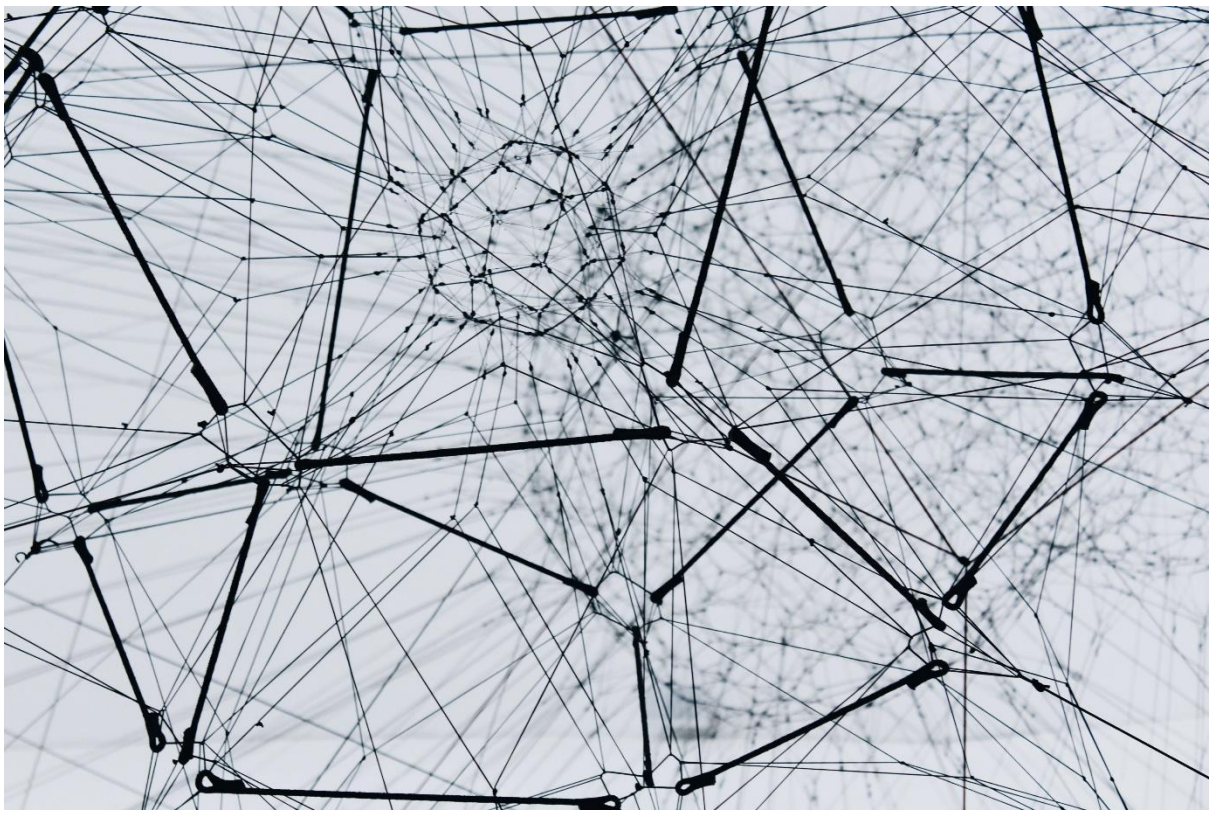
Utrecht University

Master's Thesis – master Innovation Sciences

The effect of proximity on knowledge network dynamics during economic recession: A study of the Great Recession



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Abstract

The impact of recessions on firm performance is unequal across firms, but questions on what causes these differences remain unanswered. To explain firm performance, increasing attention has been given to interfirm knowledge networks. Existing studies showed that different forms of proximity can explain the dynamics of these interfirm networks, but none of these studies analysed the effect of the proximity dimensions during times of economic recession. This study addresses this knowledge gap by answering the following research questions: *Which proximity dimensions drive the formation of innovation network ties in the European biotechnology industry? And did the effects of these driving forces change during the Great Recession?*

Previous studies found that firms prefer collaborations with proximate partners as this reduces the costs and uncertainty of collaborations. This study assumes that proximities will play an even larger role in partner selection during times of economic recession, as firms might try to minimize costs and avoid uncertainty even more than in normal times. In turn, this can harm firm innovativeness as too much proximity between partners reduces the scope of learning.

