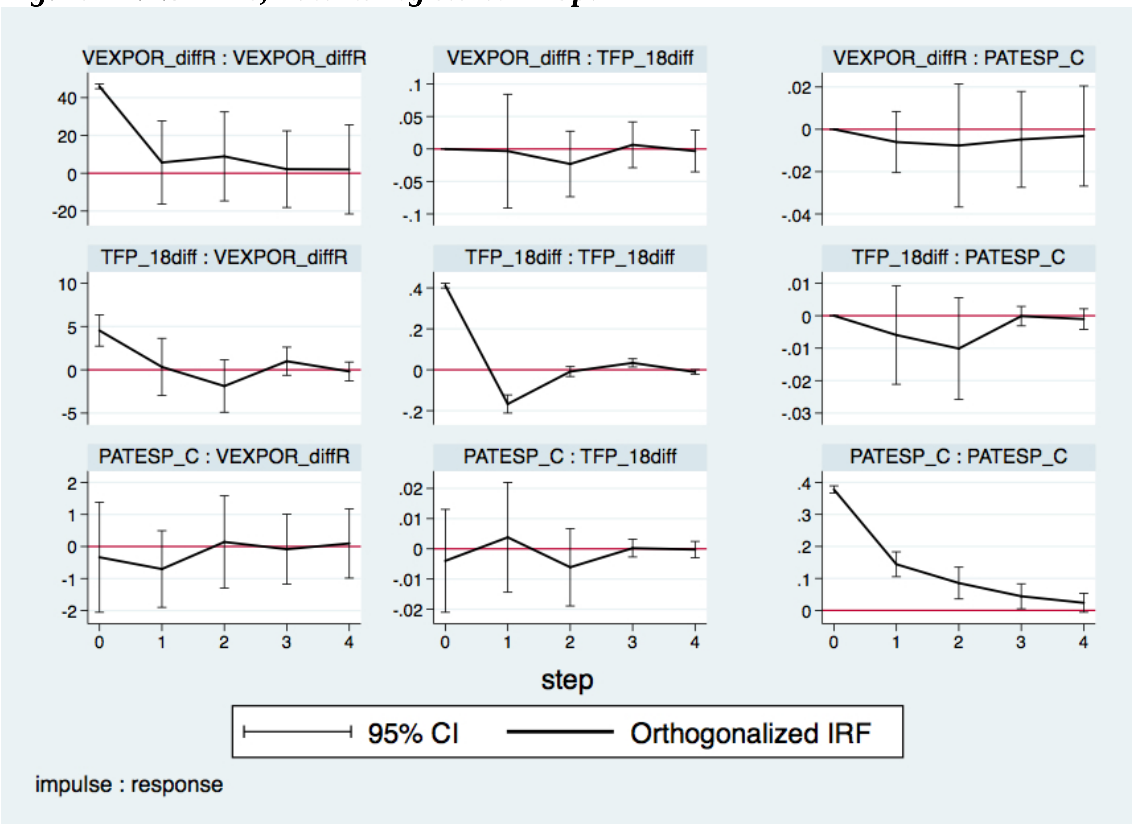


Figure A2.4.4 Cumulative IRFs, Patents registered in Spain

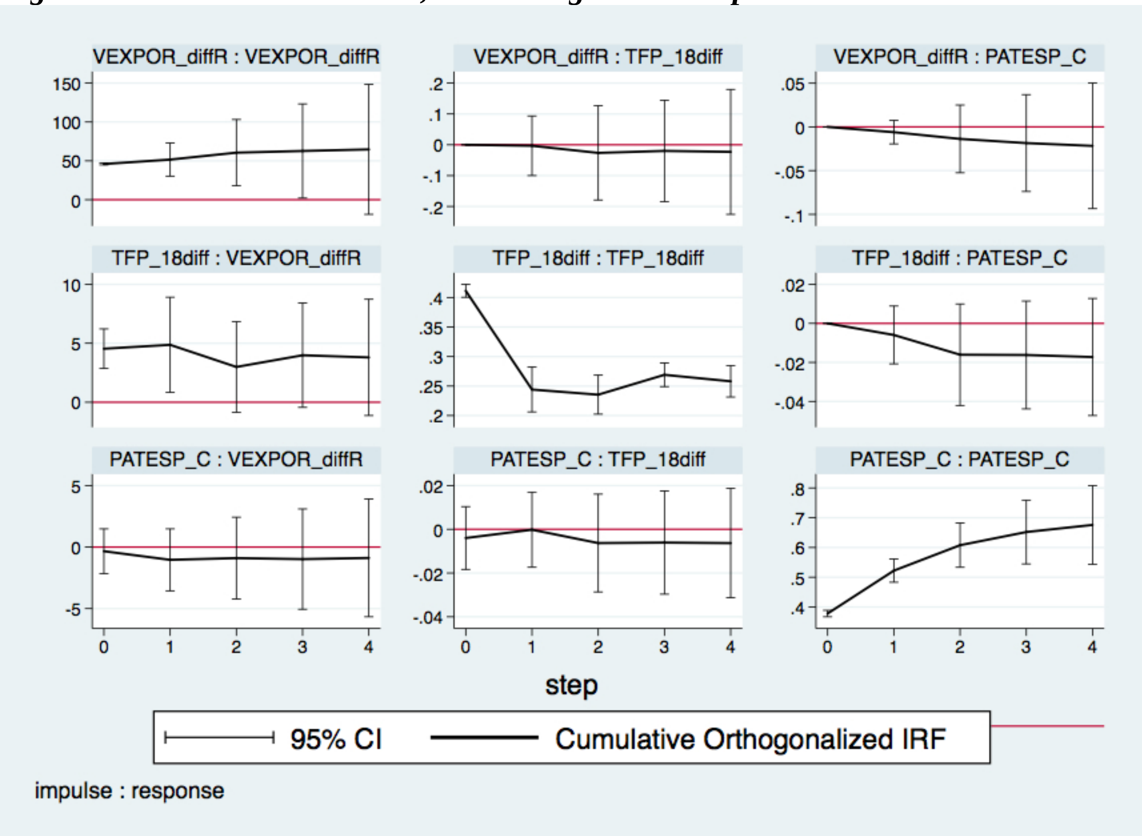


Figure A2.4.5 IRFs, Patents registered abroad

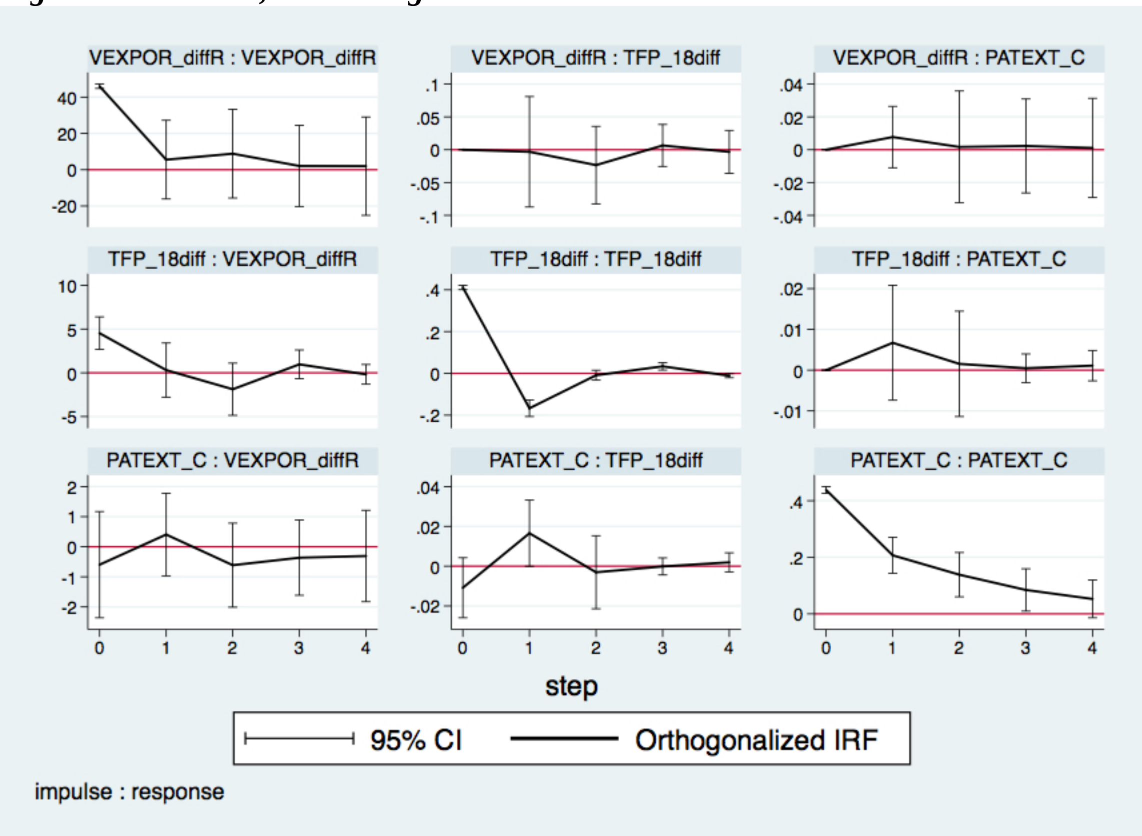


Figure A2.4.6 Cumulative IRFs, Patents registered abroad

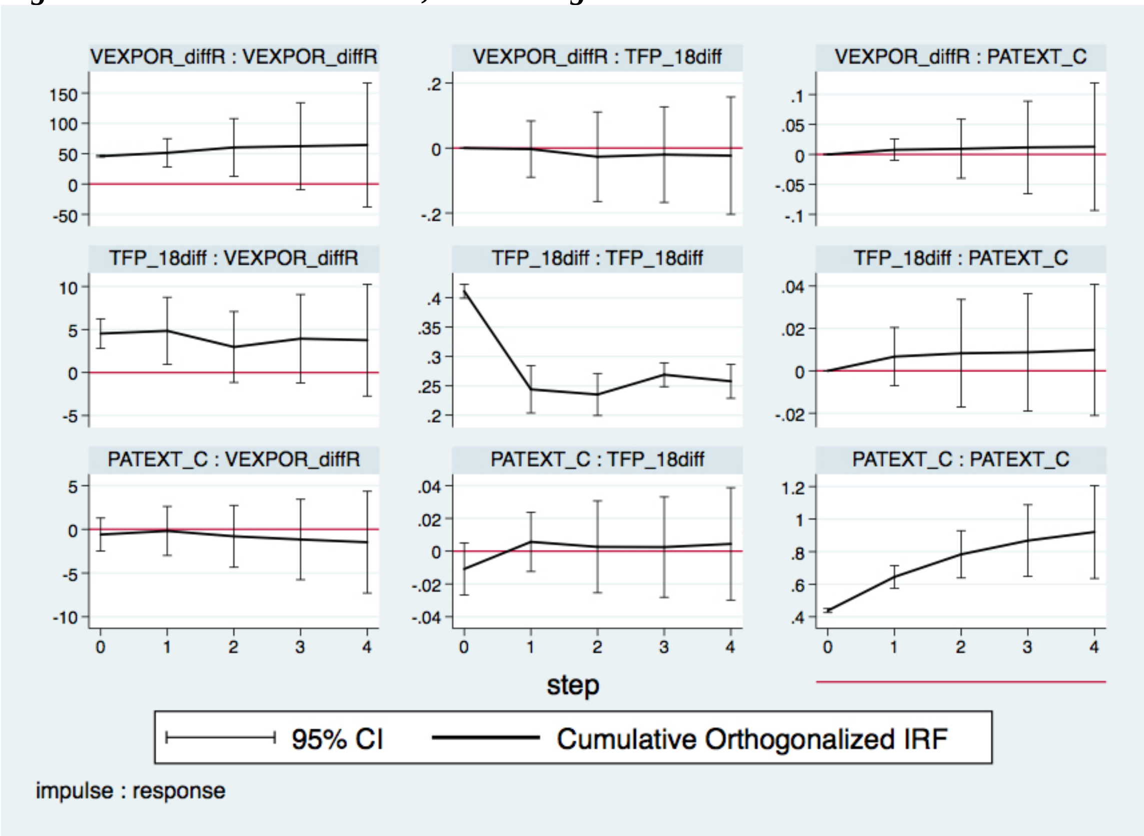
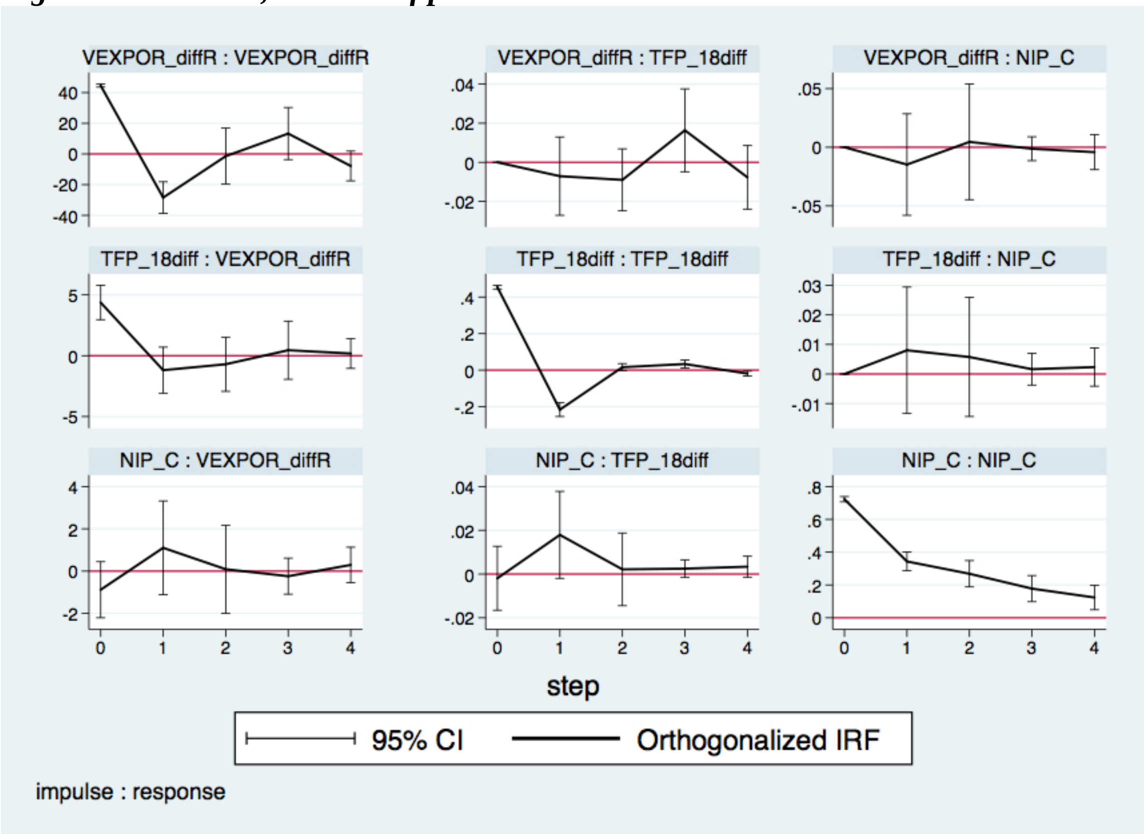


Figure A2.4.7 IRFs, Number of product innovations



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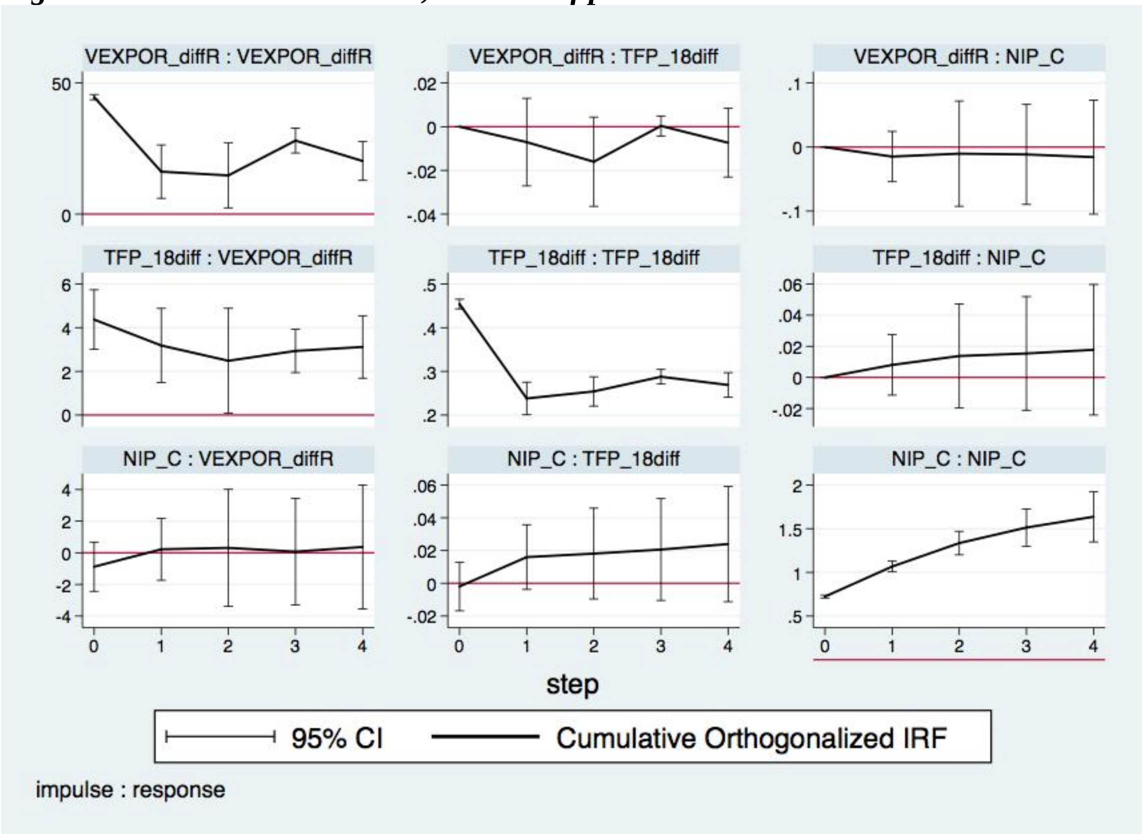


Figure A2.4.9 IRFs, Organisational innovations

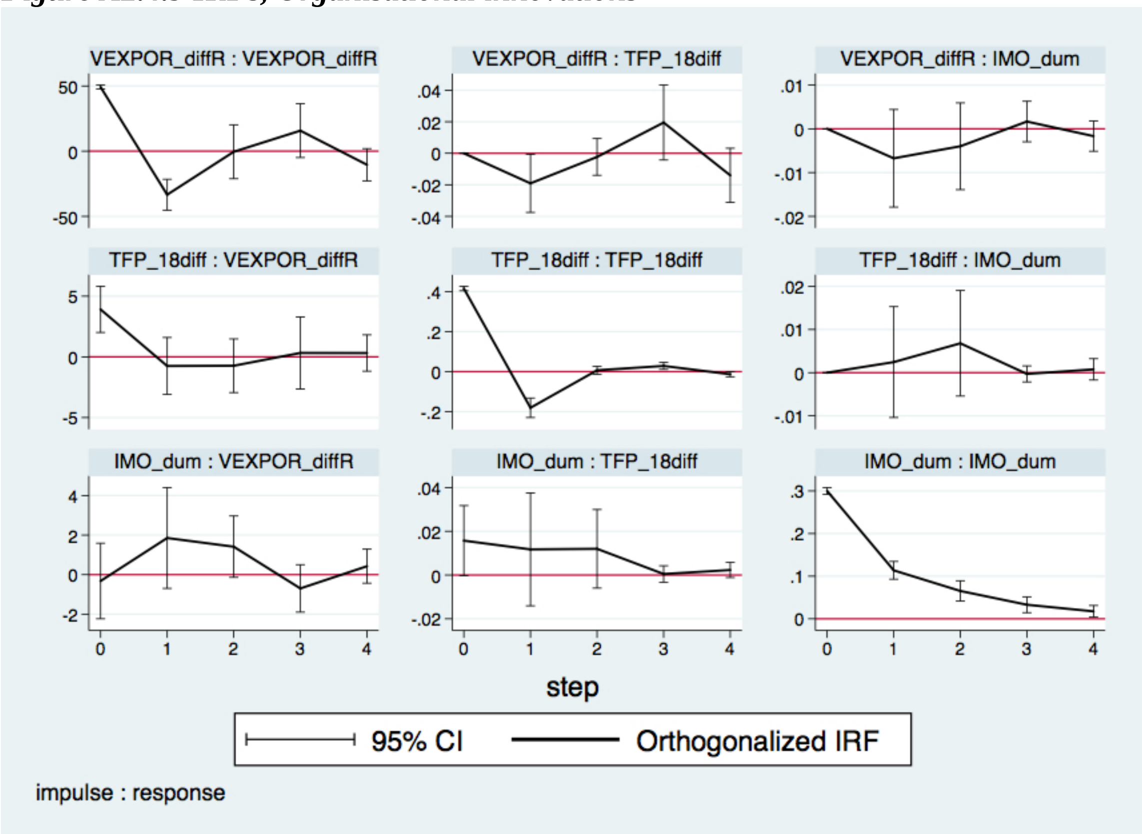


Figure A2.4.10 Cumulative IRFs, Organisational innovations

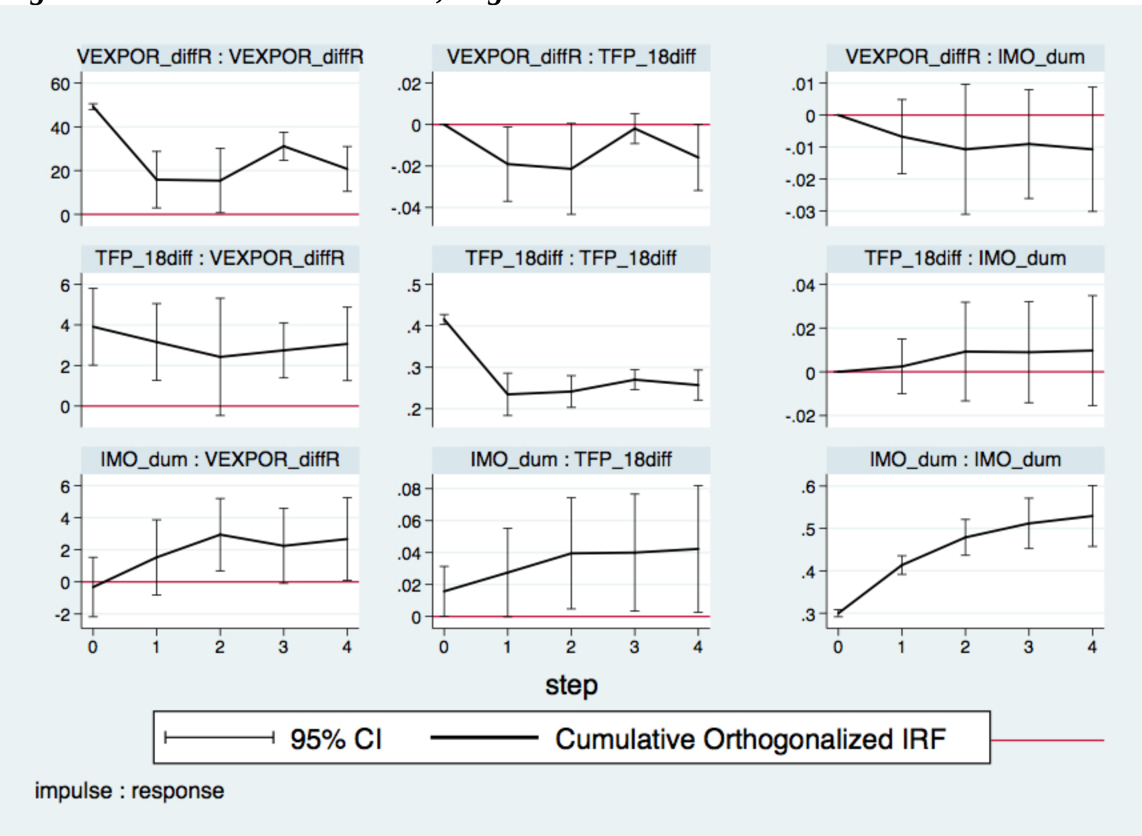


Figure A2.4.11 IRFs, Marketing innovations

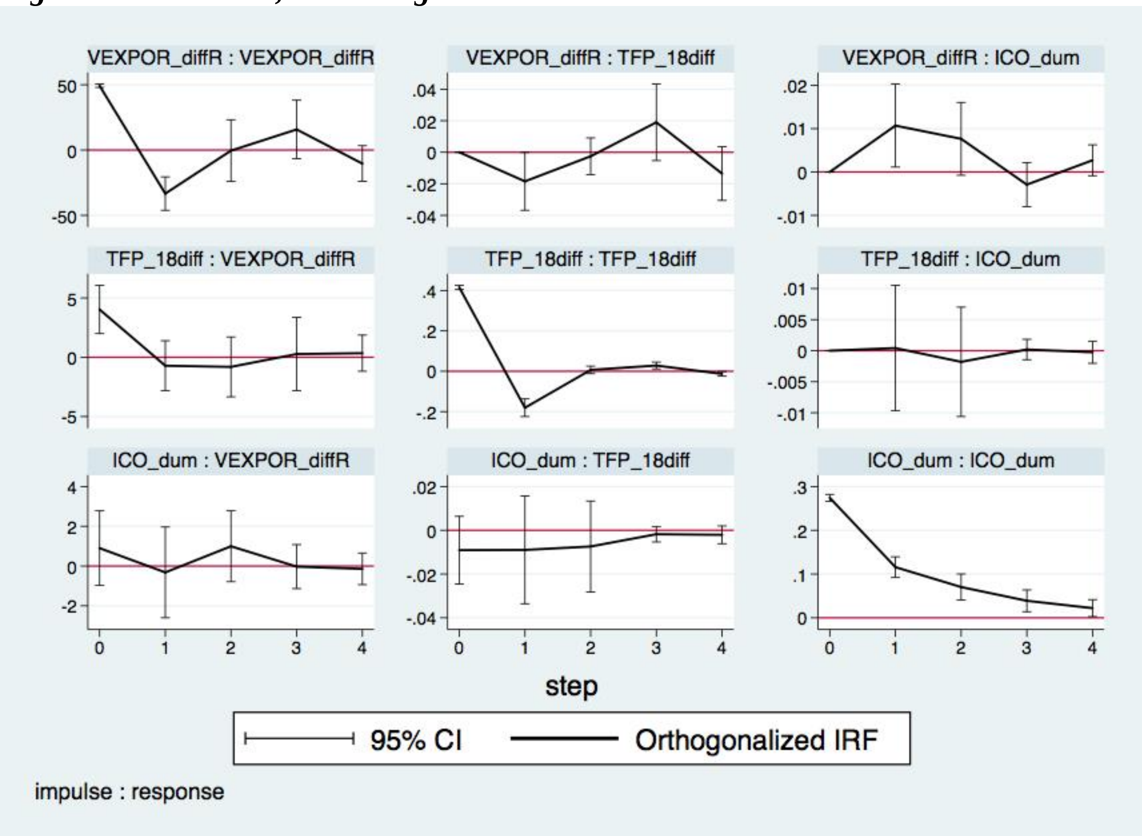


Figure A2.4.12 Cumulative IRFs, Marketing innovations

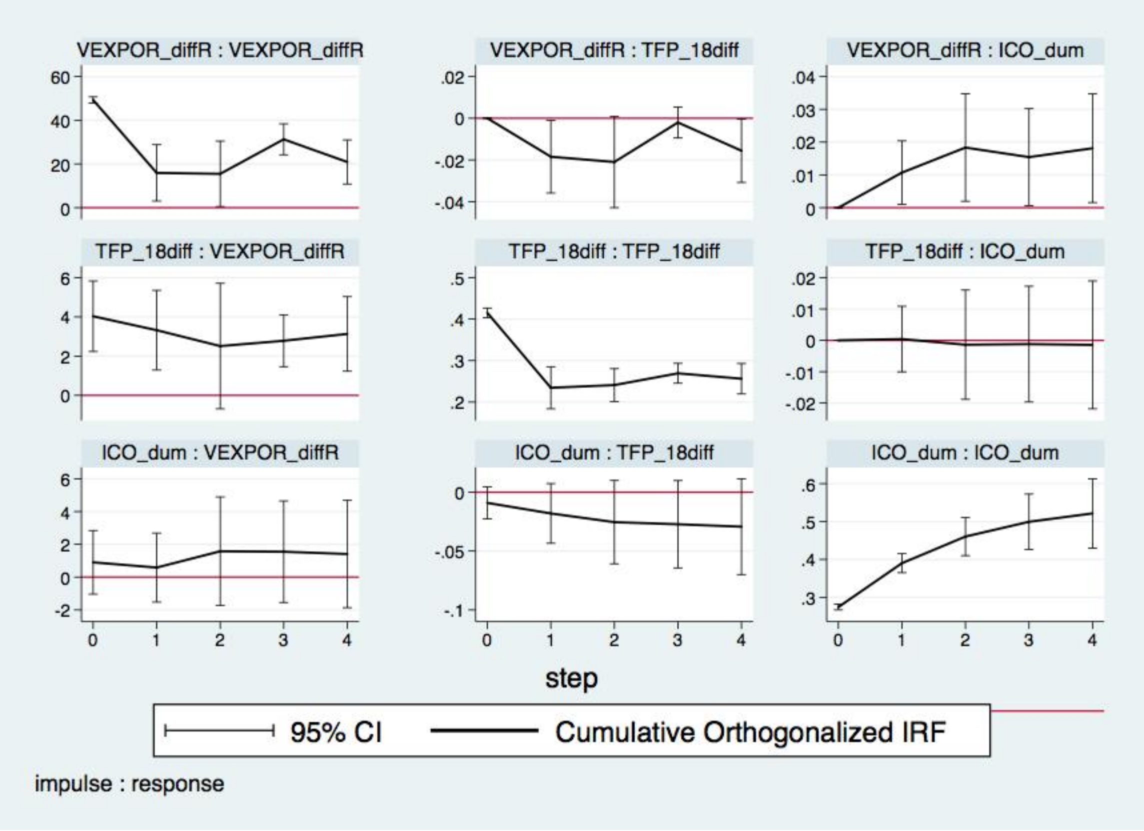


Figure A2.4.13 IRFs, Process innovations

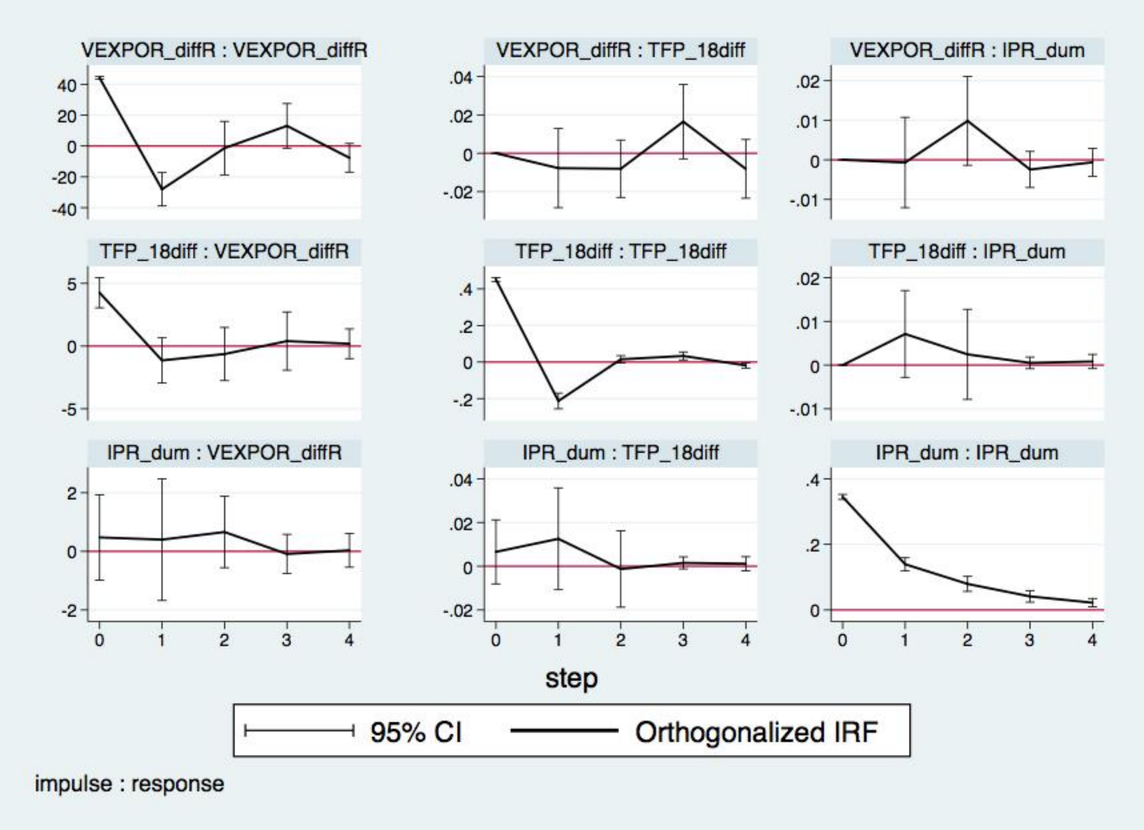
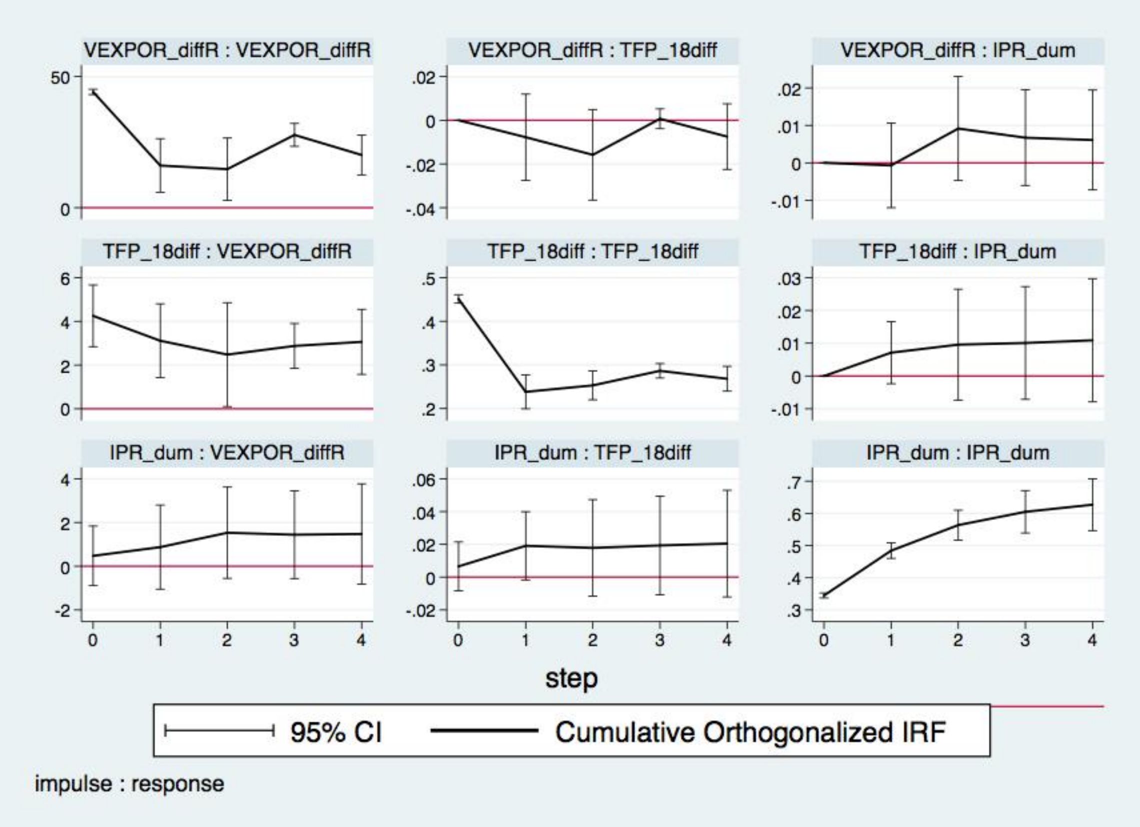


Figure A2.4.14 Cumulative IRFs, Process innovations



Appendix A2.5: IRFs and cumulative IRFs for high R&D performers subsample
Figure A2.5.1 IRFs, Patents registered in Spain

