**Collaborative innovation in emerging innovation systems:**

**Evidence from Central and Eastern Europe**

**(pre-accepted version)**

**Nebojša Stojčić**

Associate professor

University of Dubrovnik, Department of Economics and Business

Staffordshire University, Business School

nstojcic@unidu.hr

+385981621005

ORCID: <https://orcid.org/0000-0001-6638-8771>

*Abstract*

Firms often lack the competencies and capabilities for creating and commercializing innovations. The solution to this problem lies in sharing or acquiring relevant resources through collaboration. The success of collaborative relationships depends on the type and the quality of the partners involved and the proximity between them. This is particularly true in the emerging innovation systems of countries in transition from middle to high income levels where structural weaknesses of domestic innovation systems and a lack of internal resources often act as barriers to the development and commercialization of innovations. The objective of this paper is to explore whether collaboration with suppliers, customers, universities and research institutes and intra-group collaboration with partners of different origins facilitates the commercialization of existing marginally modified, incrementally novel and radically novel products in nine emerging innovation systems of Central and Eastern Europe. Treatment analysis on a sample of over 10,000 firms from the Eurostat’s Community Innovation Survey shows that domestic innovation competencies and capabilities mostly drive the commercialization of existing products and that firms rely on a diverse network of collaborators. We find evidence of the positive impact of collaboration on the commercialization of existing products and to a lesser extent on incremental and radical innovations. The relevance of individual collaboration channels differs across countries. Among foreign partners, collaboration with entities from other European Union member states facilitates commercialization of existing products while partners from United States, China and India have positive effects on the commercialization of incremental and radical innovations suggesting that cognitive proximity is more important than geographical, social, organizational and institutional proximities. Recommendations for the formulation of innovation policies in emerging innovation systems are provided.

*Keywords: collaboration, innovation, innovation systems, emerging economies*

*JEL: O14, O31, O32, O33*

1. **Introduction**

More than nine decades ago Ronald Coase (1937) argued that firms can grow only if they undertake activities more efficiently than the market. In those days, companies relied exclusively on internal resources. The Ford Motor Company of the1930s, for example, owned a railway system, sheep farms and rubber plantations. Borders between modern firms and their environment are more permeable. More than 81% of modern firms practice some form of collaboration in the innovation process (KPMG, 2015). Sharing of resources through collaborative innovation (Chesbrough, 2003) enables firms to complement and reconfigure their own innovation resources (De Maggio et al., 2009; Tsai, 2009; Malerba and McKelvey, 2018; Elia et al., 2019). These collaborative practices involve a variety of actors within local, regional, national and international innovation systems.

The practical relevance of collaborative innovation has stimulated a vast amount of empirical research on its determinants, outcomes and patterns. Studies from the advanced world have pointed to the distinctive effects of individual actors collaborating in different types of innovations and to the impact of spatial and non-spatial proximities among actors (Boschma, 2005; De Maggio et al., 2009; Tsai, 2009; Pietruzzelli, 2011; Iammarino et al., 2012; Ardito et al., 2015; Hansen and Mattes; 2017; Del Guidice et al., 2019; Elia et al., 2019). However, existing studies have failed to provide a comprehensive overview of collaborative innovation in the emerging innovation systems of advancing countries (Da-Chang et al., 2012; Lin and Huang., 2013; Barros, 2016; Fu and Li, 2016; Perri et al., 2017; Del Guidice et al., 2019; Saranga et al., 2019; Kirby and El Hadidi, 2019).

The study reported here addresses this gap by offering for the first time a comprehensive analysis of the functioning of collaborative innovation networks in emerging innovation systems of less advanced countries. In this context the investigation asks the following research questions: Does collaboration facilitate the commercialization of all types of innovations or only some of them? What is the role of different actors in collaborative innovation networks? How does the origin of partners influence the outcome of collaborative innovation? The study answers, for the first time, whether collaborative innovation in emerging innovation systems differs from patterns observed in advanced countries in earlier literature and provides evidence-based inputs for the formulation of innovation policies.

The focus of the investigation is on nine Central and East European (CEE) innovation systems characterised by low innovation and technology transfer intensity (Švarc and Dabić, 2019). The analysis relies on the data from the most recent (2014) version of Eurostat’s Community Innovation Survey, which is the most comprehensive firm-level dataset on innovation activities in Europe, to assess the determinants and outcomes of collaborative innovation by means of treatment analysis. The findings reveal the positive effect of collaboration but the relevance of individual collaboration channels differs across individual CEE countries. We find differing effects of collaborations on the commercialization of incremental and radical innovations for EU and non-EU partners such as the United States, China and India, which has important implications for the ability of the EU’s single market to drive the catching up of less advanced EU member states.

The investigation contributes to the existing body of knowledge in at least two important ways. Empirically, the study explores, for the first time, how different actors in emerging innovation systems, such as rivals, suppliers, customers, universities and research institutes and intra-group members, facilitate the commercialization of different categories of innovation defined as marginally modified, incrementally novel or radically novel products. The study also investigates whether collaborations with domestic or different types of foreign partners are more relevant for the commercialization of innovations. Such a comprehensive approach is required because the structurally weak innovation systems of advancing countries lack relevant resources and domestic firms must rely on collaborations with foreign partners (Radošević, 2017).

From a theoretical stance our study establishes a bridge between different theoretical strands used to explain collaborative innovation (such as, the resource-based view, the dynamic capabilities approach and their more recent refinements such as knowledge-based and technology-based views) and economic geography and innovation systems literature. More importantly, while theories used to explain collaborative innovation have been developed and tested in the context of advanced economies, our empirical findings offer one of the first comprehensive opportunities to examine whether their propositions are also relevant in the context of emerging innovation systems.

The paper is structured as follows. Section two provides the conceptual framework of the paper. It opens with an examination of the CEE innovation context and then moves on to provide the theoretical framework and research hypotheses. Section three lays down our empirical strategy including the model of investigation, the suitability of dataset for the purpose of our analysis and methodological issues. Section four presents the results of the investigation for the baseline model and subsequent sub-analyses; and, section five contains the concluding remarks, the limitations of research and directions for future investigation.

1. **Conceptual framework and research hypotheses**
	1. *The CEE innovation context*

Central and Eastern Europe is a term commonly applied to eleven European Union (EU) member states that joined the EU from 2004 onwards (Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia). Over the past three decades these countries have achieved impressive rates of growth, mostly on the back of foreign investment and integration in global value chains of producers from advanced countries. With the exception of Bulgaria and Romania, all other CEE countries have reached high income levels. Much of this catching-up can be attributed to the upgrading of CEE producers in their value chains towards high-value added products (Stojcic et al., 2019).

The CEE innovation model is somewhat different from those found in advanced economies. Radošević (2017) notes that CEE economies’ growth is not based on research-driven innovation but on the interaction of domestic producers with imported equipment and inputs. R&D activities in such settings rather than driving indigenous innovation efforts serve as a means of absorption of imported knowledge and technology. Moreover, most innovation activities in CEE region do not fall within the context of building innovation capabilities but rather reflect non-R&D expenditures such as acquisition of new machinery, software, equipment and so on. Iammarino et al. (2012) refer to patterns of behaviour such as building innovation competencies required for mastering novel products and services, which are converse to building the innovation capabilities required for radical innovations.

Another feature of CEE economies is their weak innovation potential. These countries are characterised by structurally weak innovation systems and their firms often lack internal resources for the autonomous development of innovations (Radošević, 2015; Radošević, 2017; Stojcic and Orlic, 2019). In March 2017, presidents of Czechia, Hungary, Poland and Slovakia signed the Warsaw declaration which acknowledges the exhaustiveness of the existing growth model and calls for the transformation of the CEE region from being the largest European production hub to being its leading research and innovation hub (Financial Times, 2017). The region delivered many innovators who reached the world technological frontier (e.g. Outfit 7, Rimac, Prezi, Sygic, Viber, Skype, TransferWize, Infobip) but these success stories have been mainly the result of individual efforts or collaborations with foreign partners rather than the products of domestic innovation systems (Financial Times, 2017).



Figure 1 presents data from the European Innovation Scoreboard overall score for 2014 and 2018. This indicator, published annually, marks the level of development of national innovation systems in EU member states. The vertical dashed line (in red) represents the EU average while the horizontal bars correspond to the scores of individual EU member states. The CEE group of countries is marked in a light grey colour. Figure 1 clearly shows that with the exception of three countries (Czech, Republic, Slovenia and Estonia) other countries form the group of least advanced EU innovation systems.

Table 1 presents results from most of the main categories and selected subcategories of the European Innovation Scoreboard for 2018 for CEE countries recognised as relevant in collaborative innovation and innovation systems literature. These results reveal that, with exception of Estonia, the CEE countries fall in the group of underperforming innovation environments and are classified as modest or moderate innovation performers. The CEEs are performing well in terms of quality of human resources encompassing new doctoral graduates, a population with tertiary education and those in lifelong learning programmes and in terms of an innovation friendly environment which involves access to digital infrastructure and opportunities created for entrepreneurs. However, in eight out of eleven countries the attractiveness of research system is labelled as modest.

Table 1: European Innovation Scoreboard results for CEE countries in 2018 (selected indicators) relative to EU28

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Indicator (as % of EU28 average score) | BG | HR | CZ | EE | HU | LV | LT | PL | RO | SK | SI | EU28 average score |
| Human resources | 53 | 50 | 75 | 110 | 44 | 63 | 95 | 58 | 14 | 70 | 103 | 18.25 |
| Attractiveness of research system | 21 | 33 | 65 | 94 | 50 | 41 | 37 | 31 | 24 | 42 | 79 | 166.16 |
| Innovation friendly environment | 54 | 41 | 75 | 88 | 92 | 91 | 121 | 125 | 77 | 58 | 89 | 85.08 |
| R&D expenditure in the public sector | 5 | 52 | 96 | 96 | 33 | 37 | 78 | 35 | 5 | 44 | 58 | 0.57 |
| Venture capital expenditures | 24 | 12 | 5 | 82 | 50 | 148 | 29 | 36 | 45 | 7 | 4 | 0.09 |
| R&D expenditures in the business sector | 38 | 30 | 83 | 44 | 72 | 9 | 22 | 48 | 20 | 34 | 102 | 0.99 |
| Non R&D innovation expenditures | 60 | 141 | 89 | 176 | 105 | 90 | 176 | 122 | 3 | 90 | 85 | 0.78 |
| Innovators in economy | 27 | 95 | 97 | 108 | 34 | 40 | 110 | 17 | 0 | 42 | 68 | 31.81 |
| Collaboration linkages of innovative SMEs | 23 | 81 | 107 | 204 | 44 | 41 | 107 | 31 | 5 | 66 | 103 | 12.23 |
| Patent, trademark and design applications | 81 | 30 | 64 | 128 | 41 | 54 | 51 | 69 | 23 | 40 | 81 | 6.02 |
| Sales of new to firm/market innovations | 29 | 50 | 100 | 82 | 46 | 50 | 118 | 32 | 16 | 175 | 56 | 11.16 |
| Buyer sophistication | 87 | 73 | 81 | 86 | 81 | 78 | 87 | 89 | 76 | 78 | 89 | 3.67 |
| Top R&D spending enterprises | 0 | 0 | 13 | 0 | 5 | 0 | 0 | 3 | 1 | 0 | 58 | 27.89 |
| Govt. procurement of advanced tech products | 94 | 71 | 89 | 106 | 80 | 83 | 86 | 86 | 71 | 89 | 74 | 3.36 |

Note: Results in Table 1 show performance on selected components of European Innovation Scoreboard used to construct aggregate scores in Figure 1 relative to the EU28 average score in 2018 (in %). EU28 average scores for each category presented in last column. Values below 50% refer to modest performers, scores between 50% and 90% to moderate performers, scores between 90% and 120% to strong innovators and scores above 120% to innovation leaders. BG, HR, CZ, EE, HU, LV, LT, PL, RO, SK and SI refer to Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia respectively.

Source: European Innovation Scoreboard, 2014 and 2018

The evidence on innovation expenditure confirms previously mentioned arguments (Radošević, 2017) about non-R&D driven innovation in these countries. R&D expenditures of public and business sector and venture capital expenditures in most countries are marked as modest, while non-R&D expenditures put these countries in the group of European leaders. The Innovation Scoreboard methodology also provides information on collaboration activities of innovative SMEs. In Bulgaria, Hungary, Latvia, Poland and Romania, collaboration intensity is marked as modest, in Croatia and Slovakia as moderate, while in other CEE countries scores suggest strong collaboration performance. It is also worth noting that in terms of innovation output measured by both patenting and sales of products new to the firm or market these countries fall below EU average. Finally, buyer sophistication and public procuremeAcnt of innovations as well as share of top R&D spending enterprises are well below EU average levels.

Together these findings suggest that the CEE can be classified as emerging innovation systems with limited potential for collaboration. This issue has been acknowledged by Radošević (2017) who notes that due to the limitations of domestic innovation systems CEE innovators are reliant on foreign knowledge. Švarc and Dabić (2019) show that commercial exploitation of knowledge created in collaboration with universities in CEE hardly exists. Such findings correspond to those about other emerging innovation systems. Da-Chang et al. (2014) note that the quality of collaborative innovation is higher for firms in advancing countries when it involves partners from advanced countries rather than firms from the local environment and other countries at a similar level of development.

* 1. *Collaborative innovation in emerging innovation systems*

The competitive advantage of organizations was for a long time viewed as an outcome of internal organizational forces (Powell et al., 1996; Baldwin and von Hippel, 2011). One of the most prominent of these views is the resource-based view (RBV) which defines firms as bundles of valuable, rare, difficult to imitate and non-substitutable resources whose heterogeneity determines the position of firms against their rivals and their ability to develop novel products and processes (Penrose, 1959; Barney, 1991; Kogut and Zander, 1992). With the increasing reliance of firms on external resources it became, however, evident that RBV offers only a partial explanation of firm behaviour. This limitation gave rise to an extended RBV (Mathews, 2003; Lavie, 2006; Lin et al., 2009; Mention, 2011). According to this literature, collaborative practices provide focal firms with opportunity to complement and extend their internal resources with knowledge, technology or the experience of their partners (Dyer and Singh, 1998; Lavie, 2006; Arya and Lin, 2007).