With the use of the state-of-the-art stochastic actor-oriented model RSiena, the effect of cognitive, organizational, geographical and social proximity on tie formation was studied in a dynamic manner for Germany, the leader in the European biotechnology industry. With the use of patent data inventor networks were constructed. Next, estimations were made for four different time periods (2005-2007; 2007-2009; 2009-2011; 2011-2013) to study how the effects of the proximity dimensions on tie formation changed during the recession.

As expected, inventors were significantly more likely to initiate collaborations with proximate partners. Strikingly, the effect of proximity on tie formation did decrease during the recession period. The German innovation strategy can partly explain these results. As governmental R&D investments increased during the recession, German firms might have been less inclined to reduce costs and choose more proximate partners.

To validate the results of Germany, they were compared to those of Denmark (deploying a similar strategy) and the Netherlands (deploying a strategy based on reducing R&D expenses). The results of Denmark were similar to those of Germany. However, for the Netherlands opposite results were found as the effect of the proximity dimensions increased during the recession. Thus, if no specific innovation schemes are in place that financially support firms in crisis periods, the effect of the proximity dimensions increases, which can harm firm innovativeness.

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1 Introduction

Economies show cyclic patterns of growth and recession. Some recessions occur more or less out of the blue due to unforeseen external events, as we are witnessing now during the outbreak of COVID-19, while others may be more predictable. For instance, many economic analysts predicted the Great Recession (2007-2009) already in 2006 based on, among others, massive foreign borrowing and excessively loose monetary policies (Frieden, 2011). If severe, recessions can have a major impact on economies with negative socio-economic consequences due to firm closures and significant job losses.

However, we know that the impact of an economic recession is not equal across firms (Burger et al., 2017; Martin, 2012). Even though a decline in the overall firm innovativeness can be observed during economic recessions, some firms are better able to maintain their performance than others (Madrid-Guijarro et al., 2013). To explain general firm performance, increasing attention has been given to interfirm knowledge networks (e.g. Boschma and Ter Wal, 2007; Boschma and Frenken, 2009; Pratono, 2018). When firms initiate and maintain alliances with each other, a network of direct and indirect relationships is created. Firms that are strongly embedded in this knowledge network have access to a diverse set of information and know-how of both direct and indirect partners (Schilling and Phelps, 2007). The recombination and reconfiguration of existing knowledge elements, either from direct or indirect partners, drive the creation of new knowledge and therefore the innovativeness of firms (Fleming, 2001; Schilling and Phelps, 2007). Thus, firms that are strongly embedded in interfirm knowledge networks tend to be more innovative and more successful (Calantone et al., 2002; Madrid-Guijarro et al., 2013). However, during recessions, the performance of many firms strongly decreases. Since interfirm networks can at least partly explain firm performance, it is relevant to study the dynamics of interfirm networks during times of economic recession as they might explain the observed differences in firm performance.

Surprisingly, little is known about the drivers of innovation network dynamics of firms in general, let alone during times of economic recession. Until recently, questions on how innovation networks are initiated and how they develop over time remain largely unanswered (Balland, 2012; Balland et al., 2013). Initial studies started to provide answers to these questions. Existing studies found that especially different forms of proximity (e.g. geographical, social and organizational proximity) between inventors can explain the dynamics of interfirm networks in an innovation context (e.g. Broekel and Boschma, 2012; Cassi and Plunket, 2014; Lazzeretti and Capone, 2016; Molina-Morales et al., 2015). For instance, a study showed that geographical and cognitive proximity became increasingly important for tie formation of firms along the life cycle of the video game industry, whereas the importance of institutional proximity decreased (Balland et al., 2013). A similar study indicated that social, geographical, technological, and organizational proximity of inventors benefit collaborations in the research field of genomics, however the research also indicated that too much proximity can harm innovativeness (Cassi and Plunket, 2014).