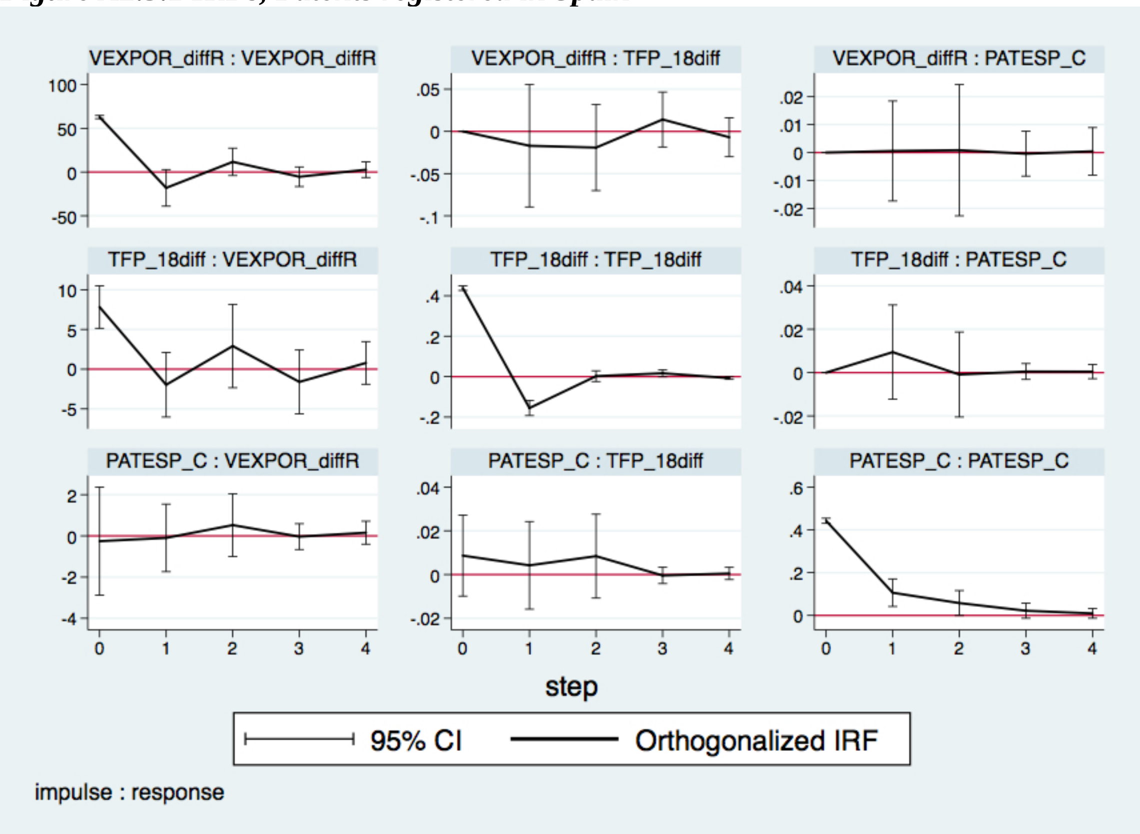


Figure A2.5.2 Cumulative IRFs, Patents registered in Spain

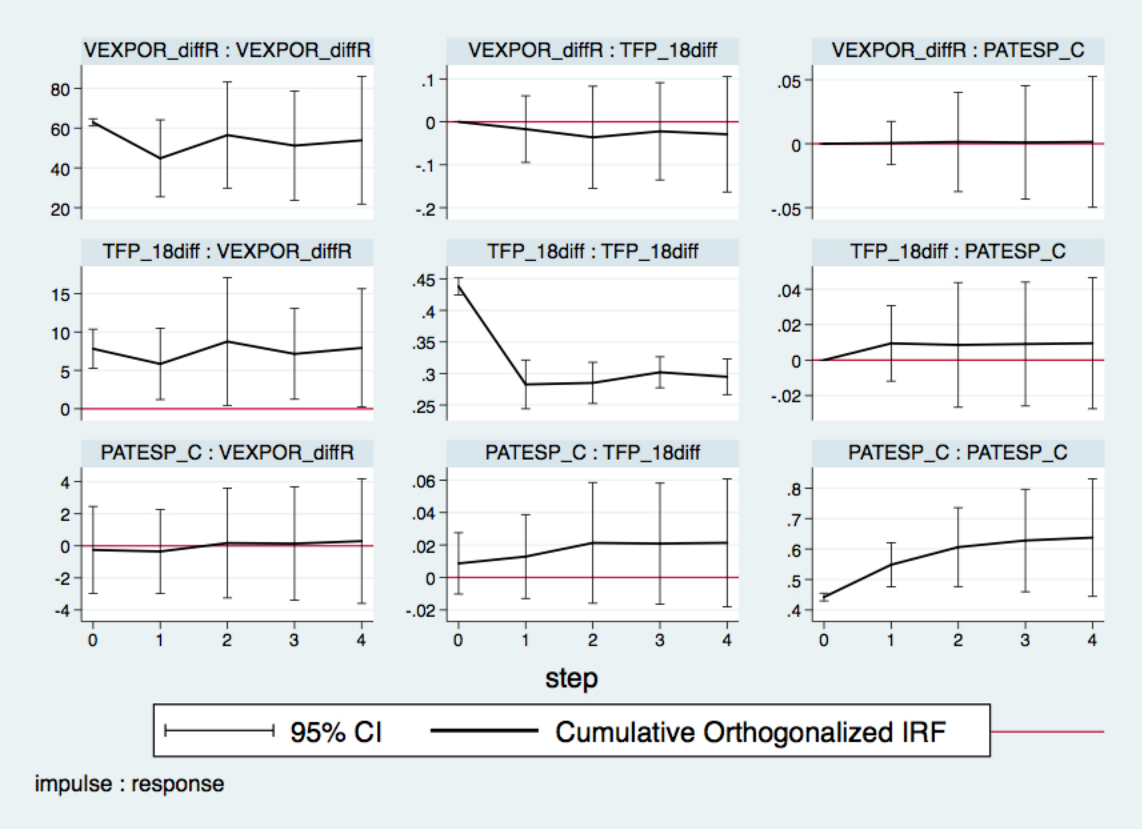


Figure A2.5.3 IRFs, Patents registered abroad

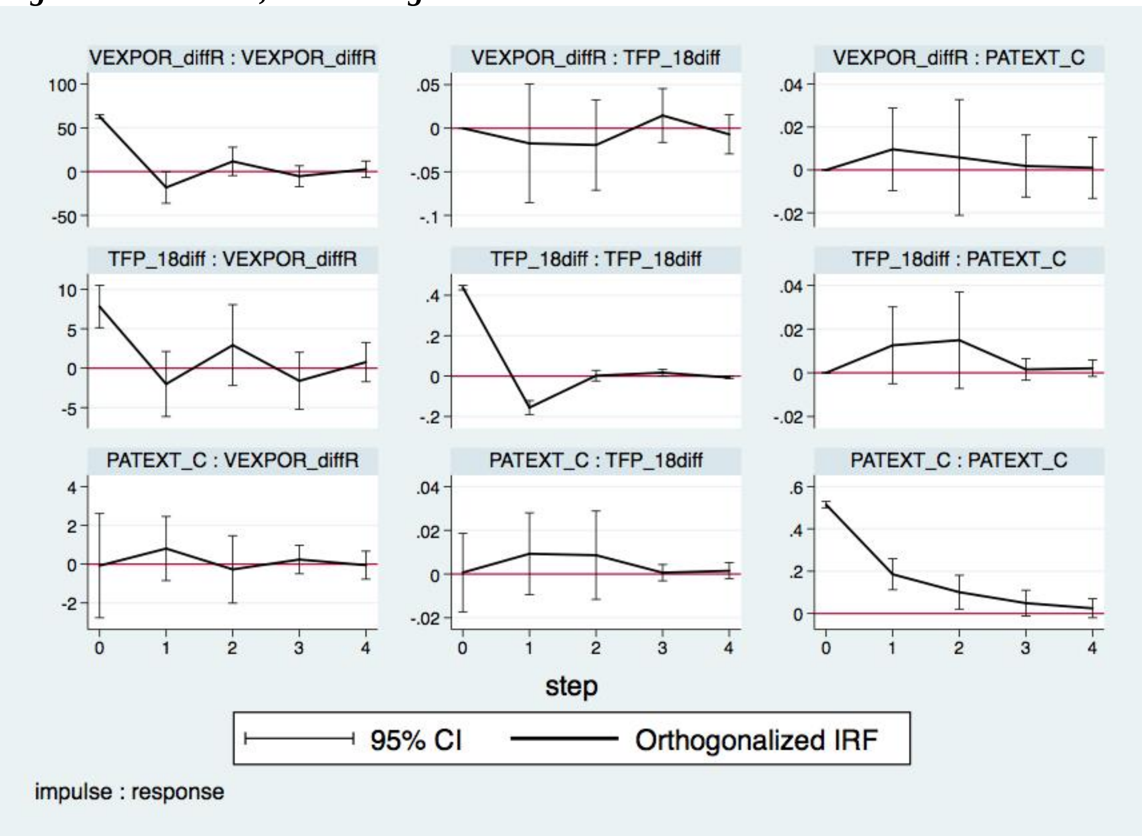


Figure A2.5.4 Cumulative IRFs, Patents registered abroad

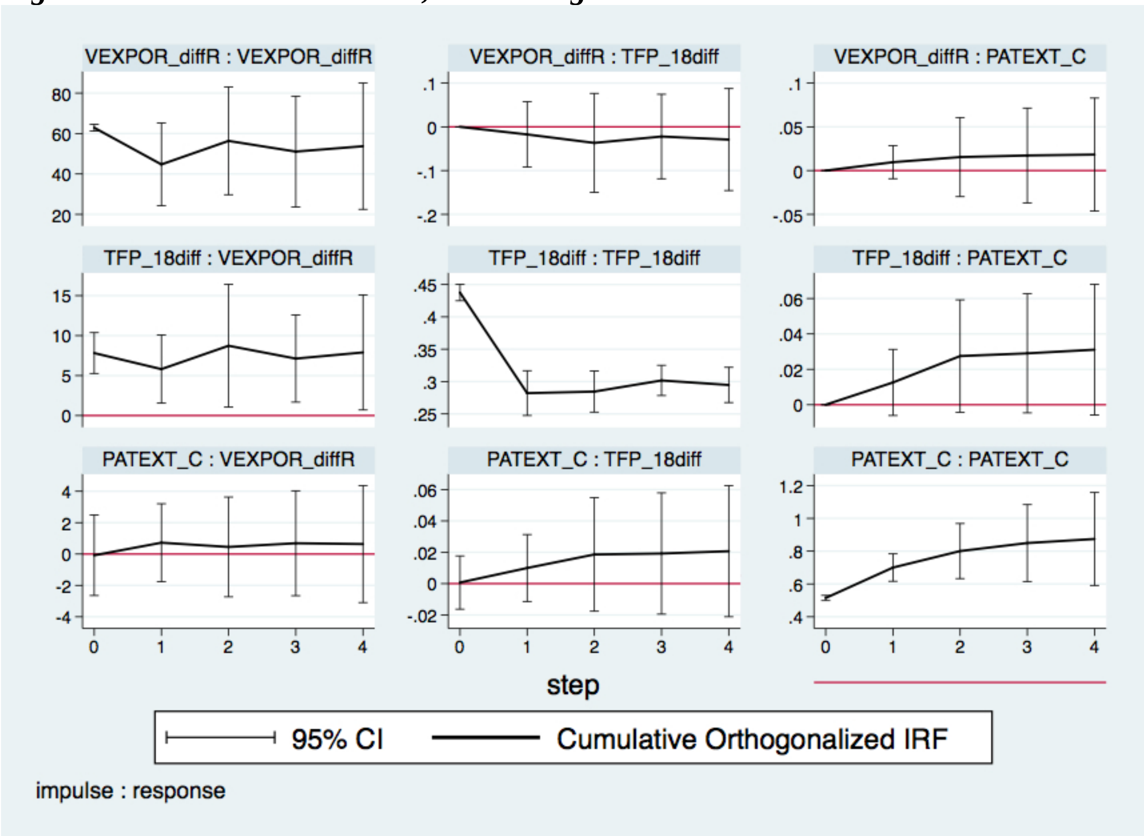


Figure A2.5.5 IRFs, Number of product innovations

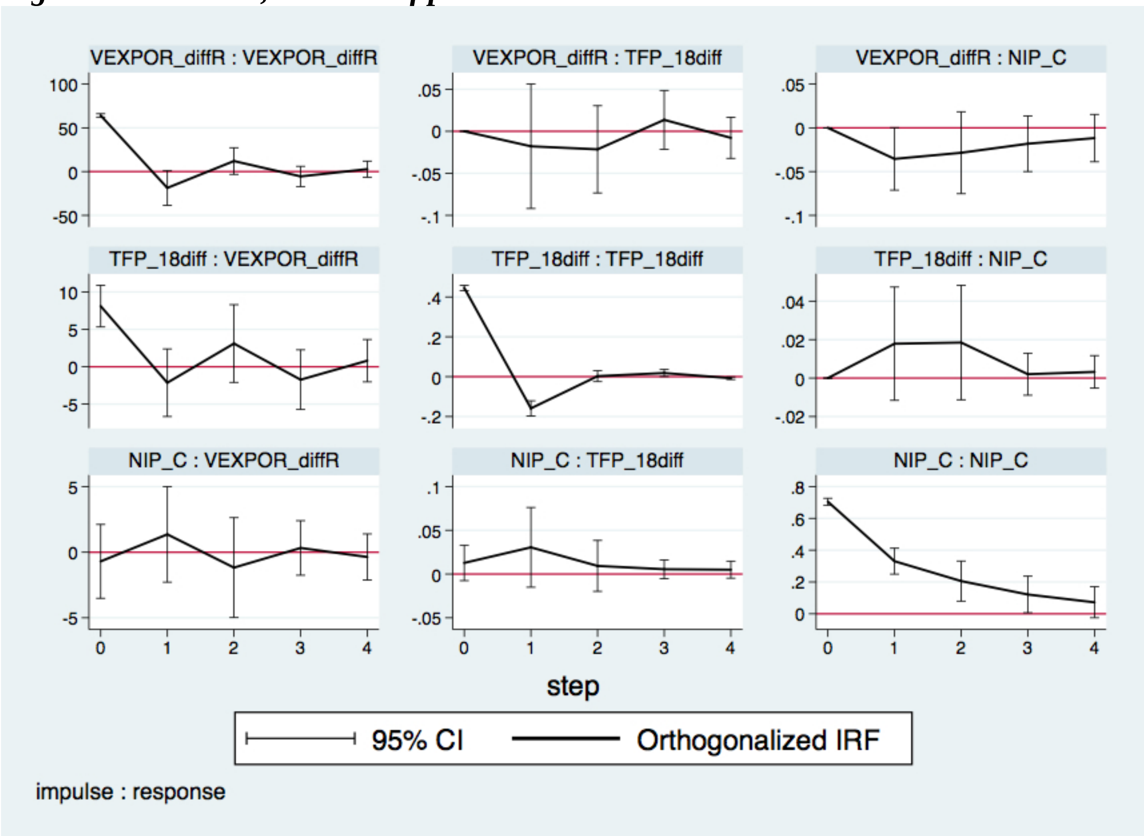


Figure A2.5.6 Cumulative IRFs, Number of product innovations

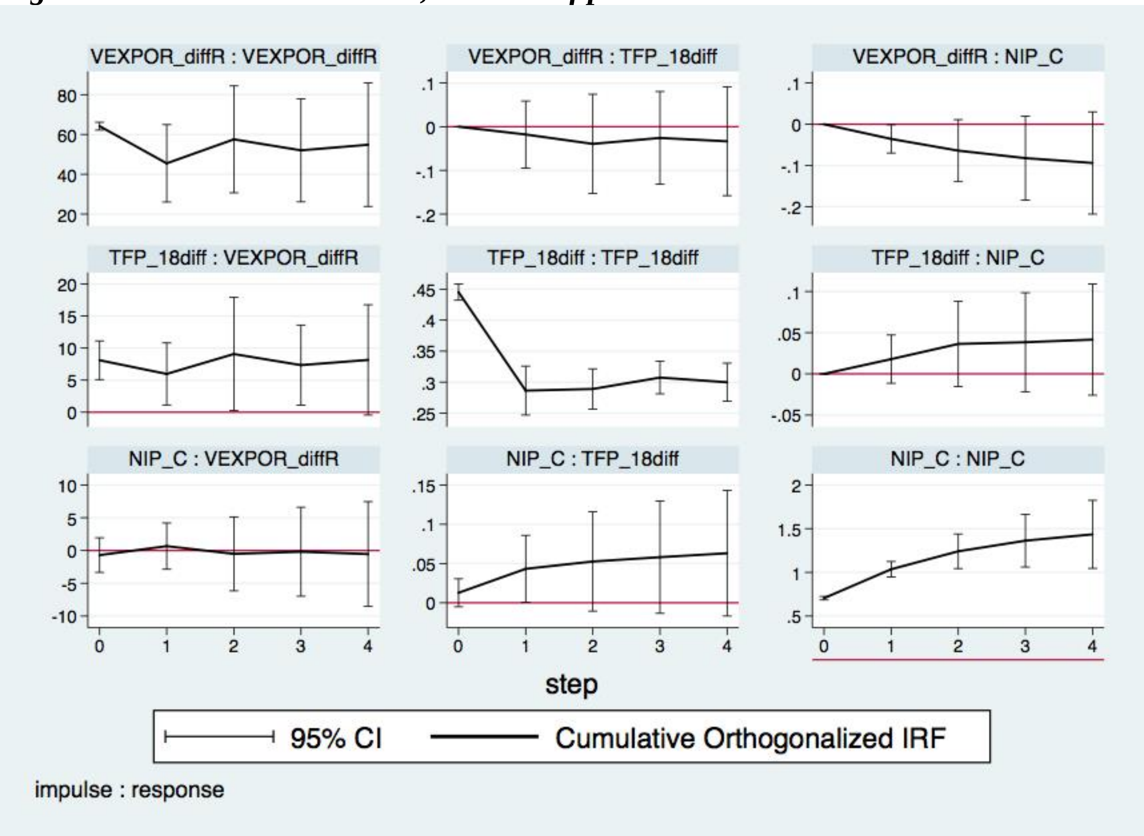


Figure A2.5.7 IRFs, Organisational innovations

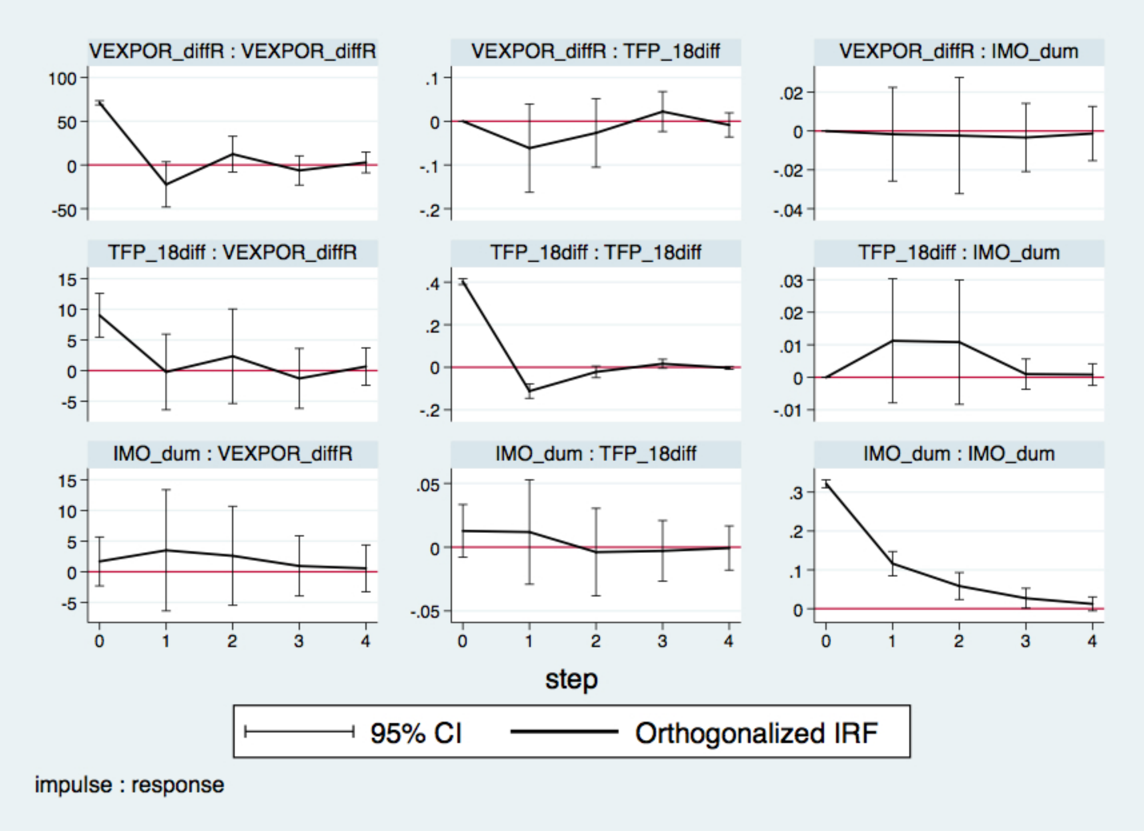


Figure A2.5.8 Cumulative IRFs, Organisational innovation

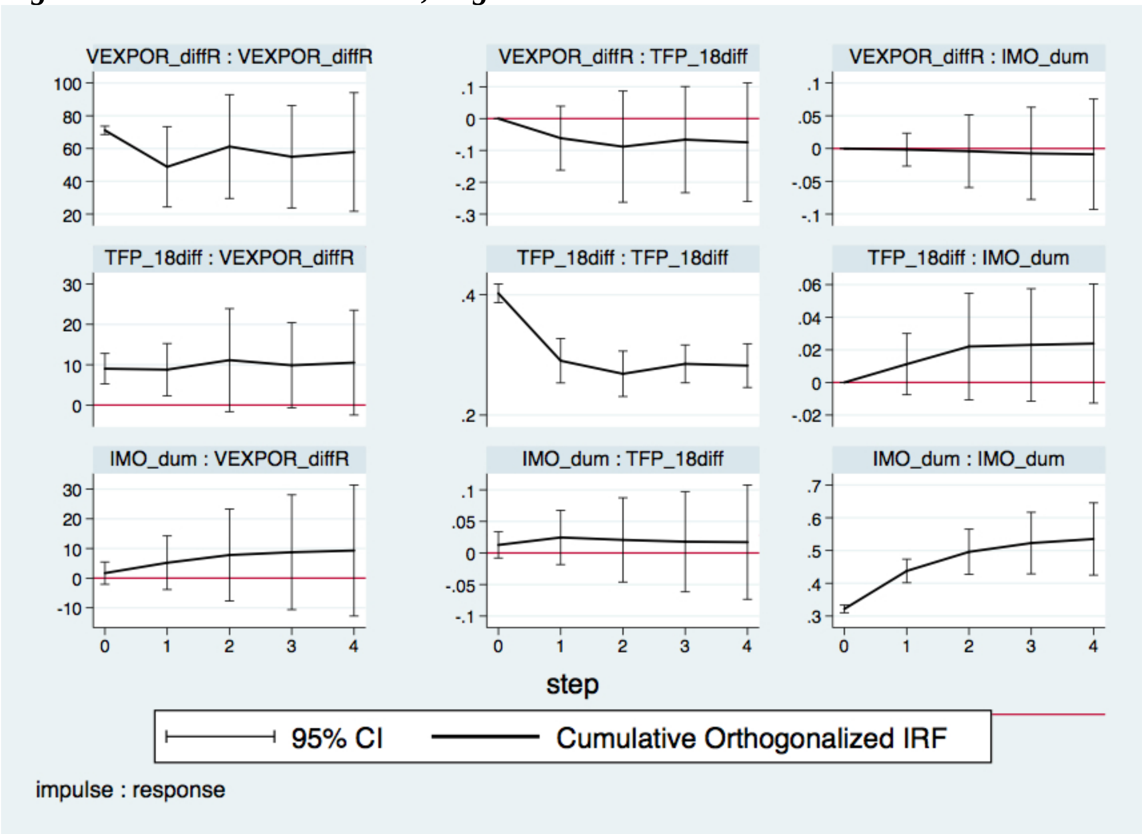


Figure A2.5.9 IRFs, Marketing innovations

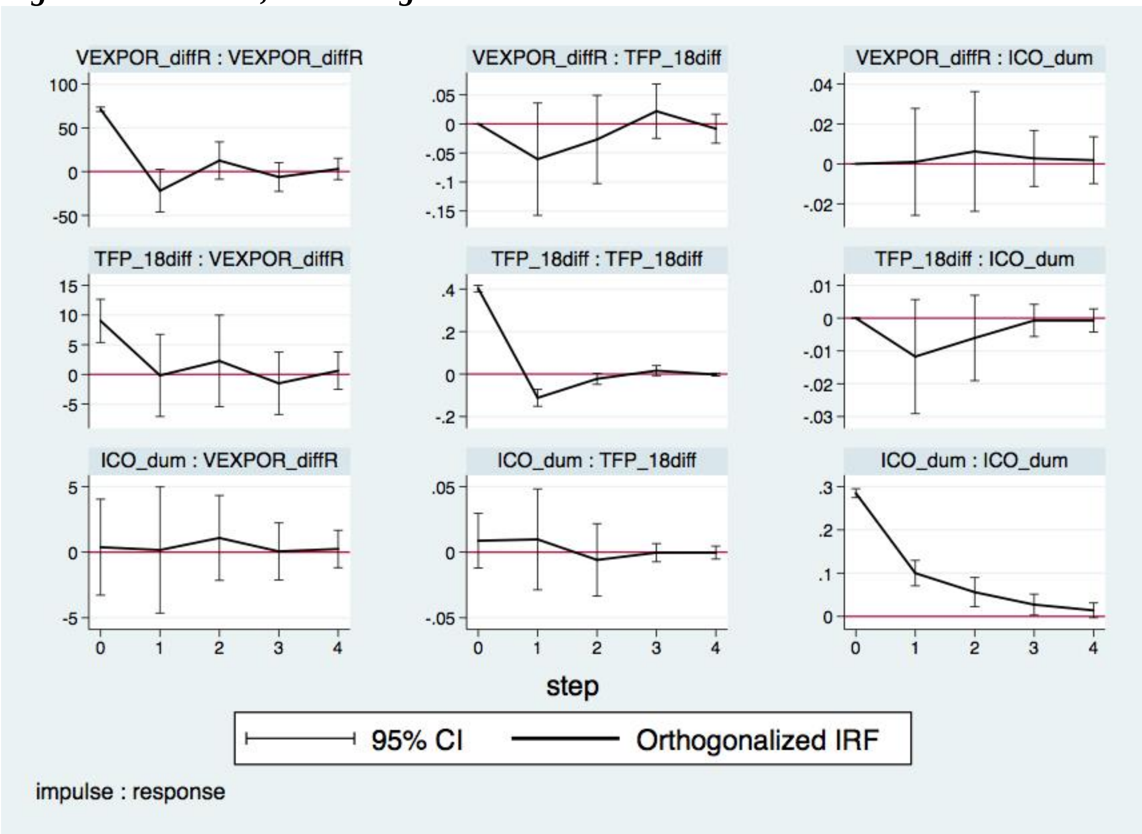


Figure A2.5.10 Cumulative IRFs, Marketing innovations

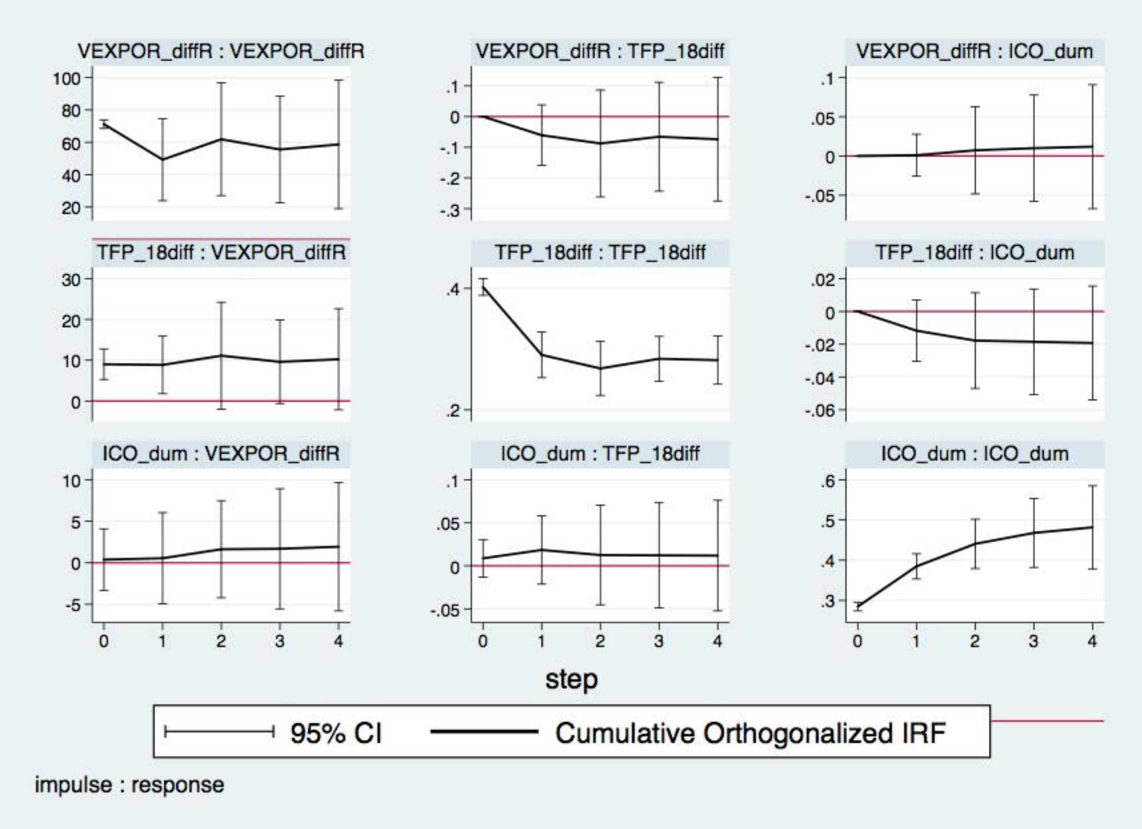


Figure A2.5.11 IRFs, Process innovations

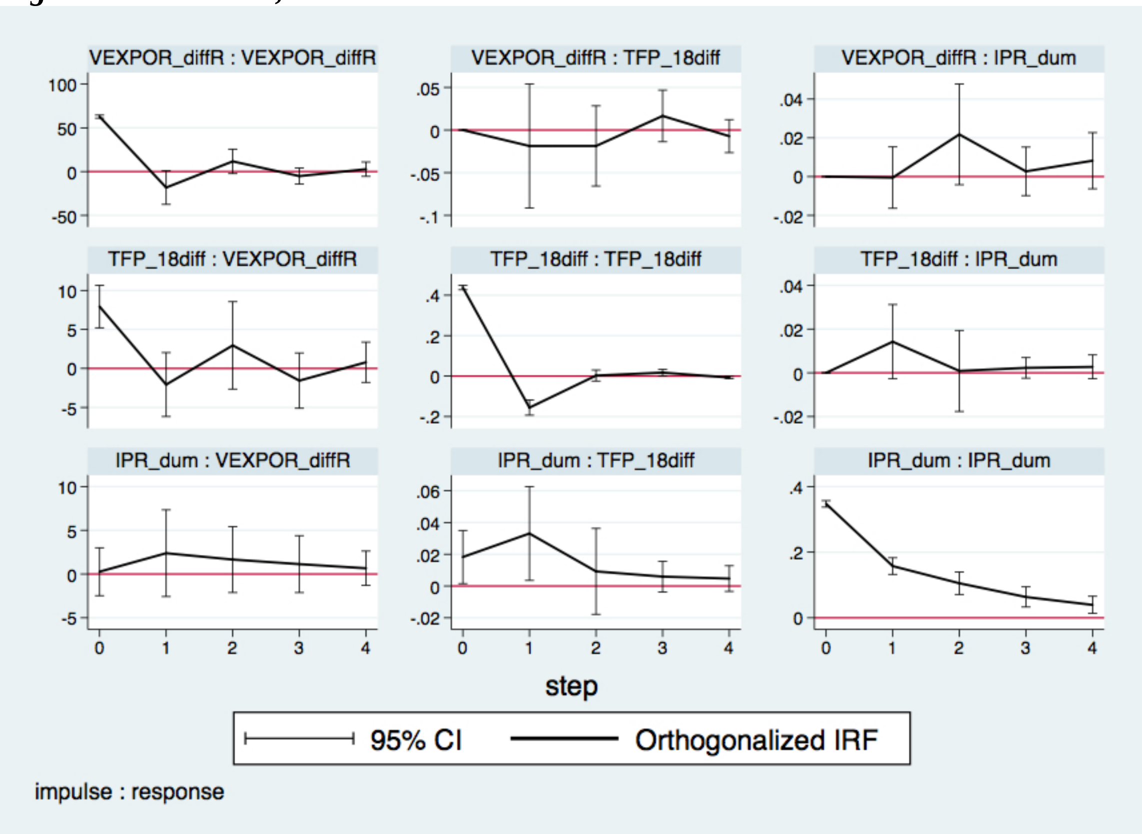
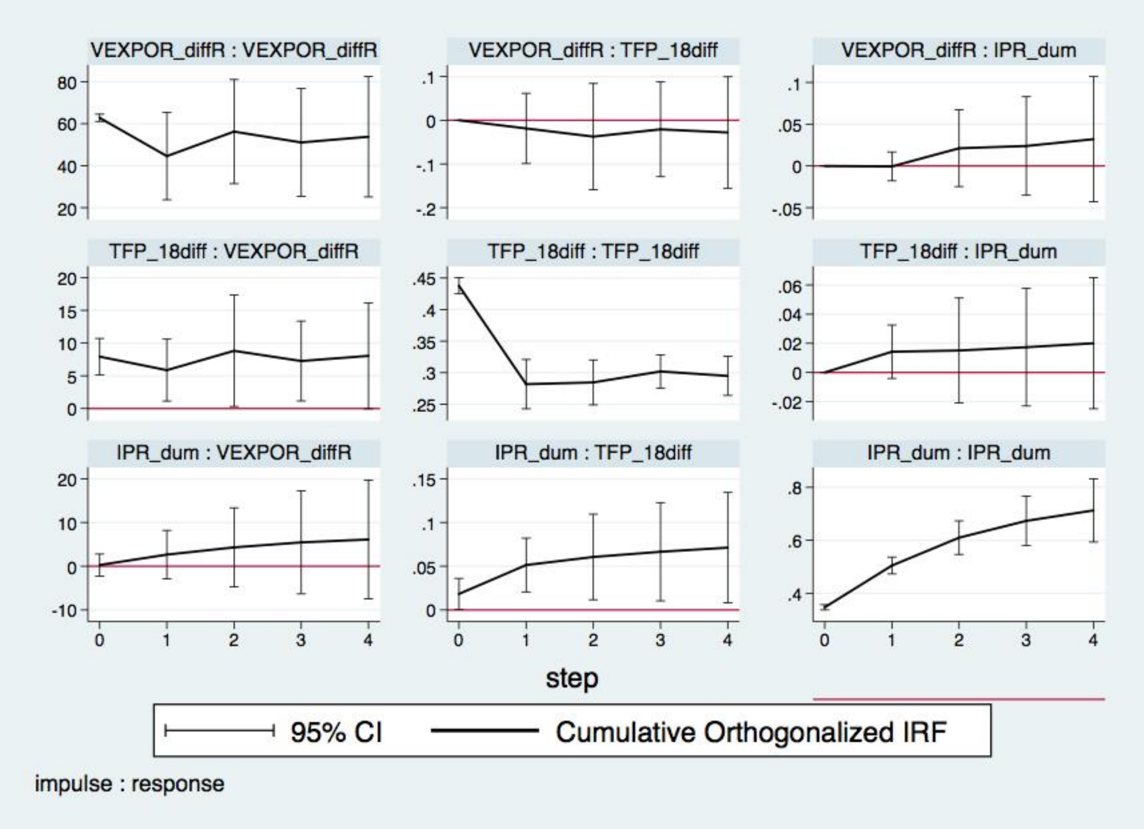


Figure A2.5.12 Cumulative IRFs, Process innovations



Appendix A2.6: IRFs and cumulative IRFs for low R&D performers subsample

Figure A2.6.1 IRFs, Patents registered in Spain

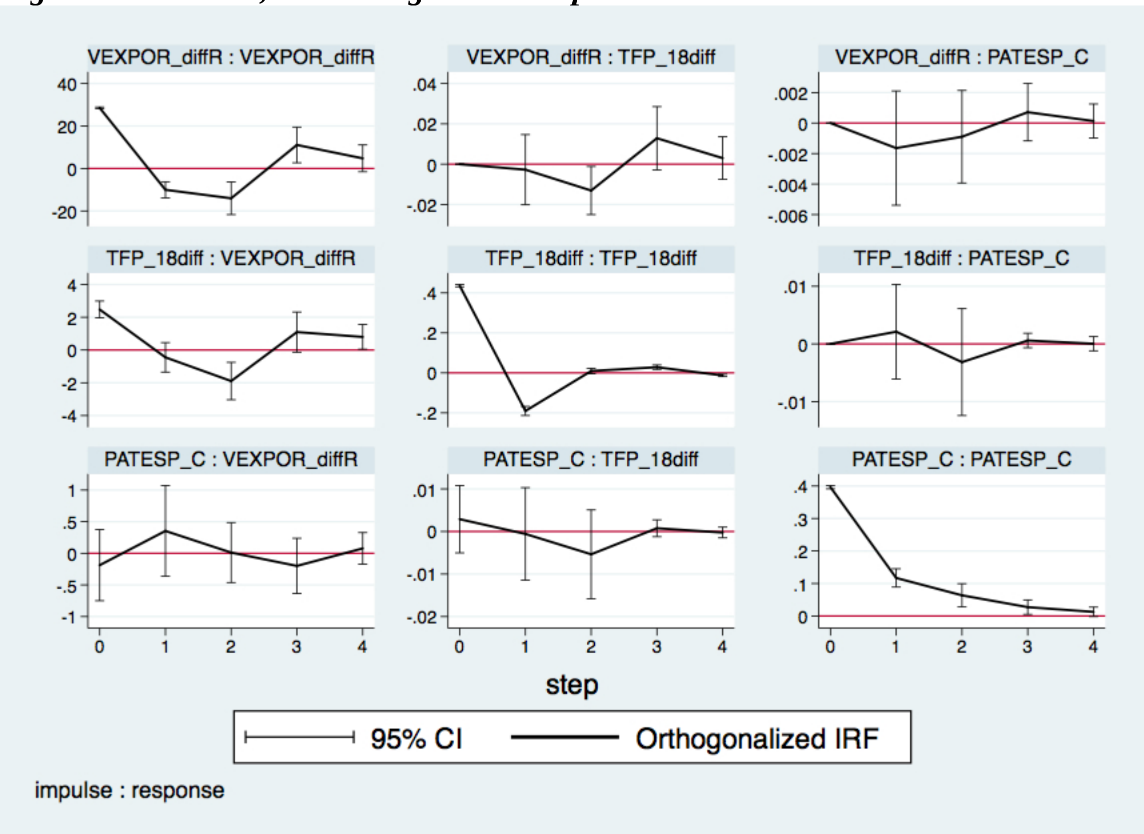


Figure A2.6.2 Cumulative IRFs, Patents registered in Spain

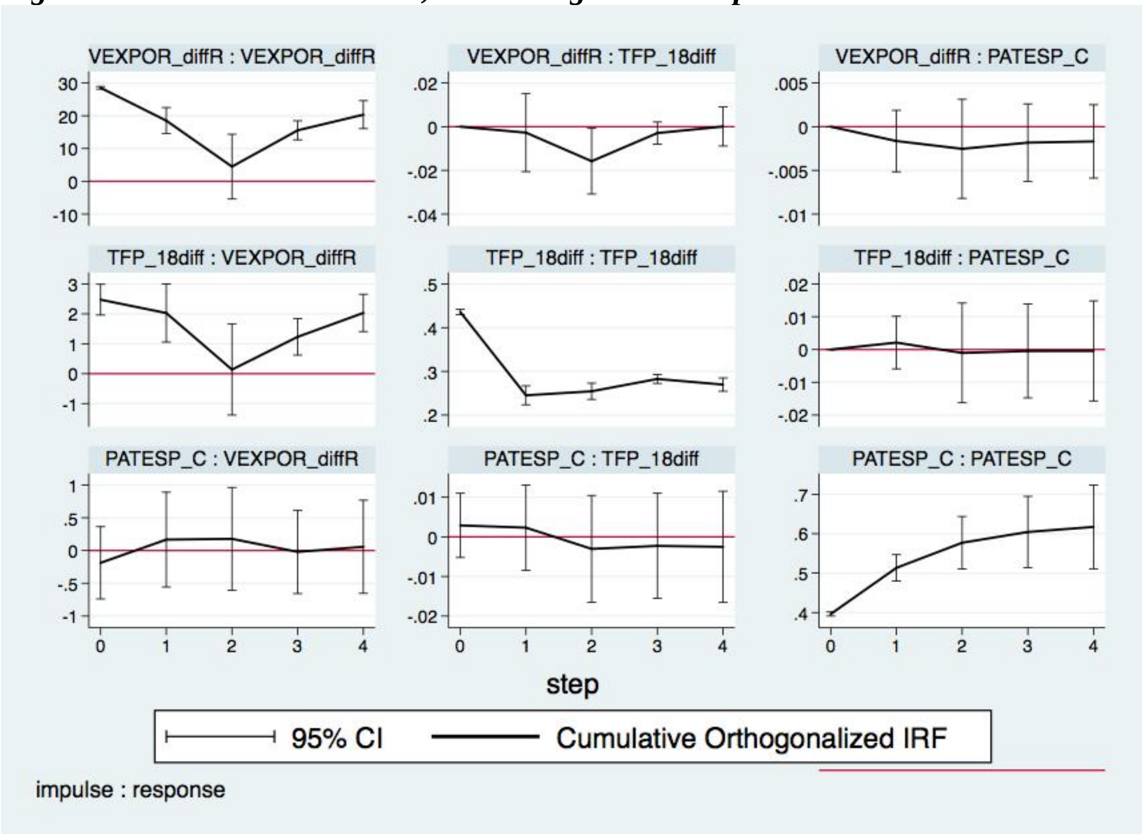


Figure A2.6.3 IRFs, Patents registered abroad

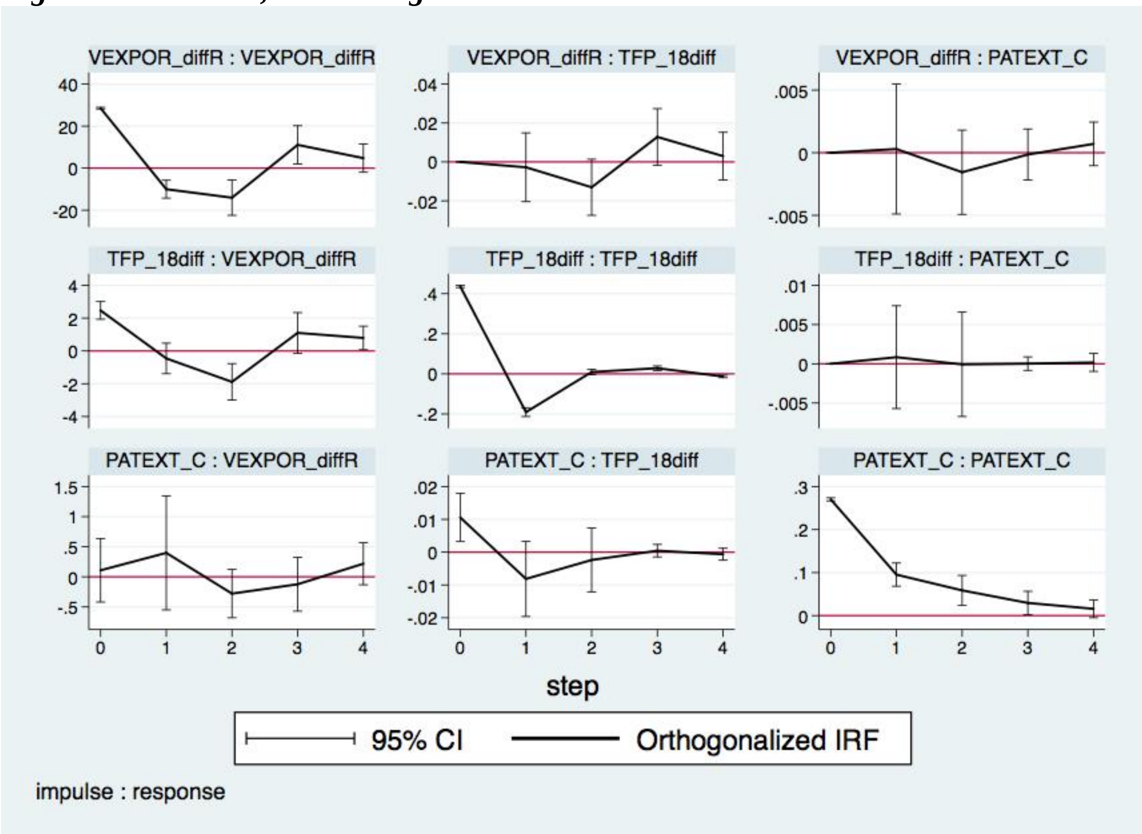


Figure A2.6.4 Cumulative IRFs, Patents registered abroad

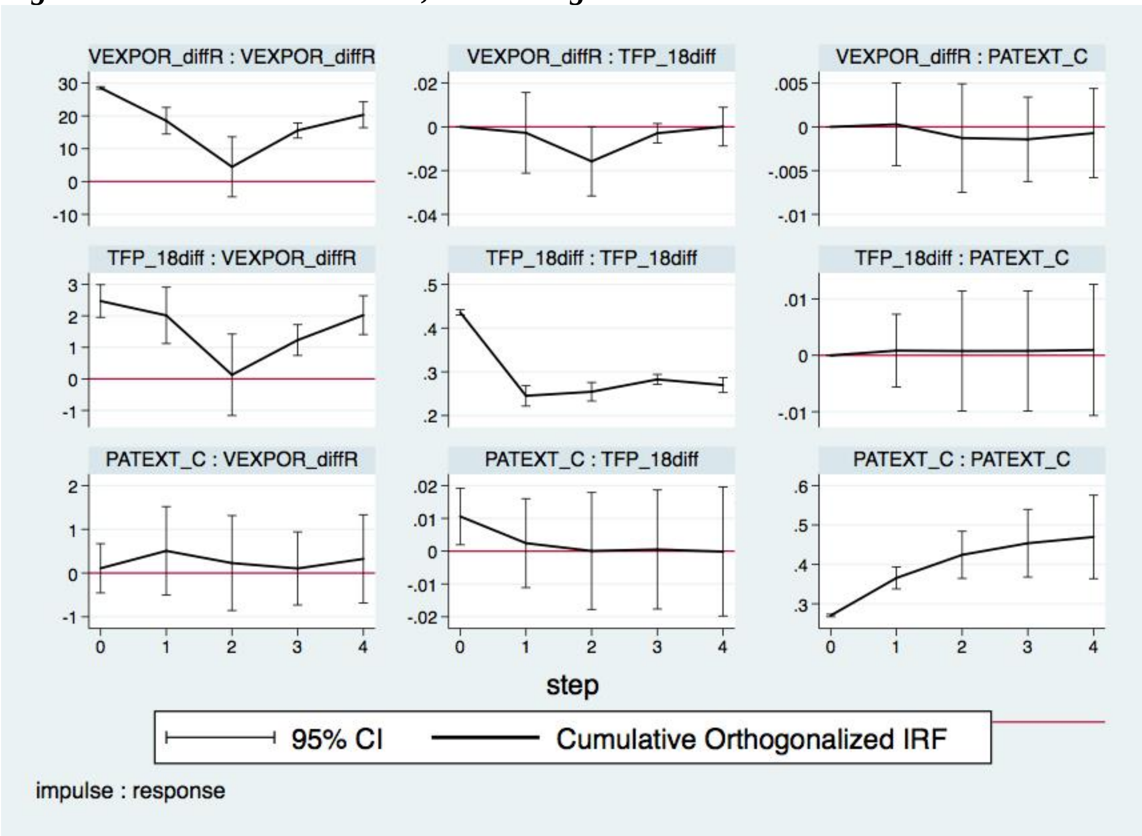


Figure A2.6.5 IRFs, Number of product innovations

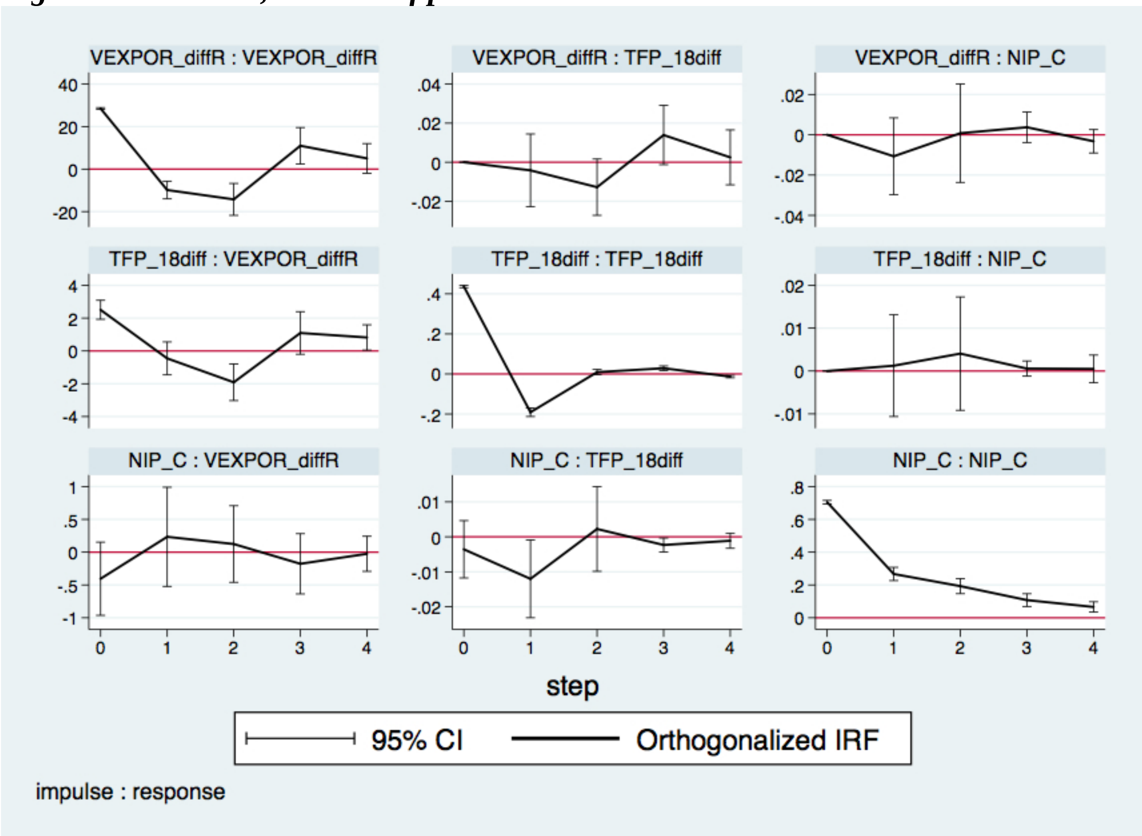


Figure A2.6.6 Cumulative IRFs, Number of product innovations

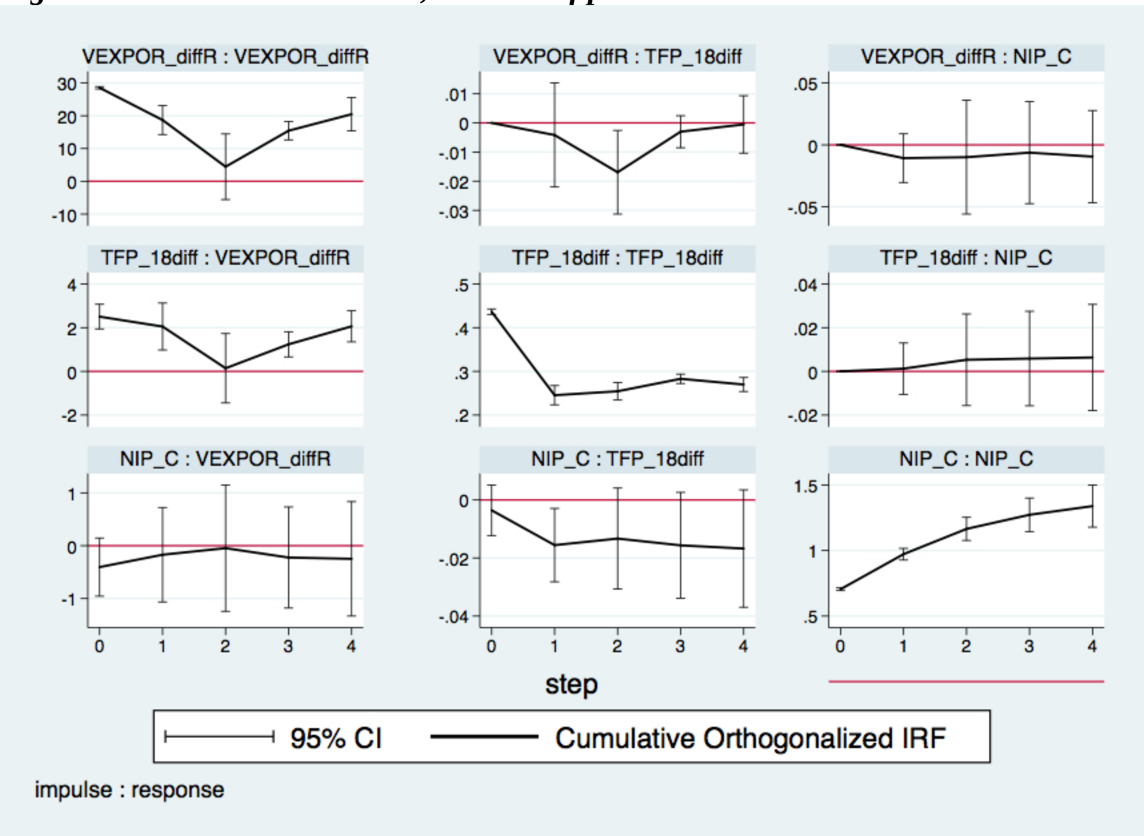


Figure A2.6.7 IRFs, Organisational innovations

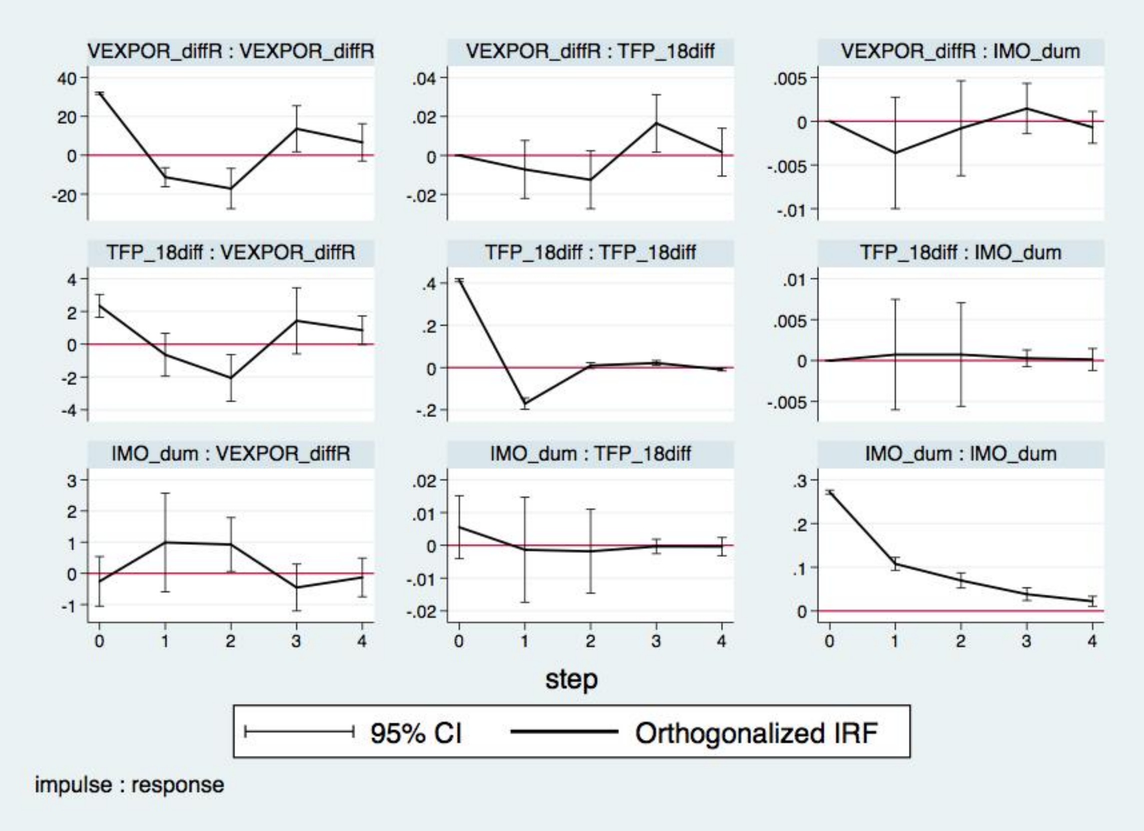


Figure A2.6.8 Cumulative IRFs, Organisational innovations

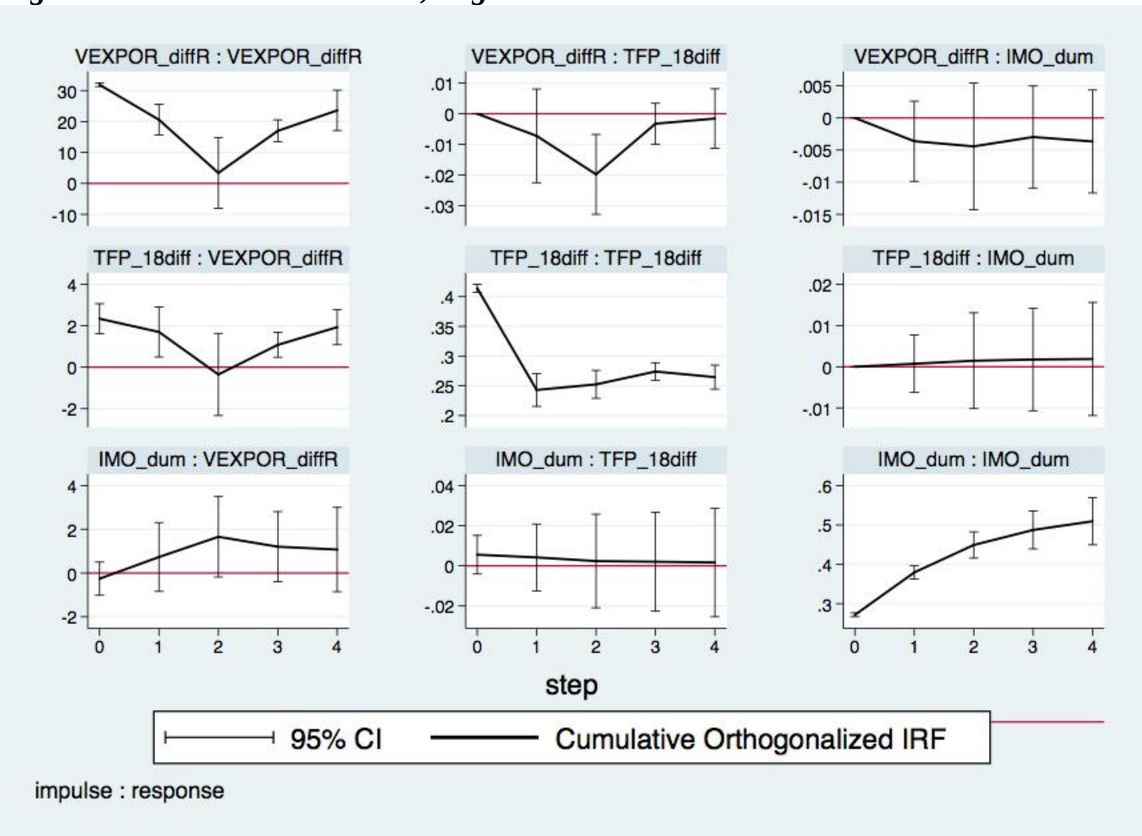


Figure A2.6.9 IRFs, Marketing innovations

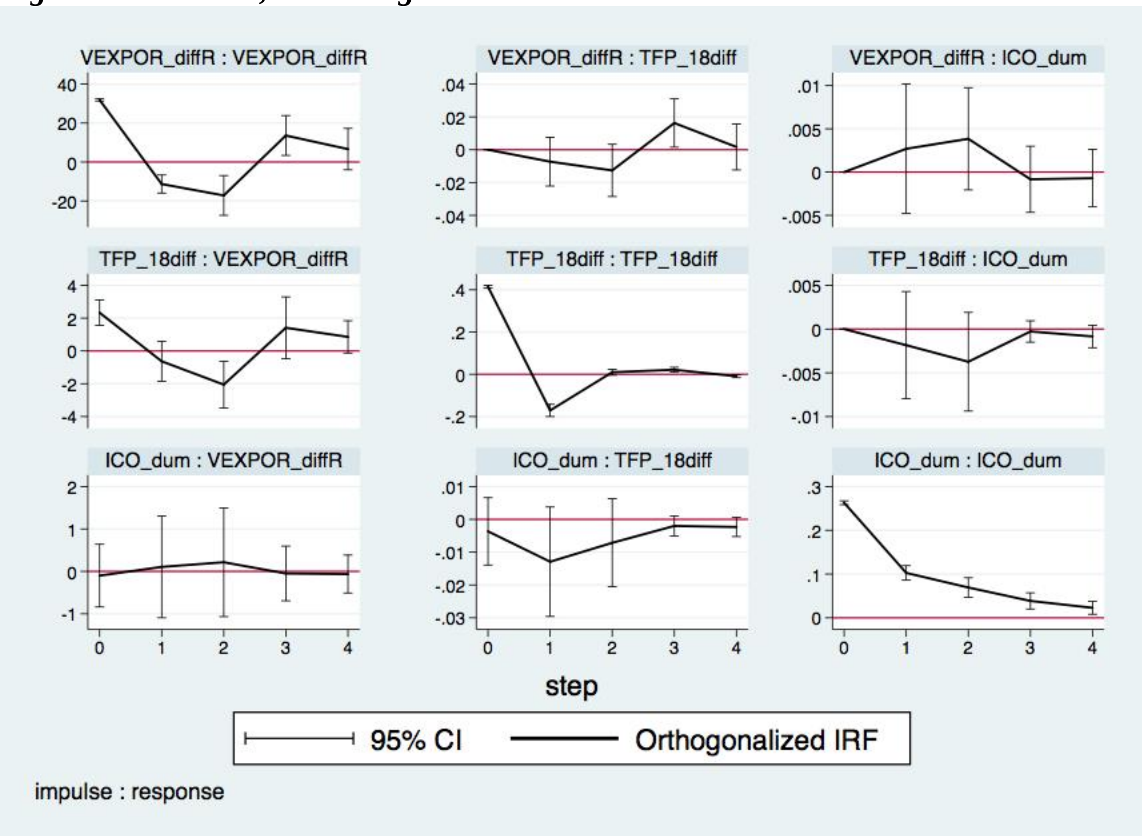


Figure A2.6.10 Cumulative IRFs, Marketing innovations

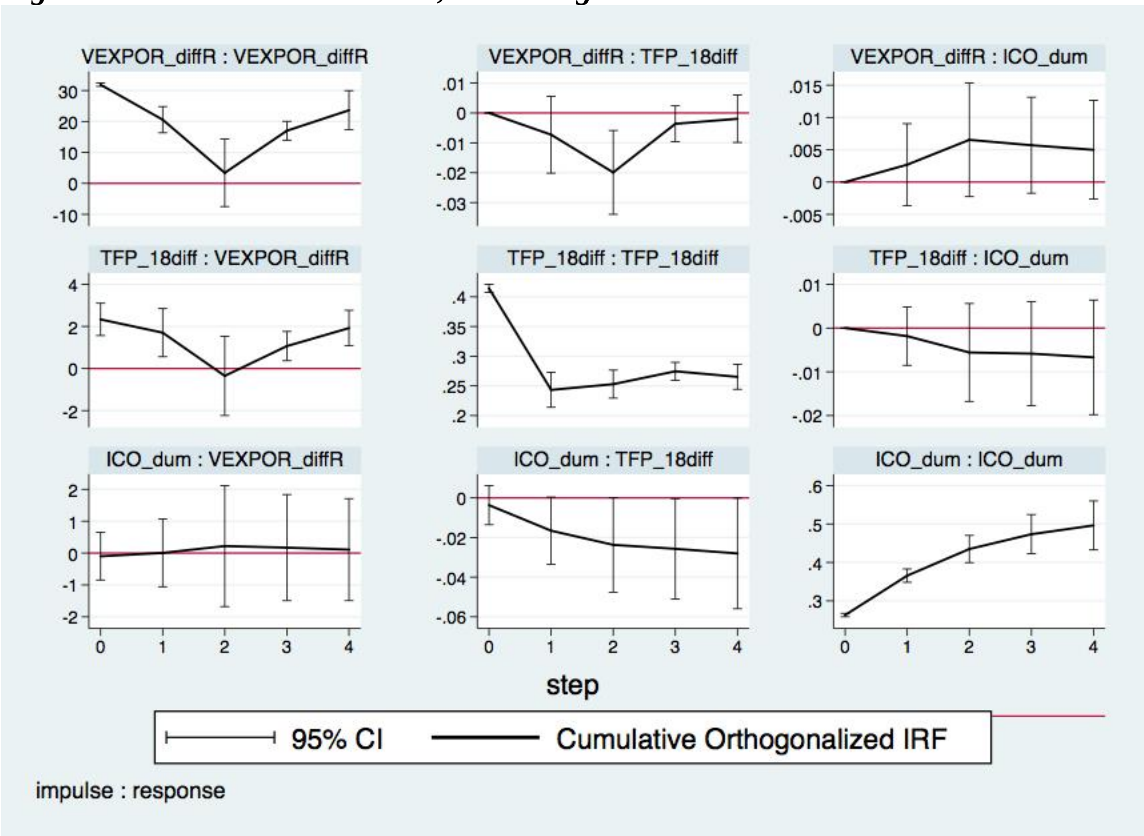


Figure A2.6.11 IRFs, Process innovations

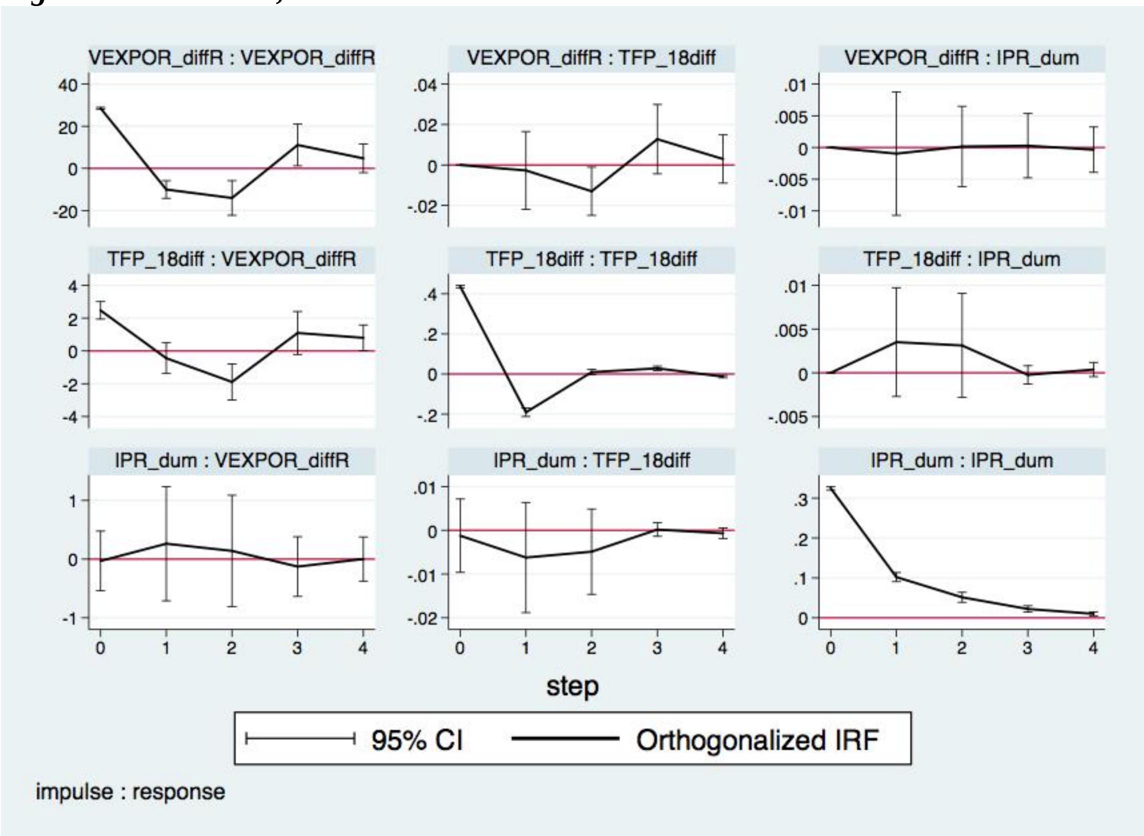
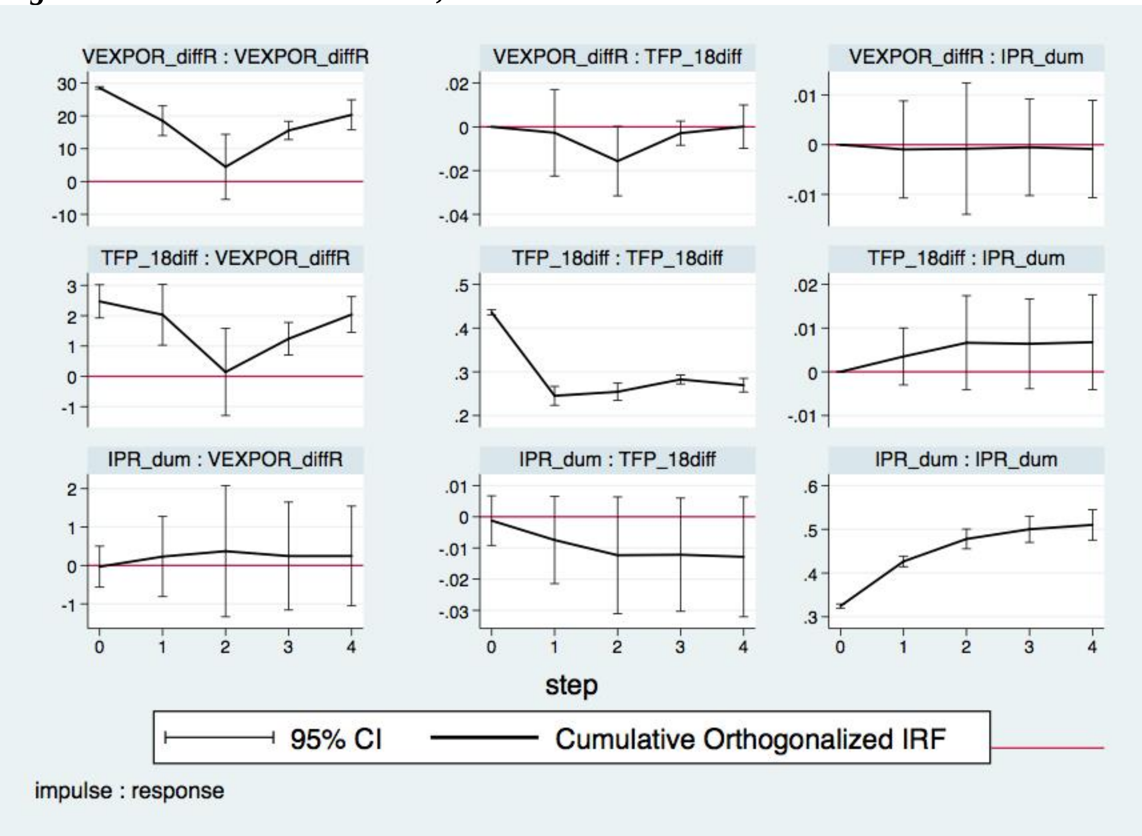


Figure A2.6.12 Cumulative IRFs, Process innovations



Appendix A2.7: IRFs and cumulative IRFs for whole sample estimations
Figure A2.7.1 IRFs, R&D expenditures