Among the collaborative practices of organizations, collaborative innovation, that is, knowledge and technology sharing in the creation of new products and services, stands as particularly relevant. Innovation requires a heterogeneous mix of resources that cannot be found within organizational boundaries (Teece, 1986). How organizations can access these resources in their environment and transform them into novel products and services has been the subject of investigations in extended RBV, dynamic capabilities approach, knowledge-based and technology-based views as well as in the economic geography and innovation systems literature (Boschma, 2005; Petruzzelli, 2008; Tsai, 2009; Du Chatenier et al., 2009; Huang and Yu, 2011; Brettel and Cleven, 2011; Wagner, 2012; Iammarino et al., 2012; Ritala and Hurmelinna-Laukkanen, 2013). While these individual streams advanced our knowledge about collaborative innovation each in its own way, the literature lacks a clear link connecting these theoretical streams into a single comprehensive theoretical framework of collaborative innovation.

One of the critiques of the extended RBV is its failure to reveal actual mechanisms through which internal and external resources facilitate the innovation process (Knudsen and Nielsen, 2010). Later contributions within dynamic capabilities, knowledge-based and technology-based views have addressed this shortcoming (Teece et al., 1997; Winter, 2003; Du Chatenier et al., 2009; Knudsen and Nielsen, 2010). The general message coming from this literature is that through collaboration firms gain access to specialized equipment, expertise or superior strategic resources such as the R&D departments of partner organizations such as rivals, suppliers, customers, consultants, universities or research centres and intra-group members (Hanel and St-Pierre, 2006; Huang and Yu, 2011; Iammarino et al., 2012; Bucic and Ngo, 2012). This collaboration, in turn, extends two types of organizational resources: competencies relevant for the development of marginally modified and incremental innovations and capabilities required for building radically novel products and services (Iammarino et al., 2012).

Both theoretical and empirical research invest a great deal of effort identifying peculiar mechanisms through which collaboration enhances creation and commercialization of innovations. Evidence suggests that collaborations involve myriad vertical and horizontal relationships among actors (Arya and Lin, 2007). Collaboration provides information about market trends (D’Este and Perkmann, 2011) and helps firms reduce the time required for the development of innovation through access to specialized product and process technologies (Tsai, 2009). The resources of other entities, such as scientific institutions, in a collaborative innovation network, reduce the costs of a search for knowledge and supplement organizational R&D activities (Link and Scott, 2019). Finally, resource complementarities serve the Schumpeterian purpose of creating new and extending existing markets (Teece, 1986; Dosi and Nelson, 1994). Each of these mechanisms involves a different set of actors from collaborative innovation networks and requires a certain extent of complementarities for collaboration to yield gains for organizations.

Neither RBV nor any of its extensions provide answers about preconditions required for the success of collaboration. Theoretical contributions within economic geography and innovation systems define these preconditions as inter-organizational proximity (Boschma, 2005; Petruzelli, 2011; Iammarino et al., 2012; Elia et al., 2019). These proximities involve complementarities in management culture and a way of doing business as well as sector-specific capabilities and expertise, ways of information transfer, knowledge complementarity and trust. The relevance of inter-organizational proximity nested collaborative innovation networks within a framework of innovation systems because it was largely held that such complementarities arise from geographical proximity among organizations. However, recent advancements in information and communication technologies have reduced the relevance of geographical proximity within collaborative innovation networks and modern collaborative innovation networks involve actors both from local, regional and national innovation systems and located beyond national borders.

Putting these elements together, a stylised theoretical framework behind collaborative innovation can be formulated. In simplest terms, collaborative innovation arises from the need of firms to complement their internal resources with the resources of their rivals, suppliers, customers, scientific institutions and other members of the firm’s group. Through such activities, firms gain access to specialized knowledge, technology and expertise that reduces the costs of research and increases the efficiency of the innovation process. The success of this innovation depends on inter-organizational proximities and may involve partners from within and beyond a national innovation system. A distinction, however, should be made between complementing and building indigenous resources through collaboration. In the short run, collaborations are primarily mechanism for complementing absent organizational resources. Over medium to long run such inter-organizational arrangements enable also development of indigenous resources through demonstration effects, accumulation of knowledge and expertise and vertical spillovers from buyers and customers.

The nexus of the theories discussed above provides a general understanding of collaborative innovation but none of the existing theories are concerned with emerging innovation systems. However, the propositions of RBV and dynamics capabilities literature can be used to build theoretical pillars of collaborative innovation even in these settings. The success of the innovation process depends on the mix of heterogeneous physical and non-physical innovation competencies such as R&D laboratories, machinery, equipment or human capital as well as innovation capabilities accumulated through adaptive learning (Von Tunzelmann and Wang, 2003). The distinction between the two is important because they lead to different types of innovations. While innovation competencies fuel the development of incremental innovations and marginal modifications to existing products, innovation capabilities lead to the creation of radical, novel to the world, products and services (Iammarino et al., 2012).

Previously cited literature about CEE innovation systems acknowledged that these countries are characterised by weak innovation and technology transfer potential (Švarc and Dabić, 2019). Being far from the technological frontier, their innovation activities involve modification of existing products and the application of existing best practices while radical innovations are scarce (Stojcic et al., 2020). Organizations in such settings search for basic innovation capabilities that are relevant for the introduction of marginally modified products and incremental innovations (﻿Goni and Maloney, 2017; Fernández-Sastre and Martín-Mayoral, 2017; Radošević, 2017). This situation signals that collaborative innovation in CEE innovation systems is more likely to facilitate commercialization of less innovation intensive novel products and services than radically novel, new to the market, products and services. This brings us to our first hypothesis.

*H1: Collaborative innovation in CEE innovation systems enhances the commercialization of existing marginally modified and incrementally novel but not radically novel products.*

* 1. *Different types of collaboration partners*

Collaborative innovation takes place through myriad vertical and horizontal mechanisms with rivals, suppliers, consumers, scientific institutions or governance-related organizations (Hanel and St-Pierre, 2006; Huang and Yu, 2011; Iammarino et al., 2012; Bucic and Ngo, 2012). Each of these entities has the potential to contribute to the creation and commercialization of innovations in a distinctive way. Following von Hippel’s (1986) seminal work on the lead user concept, empirical studies have shown that *consumers* can steer the innovation process in the right direction through provision of information about market trends or by providing feedback on unrefined versions of novel products and services as early adopters (Nieto and Santamaria, 2007; Tsai, 2009; Brettel and Cleven, 2011; D’Este and Perkmann, 2011).

At the other end of the vertical collaboration channel, *suppliers* possess knowledge about specialized product and process technologies that may shorten the time required for innovation development and improve its quality by contributing to front-end stages of innovation such as idea generation or evaluation of project feasibility (Tsai, 2009). Empirical studies report ambiguous findings on these supplier-buyer relationships (Wagner, 2012; Nieto and Santamaria, 2007; Un et al., 2010). It appears that the greatest challenge in successful collaboration between innovators and suppliers lies in the management of relationships between involved entities, particularly aversion to disclosure and sharing information about product characteristics and technical details; communication and coordination costs among partners at greater social or geographic distances but also on ability of buying firms to absorb knowledge provided by suppliers (Rosell and Lakemond, 2012).

Link and Scott (2019) note that private firms benefit from technology and knowledge created in *scientific institutions* in two ways. Publicly created R&D can be used to improve the production efficiency of firms and as an input to private R&D activities. Both channels have been found to reduce the costs of access to required knowledge and technology (Boehm and Hogan, 2013; Link and Scott, 2019). Universities and research laboratories play an increasing role in collaborative innovation through the use of intellectual property patented by the science sector in firms; collaborative and contract research; and, consulting or other forms of knowledge exchange (Nieto and Santamaria, 2007; Brettel and Cleven, 2011; D’Este and Perkmann, 2011; Perkmann et al., 2013). Hanel and St-Pierre (2006) observe that the probability of science-business collaboration increases with geographical proximity between organizations, the quality of academic institutions and absorptive capacity of collaborating firms.

In their efforts to extend and build own resource base, firms also turn to their competitors. Collaboration between rivals, known as *coopetition* creates new and expands existing markets but it comes with risks of appropriation in the presence of technological disparities (Teece, 1986; Dosi and Nelson, 1994). Some authors suggest that coopetition may be more relevant for incremental than for radical innovations (Ritala and Hurmelinna-Laukkanen, 2013). The success of coopetition may be severely constrained in the presence of the openness paradox, a reluctance of firms to reveal their strategic assets to collaborators. Nieto and Santamaria (2007) found negative effects of coopetition for the introduction of innovations while Tsai (2009) found that collaboration with competitors has a negative effect on radical innovations and a positive effect on marginal innovations. A part of the explanation for such ambiguous findings can be traced to the above paradoxical nature of coopetition.

Apart from these external channels, literature has recognised that knowledge sharing among members of governance-related groups (intra-group) of firms is particularly important in cases when the institutional framework does not provide sufficient conditions for collaboration to take place. Elia et al. (2019) note that MNCs subsidiaries act as both recipients and providers of knowledge within their firm groups. This literature became particularly relevant with the globalization of economic activity and the establishment of subsidiaries of multinational corporations across the world. Intra-group knowledge flows take place in environments characterized by low uncertainty, common organizational culture and straightforward communication channels (Hansen and Mattes, 2017). For this reason, such intra-group collaborations have been found to take place irrespective of spatial proximity.

Whether all the aforementioned channels are relevant in emerging innovation systems is a question that remains unanswered. Table 1 in the previous section and findings from previous studies (Radošević, 2017; Švarc and Dabić, 2019; Stojcic et al., 2020) reveal low buyer sophistication, weak technology transfer potential and a general lack of innovation competencies and capabilities among firms in CEE innovation systems. All actors in such settings may possess resources more relevant for marginal modifications of existing products and application of products and services that are known to the market but new to the firm. For example, weak buyer sophistication may fail to provide sufficiently strong impulse for the development of radically novel innovations just as suppliers embedded in production-driven economic frameworks may lack specialised product and process technologies for the introduction of new-to-the-market products.

Along similar lines to the ones above, weak technology transfer potential means that the science sector may fuel more input in less innovation intensive products and services but lack sophisticated knowledge required for radical innovation. Moreover, rivals may not serve as a source of resources for the development of radical innovations because they operate within the same environment as focal firms. Finally, the intra-group knowledge flows in CEE countries have proven in the past to be a source of production competencies and capabilities. When it comes to innovation-relevant knowledge and technologies these channels have generally failed to meet the expectations of policy makers in CEE countries (Holm et al., 2019; Stojcic and Orlic, 2019) For these reasons we formulate our second hypothesis as:

*H2: Collaboration with customers (H2a), suppliers (H2b), competitors (H2c), scientific institutions (H2d) and firm group members (H2e) facilitates the commercialization of existing marginally modified and incrementally novel but not radically novel products and services in CEE innovation systems.*

* 1. *The role of geographical and non-geographical proximities*

There is a long-standing argument that proximity between involved entities facilitates the success of collaboration arrangements. Within such reasoning, it has traditionally been considered that geographical proximity gives rise to the creation of different types of non-spatial proximities such as social, organizational, institutional and cognitive ones (Boschma, 2005; Petruzelli, 2011; Iammarino et al., 2012; Elia et al., 2019).). The above cited five proximities framework (Boschma, 2005) encompasses different types of proximities that determine the outcome of collaboration. Frequent social interactions enable more efficient information transfer and building of trust while organizational proximity facilitates exchange of complementary knowledge between collaboration partners. Institutional proximity can be related to similarities in management culture and knowledge about coordination principles (the way of doing business in general and culture), while cognitive proximity refers to sector-specific capabilities and expertise.

While geographical proximity may facilitate the creation of these types of proximities it is neither a necessary nor sufficient condition for knowledge sharing and learning to take place. Lack of sufficient innovation competencies and capabilities may offset any facilitating effects that may arise from geographical, social, institutional or organizational capabilities. In such instances, openness to collaboration from other geographical areas may become beneficial if cognitive proximity exists between them (Boschma, 2005). Recent technological advancements have enabled the creation of non-spatial networks among partners at greater distances (Petruzzelli, 2008; Del Guidice et al., 2019). This signals that modern innovation systems involve actors beyond national borders and that traditional notions of innovation systems as closed within national and regional borders inadequately portrays the setting in which collaboration takes place.

In the context of emerging innovation systems such as CEE countries, it appears, therefore, that proximity and sharing social, institutional and cultural values may become non-beneficial if collaborating organizations do not possess sufficient cognitive capabilities. The domestic context of these countries provides firms with social, institutional, organizational and cognitive proximity but, as we have already established, innovators in such contexts possess limited innovation competencies and capabilities. These weaknesses of domestic innovation systems motivate a search for partners beyond national borders. The success of such collaborations depends on the degree of proximity along different non-spatial dimensions. For example, collaborations between partners with high levels of cognitive proximity may be endangered if social and institutional distance is high, which is manifested through lack of trust and different views about norms, habits or laws. Similarly, the cultural dimension of institutional diversity gives rise to coordination and negotiation costs (Elia et al., 2019). Differences in communication patterns, management styles, opinions, attitudes and beliefs increase the cost of acquiring and leveraging knowledge.

Previous studies addressed the role of proximity in various aspects of the innovation process. Within the EU, Amoroso et al. (2018) find that the intensity of R&D collaborations in the EU’s 7th Framework Programmes decreases with geographical distance and institutional/language barriers, while higher levels of economic and technological proximity between geographic areas increase the intensity of R&D collaborations. In the least developed parts of the EU, such as CEE, collaboration mainly takes place within their own boundaries and cultural, institutional and technological distance plays an important role in the establishment of research collaboration among partners from these areas and more developed parts of the EU. The same study also notes that CEE regions R&D collaboration intensity is among the lowest in the EU. Findings on research collaborations between EU and non-EU partners show that in collaborative research, social and organizational proximity plays a smaller role in Europe than in North America in comparison to cognitive and institutional proximity between partners (Hardeman et al., 2015). Wang et al.’s (2017) evidence suggests that among EU member states, those countries that joined the EU after 2000 (CEE) are those whose linkages with Chinese partners in scientific collaborations have been increasing the most over the 2000-2014 period.

Among rare studies on the role of proximity in inter-firm collaborations, Hansen and Mattes (2017) have investigated cases of collaboration in innovation projects between German multinational corporations and their foreign subsidiaries in India and China. Their findings show that the extent of barriers between collaboration partners depends on their hierarchical position vis a vis one another in collaboration and knowledge base. Entities in inferior positions were found to experience more difficulties arising from geographical distance, lack of social ties, and the unwillingness of technologically superior partner to disclose strategically important knowledge. Moreover, the study shows that in such cases the motives of the technologically superior partners are to control rather than to empower counterparts in collaboration. Finally, findings suggest that institutional distance in such collaborations obscures partners’ understanding of each other’s needs. Such findings are in line with those of Elia et al. (2019) who establish that cultural diversity between partners negatively affects their innovation performance. These effects seem particularly strong when such collaborations involve subsidiaries of multinational corporations whose organizational culture embodies elements of both host and parent country.