These initial studies have provided additional insight into the role of proximities as drivers of innovation network dynamics, but they mainly focused on the dynamics throughout the lifecycle of an industry. Insights on the network dynamics and changes during times of economic recession remain underexplored. As economies show a cyclic pattern of growth and recession it is crucial to get a better understanding of network dynamics during recession so

firms can be better prepared for future ones (Amadeo, 2020). By gathering more knowledge on network dynamics during recessions, firms can be more proactive in maintaining their network and performance (Calantone et al., 2002). Moreover, recessions might be an opportunity for renewal of old and outdated structures within industries as emphasized in the evolutionary economic geography literature (Martin, 2012; Martin et al., 2016; Montresor and Quatraro, 2017). From this perspective, recessions might actually be a way towards more future-proof industries (Nyrop et al., 2020), and this study can identify first patterns of renewal that might actually benefit the competitiveness of firms, industries or entire economies in the long-term.

The context of this research is the European biotechnology industry from 2005 to 2013. The biotechnology industry was chosen as it is an example of a knowledge-based industry. Especially for knowledge-based industries the existence and maintenance of interfirm networks are crucial for their performance (Thornhill, 2006). To be competitive in the complex biotechnology industry, various sources of knowledge need to be combined and reconfigured in an innovative way (Thornhill, 2006). The specific timeframe is chosen as it contains the period before, during, and after the Great Recession (2007-2009). Consequently, the effect of proximity on network dynamics can be studied over the course of a recession. The Great Recession is relevant to study as it is the largest recession since the Second World War (Rich, 2013), and sufficient data is available to study this particular recession.

To study how the interfirm network in the biotechnology industry evolved and which role proximities played in the dynamics of the network over the Great Recession, the following research questions will be answered: (i) which proximity dimensions drive the formation of network ties in the European biotechnology industry? And (ii) did the effects of these driving forces change during the Great Recession?

To answer this research question, the stochastic actor-oriented model (SAOM) RSiena was used to analyse the evolution of the interfirm collaboration network (Snijders, 2001). The basic principle of SAOMs is that a network evolves in a stochastic manner and that the evolution is driven by the actors (Snijders, 2001). RSiena was specifically used as it is a state-of-the-art model that is specifically designed for statistical analyses of dynamic networks (Ripley et al., 2011). The modelling is done based on a continuous-time Markov chain process, where the configuration of the network at t determines the network configuration at $t+1$ (Balland et al., 2013). In RSiena the changing network itself is the dependent variable and therefore the effect of different independent variables (in this case the different proximity dimensions) on the network dynamics can be tested.

By using a SAOM to explore drivers of network evolution, this thesis contributes to existing literature as follows: Within the field of economic geography, only a limited amount of research has been performed with partly contradicting results on the importance of different forms of proximity (e.g. Ter Wal, 2014; Balland et al., 2013). This paper contributes to this ongoing debate by providing additional empirical evidence on how firms select their partners according to their social, cognitive, institutional, organizational and geographical proximity. Moreover, this thesis has a focus on network dynamics during times of economic recession, which is a novel contribution to the research field.

By analysing network dynamics in a knowledge-based industry during times of economic recession, this thesis also has a clear societal relevance. The focus on the biotechnology sector is especially relevant since biotechnology is a key enabling technology (KET). KET's are technologies that will allow European industries to maintain their competitiveness and exploit new markets, investing in these areas will create jobs and support economic growth ("Key Enabling Technologies - Horizon 2020 - European Commission", n.d.; Montresor and Quatraro, 2017). Biotechnology specifically is often seen as a technology that supports other European knowledge-based technologies with its technological, scientific and innovative base (Martin et al., 2021). By gathering more knowledge on the drivers of network dynamics during recessions, governments and industries can be more proactive in containing and expanding the network and prevent networks from collapsing. Thereby, it can limit the negative impact of an economic recession on the innovativeness and thus performance of knowledge-based industries.