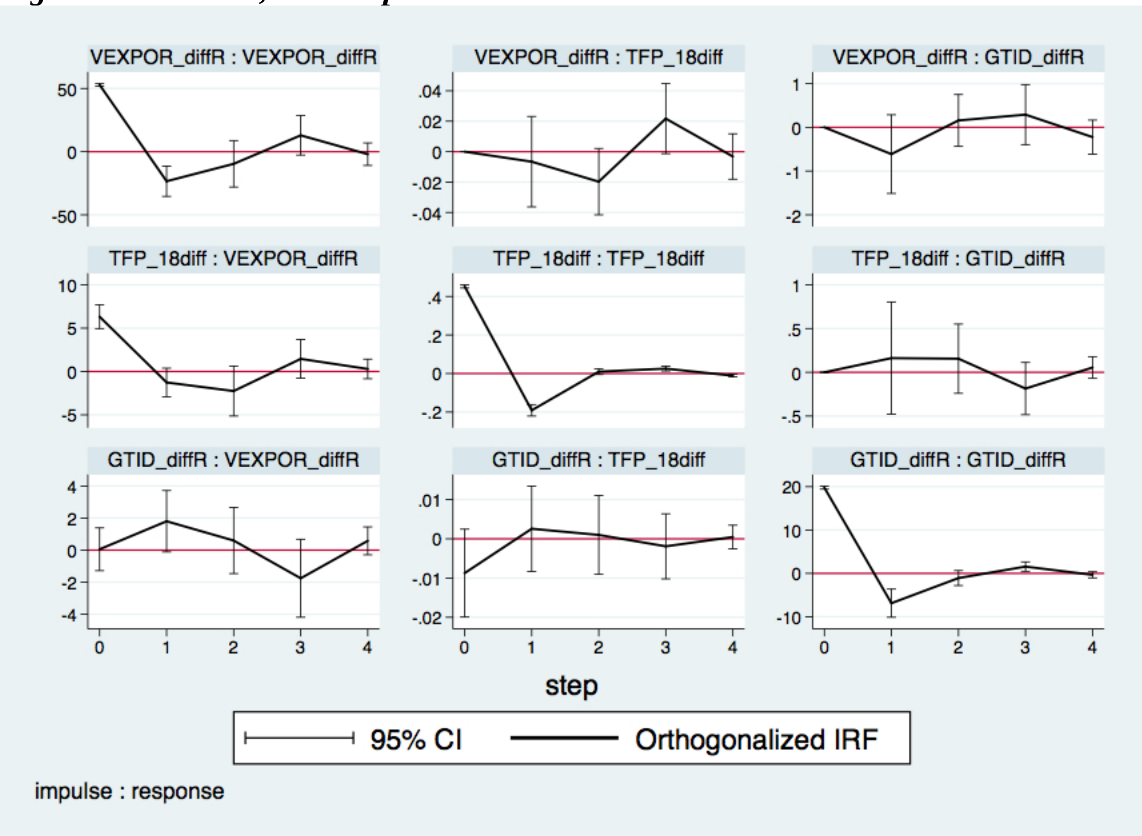


Figure A2.7.2 Cumulative IRFs, R&D expenditures

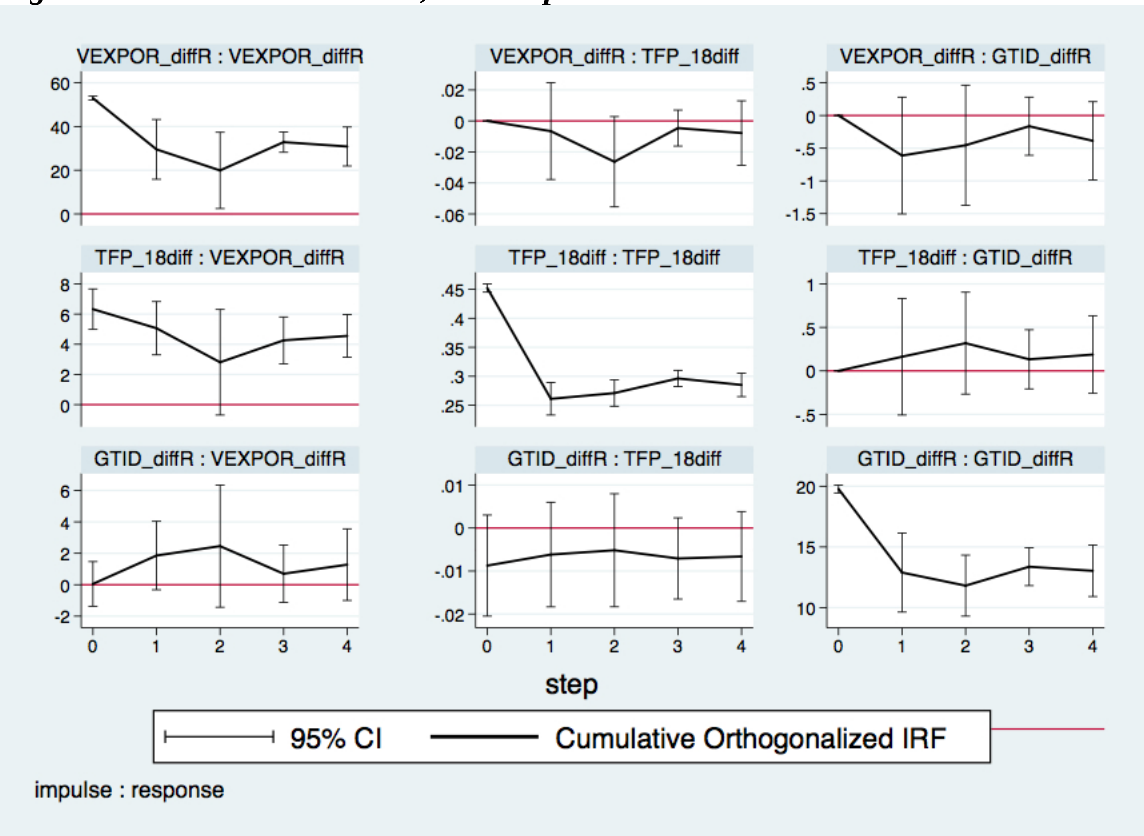


Figure A2.7.3 IRFs, Patents registered in Spain

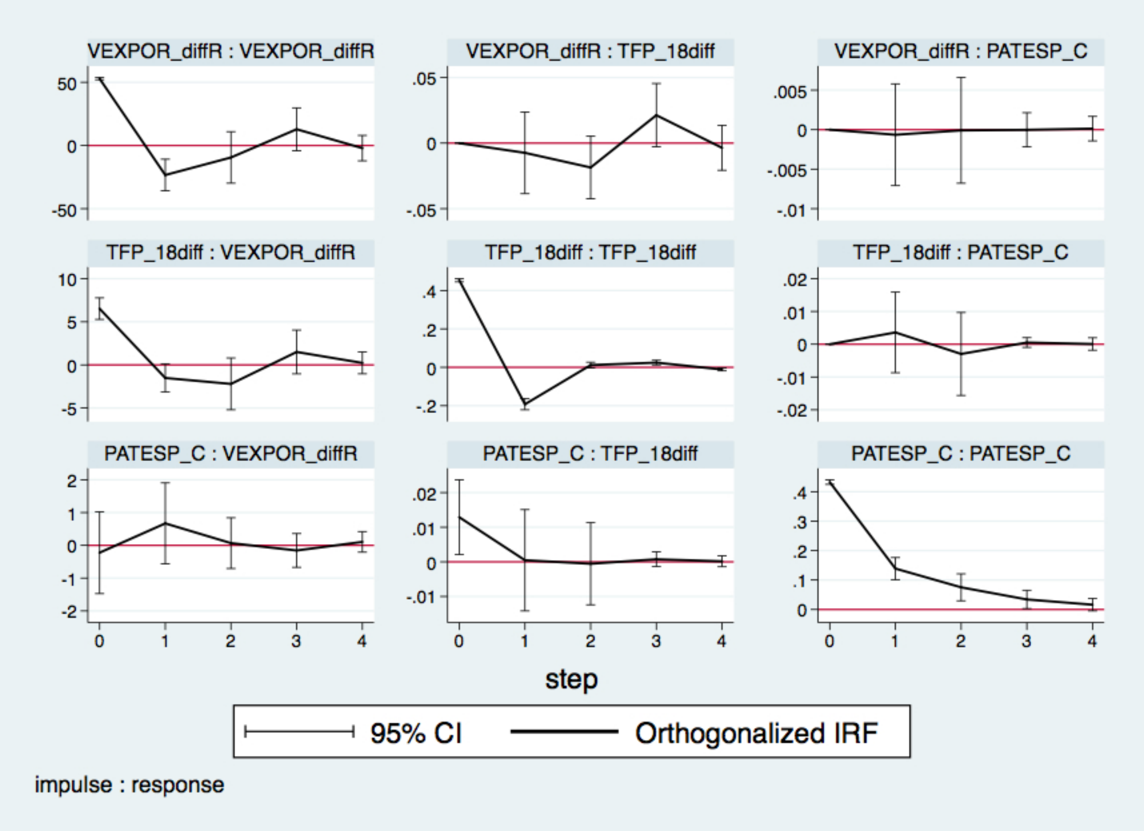


Figure A2.7.4 Cumulative IRFs, Patents registered in Spain

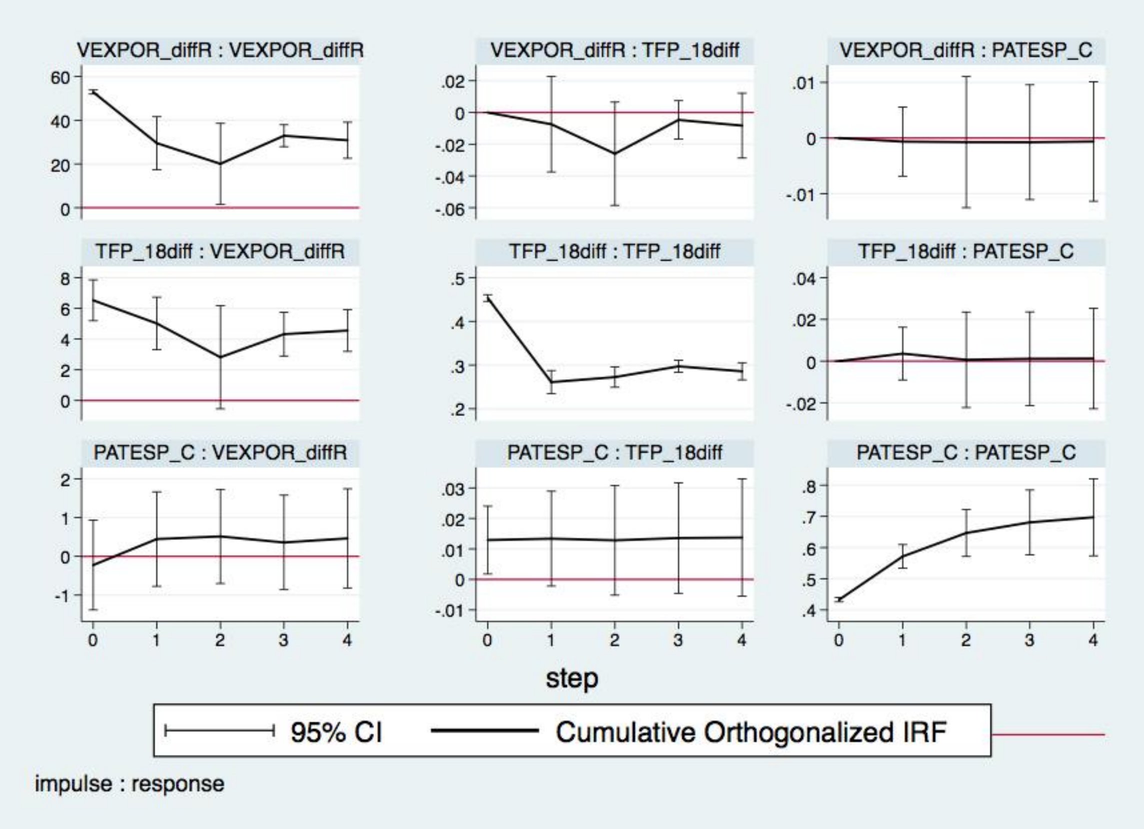


Figure A2.7.5 IRFs, Patents registered abroad

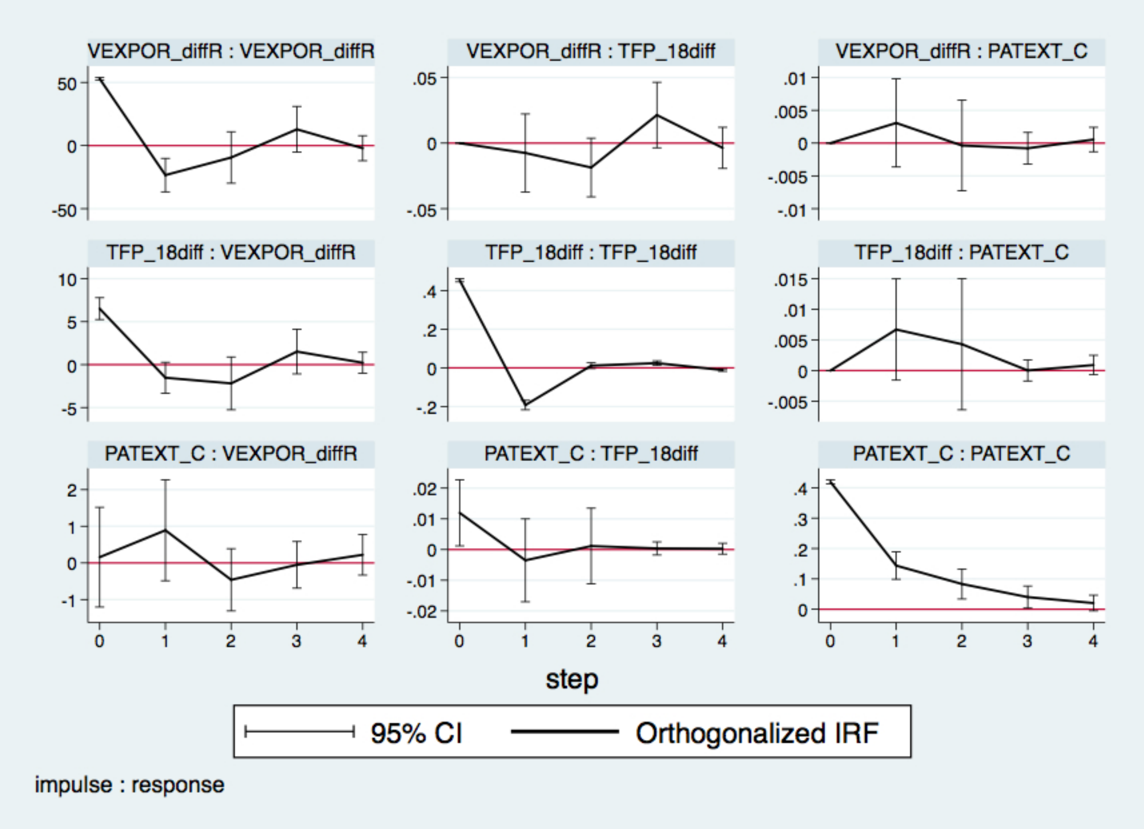


Figure A2.7.6 Cumulative IRFs, Patents registered abroad

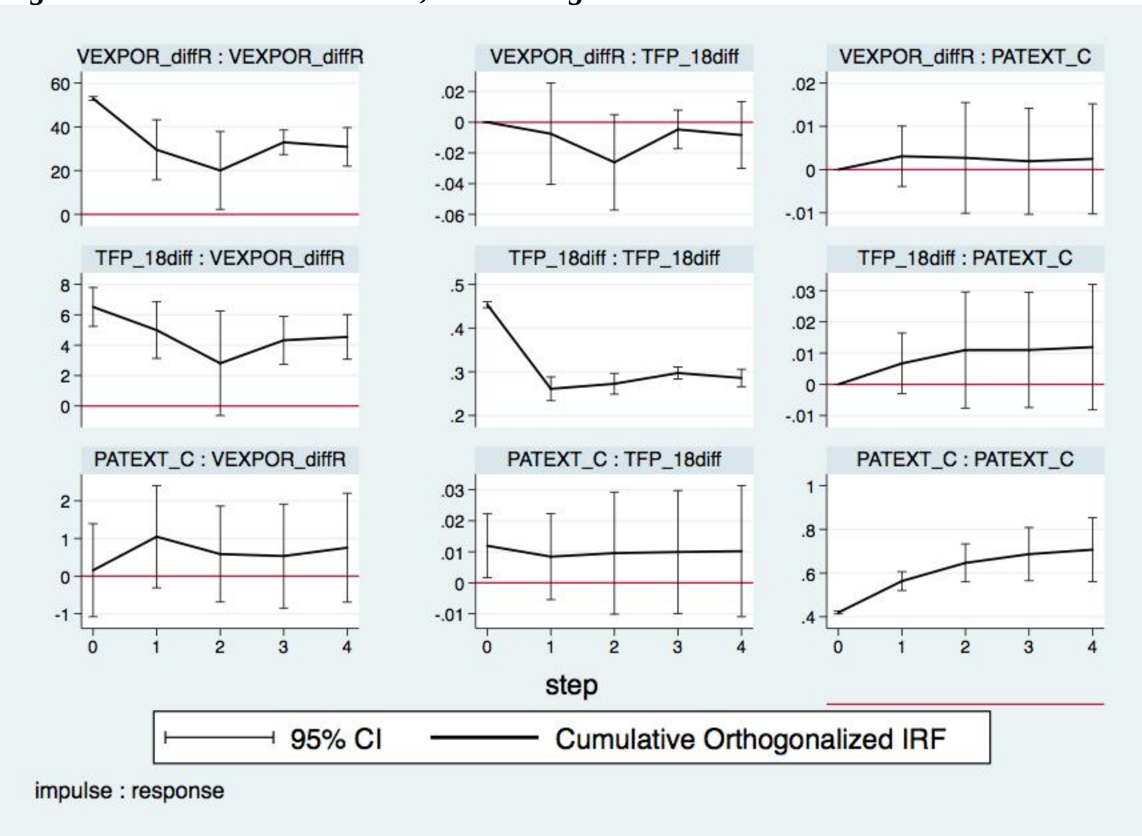


Figure A2.7.7 IRFs, Number of product innovations

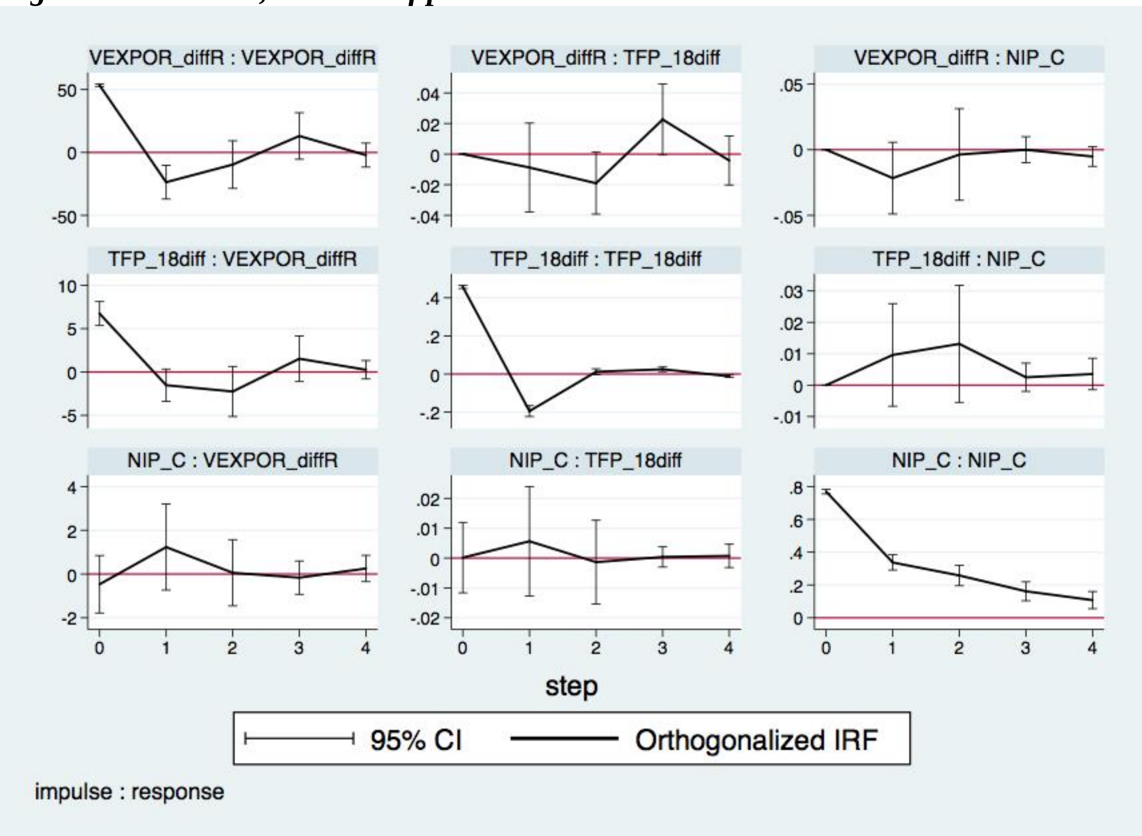


Figure A2.7.8 Cumulative IRFs, Number of product innovations

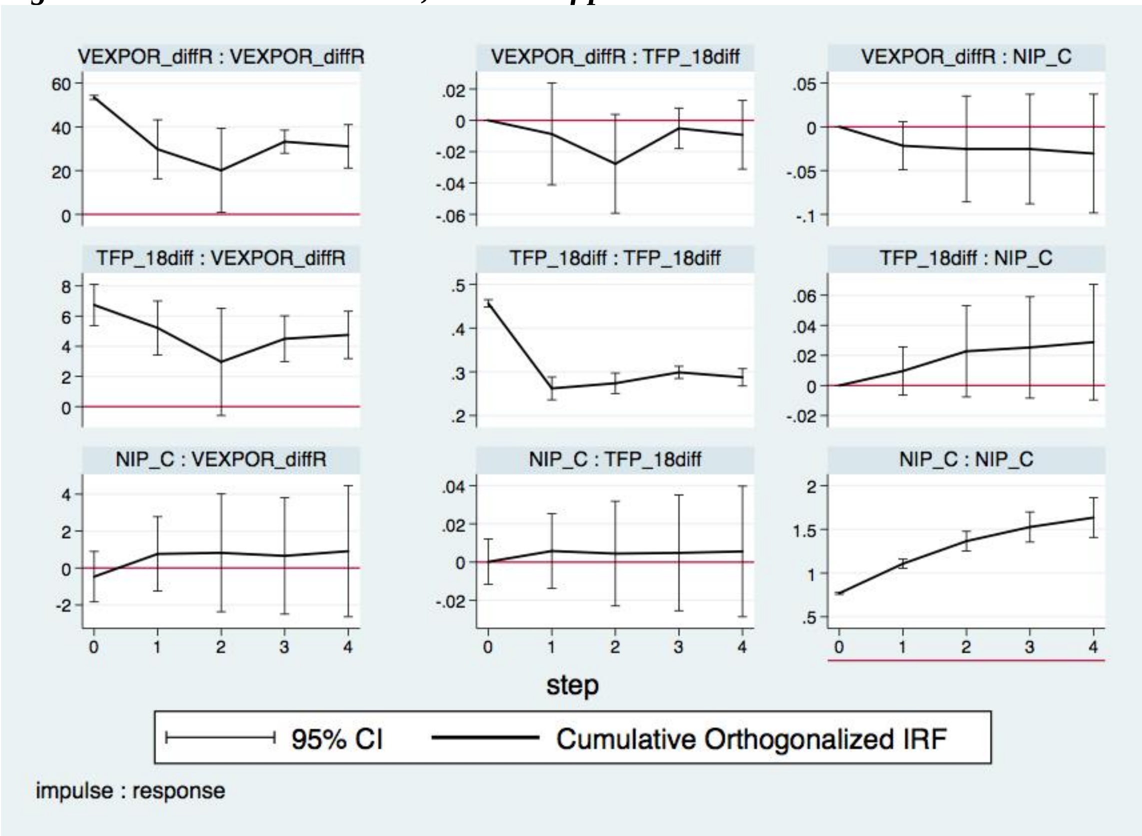


Figure A2.7.9 IRFs, Organisational innovations

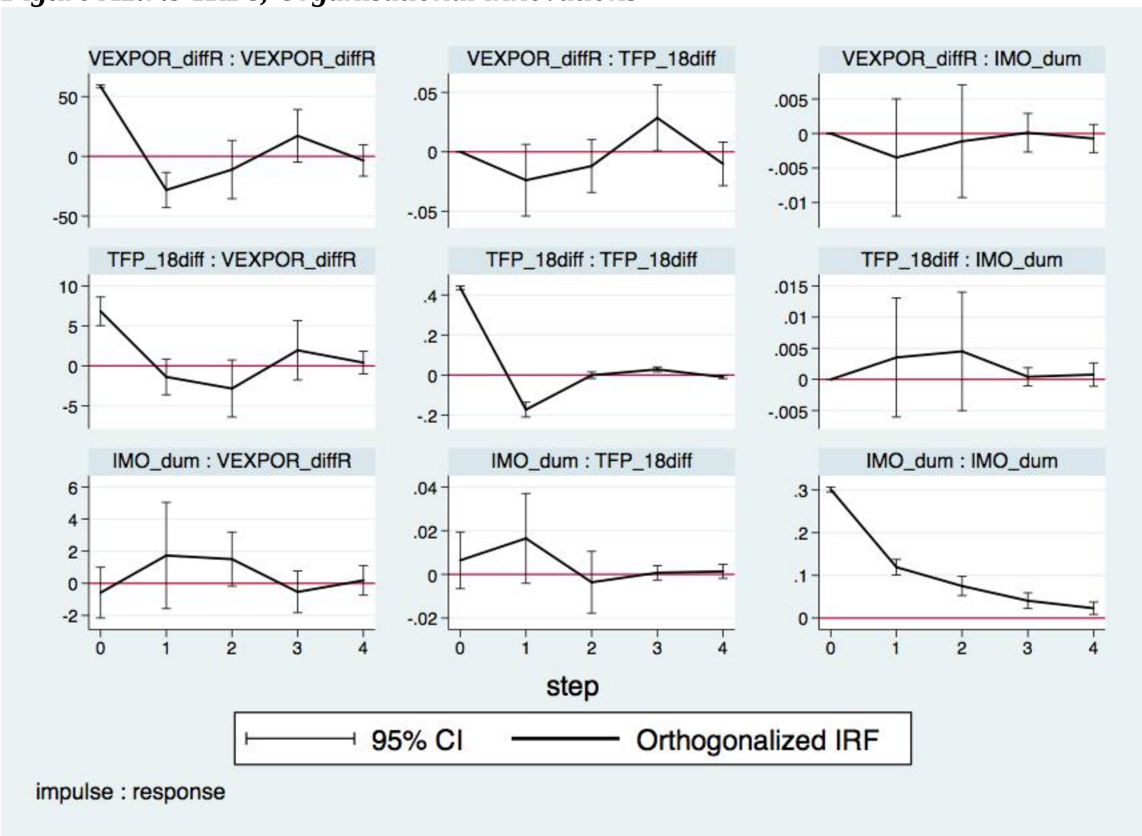


Figure A2.7.10 Cumulative IRFs, Organisational innovations

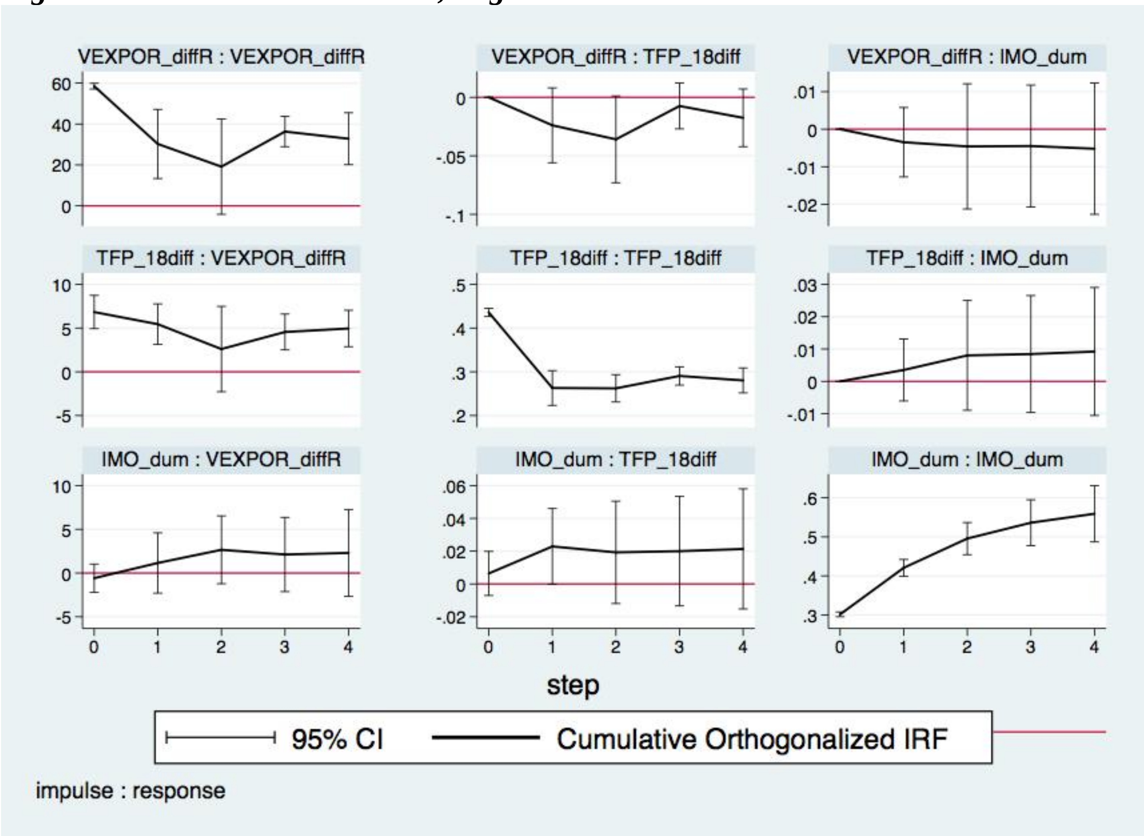


Figure A2.7.11 IRFs, Marketing innovations

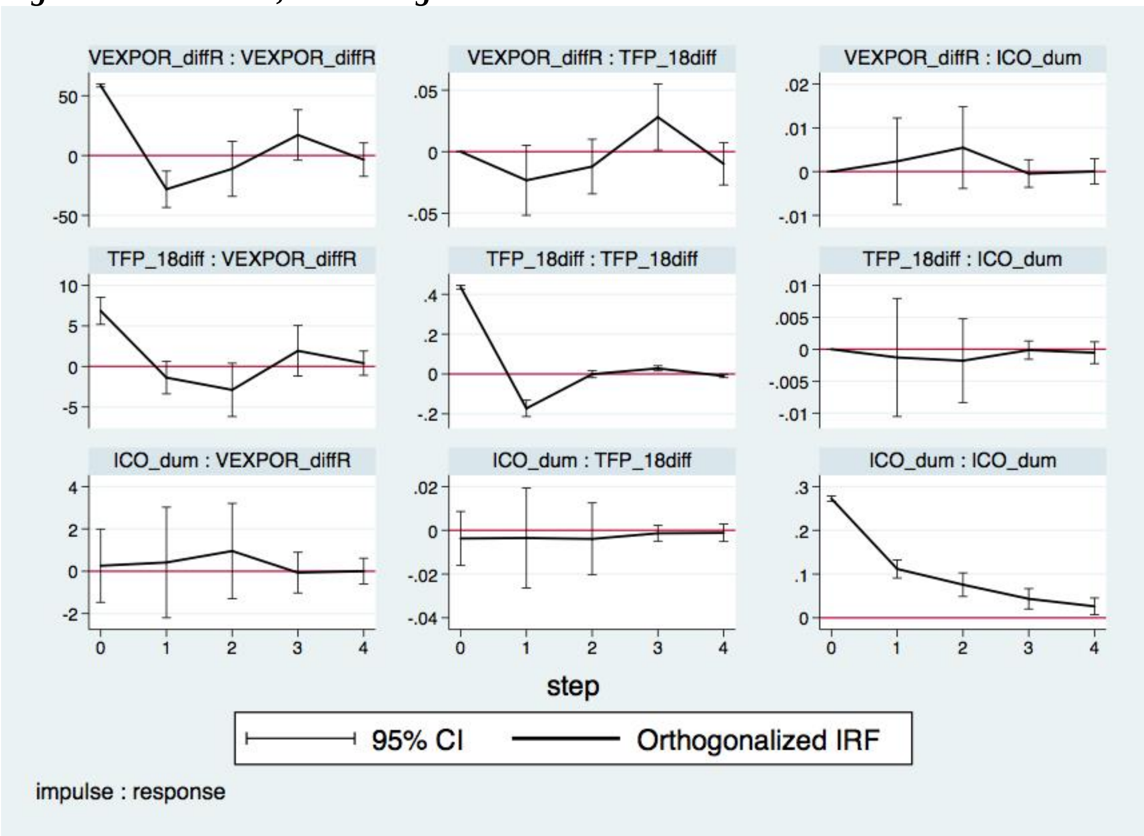


Figure A2.7.12 Cumulative IRFs, Marketing innovations

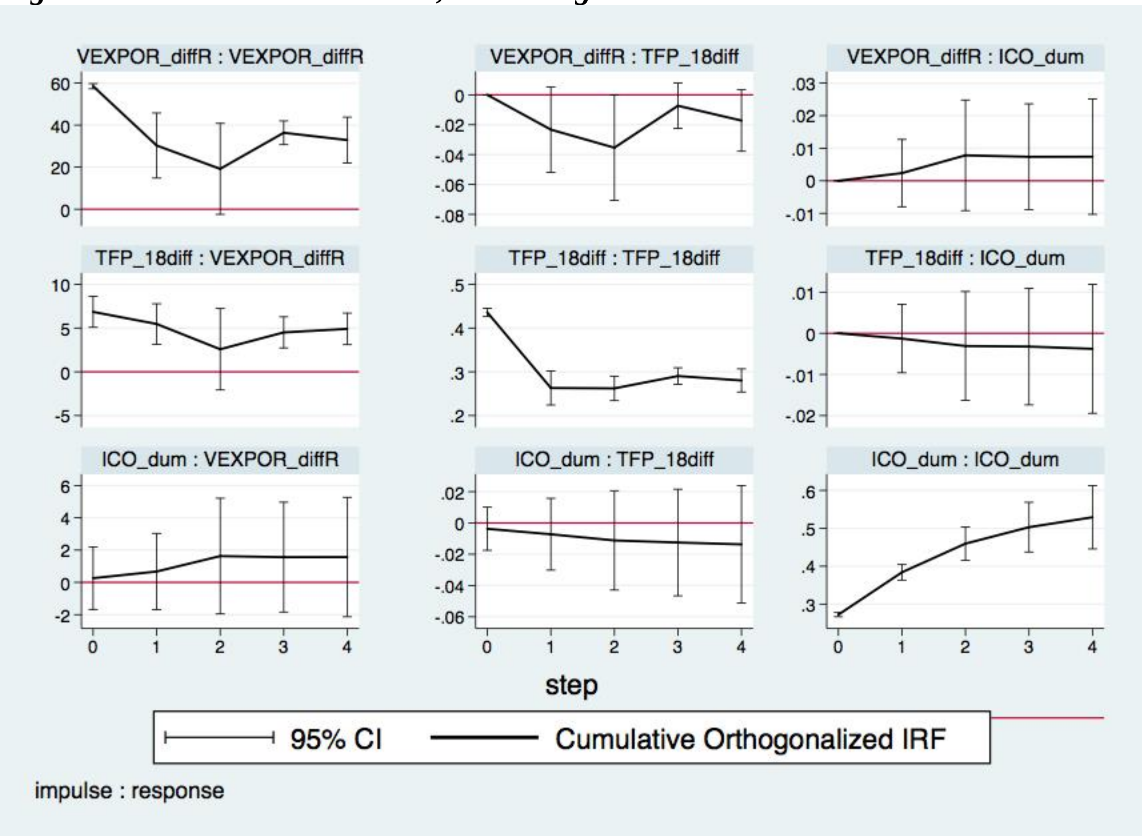


Figure A2.7.13 IRFs, Process innovations

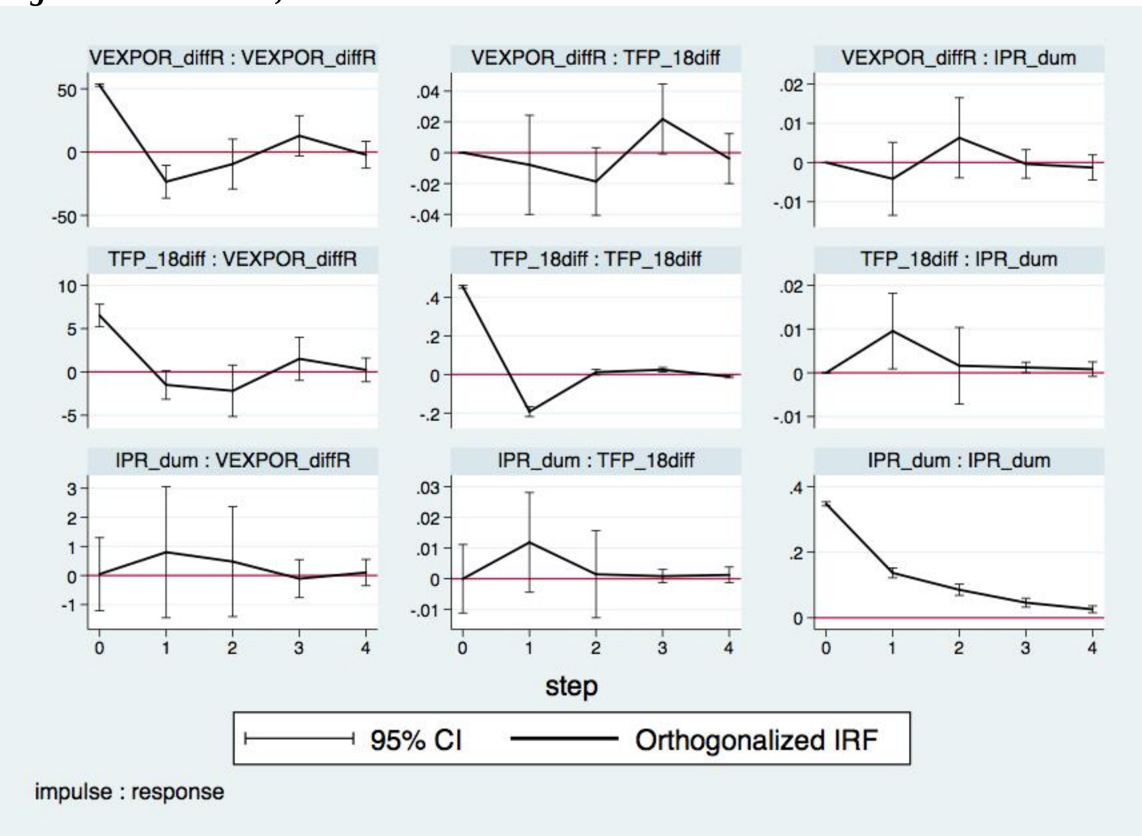
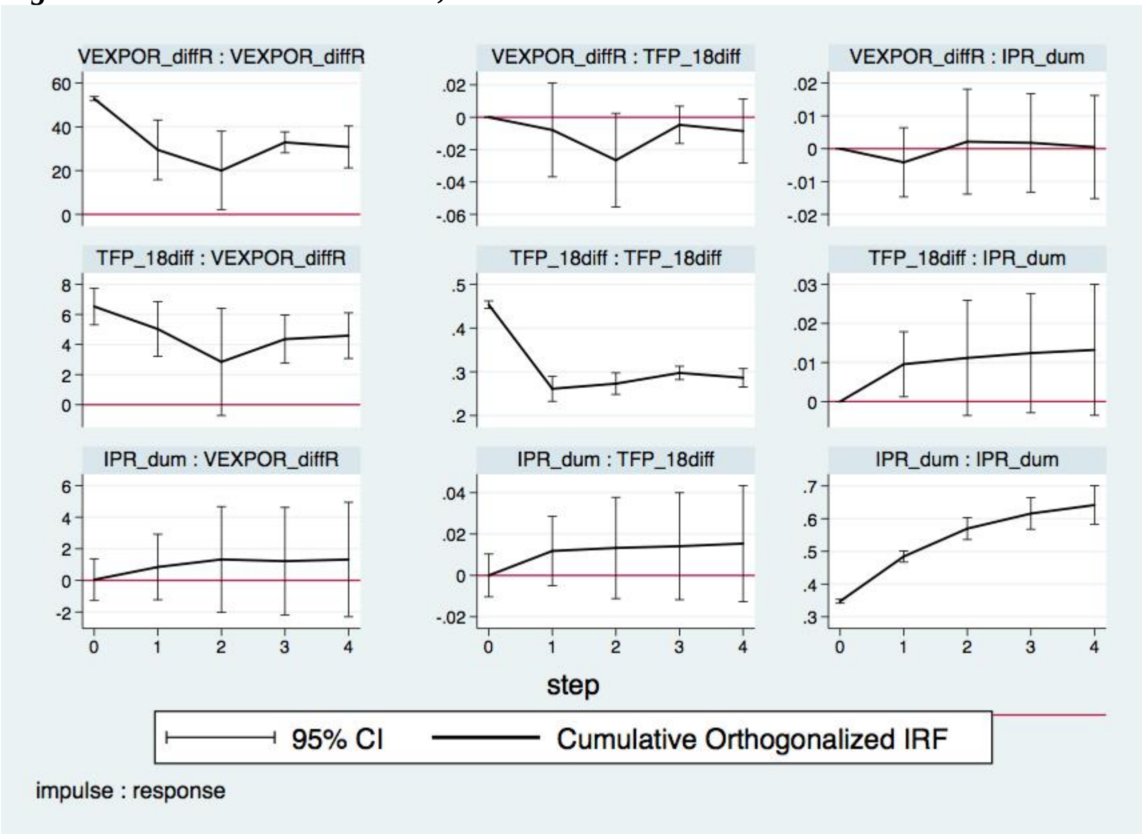