None of the above-mentioned studies, however, explored the role of partners from different countries in the commercialization of products and services. Our study is, thus, the first to assess the role of geographical and non-geographical proximities in the context of collaborations in the commercialization of innovations in emerging innovation systems. There are, however, studies which argue that in advancing economies non-spatial types of proximities may be more relevant than geographical due to the weaknesses of indigenous innovation systems (Boschma, 2005; Hansen and Mattes, 2017).

To assess these effects in our study we distinguish between four groups of partners taking into account the geopolitical context of the CEEs. Until lately, the CEE region found itself in the midst of geopolitical actions between the European Union, US and China. EU investors have been present in the region for several decades but the interest of the US in the region has grown in recent years, being evident mostly through the Three Seas initiative. Most recently, China has also shown interest in the region through its 16+1 initiative as part of its wider Belt and Road initiative to strengthen its presence in the European market (Associated Press, 2018).

To the best of our knowledge, the role of spatial and non-spatial proximities in the context of collaborative innovation in CEE innovation systems has not been examined. In our study, we intend to approach this issue from several angles. We hypothesise that, due to the similar path of development before and during the transition period, the CEE region embodies high social, institutional, organizational and cognitive proximity. For this reason, any barriers to collaboration among partners from this region might have their origin in the lack of indigenous innovation competencies and capabilities. The first group of partners, therefore, comprises domestic firms for which we expect high levels of all non-spatial proximities.[[1]](#footnote-1)

*H3a: Collaboration with domestic partners in CEE innovation systems facilitates the commercialization of innovations due to social, cognitive, organizational and institutional proximity.*

Another angle adopted in this study is related to the role of the countries under consideration in the European economic and political integration. While in such integration one can expect a high degree of social, institutional and organizational proximity, but the cognitive proximity between organizations from member states at different levels of development is likely to be low. The latter is particularly true for innovators from emerging innovation systems that seek partners with a compatible level of innovation competencies and capabilities. For the above reason, the positive effects of collaboration between partners in different countries of economic integration can be expected in less radical innovations such as marginally modified ones or products that are new to the firm but have been known to the market. The second group, therefore, comprises firms from other EU member states for which we expect high levels of social, organizational and institutional proximity but low levels of cognitive proximity.

*H3b: Collaboration with partners from other EU member states facilitates the commercialization of innovations in CEE innovation systems due to organizational, social and institutional proximities but not due to cognitive proximity.*

Finally, the last part of puzzle focuses on collaboration with partners from distant parts of the world where social, institutional and organizational diversity is likely to be high to the extent that it acts more as a barrier than facilitator of collaboration. However, firms able to overcome such barriers stand a chance of benefitting from cognitive proximity with partners from these distant countries. To this end, one should distinguish between two types of partners. Entities from countries at a similar level of development or those countries whose recent path was similar to that of indigenous one are likely to possess a lower level of innovation competencies and capabilities than partners from countries at the global technological frontier (Da-Chang et al. (2012). It is for this reason that partners from the latter group of countries might be more relevant for the development of radical innovations. However, at the same time, firms from many advancing countries that succeeded in reaching the world technological frontier have not done so by following counterparts in advanced countries but by exploiting the technological windows of opportunity (Perez and Soete, 1988). Collaborations between such firms from different emerging innovation systems may thus prove beneficial for the success of the innovation process.

Building on above the third group consists of partners from the United States (US) as our proxy for partners from distant world- leading economies. We also assess collaboration with firms from distant but less developed economies where we include China and India and a group of other countries (the rest of the world) in line with the boundaries of our data. For groups of non-EU collaborators we expect cognitive proximities among innovators to be principal drivers of collaboration.

*H3c: Collaboration with partners from the US, China and India and other non-EU member states facilitates the commercialization of innovations in CEE innovation systems due to cognitive proximity but not due to social, institutional and organizational proximity.*

It needs to be emphasised, however, that our analysis is not based on direct measures of the level of inter-organizational proximities. Such data are not available for all our analyzed pairs of countries and for most types of non-spatial proximities. Moreover, as it will be shown in the next section, we deal with an anonymised dataset that precludes identification of firms and construction of measures of organizational proximity. This is a common problem in data analysis and one of the main reasons why most studies investigating directly non-spatial proximities at firm level are based on case study analyses (Hansen and Mattes, 2017). At the risk of generalization, we rely on insights from the studies discussed above in our assessment of potential proximities that might be mechanisms driving collaboration between entities and theoretically assume a certain level of proximity across previously discussed dimensions.

1. **Empirical strategy**
	1. *Data*

Our analysis is based on firm level data coming from the Community Innovation Survey (CIS) database, a bi-annually compiled dataset of the innovation activities of firms in EU member states and some of the candidate countries. It is compiled and maintained by Eurostat and national statistical agencies in surveyed countries. The dataset is treated as confidential and access to researchers is provided only under controlled conditions of a safe room or through a secure server. Permission for access is granted on the basis of individual research proposals. The microdata (for individual firms) are commonly released with a lag of at least three years. At the time of writing this paper, the last accessible version of the dataset was the one released during 2017, covering the 2012-2014 period. This means that, at the time of writing, the dataset represents the most recent and most comprehensive source of information on innovation behaviour of firms in EU member states.

The request for access to data for this research was submitted to Eurostat in the first half of 2018 and access was granted in November of the same year. Permission to use the data included nine CEE countries, namely Bulgaria, Czechia, Croatia, Estonia, Latvia, Lithuania, Hungary, Romania and Slovakia. The CIS requires each respondent to answer only a specific set of questions. The questions related to R&D expenditure, collaboration activities and success of the innovation process are answered only by those firms involved in at least some type of innovation activity (product, process and abandoned innovations). 10.008 firms responded to all questions relevant for the purpose of our analysis. Hence, our study aims to assess how collaboration with different partners affects the performance of firms that have engaged in any type of innovation. To some extent, this presents a limitation of our research. However, it is a limitation present in any other European firm-level innovation dataset and should be addressed in future innovation datasets.

The suitability of the CIS dataset for the present analysis needs to be addressed. CIS is commonly used in investigations of firm innovation activities because it represents the most comprehensive source of information about such activities of firms in Europe (Mairesse and Mohnen, 2004; Laursen and Salter, 2006; Iammarino et al., 2012; Hashi and Stojcic, 2013; Horbach, 2016). It belongs to the group of “subject-oriented” datasets as participating firms are required to provide direct answers to questions about particular dimensions of their innovation behaviour. The interpretability, reliability and validity of the survey rely on extensive pre-testing and piloting across countries and sectors and the dataset is designed to enable it to encompass the systemic nature of innovation activities between firms and their external environment (Laursen and Salter, 2006). Iammarino et al. (2012) note that the CIS dataset is the sole database with information about different sources of innovation in EU countries including collaboration between actors.

A weakness of CIS is that each of its iterations focuses on a relatively short time frame. In the long run, the nature of the relationship between internal and external resources and the success of the innovation process becomes more complex due to an interplay between innovation competencies and capabilities. However, current knowledge does not provide any longitudinal dataset that would enable modelling of the long-term effects of collaborative innovation. To this end, one must assume a simplifying assumption of a sequential logic between the innovation competencies and capabilities (Iammarino et al., 2012) where innovation competencies drive the commercialization of existing and incrementally novel products while innovation capabilities or knowledge accumulated through learning and experience are responsible for the success in radical innovations.

Another advantage of CIS is its suitability for modelling spatial and non-spatial proximities between organizations. This is particularly emphasized in the part of the dataset on collaborative innovation. Specifically, respondents are asked about the origin of collaborating organizations and several options are offered including other EU member states, US, China and India and rest of the world (others). Finally, CIS divides the turnover of organizations by the degree of novelty of their products into the percentage of turnover coming from existing or marginally modified, incrementally novel and radically novel products and services. Overall, although prone to some weaknesses, CIS has been recognised in existing literature as the best and most comprehensive source of data on the innovation behaviour of European firms and the sole database with information on the collaborative activities of firms and thus can be regarded as the most suitable dataset for the purpose of our analysis.

Table 2: Sample structure

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Indicator (as % of EU28 average score) | BG | HR | CZ | EE | HU | LV | LT | RO | SK | Total |
| Number of firms | 2347 | 797 | 2362 | 425 | 1485 | 364 | 975 | 652 | 509 | 10.008 |
| Number of non-innovators | 881 | 230 | 605 | 169 | 495 | 128 | 375 | 273 | 205 | 3.361 |
| Number of innovators | 1.556 | 567 | 1.757 | 256 | 990 | 236 | 600 | 379 | 304 | 6.647 |
| Share of non-innovators (in %) | 36 | 29 | 26 | 40 | 33 | 35 | 38 | 42 | 40 | 34 |
| Share of innovators (in %) | 64 | 71 | 74 | 60 | 67 | 65 | 62 | 58 | 60 | 66 |

Source: Community Innovation Survey 2014

Table 2 presents the number of firms across countries and some stylised facts about the structure of our sample. From there it is evident that about 30-40% of firms in all countries can be categorized as unsuccessful innovators because they have achieved 0% of revenues from either incremental or radical innovations. Moreover, revenues from innovations form a smaller portion of total revenues of firms in all countries. As Figure 2 shows, between 75% and 85% of revenues among innovative firms in all analyzed countries originate from existing or marginally modified products which are commonly regarded as the least innovation intensive product group. These are followed with products new to the firm but known to the market which can be regarded as imitation of practices of more advanced rivals. Overall, these findings further confirm previous argumentation about the weak innovation potential of CEE economies.



On the whole, about 37% of firms have been involved in some kind of collaborative innovation (Figure 3). The greatest intensity of collaboration is found in Czechia, Slovakia, Hungary and three Baltic countries. Such a finding is not surprising given the strong technological intensity of local economies and the inflow of foreign investment they received over the past two and half decades.



It seems that the least preferred pattern of collaboration is coopetition (Figure 3). As we already argued, coopetition entails the risk of knowledge leakages and may produce suboptimal results if the technological and knowledge parities between collaborative entities are high. Among other types of collaboration, about 26% of all firms were engaged in collaboration with suppliers and about 15% of firms in collaboration with customers and with universities and research entities.

* 1. *Methodology and variables*

Our empirical strategy considers collaboration in the commercialization of innovations as a treatment received by firms and estimates its effect by means of an econometric technique of nearest neighbour matching estimation from the treatment family of estimators (Rosenbaum and Rubin, 1983; Heckman et al., 1998; Wooldridge, 2010). Treatment analyses are undertaken in two steps: the first step includes estimation of the probability of receiving a treatment (in our case being part of a collaboration) and in the second step the effect of such treatment on variables of interest is estimated. In an ideal case one should deal with subjects whose distribution between treated (collaborating firms) and non-treated (non-collaborating firms) groups is random and thus ensures independence of outcome from the treatment. However, researchers in social sciences rarely encounter datasets that satisfy such an assumption. In a concrete case, this means that there might be some factors that make firms self-select collaboration. This self-selection is the reason why outcomes and treatment cannot be considered independent and estimates from conventional regression estimations are likely to be biased.

In the presence of self-selection, estimated effects would reflect not only the treatment (collaboration) but also unobserved group differences. The way around this problem is in randomization of the analysed sample through modelling of the treatment assignment process. Such modelling defines the assignment of subjects into one of the treatment categories as a function of all factors that could drive the decision of firms to enter collaborative innovation (treatment). Well specified models with all relevant determinants included make the treatment assignment process as good as random, conditional on the included variables (Rubin, 1977; Cattaneo, 2010). Besides this conditional independence assumption (CIA), treatment models are required to meet the overlap assumption which means that each unit (firm) has a positive probability of receiving each treatment level and that the sample does not include firms which cannot receive treatment for any reason.

Matching estimators, such as the one used in this analysis, evaluate particular treatments through matching the outcomes of treated subjects with outcomes realised by subjects with similar characteristics but differences in their treatment assignment. To this end, similarity measures are applied that measure the closeness between observed units. Nearest neighbour matching procedure determines the distance between pairs of observations on the basis of predefined set of covariates. The matching, from there, takes place between subjects with the highest degrees of similarity. As a result, the means of the treatment specific predicted outcomes are produced whose contrasts can be used to obtain either average treatment effects across the population (ATE) or average treatment effects on the subset of treated subjects (ATT).

The discussion above suggests that a crucial part of treatment analysis is selection of covariates in the modelling of treatment assignment process, i.e. the determinants of the propensity towards collaborative innovation. Table 3 provides detailed definitions of all used variables. Among control variables, the model includes firm size measured by a dummy variable that takes the value of 1 if the firm belongs in a group of small and medium sized firms (*sme*). The construct of this variable was conditioned by the characteristics of the underlying dataset. Access to the dataset did not include continuous variables such as the number of employees who could be used as a proxy for firm size. Moreover, the anonymization procedure of the CIS dataset in some countries (e.g. Slovakia) does not distinguish between small and medium sized firms.

Table 3: Description of variables

|  |  |
| --- | --- |
| Variable name | Description |
| Dependent variables |
| *turnexisting* | % of turnover generated from sales of products that are unchanged |
| *turnincremental* | % of turnover generated from sales of products that are new to the firm but known to the market |
| *turnradical* | % of turnover generated from sales of products that are new to the market |
| *collaboration* | selection (treatment) variable – 1 if firm involved in collaborative innovation with: i) any partner, ii) intra-group members, iii) customers, iv) suppliers, v) coopetitors, vi) universities and research labs (science) |
| Independent variables |
| *exporter* | 1 if firm’s main markets are other EU member states or countries outside the EU |
| *organizational* | 1 if firm introduced one or more of following types of organizational innovation: i) new business practices such as supply chain or quality management or knowledge management, ii) new methods for organization of work responsibilities and decision making and iii) new methods for organization of external relations |
| *marketing* | 1 if firm introduced one or more of following types of marketing innovation: i) changes to the design or packaging, ii) product promotion, placement or sales channels and iii) new pricing methods |
| *public* | 1 if firm received public financial support for innovation or public procurement for innovation during the 2012-2014 period |
| *restructuring* | 1 if firm experienced merger, takeover, selling, closing or contracting out some of its tasks and functions |
| *appropriability* | 1 if firm applied for patent, licencing right, trademark or design right in the 3 years prior to survey |
| *sme* | 1 if firm size is small or medium |
| *r&din* | 1 if firm was involved in in-house R&D in 3 years prior to survey |
| *man* | 1 if firm is in the manufacturing sector |
| *ct1-ct9* | 1 for each of the nine countries under consideration |

Source: Author

Exporting experience, the proxy for learning by exporting is controlled by a dummy variable that takes the value of one if the firm considered the markets of the European Union and other foreign countries as its main markets (*exporter*). The model includes a categorical variable for firms that introduce organizational innovations such as new business practices, novel methods for organization of external relations and new ways of organizing work responsibilities (*organizational*) and those firms that engaged in marketing innovations such as design of their products and services, new product promotion techniques and new methods of pricing (*marketing*). In innovation literature, organizational and marketing innovations are commonly considered as innovation throughput that facilitates commercialization of product innovations (Kemp et al., 2003; Hashi and Stojcic, 2013). The need for collaboration could arise from changes in organizational structure such as mergers, acquisitions or sell outs of organizational parts. To control for this variable *restructuring* enters the model for firms that experienced mergers, takeovers, selling, closing or contracting of some of the enterprise functions.