2 Theory

2.1 Proximity dimensions

The proximity literature has a long tradition. A first proximity dimension that has been intensively studied by economic geographers is geographical proximity, a field of study that dates back to the 1950s (Perroux, 1950). These studies emphasized the many economic advantages of being co-located. Following these initial studies, in the 1990s a more comprehensive list of proximity dimensions was proposed by 'the French School' (Torre and Gilly, 2000). In their view, proximity should not be limited to the geographical dimension and two other forms of proximity were proposed: organizational and institutional proximity. Currently, the analytic distinction in five dimensions of proximity as proposed by Boschma (2005) is most often followed in economic geography and innovation studies, as will be the case in this paper. In his seminal work, Boschma made a more comprehensive overview of different proximity dimensions that are expected to stimulate interactive learning and collaborative innovation in inter-organizational relationships. Besides geographical proximity, Boschma proposed four other proximity dimensions, namely: institutional, organization, social and cognitive proximity. Additionally, he was also one of the first researchers to account for the negative effects of proximity, which will also be highlighted in this thesis.

Geographical proximity

Geographical proximity can be defined as the spatial distance between economic actors (Katz, 1994). Geographical proximity is considered an important driver of collaboration as it enhances face-to-face interactions and facilitates the transfer of tacit knowledge (Boschma, 2005). An important development in the proximity literature is that geographical proximity is “neither a sufficient nor a necessary condition for learning and interactive innovation to take place” (Boschma, 2005, p.62). Thus, firms that are co-located in the same country or region do not necessarily engage in knowledge sharing. This claim is supported by the study of Giuliani and Bell (2005), which showed that firms belonging to the same region all had very different knowledge networks with strong variations in the number of ties. Nevertheless, it is still argued that geographical proximity does play a role in the creation of knowledge networks by facilitating interactive learning (due to co-location), most likely by strengthening the other proximity dimensions (Boschma, 2005).

Organizational proximity

Organizational proximity is defined by Boschma (2005) as "the extent to which relations are shared in an organizational arrangement, either within or between organizations" (p. 65). Thus, organizational proximity is low when two actors are independent and high when they are part of the same hierarchical structure (e.g. belonging to the same parent company). Boschma proposed that firms are more likely to engage with organisationally proximate partners, as it reduces transaction costs and uncertainty. Costs can be reduced since it is easier to exchange knowledge, form working groups, or organize meetings with an organizationally proximate partner (Balland, 2012). Uncertainty can be lowered as organizational proximity lowers the change of unintended knowledge spill-overs (Boschma, 2005).

Social proximity

Social proximity refers to the social embeddedness of actors at the micro-level. A relationship is considered socially proximate when it involves trust based on friendship and mutual experiences (Boschma, 2005). Actors engage with socially proximate partners for several reasons. First of all, social proximity is thought to stimulate the innovative performance of firms because a trust-based relationship facilitates the transfer of tacit knowledge. In turn, the transfer of tacit knowledge is known to strongly contribute to the creation of more complex forms of knowledge, which forms the basis for innovation (Grant, 1996). Secondly, a socially embedded relationship reduces the risk of opportunistic behaviour (Boschma, 2005). When actors collaborate on projects, they build up a relationship based on trust and reputation and they are not random market actors anymore. Consequently, the chances of opportunistic behaviour are lower compared to a relationship that is purely market-oriented or newly established (Gössling, 2004).

Institutional proximity

Institutions are defined by North (1991) as “humanly devised constraints that structure political, economic and social interaction” (p. 97) and are commonly seen as the ‘rules of the game’ (Leftwich and Sen, 2010). A distinction can be made between formal and informal institutions (North, 1991). Formal institutions are, as the name suggests, more formalized and include written constitutions like laws and policies (Leftwich and Sen, 2010). Informal institutions are (often unwritten) customs, traditions and social norms (Leftwich and Sen, 2010). Two actors can be considered institutionally proximate when they are similar in both their formal and informal institutions (Boschma, 2005). Proximity in both formal and informal institutions eases the collaboration between firms. Having the same culture and habits (informal) and operating under the same law system (formal), provides a stable basis for collaborations as it eases knowledge exchange and lowers chances of conflicts (Boschma, 2005).

Cognitive proximity

Cognitive proximity refers to the degree to which two actors or organizations share the same knowledge base (Nooteboom, 2000). Similarity in knowledge bases increases the absorptive capacity - the ability to identify, interpret and exploit new knowledge - of organizations, which is in turn required for the effective transfer of knowledge between organizations (Cohen and Levinthal, 1990). Thus, cognitive proximity eases the exchange of knowledge between partners and thereby reduces costs. However, when the knowledge bases of firms are too proximate this might limit the scope of learning since there is little to exchange. This trade-off between communication and novelty led to the notion of 'optimal cognitive proximity' (Nooteboom, 2000), a concept that will be discussed in more detail in the next section (see 2.2). Due to this trade-off, cognitive proximity is a crucial dimension for future partner selection.