Figure A2.7.14 Cumulative IRFs, Process innovations



Appendix A2.8: IRFs and cumulative IRFs for low exporters subsample

Figure A2.8.1: IRFs, R&D expenditures

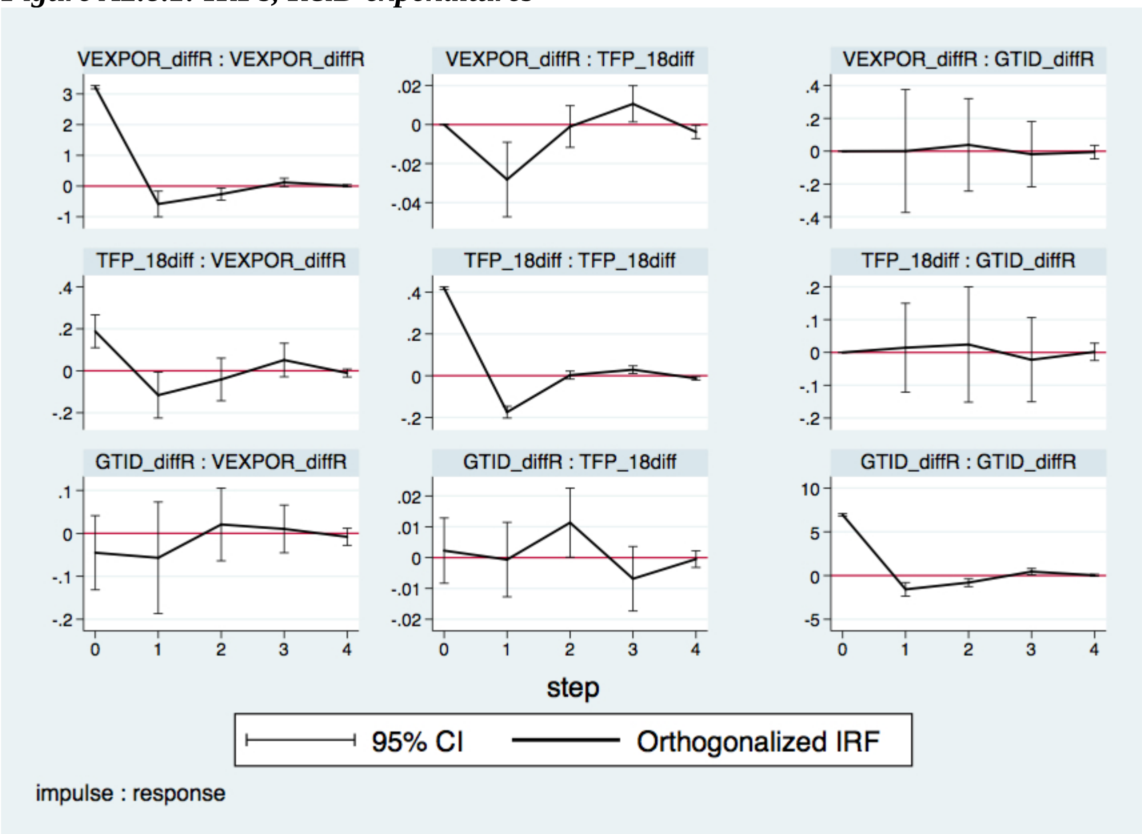


Figure A2.8.2 Cumulative IRFs, R&D expenditures

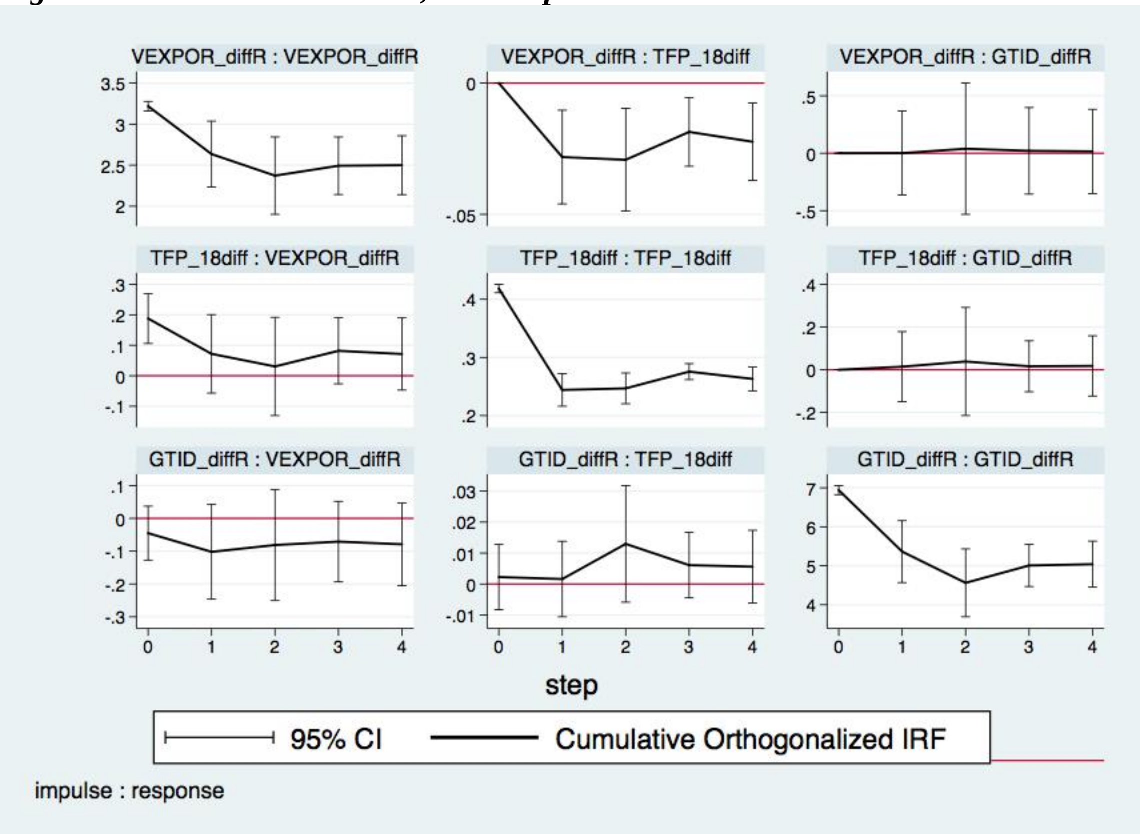


Figure A2.8.3 IRFs, Patents registered in Spain

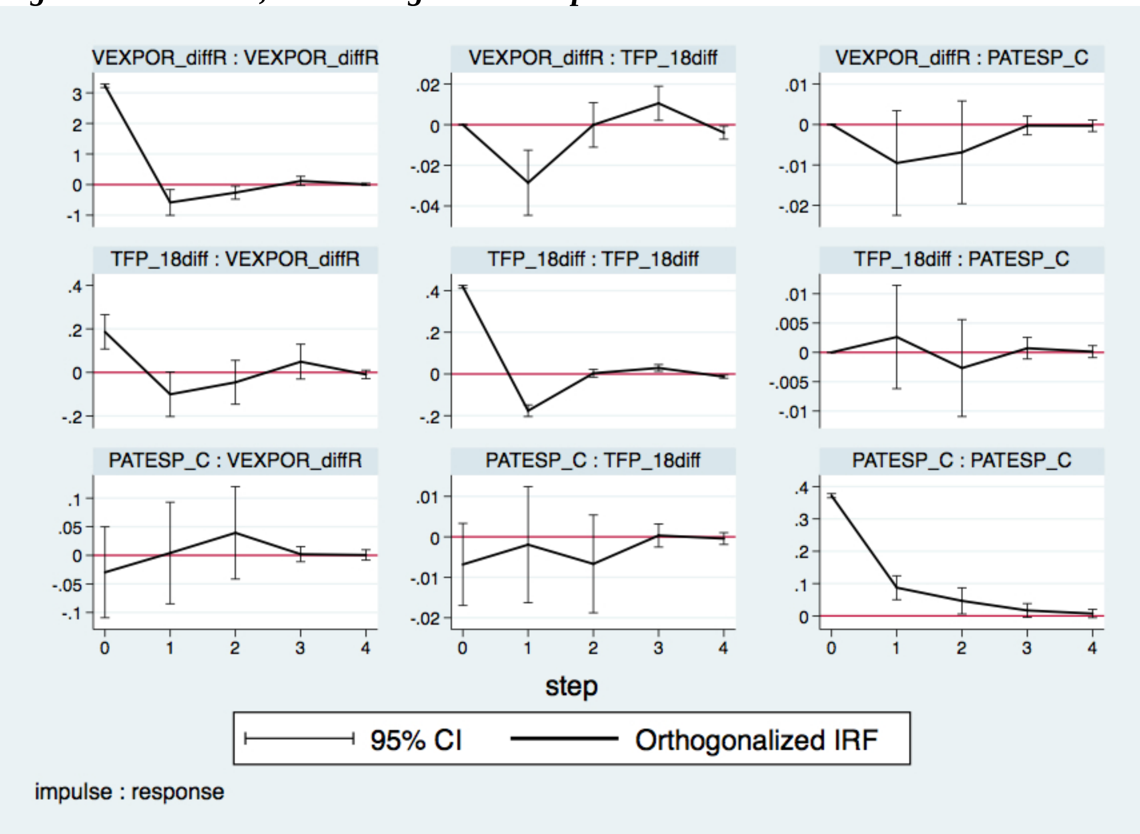


Figure A2.8.4 Cumulative IRFs, Patents registered in Spain

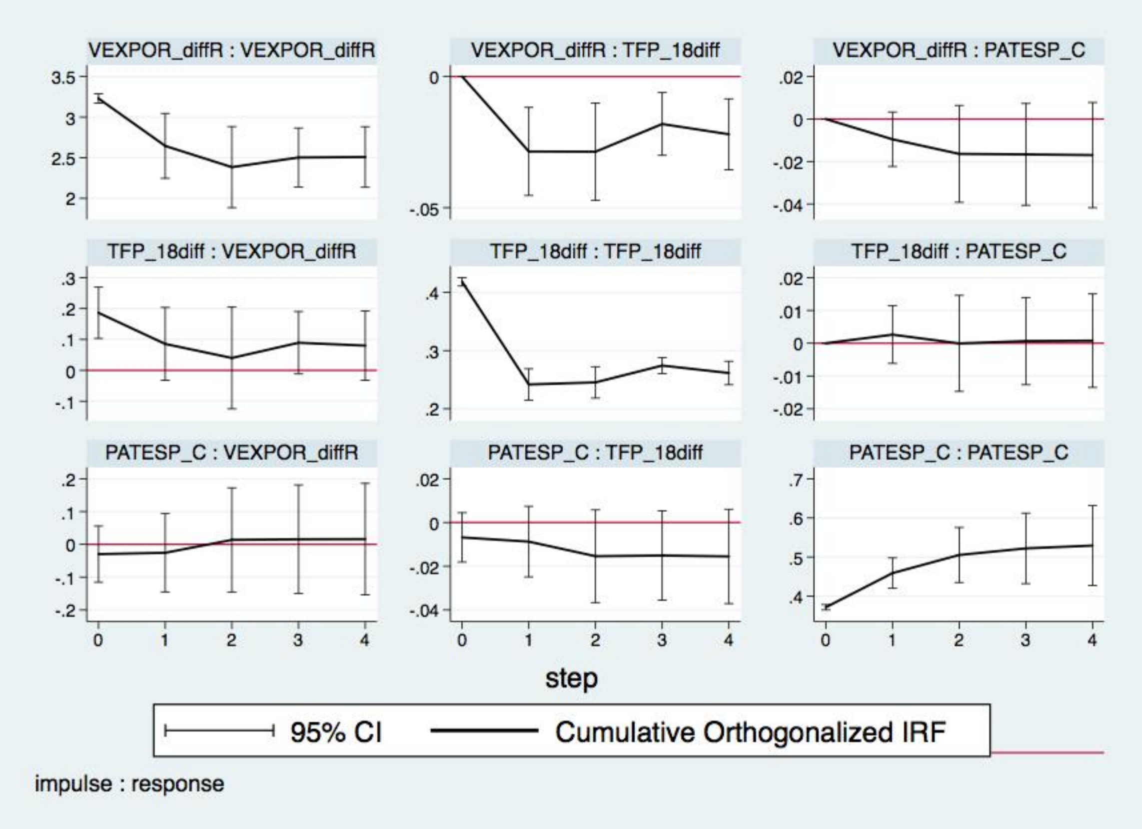


Figure A2.8.5 IRFs, Patents registered abroad

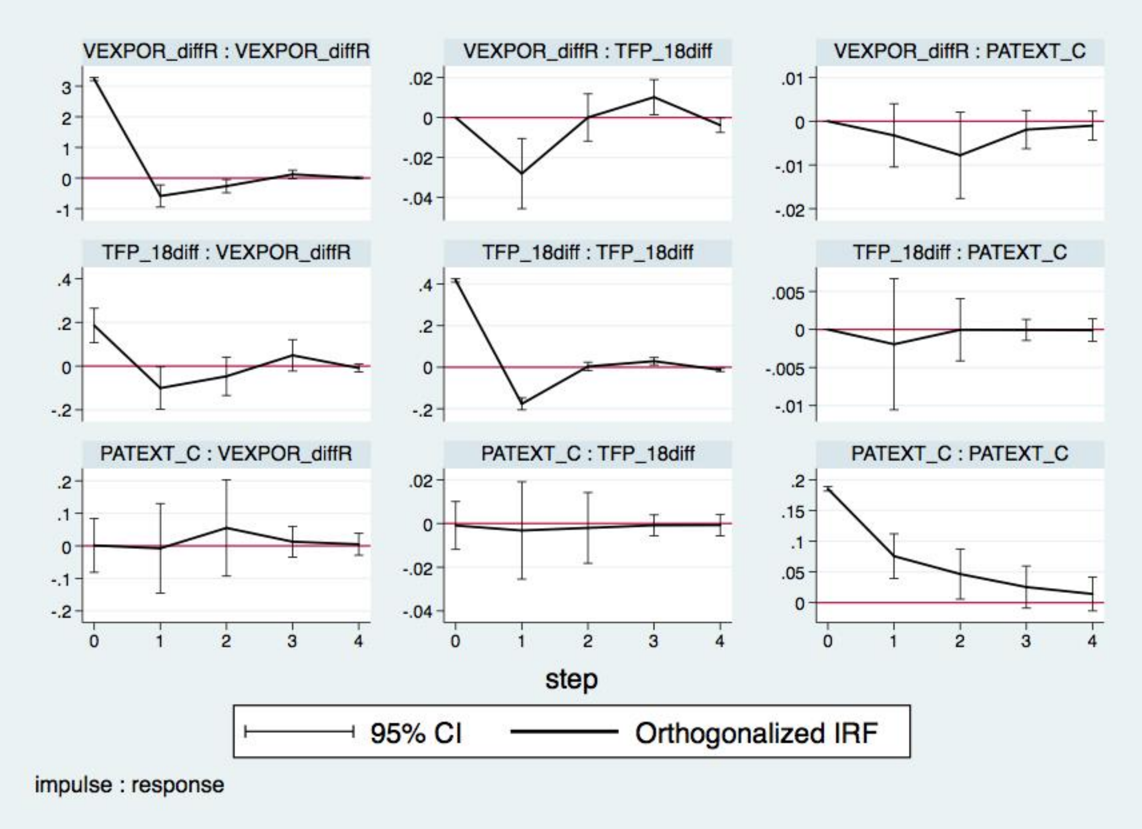


Figure A2.8.6 Cumulative IRFs, Patents registered abroad

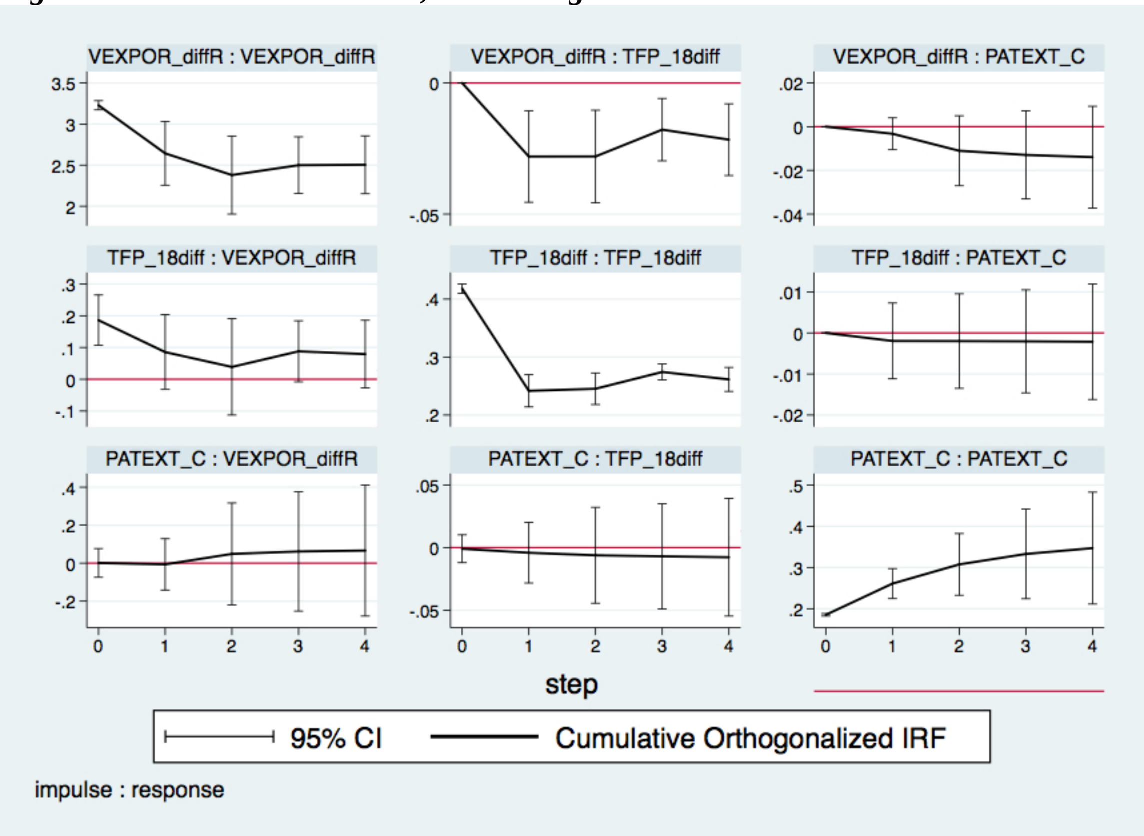


Figure A2.8.7 IRFs, Number of product innovations

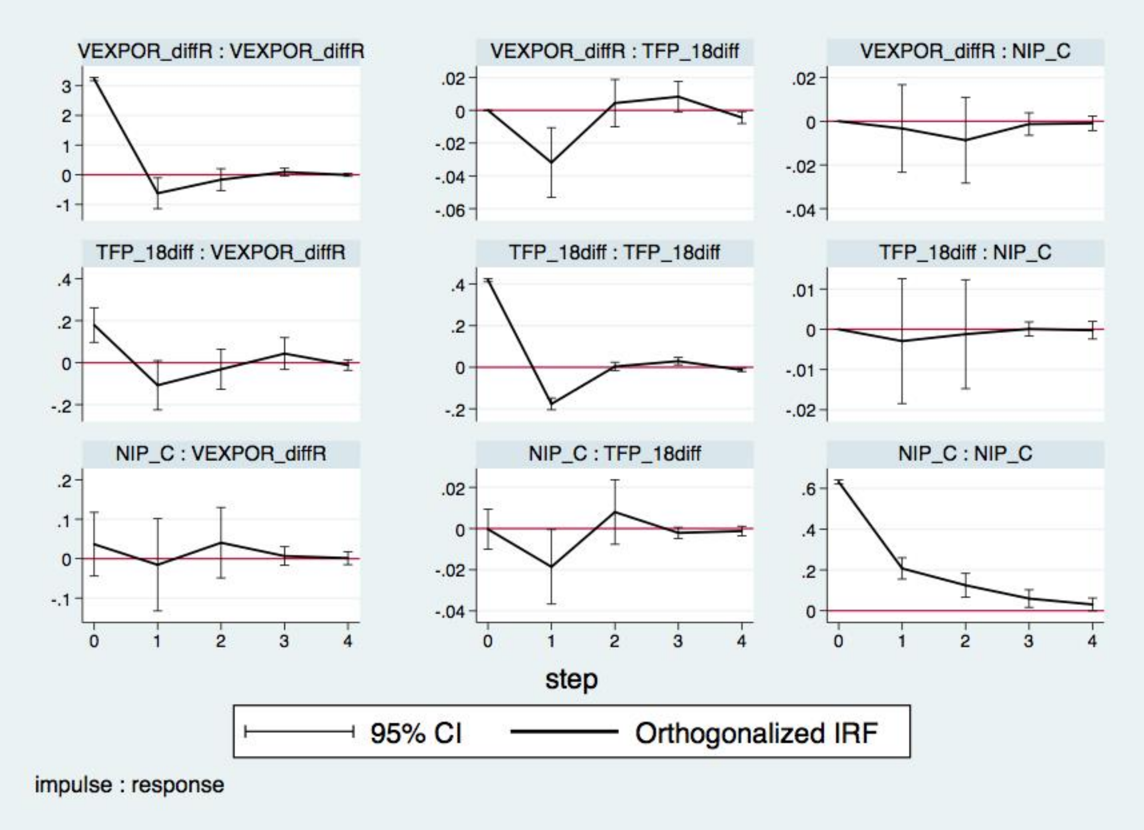


Figure A2.8.8 Cumulative IRFs, Number of product innovations

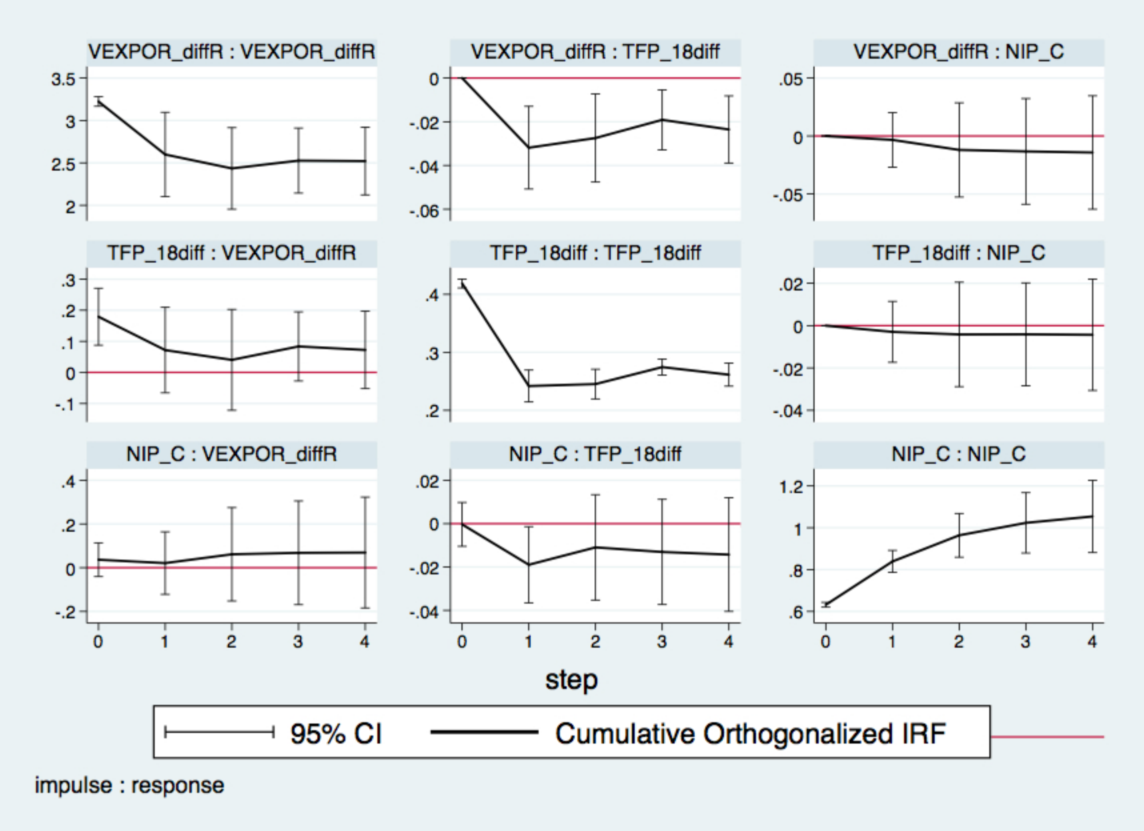


Figure A2.8.9 IRFs, Organisational innovations

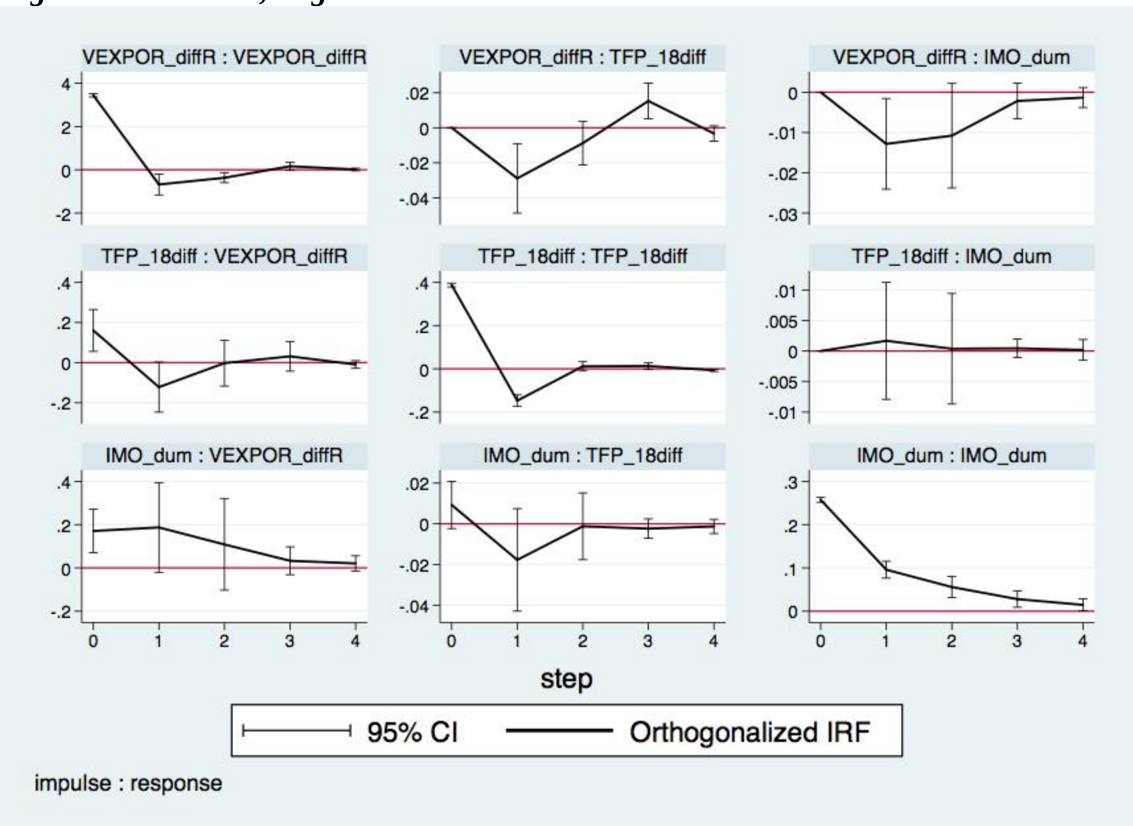


Figure A2.8.10 Cumulative IRFs, Organisational innovations

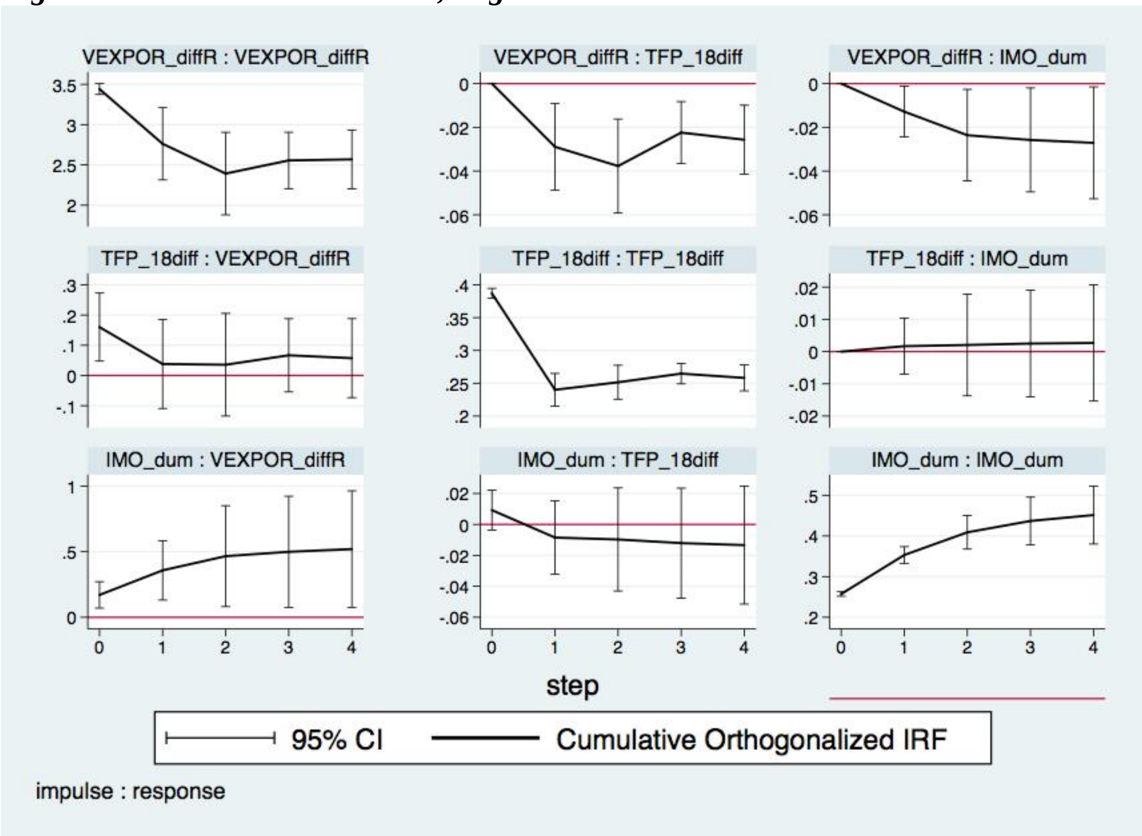


Figure A2.8.11 IRFs, Marketing innovations

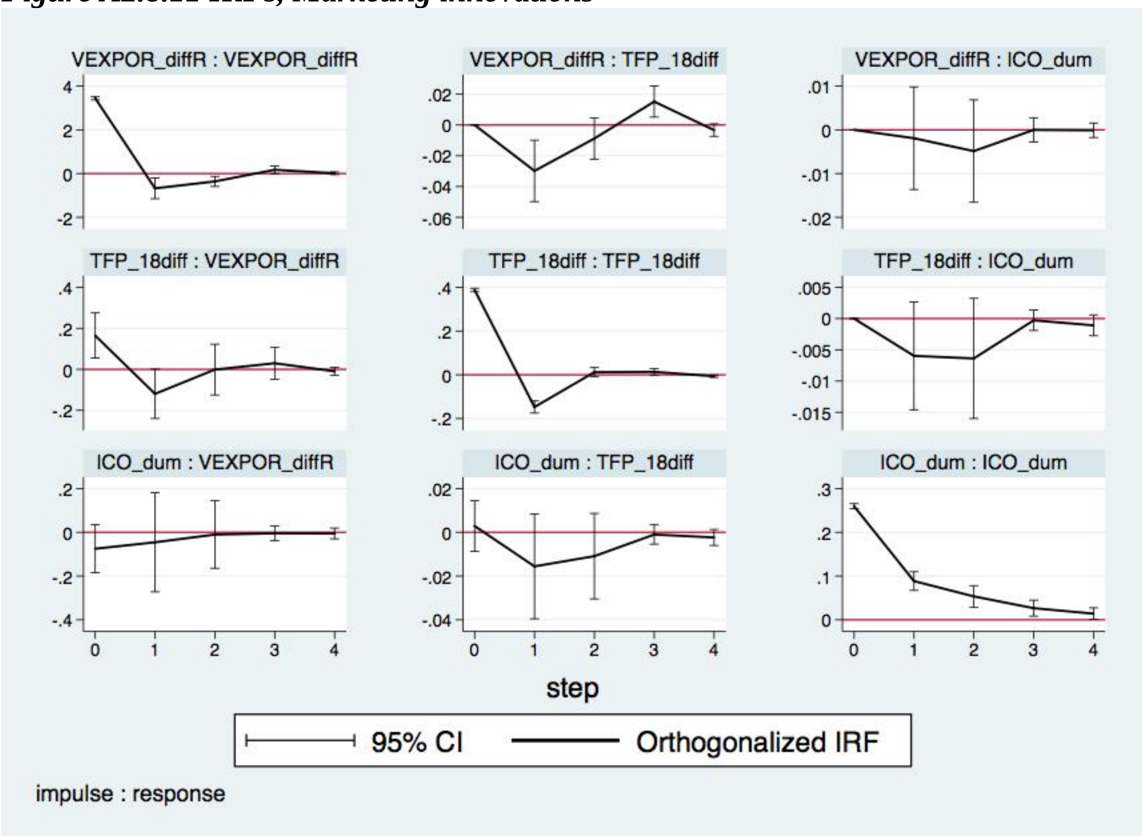


Figure A2.8.12 Cumulative IRFs, Marketing innovations

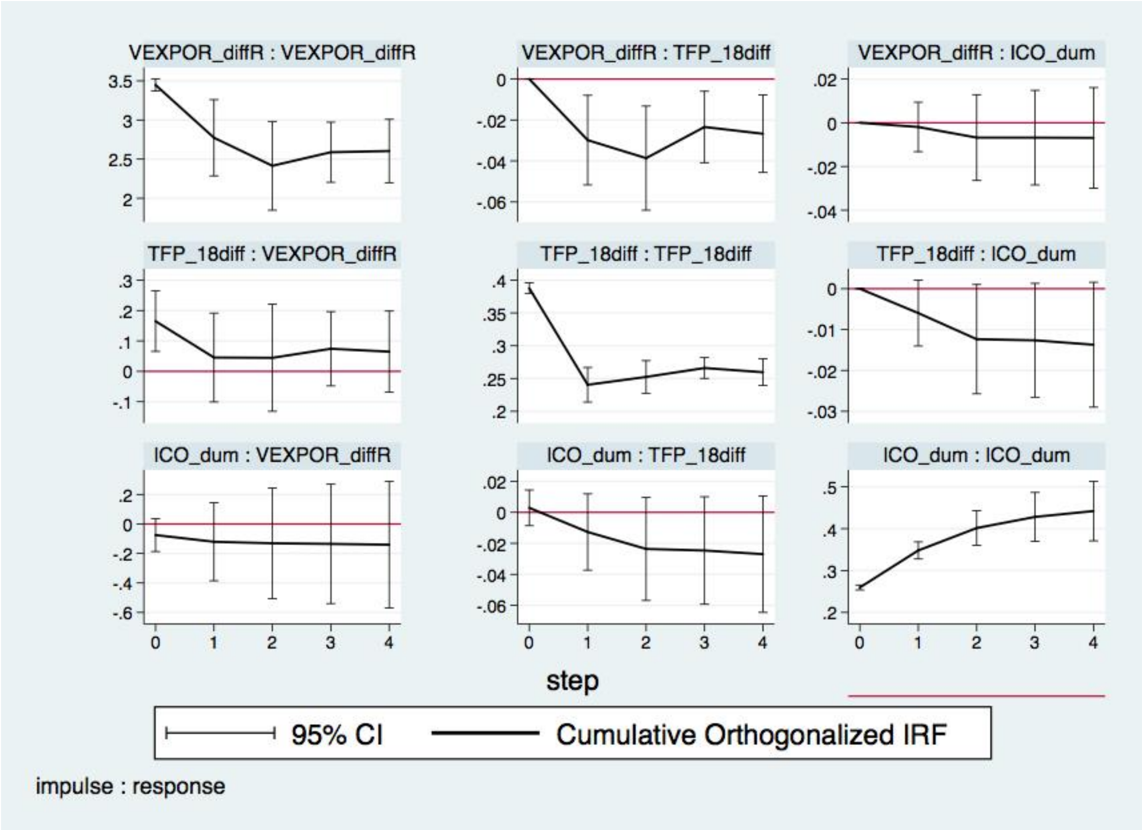


Figure A2.8.13 IRFs, Process innovations

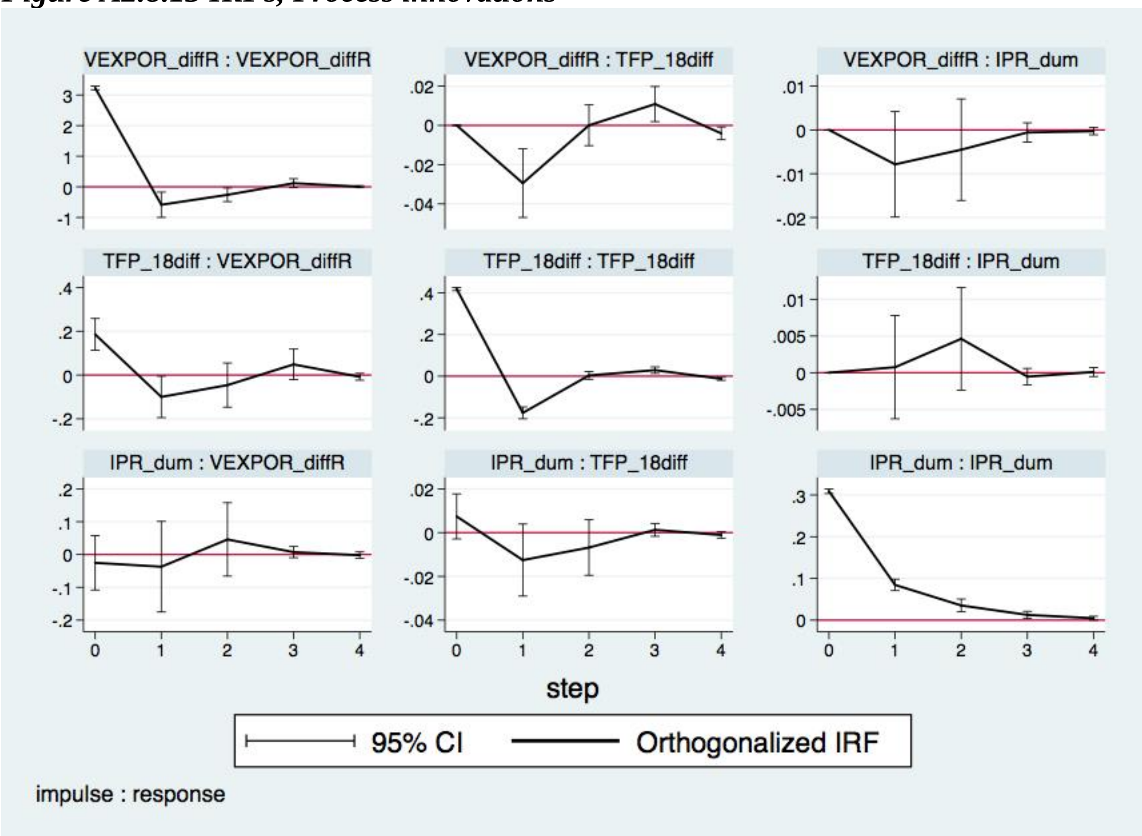
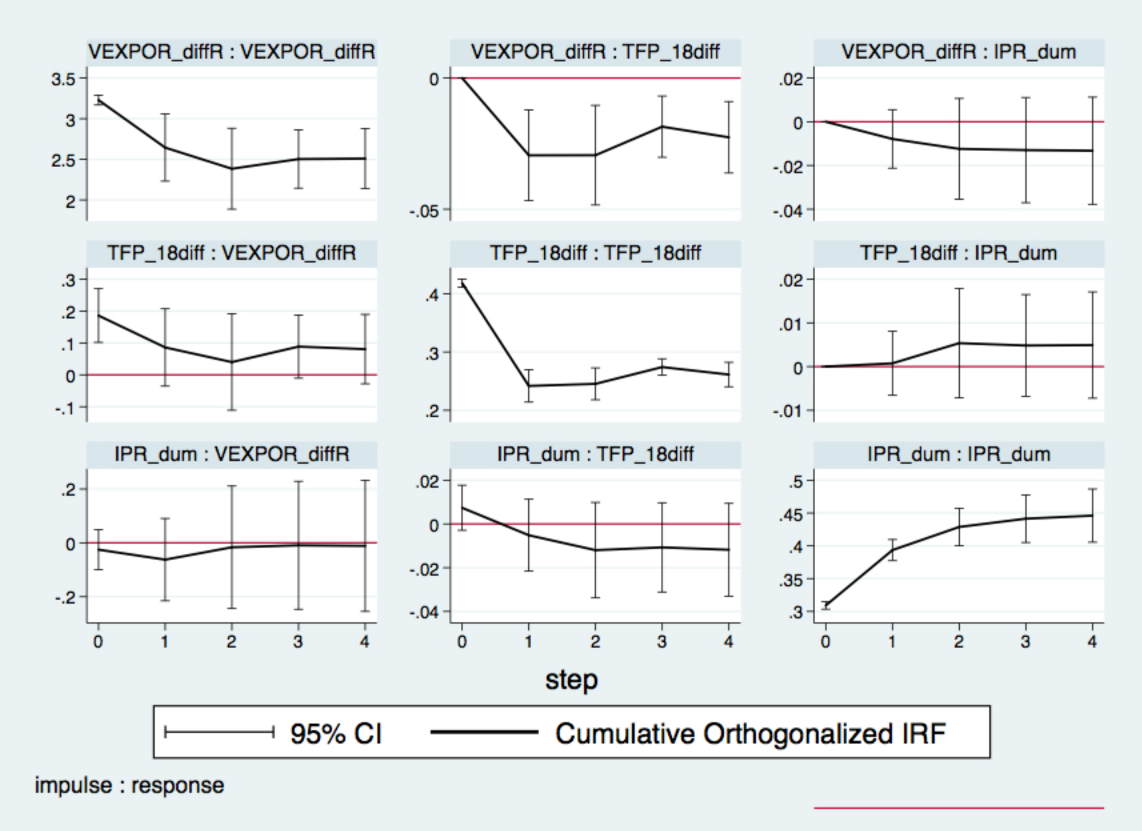


Figure A2.8.14 Cumulative IRFs, Process innovations



Appendix A2.9: IRFs and cumulative IRFs for subsample of firms that engaged in cooperation with other firms

Figure A2.9.1 IRFs, R&D expenditures

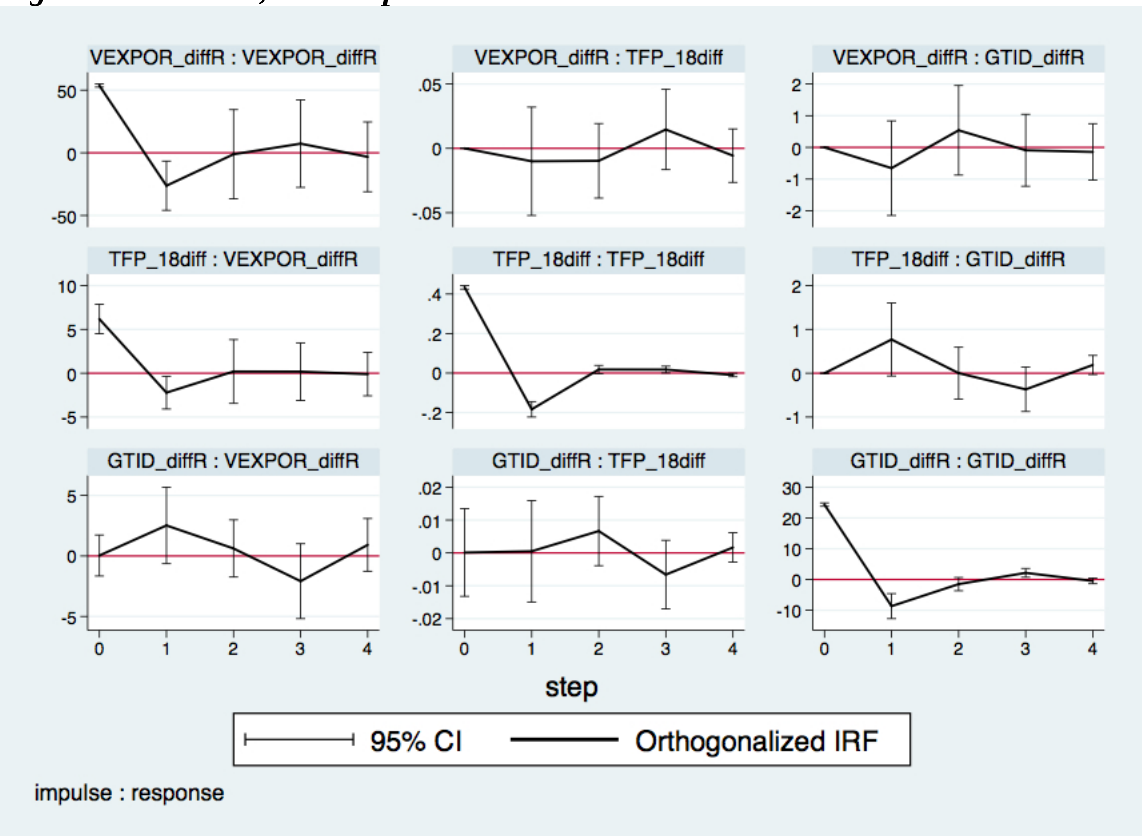


Figure A2.9.2 Cumulative IRFs, R&D expenditures

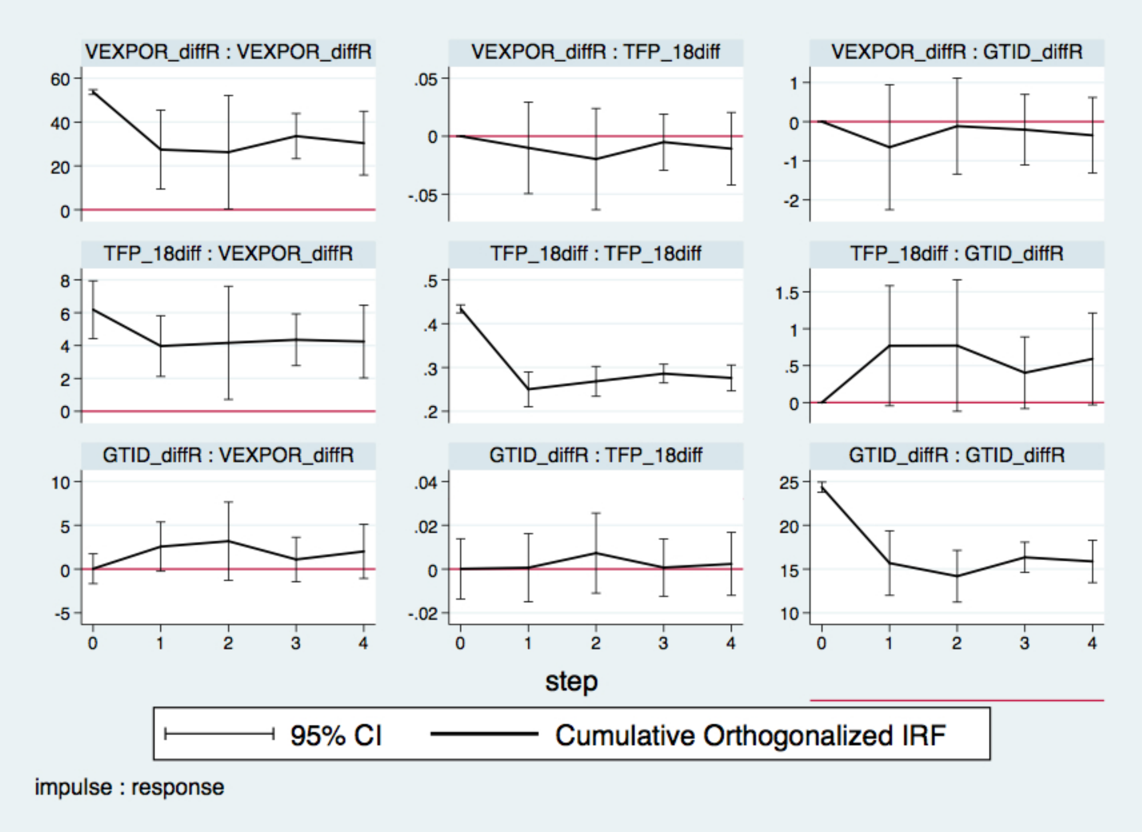


Figure A2.9.3 IRFs, Patents registered in Spain

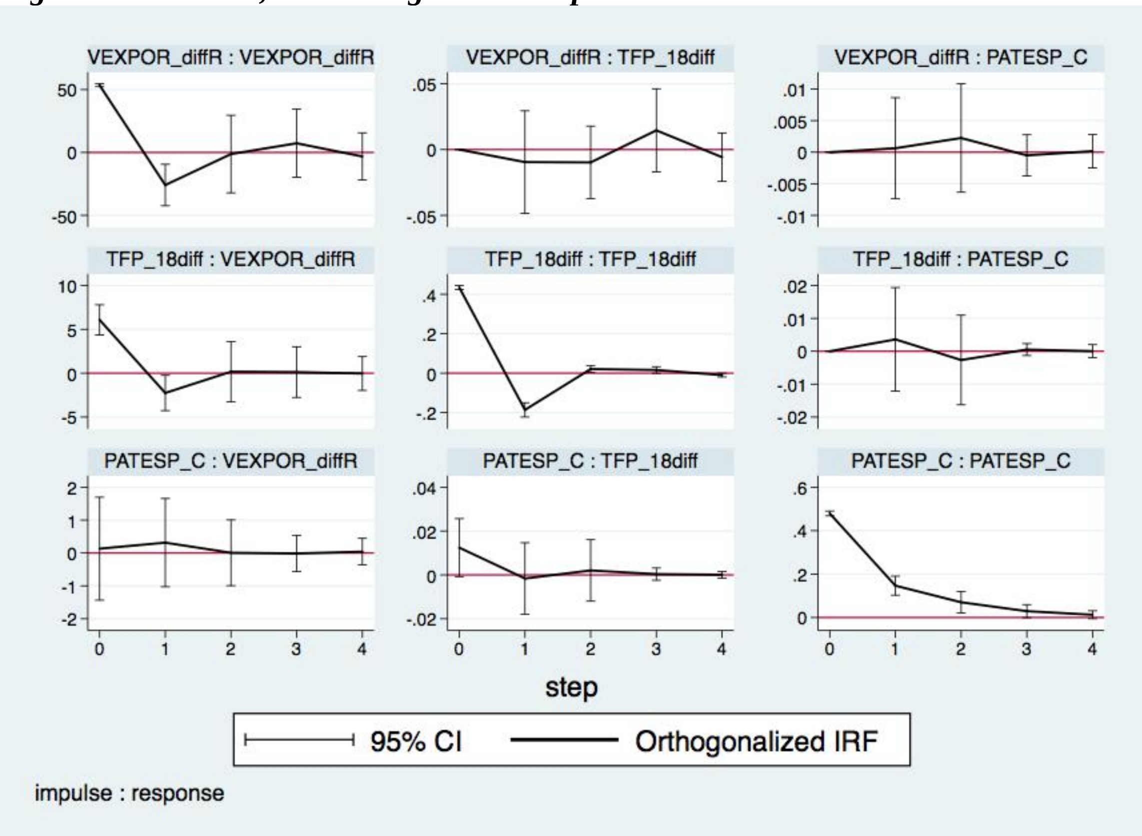


Figure A2.9.4 Cumulative IRFs, Patents registered in Spain

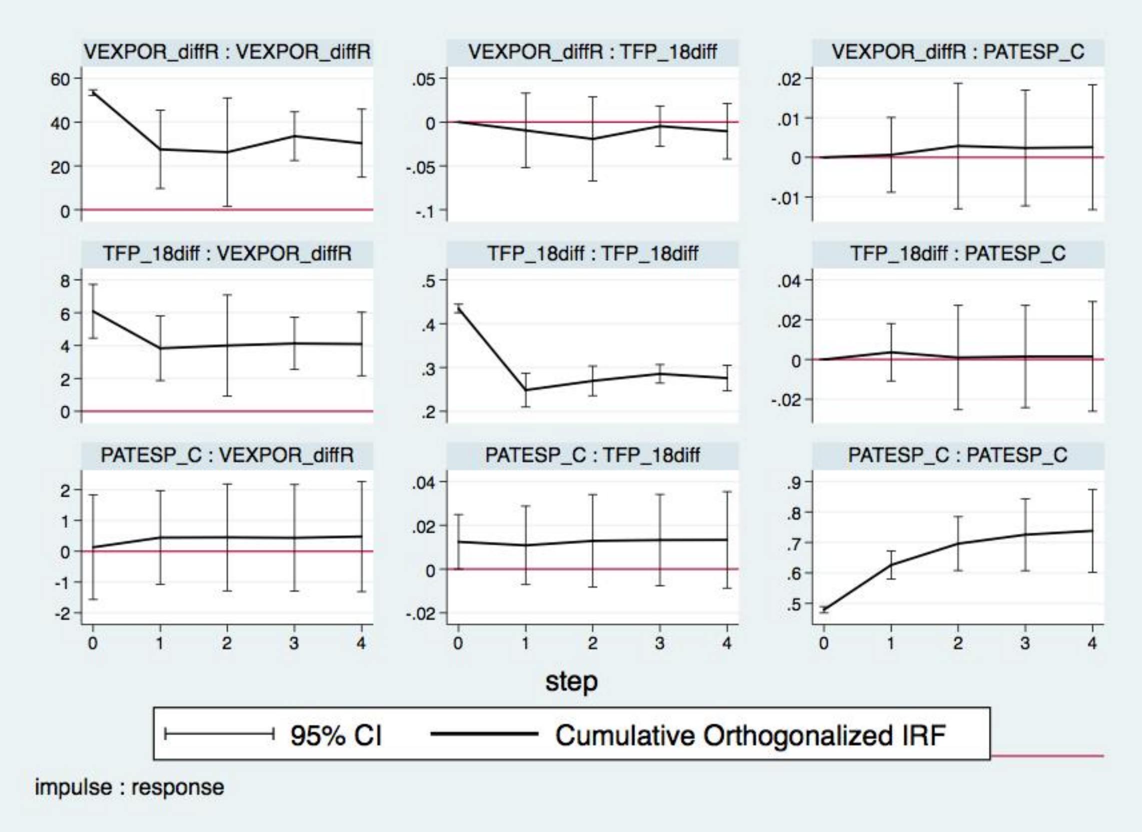


Figure A2.9.5 IRFs, Patents registered abroad

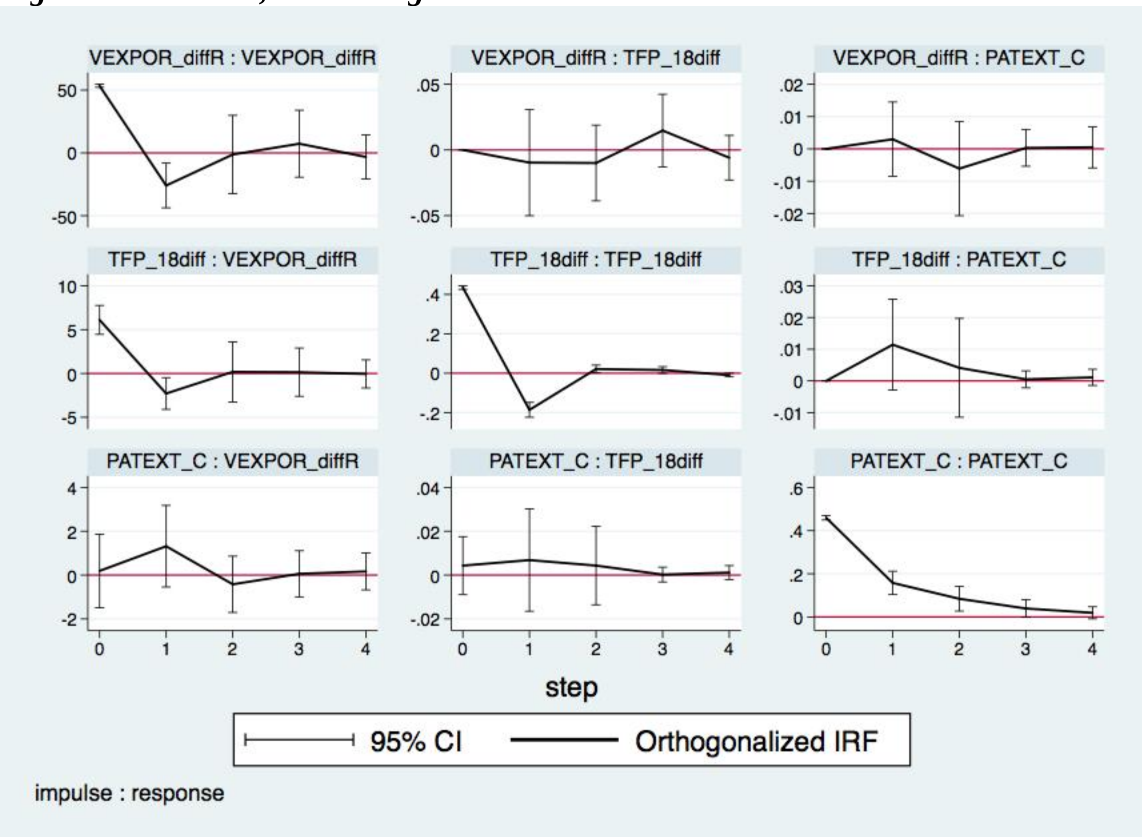


Figure A2.9.6 Cumulative IRFs, Patents registered abroad

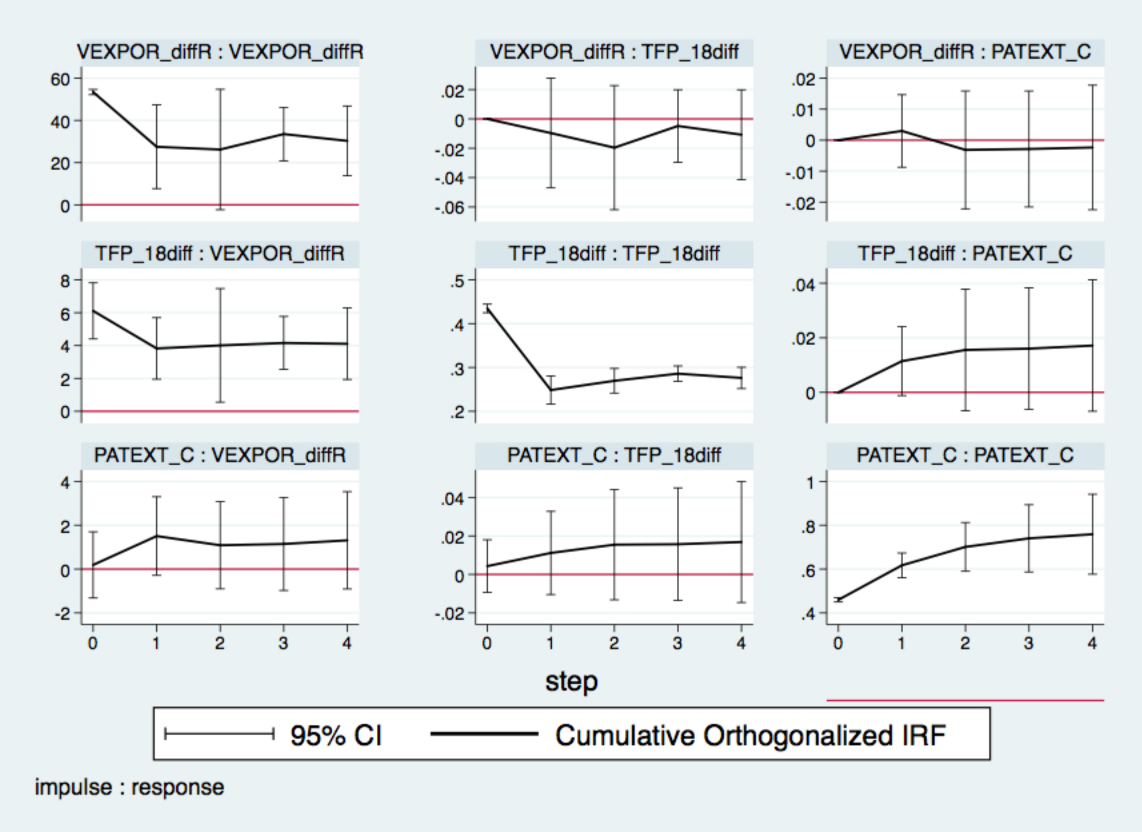


Figure A2.9.7 IRFs, Number of product innovations

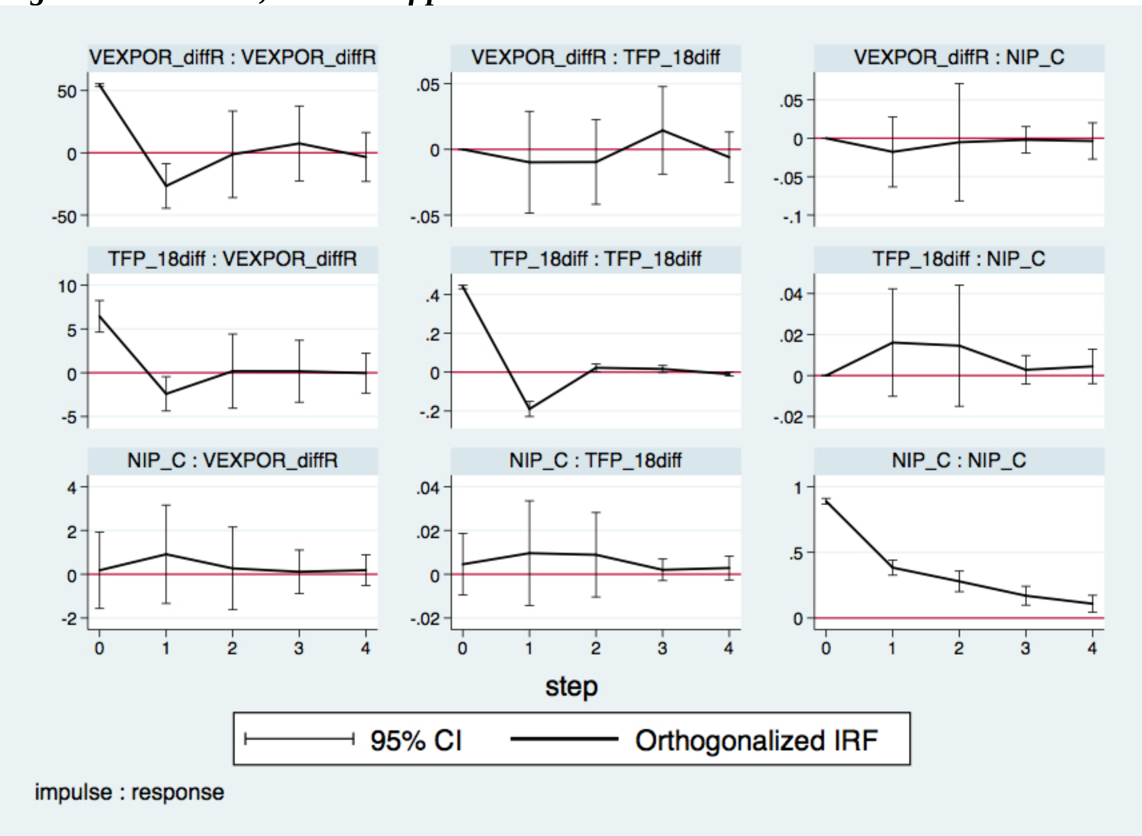


Figure A2.9.8 Cumulative IRFs, Number of product innovations

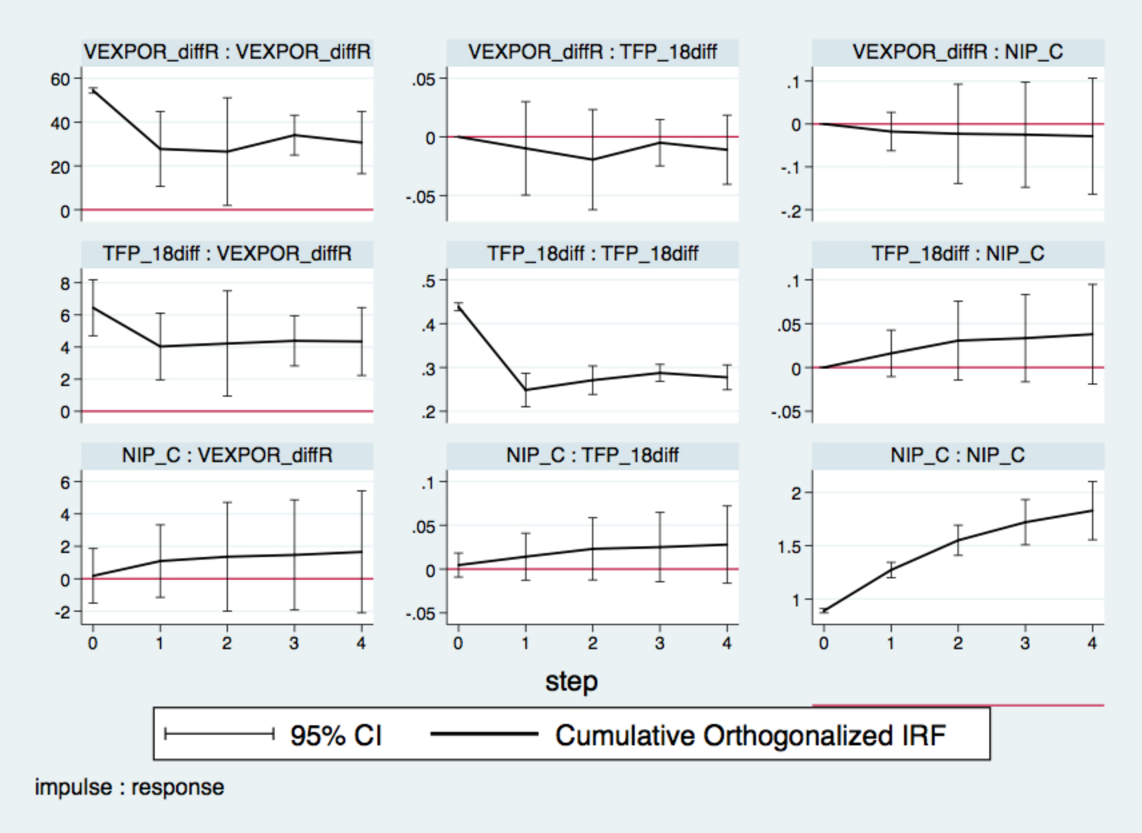


Figure A2.9.9 IRFs, Organisational innovations

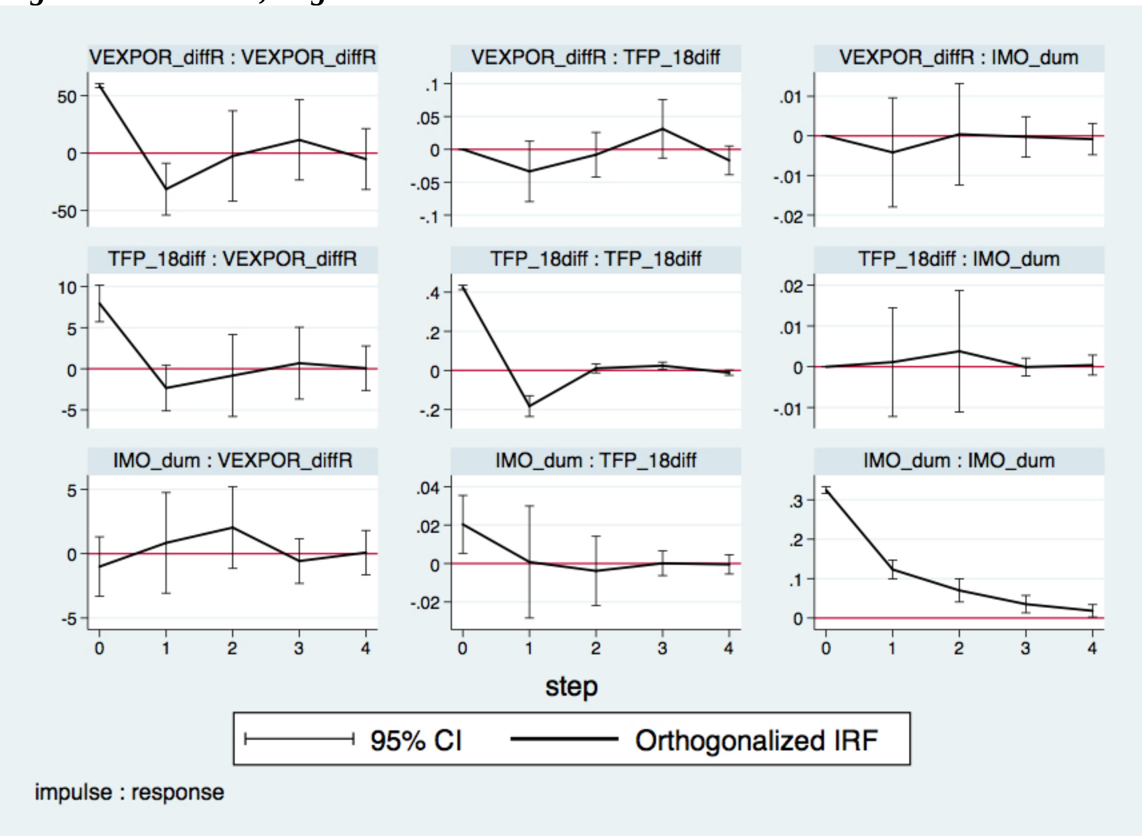


Figure A2.9.10 Cumulative IRFs, Organisational innovations

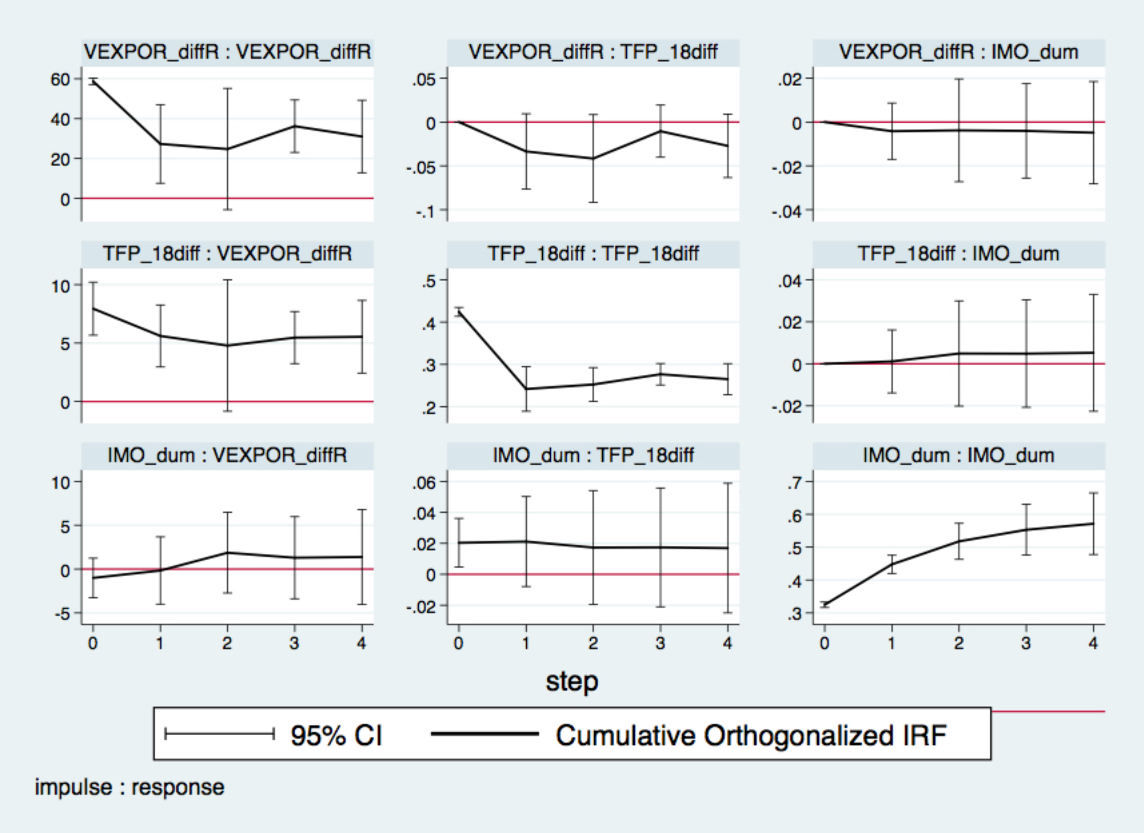


Figure A2.9.11 IRFs, Marketing innovations

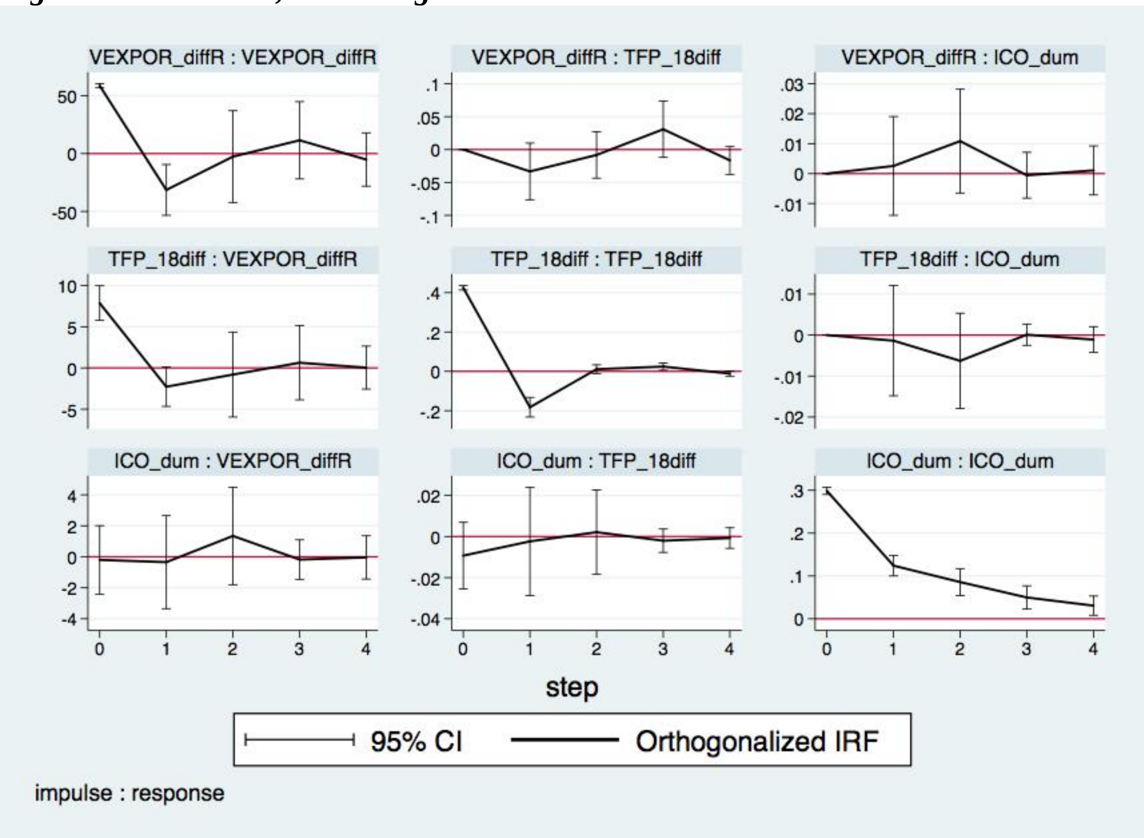


Figure A2.9.12 Cumulative IRFs, Marketing innovations

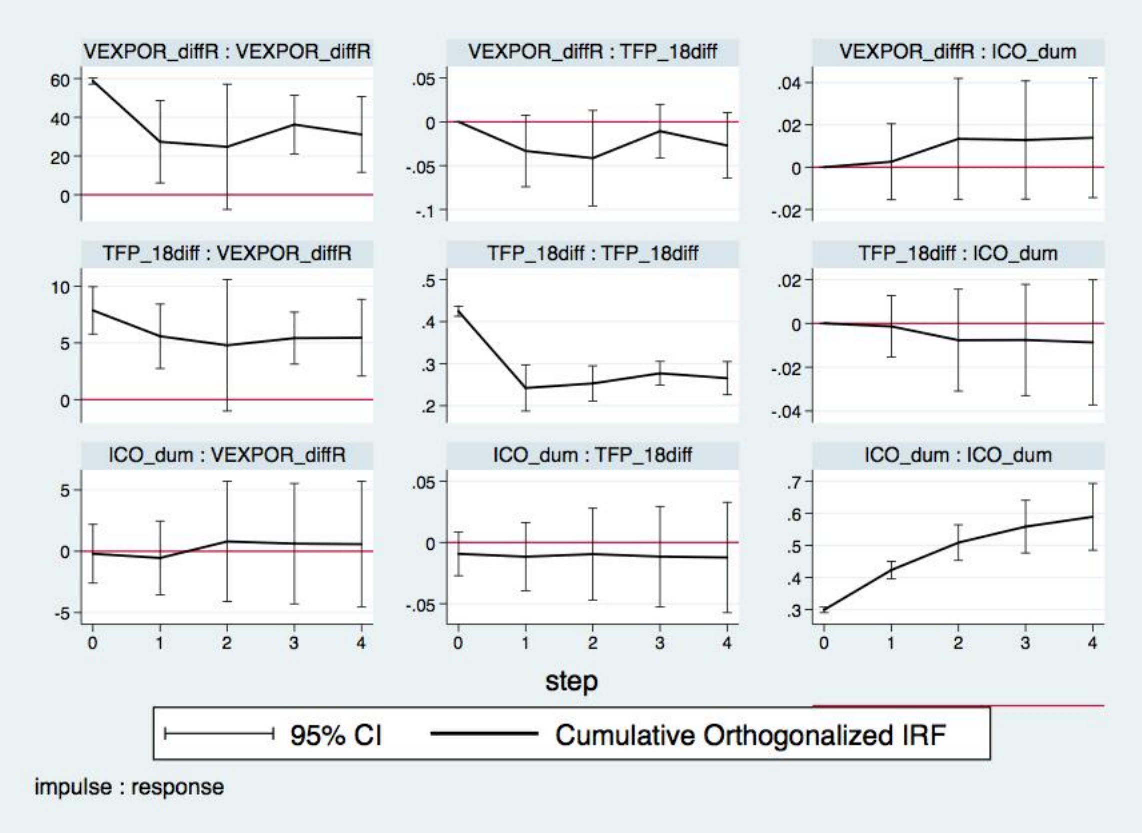


Figure A2.9.13 IRFs, Process innovations

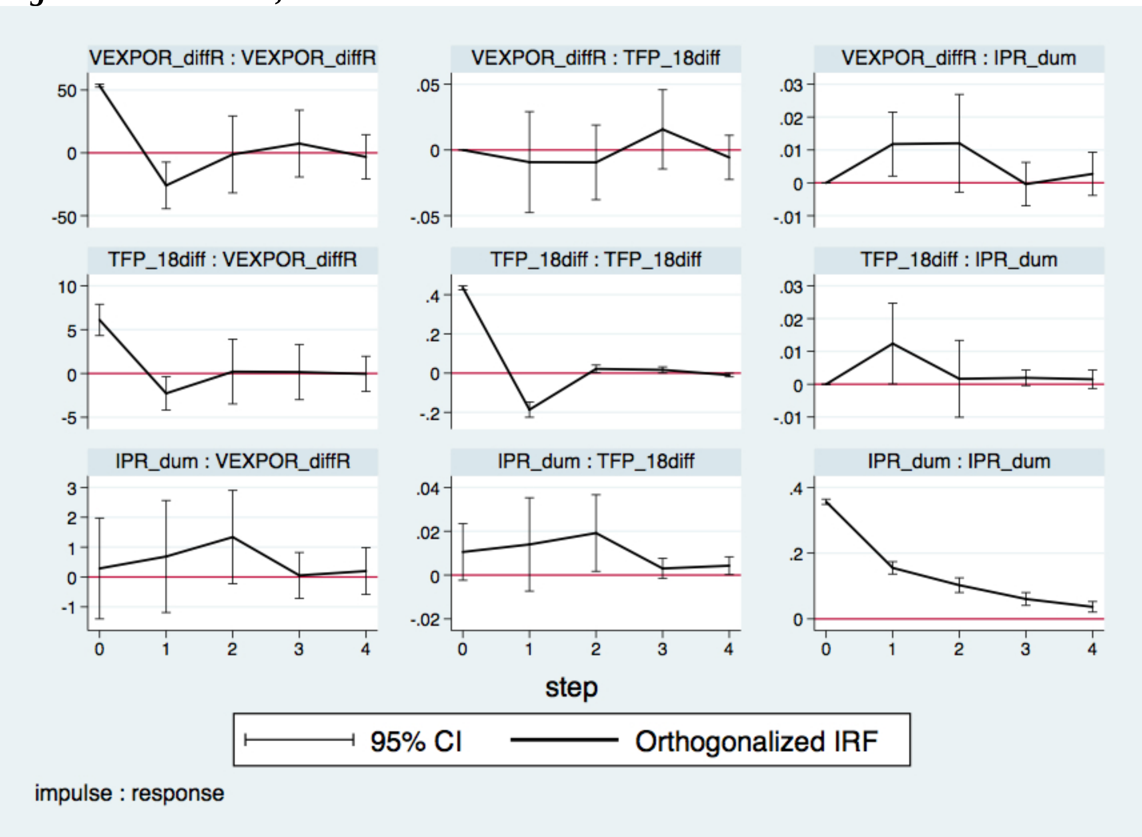
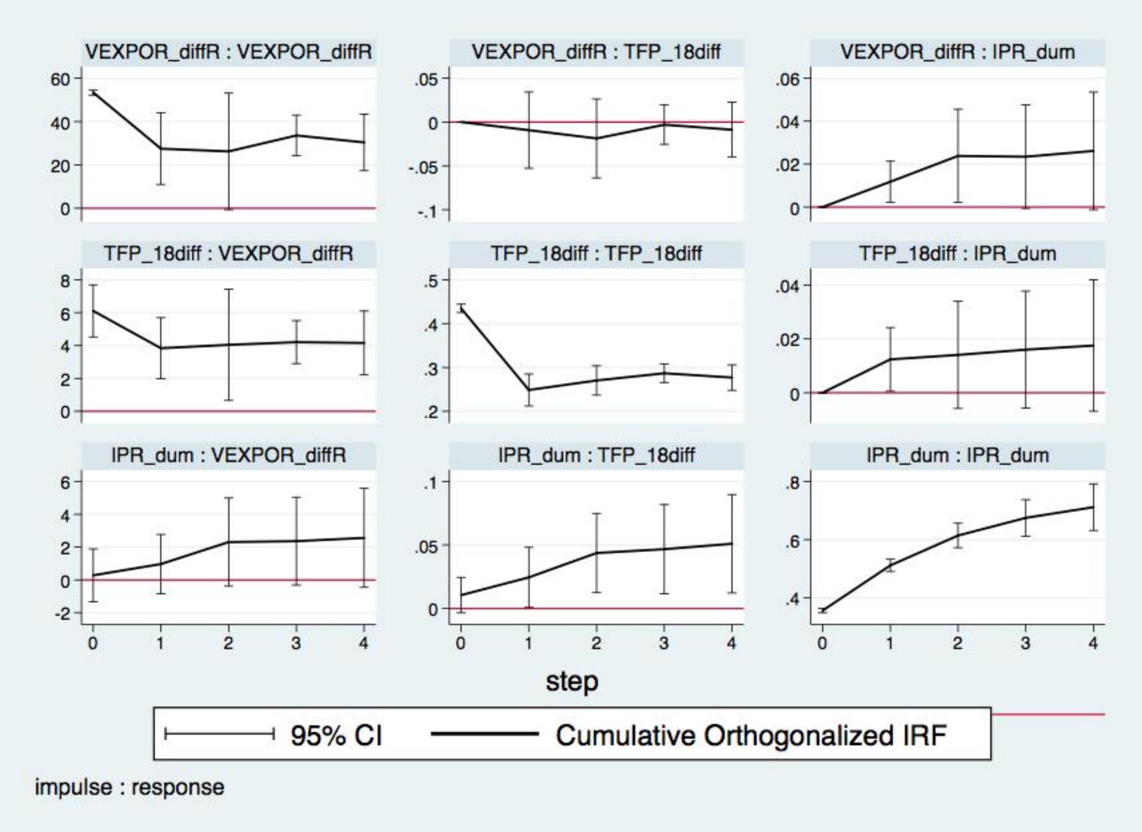


Figure A2.9.14 Cumulative IRFs, Process innovations



Appendix A2.10: IRFs and cumulative IRFs for subsample of firms that did not engage in cooperation with other firms