A categorical variable is introduced that takes the value of one if firms have employed patenting, licencing, trademarks, design rights or European utility models in three years prior to survey (*appropriability*). The propensity towards collaboration may be motivated by a public push and pull incentives such as financial subsidies or public procurement. The categorical variable *public* takes the value of 1 if the firm was a recipient of either financial support or public procurement for innovation. The success of the collaboration process depends on the absorptive capacity of involved firms. To control for this issue, we included a categorical variable that takes the value of one if the firm invested in in-house R&D activities during three years prior to the survey (*r&din*). Finally, we control for sector and country effects by including corresponding dummy variables. Summary statistics of all variables are provided in Table 4.

 Table 4: Summary statistics of variables

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Mean | St.Dev. | Min | Max |
| *turnexisting* | 51.11 | 41.56 | 0 | 100 |
| *turnincremental* | 8.32 | 19.31 | 0 | 100 |
| *turnradical* | 12.63 | 23.24 | 0 | 100 |
| *collaboration* | 0.37 | 0.48 | 0 | 1 |
| *group* | 0.16 | 0.37 | 0 | 1 |
| *customers* | 0.15 | 0.35 | 0 | 1 |
| *suppliers* | 0.26 | 0.44 | 0 | 1 |
| *coopetitors* | 0.07 | 0.25 | 0 | 1 |
| *science* | 0.14 | 0.35 | 0 | 1 |
| *exporter* | 0.35 | 0.48 | 0 | 1 |
| *organizational* | 0.40 | 0.49 | 0 | 1 |
| *marketing* | 0.41 | 0.49 | 0 | 1 |
| *public* | 0.48 | 0.50 | 0 | 1 |
| *restructuring* | 0.13 | 0.35 | 0 | 1 |
| *appropriability*  | 0.20 | 0.40 | 0 | 1 |
| *sme* | 0.80 | 0.40 | 0 | 1 |
| *r&din* | 0.43 | 0.49 | 0 | 1 |
| *man* | 0.61 | 0.49 | 0 | 1 |

 Note: Number of observations n=10.008

 Source: Author

The question that needs to be thoroughly discussed prior to any estimation of the model specified in this particular way concerns its ability to eliminate any source of hidden bias that might influence our findings. For this reason, we submitted the model to a number of relevant tests. These are, for expositional convenience, presented in an online appendix to this paper in Tables A3-A5 and Figure A1. Specifically, we examined whether the distribution of covariates is balanced and whether the difference between means of the two groups is equal to zero. Results from Table A1 do not reveal sufficient evidence to reject the null-hypothesis of balanced covariates. Another indicator of a valid treatment analysis is the overlap requirement. This states that each individual should be assigned a positive probability of receiving each treatment level. Figure A1 demonstrates satisfactorily overlap between propensity scores of control and treated groups after the matching procedure suggested that the overlap assumption is not violated.

The sensitivity of the model to hidden bias is further examined by means of the Rosenbaum (2002) bounds approach and placebo treatment analysis. The results of the Rosenbaum bounds approach (Tables A2a-A2c in Online appendix) reveal the robustness of our model to hidden bias at levels well exceeding those considered as relevant in other analyses (e.g. Michalek et al., 2016 or Srhoj et al., 2019). Finally, a placebo test was undertaken where actual collaborating firms were excluded from the sample and their role was taken by a control group of firms (Table A3 in Online appendix). With the exception of few cases with significance at 10% (and p vaues above 0.9) results from all placebo estimations were insignificant at conventional levels of significance further confirming the robustness of our model to unobserved selection bias.

The next section explores the effects of collaboration on the commercialization of three types of products and services sold by analysed firms. Sales revenues are, thus, decomposed into three categories expressed as percentages of revenues coming from: i) the unchanged or marginally improved products, ii) products that are new to the firm but have been known to the market (incremental innovations) and iii) the products that are novel to both the firm and the market (radical innovations). We first focus on firms that participated in any form of collaboration and then move to explore the effects of individual collaboration channels divided into five categories as customers, suppliers, coopetitors, science sector including universities and research laboratories and finally, firms belonging to the same enterprise group. All estimations were undertaken with Stata/MP 15.1 software operating on Mac OS platform.

1. **Results**

A common starting point in treatment analyses is the evaluation of the underlying model that determines the probability of treatment occurrence. The treatment category in our analysis is engagement in a collaborative innovation process. We begin with assessment of the probability of any type of collaborative arrangement before we move to explore individual channels of collaboration including: i) collaboration within enterprise group, ii) collaboration with suppliers, iii) collaboration with customers, iv) collaboration with coopetitors and v) collaboration with universities and scientific institutions. For each of these treatments we run a logit regression whose results are presented in Table 4.

Table 4: Results of selection equation (dep. variable: Propensity of collaboration)

|  |  |
| --- | --- |
| Variables | Type of collaboration partner |
| Any type | Intra-group | Customers | Suppliers | Coopetitors | Science |
| *exporter* | 0.34\*\*\*(0.050) | 0.65\*\*\*(0.065 | 0.19\*\*\*(0.066) | 0.23\*\*\*(0.054) | 0.24\*\*\*(0.093) | 0.26\*\*\*(0.072 |
| *organizational* | 0.45\*\*\*(0.049) | 0.71\*\*\*(0.065) | 0.56\*\*\*(0.066) | 0.50\*\*\*(0.054) | 0.51\*\*\*(0.094) | 0.32\*\*\*(0.071) |
| *marketing* | 0.24\*\*\*(0.050) | 0.34\*\*\*(0.066) | 0.26\*\*\*(0.066) | 0.36\*\*\*(0.054) | 0.50\*\*\*(0.094) | 0.19\*\*\*(0.071) |
| *public* | 0.43\*\*\*(0.047) | -0.17\*\*\*(0.062) | 0.47\*\*\*(0.063) | 0.40\*\*\*(0.051) | 0.66\*\*\*(0.092) | 1.3\*\*\*(0.074) |
| *restructuring* | 0.41\*\*\*(0.066) | 0.66\*\*\*(0.074) | 0.09(0.081) | 0.25\*\*\*(0.068) | 0.18\*(0.107) | 0.17\*(0.087) |
| *appropriability* | 0.32\*\*\*(0.058) | 0.015(0.075) | 0.31\*\*\*(0.070) | 0.31\*\*\*(0.061) | 0.37\*\*\*(0.093) | 0.63\*\*\*(0.074) |
| *r&din* | 0.63\*\*\*(0.627) | 0.39\*\*\*(0.065) | 0.80\*\*\*(0.066) | 0.35\*\*\*(0.053) | 0.94\*\*\*(0.098) | 1.6\*\*\*(0.081) |
| Constant | Yes | Yes | Yes | Yes | Yes | Yes |
| Country, sector and size dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Pseudo R2 | 0.13 | 0.17 | 0.11 | 0.12 | 0.13 | 0.23 |

Source: Authors calculations.

Note: \*\*\*,\*\* and \* denote statistical significance at 1%, 5% and 10% levels of significance.

Standard errors in parentheses. Logit estimates. Number of observations: n=10008

* 1. *Selection equation*

Across all types of collaboration, we found the positive effect of learning through exporting, and organizational and marketing innovations. Accumulation of experience increases internal capabilities and provides information about market trends or consumer satisfaction. Marketing innovations such as new design, pricing or sales channels have the strongest effect on collaboration with competitors, suggesting that creating new markets is one motive for collaboration. Public financial incentives and applying appropriability instruments also exert positive effects in all cases except collaboration between firm group members. It should be kept in mind that within firm groups, the fear of knowledge leakages is substantially smaller than in transactions with external environment. Our findings suggest the important role of absorptive capacity. The strongest effects of in-house R&D are found in collaborations with customers and coopetitors. Through such practice, firms signal their attractiveness as collaboration partners and gain relevant competencies and capabilities for collaboration. Finally, in all relationships except collaboration with customers, a positive and significant coefficient is obtained on variable controlling for enterprise restructuring.

* 1. *Results from baseline specification*

Figure 4 presents average treatment effects on the subset of treated subjects (ATT effects) whose calculation was explained in section 3.2. All collaboration channels improve the share of revenues coming from existing marginally modified products (Figure 4). Such a finding can be expected from firms in emerging innovation systems such as CEE where key players in the business ecosystem often lack core capabilities for development of radical innovations. Particularly large coefficients are found on collaborations with customers and within firm groups. Downstream entities in the innovation system help with identifying market trends while enterprise groups enable knowledge and technology transfer at lower risk of losing competitive advantages. These findings are also consistent with those from other studies. Laursen and Salter (2006) note that the development of existing marginally modified and new to the firm (incrementally novel) products mainly consists of fine-tuning a dominant design. While radically novel (new to the market) innovations require deeply specialized knowledge, development and commercialization of products known to the market but new to the firm (i.e. imitation) require a broad base of collaborators with different types of knowledge.



The only two significant collaboration channels for new to the market (radically novel) innovations are customers and coopetitors. The positive impact of customers can be associated with the anticipation of lead users about future market trends, information about consumer satisfaction with products and insights into the advantages and weaknesses of rival products. These findings also reveal the beneficial effects of knowledge and technology synergies among firms in the same sector, an indicator that firms in CEE jointly develop technological knowledge relevant for innovations. These findings offer partial support to our hypotheses H1 and H2. It appears that collaboration facilitates only commercialization of existing (marginally modified) products whose competitiveness rests on basic innovation and management resources. In the case of more innovation intensive products such as those new to the firm (incrementally novel) innovations we do not find any evidence in CEE as a whole. Our evidence also suggests that collaborations with customers and competitors are beneficial for new to the market (radically novel) innovations. From existing literature, we can interpret these findings as a sign that customers provide firms with knowledge about market trends and feedback on their radically novel products while collaboration with competitors enables firms to create new and expand existing markets (Tsai, 2009).

* 1. *Individual country estimates*

Results of the estimation for individual countries are mainly in line with those for the whole sample (Table 5). With the exception of Hungary, in all countries we observed positive effects of at least some collaboration channels on the commercialization of existing or marginally improved products. The only exception is collaboration with scientific institutions for which the coefficients are not significant in all countries. In Bulgaria, Czech Republic and Estonia intra-group collaboration and customers are main channels of collaboration. In Bulgaria, Croatia and Latvia we found positive effects of collaboration with coopetitors. Finally, in Slovakia we observed positive and significant coefficients on collaboration with customers and suppliers.

The effect on the commercialization of incremental and radical innovations is far more modest. We observed a positive impact of intra-group (with firm group members) collaboration on incrementally novel innovations in Bulgaria and Romania and on radically novel innovations in Latvia. Collaboration with customers has a positive effect on incremental innovations in Romania and on radically novel innovations in Latvia and Lithuania . We also observed a positive impact of collaboration with suppliers on incrementally novel innovations in Hungary and on radically novel ones in Latvia. Finally, there are positive effects of competitors in Romania, Slovakia and Bulgaria and collaboration with scientific institutions in Croatia and Latvia. It is evident thus that across innovation systems the relevance of individual actors in collaborative innovation differs.

Table 5: Individual country level estimates – ATT effects

|  |  |
| --- | --- |
| Countries | Type of collaboration partner |
| Any | Group | Customers | Suppliers | Competitors | Science |
| Outcome: % of sales from existing or marginally modified products |
| Bulgaria | 11.29\*\*\* (2.30) | 13.12\*\*\* (3.95) | 14.24\*\*\* (3.02) | 9.15\*\*\* (2.62) | 9.58\* (4.95) | 1.29 (4.15) |
| Czechia | 7.09\*\*\* (2.12) | 9.50\*\*\* (2.32) | 7.55\*\*\* (2.12) | 4.30\*\* (1.98) | -0.93 (3.68) | 2.40 (2.55) |
| Estonia | 6.28 (7.27) | 11.30\*\* (5.48) | 13.62\*\*\* (5.19) | 4.55 (5.99) | 6.69 (6.26) | 9.82 (6.01) |
| Croatia | 9.25\*\* (4.63) | -2.61 (4.91) | 8.23\* (4.55) | 3.66 (4.05) | 9.86\* (5.84) | -3.10 (4.56) |
| Hungary | 2.40 (2.33) | 0.49 (2.96) | -1.42 (2.89) | -0.65 (2.19) | 0.22 (3.66) | 1.20 (2.86) |
| Latvia | 3.67 (7.26) | 3.98 (6.50) | 5.89 (6.98) | -2.18 (7.01) | 13.32\*\* (5.97) | 7.52 (10.23) |
| Lithuania | 5.96\*\* (3.04) | 1.69 (4.25) | 2.79 (4.04) | -2.07 (3.19) | 2.78 (4.97) | -5.71 (4.55) |
| Romania | 10.56\*\* (4.89) | 5.85 (6.22) | 6.27 (6.37) | 7.80 (5.42) | 3.16 (7.20) | 2.84 (7.15) |
| Slovakia | 11.70\*\* (4.76) | 7.28 (6.07) | 13.07\*\*\* (4.81) | 13.24\*\* (5.86) | -0.62 (8.18) | 2.99 (5.89) |
| Outcome: % of sales from products new to the firm |
| Bulgaria | 2.09 (1.50) | 5.93\* (2.84) | 2.26 (2.05) | 1.07 (1.63) | 1.68 (3.37) | 2.45 (2.81) |
| Czechia | 0.02 (1.08) | -0.46 (1.13) | 0.14 (1.09) | 0.73 (0.99) | 1.43 (1.92) | -0.26 (1.41) |
| Estonia | 0.48 (2.11) | 0.61 (2.29) | -1.35 (3.97) | -2.93 (3.95) | -1.78 (3.78) | 1.29 (3.59) |
| Croatia | 2.62\* (1.51) | 3.43 (2.14) | 1.86 (2.42) | 2.60 (1.65) | -1.14 (5.17) | 5.43\*\* (2.17) |
| Hungary | 0.75 (1.58) | -0.87 (2.28) | 2.60 (2.09) | 2.83\* (1.50) | 0.85 (2.51) | 0.78 (2.23) |
| Latvia | 3.90 (3.04) | 3.31 (3.49) | 3.94 (3.99) | 1.83 (3.85) | -6.24 (5.44) | 13.75\*\* (5.49) |
| Lithuania | 1.75 (1.41) | 1.72 (1.79) | 1.40 (2.21) | 1.97 (1.27) | 0.58 (2.69) | 4.29\* (2.25) |
| Romania | 6.89\*\* (3.12) | 10.42\*\* (5.03) | 6.03\*\* (2.71) | 4.59 (2.89) | 12.62\*\*\* (4.66) | 6.06 (5.34) |
| Slovakia | -4.54 (3.56) | 1.09 (3.08) | -1.56 (3.09) | -4.97 (4.57) | 6.93\* (3.75) | 3.65 (3.90) |
| Outcome: % of sales from products new to the market |
| Bulgaria | -0.48 (1.39) | -4.34\*\* (2.03) | 1.32 (1.66) | -0.35 (1.32) | 4.42\* (2.62) | 2.28 (2.25) |
| Czechia | 0.58 (1.03) | 0.97 (1.17) | 1.09 (1.20) | -0.10 (1.17) | 2.32 (2.02) | -0.56 (1.20) |
| Estonia | 1.99 (2.63) | 1.60 (3.14) | 1.55 (3.28) | 2.33 (2.49) | 2.33 (3.44) | 3.04 (2.51) |
| Croatia | 1.70 (1.65) | 4.85 (3.27) | 3.14\* (1.74) | 3.51 (2.43) | 3.34 (2.60) | 5.60\*\*\* (2.04) |
| Hungary | -3.16\* (1.49) | 0.39 (1.74) | -1.18 (2.00) | -2.18 (1.67) | -1.06 (2.77) | -1.98 (1.73) |
| Latvia | 4.34 (2.79) | 4.96\*\* (2.48) | 4.39\* (2.39) | 6.00\*\*\* (2.17) | -1.68 (4.13) | 4.97 (4.72) |
| Lithuania | 3.40\* (2.06) | 0.78 (2.91) | 9.83\*\*\* (2.71) | 0.79 (2.26) | 4.54 (3.40) | 2.34 (2.87) |
| Romania | -4.73 (3.97) | -2.08 (4.80) | 6.01 (4.26) | 0.03 (4.18) | -6.19 (5.92) | -2.86 (4.91) |
| Slovakia | 0.67 (2.82) | 1.75 (2.64) | 0.16 (2.45) | 2.47 (2.90) | 6.30 (3.72) | 3.06 (2.50) |