Towards a dynamic proximity perspective on proximity

An important recent contribution to the proximity literature is the change from a static view on proximities to a dynamic one. Balland et al. (2015) argued that the tendency has been to explain collaboration as a consequence of proximity. Thus, collaborations between organizations occur because the organizations are proximate in one or more dimensions. However, this does not necessarily have to be the case, which is also argued by Padgett and Powell (2012), who state that 'in the short run, actors create relations; in the long run, relations create actors' (p. 6). In other words, proximity is an important driver of knowledge network formation in the short run, but in the long run knowledge networks also create proximity between partners. Thus, proximity between actors co-evolves with network activities over time (Balland et al., 2015).

This dynamic view is particularly relevant for this study, as it suggests that the effect of proximity on network dynamics should be studied over time rather than in a static manner. For instance, Balland et al. (2015) showed how cognitive proximity between actors increases through a dynamic process of learning. When actors interact they exchange and produce knowledge collectively, which increases the cognitive proximity between actors naturally. Another example is the dynamic nature of social proximity, described by the process of 'decoupling'. Decoupling refers to the process where relations, between organizations or individuals, can be decoupled from the original context and start to exist for themselves (Grossetti, 2008). When actors intensively collaborate over a certain period, their social proximity increases, and this can lead to 'decoupling' of their relationship. For instance, when two colleagues (or organization) have worked together extensively and they remain acquainted even after one leaves the company, their relation is decoupled from the original context (Balland et al., 2015). Thus, in their study Balland et al. (2015) showed how proximities can increase over time as a consequence of past interactions.

2.2 Knowledge networks, proximity and innovation

The embeddedness of firms in knowledge networks is perceived as an important determinant of their innovative and economic performance (Powell et al., 1996; Bell, 2005). Research indeed showed that firms that occupy a central position in knowledge networks are more innovative than competitors with a less central position (Boschma and Ter Wal, 2007; Dolfsma and Van der Eijk, 2017; Wang et al., 2018). The reason is that firms that occupy a central position in a knowledge network have access to a diverse flow of knowledge and are less likely to miss crucial information. More specifically, inter-firm knowledge networks are important for the transfer of tacit knowledge (Bell, 2005). In turn, the transfer of tacit knowledge is known to strongly contribute to the creation of more complex forms of knowledge, which is crucial for the innovativeness and competitiveness of firms (Grant, 1996).

Optimal level of proximity and the proximity paradox

It has become clear that proximity is an important driver of network formation and that in turn network formation is crucial for firm innovativeness and competitiveness. Nevertheless, scholars have also argued that too much proximity might harm firm innovativeness. Especially the cognitive proximity dimension has been popular in this respect and the notion of 'optimal cognitive proximity' has been developed (Nooteboom, 2000). Nooteboom (2000) argued that cognitive proximity can both enable and constrain learning. To a certain extent similarity in

knowledge bases is needed for efficient communication and knowledge transfer. However, when two organizations are too cognitively proximate, this can limit the scope of learning (Nooteboom, 2000). Indeed, Nooteboom et al. (2007) found evidence for an 'inverted U-shape' relationship between cognitive proximity and innovative performance of firms. Thus, for optimal innovative performance a firm should neither be too cognitively proximate or distant from its partner.

As a consequence of this finding, more research has been dedicated to the trade-offs between too much and too little proximity. Based on the concept of optimal cognitive proximity, the 'proximity paradox' has been identified (Boschma and Frenken, 2009). Boschma and Frenken (2009) argue that high levels of proximity make tie formation more likely, but these high levels of proximity might be suboptimal for firm performance. For several forms of proximity, such a paradox has been demonstrated (e.g. Cassi and Plunket, 2014; Broekel and Boschma, 2012). The research of Broekel and Boschma (2012) was one of the first to empirically test the existence of a proximity paradox. In their study on knowledge networks in the Dutch aviation industry, they found that cognitive, organizational, social and geographical proximity increased chances of collaborations between firms in the industry. However, they also found evidence that too much cognitive proximity had a negative effect on firm innovativeness, a clear example of the proximity paradox. Thus, firms need to prevent their network from becoming too closed and proximate, and forming new and more distant ties is crucial to keep innovative. Hence, not only the maintenance of a network but also its expansion is crucial for firms' innovativeness.