Figure A2.10.1 IRFs, R&D expenditures

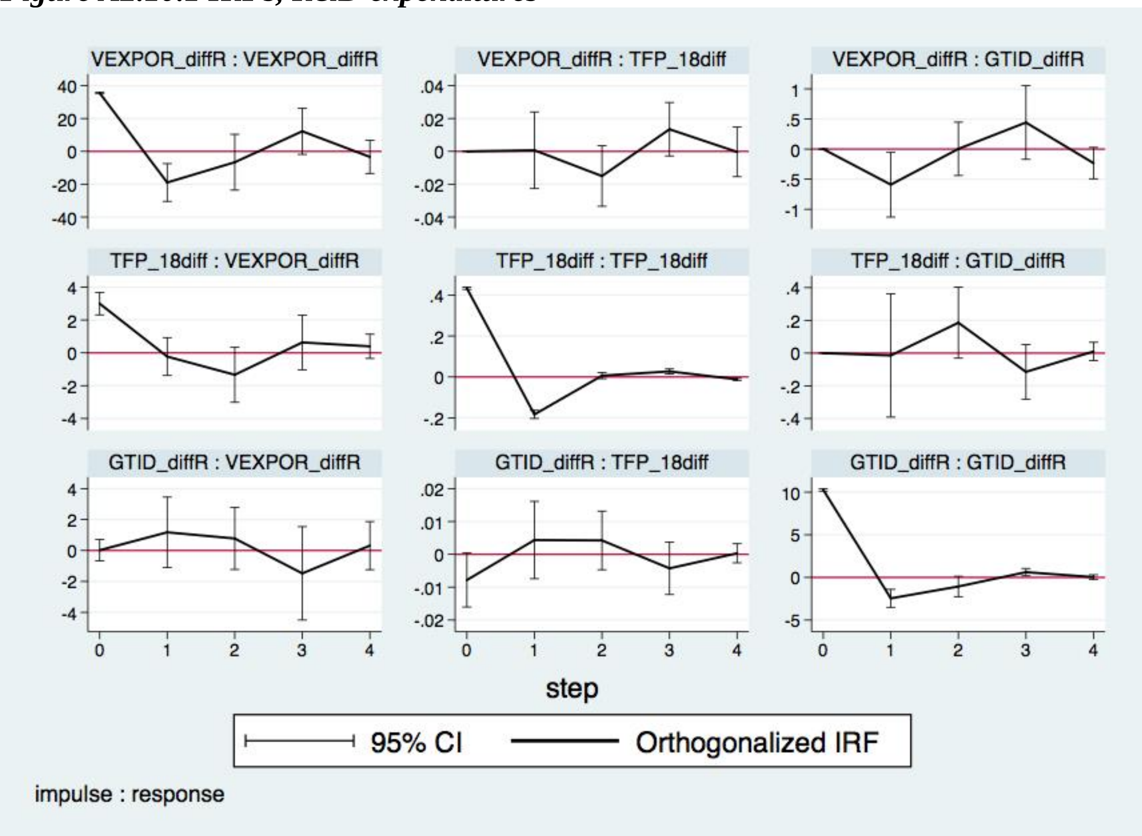


Figure A2.10.2 Cumulative IRFs, R&D expenditures

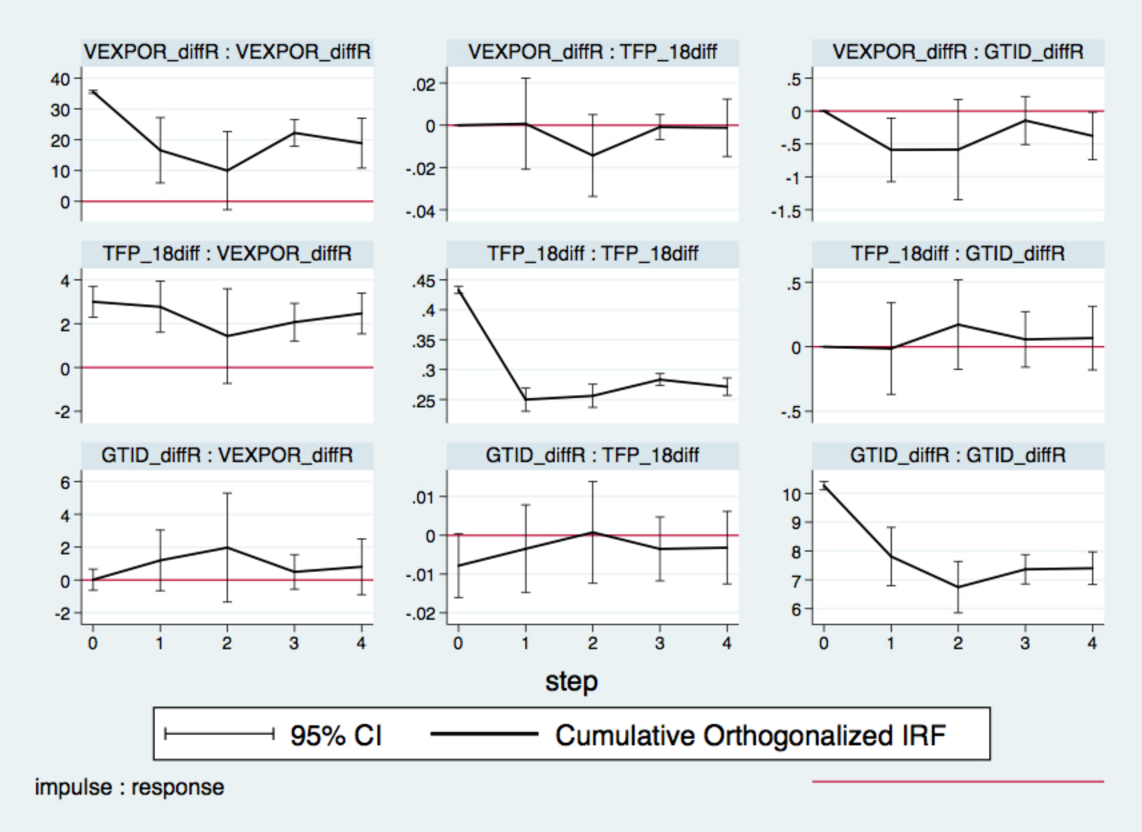


Figure A2.10.3 IRFs, Patents registered in Spain

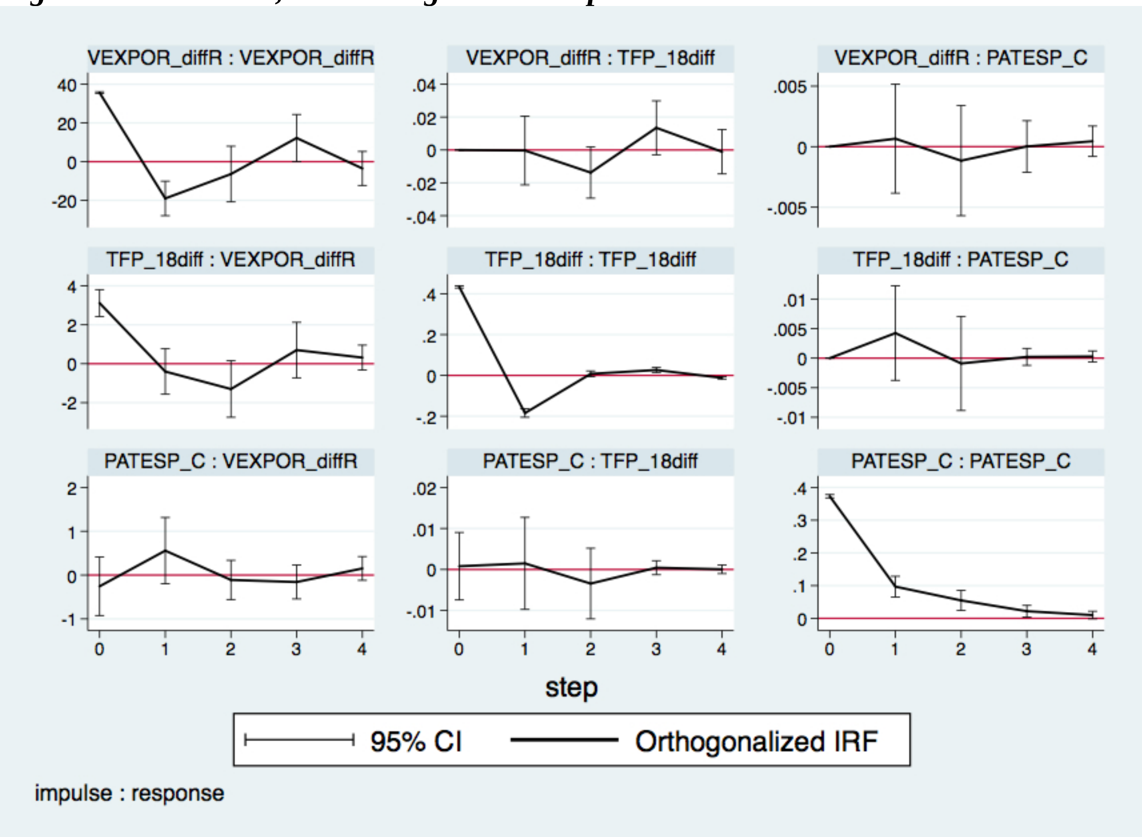


Figure A2.10.4 Cumulative IRFs, Patents registered in Spain

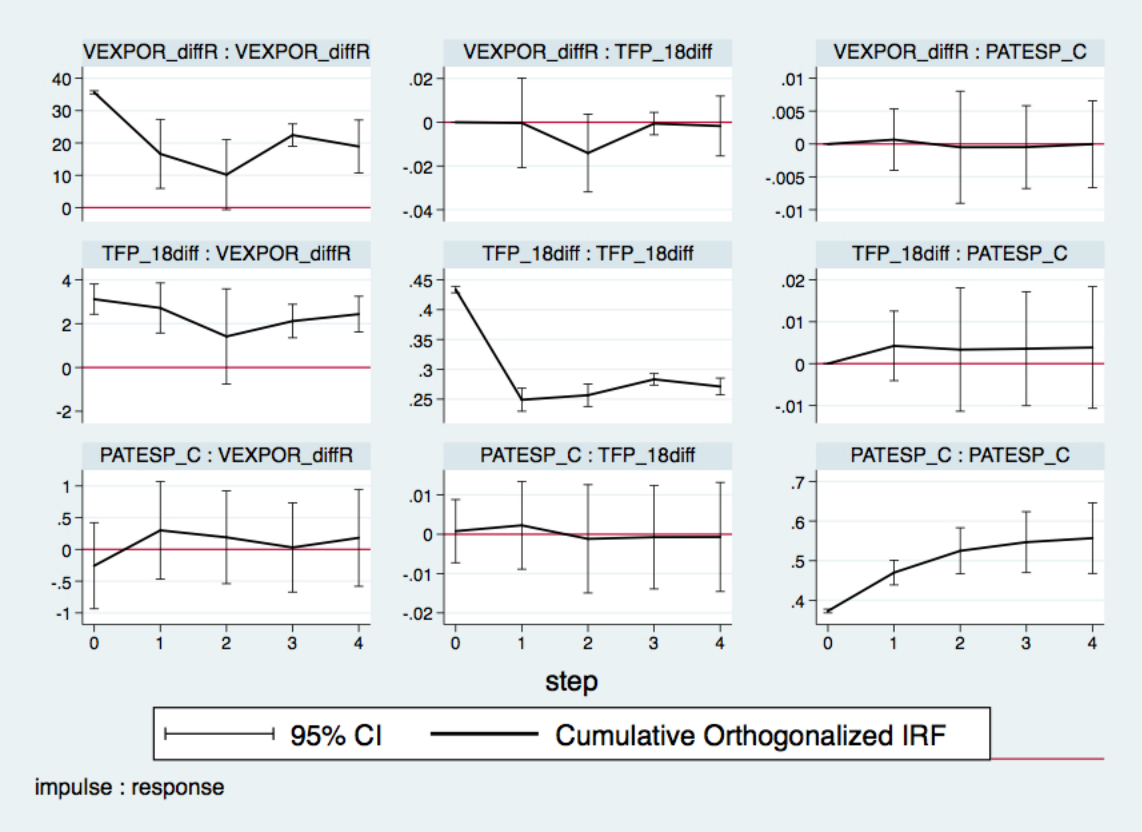


Figure A2.10.5 IRFs, Patents registered abroad

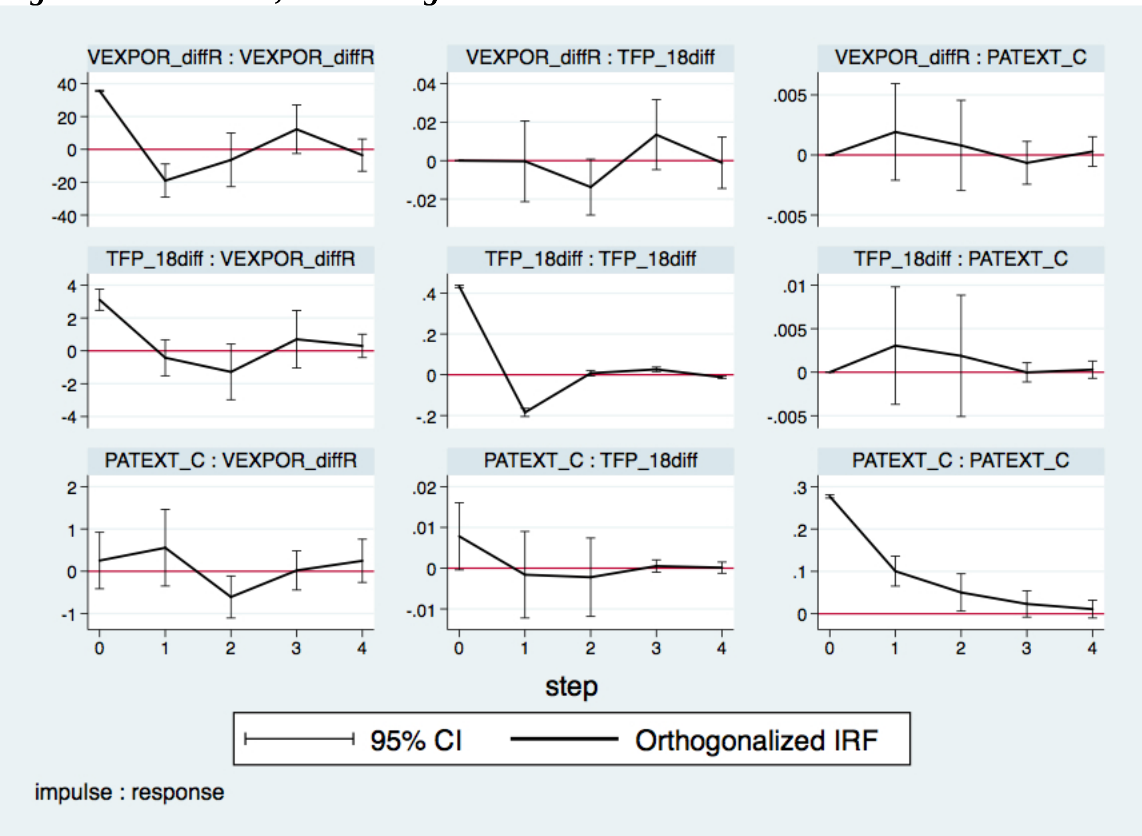


Figure A2.10.6 Cumulative IRFs, Patents registered abroad

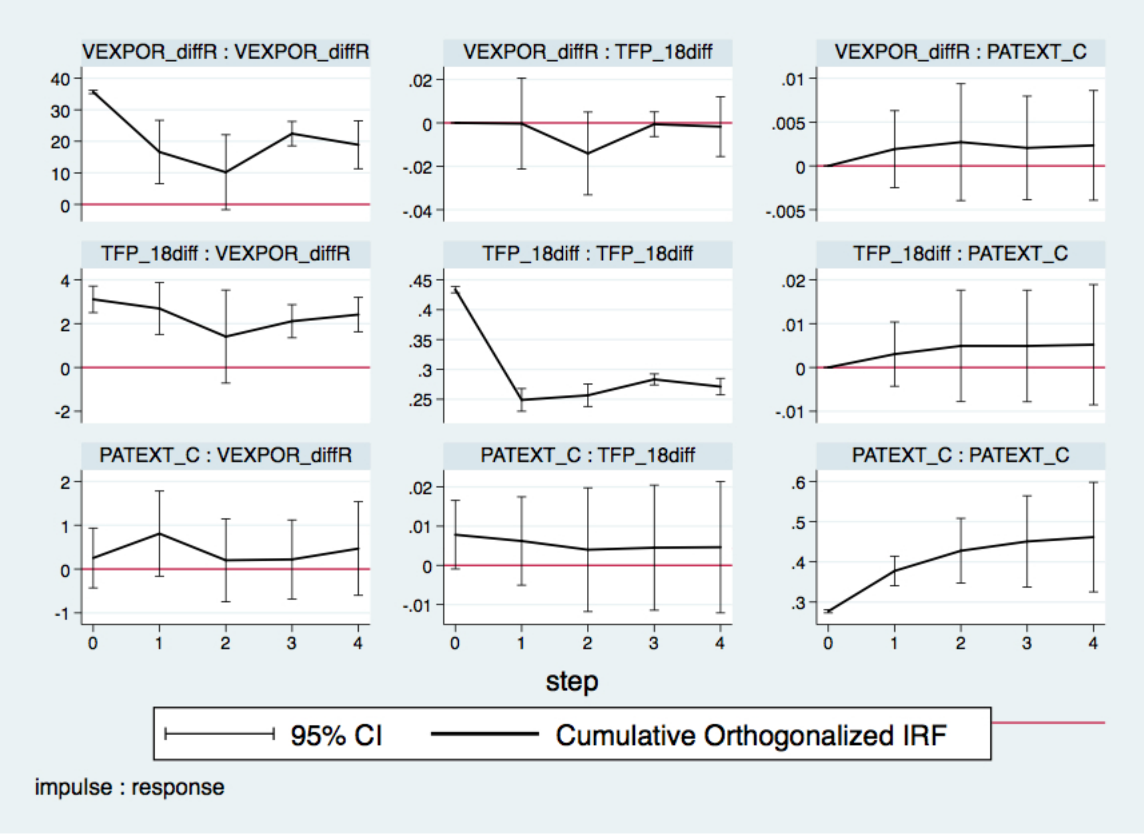


Figure A2.10.7 IRFs, Number of product innovations

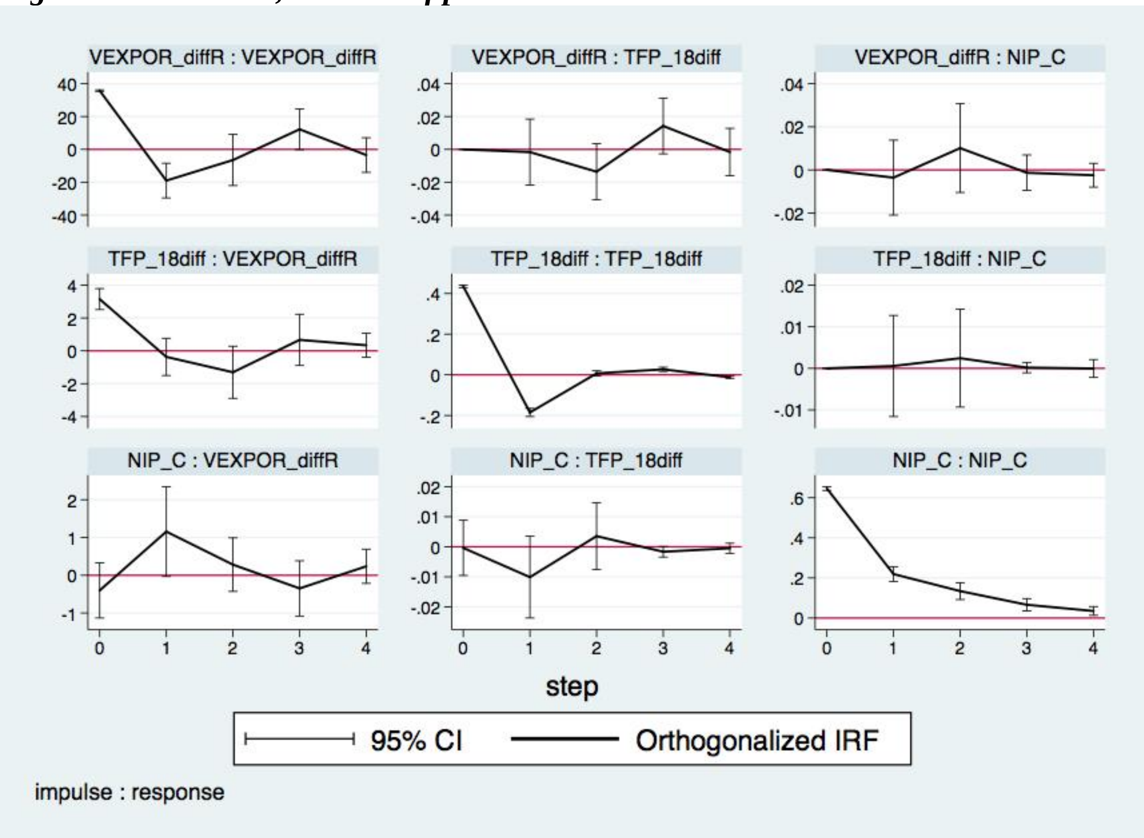


Figure A2.10.8 Cumulative IRFs, Number of product innovations

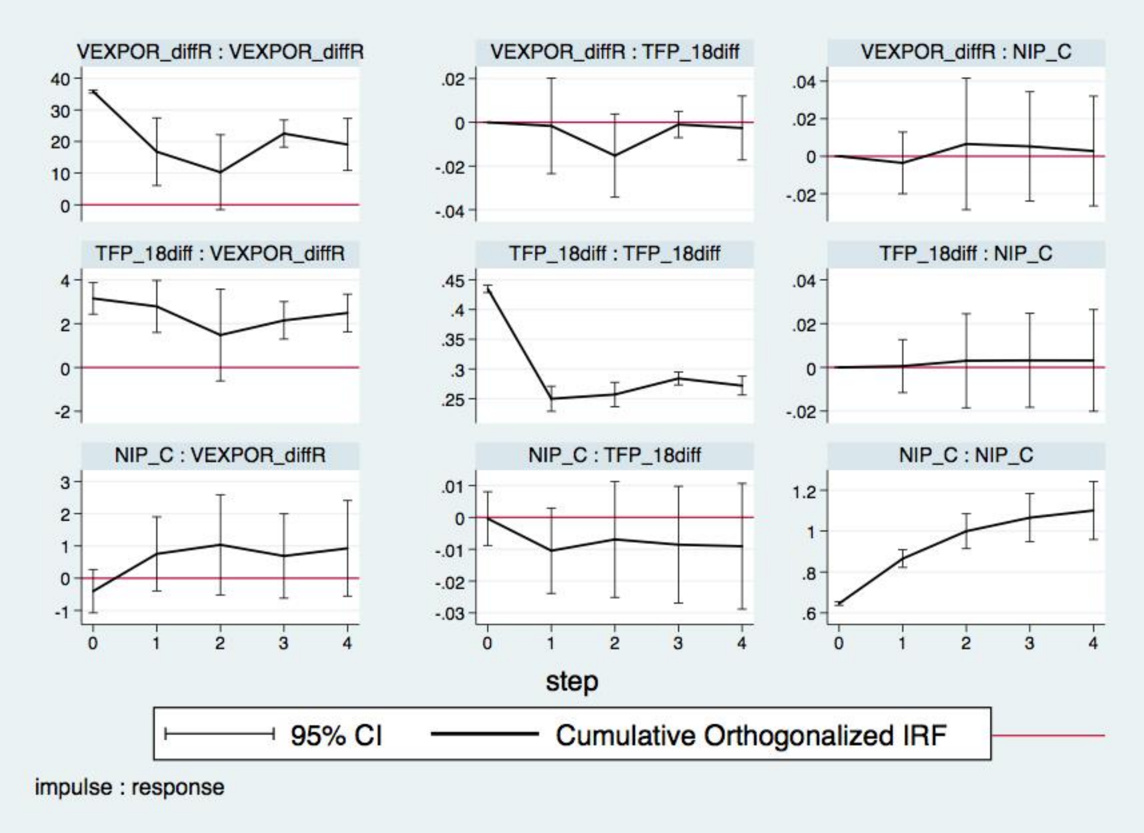


Figure A2.10.9 IRFs, Organisational innovations

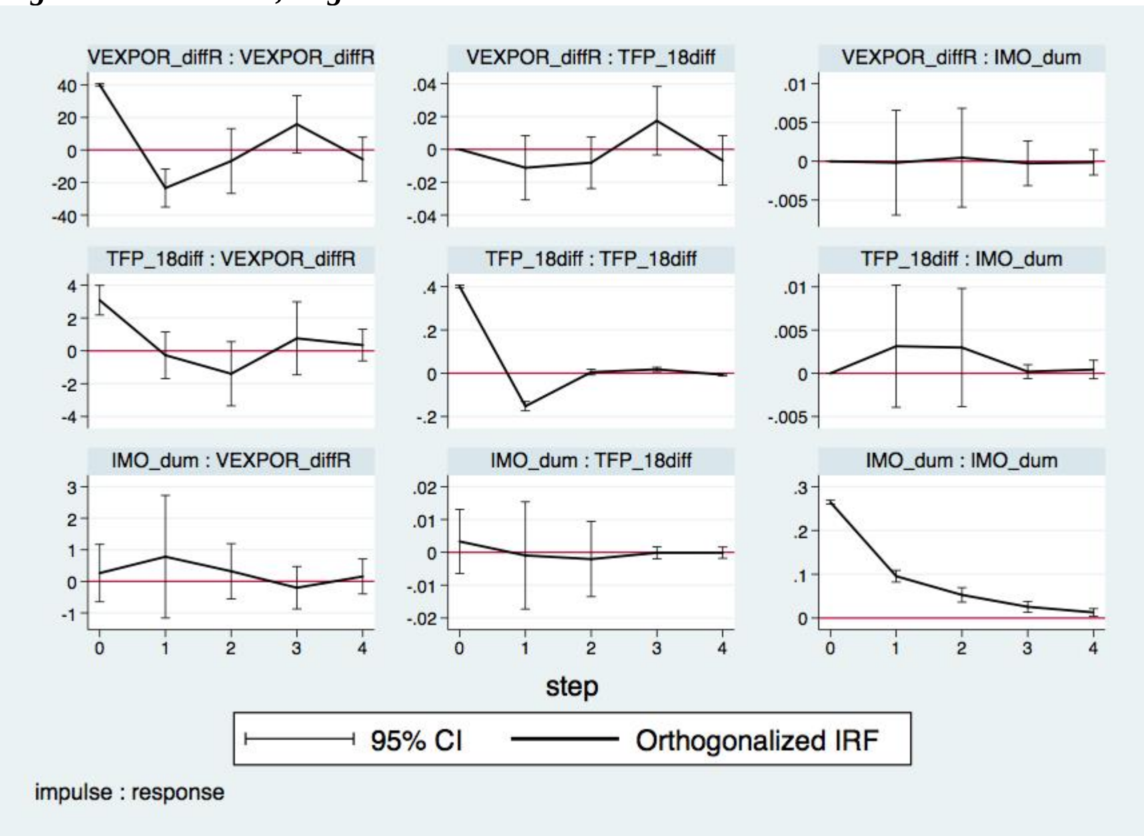


Figure A2.10.10 Cumulative IRFs, Organisational innovations

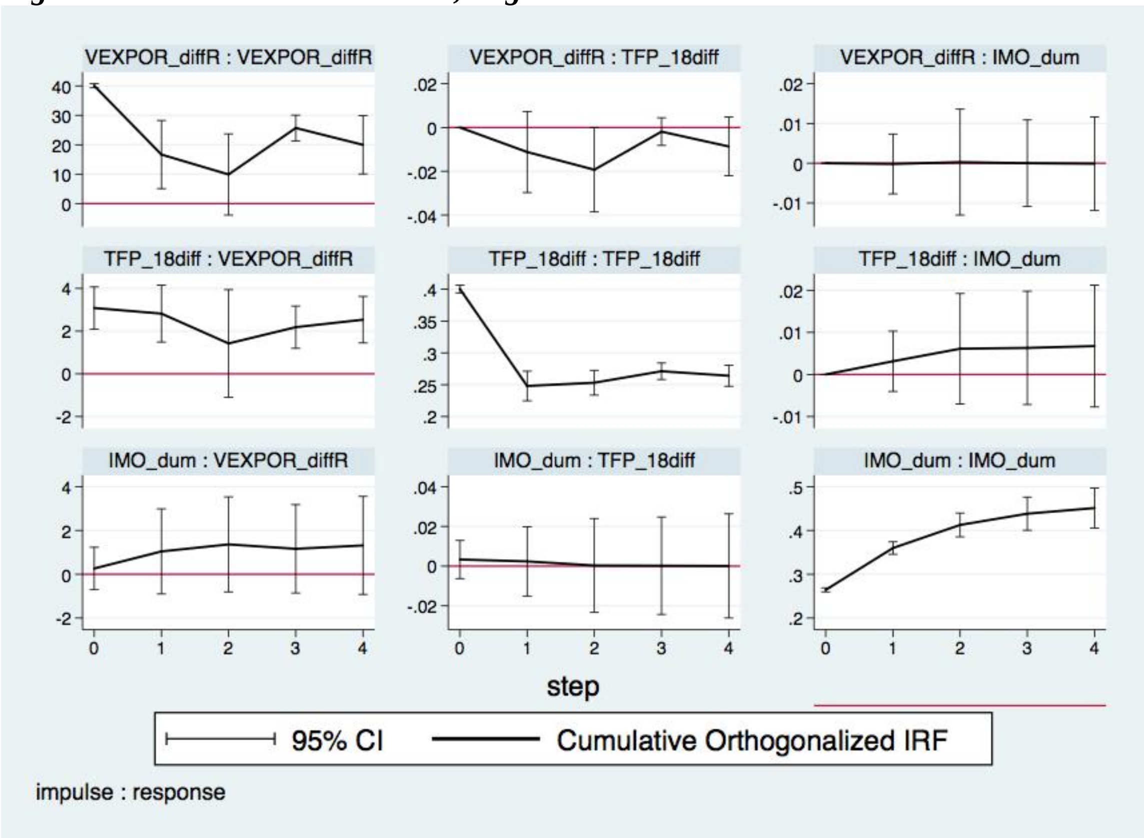


Figure A2.10.11 IRFs, Marketing innovations

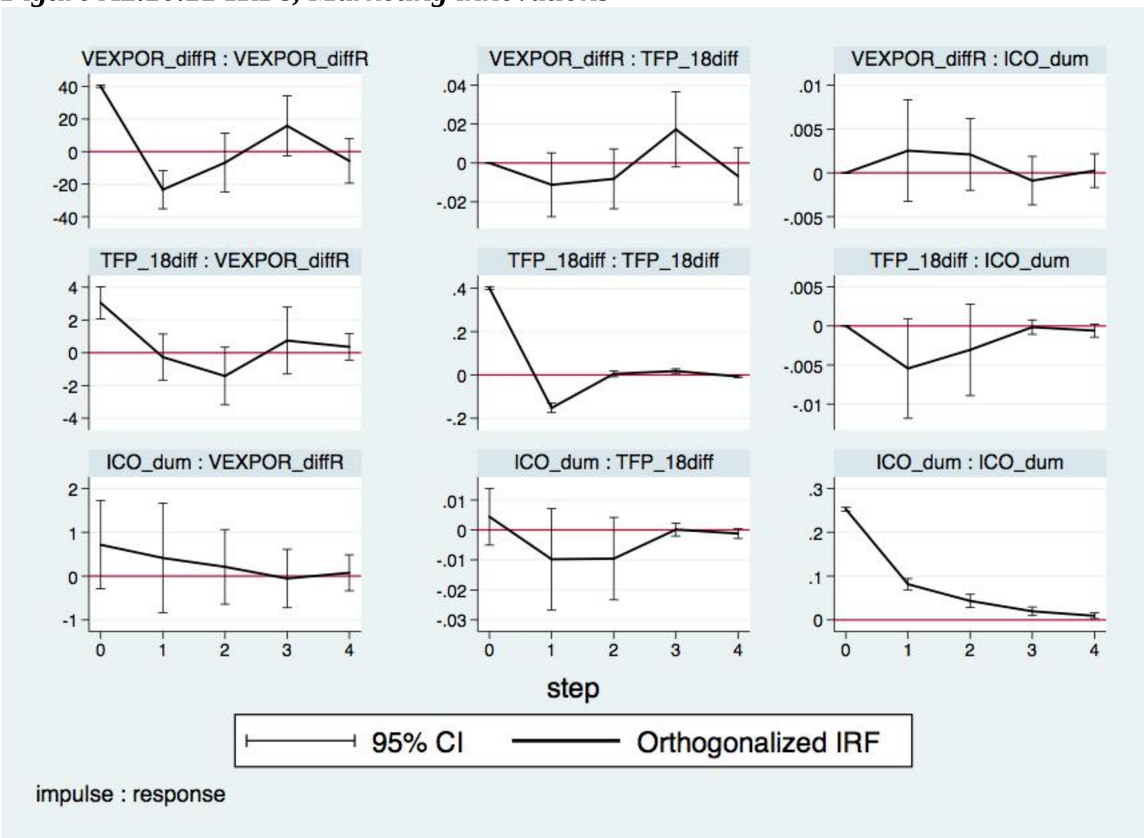


Figure A2.10.12 Cumulative IRFs, Marketing innovations

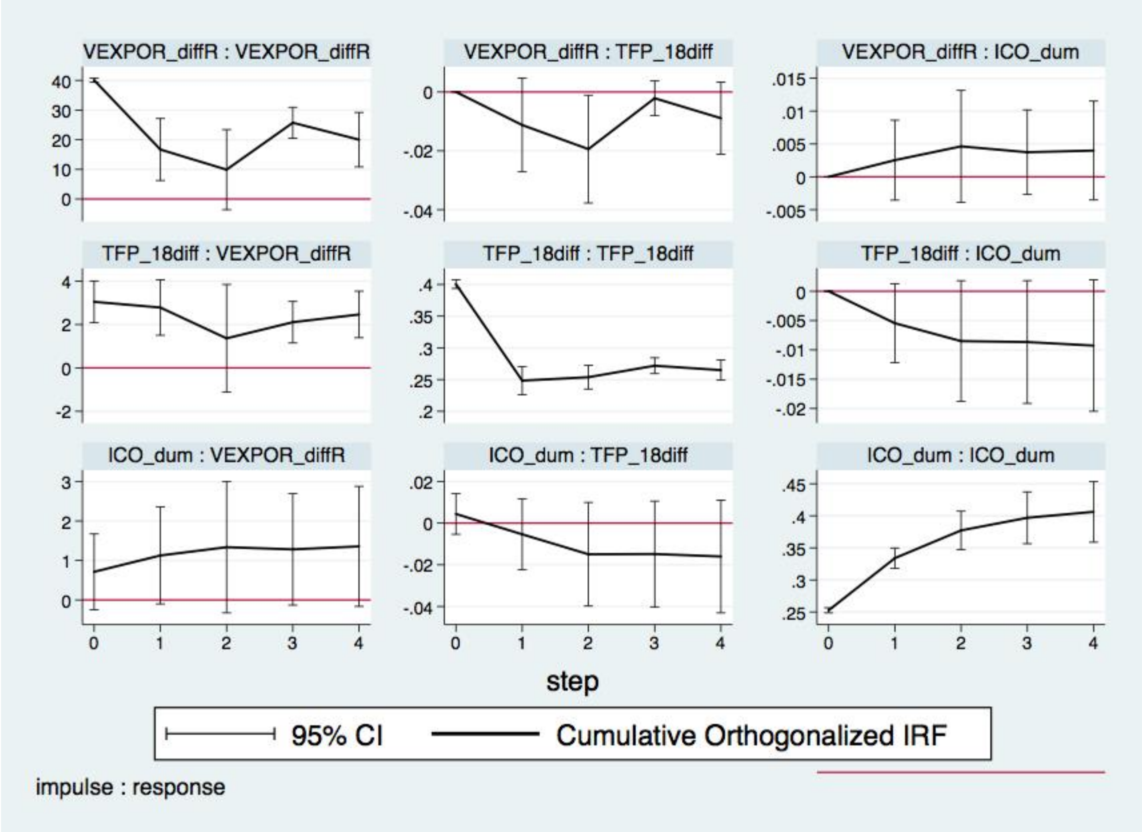


Figure A2.10.13 IRFs, Process innovations

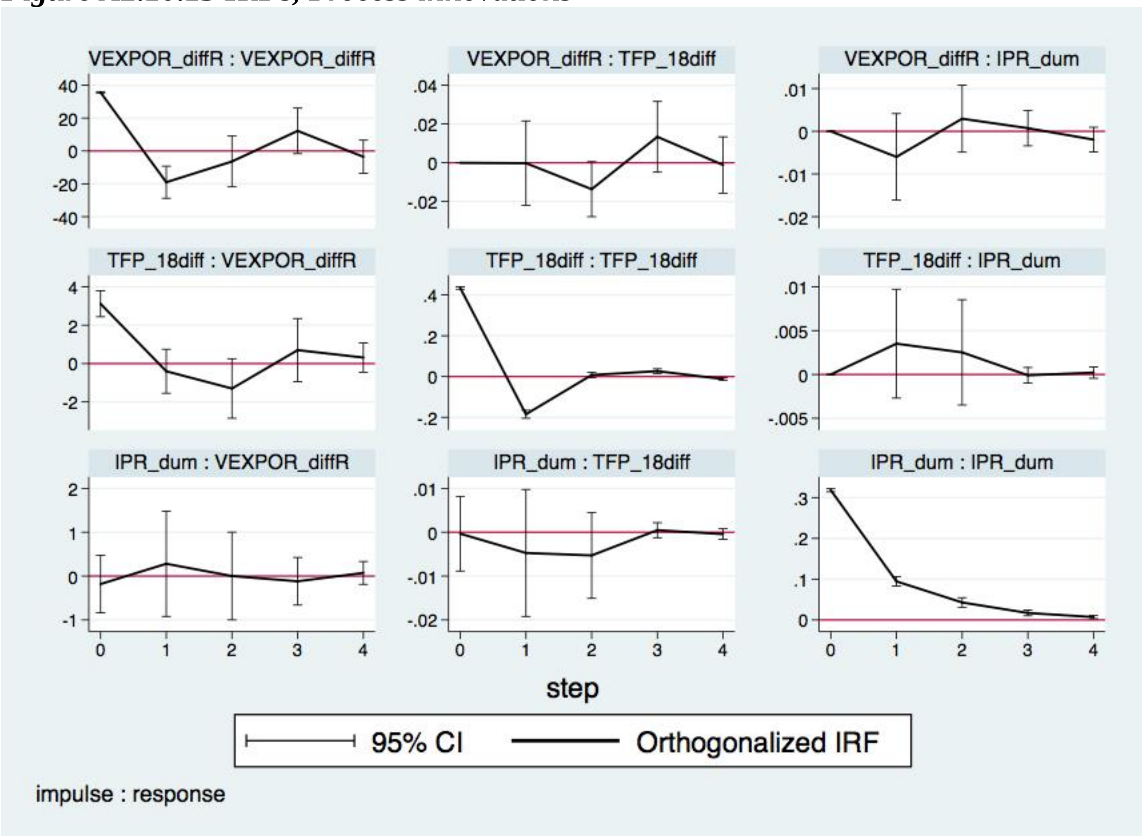
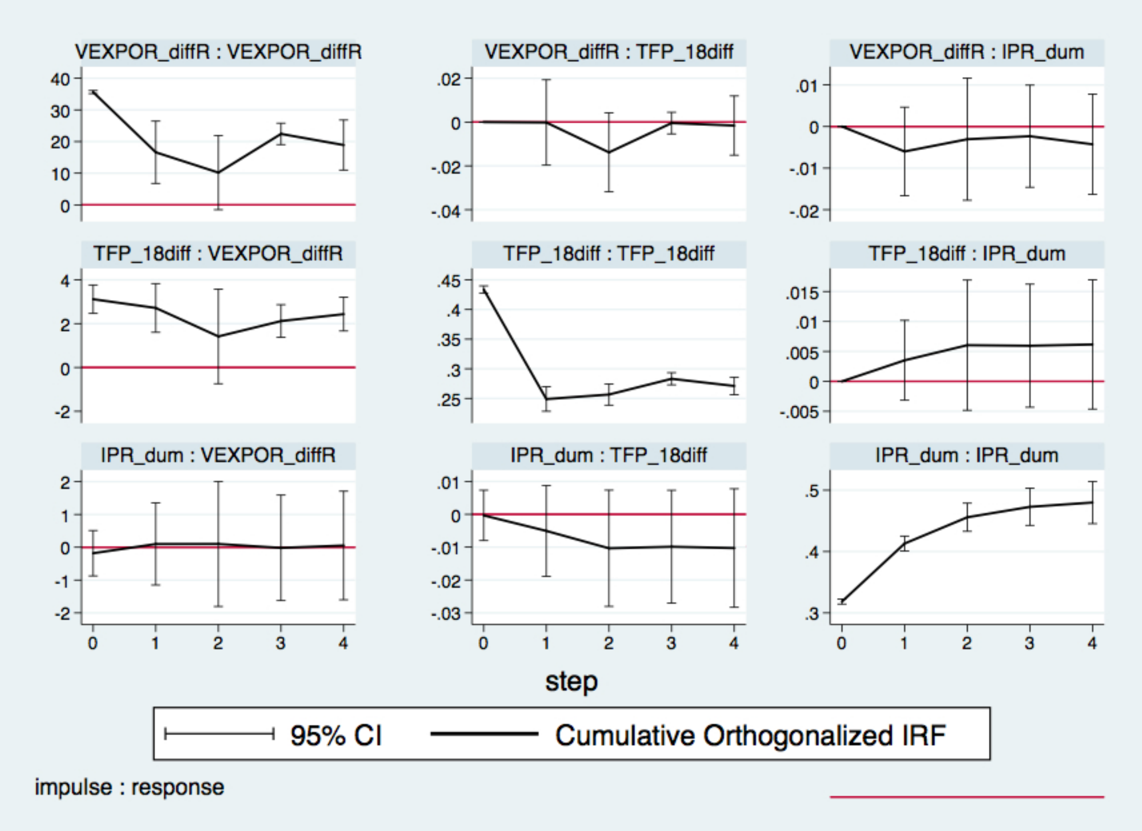


Figure A2.10.14 Cumulative IRFs, Process innovations



Appendix A2.11: IRFs and cumulative IRFs for subsample of firms that engaged in cooperation with universities