Note: \*\*\*,\*\* and \* denote statistical significance at 1%, 5% and 10% levels. Standard errors in parentheses.

Source: Authors calculations.

Findings from this section support only partially our first (H1) and second (H2) hypothesis. Our findings are in line with Radošević’s (2017) argument that innovation in CEE mainly takes place through building innovation competencies instead of capabilities. The prevalent effects of collaboration are on the commercialization of existing marginally modified and incrementally novel products thus giving support to our H1. Across countries we found a positive impact from at least one collaboration partner on the commercialization of existing and marginally modified products and, in most countries, positive effects on commercialization of incrementally novel innovations. Customers, suppliers, intra-group collaboration and collaboration among competitors emerge as positive collaboration channels in most countries (H2a, H2b, H2c and H2e). Interestingly, with the exception of Croatia we did not find any evidence for beneficial effects of collaboration between scientific institutions and innovating firms (H2d) giving only partial support to our second hypothesis.

* 1. *Geographical and non-geographical proximity*

We now turn to explore the effects of geographical and non-geographical proximity on the success of collaborative innovation. To explore whether the origin of partners makes a difference, we introduced 3 treatment categories according to the origin of collaborators (Figure 5a). These findings show that collaborations involving only domestic partners have a beneficial effect on the commercialization of existing marginally modified products, but a negative effect on revenues from radically novel innovations. This finding is consistent with our prediction that collaboration in CEE innovation systems is facilitated by social, organizational, institutional and cognitive proximity, but the level of cognitive proximity is not high enough to deliver indigenous innovation capabilities relevant for commercialization of radically novel innovations. Moreover, our findings signal that collaboration with domestic partners reduces revenues from such truly novel products and services, most likely reflecting lack of domestic competencies and capabilities but also the orientation of domestic collaborators towards existing or marginally modified products.



Collaborations involving only foreign rivals have a positive effect on the commercialization of incrementally novel innovations. This finding should be seen in light of previously mentioned arguments about modest innovation capabilities and the strong innovation competencies of CEE innovators. Finally, we observe strong positive effects on the commercialization of both incrementally and radically novel innovations in collaborations involving both domestic and foreign partners. This latter finding can be taken as evidence that the combination of indigenous and foreign capabilities and competencies provides the greatest success in the commercialization of innovations. It is thus likely that a combination of geographical proximity with some of partners and cognitive proximity with other partners from abroad act in a mutually reinforcing way.

The above findings suggest a non-negligible role for non-spatial proximities. Our investigation takes us further to the role of the origin of collaborators. As already argued, different types of proximities may drive collaborations with partners from other EU member states with whom CEE shares many traits of institutional framework and with partners from other parts of the world, particularly advanced countries such as United States (US), other countries with emerging innovation systems such as China and India or other foreign countries. In this part of analysis (Figure 5b) firms in collaboration with domestic partners only and those firms engaged in collaboration with domestic and foreign partners have been excluded because their inclusion would violate properties of treatment analysis.

The investigation revealed interesting trends. It seems that collaborations with EU partners and to a lesser extent with those from China and India (significant only at 10%) are driving revenues from existing or marginally modified products. Collaborations with partners from US and a group of other countries raise competencies of CEE firms for the commercialization of products that are new to the firm but have been known to the market (incrementally novel products). Finally, collaborations with partners from China, India and US (significant only at 10%) seem to be drivers of the commercialization of radically novel (new to the market) innovations.



How can one interpret these findings? On the one hand, it is evident that collaboration with domestic partners facilitates the commercialization of existing or marginally modified products. The commercialization of incrementally and radically novel innovations is facilitated through collaborations involving foreign partners. However, contrary to expectations, partners from other EU member states are not behind raising indigenous firms’ innovation capabilities. These firms seem to be relevant for the commercialization of existing products and developing indigenous innovation competencies. Such a finding suggests that partners from other EU member states are reluctant to share strategically important knowledge and technology resources with partners from CEEs. These findings are in line with Hansen and Mattel (2017) who show that the motives of technologically superior partners are sometimes to control rather than to empower collaboratng counterparts.

One needs to recall that the economic development of CEEs over the past decades originated from offshoring of production segments from other EU member states rather than innovation-intensive developments. It is thus likely that partners from other EU member states still perceive counterparts from CEE countries as technologically inferior entities to whom they transfer knowledge relevant only for incrementally novel innovation. However, it seems that collaboration with partners from other parts of the world such as US, China and India marginally facilitates the commercialization of both incrementally and radically novel innovations. The positive impact on incrementally novel innovations signals that firms outside EU do not perceive CEE firms as direct threat and thus exploit cognitive proximities which outweigh social, institutional and cultural distances.

Finally, the most interesting finding concerns radically novel innovations. Our results suggest that collaboration with partners from China, India and US enhances success in commercialization of innovations that are new to the market. These findings should be seen in light of previously mentioned successes of CEE firms in reaching world innovation frontier in several emerging industries such as software or electrical mobility which are also areas where their counterparts from other emerging innovation systems such as China and India are seeking their opportunities. The positive impact of collaboration with US partners (albeit significant only at 10%) is likely to be driven by similar motives to create new markets and raise technological and knowledge frontiers in emerging sectors. Overall, these findings signal that non-geographical proximities between partners have far greater relevance than geographical ones. Bearing in mind the social, institutional and cultural disparities between CEEs, China, India and US, our findings justify suggesting that the principal driver of such collaborations is dominance of cognitive proximity over the lack of proximity in other non-spatial dimensions.

Putting these findings together we find partial support for H3a, H3b and H3c. Collaboration with domestic partners is beneficial for the commercialization of existing marginally modified products (H3a), but we do not find effects on incrementally novel products and even find negative effects on radically novel products, suggesting lack of complementarities in collaboration. The positive effects of collaborations involving domestic and foreign partners signals that foreign organizations in CEEs supplement the missing resources of domestic organizations in the commercialization of incrementally and radically novel products thus paving the way for supporting H3b and H3c. Our subsequent findings reveal that collaborations with partners with a high degree of social, institutional and organizational proximity, such as those from EU, are beneficial for the commercialization of existing marginally modified products (H3b).

Finally, partners from those countries where organizational, social and institutional proximity is low but cognitive proximity may be high, appear to be most relevant for the commercialization of radically novel innovations but not for existing and marginally modified products. This finding is opposite from H3c. How can this finding be explained? Lee (2018) describes the collaboration experience of the South Korean car-maker Hyundai with Japanese counterparts (Mitsubishi) in the last decades of the 20th century. While technologically superior Japanese producers were keen to share knowledge relevant for the commercialization of existing and marginally modified products, they were less open to sharing strategically important knowledge required for radical innovations. This ultimately forced Hyundai to search for missing resources through collaboration with specialized R&D firms from England and other parts of the world. If one bears in mind that CEE countries are deeply embedded in production (but not innovation) networks of other EU member states and that they all compete in the EU single market, the former case may provide explanation for our rejection of H3c.

1. **Concluding remarks**

Increasingly the competitive global environment forces firms to search continuously for new sources of competitiveness such as knowledge, technology and skills through various forms of collaboration with entities from business ecosystem. Such practice is particularly relevant for firms in countries in transition from production towards innovation-driven growth such as CEE. The structurally weak innovation systems of these countries do not provide sufficient incentive to domestic innovators and firms must search for missing resources beyond domestic borders. However, the low absorptive capacity of indigenous firms and the reluctance of foreign partners to reveal strategically important resources were the most common reasons for limited success such collaborations. Recently, research has led to an understanding about the relevance of different types of proximities among firms such as social, institutional, cultural or cognitive and about how the interplay between these different types of proximities determine the success of collaborative innovation.

At the risk of doing too much, our study attempted to answer three important questions about collaborative innovation in advancing countries. We investigated: whether collaboration facilitates the commercialization of all types of innovative products or only some of them; what is the role of individual types of partners; and, whether the country of origin of partners has any role in the success of collaborations. Using the most comprehensive dataset on innovation behaviour of European firms, the Community Innovation Survey, our study focused on a group of CEE countries that joined the EU from 2004 onwards. The investigation comes at particularly timely moment from a scientific and geopolitical perspective when the many routinised jobs that prevail in these countries are under threat from digitalization and automation, making building innovation competencies urgent. Being embedded in a production network of advanced EU member states for some time, the region recently found itself of increased interest to US and Asian investors who seek their way into the EU market.

Findings from our study reveal that domestic potential for the creation of innovations is indeed low and that domestic collaborations mostly fuel the commercialization of existing or marginally modified products. In development of less novel products and services, firms rely on a diverse network of collaborators including suppliers, customers, rivals and universities. However, we also found the evidence that specialized knowledge (of consumers and rivals) about the current and future needs of consumers and market creating strategies are principal channels through which collaboration in emerging innovation systems facilitates the creation of radical innovations. Our findings also reveal the limited success of collaborations with partners from other EU member states. While EU partners contribute to the commercialization of less innovative products, partners from other parts of the world, particularly US, China and India contribute to the commercialization of both incremental and radical innovations from the CEE region.

From a theoretical perspective, our findings support the propositions of the extended resource-based view about the supplementing role of external resources in developing organizational competitive advantages. However our findings also challenge the traditional notion of innovation systems as networks within national boundaries. They imply, too, that geographical proximity is neither a precondition nor a guarantee of successful collaboration. Rather, the results of our investigation signal that in a digitally connected world non-spatial proximities among partners at a greater distances are more beneficial in collaborations for local firms from the CEE and similar innovation systems. Such findings question the incentives that the EU single marke offers CEE countries in building indigenous innovation capabilities. However, they also show a, rarely addressed and indirect, channel for countries such as the CEEs to benefit to: that is, the higher attractiveness for collaboration with partners from other parts of the world who wish to participate in a large integrated market.

The question that arises from all these findings is what should policy makers do? Our analysis pointed to several potential areas for policy intervention. For example, our findings point to the reluctance of partners from other EU member states to reveal superior technology and knowledge thereby raising indigenous innovation capabilities. Experiences of countries like Ireland or South Korea have taught us that unless made compulsory, knowledge flows from firms in advanced countries to those in advancing world rarely occur. Bearing in mind the strong presence of such firms in the CEE region and the embeddedness of local producers in their value chains, policies should be made to secure raising indigenous technological capabilities through this channel.

Our findings reveal the limited extent of collaboration between universities and research entities and innovating firms. Even where such collaboration exists it is limited to incremental innovations and imitations. Public policies should find a way to strengthen university industry linkages. Action in that direction might be the introduction of measures for directing domestic science towards businesses and raising the absorptive capacity in the business sector for knowledge generation in the science sector. Throughout the investigation we established the strong effect of collaboration with firms from the same sector and the importance of appropriability instruments for such collaboration. Policies should ensure the development and enforceability of intellectual property rights in order to enable knowledge flows between firms at different levels of technological parity.

An important policy implication is that arising from our analysis of the contribution made by partners from countries outside EU to the commercialization of innovations arising in the CEE. The beneficial effects of partners from these countries, particularly US and China and India signal that incentives coming from these parts of the world should not be, *a priori*, discarded. Collaboration with partners from such countries offers twofold opportunities. On the one hand, such collaboration offers greater opportunities for building indigenous innovation competencies and capabilities while, on the other hand, it may open the door of the large markets of these countries to CEE producers. However, it must be noted that such collaborative arrangements face a realistic risk of failure due to the social, cultural and institutional distance between partners. Future educational policies should be constructed to build local competencies for the maximization of benefits from cross-cultural collaborations.

To conclude, we reflect on the limitations and directions of the study for future research. Our analysis was focused on the impact of collaborative efforts on the outcomes of the innovation process. This was hampered by the lack of data which would enable the assessment of the collaborations on the decision of firms to innovate. Our investigation was, like most of others in the field, based on cross-sectional dataset that prevented the analysis of more complex relationships recognised in collaborative innovation literature as emerging over time. The reason for this was that longitudinal data for this analytical purpose does not exist. This is a limitation that could be addressed in future should such data become available. Our analysis was also based on a rather simplistic assumption that geographical proximity can be taken as a proxy for different types of non-spatial proximities. Although this assumption has often been made in other studies, it must be acknowledged that it presents a degree of departure from reality. Future studies, subject to available datasets, should delve deeper into the topic of spatial and non-spatial proximities and extend our findings on the relevance of each of these individual channels. These directions would expand our knowledge of the innovation behaviour of firms in advancing economies.