Threat of the proximity paradox during recessions

The underlying assumption of the five proximity dimensions is that proximity reduces the costs or risks of collaborations and therefore proximity increases the likelihood of actors to form partnerships (Boschma, 2005). The assumption that being proximate reduces costs and risks of collaborations might be especially relevant in times of economic recession. Research indicates that firms respond to economic crises primarily by reducing both their operational and investment activities and expenses, aiming at short-term survival (Loukis et al., 2020). Furthermore, economic recessions can lead to a substantial increase in risk aversion of individuals, as was demonstrated for the Great Recession (Guiso, 2012). Thus, during recession individuals and firms alike are more risk-averse and try to minimize cost, and therefore they are more likely to initiate collaboration with actors that are proximate since being proximate reduces the costs and risks of collaboration. Thus, the proximity paradox might be a real threat to firms during times of economic recession, and according to earlier empirical studies this can have a detrimental impact on firm innovativeness and performance (e.g. Broekel and Boschma, 2012). Based on the effect of the proximity dimensions on tie formation over the course of the recession, some initial indications for the existence of a proximity paradox can be found. However, with the research approach that was used for this thesis it is not possible to prove the existence of the proximity paradox as firm innovativeness and performance was not measured in the study.

2.3 Hypothesis development

Throughout the theory section, it has become clear that proximity increases the likelihood to form partnerships, regardless of its possible negative consequences (Boschma, 2005; Balland et al., 2013). Furthermore, the dynamic nature of interfirm networks was emphasized, and it was argued that networks should be studied in a dynamic way (Balland et al., 2015). Now the literature streams on proximity and network dynamics will be combined to derive hypotheses for the effects of proximities on tie formation over the course of the Great Recession.

General hypothesis: Table 1 shows an overview of the most recent studies that apply dynamic network models[1] to study the effect of proximity on tie formation in an innovation context, within various industries.

Table 1: Comparison between findings of research and previous studies on the effect of different proximity dimensions on innovation network dynamics. Adapted from Lazzeretti and Capone (2016).[2]

Contribution	Setting	Timeframe	Approach	Proximities			
				Cog	Org	Geo	Soc
Balland (2012)	Satellite navigation system projects (EU)	2004-2007	Dynamic (RSiena)	0	+	+	0
Balland et al. (2013)	Video game industry (Japan)	1987-2007	Dynamic (RSiena)	+	+	+	+
Lazzeretti and Capone (2016)	High technology applied to cultural goods (Italy)	1995-2012	Dynamic (RSiena)	+	+	+	+
Ter Wal (2014)	Inventor network in German biotechnology industry	1970-2000	Dynamic (RSiena)	NA	NA	+	+
Teng et al. (2021)	Photovoltaic industry in China	2006-2015	Dynamic (RSiena)	NA	+	+	NA

The study of Balland (2012) is one of the first studies that applied RSiena in an economic geography context. In his research he analysed the effect of different proximity dimensions on the dynamics of collaboration networks in the Global Navigation Satellite System (GNSS) industry. The results indicated that organizational and geographical proximity favour collaborations, whereas for cognitive and social proximity no significant effect on tie formation was found. One year later, Balland et al. (2013) performed a similar study, applied to a different industry. In this research they studied which proximity dimensions explained the evolution of inter-firm networks in the Japanese video game industry from 1987 to 2007. In contrast to the earlier study on the GNSS industry, all proximity dimensions generally increased chances of tie formation over the analysed period. Lazzeretti and Capone (2016) found similar results for the effect of the proximity dimensions on tie formation in inter-organizational networks in the high technology applied to cultural goods (HTCG) industry in Italy (an industry focused on applying new technologies for the restoration and safeguarding of cultural goods). In their research, they also found a positive effect of all proximity dimensions on the formation of