Figure A2.11.1 IRFs, R&D expenditures

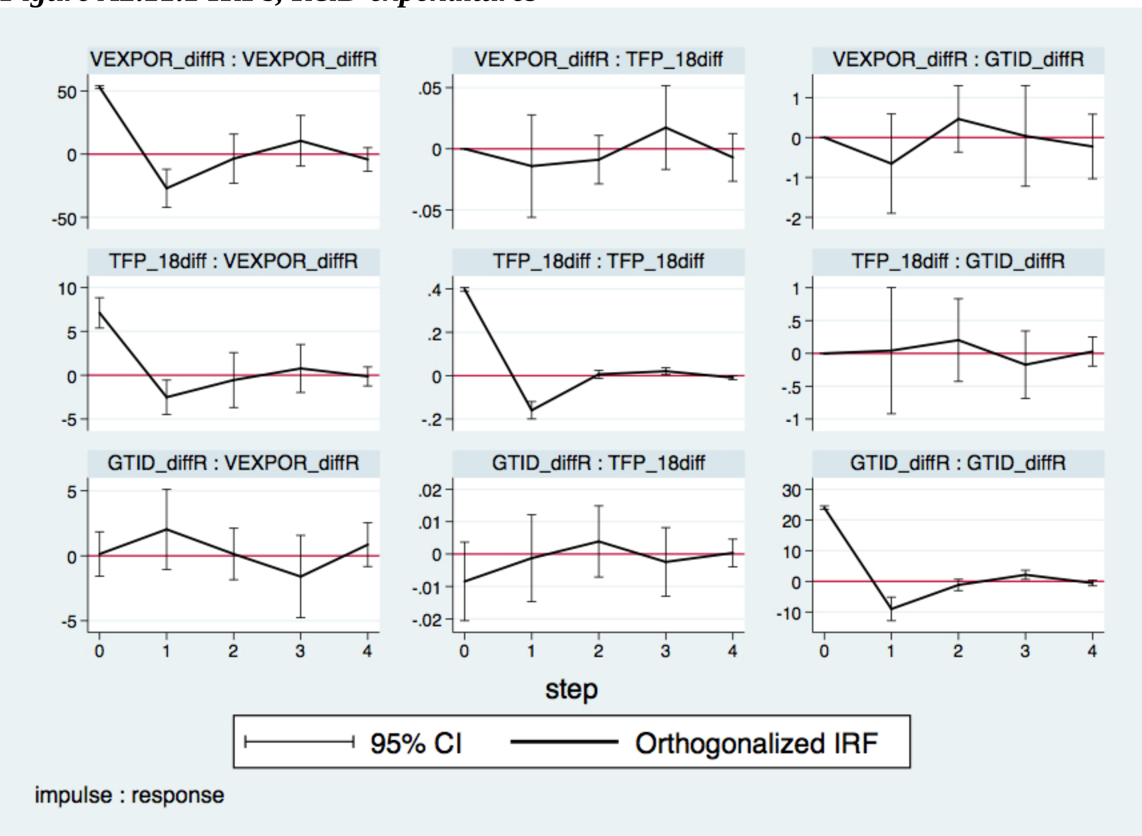


Figure A2.11.2 Cumulative IRFs, R&D expenditures

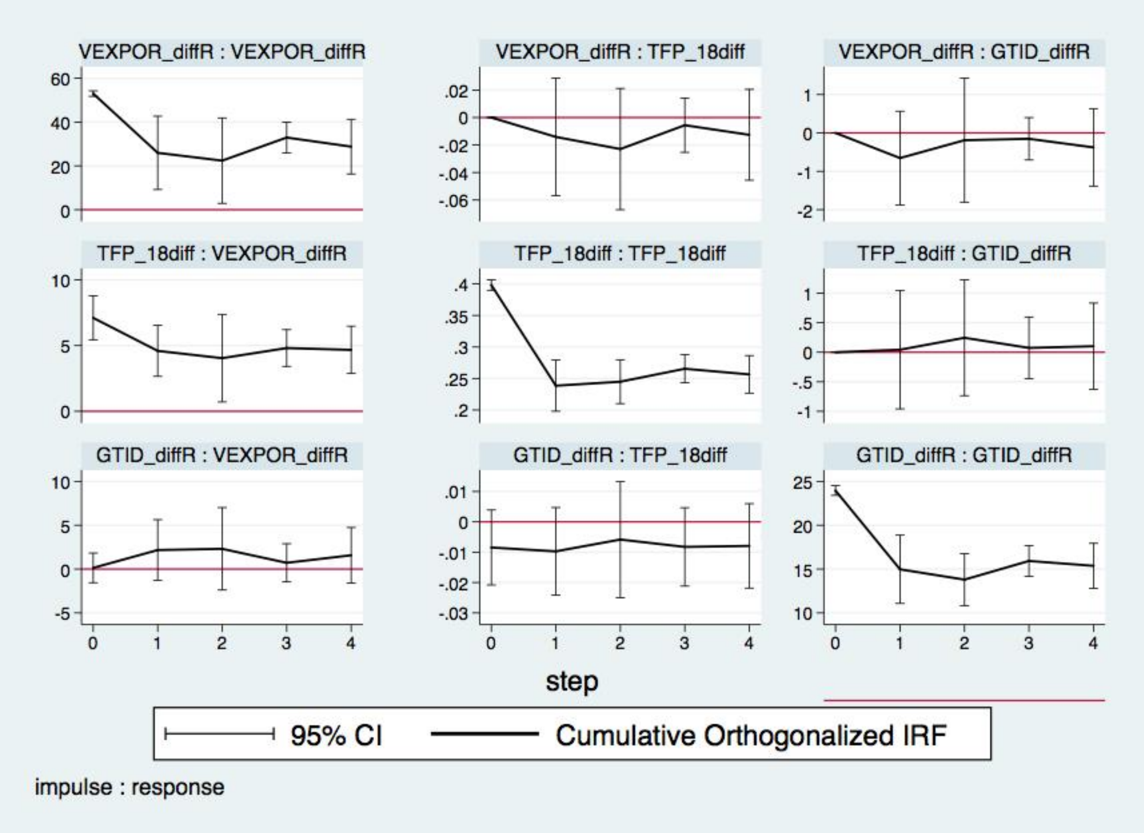


Figure A2.11.3 IRFs, Patents registered in Spain

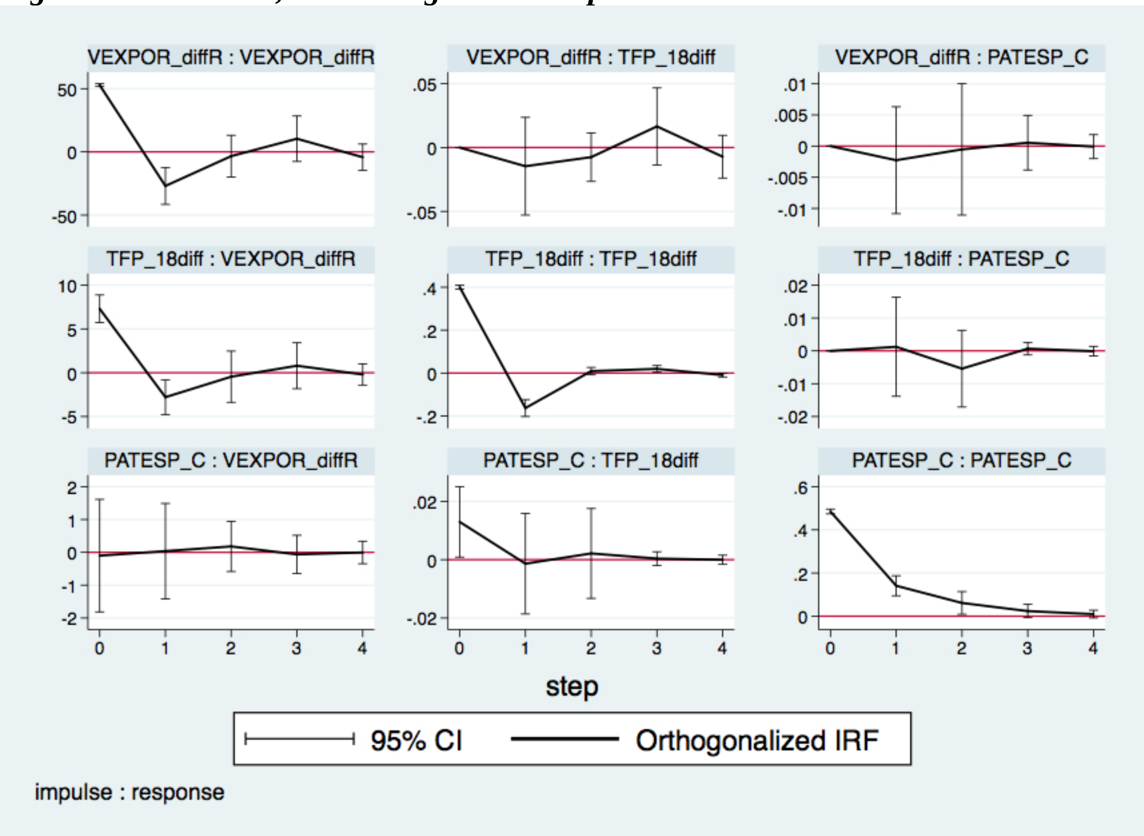


Figure A2.11.4 Cumulative IRFs, Patents registered in Spain

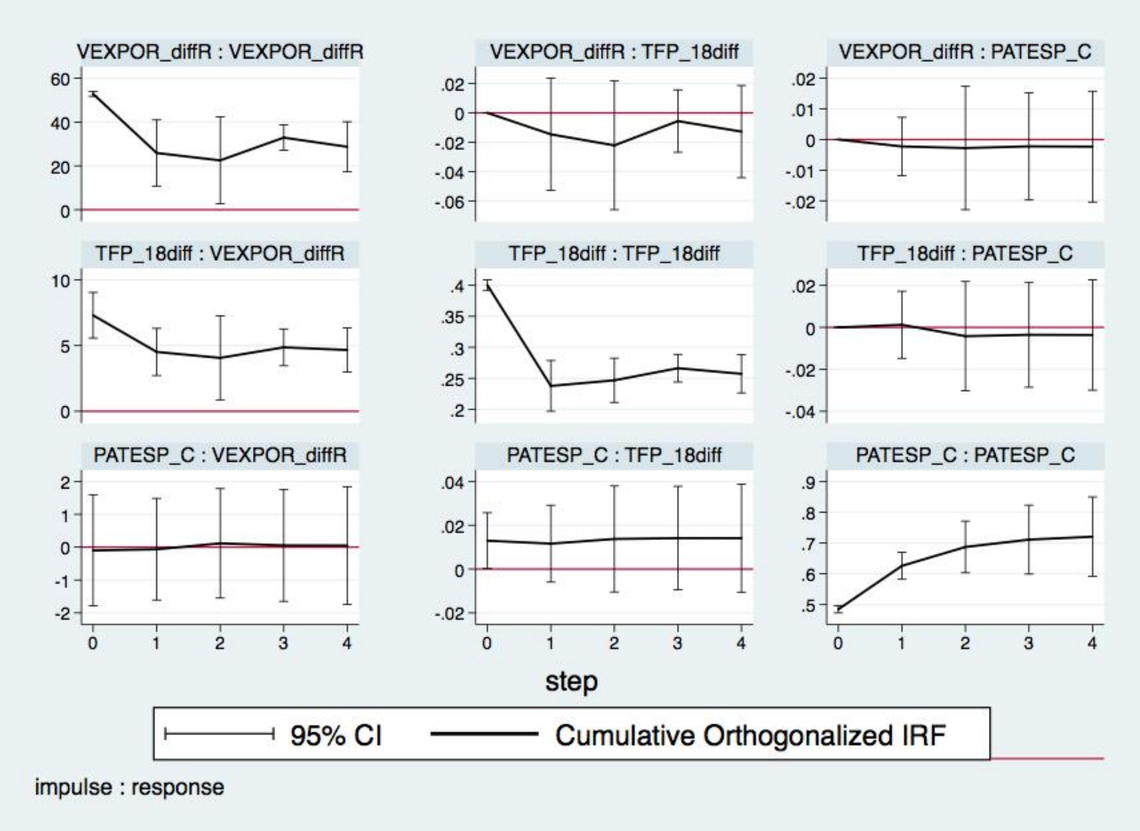


Figure A2.11.5 IRFs, Patents registered abroad

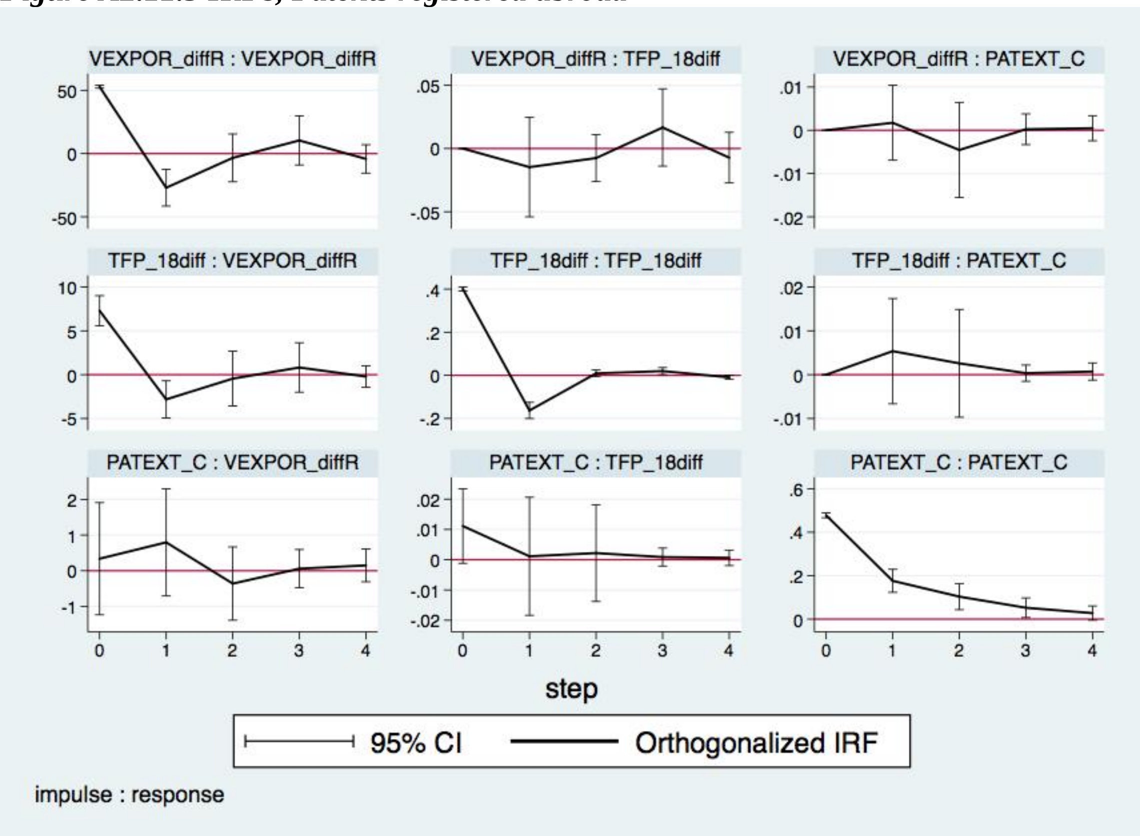


Figure A2.11.6 Cumulative IRFs, Patents registered abroad

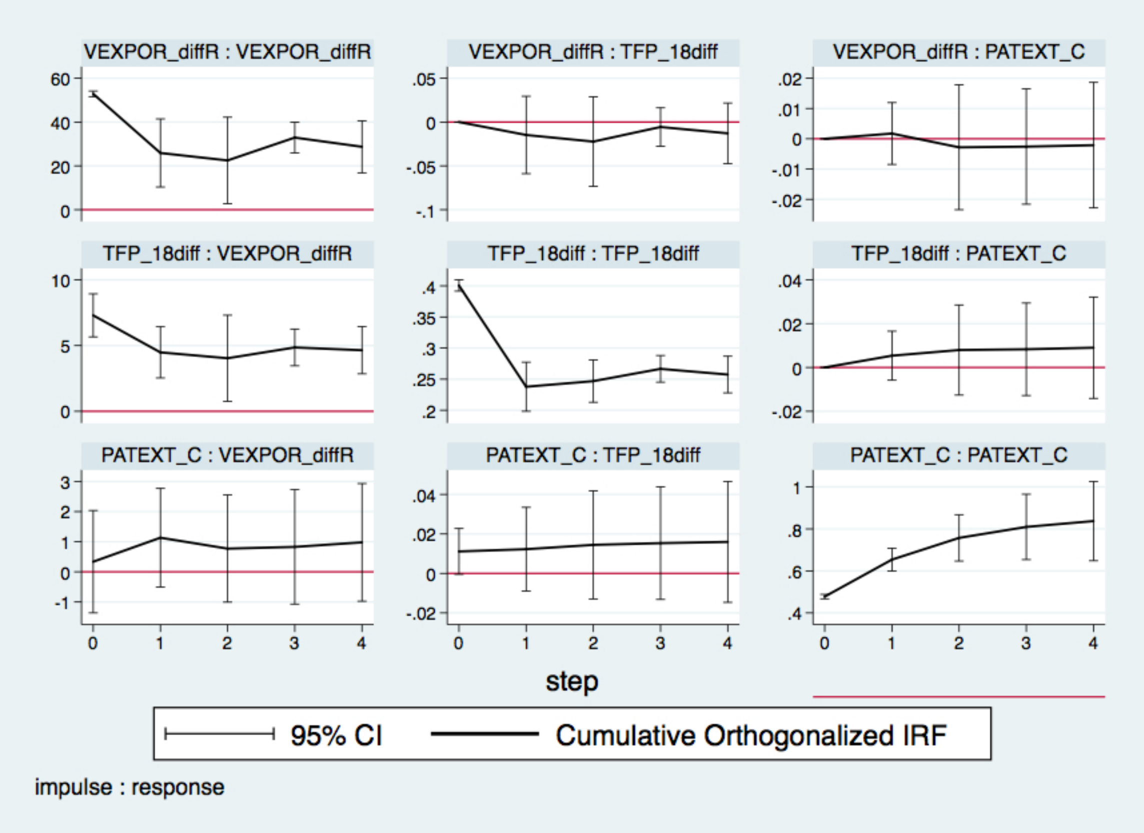


Figure A2.11.7 IRFs, Number of product innovations

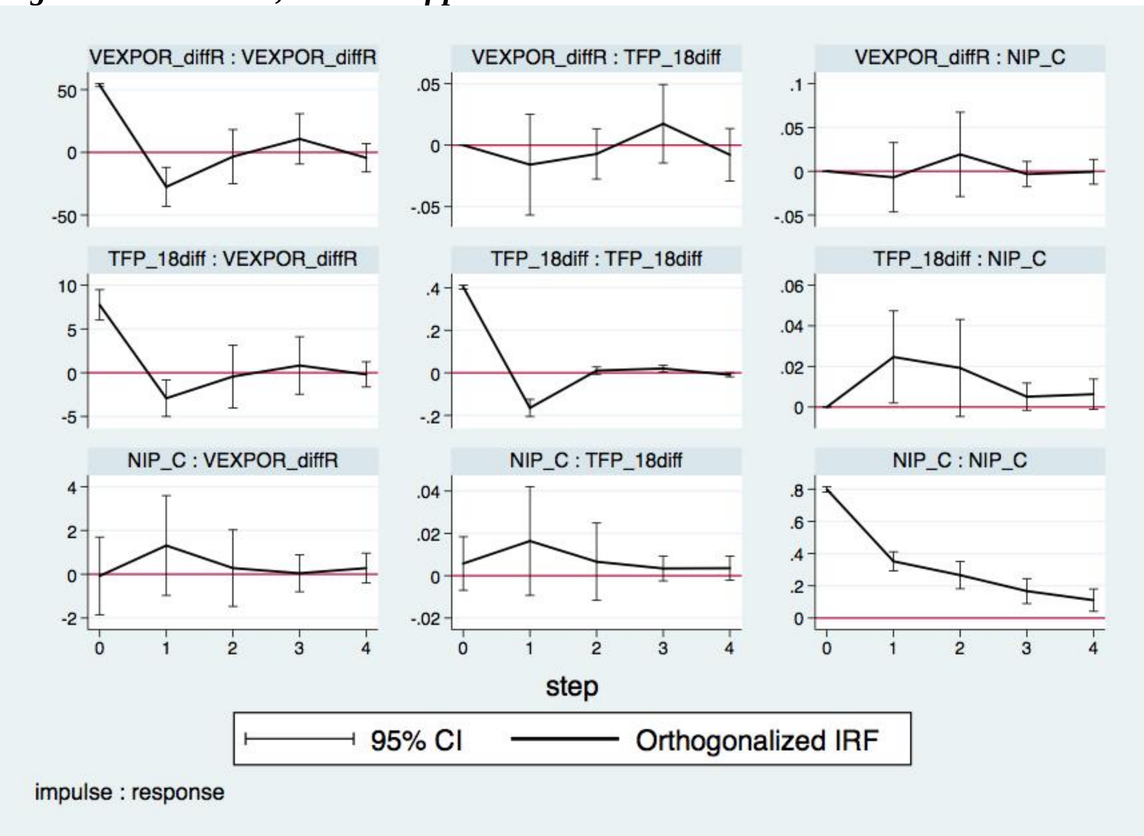


Figure A2.11.8 Cumulative IRFs, Number of product innovations

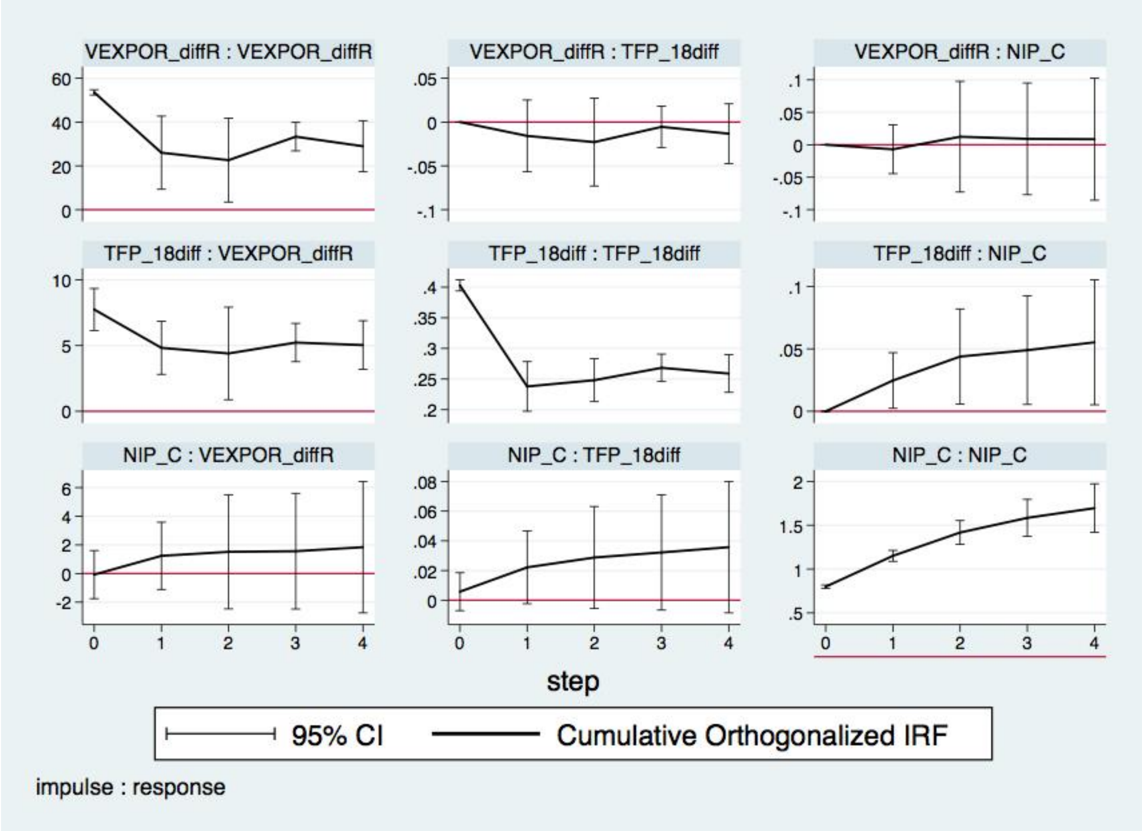


Figure A2.11.9 IRFs, Organisational innovations

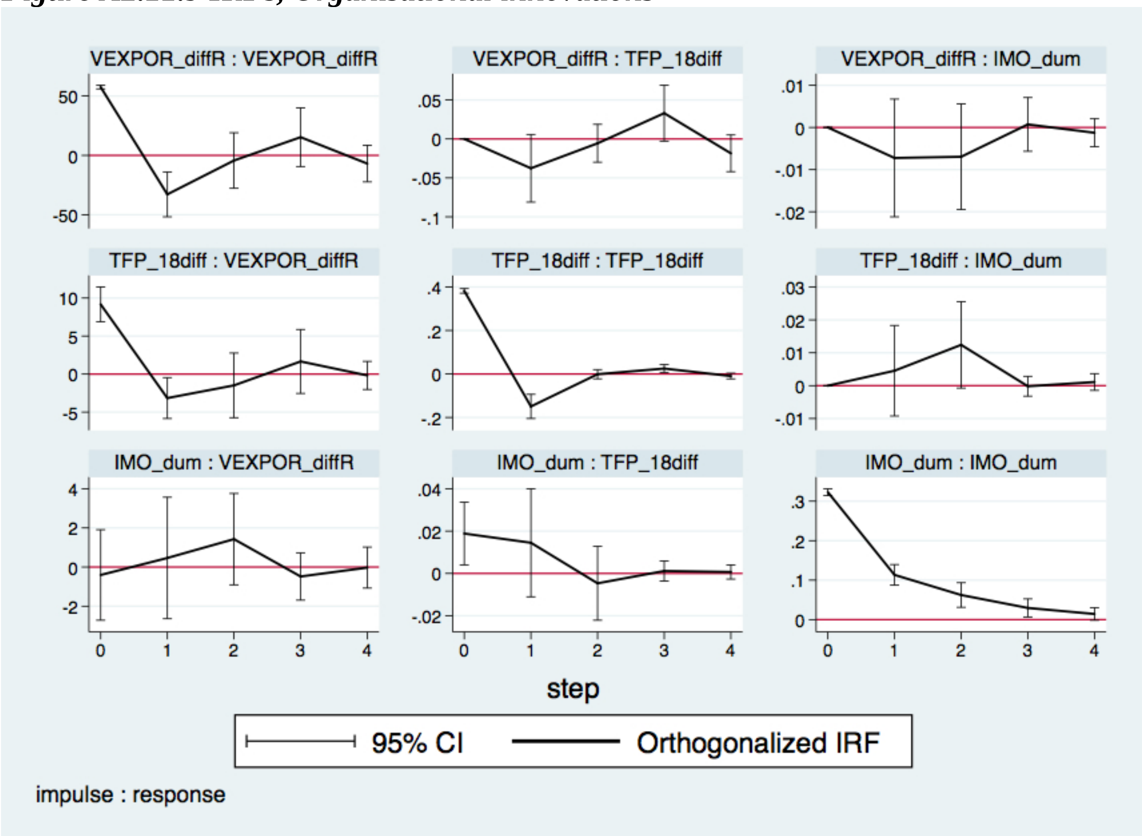


Figure A2.11.10 Cumulative IRFs, Organisational innovations

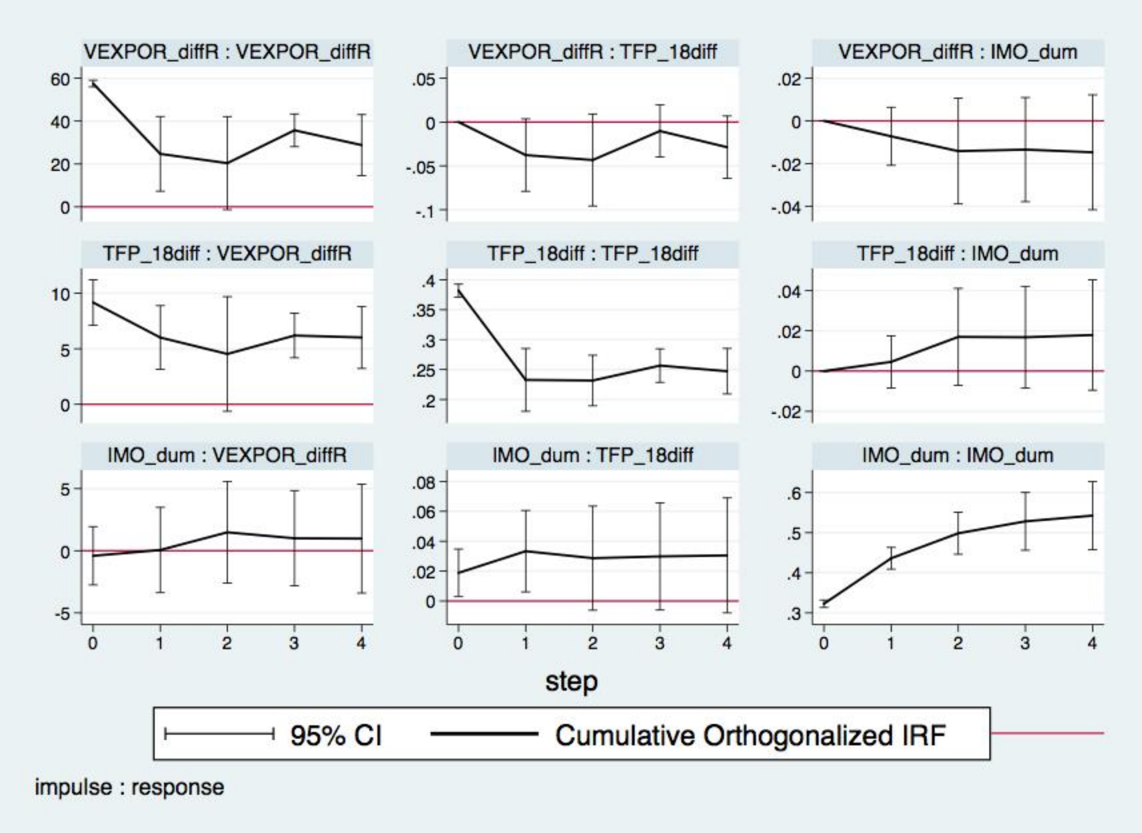


Figure A2.11.11 IRFs, Marketing innovations

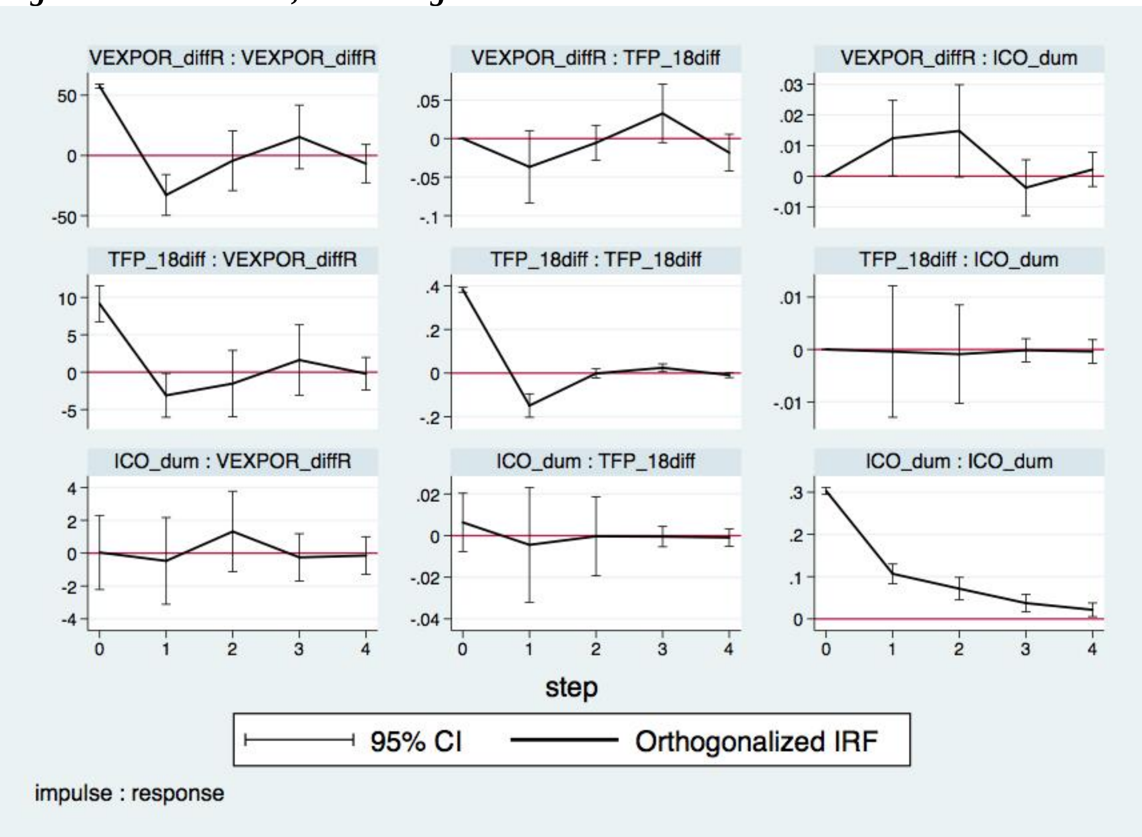


Figure A2.11.12 Cumulative IRFs, Marketing innovations

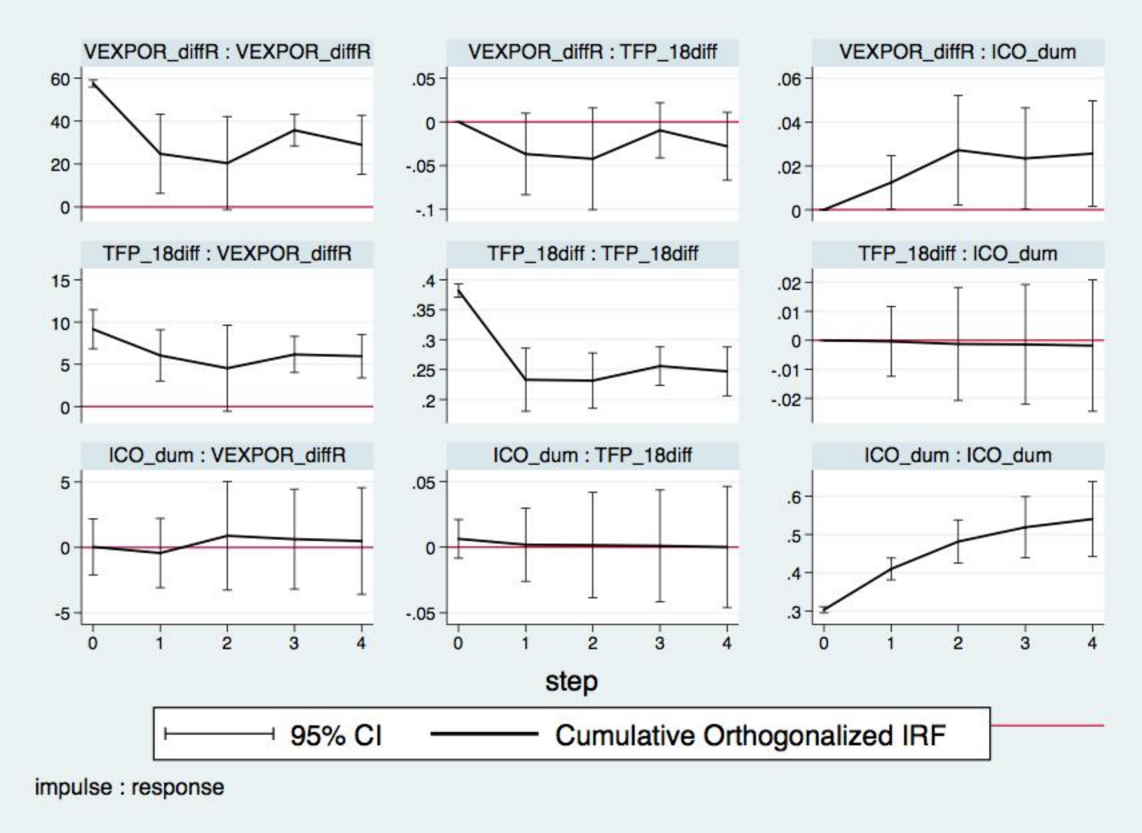


Figure A2.11.13 IRFs, Process innovations

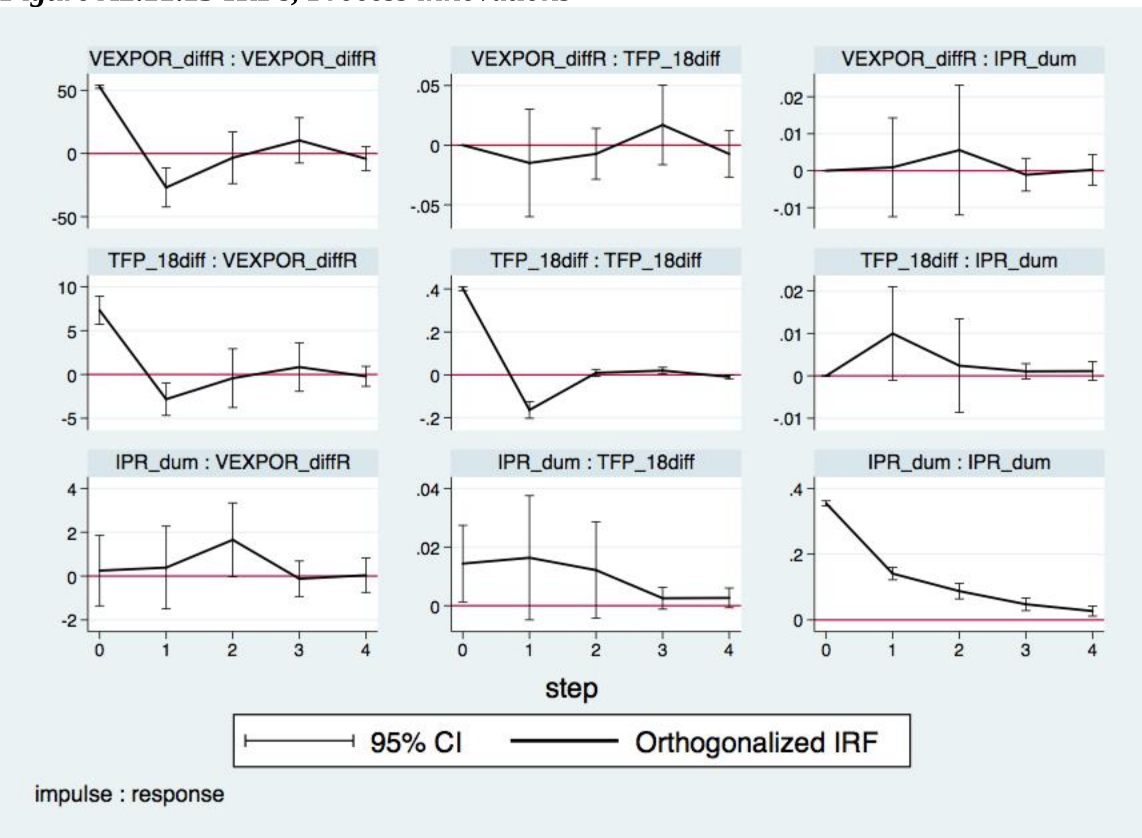
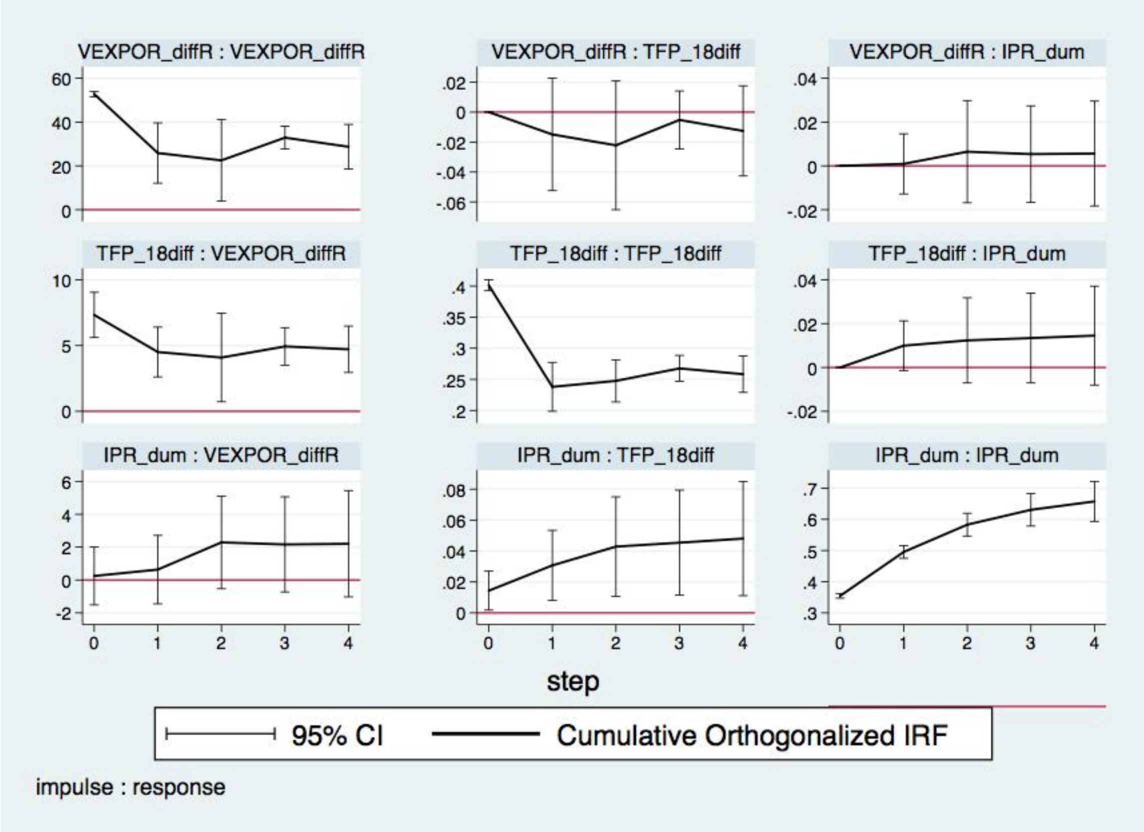


Figure A2.11.14 Cumulative IRFs, Process innovations



Appendix A2.12: IRFs and cumulative IRFs for subsample of firms that did not engage in cooperation with universities

Figure A2.12.1 IRFs, R&D expenditures

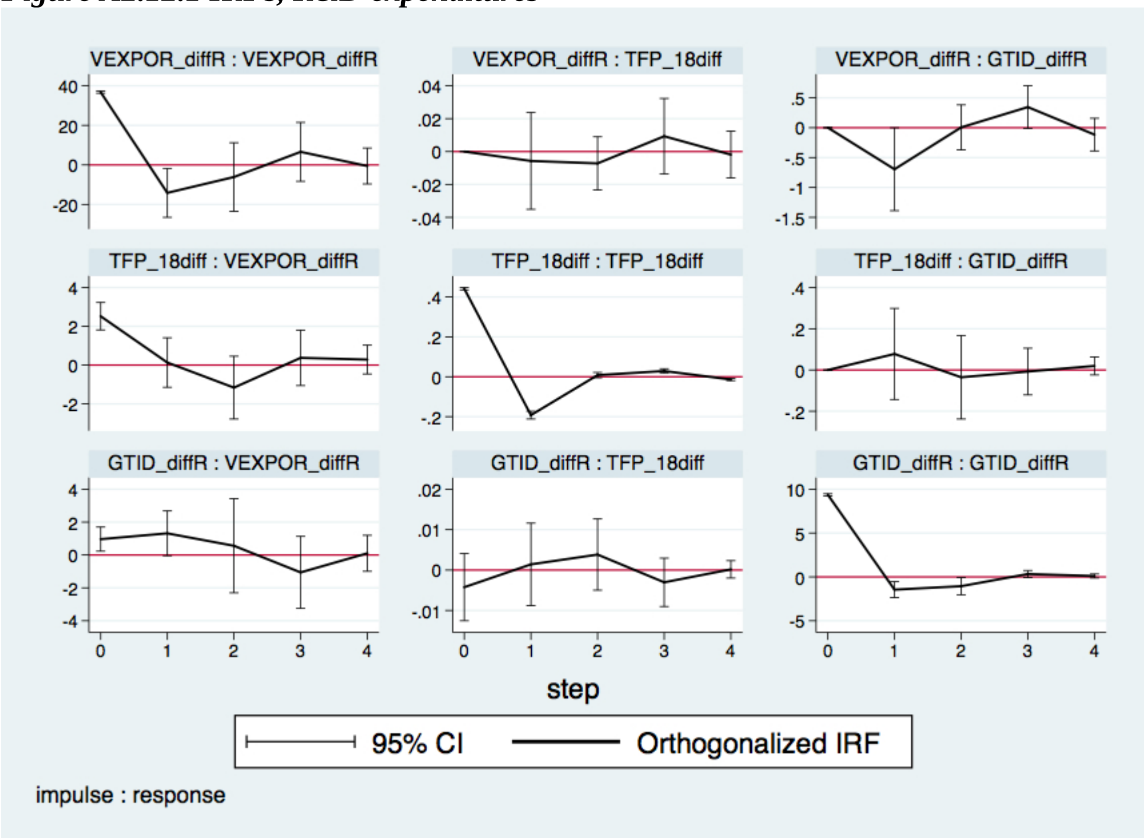


Figure A2.12.2 Cumulative IRFs, R&D expenditures

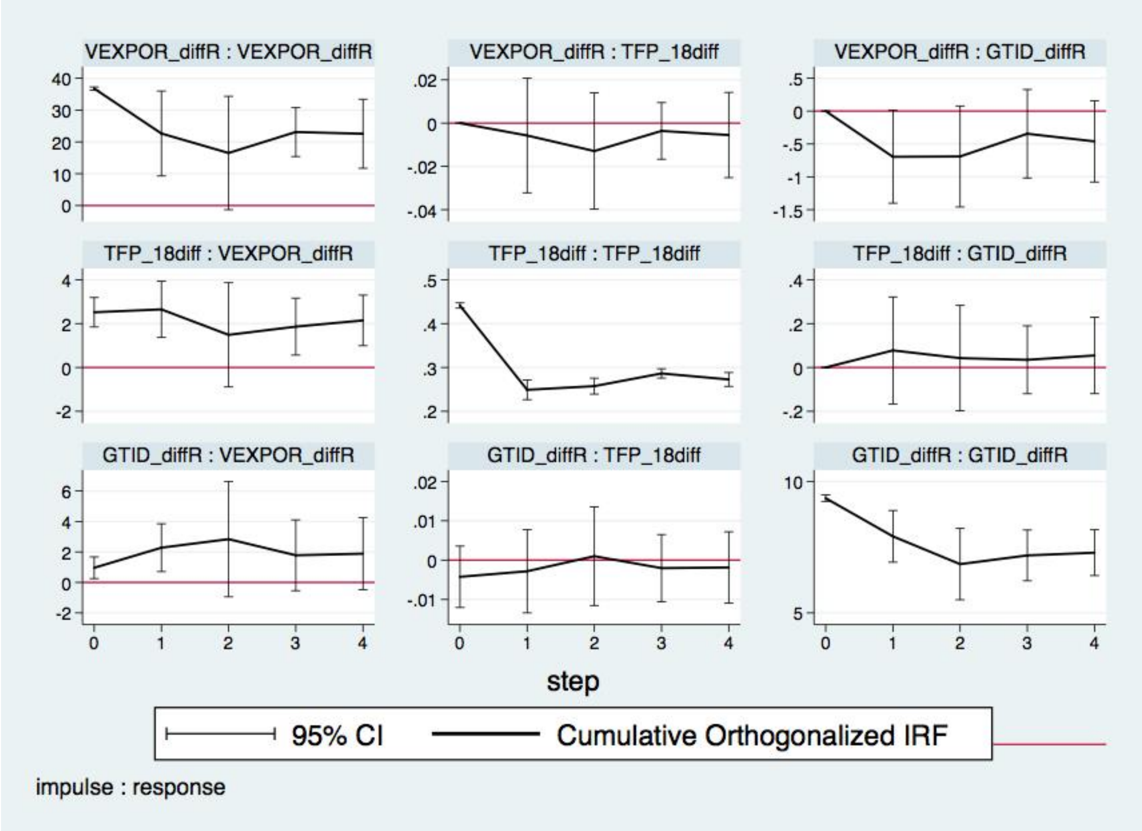


Figure A2.12.3 IRFs, Patents registered in Spain

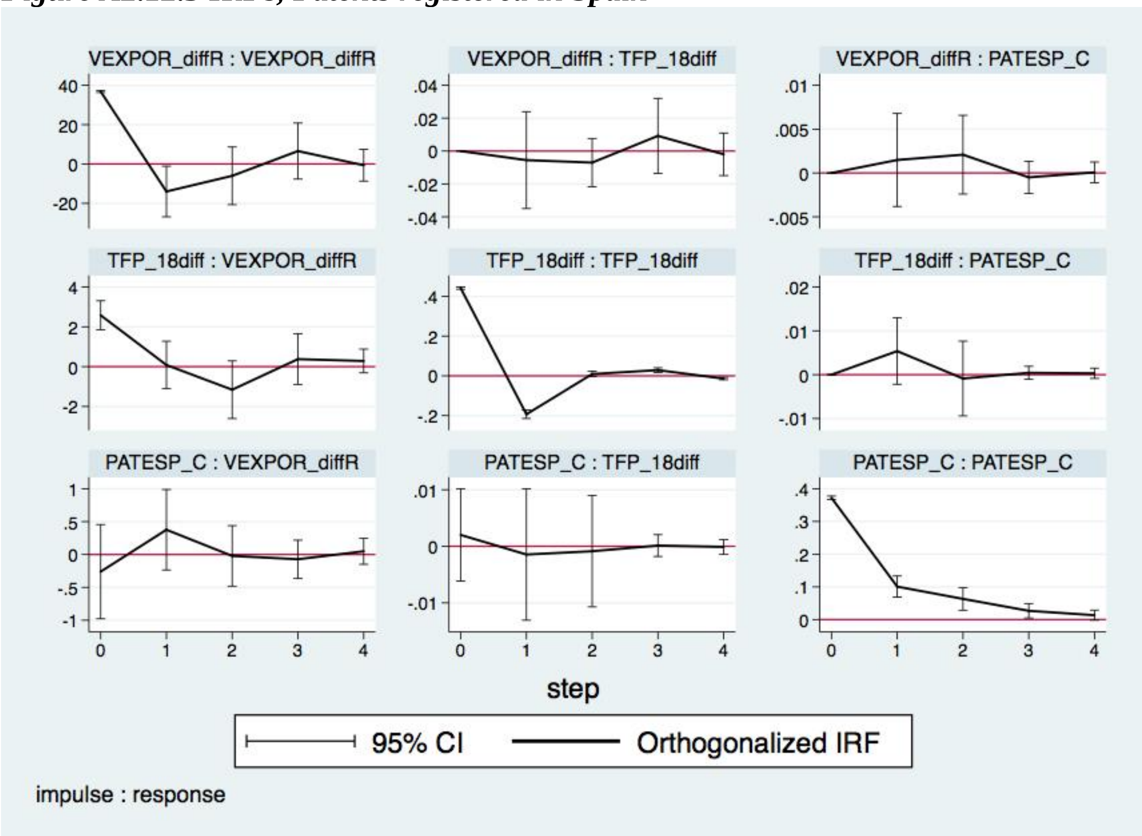


Figure A2.12.4 Cumulative IRFs, Patents registered in Spain

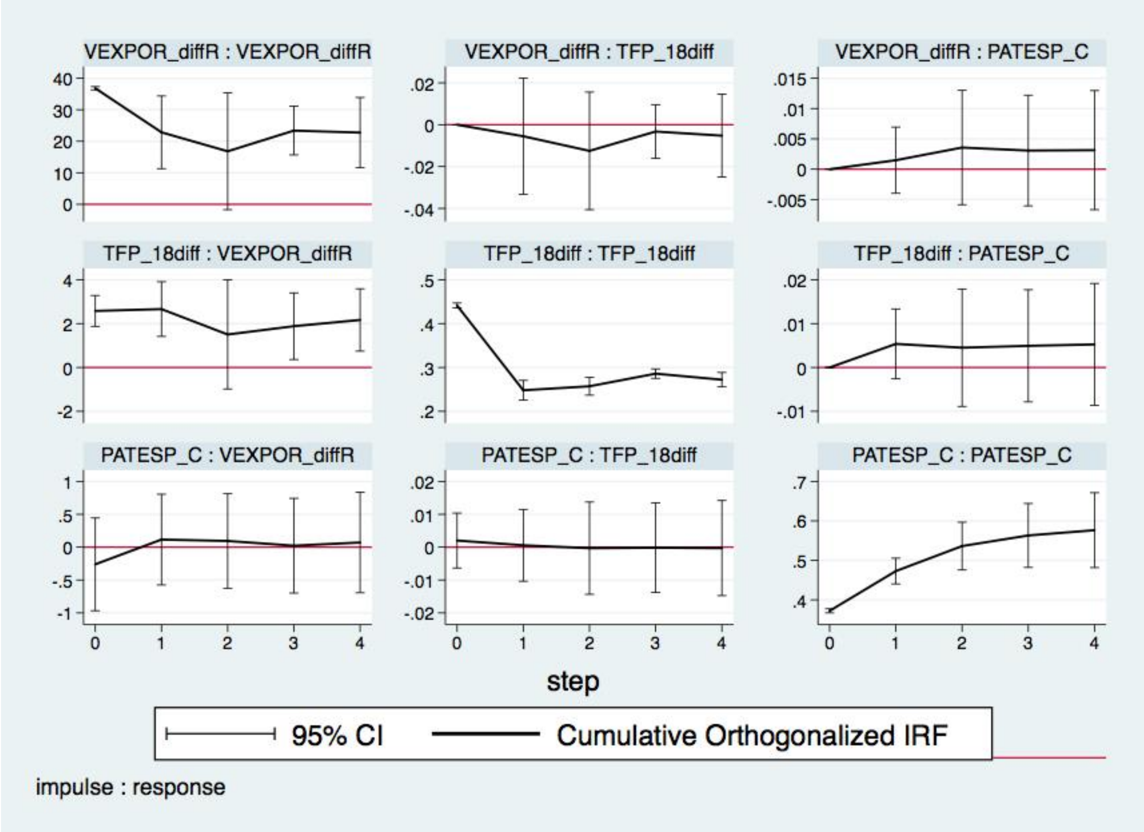


Figure A2.12.5 IRFs, Patents registered abroad

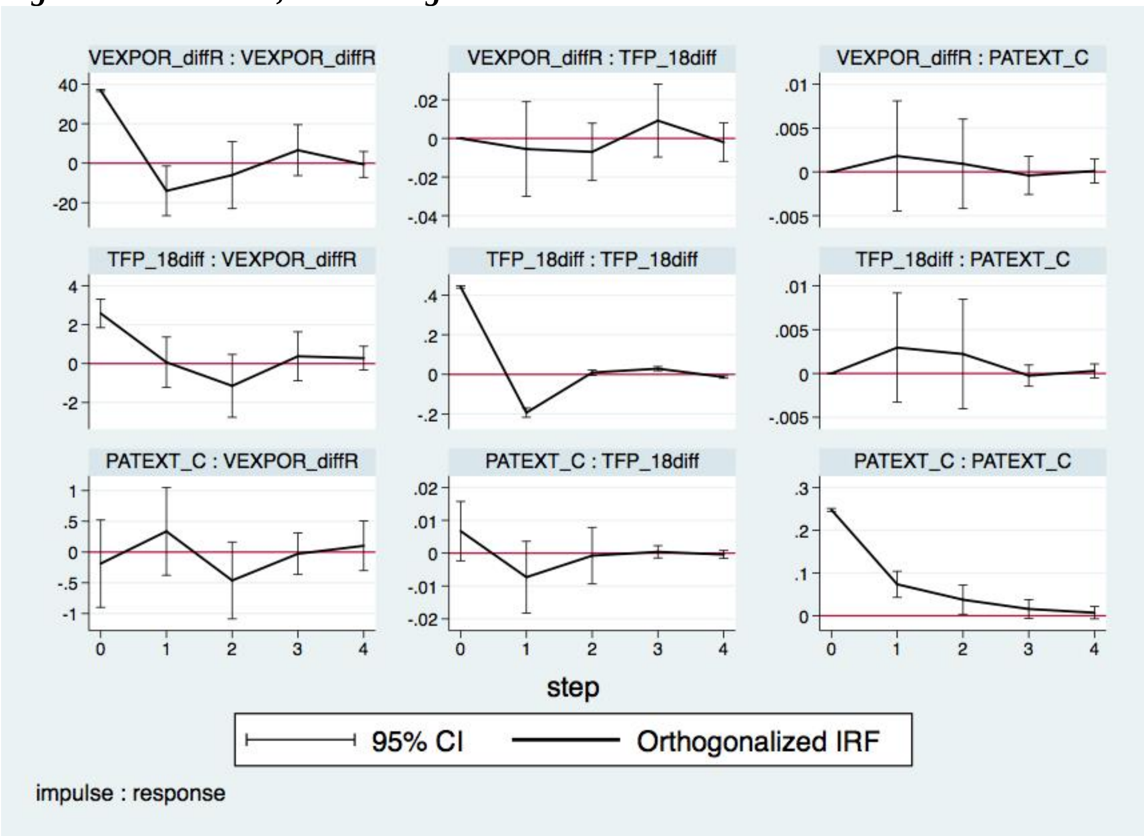


Figure A2.12.6 Cumulative IRFs, Patents registered abroad

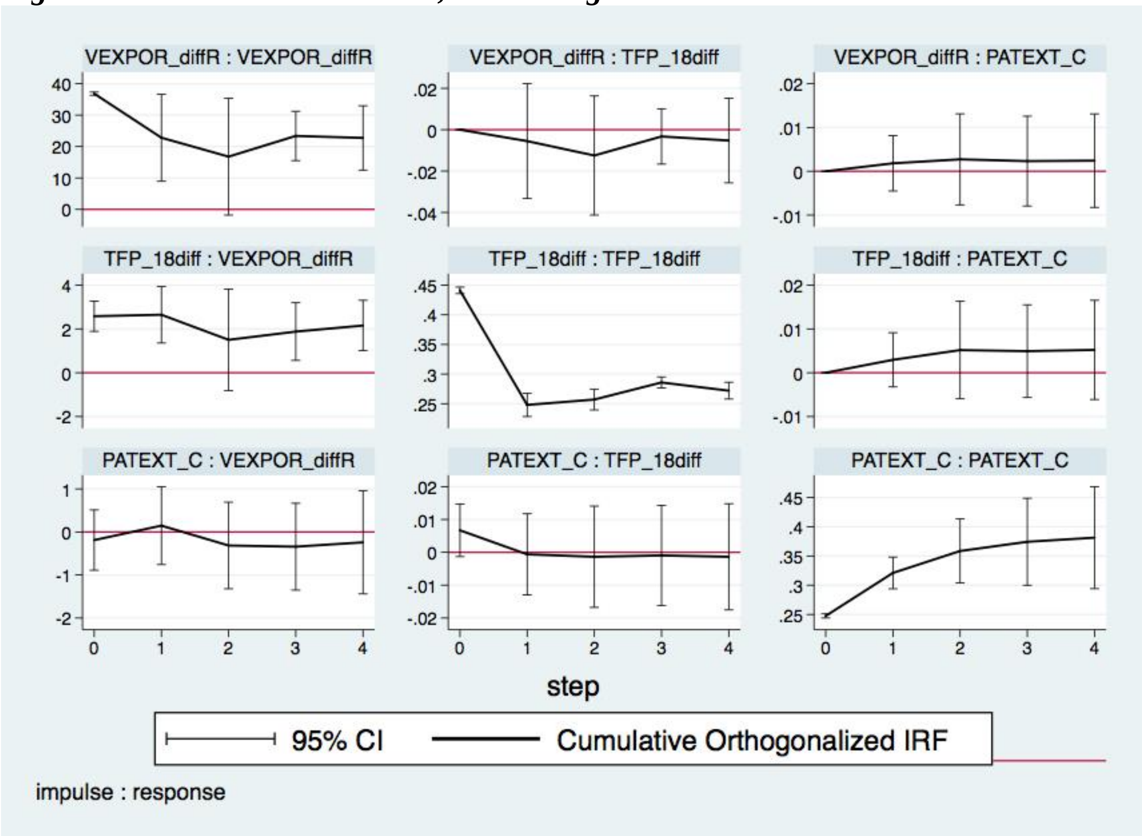


Figure A2.12.7 IRFs, Number of product innovations

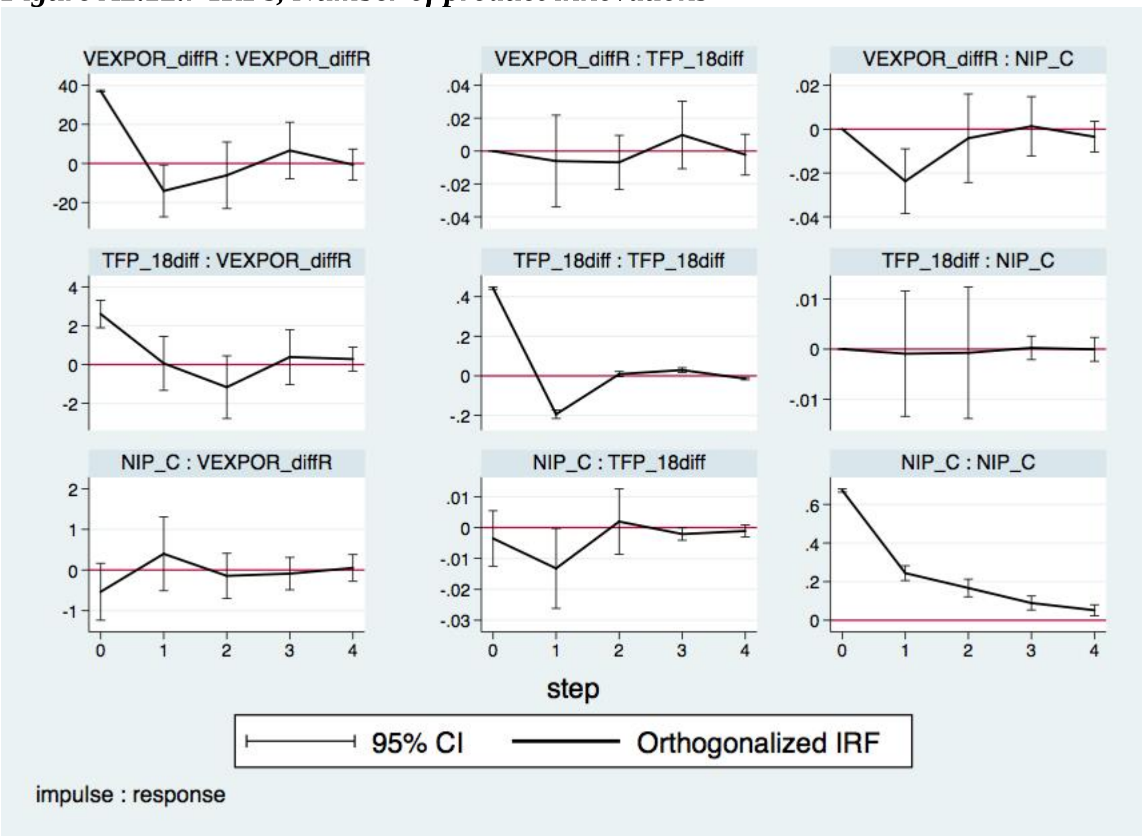


Figure A2.12.8 Cumulative IRFs, Number of product innovations

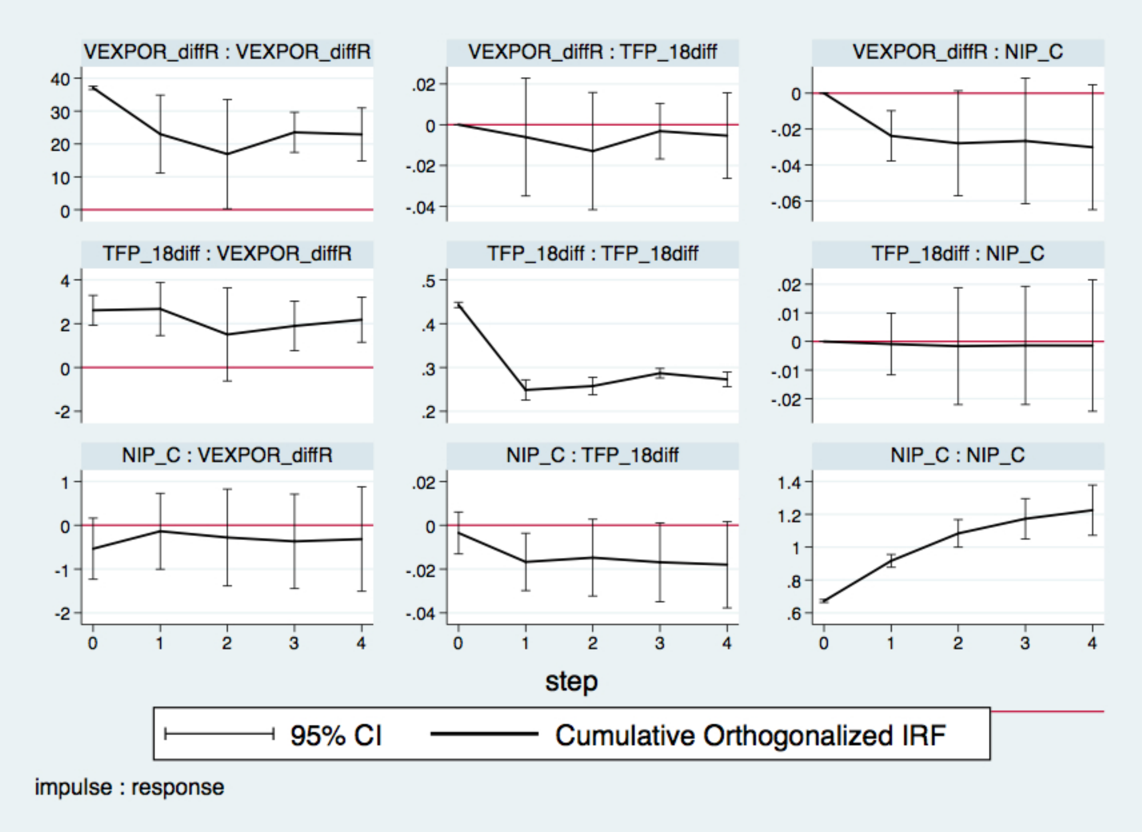


Figure A2.12.9 IRFs, Organisational innovations

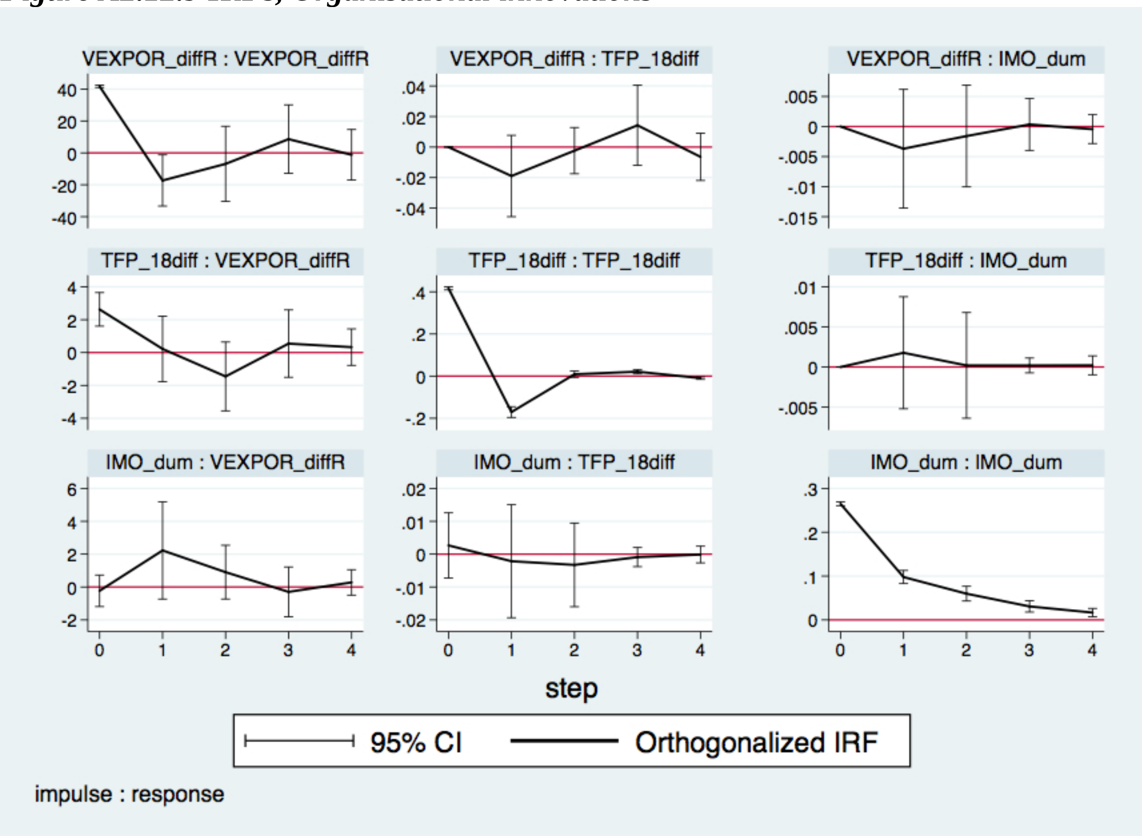


Figure A2.12.10 Cumulative IRFs, Organisational innovations

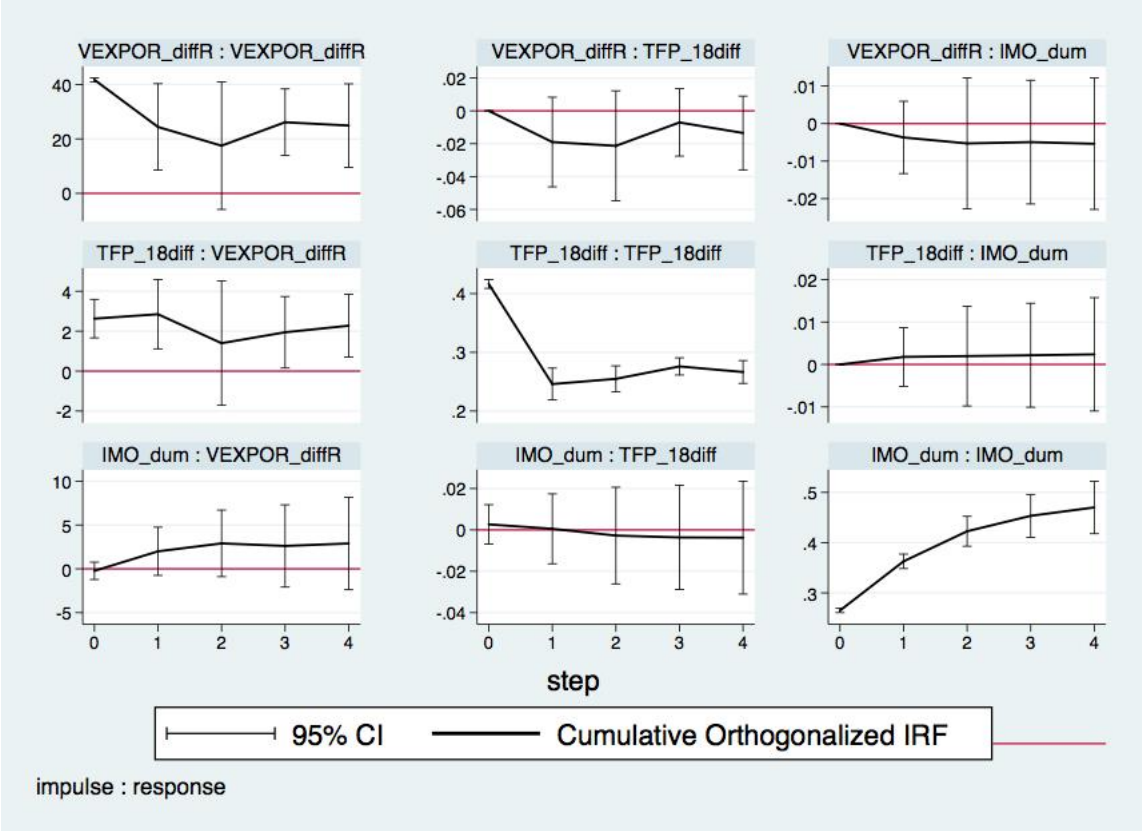


Figure A2.12.11 IRFs, Marketing innovations

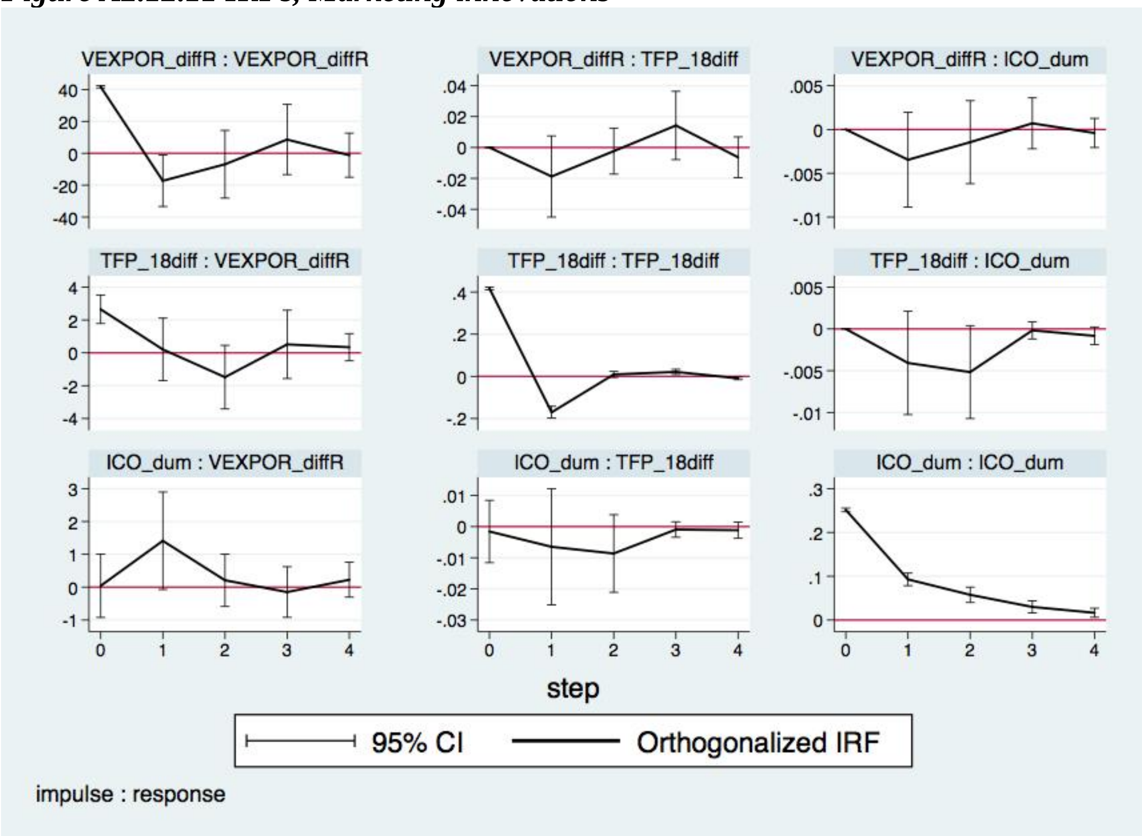


Figure A2.12.12 Cumulative IRFs, Marketing innovations

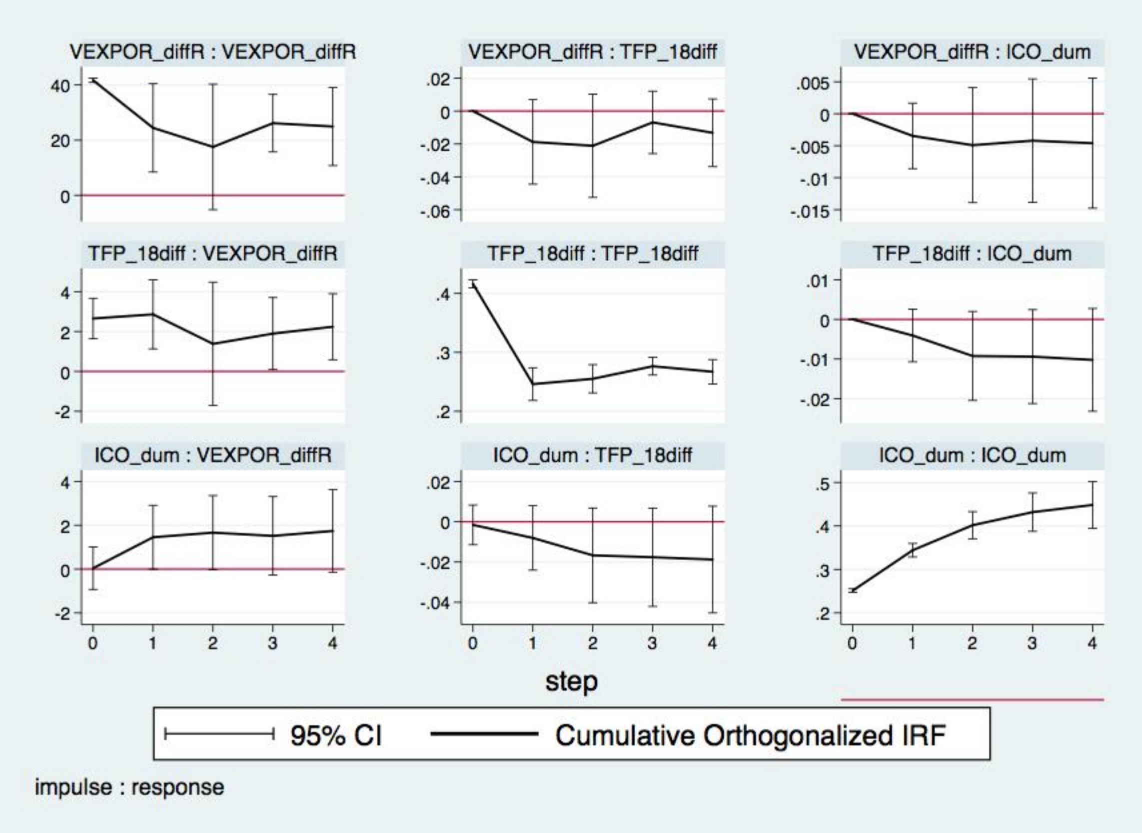


Figure A2.12.13 IRFs, Process innovations

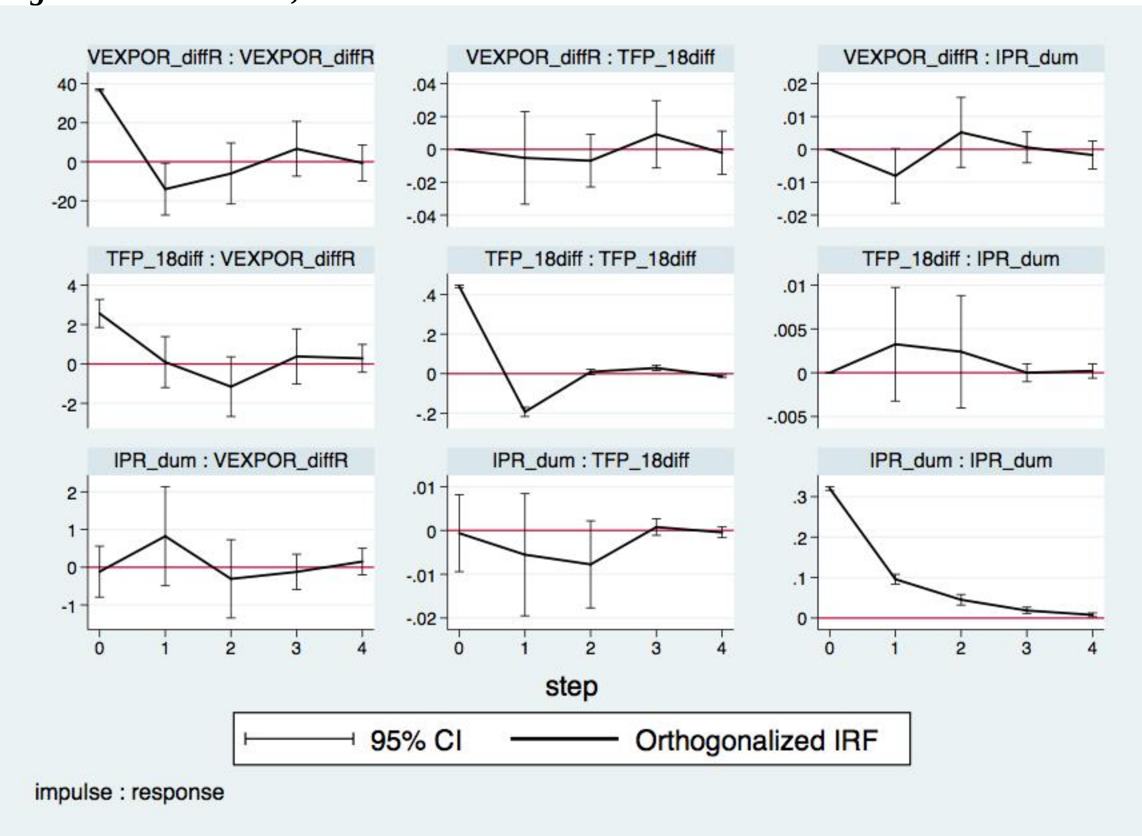
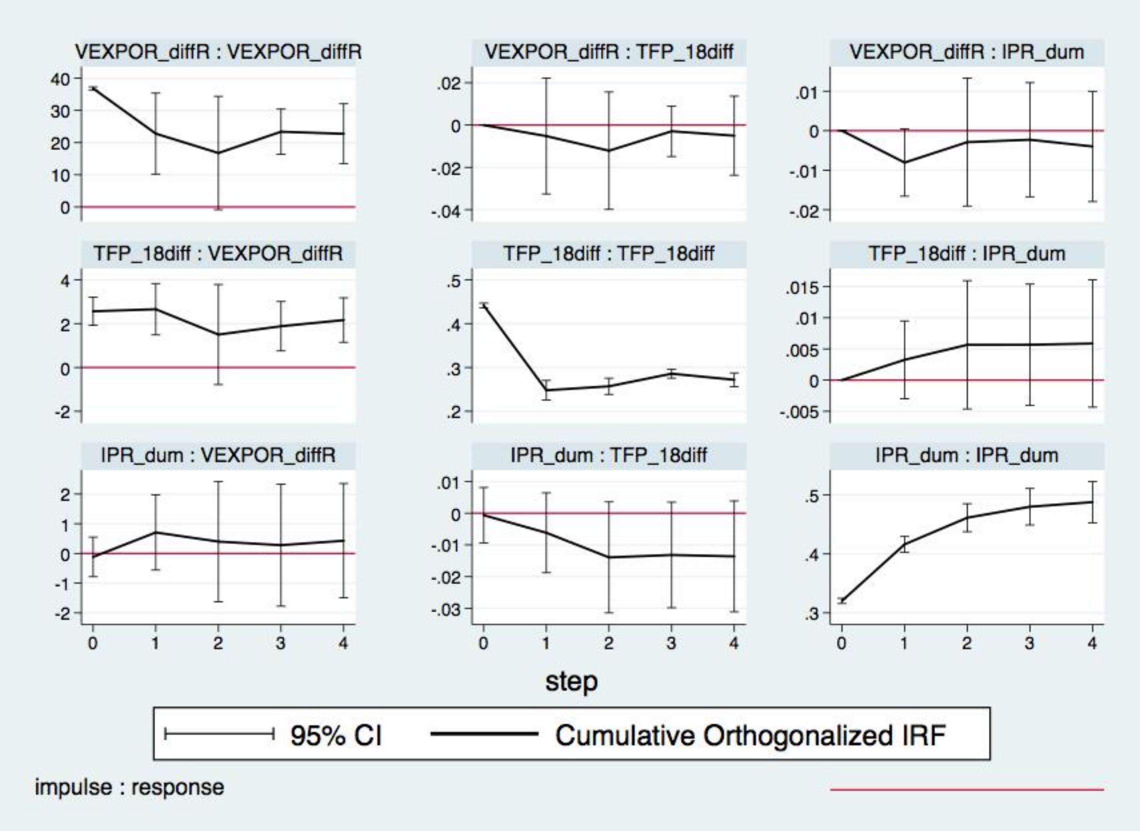