Conflict of Interest: The author declares no conflict of interest.

**REFERENCES**

1. Amoroso, S., Coad, A. and Grassano, N. (2018). European R&D networks: A snapshot from the 7th EU Framework Programme. Economics of Innovation and New Technology. 27(5-6). 404-419. https://doi.org/10.1080/10438599.2017.1374037
2. Ardito, A., Petruzzelli, A.M. and Albino, V. (2015). From Technological Inventions to New Products: A Systematic Review and Research Agenda of the Main Enabling Factors. European Management Review. 12, 113-147. DOI: 10.1111/emre.12047
3. Associated Press. (2018). US, EU and China vie for influence in Eastern Europe. Retrieved January 2nd, 2020 from https://apnews.com/3f6d8e2140fb4e318cac56f342eb8d2f/US,-EU-and-China-vie-for-influence-in-Eastern-Europe
4. Arya, B. and Lin, Z. (2007). ﻿Understanding Collaboration Outcomes From an Extended Resource-Based View Perspective: The Roles of Organizational Characteristics, Partner Attributes, and Network Structures. Journal of Management. 33(5), 697-723. ﻿DOI: 10.1177/0149206307305561
5. Baldwin, C., and von Hippel, E.A. (2011). Modeling a Paradigm Shift: From Producer Innovation to User and Open Collaborative Innovation.” Organization Science 22(6), 1399–1417.
6. Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. Journal of Management , 17(1), 99-120
7. Barros, H.M. (2016). Exploring the use of patents in a weak institutional environment: The effects of innovation partnerships, firm ownership, and new management practices. Technovation. 45-46, 63-77. DOI: 10.1016/j.technovation.2015.05.003.
8. Boehm, N.D. and Hogan, T. (2013). Science-to-Business collaborations: A science-to-business marketing perspective on scientific knowledge commercialization. Industrial Marketing Management, 42(4), 564-579
9. Boschma, R. (2005). Proximity and innovation: A critical assessment. Regional Studies. 39(1), 61-74. DOI: 10.1080/0034340052000320887
10. Bucic, T. and Ngo, L. V. (2012). Examining drivers of collaborative inbound open innovation: Empirical evidence from Australian firms. International Journal of Innovation Management. 16(4), 1250017. DOI: 10.1142/S1363919611003660.
11. Boschma, R., and Frenken, K. (2011). Technological relatedness and regional branching. In H. Bathelt, M. Feldman, and D. Kogler (Eds.), Beyond Territory: Dynamic Geographies of Knowledge Creation, Diffusion and Innovation (2011). Abingdon: Routledge.
12. Brettel, M. and Cleven, N. (2011). Innovation Culture, Collaboration with External Partners and NPD Performance. Creativity and Innovation Management. 20(4), 253-272
13. Bruneel, J., D'Este, P. and Salter, A. (2010) Investigating the factors that diminish the barriers to university–industry collaboration. Research Policy, 39, 858-868
14. Cattaneo, M. D., (2010). Efficient semiparametric estimation of multi-valued treatment effects under ignorability. Journal of Econometrics. 155, 2, 138–154. https://doi.org/10.1016/j.jeconom.2009.09.023.
15. Chesbrough, H. (2003). Open innovation. Cambridge, MA: Harvard University Press.
16. Coase, R. (1937). The nature of the firm. Economica, 4(16), 386-405
17. Cohen,W.M. and Levinthal, D.A. (1990). Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly, 35(1), 128–152.
18. Da-Chang P., Chun-Yao T. and Cheng-Hwai L. (2012) Collaborative innovation in emerging economies: Case of India and China, Innovation, 14(3), 467-476
19. D'Este, P. and Perkmann, M. (2011) Why do academics engage with industry? The entrepreneurial university and individual motivations. Journal of Technology Transfer, 36, 316-339
20. De Maggio, M., Gloor, P.A. and Passiante, G. (2009) Collaborative innovation networks, virtual communities and geographical clustering. International Journal of Innovation and Regional Development 1(4), 387 – 404. DOI: 10.1504/IJIRD.2009.022729
21. Del Guidice, M., Scuotto, V., Garcia-Perez, A. and Petruzzelli, A. (2019). Shifting Wealth II in Chinese economy. The effect of the horizontal technology spillover for SMEs for international growth. Technological Forecasting & Social Change. 145, 307-316.
22. Dosi, G. and Nelson, R. (1994). An introduction to evolutionary theory in economics. Journal of Evolutionary Economics, 4(3), 153-172
23. Dyer, J. H., & Singh, H. 1998. The relational view: Cooperative strategy and source of interorganizational competitive advantage. Academy of Management Review, 23(4): 660-679.
24. Du Chatenier, E., Verstegen, J.A.A.M., Biemans, H.J.A., Mulder, M. and Omta, O. (2009) The challenges of collaborative knowledge creation in open innovation teams. Human resource development review. 8(3), 350-381
25. Elia, S., Petruzzelli, A.M., Piscitello, L. (2019). The impact of cultural diversity on innovation performance of MNC subsidiaries in strategic alliances. Journal of Business Research, 98, 204-213. <https://doi.org/10.1016/j.jbusres.2019.01.062>
26. Fernández-Sastre, J. and Martin-Mayoral, F. (2017). Assessing the impact of public support for innovation in an emerging innovation system. International Journal of Technological Learning, Innovation and Development, 9(1), 42-64. doi: 10.1504/IJTLID.2017.082755
27. Financial Times (2017). Central and Eastern Europe unveils its tech ambitions. Special report. Retrieved October 6, 2019 from https://www.ft.com/content/889422a8-09ad-11e7-ac5a-903b21361b43
28. Fu, X. and Li, J.Z. (2016). Collaboration with foreign universities for innovation: evidence from Chinese manufacturing firms. International Journal of Technology Management. 70(2-3), 193-217. DOI: 10.1504/IJTM.2016.075162.
29. ﻿Goñi, E. and Maloney, W.F., (2017) Why don’t poor countries do R&D? Varying rates of factor returns across the development process. European Economic Review 94, 126–147.
30. Hashi, I. and Stojcic, N. (2013). The impact of innovation activities on firm performance using a multi-stage model: Evidence from the Community Innovation Survey 4. Research Policy. 42(2), 353-366. <https://doi.org/10.1016/j.respol.2012.09.011>.
31. Hanel, P. and St-Pierre, M. (2006). Industry–University Collaboration by Canadian Manufacturing Firms. The Journal of Technology Transfer. 31, 485-499.
32. Hansen, T. and Mattes, J. (2017). Proximity and power in collaborative innovation projects. Regional Studies. 52(1), 35-46 https://doi.org/10.1080/00343404.2016.1263387
33. Hardeman, S., Frenken, K., Nomaler, O. and Ter Wal, A. L. J. (2015). Characterizing and comparing innovation systems by different “modes” of knowledge production: A proximity approach. Science and Public Policy. 42, 530-548. doi:10.1093/scipol/scu070
34. Heckman, J. J., Ichimura, H., Todd, P., (1998). Matching as an econometric evaluation estimator. The Review of Economic Studies. 65, 2, 261–294. https://doi.org/10.1111/1467-937x.00044.
35. ﻿Holm, J.R., Timmermans, B., Østergaard, C.R., Coad, A., Grassano, N., Vezzani, A., (2019). Labor mobility from R&D-intensive multinational companies: Implications for knowledge and technology transfer. Paper presented at DRUID Society Conference 2019, Copenhagen, Denmark.
36. Horbach, J. (2016). Empirical determinants of eco-innovation in European countries using the community innovation survey. Environmental Innovation and Societal Transitions. 19, 1-14. https://doi.org/10.1016/j.eist.2015.09.005
37. Huang, K.F. and Yu, C.M.J. (2011) The effect of competitive and non-competitive R&D collaboration on firm innovation. Journal of Technology Transfer 36, 383-403. DOI 10.1007/s10961-010-9155-x
38. Iammarino S., Piva M., Vivarelli, M. and Von Tunzelmann, N. (2012) Technological Capabilities and Patterns of Innovative Cooperation of Firms in the UK Regions, Regional Studies, 46(10), 1283-1301
39. Kemp, R.G.M., Folkeringa M., de Jong, J.P.J., Wubben E.F.M., 2003. Innovation and firm performance. Scales research reports. Zoetermeer: EIM business and policy research (retrieved from http://ondernemerschap.panteia.nl/pdf-ez/n200213.pdf on 30 September 2019).
40. Kirby, D. and El Hadidi, H. (2019). University technology transfer efficiency in a factor driven economy: the need for a coherent policy in Egypt. The Journal of Technology Transfer. Online first. https://doi.org/10.1007/s10961-019-09737-w
41. Knudsen, L. and Nielsen, B. (2010). Collaborative capability in R&D alliances: exploring the link between organisational- and individual-level factors. International Journal of Knowledge Management Studies. 4(2), 152-175.
42. Kogut, B., and Zander, U. (1992). Knowledge of the firm, combinative capabilities and the replication of technology. Organization Science *,* 3(3), 383-397
43. KPMG (2015). Global manufacturing outlook: Preparing for battle: Manufacturers get ready for transformation, KPMG International Cooperative 2015
44. Laursen, K. and Salter, A. (2006). Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. Strategic Management Journal. 27, 131-150. DOI: 10.1002/smj.507
45. Lavie, D. (2006). The competitive advantage of interconnected firms: An extension of the resource-based view. Academy of Management Review, 31(3): 638-658.
46. Lee, K., and Malerba, F. (2017). Catch-up cycles and changes in industrial leadership: Windows of opportunity and responses of firms and countries in the evolution of sectoral systems. Research Policy, 42(1), 338–351
47. Lin, M.J. and Huang, C.H. (2013) The impact of customer participation on NPD performance: the mediating role of inter-organisation relationship. Journal of Business and Industrial Marketing 28(1), 3-15
48. Lin, Z., Yang, H. and Arya, B. (2009) Alliance partners and firm performance: resource complementarity and status association. Strategic Management Journal. 30, 921–940 <https://doi.org/10.1002/smj.773>
49. Link, A. and Scott, J.T. (2019). The Economic Benefits of Technology Transfer from U.S. federal laboratories. The Journal of Technology Transfer (Online first). <https://doi.org/10.1007/s10961-019-09734-z>
50. Lundvall, B.-Å. (1993). National systems of innovation: towards a theory of innovation and interactive learning. London: Pinter.
51. Mairesse, J. and Mohnen, P. (2004). The Importance of R&D for Innovation: A Reassessment Using French Survey Data. The Journal of Technology Transfer. 30(1-2), 183-197. https://doi.org/10.1007/s10961-004-4365-8
52. Malerba, F. and McKelvey, M. (2018). Knowledge-intensive innovative entrepreneurship integrating Schumpeter, evolutionary economics, and innovation systems. Small Business Economics, 1-20
53. Mathews, J. (2003). ﻿Competitive dynamics and economic learning: An extended resource-based view. Industrial and Corporate Change. 12(1), 115-145
54. ﻿Mention, A.L. (2011). Co-operation and co-opetition as open innovation practices in the service sector: which influence on innovation novelty? Technovation 31, 44–53
55. Michalek, J., Ciaian, P., & Kancs, D. A. (2016). Investment crowding out: Firm-level evidence from northern Germany. Regional Studies, 50(9), 1579-1594.
56. Nieto, M.J., Santamaría, L. (2007). The importance of diverse collaborative networks for the novelty of product innovation. Technovation 27 (3), 367–377.
57. Nonaka, I., and Takeuchi, H. (1995). The knowledge creating company: How Japanese companies create the dynamics of innovation. Oxford, UK: Oxford University Press.
58. Penrose, E. (1959). The Theory of the Growth of the Firm. Oxford University Press: New York.
59. Perez, C and Soete, L. (1988). Catching Up in Technology: Entry Barriers and Windows of Opportunity. in G. Dosi et al. eds. Technical Change and Economic Theory, London: Francis Pinter, pp. 458-479
60. Perri, A., Scalera, V.G. and Mudambi, R. (2017). What are the most promising conduits for foreign knowledge inflows? innovation networks in the Chinese pharmaceutical industry. Industrial and Corporate Change. 26(2), 333-355. DOI: 10.1093/icc/dtx004.
61. Perkman, M., Tartari, V., McKelvey, M., Autio, E., Brostrom, A., D'Este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, A., Krabel, S., Kitson, M., Llerena, P., Lissoni, F., Salter, A. and Sobrero, M. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. Research Policy, 42, 423-442. <http://dx.doi.org/10.1016/j.respol.2012.09.007>
62. Petruzelli, A.M. (2011) The impact of technological relatedness, priorties and geographical distance on university–industry collaborations: A joint-patent analysis. Technovation. 31, 309-319
63. Powell, W.W., Koput, K.W. and Smith-Doerr, L. (1996). Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology. Administrative Science Quarterly. 41(1), 116-145.
64. Radošević, S. (2017). Upgrading technology in Central and Eastern European Economies. IZA World of Labor. 338, 1-11. doi: 10.15185/izawol.338
65. Radošević, S. (2015). Synthesis Report: Innovation, Entrepreneurship and Industrial Dynamics. Technology Upgrading and Innovation Policy in Central and Eastern Europe, GRINCOH Working Paper Series, No. 3
66. Ritala, P. and Hurmelinna-Laukkanen, P. (2013). Incremental and Radical Innovation in Coopetition—The Role of Absorptive Capacity and Appropriability. Journal of Product Innovation Management, 30(1), 154-169
67. Rosell, D. and Lakemond, N. (2012). Collaborative Innovation with Suppliers: A Conceptual Model for Characterising Supplier Contributions to NPD. International Journal of Technology Intelligence and Planning 8(2):197 – 214 DOI: 10.1504/IJTIP.2012.048477
68. Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41–55. <https://doi>. org/10.1093/biomet/70.1.41.
69. Rubin, D.B., (1977). Assignment to treatment group on the basis of a covariate. Journal of Educational Statistics, 2, 1, 1–26. https://doi.org/10.2307/1164933.
70. Saranga, H., Schotter, A.P.J. and Mudambi, R. (2019). The double helix effect: Catch-up and local-foreign co-evolution in the Indian and Chinese automotive industries. International Business Review. 28(5), 101495. DOI: 10.1016/j.ibusrev.2018.03.010
71. Srhoj, S., Škrinjarić, B., & Radas, S. (2019). Bidding against the odds? The impact evaluation of grants for young micro and small firms during the recession. Small Business Economics, Online first. <https://doi.org/10.1007/s11187-019-00200-6>
72. Stojcic, N., Srhoj, S. and Coad, A. (2020). ﻿Innovation procurement as capability-building: Evaluating innovation policies in eight Central and Eastern European countries. European Economic Review. 121. 103330. ﻿<https://doi.org/10.1016/j.euroecorev.2019.103330>
73. Stojcic, N. and Orlic, E. (2019). Spatial dependence, foreign investment and productivity spillovers in new EU member states. Regional Studies. Online first. doi:10.1080/00343404.2019.1653451
74. Stojcic, N., Anic, I. D. and Aralica, Z. (2019). Spatio – temporal determinants of structural and productive transformation of regions in Central and East European Countries. Economic Systems. 43(3-4), 100715. doi:10.1016/j.ecosys.2019.100715
75. Švarc, J. and Dabić, M. (2019). The Croatian path from socialism to European membership through the lens of technology transfer policies. The Journal of Technology Transfer. 44, 1476-1504. <https://doi.org/10.1007/s10961-019-09732-1>
76. Teece, D.J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. Research Policy, 15(6), 285-305
77. Teece, D. J, Pisano, G. and Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(73), 509–533.
78. Tsai, K-H. (2009). Collaborative networks and product innovation performance: Toward a contingency perspective. Research Policy 38, 765-778
79. Un, C.A., Cuervo-Cazurra, A. and Asakawa, K. (2010). R&D Collaborations and Product Innovation. Journal of Product Innovation Management 27(5), 673-689.
80. Von Tunzelmann, N. and Wang, Q. (2003). An evolutionary view of dynamic capabilities, Economie Appliquée 6, 33–64.
81. Wagner, S. (2012). Tapping supplier innovation. Journal of Supply Chain Management, 48(2), 37-52.
82. Wang, L., Wang, X. and Philipsen, N. J. (2017). Network structure of scientific collaborations between China and the EU member states. Scientometrics. 113, 765-781. <https://doi.org/10.1007/s11192-017-2488-6>
83. Winter, S. G. (2003). Understanding dynamic capabilities. Strategic Management Journal, 24, 91–995
84. Wooldridge, J., 2010. Econometric Analysis of Cross-Section and Panel Data. Second edition. MIT press, Cambridge Massachusetts.
85. Zander, U. and Kogut, B. (1995). Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test, 6(1), 1-145

Online appendix

1. Correlation matrix

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | *turnexisting* | *turnincremental* | *turnradical* | *collaboration* | *group* | *customers* | *suppliers* | *coopetitors* | *science* | *exporter* | *organizational* | *marketing* | *public* |
| *turnexisting* | 1.00 |  |  |  |  |  |  |  |  |  |  |  |  |
| *turnincremental* | -0.16\*\*\* | 1.00 |  |  |  |  |  |  |  |  |  |  |  |
| *turnradical* | -0.18\*\*\* | -0.03\*\*\* | 1.00 |  |  |  |  |  |  |  |  |  |  |
| *collaboration* | 0.12\*\*\* | 0.08\*\*\* | -0.01 | 1.00 |  |  |  |  |  |  |  |  |  |
| *group* | 0.09\*\*\* | 0.05\*\*\* | 0.00 | 0.57\*\*\* | 1.00 |  |  |  |  |  |  |  |  |
| *customers* | 0.09\*\*\* | 0.08\*\*\* | 0.03\*\*\* | 0.54\*\*\* | 0.33\*\*\* | 1.00 |  |  |  |  |  |  |  |
| *suppliers* | 0.09\*\*\* | 0.06\*\*\* | 0.00 | 0.77\*\*\* | 0.42\*\*\* | 0.47\*\*\* | 1.00 |  |  |  |  |  |  |
| *coopetitors* | 0.07\*\*\* | 0.06\*\*\* | 0.02\* | 0.35\*\*\* | 0.22\*\*\* | 0.38\*\*\* | 0.32\*\*\* | 1.00 |  |  |  |  |  |
| *science* | 0.09\*\*\* | 0.10\*\*\* | 0.00 | 0.53\*\*\* | 0.28\*\*\* | 0.39\*\*\* | 0.37\*\*\* | 0.35\*\*\* | 1.00 |  |  |  |  |
| *exporter* | -0.03\*\* | 0.06\*\*\* | 0.04\*\*\* | 0.10\*\*\* | 0.15\*\*\* | 0.05\*\*\* | 0.08\*\*\* | 0.02\*\* | 0.08\*\*\* | 1.00 |  |  |  |
| *organizational* | 0.06\*\*\* | 0.10\*\*\* | 0.05\*\*\* | 0.18\*\*\* | 0.19\*\*\* | 0.15\*\*\* | 0.18\*\*\* | 0.12\*\*\* | 0.14\*\*\* | 0.05\*\*\* | 1.00 |  |  |
| *marketing* | 0.12\*\*\* | 0.11\*\*\* | 0.04\*\*\* | 0.14\*\*\* | 0.12\*\*\* | 0.12\*\*\* | 0.15\*\*\* | 0.11\*\*\* | 0.12\*\*\* | -0.06\*\*\* | 0.40\*\*\* | 1.00 |  |
| *public* | 0.10\*\*\* | 0.05\*\*\* | -0.04\*\*\* | 0.14\*\*\* | 0.01 | 0.12\*\*\* | 0.12\*\*\* | 0.11\*\*\* | 0.24\*\*\* | -0.08\*\*\* | 0.10\*\*\* | 0.10\*\*\* | 1.00 |
| *restructuring* | 0.06\*\*\* | 0.00 | -0.02\*\* | 0.14\*\*\* | 0.18\*\*\* | 0.07\*\*\* | 0.11\*\*\* | 0.07\*\*\* | 0.09\*\*\* | 0.02 | 0.17\*\*\* | 0.11\*\*\* | 0.06\*\*\* |
| *appropriability*  | 0.07\*\*\* | 0.13\*\*\* | 0.01 | 0.12\*\*\* | 0.05\*\*\* | 0.11\*\*\* | 0.11\*\*\* | 0.11\*\*\* | 0.17\*\*\* | -0.00 | 0.13\*\*\* | 0.21\*\*\* | 0.13\*\*\* |
| *sme* | -0.09\*\*\* | 0.00 | 0.03\*\*\* | -0.20\*\*\* | -0.27\*\*\* | -0.11\*\*\* | -0.18\*\*\* | -0.06\*\*\* | -0.17\*\*\* | -0.19\*\*\* | -0.15\*\*\* | -0.06\*\*\* | -0.02\* |
| *r&din* | 0.15\*\*\* | 0.15\*\*\* | -0.00 | 0.24\*\*\* | 0.16\*\*\* | 0.20\*\*\* | 0.18\*\*\* | 0.16\*\*\* | 0.33\*\*\* | 0.11\*\*\* | 0.14\*\*\* | 0.13\*\*\* | 0.18\*\*\* |
| *man* | 0.06\*\*\* | -0.03\*\*\* | 0.05\*\*\* | -0.04\*\*\* | -0.02\*\* | -0.04\*\*\* | -0.02\*\* | -0.07\*\*\* | 0.01 | 0.24\*\*\* | -0.07\*\*\* | -0.05\*\*\* | -0.03\*\*\* |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | *restructuring* | *appropriability* | *sme* | *r&din* | *man* |
| *restructuring* | 1.00 |  |  |  |  |
| *appropriability* | 0.07\*\*\* | 1.00 |  |  |  |
| *sme* | -0.18\*\*\* | -0.08\*\*\* | 1.00 |  |  |
| *r&din* | 0.08\*\*\* | 0.16\*\*\* | -0.12\*\*\* | 1.00 |  |
| *man* | -0.09\*\*\* | -0.00 | -0.09\*\*\* | -0.00 | 1.00 |

Note: \*\*\*,\*\* and \* denote significance at 1%, 5% and 10% levels respectively

1. Sensitivity to hidden bias
	1. *Balance of covariates and region of common support*

Table A1. Balance of covariates

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Any type of collaboration****(1)** | **Intra-group collaboration****(2)** | **Customers****(3)** |
|  | Stand. differences | Variance ratio | Stand. differences | Variance ratio | Stand. differences | Variance ratio |
|  | Raw | Matched | Raw | Matched | Raw | Matched | Raw | Matched | Raw | Matched | Raw | Matched |
| Exporter | 0.21 | -0.05 | 1.13 | 0.99 | 0.40 | -0.04 | 1.15 | 1.00 | 0.13 | -0.01 | 1.07 | 1.00 |
| Organizational | 0.38 | 0.02 | 1.12 | 1.00 | 0.54 | -0.01 | 1.02 | 1.00 | 0.44 | -0.01 | 1.04 | 1.00 |
| Marketing | 0.29 | 0.00 | 1.09 | 1.00 | 0.33 | 0.03 | 1.05 | 1.00 | 0.33 | 0.02 | 1.05 | 1.00 |
| Public | 0.30 | -0.00 | 1.00 | 1.00 | 0.03 | 0.01 | 1.00 | 1.00 | 0.34 | 0.00 | 0.94 | 1.00 |
| Restructuring | 0.28 | 0.03 | 1.79 | 1.05 | 0.44 | 0.01 | 2.09 | 1.01 | 0.19 | 0.07 | 1.43 | 1.13 |
| Appropriability  | 0.24 | 0.01 | 1.40 | 1.01 | 0.13 | 0.04 | 1.18 | 1.05 | 0.29 | 0.01 | 1.41 | 1.00 |
| Sme | -0.40 | -0.02 | 1.75 | 1.01 | -0.67 | -0.02 | 1.90 | 1.00 | -0.29 | -0.03 | 1.43 | 1.02 |
| r8din | 0.51 | -0.01 | 1.09 | 1.00 | 0.43 | -0.01 | 1.00 | 1.01 | 0.58 | -0.00 | 0.94 | 1.00 |
| Sector | -0.09 | 0.00 | 1.04 | 1.00 | -0.06 | 0.01 | 1.03 | 1.00 | -0.13 | 0.01 | 1.05 | 1.00 |
|  | **Suppliers****(4)** | **Coopetitors****(5)** | **Science sector****(6)** |
|  | Stand. differences | Variance ratio | Stand. differences | Variance ratio | Stand. differences | Variance ratio |
|  | Raw | Matched | Raw | Matched | Raw | Matched | Raw | Matched | Raw | Matched | Raw | Matched |
| Exporter | 0.17 | 0.01 | 1.10 | 1.00 | 0.08 | 0.02 | 1.05 | 1.01 | 0.21 | 0.01 | 1.11 | 1.00 |
| Organizational | 0.42 | -0.02 | 1.08 | 1.00 | 0.49 | -0.02 | 0.99 | 1.01 | 0.39 | 0.02 | 1.04 | 1.00 |
| Marketing | 0.35 | -0.00 | 1.07 | 1.00 | 0.46 | 0.01 | 0.99 | 1.00 | 0.34 | -0.02 | 1.04 | 1.00 |
| Public | 0.27 | -0.05 | 0.98 | 1.02 | 0.47 | -0.02 | 0.85 | 1.02 | 0.74 | -0.02 | 0.70 | 1.03 |
| Restructuring | 0.25 | 0.06 | 1.62 | 1.11 | 0.27 | 0.01 | 1.59 | 1.01 | 0.24 | 0.07 | 1.56 | 1.11 |
| Appropriability  | 0.25 | -0.01 | 1.38 | 0.99 | 0.39 | 0.02 | 1.48 | 1.01 | 0.45 | 0.02 | 1.61 | 1.01 |
| Sme | -0.39 | -0.04 | 1.65 | 1.03 | -0.23 | -0.08 | 1.33 | 1.08 | -0.45 | -0.02 | 1.62 | 1.01 |
| r8din | 0.40 | -0.01 | 1.04 | 1.00 | 0.67 | -0.01 | 0.83 | 1.01 | 1.08 | -0.01 | 0.61 | 1.02 |
| Sector | -0.05 | 0.03 | 1.02 | 0.99 | -0.28 | 0.05 | 1.07 | 1.01 | 0.02 | -0.03 | 0.99 | 1.01 |



Note: Region of common support overlap plots presented only for baseline model. Plots for other

models available on request.

* 1. *Rosenbaum bounds analysis*

Our examination so far does not reveal presence of hidden selection bias. To further strengthen this argument, we move to a group of tests that can be undertaken after matching estimators. We perform sensitivity analysis of Rosenbaum (2002) bounds. This analysis, applied in some recent studies (e.g. Michalek, Ciaian and Kancs, 2016 or Srhoj, Skrinjaric and Radas, 2019) introduces a hidden bias in order to estimate sensitivity of results to unobservables. The method relies on the sensitivity parameter Γ. This estimates the magnitude of the hidden bias that would render the test statistics of the study inference insignificant. When Γ = 1, the treatment effect is bias free (i.e., the assignment to treatment is random), while higher values of Γ indicate departure from randomness by showing the extent of impact that confounding variables have on the selection into treatment. The bounding approach does not test the unconfoundedness assumption itself, because this would amount to testing that there are no (unobserved) variables that influence the selection into treatment. Instead, Rosenbaum bounds provide evidence on the degree to which any significance results hinge on this untestable assumption (Becker and Caliendo, 2007). Rosenbaum bounds method is valid regardless of the strength of the confounding variable on the outcome (DiPrete and Gangl 2004). Table A4 below shows Rosenbaum bounds for all outcomes and treatments. Literature suggests use of rbounds package in Stata for continuous outcomes and mhbounds package for categorical outcomes (Becker and Caliendo, 2007). As our dependent variables are continuous, we used rbounds package.