Figure A2.12.14 Cumulative IRFs, Process innovations



Appendix 3: Relationships with ordering reversed

Figure A3.1 Cumulative IRF from productivity to exporting (organisational innovation used as a measure of innovation; all firms; 2001-2016)

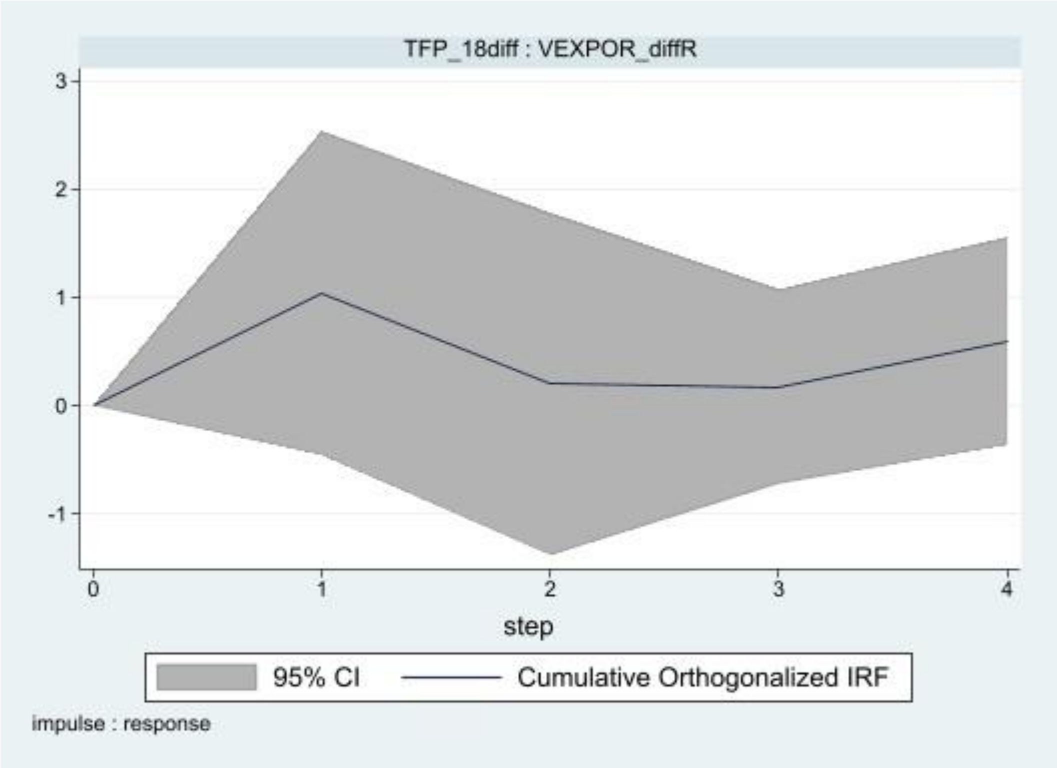
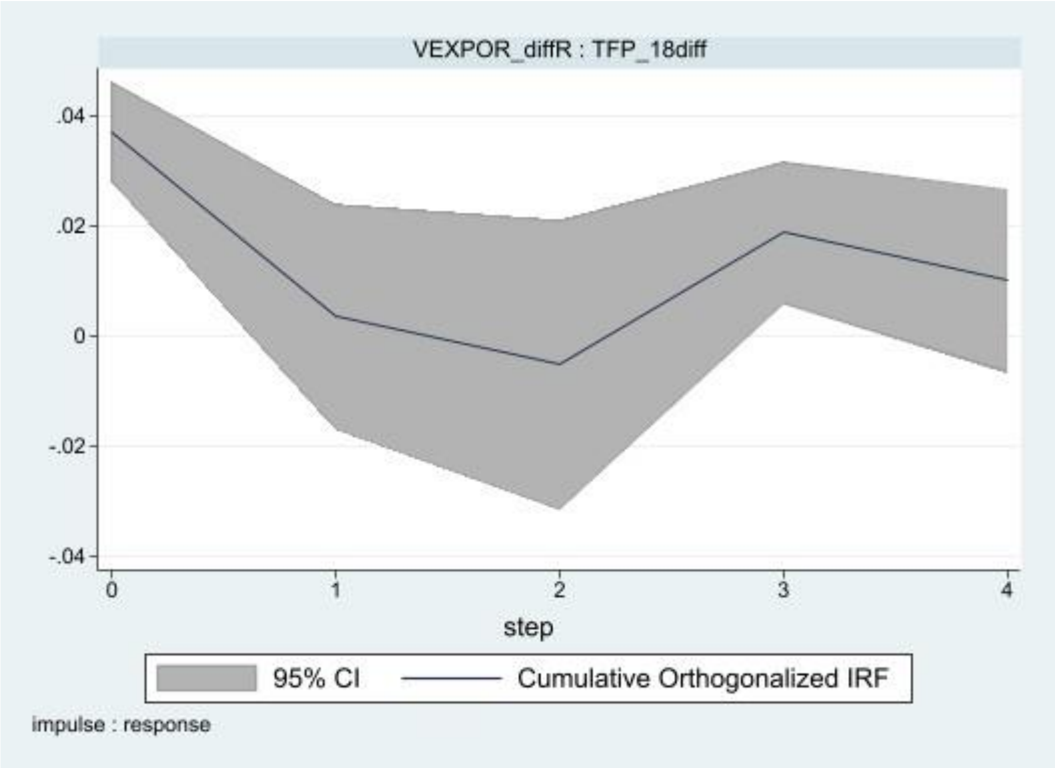


Figure A3.2 Cumulative IRF from exporting to productivity (organisational innovation used as a measure of innovation; all firms; 2001-2016)



Appendix 4: Labour productivity estimates for empirical investigation in Chapter 6

Table A4.1 The links between innovation, exporting and labour productivity for all firms*

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	14,349	5,577	8,772	14,477	5,632	8,845	14,484	5,632	8,852	14,173	5,479	8,694
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation												
Innovation—Productivity												
Exporting—Productivity			Period 1 (-) *Cumulative (-, NAS)*						Period 1 (-) *Cumulative (-, NAS)*			Period 1 (-) *Cumulative (-, NAS)*
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting		Period 0 (-)					Period 2 (-)					

		Cumulative (+/-, NAS)					*Cumulative (+/-, NAS)*					
Exporting—Innovation												

Table A4.1 The links between innovation, exporting and labour productivity for all firms (cont)*

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	8,859	*No observations*	8,859	8,859	*No observations*	8,859	14,495	5,636	8,859
Stability of the model	Stable		Stable	Stable		Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+)*		Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*		Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*		Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*		Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Productivity—Innovation									
Innovation—Productivity									
Exporting—Productivity	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*			Period 1 (-) *Cumulative (-, NAS)*
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting									
Exporting—Innovation									

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

Table A4.2 The links between innovation, exporting and productivity for small firms*, **

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	7,074	2,646	4,428	7,085	2,654	4,431	7,085	2,654	4,431	7,035	2,619	4,416
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 +), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+, NAS)*
Productivity—Innovation												
Innovation—Productivity			Period 0 (+) *Cumulative (+, NAS)*						Period 0 (+) *Cumulative (+, NAS)*			
Exporting—Productivity	Period 2 (-), Period 4 (+)		Period 2 (-), Period 4 (+)	Period 2 (-) Period 4 (+) *Cumulative (+/-, NAS)*		Period 2 (-), Period 4 (+)	Period 2 (-), Period 4 (+)		Period 2 (-), Period 4 (+)	Period 2 (-) *Cumulative (+/-, NAS)*		Period 2 (-), Period 4 (+)

	Cumulative (+/-, NAS)		*Cumulative (+/-, NAS)*			*Cumulative (+, NAS)*	*Cumulative (+/-, NAS)*		*Cumulative (+/-, NAS)*			*Cumulative (+/-, NAS)*
Productivity—Exporting	Period 0 (+) *Cumulative (+/-, NAS)*		Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*		Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*		Period 0 (+) *Cumulative (+/-, NAS)*
Innovation—Exporting							Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*				
Exporting—Innovation											Period 2 (-) *Cumulative (-, NAS)*	

Table A4.2 The links between innovation, exporting and productivity for small firms (cont)*, **

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	4,432	No observations	4,432	4,432	No observations	4,432	7,086	2,654	4,432
Stability of the model	Stable		Stable	Stable		Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+), Period 1 (-) *Cumulative (+)*		Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*		Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+, NAS)*		Period 0 (+), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+, NAS)*		Period 0 (+), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 2 (-), Period 3 (+), Period 4 (+) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity							Period 2 (-) *Cumulative (+/-, NAS)*		Period 2 (-) *Cumulative (-, NAS)*
Exporting—Productivity	Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*		Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*	Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*		Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*	Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*		Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*
Productivity—Exporting	Period 0 (+) *Cumulative (+/-, NAS)*		Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*		Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*		Period 0 (+) *Cumulative (+/-, NAS)*
Innovation—Exporting									
Exporting—Innovation									

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Small firms are those that employ fewer than 50 employees.

Table A4.3 The links between innovation, exporting and productivity for medium firms *, **

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	4,286	1,512	2,774	4,359	1,533	2,826	4,360	1,533	2,827	4,248	1,499	2,749
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation												
Innovation—Productivity	Period 0 (-) *Cumulative (-, NAS)*	Period 0 (-) *Cumulative (-)*	Period 0 (-) *Cumulative (-, NAS)*									
Exporting—Productivity												
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting		Period 0 (-) *Cumulative (+/-, NAS)*										
Exporting—Innovation												

Table A4.3 The links between innovation, exporting and productivity for medium firms (cont)*, **

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	2,831	No observations	2,831	2,831	No observations	2,831	4,364	1533	2831
Stability of the model	Stable		Stable	Stable		Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+)*		Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*		Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*		Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity									
Exporting—Productivity									
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting								Period 2 (-) *Cumulative (+/-, NAS)*	
Exporting—Innovation									

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Medium firms employ from 50 to 249 employees.

Table A4.4 The links between innovation, exporting and productivity for large firms *, **

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	2,989	1,419	1,570	3,033	1,445	1,588	3,039	1,445	1,594	2,890	1,361	1,529
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Productivity—Innovation												
Innovation—Productivity		Period 2 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+, NAS)*									
Exporting—Productivity												
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	
Innovation—Exporting		Period 0 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 2 (-) *Cumulative (-, NAS)*		Period 2 (-) *Cumulative (-, NAS)*			

Exporting—Innovation												Period 1 (-) *Cumulative* *(-, NAS)*

Table A4.4 The links between innovation, exporting and productivity for large firms (cont)*, *

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	1,596	No observations	1,596	1,596	No observations	1,596	3,045	1,449	1,596
Stability of the model	Stable		Stable	Stable		Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity	Period 0 (-) *Cumulative (-, NAS)*		Period 0 (-) *Cumulative (-, NAS)*						
Exporting—Productivity									
Productivity—Exporting							Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	
Innovation—Exporting								Period 0 (+) *Cumulative (+, NAS)*	
Exporting—Innovation									

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Large firms employ more than and including 250 employees.

Table A4.5 The links between innovation, exporting and labour productivity for high R&D performers*, *

Innovation variable	**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	2,629	1,077	1,552	2,635	1,077	1,558	2,490	1,020	1,470
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity								Period 1 (+) *Cumulative (+, NAS)*	Period 0 (-) *Cumulative (+/-, NAS)*
Exporting—Productivity	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*			Period 1 (-) *Cumulative (-, NAS)*		
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting									Period 0 (-) *Cumulative (-, NAS)*
Exporting—Innovation				Period 1 (+) *Cumulative (+, NAS)*					Period 1 (-) *Cumulative (-, NAS)*

Table A4.5 The links between innovation, exporting and labour productivity for high R&D performers (cont)*, *

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	1,562	No observations	1,562	1,562	No observations	1,562	2,643	1,081	1,562
Stability of the model	Stable		Stable	Stable		Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity									
Exporting—Productivity	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting									
Exporting—Innovation								Period 2 (+) *Cumulative (+, NAS)*	Period 1 (-) *Cumulative (+/-, NAS)*

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** High R&D performers are firms that invested more than average of all the firms in the sample in any year.

Table A4.6 The links between innovation, exporting and labour productivity for low R&D performers*, **

Innovation variable	**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	11,848	4,555	7,293	11,849	4,555	7,294	11,683	4,459	7,224
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity								Period 1 (-) *Cumulative (-, NAS)*	Period 2 (+) *Cumulative (+, NAS)*
Exporting—Productivity									Period 3 (+) *Cumulative (-, NAS)*
Productivity—Exporting	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 2 (-) *Cumulative (+/-, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*
Innovation—Exporting					Period 0 (-) *Cumulative (-, NAS)*				
Exporting—Innovation									

Table A4.6 The links between innovation, exporting and labour productivity for all firms (cont)*, **

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	7,297	No observations	7,297	7,297	No observations	7,297	11,852	4,555	7,297
Stability of the model	Stable		Stable	Stable		Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*		Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*		Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*		Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*		Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-), Period 3 (+) *Cumulative (+, NAS)*
Productivity—Innovation								Period 2 (+) *Cumulative (+, NAS)*	
Innovation—Productivity				Period 2 (-) *Cumulative (-, NAS)*		Period 2 (-) *Cumulative (-, NAS)*			Period 0 (-) *Cumulative (-, NAS)*
Exporting—Productivity									
Productivity—Exporting	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*		Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*		Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 2 (-), Period 4 (+) *Cumulative (+/-, NAS)*
Innovation—Exporting	Period 2 (+) *Cumulative (+/-, NAS)*		Period 2 (+) *Cumulative (+/-, NAS)*						
Exporting—Innovation									

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.
** Low R&D performers are remaining firms that were not classified as high R&D perfomers (high R&D performers are firms that invested more than average of all the firms in the sample in any year).

Table A4.7 The links between innovation, exporting and labour productivity for high exporters*, *

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	7,306	2,843	4,463	7,399	2,874	4,525	7,400	2,874	4,526	7,179	2,782	4,397
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation								Period 1 (+) *Cumulative (+, NAS)*			Period 2 (+) *Cumulative (+, NAS)*	
Innovation—Productivity		Period 2 (+) *Cumulative (+/-, NAS)*										
Exporting—Productivity						Period 1 (-) *Cumulative (-, NAS)*			Period 1 (-) *Cumulative (-, NAS)*			Period 1 (-) *Cumulative (-, NAS)*

Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting		Period 0 (-) *Cumulative (+/-, NAS)*										
Exporting—Innovation												

Table A4.7 The links between innovation, exporting and labour productivity for high exporters (cont)*, **

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	4,533	No observations	4,533	4,533	No observations	4,533	7,410	2,877	4,533
Stability of the model	Stable		Stable	Stable		Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*		Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*		Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation									Period 2 (-) *Cumulative (-, NAS)*
Innovation—Productivity									
Exporting—Productivity	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*			Period 1 (-) *Cumulative (-, NAS)*
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting									
Exporting—Innovation								Period 2 (+) *Cumulative (+, NAS)*	

*NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

**High exporters are firms that exported more than average of all the firms in the sample in any year.

Table A4.8 The links between innovation, exporting and labour productivity for low exporters*, *

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	7,043	2,734	4,309	7,078	2,758	4,320	7,084	2,758	4,326	6,994	2,697	4,297
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 2 (+), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (+), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (+), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (+), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*
Productivity—Innovation												
Innovation—Productivity		Period 0 (-) *Cumulative (-, NAS)*						Period 0 (-) *Cumulative (-, NAS)*				
Exporting—Productivity	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*		Period 0 (+), Period 1 (-), Period 2 (+) *Cumulative (+, NAS)*		Period 2 (-) *Cumulative (-, NAS)*							
Exporting—Innovation											Period 2 (-) *Cumulative (-, NAS)*	

Table A4.8 The links between innovation, exporting and labour productivity for low exporters (cont)*, **

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	4,326	No observations	4,326	4,326	No observations	4,326	7,085	2,759	4,326
Stability of the model	Stable		Stable	Stable		Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*		Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*		Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (+), Period 3 (+), Period 4 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*		Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*		Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*		Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 2 (-) *Cumulative (+)*
Productivity—Innovation									
Innovation—Productivity									
Exporting—Productivity	Period 1 (-), Period 3 (+) *Cumulative (-, NAS)*		Period 1 (-), Period 3 (+), Period 4 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*		Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting	Period 0 (+) *Cumulative (+)*		Period 0 (+) *Cumulative (+)*	Period 0 (-) *Cumulative (-, NAS)*		Period 0 (-) *Cumulative (-, NAS)*			
Exporting—Innovation									

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Low exporters are the remaining firms that were not classified as high exporters (high exporters are firms that exported more than average of all the firms in the sample in any year).

Table A4.9 The links between innovation, exporting and productivity for firms that engaged in cooperation with other firms*, *

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	4,463	4,231	4,343	4,550	4,317	4,428	4,555	4,322	4,433	4,342	4,112	4,224
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation												
Innovation—Productivity												
Exporting—Productivity			Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*								
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting												
Exporting—Innovation											Period 1 (-) *Cumulative (-, NAS)*	

Table A4.9 The links between innovation, exporting and productivity for firms that engaged in cooperation with other firms (cont)*,**

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	2,753	2,520	2,753	2,753	2,520	2,753	4,563	4,330	4,440
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+/-, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity								Period 2 (+) *Cumulative (+/-, NAS)*	
Exporting—Productivity	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting									
Exporting—Innovation									

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Firms that engaged in cooperation with other firms are firms that engaged in cooperation with customers, competitors or suppliers any time within the last three years.

Table A4.10 The links between innovation, exporting and productivity for firms that did not engage in cooperation with other firms*,**

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	11,614	11,389	11,485	11,692	11,459	11,555	11,695	11,462	11,558	11,548	11,322	11,416
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*
Productivity—Innovation												
Innovation—Productivity	Period 0 (-) *Cumulative (-, NAS)*	Period 0 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*							Period 2 (+) *Cumulative (+/-, NAS)*		
Exporting—Productivity												
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting							Period 2 (-) *Cumulative (+, NAS)*	Period 2 (-) *Cumulative (+, NAS)*		Period 1 (+)		Period 1 (-) *Cumulative (+/-, NAS)*

										Cumulative (+/-, NAS)		
Exporting—Innovation	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-), Period 4 (-) *Cumulative (-, NAS)*									

Table A4.10 The links between innovation, exporting and productivity for firms that did not engage in cooperation with other firms (cont)*,**

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	7,264	7,031	7,264	7,264	7,031	7,264	11,701	11,468	11,564
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity									
Exporting—Productivity									
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting									
Exporting—Innovation								Period 1 (-) *Cumulative (-, NAS)*	

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Firms that did not engage in cooperation with other firms are firms that did not engage in cooperation with customers, competitors or suppliers any time within the last three years.

Table A4.11 The links between innovation, exporting and productivity for firms that engaged in cooperation with universities*, **

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	4,374	4,148	4,232	4,442	4,216	4,299	4,440	4,213	4,297	4,250	4,028	4,115
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+)*
Innovation—Innovation	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (-), Period 3 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative* *(+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative* *(+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative* *(+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative* *(+)*	Period 0 (+), Period 1 (-) *Cumulative* *(+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative* *(+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative* *(+)*	Period 0 (+), Period 1 (-) *Cumulative* *(+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative* *(+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative* *(+)*	Period 0 (+), Period 1 (-) *Cumulative* *(+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative* *(+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative* *(+)*	Period 0 (+), Period 1 (-) *Cumulative* *(+, NAS)*
Productivity—Innovation												
Innovation—Productivity												
Exporting—Productivity		Period 1 (-) *Cumulative* *(-, NAS)*			Period 1 (-) *Cumulative* *(-, NAS)*			Period 1 (-) *Cumulative* *(-, NAS)*				
Productivity—Exporting	Period 0 (+) *Cumulative* *(+, NAS)*	Period 0 (+) *Cumulative* *(+, NAS)*	Period 0 (+) *Cumulative* *(+, NAS)*	Period 0 (+) *Cumulative* *(+, NAS)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+, NAS)*	Period 0 (+) *Cumulative* *(+, NAS)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+, NAS)*	Period 0 (+) *Cumulative* *(+, NAS)*	Period 0 (+) *Cumulative* *(+)*	Period 0 (+) *Cumulative* *(+, NAS)*
Innovation—Exporting												
Exporting—Innovation												

Table A4.11 The links between innovation, exporting and productivity for firms that engaged in cooperation with universities (cont)*, **

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	2,789	2,562	2,789	2,789	2,562	2,789	4,450	4,223	4,307
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity									
Exporting—Productivity	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*	
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting								Period 2 (+) *Cumulative (+, NAS)*	
Exporting—Innovation				Period 1 (+) *Cumulative (+, NAS)*		Period 1 (+) *Cumulative (+, NAS)*			

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Firms that engaged in cooperation with universities are firms that engaged in cooperation with universities or technological centres any time within the last three years.

Table A4.12 The links between innovation, exporting and productivity for firms that did not engage in cooperation with universities*, *

Innovation variable	**R&D expenditures**			**Patents registered in Spain**			**Patents registered outside of Spain**			**Number of product innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	11,728	11,494	11,604	11,807	11,569	11,681	11,817	11,579	11,691	11,641	11,411	11,522
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:												
Productivity—Productivity	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation												
Innovation—Productivity												
Exporting—Productivity												
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting	Period 0 (+), Period 1 (+) *Cumulative (+, NAS)*											
Exporting—Innovation	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*							Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*

Table A4.12 The links between innovation, exporting and productivity for firms that did not engage in cooperation with universities (cont)*, *

Innovation variable	**Organisational innovations**			**Marketing innovations**			**Process innovations**		
Time period	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016	2001-2016	2001-2008	2009-2016
Number of observations	7,210	6,972	7,210	7,210	6,972	7,210	11,818	11,580	11,692
Stability of the model	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Links between:									
Productivity—Productivity	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*	Period 0 (+) *Cumulative (+)*
Innovation—Innovation	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*	Period 0 (+), Period 1 (+), Period 2 (+), Period 3 (+), Period 4 (+) *Cumulative (+)*
Exporting—Exporting	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*	Period 0 (+), Period 1 (-) *Cumulative (+, NAS)*
Productivity—Innovation									
Innovation—Productivity									
Exporting—Productivity	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*	Period 1 (-) *Cumulative (-, NAS)*		Period 1 (-) *Cumulative (-, NAS)*			
Productivity—Exporting	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*	Period 0 (+) *Cumulative (+, NAS)*
Innovation—Exporting				Period 1 (+) *Cumulative (+, NAS)*		Period 1 (+) *Cumulative (+, NAS)*			
Exporting—Innovation									

* NAS stands for *Not always significant*, which indicates that the cumulative effects are not significant in all time periods.

** Firms that did not engage in cooperation with universities are firms that did not engage in cooperation with universities or technological centres any time within the last three years.

Appendix 5 – Exploration of the missing variable in ESEE dataset

Prior to the empirical investigation, patterns of missing values were investigated in the dataset.[196] Table A4.1 shows the number of missing and non-missing values for the variables that will be utilised in the empirical investigation in this thesis.

Table A5.1 Missing and non-missing variables for the variables in the ESEE both before attrition is accounted for and after attrition is accounted for (idsit = 1)

		Before attrition is accounted for		**After attrition is accounted for (idsit = 1)**	
Variable	**Description**	**Missing values**	**Non-missing values**	**Missing values**	**Non-missing values**
BSFE_dum	Dummy variable indicating whether a firm has unsuccessfully applied for external financing for innovation (0 = No, 1 = Yes)	64,910	28,355	n/a**	n/a
CTCL_dum	Dummy variable indicating whether a firm cooperated with customers (0 = No, 1 = Yes)	64,910	28,355	n/a	n/a
CTCO_dum	Dummy variable indicating whether a firm cooperated with competitors (0 = No, 1 = Yes)	64,910	28,355	n/a	n/a
CTPR_dum	Dummy variable indicating whether a firm cooperated with suppliers (0 = No, 1 = Yes)	64,910	28,355	n/a	n/a

[196] Missing values were explored using the Stata commands *misstable sum* and *misstable patterns*.

CUCT_dum	Dummy variable indicating whether a firm cooperated with universities and/or technological centres (0 = No, 1 = Yes)	64,910	28,355	n/a	n/a
DEDID2015prices	Value of tax deductions for R&D applied to company income tax (in Euros, deflated by CPI)	64,910	28,355	n/a	n/a
DEDIT2015prices	Value of tax deductions for technological innovations applied to the company income tax (in Euros, deflated by CPI)	64,910	28,355	n/a	n/a
EMPIDT	Total employment in R&D	43,904	49,361	500	27,855
FPIDCA2015prices1	Value of R&D funding provided by regional governments (in Euros, deflated by CPI)	64,915	28,350	5	28,350
FPIDES2015prices1	Value of R&D funding provided by central government (in Euros, deflated by CPI)	64,919	28,346	9	28,346
FPIDOT2015prices1	Value of R&D funding provided by other R&D agencies (in Euros, deflated by CPI)	64,920	28,345	10	28,345
FPIDTO2015prices1	Value of R&D funding provided by administration at all	64,923	28,342	13	28,342

	levels (in Euros, deflated by CPI)				
GEID2015prices	Total external expenses on R&D activities (in Euros, deflated by CPI)	64,950	28,315	40	28,315
GIID2015prices	Total internal expenses on R&D activities (in Euros, deflated by CPI)	65,027	28,238	117	28,238
GTID2015prices	Total expenses on R&D activities (in Euros, deflated by CPI)	65,024	28,241	114	28,241
NACECLIO	Firm's main activity	64,910	28,355	n/a	n/a
PCAEXT	Direct or indirect participation of foreign capital into the social capital of a firm (%)	64,928	28,337	18	28,337
PERSOC_dum	Dummy variable indicating whether a firm belongs to a corporate group (0 = Yes, 1 = No)	38,930	54,335	1,268	27,087
TFP_18	Total factor productivity	68,443	24,822	3,533	24,822
VEXPOR2015prices	Value of exports (in Euros, deflated by CPI)	64,944	28,321	34	28,321
LP2015prices	Labour productivity	65,018	28,247	108	28,247

* Number of firms in the dataset = 5,840; number of years in the dataset = 16 ranging from 2001 until 2016

** n/a denotes that there are no missing values once attrition is accounted for

Although the number of missing values appears high in the third column of Table A4.1, most are the direct result of attrition of firms from the sample. Once observations when firms cease trading, which disappear and which stop responding to the survey are excluded,[197] the number of missing values significantly decreases as demonstrated in the second part of Table A4.1. The attrition account for data only in years when missing.

If we examine the fifth and sixth columns of Table A4.1, we observe that the percentage of missing values out of the total number of observations ranges between 0.03% and 12.5%. The average percentage of missing values per variable is 1.6%. The largest numbers of missing values arise from the total factor productivity variable (TFP_18) and the categorical variable that indicates whether the firm belongs to a corporate group (PERSOC_dum). Total factor productivity is a product of estimation and is always missing for the first year in the dataset (in this case, 2001). Once 2001 is excluded, the number of missing values for total factor productivity is reduced to 1,812 (comprising 6.8% of the total number of observations). All of the variables included in the estimation of TFP were explored for missingness as well. For all of the variables used in the TFP estimation, apart from age, the number of missing values is low. The variable age is generated from the underlying variable stating the year when the firm was founded, which is gathered every four years. The variable indicating the year when a firm was founded was interpolated where it was possible; however, the number of missing values still remains above average.[198] The variable PERSOC_dum is collected every four years. Hence, if a firm fails to respond to the question once, it automatically creates missing values for four years of data, which might be driving the relatively larger number of missing values for this variable. The variable PERSOC_dum was interpolated prior to exploration of missing values took place.[199]

It was further explored whether the missingness of TFP_18 and PERSOC_dum variables were related to: (1) firm size, (2) whether a firm is high or low R&D performer,[200] (3)

[197] The idsit variable in the ESEE is used to account for attrition. This is a categorical variable which takes values of: (i) 0 if a firm cannot be contacted or is temporarily closed; (ii) 1 if firm responds to the survey or if a firm transformation occurred or if a new firm responds to the survey; (iii) 2 if a firm that ceased to exist, is in liquidation, switches to non-manufacturing activity or if is taken over by another firm; and (iv) 3 if a firm refuses to collaborate. Value of idsit of 0, 2 and 3 are regarded as attrition. Idsit can also take the form of a missing value. In case when idsit takes values of 0, 2 and 3, then the reason for missingness is known. It can be conjectured that in the cases where when idsit is missing variable, then the reason for missingness is unknown.

[198] In some cases, it was not possible to interpolate the variable. This variable is gathered every four years, so if a firm entered a dataset for a brief period of time and was never asked a question about when it was founded, it was not possible to interpolate this variable. Additionally, as the variable when the firm was founded is not constant over the whole time period (e.g. if a firm experienced a merger or any other transformation), the variable was not interpolated for the year 2001 – the first year it appears is 2002.

[199] If a firm entered the dataset only briefly and was never asked a question related to this variable, interpolation could not be done.

[200] The same definitions of high vs low R&D or export performance applied in the previous chapters were also applied here.

whether a firm is high or low exporter, (4) whether firm cooperates with other firms, customers, suppliers or universities, and (5) firm activity. The results of this investigation are presented in Table A4.2. Proportion comparison tests are reported for each group in the last column of Table A4.2.

Table A5.2 Pattern of missing values for TFP_18 and PERSOC_dum in relation to firm characteristics after taking into account the attrition (idsit =1) and excluding 2001

Variable	**Firm characteristics**	**Number of missing values**	**Number of non-missing values**	**Percentage of missing values (%)**	**Proportion comparison test (p-value for Ha: diff != 0)**
Size of a firm					
TFP_18	Small firms	900	12,373	6.78	n/a
	Medium firms	613	7,635	7.43	
	Large firms	299	4,814	5.85	
PERSOC_dum	Small firms	726	12,547	5.47	n/a
	Medium firms	479	7,769	5.81	
	Large firms	63	5,050	1.23	
R&D performance					
TFP_18	High R&D performance	256	3,980	6.04	0.0310
	Low R&D performance	1,556	20,842	6.95	
PERSOC_dum	High R&D performance	75	4,161	1.77	0.0000
	Low R&D performance	1,193	21,205	5.33	
Export performance					
TFP_18	High exporters	725	12,085	5.66	0.0000
	Low exporters	1,087	12,737	7.86	
PERSOC_dum	High exporters	480	12,330	3.75	0.0000
	Low exporters	788	13,036	5.70	
Cooperation					

TFP_18	Cooperated with customers	253	4,202	5.68	0.0011
	Did not cooperate with customers	1,559	20,620	7.03	
PERSOC_sum	Cooperated with customers	149	4,306	3.34	0.0000
	Did not cooperate with customers	1,119	21,060	5.05	
TFP_18	Cooperated with competitors	42	626	6.29	0.5913
	Did not cooperate with competitors	1,770	24,196	6.82	
PERSOC_dum	Cooperated with competitors	22	646	3.29	0.0704
	Did not cooperate with competitors	1,246	24,720	4.80	
TFP_18	Cooperated with suppliers	350	4,996	6.55	0.4062
	Did not cooperate with suppliers	1,462	19,826	6.87	
PERSOC_dum	Cooperated with suppliers	212	5,134	3.97	0.0024
	Did not cooperate with suppliers	1,056	20,232	4.96	
TFP_18	Cooperated with	407	5,634	6.74	0.8281

	universities or technological centers				
	Did not cooperate with universities or technological centers	1,405	19,188	6.82	
PERSOC_dum	Cooperated with universities or technological centers	231	5,810	3.82	0.0001
	Did not cooperate with universities or technological centers	1,037	19,556	5.04	
Firm activity					
TFP_18	Meat products	93	840	9.97	n/a
	Food and tobacco	245	2,579	8.68	
	Beverage	50	501	9.07	
	Textiles and clothing	77	1,782	4.14	
	Leather, fur and footwear	71	689	9.34	
	Timber	44	884	4.74	
	Paper	87	946	8.42	
	Printing	76	1,129	6.31	
	Chemicals and pharmaceuticals	146	1,678	8.00	
	Plastic and rubber products	107	1,335	7.42	

	Nonmetal mineral products	97	1,822	5.05	
	Basic metal products	61	815	6.96	
	Fabricated metal products	220	3,192	6.45	
	Machinery and equipment	105	1,500	6.54	
	Computer products, electronics and optical	32	500	6.02	
	Electric materials and accessories	91	1,013	8.24	
	Vehicles and accessories	73	1,246	5.53	
	Other transport equipment	49	524	8.55	
	Furniture	63	1,226	4.89	
	Other manufacturing	25	621	3.87	
PERSOC_dum	Meat products	79	854	8.47	n/a
	Food and tobacco	179	2,645	6.34	
	Beverage	23	528	4.17	
	Textiles and clothing	65	1,794	3.50	
	Leather, fur and footwear	61	699	8.03	
	Timber	34	894	3.66	
	Paper	60	973	5.81	
	Printing	59	1,146	4.90	

	Chemicals and pharmaceuticals	96	1,728	5.26	
	Plastic and rubber products	88	1,354	6.10	
	Nonmetal mineral products	64	1,855	3.34	
	Basic metal products	35	841	4.00	
	Fabricated metal products	179	3,233	5.25	
	Machinery and equipment	77	1,528	4.80	
	Computer products, electronics and optical	27	505	5.08	
	Electric materials and accessories	36	1,068	3.26	
	Vehicles and accessories	33	1,286	2.50	
	Other transport equipment	9	564	1.57	
	Furniture	49	1,240	3.80	
	Other manufacturing	15	631	2.32	

In Table A4.2, we can observe that only very small differences appear in the pattern of missing values when matched against firm characteristics. The percentage of missing values in all groups ranges up to 10 percent at most. Although the proportion comparison tests mainly, but not uniformly,reject the null hypothesis that differences in proportions are zero, these results reflect a very large sample size. While there may be some bias for some variables mainly associated with cooperation with customers and suppliers, this does not affect the main purpose of the study, which is to compare two approaches to estimate the effects of tax credits.

Table A4.3 explores the patterns of missing values once attrition is accounted for and year 2001 is excluded. The first row shows the variables explored (the names of the variables are listed at the bottom of the table). The first column shows the percentage of observations belonging to a specific pattern. Finally, the main body of the table shows patterns of missing values – 1 indicates that there are no missing values. 93% of the data is complete and contains no missing values, while for an additional 3% the only missing values are for the variables TFP_18 and PERSOC_sum, discussed above. No apparent pattern emerges in terms of missing values from this table.

Table A5.3 Pattern of missing values once attrition is accounted for (idsit = 1) and year 2001 is excluded

Missing-value patterns
(1 means complete)

	Pattern												
Percent	1	2	3	4	5	6	7	8	9	10	11	12	13
93%	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	0	0
2	1	1	1	1	1	1	1	1	1	1	1	1	0
2	1	1	1	1	1	1	1	1	1	1	0	0	0
<1	1	1	1	1	1	1	1	0	1	1	1	1	0
<1	1	1	1	1	1	1	1	1	0	0	1	1	1
<1	1	1	1	1	1	1	1	1	1	1	1	0	1
<1	1	1	1	1	1	0	1	1	1	1	1	1	1
<1	1	1	1	1	1	1	0	1	0	0	1	1	1
<1	1	1	1	1	0	1	1	1	1	1	1	1	1
<1	1	1	1	1	1	1	1	1	1	1	0	1	0
<1	1	1	1	1	1	1	1	1	1	1	0	1	1
<1	1	1	1	1	1	1	1	1	0	0	1	1	0
<1	1	1	1	1	1	1	0	1	1	0	1	1	1
<1	1	1	1	1	1	1	1	1	0	0	1	0	0
<1	1	1	0	0	1	1	1	1	1	1	1	1	1
<1	1	1	1	1	1	1	1	0	1	1	0	0	0
<1	0	0	1	0	1	1	0	1	0	0	1	1	1
<1	1	0	0	0	0	1	1	1	1	1	1	1	1
<1	1	1	1	1	1	0	1	1	1	1	1	1	0
<1	1	1	1	1	1	1	0	0	0	0	1	1	0
<1	1	1	1	1	1	1	0	1	0	0	1	1	0
<1	1	1	1	1	1	1	1	1	0	0	0	0	0
<1	1	1	1	1	1	1	1	1	0	0	0	1	0
<1	0	0	0	0	1	1	0	1	0	0	0	1	0
<1	0	0	0	0	1	1	1	1	1	1	1	1	1
<1	0	0	1	1	1	1	1	1	1	1	1	1	1
<1	1	0	0	0	1	1	1	1	1	1	1	1	1
<1	1	0	1	0	1	1	1	1	1	1	1	1	1
<1	1	1	1	1	0	1	1	1	1	1	1	1	0
<1	1	1	1	1	1	0	0	1	0	0	1	1	1
<1	1	1	1	1	1	0	1	0	1	1	1	1	0
<1	1	1	1	1	1	0	1	1	1	1	1	0	0
<1	1	1	1	1	1	1	0	1	0	0	0	0	0
<1	1	1	1	1	1	1	0	1	0	1	1	1	0
<1	1	1	1	1	1	1	0	1	0	1	1	1	1
<1	1	1	1	1	1	1	1	0	1	1	1	0	0
100%													

Variables are (1) **FPIDCA2015prices1** (2) **FPIDES2015prices1** (3) **FPIDOT2015prices1** (4) **FPIDTO2015prices1** (5) **PCAEXT** (6) **VEXPOR2015prices**
(7) **GEID2015prices** (8) **LP2015prices** (9) **GTID2015prices** (10) **GIID2015prices** (11) **EMPIDT** (12) **PERSOC_dum** (13) **TFP_18**

Next, we explore whether there are any differences in means when using the dataset when attrition is accounted for (i.e. when the value of idsit variable is equal to 1) and squared dataset (i.e. when the data is available for all 16 years) for a number of variables that are going to be utilized in the empirical investigation in Chapter 8. In Figure A4.1, sample denoted "x" is a squared dataset, while sample denoted "y" is a full sample when attrition is accounted for. Two sample t tests with equal variances for all variables show statistically significant differences in mean between two samples for all variables explored, as demonstrated in Figure A4.1. However, this result is expected, given that the squared dataset contains only firms which are surviving, while the sample when attrition is accounted for also contains less successful firms (i.e. firms that failed) or exited the sample for other reasons, including mergers and acquisitions. The reduction in the number of observations is very large, justifying the non-use of the squared dataset.

Figure A5.1a Two-sample t test with equal variances for real R&D expenditures ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,806     2285975    216885.8    1.79e+07     1860811     2711139
       y |  28,241     1150528    75180.49    1.26e+07     1003171     1297886
---------+--------------------------------------------------------------------
combined |  35,047     1371028    73820.78    1.38e+07     1226337     1515719
---------+--------------------------------------------------------------------
    diff |             1135446    186517.7                769865.5     1501027
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =   6.0876
Ho: diff = 0                                     degrees of freedom =    35045

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Figure A5.1b Two-sample t test with equal variances for real value of tax deductions for technological innovations ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,832    10688.79     1672.32    138227.1    7410.524    13967.06
       y |  28,355    6908.843    660.2819    111184.5    5614.659    8203.027
---------+--------------------------------------------------------------------
combined |  35,187    7642.768    623.3695    116932.9    6420.944    8864.591
---------+--------------------------------------------------------------------
    diff |            3779.948    1575.831                691.2699    6868.627
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =   2.3987
Ho: diff = 0                                     degrees of freedom =    35185

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9918         Pr(|T| > |t|) = 0.0165          Pr(T > t) = 0.0082
```

Figure A5.1c Two-sample t test with equal variances for real value of tax deductions for R&D applied to company income tax ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,832    177541.2    16633.63     1374868    144934.1    210148.3
       y |  28,355    83704.43    5157.646    868493.1     73595.2    93813.67
---------+--------------------------------------------------------------------
combined |  35,187      101924    5267.116    988016.1    91600.31    112247.7
---------+--------------------------------------------------------------------
    diff |            93836.76    13306.56                67755.48      119918
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =   7.0519
Ho: diff = 0                                     degrees of freedom =    35185

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Figure A5.1d Two-sample t test with equal variances for total factor productivity ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,279    7.096922    .0115471    .9149918    7.074285    7.119558
       y |  24,822    7.133084    .0059867    .9432096     7.12135    7.144818
---------+--------------------------------------------------------------------
combined |  31,101    7.125783     .005317    .9376789    7.115362    7.136205
---------+--------------------------------------------------------------------
    diff |           -.0361625    .0132444               -.0621221    -.010203
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =  -2.7304
Ho: diff = 0                                     degrees of freedom =    31099

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0032         Pr(|T| > |t|) = 0.0063          Pr(T > t) = 0.9968
```

Figure A5.1e Two-sample t test with equal variances for labour productivity ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,813    36389.91     639.764    52806.69    35135.77    37644.05
       y |  28,247    31944.37     202.831     34089.5    31546.81    32341.93
---------+--------------------------------------------------------------------
combined |  35,060    32808.25    205.5405    38486.05    32405.38    33211.11
---------+--------------------------------------------------------------------
    diff |            4445.538    518.9268                3428.426    5462.651
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =   8.5668
Ho: diff = 0                                     degrees of freedom =    35058

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Figure A5.1f Two-sample t test with equal variances for age ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,405    35.16643    .2843148    22.75407    34.60908    35.72378
       y |  25,340    29.89925    .1263226    20.10872    29.65165    30.14685
---------+--------------------------------------------------------------------
combined |  31,745    30.96198    .1166135    20.77717    30.73341    31.19055
---------+--------------------------------------------------------------------
    diff |            5.267182    .2890737                4.700587    5.833778
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =  18.2209
Ho: diff = 0                                     degrees of freedom =    31743

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Figure A5.1g Two-sample t test with equal variances for dummy variable indicating cooperation with customers ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,832    .2333138    .0051173    .4229712    .2232824    .2433452
       y |  28,355     .168718    .0022241    .3745093    .1643588    .1730773
---------+--------------------------------------------------------------------
combined |  35,187    .1812601    .0020537     .385239    .1772348    .1852855
---------+--------------------------------------------------------------------
    diff |            .0645958    .0051806                .0544416    .0747499
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =  12.4687
Ho: diff = 0                                     degrees of freedom =    35185

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Figure A5.1h Two-sample t test with equal variances for dummy variable indicating cooperation with competitors ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. local obs2=r(N)

. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,832    .0393735    .0023531    .1944963    .0347608    .0439863
       y |  28,355    .0254629    .0009355     .157529    .0236292    .0272965
---------+--------------------------------------------------------------------
combined |  35,187    .0281638     .000882     .165443    .0264351    .0298925
---------+--------------------------------------------------------------------
    diff |            .0139107    .0022285                .0095427    .0182786
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =   6.2421
Ho: diff = 0                                     degrees of freedom =    35185

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Figure A5.1i Two-sample t test with equal variances for dummy variable indicating cooperation with suppliers ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,832     .264637    .0053375     .441172    .2541739    .2751001
       y |  28,355    .2021513     .002385    .4016116    .1974766     .206826
---------+--------------------------------------------------------------------
combined |  35,187    .2142837    .0021875    .4103303    .2099962    .2185712
---------+--------------------------------------------------------------------
    diff |            .0624857    .0055202                 .051666    .0733054
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =  11.3195
Ho: diff = 0                                     degrees of freedom =    35185

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Figure A5.1j Two-sample t test with equal variances for dummy variable indicating cooperation with universities/technological centres ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,832    1.711358    .0054825    .4531641    1.700611    1.722106
       y |  28,355    1.773197    .0024869    .4187715    1.768322    1.778071
---------+--------------------------------------------------------------------
combined |  35,187     1.76119    .0022729    .4263623    1.756735    1.765645
---------+--------------------------------------------------------------------
    diff |           -.0618387    .0057368               -.073083   -.0505943
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t = -10.7793
Ho: diff = 0                                     degrees of freedom =    35185

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Figure A5.1k Two-sample t test with equal variances for real R&D funding provided by central government ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,830    174746.5    34913.21     2885361    106305.7    243187.2
       y |  28,346    104894.4     12935.7     2177889    79539.83      130249
---------+--------------------------------------------------------------------
combined |  35,176    118457.3    12435.04     2332225    94084.27    142830.4
---------+--------------------------------------------------------------------
    diff |            69852.03    31434.97                8238.503    131465.6
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =   2.2221
Ho: diff = 0                                     degrees of freedom =    35174

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9869         Pr(|T| > |t|) = 0.0263          Pr(T > t) = 0.0131
```

Figure A5.1l Two-sample t test with equal variances for real R&D funding provided by regional governments ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,832    35354.63    7242.766    598657.5    21156.56    49552.71
       y |  28,350    18441.18    2300.564    387356.6    13931.96    22950.39
---------+--------------------------------------------------------------------
combined |  35,182     21725.6    2327.192    436508.3    17164.23    26286.97
---------+--------------------------------------------------------------------
    diff |            16913.46     5882.44                5383.692    28443.23
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =   2.8752
Ho: diff = 0                                     degrees of freedom =    35180

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9980         Pr(|T| > |t|) = 0.0040          Pr(T > t) = 0.0020
```

Figure A5.1l Two-sample t test with equal variances for real R&D funding provided by other agencies ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,829    19403.28    2935.599    242591.3    13648.59    25157.97
       y |  28,345    10476.88     1000.15    168384.9    8516.539    12437.22
---------+--------------------------------------------------------------------
combined |  35,174    12209.93    987.2881    185163.2    10274.82    14145.05
---------+--------------------------------------------------------------------
    diff |            8926.401    2495.606                4034.934    13817.87
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =   3.5768
Ho: diff = 0                                     degrees of freedom =    35172

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9998         Pr(|T| > |t|) = 0.0003          Pr(T > t) = 0.0002
```

Figure A5.1m Two-sample t test with equal variances for real R&D funding provided by administration at all levels ("x" is squared dataset, "y" full sample when attrition is accounted for)

```
. ttesti  `obs1' `mean1' `sd1' `obs2' `mean2' `sd2'

Two-sample t test with equal variances
------------------------------------------------------------------------------
         |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       x |   6,829    229545.4    38345.72     3168805    154375.8    304714.9
       y |  28,342    133845.5    14190.08     2388911    106032.3    161658.7
---------+--------------------------------------------------------------------
combined |  35,171    152427.1    13646.37     2559232    125679.8    179174.5
---------+--------------------------------------------------------------------
    diff |            95699.85    34495.85                28086.91    163312.8
------------------------------------------------------------------------------
    diff = mean(x) - mean(y)                                      t =   2.7742
Ho: diff = 0                                     degrees of freedom =    35169

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9972         Pr(|T| > |t|) = 0.0055          Pr(T > t) = 0.0028
```

Appendix 6 – Endogeneity check

Stata/SE 17.0 - C:\Users\et22\Desktop\PhD work\All datafiles merged - Unbalanced panel - v09032021.dta

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```
Iteration 4:   log likelihood = -27440.463
Iteration 5:   log likelihood = -27440.462

Tobit regression                                        Number of obs     =     17,023
                                                               Uncensored =      6,059
Limits: Lower =    0                                        Left-censored =     10,964
        Upper = +inf                                       Right-censored =          0

                                                        LR chi2(27)       =   11334.20
                                                        Prob > chi2       =     0.0000
Log likelihood = -27440.462                             Pseudo R2         =     0.1712
```

GTIDnew	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
TFP_18	.6598148	.1646181	4.01	0.000	.3371463	.9824833
VEXPORnew	.01224	.0007457	16.41	0.000	.0107784	.0137016
PERTOTnew	8.879734	3.19894	2.78	0.006	2.609481	15.14999
NACECLIO	.0110978	.0295035	0.38	0.707	-.0467321	.0689276
DEDITnew	-.0990744	.0114116	-8.68	0.000	-.1214424	-.0767064
EMPIDT	.1270075	.0023591	53.84	0.000	.1223834	.1316316
FPIDCAnew	-.5891695	.302517	-1.95	0.051	-1.182134	.0037952
FPIDESnew	1.391583	.0726735	19.15	0.000	1.249135	1.53403
FPIDOTnew	1.763463	.6223756	2.83	0.005	.5435419	2.983383
CUCT_dum	6.127284	.3605152	17.00	0.000	5.420636	6.833931
CTCO_dum	-1.74802	.7803776	-2.24	0.025	-3.27764	-.2183987
CTCL_dum	4.985252	.4285933	11.63	0.000	4.145164	5.825339
CTPR_dum	9.049368	.4217616	21.46	0.000	8.222671	9.876064
PERSOC_dum	-4.447305	.3279914	-13.56	0.000	-5.090202	-3.804408
OLS_res	1.15e-07	1.46e-07	0.79	0.431	-1.72e-07	4.02e-07
year_dum2	0	(omitted)				
year_dum3	0	(omitted)				
year_dum4	1.134321	.7949655	1.43	0.154	-.4238935	2.692536
year_dum5	1.841572	.7971794	2.31	0.021	.2790174	3.404126
year_dum6	1.208999	.8164829	1.48	0.139	-.3913924	2.809389
year_dum7	.5716317	.8357109	0.68	0.494	-1.066448	2.209712
year_dum8	.6361027	.7763836	0.82	0.413	-.8856895	2.157895
year_dum9	.5893843	.7731797	0.76	0.446	-.9261281	2.104897
year_dum10	.8798932	.7764755	1.13	0.257	-.6420791	2.401866
year_dum11	.2544754	.7895035	0.32	0.747	-1.293033	1.801984
year_dum12	.4636666	.7865885	0.59	0.556	-1.078128	2.005462
year_dum13	-.6274723	.7938095	-0.79	0.429	-2.183421	.9284765
year_dum14	-.0791762	.8067823	-0.10	0.922	-1.660553	1.502201
year_dum15	.4145083	.7959854	0.52	0.603	-1.145705	1.974722
year_dum16	0	(omitted)				
_cons	-20.85452	1.315435	-15.85	0.000	-23.43291	-18.27614
var(e.GTIDnew)	212.7643	3.851997			205.3464	220.4502

Appendix 7 – Investigation 1 regression coefficients

Viewer - view "C:\Users\et22\Desktop\PhD work\Final estimates - Chapter 7 - part 1.smcl"

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```
Random-effects tobit regression                 Number of obs     =    22,908
                                                   Uncensored     =     8,029
Limits: Lower =      0                           Left-censored    =    14,879
        Upper =   +inf                          Right-censored    =         0

Group variable: Col1                            Number of groups  =     3,313
Random effects u_i ~ Gaussian                   Obs per group:
                                                              min =         1
                                                              avg =       6.9
                                                              max =        15