Table A2a: Rosenbaum bounds for baseline model – sales from existing products.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Any type of collaboration | Intra-group | Customers | Suppliers | Coopetitors | Science |
| Gamma | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig- levels | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig. levels |
| 1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.05 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.15 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.20 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.25 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.30 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.010 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.35 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.049 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.40 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.165 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.45 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.387 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.50 | 0.000 | 0.046 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.642 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.55 | 0.000 | 0.184 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.838 | 0.000 | 0.001 | 0.000 | 0.000 |
| 1.60 | 0.000 | 0.441 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.943 | 0.000 | 0.002 | 0.000 | 0.000 |
| 1.65 | 0.000 | 0.712 | 0.000 | 0.000 | 0.000 | 0.011 | 0.000 | 0.985 | 0.000 | 0.005 | 0.000 | 0.000 |
| 1.70 | 0.000 | 0.896 | 0.000 | 0.075 | 0.000 | 0.037 | 0.000 | 0.997 | 0.000 | 0.011 | 0.000 | 0.000 |
| 1.75 | 0.000 | 0.973 | 0.000 | 0.171 | 0.000 | 0.102 | 0.000 | 0.999 | 0.000 | 0.023 | 0.000 | 0.000 |
| 1.80 | 0.000 | 0.995 | 0.000 | 0.313 | 0.000 | 0.231 | 0.000 | 0.999 | 0.000 | 0.048 | 0.000 | 0.000 |
| 1,85 | 0.000 | 0.999 | 0.000 | 0.482 | 0.000 | 0.422 | 0.000 | 0.999 | 0.000 | 0.093 | 0.000 | 0.000 |
| 1.90 | 0.000 | 0.999 | 0.000 | 0.647 | 0.000 | 0.624 | 0.000 | 1.000 | 0.000 | 0.166 | 0.000 | 0.000 |
| 1.95 | 0.000 | 0.999 | 0.000 | 0.783 | 0.000 | 0.789 | 0.000 | 1.000 | 0.000 | 0.274 | 0.000 | 0.010 |
| 2 | 0.000 | 0.999 | 0.000 | 0.878 | 0.000 | 0.899 | 0.000 | 1.000 | 0.000 | 0.414 | 0.000 | 0.012 |

Note: Gamma is odds of differential assignment to treatment due to unobserved factors.

Table A2b: Rosenbaum bounds for baseline model – sales from incremental innovations.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Any type of collaboration | Intra-group | Customers | Suppliers | Coopetitors | Science |
| Gamma | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig- levels | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig. levels |
| 1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.05 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.15 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.20 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.25 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.30 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.35 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.40 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.004 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.45 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.015 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.50 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.005 | 0.000 | 0.048 | 0.000 | 0.023 | 0.000 | 0.000 |
| 1.55 | 0.000 | 0.045 | 0.000 | 0.000 | 0.000 | 0.015 | 0.000 | 0.119 | 0.000 | 0.054 | 0.000 | 0.000 |
| 1.60 | 0.000 | 0.170 | 0.000 | 0.000 | 0.000 | 0.038 | 0.000 | 0.237 | 0.000 | 0.105 | 0.000 | 0.000 |
| 1.65 | 0.000 | 0.400 | 0.000 | 0.000 | 0.000 | 0.081 | 0.000 | 0.395 | 0.000 | 0.180 | 0.000 | 0.000 |
| 1.70 | 0.000 | 0.662 | 0.000 | 0.017 | 0.000 | 0.149 | 0.000 | 0.567 | 0.000 | 0.277 | 0.000 | 0.000 |
| 1.75 | 0.000 | 0.856 | 0.000 | 0.049 | 0.000 | 0.244 | 0.000 | 0.721 | 0.000 | 0.389 | 0.000 | 0.000 |
| 1.80 | 0.000 | 0.954 | 0.000 | 0.114 | 0.000 | 0.360 | 0.000 | 0.840 | 0.000 | 0.507 | 0.000 | 0.000 |
| 1,85 | 0.000 | 0.988 | 0.000 | 0.217 | 0.000 | 0.487 | 0.000 | 0.917 | 0.000 | 0.619 | 0.000 | 0.001 |
| 1.90 | 0.000 | 0.998 | 0.000 | 0.352 | 0.000 | 0.611 | 0.000 | 0.962 | 0.000 | 0.719 | 0.000 | 0.007 |
| 1.95 | 0.000 | 0.999 | 0.000 | 0.503 | 0.000 | 0.721 | 0.000 | 0.984 | 0.000 | 0.801 | 0.000 | 0.029 |
| 2 | 0.000 | 0.999 | 0.000 | 0.648 | 0.000 | 0.811 | 0.000 | 0.994 | 0.000 | 0.865 | 0.000 | 0.102 |

Note: Gamma is odds of differential assignment to treatment due to unobserved factors.

Table A2c: Rosenbaum bounds for baseline model – sales from radical innovations.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Any type of collaboration | Intra-group | Customers | Suppliers | Coopetitors | Science |
| Gamma | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig- levels | Lower bound sig. levels | Upper bound sig. levels | Lower bound sig. levels | Upper bound sig. levels |
| 1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.05 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.15 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.20 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.25 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.008 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.30 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.036 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.35 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.114 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.40 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.264 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.45 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.003 | 0.000 | 0.466 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1.50 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.011 | 0.000 | 0.671 | 0.000 | 0.020 | 0.000 | 0.000 |
| 1.55 | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 | 0.034 | 0.000 | 0.828 | 0.000 | 0.047 | 0.000 | 0.000 |
| 1.60 | 0.000 | 0.014 | 0.000 | 0.006 | 0.000 | 0.082 | 0.000 | 0.924 | 0.000 | 0.094 | 0.000 | 0.000 |
| 1.65 | 0.000 | 0.075 | 0.000 | 0.021 | 0.000 | 0.165 | 0.000 | 0.972 | 0.000 | 0.163 | 0.000 | 0.000 |
| 1.70 | 0.000 | 0.236 | 0.000 | 0.059 | 0.000 | 0.282 | 0.000 | 0.991 | 0.000 | 0.255 | 0.000 | 0.000 |
| 1.75 | 0.000 | 0.488 | 0.000 | 0.133 | 0.000 | 0.423 | 0.000 | 0.997 | 0.000 | 0.363 | 0.000 | 0.000 |
| 1.80 | 0.000 | 0.736 | 0.000 | 0.247 | 0.000 | 0.570 | 0.000 | 0.999 | 0.000 | 0.479 | 0.000 | 0.000 |
| 1,85 | 0.000 | 0.897 | 0.000 | 0.393 | 0.000 | 0.704 | 0.000 | 0.999 | 0.000 | 0.592 | 0.000 | 0.004 |
| 1.90 | 0.000 | 0.967 | 0.000 | 0.549 | 0.000 | 0.810 | 0.000 | 0.999 | 0.000 | 0.694 | 0.000 | 0.022 |
| 1.95 | 0.000 | 0.993 | 0.000 | 0.692 | 0.000 | 0.888 | 0.000 | 0.999 | 0.000 | 0.780 | 0.000 | 0.078 |
| 2 | 0.000 | 0.999 | 0.000 | 0.806 | 0.000 | 0.938 | 0.000 | 0.999 | 0.000 | 0.848 | 0.000 | 0.196 |

Note: Gamma is odds of differential assignment to treatment due to unobserved factors.

Evidence from Tables A4a-A4c show that our analyses of effects on all outcomes are insensitive to both underestimation and overestimation due to hidden bias. We can thus even strongly claim that our model is not sensitive to selection bias. Overall, our estimates seem to be insensitive to hidden bias problem at levels exceeding those commonly found in papers published in leading journals. For example, Srhoj, Škrinjarić and Radas (Small Business Economics, 2019) suggest robustness of estimates at levels of 20-25% while Michalek, Ciaian and Kancs (Regional Studies, 2015) interpret their findings as sensitive to bias based on findings of bias magnitude of 5-10%. Our findings suggest, on the other hand, that doubling of odds ratio from 1 to 1.3 (in case of suppliers) or higher in other equations (i.e. up to bias of 40% and above) would not alter statistical significance of our findings. Following Becker and Caliendo (2007) interpretation, this would imply that our estimation results are insensitive to underestimation and overestimation to the extent when odds of treatment assignment between treated and control group increase for 50%.

Next step in our analysis is estimation of placebo effects or falsification tests (Heckman and Hotz, 1989; Rosenbaum, 1987). Here we exclude the treated group and assign to our matched control group from original analysis label “placebo treated” and rerun matching procedure. Table A5 presents results from placebo estimations. With exception of marginal significance at 10% level (with p values above 0.9) in three cases in all other cases we find insignificant effects. Overall this signals that our estimates are showing the causal effect which is due to the particular treatment of collaborative innovation.

Table A3: Results from placebo treatment estimations (ATT effects)

|  |  |  |  |
| --- | --- | --- | --- |
| Outcome | Existing products | Incremental innovations | Radical innovations |
| Any type of collaboration | 0.830 | -0.963 | -2.06\* |
| Intra-group | -0.495 | 0.885 | -2.58\* |
| Customers | -0.603 | -0.565 | -0.883 |
| Suppliers | 2.821 | -1.43\* | -0.293 |
| Coopetitors | 2.182 | 0.481 | -6.111 |
| Science | 0.354 | 0.169 | -1.479 |

 \*\*\*,\*\* and \* denote statistical significance at 1%, 5% and 10% levels respectively.

1. Explorative analysis of non-spatial proximities between analysed countries

A question arises whether indeed some types of non-spatial proximities are more relevant than others between individual pairs of countries in our analysis. In order to verify that our hypotheses are based on both theory and real world evidence we made brief exercise based on the available data. Specifically, for construction of measures of institutional, social and cognitive capabilities we follow approach originally developed by Kogut and Singh (1988) and applied by Hofstede (2001), Hofstede et al. (2010) and Elia et al. (2019) in measurement of inter-organizational cultural proximity. The index is constructed in a way that it can be applied, subject to available data, to other dimensions of proximity as well. We also rely closely on Boschma (2005) and later studies in its tradition in definitions of different types of proximities and use above mentioned index to measure institutional, cognitive and social proximity while organizational proximity measure is constructed in a way that will be elaborated below. The index takes following form:

$Div\_{jh}=\sum\_{i=1}^{n}\frac{(I\_{ij}-I\_{jh})^{2}/V\_{I}}{n}$

Where Div is value of index of diversity along one category between countries *j* and *h*. Ii stands for one of proximity subdimensions, n is number of subdimensions of index and VI is variance of subdimension. Such defined index is first applied to construction of measure of institutional proximity. Institutional proximity involves as argued in our paper factors such as rules, regulations, culture etc. Hofstede et al. (2010) have collected through survey and provided freely available data on six cultural dimensions defined as individualism, power distance, masculinity, uncertainty avoidance long term orientation and indulgence for more than 80 countries in 2010. At the risk of generalization, we used (identical to Elia et al., 2019) this dataset to construct measures of institutional proximity. Results of this index are presented in Table A4. Lower values of index denote greater proximity. Lowest values of proximity are found among CEE and other EU member states but highest among CEE and China and CEE and USA. Such finding should hardly come as surprise.

Table A4: Indices of non-spatial proximity.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Institutional proximity\* | Cognitive proximity\* | Social proximity\* | Organizational proximity\*\* |
| CEE – China | 3,35 | 0,01 | 2,24 | 0,04 |
| CEE USA | 2,74 | 3,66 | 2,92 | 0,12 |
| CEE – other EU member states | 0,68 | 3,26 | 1,30 | 1,99 |

Note: \*higher values denote lower proximity (greater diversity), \*\*higher values denote higher proximity

Cognitive proximity is commonly measured through similarity in knowledge bases. For example, Amoroso et al. (2018) use technological proximity measured through patent applications as indicator of cognitive proximity. Patent data are not only dimension of cognitive proximity but they are among datasets that are available for all analysed countries over longer period of time (in this case 1999-2015 period was used). For the purpose of this exercise we used data on triadic patent applications, the series for which we have comparable data on all countries. Results from Table A4 again support our hypotheses. Cognitive proximity is highest (lowest values of index) among CEE and China, countries that fall in category of production-driven economies. Innovative Western European and US economies have far more triadic patent applications annually and therefore have greater cognitive diversity from CEE.

Boschma (2005) defines social proximity through exchange of tacit knowledge and through trust-building activites. In context of innovation process joint patenting activity may act as proxy of such social proximity as it requires disclosure of tacit and strategically important knowledge. This is also measure that was available for all analysed countries albeit for 2010-2015 period. Specifically, we look into three dimensions defined as % of patents owned by foreigners, % of patents invented abroad and % of patents co-invented with foreigners. As results from Table A4 reveal lowest values of index are found between CEE and other EU member states although even here values of index are relatively high.

Finally, organizational proximity is only type of proximity whose measures should be constructed at micro level (Boschma, 2005). In essence, it involves intensity of inter-organizational ties. One way to approach this issue would be through mutual integration in each others backward and forward value chains between two countries. However, such data does not exist for all analysed countries and even in cases where it does exist it is confined on backward integration. Alternative is to analyse inward and outward foreign ownership of firms between pairs of countries as proxy for interorganizational ties. The data on origin of ownership is provided by, for example, Eurostat on most of analysed countries (but not all) in between 2010 and 2015 although in some years information is missing. Data on outward foreign ownership is provided for some sectors, with far more missing variables and lack of data on some analysed countries at all. For this reason, we departed from index used to calculate previous three distance measures and measure organizational proximity as share of firms owned by country where collaboration partner is located in total number of firms in CEE countries. Although this data does not cover all countries and all years it shows us that higher intensity of such inter-organizational ties can be found between CEE and EU than between CEE and other analysed countries.

Putting these pieces together we can summarize as follows. Institutional proximity is highest among CEE and other EU member states. Cognitive proximity is highest between CEE and China, social proximity is highest between CEE and other EU member states as well as organizational proximity. This further supports our formulation of hypothesis although one must bear in mind quality of data and the fact that these measures do not cover some periods and that some of them do not include all analysed CEE countries. Their quality for practical analysis is low but they may have some value for the purpose of explorative investigation.

References used in Appendix:

Becker, S. and Caliendo, M. (2007). Sensitivity analysis for average treatment effects. The Stata Journal. 7(1), 71-83

DiPrete, T. A., & Gangl, M. (2004). 7. Assessing Bias in the Estimation of Causal Effects: Rosenbaum Bounds on Matching Estimators and Instrumental Variables Estimation with Imperfect Instruments. Sociological methodology, 34(1), 271-310.

Heckman, J.J. and Hotz, V.J. (1989). Choosing Among Alternative Nonexperimental Methods for Estimating the Impact of Social Programs: The Case of Manpower Training. Journal of the American Statistical Association, 84(408), 862-874. DOI: 10.2307/2290059

Hofstede, G. (2001). Culture's consequences: Comparing values, behaviors, institutions and organizations across nations (2nd ed.). Thousand Oaks, CA: Sage.

Hofstede, G., Hofstede, G.J. and Minkov, M. (2010). Cultures and Organizations: Software of the Mind. Revised and expanded 3rd Edition. New York: McGraw-Hill. ISBN 978-0-07-166418-9

Kogut, B., & Singh, H. (1988). The effect of national culture on the choice of entry mode. Journal of International Business Studies, 19(3), 411–432.

Rosenbaum, P. R. (1987). The Role of a Second Control Group in an Observational Study (with discussion). Statistical Science, 2(3), 292-316.

1. To verify the soundness of theoretical assumption about the existence of individual types of non-spatial proximities between analysed countries, an exploratory analysis was undertaken. Details can be found in Section 3 of an Online appendix to the paper. [↑](#footnote-ref-1)