Integration method: mvaghermite                 Integration pts.  =        12

                                                Wald chi2(175)    =  13954.89
Log likelihood = -27198.011                     Prob > chi2       =    0.0000
```

lnGTIDnew2	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lagGTID	.6484182	.0138287	46.89	0.000	.6213146	.6755219
TFP2	-.1468129	.0994651	-1.48	0.140	-.3417609	.0481352
VEXPOR2	-.0003998	.0004059	-0.98	0.325	-.0011953	.0003957
DEDID2	7.078691	2.320477	3.05	0.002	2.530641	11.62674
NACECLIO						
2	.8774798	.6584013	1.33	0.183	-.4129631	2.167923
3	1.285324	.9008752	1.43	0.154	-.4803594	3.051006
4	.3197399	.695087	0.46	0.646	-1.042606	1.682085
5	-.0272329	.8295214	-0.03	0.974	-1.653065	1.598599
6	-.3055524	.8041849	-0.38	0.704	-1.881726	1.270621
7	.2277405	.7905519	0.29	0.773	-1.321713	1.777194

Viewer - view "C:\Users\et22\Desktop\PhD work\Final estimates - Chapter 7 - part 1.smcl"

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7	.2277405	.7905519	0.29	0.773	-1.321713	1.777194
8	-1.625325	.798626	-2.04	0.042	-3.190603	-.0600466
9	2.108866	.6810564	3.10	0.002	.7740201	3.443712
10	1.333671	.6983057	1.91	0.056	-.0349828	2.702325
11	1.125741	.6951133	1.62	0.105	-.2366556	2.488138
12	1.088676	.7989942	1.36	0.173	-.4773234	2.654676
13	-.1532662	.6506444	-0.24	0.814	-1.428506	1.121973
14	.8201974	.7013601	1.17	0.242	-.5544431	2.194838
15	.7824811	.8242357	0.95	0.342	-.8329911	2.397953
16	.9969055	.7420009	1.34	0.179	-.4573895	2.4512
17	1.421935	.6885212	2.07	0.039	.0724577	2.771411
18	.9755366	.8401545	1.16	0.246	-.6711361	2.622209
19	-.4794968	.773917	-0.62	0.536	-1.996346	1.037353
20	-.0288434	.9043999	-0.03	0.975	-1.801435	1.743748
NACECLIO#c.DEDID2						
2	-3.80536	2.729048	-1.39	0.163	-9.154196	1.543475
3	.3480271	3.807291	0.09	0.927	-7.114126	7.81018
4	4.23675	7.368115	0.58	0.565	-10.20449	18.67799
5	29.56561	32.1892	0.92	0.358	-33.52406	92.65529
6	9.729391	11.65521	0.83	0.404	-13.1144	32.57318
7	-1.647241	4.938192	-0.33	0.739	-11.32592	8.031438
8	3.282528	11.26955	0.29	0.771	-18.80538	25.37044
9	-7.111772	2.322521	-3.06	0.002	-11.66383	-2.559714
10	-7.123997	2.400793	-2.97	0.003	-11.82946	-2.41853
11	-6.745486	2.338584	-2.88	0.004	-11.32903	-2.161947
12	-4.320329	2.460712	-1.76	0.079	-9.143237	.5025785
13	-6.248629	2.443896	-2.56	0.011	-11.03858	-1.45868
14	-6.515935	2.509664	-2.60	0.009	-11.43479	-1.597085
15	-6.986132	2.32675	-3.00	0.003	-11.54648	-2.425785
16	-6.597586	2.35125	-2.81	0.005	-11.20595	-1.98922
17	-7.036441	2.32115	-3.03	0.002	-11.58581	-2.487071
18	-7.107443	2.321941	-3.06	0.002	-11.65836	-2.556522

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12	-4.320329	2.460712	-1.76	0.079	-9.143237	.5025785
13	-6.248629	2.443896	-2.56	0.011	-11.03858	-1.45868
14	-6.515935	2.509664	-2.60	0.009	-11.43479	-1.597085
15	-6.986132	2.32675	-3.00	0.003	-11.54648	-2.425785
16	-6.597586	2.35125	-2.81	0.005	-11.20595	-1.98922
17	-7.036441	2.32115	-3.03	0.002	-11.58581	-2.487071
18	-7.107443	2.321941	-3.06	0.002	-11.65836	-2.556522
19	-4.343591	3.917661	-1.11	0.268	-12.02207	3.334883
20	-4.40323	7.517642	-0.59	0.558	-19.13754	10.33108
Subsidies2	3.114006	1.72385	1.81	0.071	-.264678	6.49269
c.DEDID2#c.Subsidies2	-2.362446	2.608944	-0.91	0.365	-7.475882	2.750989
NACECLIO#c.Subsidies2						
2	-2.706155	1.820176	-1.49	0.137	-6.273635	.8613249
3	2.676851	2.525741	1.06	0.289	-2.27351	7.627212
4	-1.544857	2.013636	-0.77	0.443	-5.491511	2.401797
5	8.499655	10.83355	0.78	0.433	-12.7337	29.73301
6	30.03267	9.979291	3.01	0.003	10.47362	49.59172
7	-.943576	1.956975	-0.48	0.630	-4.779176	2.892024
8	2.614102	3.236093	0.81	0.419	-3.728524	8.956729
9	-3.083582	1.730315	-1.78	0.075	-6.474937	.3077735
10	-2.305963	2.034414	-1.13	0.257	-6.293342	1.681416
11	-2.140786	1.854881	-1.15	0.248	-5.776286	1.494713
12	-3.049535	1.744438	-1.75	0.080	-6.468571	.3695008
13	-2.109652	1.847837	-1.14	0.254	-5.731347	1.512042
14	-3.100735	1.795971	-1.73	0.084	-6.620775	.4193038
15	-3.248987	1.728904	-1.88	0.060	-6.637577	.1396026
16	-3.163653	1.835086	-1.72	0.085	-6.760356	.4330493
17	-3.114393	1.723968	-1.81	0.071	-6.493309	.2645221
18	-3.08979	1.724293	-1.79	0.073	-6.469341	.2897622

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18	-3.08979	1.724293	-1.79	0.073	-6.469341	.2897622
19	-.1060346	5.759258	-0.02	0.985	-11.39397	11.1819
20	-4.499356	5.935327	-0.76	0.448	-16.13238	7.133672
NACECLIO#c.DEDID2#c.Subsidies2						
2	1.742084	2.853119	0.61	0.541	-3.849928	7.334095
3	-9.936026	12.61435	-0.79	0.431	-34.65969	14.78764
4	105.8659	55.56066	1.91	0.057	-3.031037	214.7627
5	-540.3698	503.7547	-1.07	0.283	-1527.711	446.9712
6	291.0068	85.25181	3.41	0.001	123.9163	458.0972
7	-4.171907	8.946335	-0.47	0.641	-21.7064	13.36259
8	-70.58094	65.7915	-1.07	0.283	-199.5299	58.36802
9	2.358024	2.609035	0.90	0.366	-2.75559	7.471638
10	2.447779	2.915998	0.84	0.401	-3.267472	8.163031
11	2.406049	2.630839	0.91	0.360	-2.7503	7.562398
12	1.897823	2.763345	0.69	0.492	-3.518234	7.313881
13	1.587413	3.750832	0.42	0.672	-5.764082	8.938909
14	2.033709	2.936329	0.69	0.489	-3.72139	7.788809
15	2.345122	2.609049	0.90	0.369	-2.76852	7.458764
16	2.595138	2.846168	0.91	0.362	-2.983249	8.173526
17	2.362447	2.608948	0.91	0.365	-2.750997	7.475891
18	2.361327	2.608945	0.91	0.365	-2.75211	7.474765
19	-8.537864	60.54042	-0.14	0.888	-127.1949	110.1192
20	2.044515	9.453489	0.22	0.829	-16.48398	20.57301
PERTOT2	10.27137	3.016666	3.40	0.001	4.358815	16.18393
DEDIT2	.0047597	.0033112	1.44	0.151	-.0017301	.0112496
EMPIDT2	.0014304	.0015935	0.90	0.369	-.0016927	.0045535
CUCT2	1.49412	.1450859	10.30	0.000	1.209757	1.778483
CTCO2	-.0403466	.2672928	-0.15	0.880	-.5642308	.4835375
CTCL2	2.55596	.161147	15.86	0.000	2.240118	2.871802
CTPR2	4.138983	.1485052	27.87	0.000	3.847918	4.430047

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EMPIDT2	.0014304	.0015935	0.90	0.369	-.0016927	.0045535
CUCT2	1.49412	.1450859	10.30	0.000	1.209757	1.778483
CTCO2	-.0403466	.2672928	-0.15	0.880	-.5642308	.4835375
CTCL2	2.55596	.161147	15.86	0.000	2.240118	2.871802
CTPR2	4.138983	.1485052	27.87	0.000	3.847918	4.430047
PERSOC2	.1508443	.1968038	0.77	0.443	-.234884	.5365726
year_dum3	-.5888321	.2316882	-2.54	0.011	-1.042933	-.1347317
year_dum4	-.1475766	.2311851	-0.64	0.523	-.600691	.3055379
year_dum5	-.2536704	.2359055	-1.08	0.282	-.7160366	.2086959
year_dum6	-.3280986	.2220869	-1.48	0.140	-.763381	.1071837
year_dum7	-.4701839	.2213428	-2.12	0.034	-.9040079	-.0363599
year_dum8	-.1707177	.2213571	-0.77	0.441	-.6045695	.2631342
year_dum9	-.4144365	.2240225	-1.85	0.064	-.8535125	.0246394
year_dum10	-.0975895	.2242826	-0.44	0.663	-.5371754	.3419963
year_dum11	-.9977066	.229042	-4.36	0.000	-1.446621	-.5487926
year_dum12	-.7520566	.2355978	-3.19	0.001	-1.21382	-.2902935
year_dum13	-1.092077	.2433702	-4.49	0.000	-1.569074	-.6150803
year_dum14	-.4337715	.2406952	-1.80	0.072	-.9055254	.0379823
year_dum15	-.6489885	.2454568	-2.64	0.008	-1.130075	-.167902
year_dum16	-.4678992	.2511648	-1.86	0.062	-.9601732	.0243747
lnGTIDnew2_IN	.4079786	.0208991	19.52	0.000	.3670171	.4489401
TFP_MI	.4094952	.1789217	2.29	0.022	.0588151	.7601753
VEXPORnew_MI	-.0006416	.0009876	-0.65	0.516	-.0025772	.001294
PERTOTnew_MI	2.941138	3.068447	0.96	0.338	-3.072907	8.955183
DEDIDnew_MI	50.42601	16.91516	2.98	0.003	17.27289	83.57912
NACECLIO#c.DEDIDnew_MI						
2	-50.45316	16.95316	-2.98	0.003	-83.68075	-17.22557
3	-60.60245	20.51532	-2.95	0.003	-100.8117	-20.39317
4	-27.89132	19.52487	-1.43	0.153	-66.15936	10.37671
5	-10.32511	89.95686	-0.11	0.909	-186.6373	165.9871
6	-59.88134	41.24666	-1.45	0.147	-140.7233	20.96063

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NACECLIO#c.DEDIDnew_MI						
2	-50.45316	16.95316	-2.98	0.003	-83.68075	-17.22557
3	-60.60245	20.51532	-2.95	0.003	-100.8117	-20.39317
4	-27.89132	19.52487	-1.43	0.153	-66.15936	10.37671
5	-10.32511	89.95686	-0.11	0.909	-186.6373	165.9871
6	-59.88134	41.24666	-1.45	0.147	-140.7233	20.96063
7	-48.53765	19.84031	-2.45	0.014	-87.42394	-9.651347
8	125.3482	61.48537	2.04	0.041	4.839074	245.8573
9	-50.85629	16.92538	-3.00	0.003	-84.02942	-17.68316
10	-48.6895	16.92961	-2.88	0.004	-81.87091	-15.50808
11	-50.02861	17.44601	-2.87	0.004	-84.22215	-15.83506
12	-49.98669	17.58888	-2.84	0.004	-84.46026	-15.51311
13	-46.99729	17.02828	-2.76	0.006	-80.3721	-13.62247
14	-48.69615	17.36826	-2.80	0.005	-82.73731	-14.65499
15	-51.02026	16.94949	-3.01	0.003	-84.24065	-17.79987
16	-51.21193	16.94038	-3.02	0.003	-84.41446	-18.00939
17	-50.91106	16.95057	-3.00	0.003	-84.13357	-17.68854
18	-51.29555	16.95234	-3.03	0.002	-84.52154	-18.06957
19	-16.43043	23.95004	-0.69	0.493	-63.37165	30.51078
20	-41.86948	23.09204	-1.81	0.070	-87.12906	3.390091
Subsidies_MI	35.6522	8.52251	4.18	0.000	18.94839	52.35601
c.DEDIDnew_MI#c.Subsidies_MI	-370.7408	105.2438	-3.52	0.000	-577.0149	-164.4667
NACECLIO#c.Subsidies_MI						
2	-25.61874	9.554343	-2.68	0.007	-44.34491	-6.892571
3	-23.47177	29.09159	-0.81	0.420	-80.49023	33.54669
4	-31.73792	9.988117	-3.18	0.001	-51.31427	-12.16157
5	-19.82242	30.74628	-0.64	0.519	-80.08402	40.43918
6	27.84082	37.98677	0.73	0.464	-46.61188	102.2935

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Subsidies_MI	35.6522	8.52251	4.18	0.000	18.94839	52.35601
c.DEDIDnew_MI#c.Subsidies_MI	-370.7408	105.2438	-3.52	0.000	-577.0149	-164.4667
NACECLIO#c.Subsidies_MI						
2	-25.61874	9.554343	-2.68	0.007	-44.34491	-6.892571
3	-23.47177	29.09159	-0.81	0.420	-80.49023	33.54669
4	-31.73792	9.988117	-3.18	0.001	-51.31427	-12.16157
5	-19.82242	30.74628	-0.64	0.519	-80.08402	40.43918
6	27.84082	37.98677	0.73	0.464	-46.61188	102.2935
7	-35.51309	10.2464	-3.47	0.001	-55.59567	-15.43052
8	-21.11619	15.34834	-1.38	0.169	-51.19838	8.966003
9	-37.17815	8.613253	-4.32	0.000	-54.05981	-20.29648
10	-38.78128	9.077102	-4.27	0.000	-56.57208	-20.99049
11	-34.4539	9.100642	-3.79	0.000	-52.29083	-16.61697
12	-37.13127	8.749228	-4.24	0.000	-54.27944	-19.9831
13	-27.55029	9.3475	-2.95	0.003	-45.87105	-9.229524
14	-35.74112	8.644876	-4.13	0.000	-52.68477	-18.79747
15	-36.28649	8.536946	-4.25	0.000	-53.01859	-19.55438
16	-36.13438	8.56947	-4.22	0.000	-52.93024	-19.33853
17	-35.66497	8.534049	-4.18	0.000	-52.3914	-18.93854
18	-35.73946	8.523573	-4.19	0.000	-52.44535	-19.03356
19	-23.31408	32.69289	-0.71	0.476	-87.39098	40.76281
20	4.971471	29.71622	0.17	0.867	-53.27125	63.21419
NACECLIO#c.DEDIDnew_MI#c.Subsidies_MI						
2	338.9056	107.6234	3.15	0.002	127.9675	549.8436
3	317.7628	192.7973	1.65	0.099	-60.11296	695.6386
4	264.6127	130.0429	2.03	0.042	9.733195	519.4922
5	-375.8192	2007.818	-0.19	0.852	-4311.07	3559.431
6	180.2233	150.2833	1.20	0.230	-114.3265	474.7731
7	369.0413	105.591	3.50	0.000	162.0868	575.9959

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NACECLIO#c.DEDIDnew_MI#c.Subsidies_MI						
2	338.9056	107.6234	3.15	0.002	127.9675	549.8436
3	317.7628	192.7973	1.65	0.099	-60.11296	695.6386
4	264.6127	130.0429	2.03	0.042	9.733195	519.4922
5	-375.8192	2007.818	-0.19	0.852	-4311.07	3559.431
6	180.2233	150.2833	1.20	0.230	-114.3265	474.7731
7	369.0413	105.591	3.50	0.000	162.0868	575.9959
8	8.344852	497.8699	0.02	0.987	-967.4621	984.1518
9	370.91	105.2443	3.52	0.000	164.635	577.185
10	371.9066	105.3018	3.53	0.000	165.5188	578.2943
11	370.0915	105.2422	3.52	0.000	163.8206	576.3624
12	372.059	105.609	3.52	0.000	165.0691	579.0488
13	339.4551	106.3534	3.19	0.001	131.0061	547.904
14	368.5152	105.3693	3.50	0.000	161.9952	575.0352
15	370.8012	105.2441	3.52	0.000	164.5266	577.0758
16	369.1568	105.2676	3.51	0.000	162.836	575.4775
17	370.7491	105.2438	3.52	0.000	164.4749	577.0232
18	370.7704	105.2428	3.52	0.000	164.4983	577.0426
19	167.2999	394.455	0.42	0.671	-605.8177	940.4175
20	37.74815	289.559	0.13	0.896	-529.777	605.2733
DEDITnew_MI	.0165235	.0265595	0.62	0.534	-.0355322	.0685793
EMPIDT_MI	-.0003116	.0050903	-0.06	0.951	-.0102883	.0096652
CUCT_MI	2.423391	.3115757	7.78	0.000	1.812713	3.034068
CTCL_MI	1.865119	.3939865	4.73	0.000	1.092919	2.637318
CTCO_MI	-1.032376	.7900769	-1.31	0.191	-2.580898	.5161464
CTPR_MI	4.424501	.4035319	10.96	0.000	3.633593	5.215409
PERSOC_MI	-1.708273	.2179038	-7.84	0.000	-2.135356	-1.281189
_cons	-9.759241	1.436642	-6.79	0.000	-12.57501	-6.943476
/sigma_u	3.391645	.1016468	33.37	0.000	3.192421	3.590869
/sigma_e	4.233127	.038818	109.05	0.000	4.157045	4.309209

Appendix 8 – Combined effects derived from tobit estimation of R&D expenditures

Variable	Description	dy/dx	Delta-method standard errors	z	P > |z|	95% confidence interval	
lagGTID	Lagged value of dependent variable	.194	.005	35.73	0.000	.183	.205
lnGTIDnew2_IN	Initial condition	.122	.006	19.67	0.000	.110	.134
DEDIDnew_MI	Value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI) – between variation	5.659	1.693	3.34	0.001	2.340	8.977
DEDID2	Value of tax deductions for R&D applied to company income tax (in 1,000,000 Euros, deflated by CPI) – within variation	1.530	.476	3.21	0.001	.597	2.462
DEDITnew_MI	Value of tax deductions for technological innovations applied to the company income tax (in Euros, deflated	.005	.008	0.62	0.534	-.011	.021

	by CPI) – between variation						
DEDIT2	Value of tax deductions for technological innovations applied to the company income tax (in Euros, deflated by CPI) – within variation	.001	.001	1.44	0.151	-.0005	.003
Subsidies_MI	R&D subsidies provided by governments at all levels (in 1,000,000 Euros, deflated by CPI) – between variation	3.016	.963	3.13	0.002	1.129	4.903
Subsidies2	R&D subsidies provided by governments at all levels (in 1,000,000 Euros, deflated by CPI) – within variation	.935	.218	4.29	0.000	.508	1.362
VEXPORnew_MI	Exporting – between variation	-.0002	.0003	-0.65	0.516	-.0008	.0004
VEXPOR2	Exporting – within variation	-.0001	.0001	-0.98	0.325	-.0004	.0001
TFP_MI	Total factor productivity – between variation	.122	.054	2.29	0.022	.018	.227

TFP2	Total factor productivity – within variation	-.044	.03	-1.48	0.140	-.102	.014
PERSOC_MI	Dummy variable indicating whether a firm belongs to a corporate group (0 = Yes, 1 = No) – between variation	-.511	.066	-7.80	0.000	-.639	-.383
PERSOC2	Dummy variable indicating whether a firm belongs to a corporate group (0 = Yes, 1 = No) – within variation	.045	.059	0.77	0.443	-.070	.161
CUCT_MI	Dummy variable indicating whether a firm cooperated with universities and/or technological centres (0 = No, 1 = Yes) – between variation	.725	.093	7.77	0.000	.542	.908
CUCT2	Dummy variable indicating whether a firm cooperated with universities and/or technological centres (0 = No, 1 = Yes) – within variation	.447	.044	10.24	0.000	.361	.533

CTCL_MI	Dummy variable indicating whether a firm cooperated with customers (0 = No, 1 = Yes) – between variation	.558	.118	4.73	0.000	.327	.789
CTCL2	Dummy variable indicating whether a firm cooperated with customers (0 = No, 1 = Yes) – within variation	.765	.049	15.58	0.000	.668	.861
CTPR_MI	Dummy variable indicating whether a firm cooperated with suppliers (0 = No, 1 = Yes) – between variation	1.324	.121	10.95	0.000	1.087	1.560
CTPR2	Dummy variable indicating whether a firm cooperated with suppliers (0 = No, 1 = Yes) – within variation	1.238	.047	26.38	0.000	1.146	1.330
CTCO_MI	Dummy variable indicating whether a firm cooperated with competitors (0 = No, 1 = Yes) – between variation	-.309	.236	-1.31	0.191	-.772	.154
CTCO2	Dummy variable indicating whether a	-.012	.08	-0.15	0.880	-.169	.145

	firm cooperated with competitors (0 = No, 1 = Yes) – within variation						
PERTOTnew_MI	Total employment – between variation	.88	.918	0.96	0.338	-.919	2.679
PERTOT2	Total employment – within variation	3.072	.903	3.40	0.001	1.303	4.842
EMPIDT_MI	Total employment in R&D – between variation	-.00009	.002	-0.06	0.951	-.003	.003
EMPIDT2	Total employment in R&D – within variation	.0004	.0005	0.90	0.369	-.0005	.001

Note:A description of variables is provided in the Descriptive statistics section. All variables with the extension “_MI” represent between variation, whereas all variables with extension “2” represent within variation

Appendix 9 – Investigation 1 regression coefficients with dummy variable included in the estimation

```
Random-effects tobit regression                 Number of obs     =  22,908
                                                      Uncensored =   8,029
Limits: Lower =    0                              Left-censored =  14,879
        Upper = +inf                             Right-censored =       0

Group variable: Col1                            Number of groups  =   3,313
Random effects u_i ~ Gaussian                   Obs per group:
                                                              min =       1
                                                              avg =     6.9
                                                              max =      15

Integration method: mvaghermite                 Integration pts.  =      12

                                                Wald chi2(176)    = 3567.18
Log likelihood = -11437.188                     Prob > chi2       =  0.0000
```

lnGTIDnew2	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lagGTID	.0615331	.003621	16.99	0.000	.0544362	.0686301
dum	-20.21563	152.0383	-0.13	0.894	-318.2051	277.7739
TFP2	-.0582144	.0249123	-2.34	0.019	-.1070416	-.0093872
VEXPOR2	.0000393	.0000821	0.48	0.632	-.0001217	.0002002
DEDID2	.6600322	.4776779	1.38	0.167	-.2761993	1.596264
NACECLIO						
2	-.3535964	.260409	-1.36	0.175	-.8639887	.1567959
3	-.4740936	.3351022	-1.41	0.157	-1.130882	.1826946
4	-.4571346	.2786106	-1.64	0.101	-1.003201	.0889321
5	-.5488551	.3298943	-1.66	0.096	-1.195436	.0977259
6	-.721811	.3329066	-2.17	0.030	-1.374296	-.069326

7	-.3278395	.3031699	-1.08	0.280	-.9220416	.2663626
8	-.600208	.3427498	-1.75	0.080	-1.271985	.0715693
9	.1526962	.2608446	0.59	0.558	-.3585498	.6639421
10	.1687487	.2682195	0.63	0.529	-.3569519	.6944493
11	-.4208209	.2734538	-1.54	0.124	-.9567804	.1151387
12	-.0471677	.2990523	-0.16	0.875	-.6332994	.538964
13	-.3626875	.2597452	-1.40	0.163	-.8717788	.1464038
14	-.1252688	.2680126	-0.47	0.640	-.6505639	.4000263
15	.220964	.2876161	0.77	0.442	-.3427531	.7846811
16	-.1085452	.2735789	-0.40	0.692	-.6447501	.4276596
17	.4439525	.2621998	1.69	0.090	-.0699496	.9578546
18	.0799956	.3023627	0.26	0.791	-.5126245	.6726156
19	-1.180809	.3122024	-3.78	0.000	-1.792714	-.5689034
20	-.0179574	.3576831	-0.05	0.960	-.7190035	.6830886
NACECLIO#c.DEDID2						
2	.1898863	.5590004	0.34	0.734	-.9057344	1.285507
3	.7959457	.7745964	1.03	0.304	-.7222353	2.314127
4	3.501737	1.593977	2.20	0.028	.3775993	6.625875
5	3.929095	6.990396	0.56	0.574	-9.771829	17.63002
6	1.788417	2.426444	0.74	0.461	-2.967325	6.54416
7	-.1241968	1.037736	-0.12	0.905	-2.158123	1.909729
8	-1.432021	2.271027	-0.63	0.528	-5.883152	3.01911
9	-.6218335	.4780816	-1.30	0.193	-1.558856	.3151893
10	-.3348872	.4933721	-0.68	0.497	-1.301879	.6321045
11	-.5482319	.4811864	-1.14	0.255	-1.49134	.3948762
12	.2264789	.5076341	0.45	0.655	-.7684657	1.221423
13	.4336817	.5029983	0.86	0.389	-.5521768	1.41954
14	-.177939	.5159142	-0.34	0.730	-1.189112	.8332343
15	-.6492407	.478932	-1.36	0.175	-1.58793	.2894488

16	-.535685	.4836723	-1.11	0.268	-1.483665	.4122952
17	-.6216639	.4777874	-1.30	0.193	-1.55811	.3147822
18	-.6644899	.4779744	-1.39	0.164	-1.601303	.2723227
19	1.05031	.8142638	1.29	0.197	-.545618	2.646237
20	-2.330556	1.507973	-1.55	0.122	-5.286129	.6250166
Subsidies2	.5691404	.352299	1.62	0.106	-.121353	1.259634
c.DEDID2#c.Subsidies2	-.5138412	.5337183	-0.96	0.336	-1.55991	.5322275
NACECLIO#c.Subsidies2						
2	-.3781766	.3713401	-1.02	0.308	-1.10599	.3496366
3	.1040582	.5187252	0.20	0.841	-.9126244	1.120741
4	.0808101	.4116829	0.20	0.844	-.7260735	.8876937
5	4.439511	2.273143	1.95	0.051	-.015768	8.894791
6	3.204891	2.175379	1.47	0.141	-1.058773	7.468555
7	.0774723	.4053437	0.19	0.848	-.7169867	.8719313
8	-.3892711	.7185373	-0.54	0.588	-1.797578	1.019036
9	-.5405392	.3535701	-1.53	0.126	-1.233524	.1524455
10	-.051915	.4142815	-0.13	0.900	-.8638918	.7600618
11	-.2969973	.3781409	-0.79	0.432	-1.03814	.4441452
12	-.5599164	.3563281	-1.57	0.116	-1.258307	.1384738
13	-.2084366	.3773591	-0.55	0.581	-.9480468	.5311735
14	-.49065	.3665766	-1.34	0.181	-1.209127	.2278269
15	-.6023312	.3533584	-1.70	0.088	-1.294901	.0902385
16	-.2350449	.374886	-0.63	0.531	-.969808	.4997182
17	-.564039	.3523225	-1.60	0.109	-1.254578	.1265003
18	-.5608995	.3523786	-1.59	0.111	-1.251549	.12975
19	.4833511	1.162208	0.42	0.677	-1.794535	2.761237
20	.0076813	1.188099	0.01	0.995	-2.320949	2.336312

NACECLIO#c.DEDID2#c.Subsidies2						
2	.6225405	.5817488	1.07	0.285	-.5176661	1.762747
3	-.8421424	2.556755	-0.33	0.742	-5.853289	4.169004
4	29.67764	11.89224	2.50	0.013	6.369285	52.986
5	-33.04548	109.5716	-0.30	0.763	-247.802	181.711
6	29.67303	18.37452	1.61	0.106	-6.340359	65.68642
7	1.369445	1.91514	0.72	0.475	-2.38416	5.123049
8	-10.70126	13.23884	-0.81	0.419	-36.64891	15.24639
9	.5162136	.5337359	0.97	0.333	-.5298896	1.562317
10	.5807674	.5937455	0.98	0.328	-.5829525	1.744487
11	.5097729	.537994	0.95	0.343	-.5446761	1.564222
12	.4336718	.5645055	0.77	0.442	-.6727387	1.540082
13	-.0337414	.7611436	-0.04	0.965	-1.525555	1.458073
14	.5618338	.5988246	0.94	0.348	-.6118409	1.735508
15	.5112018	.5337308	0.96	0.338	-.5348914	1.557295
16	.2205514	.5803496	0.38	0.704	-.9169129	1.358016
17	.51453	.5337192	0.96	0.335	-.5315404	1.5606
18	.513622	.5337184	0.96	0.336	-.5324469	1.559691
19	-8.88871	12.23985	-0.73	0.468	-32.87837	15.10095
20	-.1371891	1.891715	-0.07	0.942	-3.844883	3.570505
PERTOT2	3.383019	.6295577	5.37	0.000	2.149108	4.616929
DEDIT2	.0014447	.000672	2.15	0.032	.0001276	.0027618
EMPIDT2	.0009306	.0003198	2.91	0.004	.0003039	.0015573
CUCT2	.2162866	.033998	6.36	0.000	.1496517	.2829216
CTCO2	.0447424	.055559	0.81	0.421	-.0641513	.1536361
CTCL2	.0394019	.035037	1.12	0.261	-.0292694	.1080732
CTPR2	.0916358	.0328817	2.79	0.005	.0271889	.1560828
PERSOC2	.1033044	.0463444	2.23	0.026	.0124711	.1941377
year_dum3	-.038086	.0554802	-0.69	0.492	-.1468252	.0706531
year_dum4	-.0182374	.0550232	-0.33	0.740	-.1260809	.0896061
year_dum5	-.0639058	.0563982	-1.13	0.257	-.1744443	.0466326

year_dum6	-.0413228	.0539701	-0.77	0.444	-.1471023	.0644568
year_dum7	-.1161461	.0540952	-2.15	0.032	-.2221708	-.0101214
year_dum8	-.1524396	.0541333	-2.82	0.005	-.2585389	-.0463404
year_dum9	-.1199416	.0548752	-2.19	0.029	-.227495	-.0123881
year_dum10	-.0777791	.0552697	-1.41	0.159	-.1861057	.0305476
year_dum11	-.171676	.0565031	-3.04	0.002	-.2824199	-.060932
year_dum12	-.1890189	.0578809	-3.27	0.001	-.3024633	-.0755745
year_dum13	-.1550539	.0600079	-2.58	0.010	-.2726672	-.0374405
year_dum14	-.1950512	.0599168	-3.26	0.001	-.3124859	-.0776165
year_dum15	-.2303037	.0608892	-3.78	0.000	-.3496444	-.1109631
year_dum16	-.1349488	.062638	-2.15	0.031	-.2577171	-.0121805
lnGTIDnew2_IN	.0370881	.0062563	5.93	0.000	.024826	.0493501
TFP_MI	.0963861	.0552431	1.74	0.081	-.0118883	.2046604
VEXPORnew_MI	-.0007667	.0002742	-2.80	0.005	-.0013042	-.0002293
PERTOTnew_MI	6.344127	.8888796	7.14	0.000	4.601955	8.086299
DEDIDnew_MI	4.321476	4.971248	0.87	0.385	-5.421992	14.06494
NACECLIO#c.DEDIDnew_MI						
2	-3.687729	4.978079	-0.74	0.459	-13.44459	6.069126
3	-3.739436	5.677336	-0.66	0.510	-14.86681	7.387938
4	4.981303	5.602241	0.89	0.374	-5.998888	15.96149
5	-12.74623	24.38445	-0.52	0.601	-60.53888	35.04642
6	8.208808	11.50585	0.71	0.476	-14.34224	30.75986
7	-.0292318	5.608264	-0.01	0.996	-11.02123	10.96276
8	49.33593	17.82634	2.77	0.006	14.39694	84.27493
9	-3.65496	4.97421	-0.73	0.462	-13.40423	6.094312
10	-4.173452	4.974454	-0.84	0.401	-13.9232	5.576298
11	-3.120596	5.071469	-0.62	0.538	-13.06049	6.819301
12	-.7682464	5.165582	-0.15	0.882	-10.8926	9.356107
13	-1.817206	4.996108	-0.36	0.716	-11.6094	7.974985
14	.5727818	5.083732	0.11	0.910	-9.39115	10.53671

12	-.7682464	5.165582	-0.15	0.882	-10.8926	9.356107
13	-1.817206	4.996108	-0.36	0.716	-11.6094	7.974985
14	.5727818	5.083732	0.11	0.910	-9.39115	10.53671

15	-3.662061	4.97981	-0.74	0.462	-13.42231	6.098188
16	-2.857876	4.979153	-0.57	0.566	-12.61684	6.901085
17	-4.370558	4.980137	-0.88	0.380	-14.13145	5.390331
18	-3.359789	4.98161	-0.67	0.500	-13.12357	6.403987
19	4.869443	7.263393	0.67	0.503	-9.366544	19.10543
20	.8692205	6.082971	0.14	0.886	-11.05318	12.79163
Subsidies_MI	3.288738	2.706862	1.21	0.224	-2.016614	8.594091
c.DEDIDnew_MI#c.Subsidies_MI	-29.46644	30.92385	-0.95	0.341	-90.07607	31.1432
NACECLIO#c.Subsidies_MI						
2	-.5210171	2.96907	-0.18	0.861	-6.340288	5.298254
3	6.948809	8.567343	0.81	0.417	-9.842876	23.74049
4	-.7315485	3.104404	-0.24	0.814	-6.816069	5.352972
5	-.6653621	7.975357	-0.08	0.934	-16.29677	14.96605
6	-2.072418	10.69901	-0.19	0.846	-23.0421	18.89726
7	-3.681944	3.098192	-1.19	0.235	-9.754289	2.390401
8	5.351846	4.797972	1.12	0.265	-4.052006	14.7557
9	-1.852712	2.729946	-0.68	0.497	-7.203308	3.497884
10	-1.634583	2.822012	-0.58	0.562	-7.165625	3.896458
11	-.937477	2.847764	-0.33	0.742	-6.518992	4.644038
12	-2.878972	2.76568	-1.04	0.298	-8.299606	2.541661
13	.149507	2.90826	0.05	0.959	-5.550579	5.849593
14	-1.93671	2.731687	-0.71	0.478	-7.290718	3.417298
15	-3.033717	2.709849	-1.12	0.263	-8.344923	2.277489
16	-2.662947	2.714711	-0.98	0.327	-7.983682	2.657788
17	-3.049198	2.709709	-1.13	0.260	-8.36013	2.261734
18	-3.237108	2.706966	-1.20	0.232	-8.542664	2.068448

18	-3.237108	2.706966	-1.20	0.232	-8.542664	2.068448
19	.6744658	9.379239	0.07	0.943	-17.7085	19.05744
20	-4.374542	8.340096	-0.52	0.600	-20.72083	11.97175
IACECLIO#c.DEDIDnew_MI#c.Subsidies_MI						
2	27.41912	31.70287	0.86	0.387	-34.71737	89.5556
3	-11.37866	56.67127	-0.20	0.841	-122.4523	99.69499
4	-11.34326	36.99749	-0.31	0.759	-83.85701	61.1705
5	659.1312	533.2671	1.24	0.216	-386.0531	1704.316
6	19.48689	43.02505	0.45	0.651	-64.84066	103.8144
7	27.21609	31.00021	0.88	0.380	-33.54321	87.97539
8	-286.9966	155.6877	-1.84	0.065	-592.1389	18.14565
9	29.22796	30.92408	0.95	0.345	-31.38212	89.83804
10	28.64036	30.93862	0.93	0.355	-31.99821	89.27894
11	28.57523	30.9253	0.92	0.355	-32.03724	89.1877
12	27.32764	31.02733	0.88	0.378	-33.4848	88.14009
13	19.43962	31.17589	0.62	0.533	-41.664	80.54323
14	25.13899	30.95771	0.81	0.417	-35.537	85.81498
15	29.37206	30.92392	0.95	0.342	-31.23772	89.98183
16	29.07767	30.93083	0.94	0.347	-31.54564	89.70098
17	29.43967	30.92386	0.95	0.341	-31.16997	90.04932
18	29.41811	30.92358	0.95	0.341	-31.191	90.02722
19	55.81057	110.0918	0.51	0.612	-159.9653	271.5864
20	55.75408	80.48478	0.69	0.488	-101.9932	213.5014
DEDITnew_MI	-.0007052	.0073049	-0.10	0.923	-.0150226	.0136122
EMPIDT_MI	.0042489	.0013888	3.06	0.002	.0015269	.0069709
CUCT_MI	.3920863	.0902884	4.34	0.000	.2151242	.5690484
CTCL_MI	-.0391607	.1090625	-0.36	0.720	-.2529192	.1745979
CTCO_MI	-.2253892	.2133688	-1.06	0.291	-.6435843	.1928059
CTPR_MI	.3632062	.1112124	3.27	0.001	.1452338	.5811785

DEDITnew_MI	-.0007052	.0073049	-0.10	0.923	-.0150226	.0136122
EMPIDT_MI	.0042489	.0013888	3.06	0.002	.0015269	.0069709
CUCT_MI	.3920863	.0902884	4.34	0.000	.2151242	.5690484
CTCL_MI	-.0391607	.1090625	-0.36	0.720	-.2529192	.1745979
CTCO_MI	-.2253892	.2133688	-1.06	0.291	-.6435843	.1928059
CTPR_MI	.3632062	.1112124	3.27	0.001	.1452338	.5811785
PERSOC_MI	-.9290746	.0710325	-13.08	0.000	-1.068296	-.7898536
_cons	10.44867	.4704764	22.21	0.000	9.526555	11.37079
/sigma_u	.9866724	.0239737	41.16	0.000	.9396849	1.03366
/sigma_e	.8449916	.007491	112.80	0.000	.8303095	.8596737
rho	.5768908	.0131903			.550891	.6025599

LR test of sigma_u=0: chibar2(01) = 2807.96 Prob >= chibar2 = 0.000

Appendix 10 – Investigation 2 user-cost estimates

Stata/SE 17.0 - C:\Users\et22\Desktop\PhD work\All datafiles merged - Unbalanced panel - v09032021.dta

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```
. xtabond2 lnGTIDnew2 l.lnGTIDnew2 TFP_18 VEXPOR2015prices i.NACECLIO UC_industry Subsidies PERTOT DEDIT2015prices EMPIDT ///
> CUCT CTCO CTCL CTPR PERSOC year_dum3-year_dum16 lnGTIDnew2_IN if UC_industry > 0 & profit2015prices > 0 & DEDID2015prices > 0, ///
> gmm (l.lnGTIDnew2, laglimits (2 .) collapse) ///
> gmm (UC_industry, laglimits (2 2) collapse) ///
> iv (TFP_18 VEXPOR2015prices Subsidies i.NACECLIO PERTOT DEDIT2015prices EMPIDT ///
> CUCT CTCO CTCL CTPR PERSOC year_dum3-year_dum16) twostep robust
Favoring speed over space. To switch, type or click on mata: mata set matafavor space, perm.
1b.NACECLIO dropped due to collinearity
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: Col1                            Number of obs      =      2555
Time variable : year                            Number of groups   =       727
Number of instruments = 61                      Obs per group: min =         1
Wald chi2(47) =  18757.86                                      avg =      3.51
Prob > chi2   =     0.000                                      max =        15
------------------------------------------------------------------------------
             |              Corrected
  lnGTIDnew2 | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
  lnGTIDnew2 |
         L1. |   .9634724   .1392253     6.92   0.000     .6905958    1.236349
             |
      TFP_18 |   .1136511   .2225696     0.51   0.610    -.3225773    .5498795
VEXPOR2015prices | 1.91e-10 4.53e-10   0.42   0.673    -6.97e-10    1.08e-09

    NACECLIO |
          2  |  -1.576159   1.117262    -1.41   0.158    -3.765953    .6136345
          3  |  -1.629153   1.329131    -1.23   0.220    -4.234201    .9758947
          4  |  -1.846592   1.325655    -1.39   0.164    -4.444828    .7516435
          5  |  -1.341484   1.805419    -0.74   0.457    -4.880039    2.197072
          6  |   1.560069   1.671484     0.93   0.351    -1.715978    4.836117
          7  |  -.9568137   1.363786    -0.70   0.483    -3.629784    1.716157
          8  |   .8456436   3.421274     0.25   0.805     -5.85993    7.551217
          9  |  -3.026326   1.331891    -2.27   0.023    -5.636784   -.4158686
         10  |  -1.445362   1.275573    -1.13   0.257    -3.945439    1.054716
         11  |  -1.513141   1.260936    -1.20   0.230    -3.984531     .958249
         12  |  -1.975183   1.253959    -1.58   0.115    -4.432898    .4825316
         13  |  -1.808463   1.198364    -1.51   0.131    -4.157213    .5402867
         14  |  -2.766657   1.269605    -2.18   0.029    -5.255037   -.2782764
         15  |  -3.574316   1.476036    -2.42   0.015    -6.467293   -.6813391
         16  |  -3.230785   1.440593    -2.24   0.025    -6.054295   -.4072747
         17  |   -2.21157   1.257582    -1.76   0.079    -4.676386    .2532461
         18  |  -2.656075   1.413771    -1.88   0.060    -5.427016    .1148652
         19  |   -2.21185   1.346418    -1.64   0.100    -4.850781    .4270805
         20  |   .8774517   2.382434     0.37   0.713    -3.792032    5.546936
             |
 UC_industry |  -12.38385   22.51556    -0.55   0.582    -56.51353    31.74583
   Subsidies |   .0220582   .0347992     0.63   0.526     -.046147    .0902634
      PERTOT |  -.0002328   .0003546    -0.66   0.511    -.0009279    .0004622
DEDIT2015prices | 3.91e-07  5.41e-07     0.72   0.470    -6.69e-07    1.45e-06
      EMPIDT |  -.0015336   .0012846    -1.19   0.233    -.0040514    .0009842
        CUCT |   .7555867   .4154705     1.82   0.069    -.0587205    1.569894
        CTCO |   .0656594   .3581009     0.18   0.855    -.6362055    .7675242
        CTCL |   -.399044   .2546316    -1.57   0.116    -.8990127    .0991248
```

Stata/SE 17.0 - C:\Users\et22\Desktop\PhD work\All datafiles merged - Unbalanced panel - v09032021.dta

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CTCO	.0656594	.3581009	0.18	0.855	-.6362055	.7675242
CTCL	-.399944	.2546316	-1.57	0.116	-.8990127	.0991248
CTPR	-.4259944	.2932859	-1.45	0.146	-1.000824	.1488354
PERSOC	-.9960086	.4569368	-2.18	0.029	-1.891588	-.100429
year_dum3	-.2177937	.2512649	-0.87	0.386	-.7102639	.2746765
year_dum4	.4027825	.291383	1.38	0.167	-.1683177	.9738826
year_dum5	.4980126	.3982652	1.25	0.211	-.2825729	1.278598
year_dum6	.3386121	.3396273	1.00	0.319	-.3270452	1.004269
year_dum7	.3399888	.3324874	1.02	0.307	-.3116745	.9916522
year_dum8	.7402488	.7943395	0.93	0.351	-.816628	2.297126
year_dum9	.7276911	.6035841	1.21	0.228	-.4553121	1.910694
year_dum10	1.086218	.6077616	1.79	0.074	-.1049731	2.277408
year_dum11	.7754274	.4744972	1.63	0.102	-.1545701	1.705425
year_dum12	.8482709	.6444306	1.32	0.188	-.4147899	2.111332
year_dum13	1.059432	.638913	1.66	0.097	-.1928142	2.311679
year_dum14	.9304283	.7402118	1.26	0.209	-.5203602	2.381217
year_dum15	.7386354	.7700975	0.96	0.337	-.770728	2.247999
year_dum16	1.125441	.7747486	1.45	0.146	-.393038	2.643921
lnGTIDnew2_IN	.4731181	.1637419	2.89	0.004	.15219	.7940463
_cons	.564476	6.429836	0.09	0.930	-12.03777	13.16672

Appendix 11 – Investigation 2 additionality estimates

```
. xtabond2 lnGTIDnew2 l.lnGTIDnew2 TFP_18 VEXPOR2015prices i.NACECLIO lnDEDID Subsidies PERTOT DEDIT2015prices EMPIDT ///
> CUCT CTCO CTCL CTPR PERSOC year_dum3-year_dum16 lnGTIDnew2_IN if UC_industry > 0 & profit2015prices > 0 & DEDID2015prices > 0, ///
> gmm (l.lnGTIDnew2, laglimits (2 .) collapse) ///
> iv (TFP_18 lnDEDID VEXPOR2015prices Subsidies i.NACECLIO PERTOT DEDIT2015prices EMPIDT ///
> CUCT CTCO CTCL CTPR PERSOC year_dum3-year_dum16) twostep robust
Favoring speed over space. To switch, type or click on mata: mata set matafavor space, perm.
1b.NACECLIO dropped due to collinearity
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step system GMM

Group variable: Col1                          Number of obs      =      2555
Time variable : year                          Number of groups   =       727
Number of instruments = 60                    Obs per group: min =         1
Wald chi2(47) = 195452.58                                    avg =      3.51
Prob > chi2   =     0.000                                    max =        15

                            Corrected
      lnGTIDnew2  Coefficient  std. err.      z    P>|z|     [95% conf. interval]

      lnGTIDnew2
             L1.     .4254165   .1126131     3.78   0.000     .2046988    .6461341

          TFP_18    -.1591442   .1167354    -1.36   0.173    -.3879414    .0696529
VEXPOR2015prices    -8.39e-12   1.59e-10    -0.05   0.958    -3.20e-10    3.03e-10
```

```
        NACECLIO
               2    -.5532947   .3917154    -1.41   0.158    -1.321043    .2144534
               3    -.2803398   .4308614    -0.65   0.515    -1.124813    .5641329
               4    -.6023854   .4290039    -1.40   0.160    -1.443218    .2384468
               5    -1.357612   1.118592    -1.21   0.225    -3.550012    .8347876
               6    -.1165646     .53206    -0.22   0.827    -1.159383    .9262539
               7    -1.202174   .4969703    -2.42   0.016    -2.176218   -.2281301
               8     .2867595   .9191842     0.31   0.755    -1.514808    2.088327
               9    -.2362752   .5041996    -0.47   0.639    -1.224488    .7519379
              10    -.4470479    .368828    -1.21   0.225    -1.169937    .2758416
              11     -.613524    .448873    -1.37   0.172    -1.493299    .2662509
              12    -.2893605   .4197742    -0.69   0.491    -1.112103    .5333819
              13    -.1972468   .3662465    -0.54   0.590    -.9150766    .5205831
              14    -.3274723   .5007729    -0.65   0.513    -1.308969    .6540246
              15     .0682833   .6293893     0.11   0.914    -1.165297    1.301864
              16    -.0205115   .5971462    -0.03   0.973    -1.190897    1.149874
              17    -.5508778   .4370326    -1.26   0.207    -1.407446    .3056904
              18    -.1571398    .502185    -0.31   0.754    -1.141404    .8271247
              19    -.5765975   .5141397    -1.12   0.262    -1.584293    .4310978
              20    -.6986562   1.078161    -0.65   0.517    -2.811812      1.4145

         lnDEDID     .3563942   .0915403     3.89   0.000     .1769784      .53581
       Subsidies     .0184511   .0096983     1.90   0.057    -.0005572    .0374594
          PERTOT     .0000385   .0000866     0.44   0.656    -.0001312    .0002083
 DEDIT2015prices     1.05e-07   2.27e-07     0.47   0.642    -3.39e-07    5.50e-07
          EMPIDT     .0005077   .0004325     1.17   0.240      -.00034    .0013553
            CUCT    -.2800128   .1832765    -1.53   0.127    -.6392281    .0792025
            CTCO    -.2037756   .1432696    -1.42   0.155    -.4845788    .0770277
            CTCL    -.1914587   .0872549    -2.19   0.028    -.3624751   -.0204423
```


```
         lnDEDID     .3563942   .0915403     3.89   0.000     .1769784      .53581
       Subsidies     .0184511   .0096983     1.90   0.057    -.0005572    .0374594
          PERTOT     .0000385   .0000866     0.44   0.656    -.0001312    .0002083
 DEDIT2015prices     1.05e-07   2.27e-07     0.47   0.642    -3.39e-07    5.50e-07
          EMPIDT     .0005077   .0004325     1.17   0.240      -.00034    .0013553
            CUCT    -.2800128   .1832765    -1.53   0.127    -.6392281    .0792025
            CTCO    -.2037756   .1432696    -1.42   0.155    -.4845788    .0770277
            CTCL    -.1914587   .0872549    -2.19   0.028    -.3624751   -.0204423
```


```
            CTPR    -.4783571   .1746118    -2.74   0.006      -.82059   -.1361242
          PERSOC     .2141957   .1906043     1.12   0.261    -.1593819    .5877733
       year_dum3    -.1403779   .1096022    -1.28   0.200    -.3551943    .0744386
       year_dum4    -.0433952    .121353    -0.36   0.721    -.2812427    .1944523
       year_dum5     .0187972   .1430297     0.13   0.895    -.2615358    .2991303
       year_dum6    -.1615722   .1529711    -1.06   0.291    -.4613901    .1382456
       year_dum7    -.1466433   .1538977    -0.95   0.341    -.4482773    .1549907
       year_dum8    -.1550119   .2298666    -0.67   0.500    -.6055421    .2955183
       year_dum9    -.1247095   .2253636    -0.55   0.580     -.566414     .316995
      year_dum10    -.1324547   .2493865    -0.53   0.595    -.6212433    .3563338
      year_dum11    -.3691096   .2411409    -1.53   0.126    -.8417372    .1035179
      year_dum12    -.4069783   .2755002    -1.48   0.140    -.9469487    .1329922
      year_dum13     -.775331   .3461558    -2.24   0.025    -1.453784   -.0968781
      year_dum14    -.6023857   .2974337    -2.03   0.043    -1.185345   -.0194264
      year_dum15    -.6805718   .3022565    -2.25   0.024    -1.272984   -.0881599
      year_dum16    -.4947046   .3076257    -1.61   0.108     -1.09764    .1082307
   lnGTIDnew2_IN     .0007006   .0881028     0.01   0.994    -.1719777    .1733788
           _cons     6.610244   1.772827     3.73   0.000     3.135566    10.08492

Instruments for first differences equation
  Standard
```

Appendix 12 – Total factor productivity estimates

```
op productivity estimator                        Cobb-Douglas PF

Dependent variable: value added                  Number of obs      =        840
Group variable (id): Col1                        Number of groups   =        117
Time variable (t): year
                                                 Obs per group: min =          1
                                                                avg =        7.2
                                                                max =         15
```

lnVA	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lnHETN	.8068111	.065699	12.28	0.000	.6780434	.9355789
lnRIMVA	.2039971	.009865	20.68	0.000	.1846621	.2233321
lnINM	-.0080601	.0099835	-0.81	0.419	-.0276274	.0115072
age	-.0014631	.0097687	-0.15	0.881	-.0206093	.0176832
UC	.0071254	.0045852	1.55	0.120	-.0018615	.0161123
PIL	.0597589	.0125442	4.76	0.000	.0351727	.0843451

```
Wald test on Constant returns to scale: Chi2 = 1.07
                                           p = (0.30)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 2, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                        Cobb-Douglas PF

Dependent variable: value added                  Number of obs      =       2579
Group variable (id): Col1                        Number of groups   =        352
Time variable (t): year
                                                 Obs per group: min =          1
                                                                avg =        7.3
                                                                max =         15
```

lnVA	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lnHETN	.6875055	.0390168	17.62	0.000	.611034	.763977
lnRIMVA	.2898333	.0140005	20.70	0.000	.2623928	.3172737
lnINM	.008666	.0107822	0.80	0.422	-.0124667	.0297987
age	-.0000104	.0056421	-0.00	0.999	-.0110687	.0110479
UC	.0033197	.0014676	2.26	0.024	.0004432	.0061962
PIL	.0359727	.0115036	3.13	0.002	.013426	.0585194

```
Wald test on Constant returns to scale: Chi2 = 0.31
                                           p = (0.58)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 3, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                        Cobb-Douglas PF

Dependent variable: value added                  Number of obs      =        501
Group variable (id): Col1                        Number of groups   =         67
Time variable (t): year
                                                 Obs per group: min =          1
                                                                avg =        7.5
                                                                max =         15
```

lnVA	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lnHETN	.8234974	.1324972	6.22	0.000	.5638077	1.083187
lnRIMVA	.1748828	.0163529	10.69	0.000	.1428316	.206934
lnINM	.0585772	.0136335	4.30	0.000	.0318561	.0852984
age	.010525	.0069516	1.51	0.130	-.0030999	.0241499
UC	-.0009596	.0036902	-0.26	0.795	-.0081923	.006273
PIL	.0240183	.011332	2.12	0.034	.001808	.0462287

```
Wald test on Constant returns to scale: Chi2 = 0.43
                                           p = (0.51)
```

```
. prodest lnVA if NACECLIO == 4, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                         Cobb-Douglas PF

Dependent variable: value added                   Number of obs      =      1782
Group variable (id): Col1                         Number of groups   =       292
Time variable (t): year
                                                  Obs per group: min =         1
                                                                 avg =       6.1
                                                                 max =        15

------------------------------------------------------------------------------
        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .8969948   .0403542    22.23   0.000     .8179021    .9760876
     lnRIMVA |    .160782   .0043075    37.33   0.000     .1523394    .1692246
       lnINM |   .0255875   .0071221     3.59   0.000     .0116284    .0395466
         age |   .0066177   .0074461     0.89   0.374    -.0079764    .0212118
          UC |   .0034904   .0013808     2.53   0.011     .0007839    .0061968
         PIL |   .0095877   .0090573     1.06   0.290    -.0081643    .0273397
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 6.69
                                          p = (0.01)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 5, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                         Cobb-Douglas PF

Dependent variable: value added                   Number of obs      =       689
Group variable (id): Col1                         Number of groups   =       114
Time variable (t): year
                                                  Obs per group: min =         1
                                                                 avg =       6.0
                                                                 max =        15

------------------------------------------------------------------------------
        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .8941265   .0760639    11.75   0.000      .745044    1.043209
     lnRIMVA |   .1635545   .0084999    19.24   0.000     .1468951     .180214
       lnINM |   .0152452   .0070222     2.17   0.030      .001482    .0290084
         age |    .010345   .0103028     1.00   0.315    -.0098482    .0305381
          UC |   .0032102   .0028911     1.11   0.267    -.0024563    .0088766
         PIL |   .0289414    .007954     3.64   0.000     .0133518    .0445309
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 2.50
                                          p = (0.11)
```

```
end of do-file

. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 6, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                         Cobb-Douglas PF

Dependent variable: value added                   Number of obs      =       884
Group variable (id): Col1                         Number of groups   =       145
Time variable (t): year
                                                  Obs per group: min =         1
                                                                 avg =       6.1
                                                                 max =        15

------------------------------------------------------------------------------
        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .9218516   .0635487    14.51   0.000     .7972985    1.046405
     lnRIMVA |   .0945063   .0120069     7.87   0.000     .0709733    .1180393
       lnINM |   .0250325   .0100956     2.48   0.013     .0052456    .0448195
         age |    .019796   .0136497     1.45   0.147     -.006957     .046549
          UC |   .0031719   .0035549     0.89   0.372    -.0037957    .0101395
         PIL |    .040879   .0094131     4.34   0.000     .0224297    .0593282
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 2.65
                                          p = (0.10)

.
end of do-file
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 7, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                         Cobb-Douglas PF

Dependent variable: value added                   Number of obs      =       945
Group variable (id): Col1                         Number of groups   =       131
Time variable (t): year
                                                  Obs per group: min =         1
                                                                 avg =       7.2
                                                                 max =        15

------------------------------------------------------------------------------
        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .7828844   .0606093    12.92   0.000     .6640922    .9016765
     lnRIMVA |   .2726454   .0069216    39.39   0.000     .2590792    .2862115
       lnINM |    .003969   .0070774     0.56   0.575    -.0099025    .0178404
         age |   .0136327   .0071797     1.90   0.058    -.0004393    .0277048
          UC |   .0081142   .0031277     2.59   0.009      .001984    .0142443
         PIL |   .0025642   .0088622     0.29   0.772    -.0148054    .0199337
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 2.00
                                          p = (0.16)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 8, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50


op productivity estimator                       Cobb-Douglas PF

Dependent variable: value added                 Number of obs      =      1129
Group variable (id): Col1                       Number of groups   =       188
Time variable (t): year
                                                Obs per group: min =         1
                                                               avg =       6.0
                                                               max =        15

------------------------------------------------------------------------------
        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .9114192   .0487577    18.69   0.000     .8158558    1.006983
     lnRIMVA |   .1798274   .0120407    14.93   0.000      .156228    .2034268
       lnINM |   .0239762   .0095071     2.52   0.012     .0053427    .0426097
         age |   .0079346   .0106952     0.74   0.458    -.0130276    .0288967
          UC |    .006005   .0023105     2.60   0.009     .0014766    .0105335
         PIL |    .016848   .0054016     3.12   0.002     .0062611    .0274349
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 7.28
                                           p = (0.01)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 9, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50


op productivity estimator                       Cobb-Douglas PF

Dependent variable: value added                 Number of obs      =      1678
Group variable (id): Col1                       Number of groups   =       224
Time variable (t): year
                                                Obs per group: min =         1
                                                               avg =       7.5
                                                               max =        15

------------------------------------------------------------------------------
        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .8482125   .0401417    21.13   0.000     .7695362    .9268888
     lnRIMVA |   .1801268   .0141857    12.70   0.000     .1523234    .2079302
       lnINM |   .0405759   .0143909     2.82   0.005     .0123703    .0687815
         age |    -.00031   .0091297    -0.03   0.973    -.0182039     .017584
          UC |   .0025528   .0017922     1.42   0.154    -.0009599    .0060655
         PIL |   .0186276   .0086091     2.16   0.030     .0017541    .0355011
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 4.27
                                           p = (0.04)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 10, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50


op productivity estimator                       Cobb-Douglas PF

Dependent variable: value added                 Number of obs      =      1335
Group variable (id): Col1                       Number of groups   =       205
Time variable (t): year
                                                Obs per group: min =         1
                                                               avg =       6.5
                                                               max =        15

------------------------------------------------------------------------------
        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .8601366   .0507514    16.95   0.000     .7606656    .9596075
     lnRIMVA |   .1912628    .006679    28.64   0.000     .1781721    .2043534
       lnINM |   .0048452   .0092429     0.52   0.600    -.0132706     .022961
         age |   .0240532   .0082898     2.90   0.004     .0078054     .040301
          UC |   .0072541   .0019904     3.64   0.000      .003353    .0111551
         PIL |   .0088909   .0066114     1.34   0.179    -.0040671    .0218489
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 3.03
                                           p = (0.08)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 11, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50


op productivity estimator                       Cobb-Douglas PF

Dependent variable: value added                 Number of obs      =      1822
Group variable (id): Col1                       Number of groups   =       262
Time variable (t): year
                                                Obs per group: min =         1
                                                               avg =       7.0
                                                               max =        15

------------------------------------------------------------------------------
        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .8270998   .0390085    21.20   0.000     .7506445    .9035552
     lnRIMVA |   .2157006   .0023696    91.03   0.000     .2110563    .2203448
       lnINM |   .0168919   .0111748     1.51   0.131    -.0050103     .038794
         age |   .0113297   .0084679     1.34   0.181     -.005267    .0279264
          UC |   .0090831   .0015226     5.97   0.000     .0060988    .0120674
         PIL |   .0266483   .0084838     3.14   0.002     .0100204    .0432763
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 7.39
                                           p = (0.01)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 12, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                         Cobb-Douglas PF

Dependent variable: value added                   Number of obs      =       815
Group variable (id): Col1                         Number of groups   =       116
Time variable (t): year
                                                  Obs per group: min =         1
                                                                 avg =       7.0
                                                                 max =        15

        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .7221136    .082587     8.74   0.000     .5602461    .8839811
     lnRIMVA |   .2738638   .0074602    36.71   0.000      .259242    .2884855
       lnINM |   .0237734   .0063432     3.75   0.000      .011341    .0362059
         age |   .0035929   .0053394     0.67   0.501    -.0068721    .0140579
          UC |   .0097459   .0028564     3.41   0.001     .0041474    .0153443
         PIL |   .0133131   .0049327     2.70   0.007     .0036452    .0229809
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 0.33
                                           p = (0.57)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 13, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                         Cobb-Douglas PF

Dependent variable: value added                   Number of obs      =      3192
Group variable (id): Col1                         Number of groups   =       485
Time variable (t): year
                                                  Obs per group: min =         1
                                                                 avg =       6.6
                                                                 max =        15

        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .8919292   .0321771    27.72   0.000     .8288632    .9549952
     lnRIMVA |   .1392283   .0087786    15.86   0.000     .1220226     .156434
       lnINM |   .0166884   .0065581     2.54   0.011     .0038348     .029542
         age |   .0148364   .0093331     1.59   0.112    -.0034561     .033129
          UC |    .005701   .0010836     5.26   0.000     .0035772    .0078248
         PIL |   .0162708   .0088504     1.84   0.066    -.0010757    .0336172
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 5.84
                                           p = (0.02)
```

```
.
end of do-file

. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 14, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                         Cobb-Douglas PF

Dependent variable: value added                   Number of obs      =      1500
Group variable (id): Col1                         Number of groups   =       233
Time variable (t): year
                                                  Obs per group: min =         1
                                                                 avg =       6.4
                                                                 max =        15

        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .8921963   .0395896    22.54   0.000     .8146022    .9697905
     lnRIMVA |   .1250346   .0025417    49.19   0.000      .120053    .1300162
       lnINM |   .0204815   .0068354     3.00   0.003     .0070843    .0338786
         age |   .0055203    .007609     0.73   0.468    -.0093931    .0204336
          UC |   .0056213   .0014607     3.85   0.000     .0027584    .0084842
         PIL |   .0057607   .0069054     0.83   0.404    -.0077737     .019295
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 1.82
                                           p = (0.18)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 15, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                         Cobb-Douglas PF

Dependent variable: value added                   Number of obs      =       500
Group variable (id): Col1                         Number of groups   =        88
Time variable (t): year
                                                  Obs per group: min =         1
                                                                 avg =       5.7
                                                                 max =        15

        lnVA | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      lnHETN |   .7446404   .1083445     6.87   0.000      .532289    .9569918
     lnRIMVA |   .1282169   .0120504    10.64   0.000     .1045985    .1518352
       lnINM |   .0120613   .0123711     0.97   0.330    -.0121857    .0363083
         age |   .0023928   .0112712     0.21   0.832    -.0196983    .0244839
          UC |   .0081657   .0032011     2.55   0.011     .0018917    .0144397
         PIL |  -.0000235   .0083687    -0.00   0.998    -.0164258    .0163788
------------------------------------------------------------------------------
Wald test on Constant returns to scale: Chi2 = 0.98
                                           p = (0.32)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 16, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                     Cobb-Douglas PF

Dependent variable: value added               Number of obs      =     1013
Group variable (id): Col1                     Number of groups   =      150
Time variable (t): year
                                              Obs per group: min =        1
                                                             avg =      6.8
                                                             max =       15
```

lnVA	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lnHETN	.9931896	.0527533	18.83	0.000	.889795	1.096584
lnRIMVA	.0790096	.0131213	6.02	0.000	.0532923	.104727
lnINM	.0074884	.0126868	0.59	0.555	-.0173772	.0323541
age	.0039016	.0063877	0.61	0.541	-.0086181	.0164213
UC	.0049373	.0017678	2.79	0.005	.0014726	.008402
PIL	.0039286	.0094353	0.42	0.677	-.0145643	.0224215

```
Wald test on Constant returns to scale: Chi2 = 3.04
                                        p = (0.08)
```

```
. do "C:\Users\et22\AppData\Local\Temp\STD1b44_000000.tmp"

. prodest lnVA if NACECLIO == 17, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                     Cobb-Douglas PF

Dependent variable: value added               Number of obs      =     1246
Group variable (id): Col1                     Number of groups   =      174
Time variable (t): year
                                              Obs per group: min =        1
                                                             avg =      7.2
                                                             max =       15
```

lnVA	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lnHETN	.7162201	.0473439	15.13	0.000	.6234276	.8090125
lnRIMVA	.2548283	.0080651	31.60	0.000	.2390211	.2706356
lnINM	.0208514	.012436	1.68	0.094	-.0035227	.0452254
age	.012436	.0087551	1.42	0.155	-.0047237	.0295957
UC	.007035	.001698	4.14	0.000	.0037069	.010363
PIL	.0194296	.01096	1.77	0.076	-.0020517	.0409108

```
Wald test on Constant returns to scale: Chi2 = 0.43
                                        p = (0.51)
```

```
. prodest lnVA if NACECLIO == 18, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                     Cobb-Douglas PF

Dependent variable: value added               Number of obs      =      524
Group variable (id): Col1                     Number of groups   =       74
Time variable (t): year
                                              Obs per group: min =        1
                                                             avg =      7.1
                                                             max =       15
```

lnVA	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lnHETN	1.050104	.0846008	12.41	0.000	.8842895	1.215918
lnRIMVA	.0443617	.0070857	6.26	0.000	.030474	.0582495
lnINM	.0320136	.0084664	3.78	0.000	.0154196	.0486075
age	.0059001	.0080971	0.73	0.466	-.0099698	.0217701
UC	.0051913	.0017441	2.98	0.003	.001773	.0086096
PIL	.0127531	.0062371	2.04	0.041	.0005286	.0249776

```
Wald test on Constant returns to scale: Chi2 = 3.30
                                        p = (0.07)
```

```
. prodest lnVA if NACECLIO == 20, method (op) free (lnHETN) proxy (lnCIM) state (lnRIMVA lnINM age) control (UC PIL) valueadded attrition reps (50)
.........10.........20.........30.........40.........50

op productivity estimator                     Cobb-Douglas PF

Dependent variable: value added               Number of obs      =      621
Group variable (id): Col1                     Number of groups   =       97
Time variable (t): year
                                              Obs per group: min =        1
                                                             avg =      6.4
                                                             max =       15
```

lnVA	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lnHETN	.8123443	.0571646	14.21	0.000	.7003038	.9243847
lnRIMVA	.2792656	.0086603	32.25	0.000	.2622918	.2962394
lnINM	.0085472	.0087723	0.97	0.330	-.0086463	.0257406
age	.0231096	.008853	2.61	0.009	.005758	.0404612
UC	.0072886	.0018555	3.93	0.000	.0036519	.0109253
PIL	-.0014519	.0037958	-0.38	0.702	-.0088915	.0059877

```
Wald test on Constant returns to scale: Chi2 = 5.44
                                        p = (0.02)
```