[1]The table shows previous studies using RSiena to determine the effect of the different proximity dimensions on tie formation in a dynamic manner. RSiena is currently the most often used to estimate. SOAMs

[2]Note: Institutional proximity was excluded from the analysis due to data constraints, for a more detailed explanation please see 3.3

innovation networks within this industry. Similar to this thesis, Ter Wal (2014) analysed the effect of different proximity dimensions on the evolution of inventor networks in the German biotechnology industry. However, the context was different as Ter Wal studied the effect of geographical and social proximity during the emergence of the biotechnology sector in Germany between the years 1970 and 2000. For both proximity dimensions a positive effect on tie formation was found. The last research that is included in the overview is the recent study by Teng et al. (2021), in which the effect of organizational and geographical proximity on the evolution of innovation networks in the Chinese photovoltaics industry was analysed. For both dimensions a positive effect on tie formation was found, the effect of organizational proximity being stronger than the effect of social proximity.

The literature overview clearly shows that the different proximity dimensions in general have a positive effect on tie formation in either inter-firm or inventor networks. Combining the empirical results of previous studies with the theory on proximity and its positive effect on tie formation, one can expect a positive relationship between cognitive, organizational, geographical and social proximity and tie formation in the German biotechnology sector. Thus, the following four general hypotheses can be formulated, one for each proximity dimension[3]:

Hypothesis 1a: Organizations are more likely to collaborate with actors when they share a cognitive proximity.

Hypothesis 2a: Organizations are more likely to collaborate with actors when they share an organizational proximity.

Hypothesis 3a: Organizations are more likely to collaborate with actors when they share a geographical proximity.

Hypothesis 4a: Organizations are more likely to collaborate with actors when they share a social proximity.

Crisis hypothesis: Whereas a lot of studies have been performed on the effect of the different proximity dimensions on tie formation in various industries, little is known about the effects of proximity dimensions over the course of a recession. Even though previous studies analysed the effects of the different proximity dimensions in a dynamic manner, the results are highly context specific. Therefore, the hypotheses on how the effects of the proximity dimensions change during the Great Recession cannot be supported by much empirical evidence.

To derive crisis-specific hypotheses that guide the empirical analysis, theory on the changes in firms' behaviour during times of uncertainty will be combined with the results of initial empirical studies that analysed the role of proximity on tie formation at times of economic recession to formulate hypotheses. The focus of the theory to derive crisis-specific hypotheses will be on economic considerations of firms, such as cost reduction strategies, increases in risk aversion, and lowering chances of opportunistic behaviour.

The first dimension that will be discussed is cognitive proximity. Previous studies found that firms try to avoid costs and lower uncertainty during times of economic recession (Guiso, 2012;

[3]Note: Hypotheses are formulated separately as they will be discussed separately in the results section as well

Loukis et al., 2020). Cognitive proximity can also be related to the costs of a collaboration as too little cognitive proximity between partners can hamper efficient collaboration and knowledge transfer, which makes collaborations more time consuming and uncertain, and thereby more costly (Cohen and Levinthal, 1990). This is supported by the findings of Nootenboom (2000), who found that to a certain extent similarity in knowledge bases is needed for efficient communication and knowledge transfer, even though too much cognitive proximity can harm firm innovativeness (Nootenboom et al., 2007). Thus, based on cost considerations, it is likely that firms will prefer to collaborate with more cognitively proximate partners during times of economic recession although it might harm their innovativeness. Accordingly, the following crisis-specific hypothesis can be formulated for cognitive proximity:

Hypothesis 1b: The positive effect of cognitive proximity on tie formation will increase during the Great Recession

In his seminal work, Boschma (2005) argued that especially too little organizational proximity is associated with risks of opportunistic behaviour. Thus, when firms do not belong to the same organizational group, changes of opportunistic behaviour increase (Boschma, 2005). As opportunistic behaviour can be costly for firms, this is something they want to avoid, certainly during times of economic recession. Therefore, it is likely that intra-organizational collaboration is preferred over inter-organizational collaboration during times of economic recession to lower the chances of opportunistic behaviour. This reasoning is supported by the findings of Moldavanova and Akbulut-Gok (2020), who found that engaging in inter-firm collaborations was one of the strategies that organizations engaged in only in the aftermath of the Great Recession, but not during the recession. Based on the theory that too little organizational proximity increases chances of opportunistic behaviour, combined with the findings that firms are reluctant to engage in inter-organizational collaborations during times of economic recession, the following hypothesis can be formulated:

Hypothesis 2b: The positive effect of organizational proximity on tie formation will increase during the Great Recession

The third form of proximity that will be analysed, geographical proximity, has mainly been associated with costs: when firms share a geographical proximity, it is likely to reduce the costs of the collaboration (e.g. travel costs) and it eases the coordination of joint innovative activities (Balland et al., 2015). As was described in the previous section, firms respond to economic crises primarily by reducing both their operational and investment activities and expenses, aiming at short-term survival (Loukis et al., 2020). Therefore it is likely that firms will choose more geographically proximity partners during times of economic recession due to cost considerations. A recent study supports this reasoning as it showed that geographical proximity was an important determinant of partner selection during the Great Recession in the ICT sector of Trentino, Italy (Tsouri, 2019). According to the study of Tsouri, geographical proximity was even a stronger determinant of partner selection than institutional or organizational proximity. Based on the assumption that firms are more likely to deploy costs reduction strategies during a recession, the following hypothesis can be formulated:

Hypothesis 3b: The positive effect of geographical proximity on tie formation will increase during the Great Recession

Lastly, the effect of social proximity of the course of the Great Recession will be discussed. According to Boschma (2005), a relationship is considered socially proximate when it involves trust based on friendship and mutual experiences, and similar to organizational proximity too little social proximity is also associated with risks of opportunistic behaviour. Thus, it would be likely that firms increasingly initiate ties with socially proximate partners during times of economic recession to lower changes of opportunistic behaviour. This assumption is supported by the previously discussed study of Tsouri (2019). Whereas she found a positive relationship between geographical, organizational and institutional proximity and tie formation during the recession, the strongest determinant for collaboration was a trustful relationship based on an earlier collaboration. Thus, to avoid uncertainties during recession the most trustworthy partners may be selected which is often based on previous experiences. Based on the assumption of risk averse firms during times of recession, the following hypothesis can be formulated:

Hypothesis 4b: The positive effect of social proximity on tie formation will increase during the Great Recession

3 Method

3.1 Data collection

Patent data was used to study the dynamics of knowledge networks as patents are increasingly used, and prove to be reliable, as relational data between firms or inventors to construct knowledge networks (Breschi and Lissoni, 2004; Wang et al., 2014). With the use of patent data, inventor-patent networks could be constructed, where nodes represent inventors and ties represent co-developed patents. Patent data is especially reliable for analysing innovation in the biotechnology industry as this industry always had a strong propensity to protect their inventions by patenting (Giugni and Giugni, 2006). Inventors, instead of firms, were used as the unit of analysis as they form the most detailed and pure level of collaboration data (Ter Wal, 2014). For instance, when firms file a patent they often do so by assigning it to the head office of the company and not to the research institute where a certain invention is developed. As a result, studying the spatial structure of the network becomes problematic (Ter Wal, 2014). Since the inventor-patent networks closely represent inter-firm collaboration in innovation, there are also no problems with confirming or rejecting the hypotheses (which are formulated on the firm level) when using inventor-patent networks.

The required data were retrieved from the RISIS patent database. The data of the RISIS patent database is cleaned and harmonized on the inventor level by the use of the inventors' addresses (Laurens et al., 2019). The data needed for geographical, organizational, institutional and cognitive proximity were also retrieved from the RISIS PATSTAT database. The data required for the social proximity dimensions were calculated based on the modelled networks. All data was processed in the software environment R using the packages ‘dplyr’ (Wickham et al., 2018) and ‘tidyr’ (Wickham, 2021).

Data of 33 IPC classes, which were categorized by the EPO as ‘biotechnology classes’, were extracted (OECD, 2009). These classes cover a large range of biotechnologies, from medical biotechnologies (e.g. vaccines or brain and neuronal therapies) to plant biotechnology (e.g. genetic engineering of plants to improve yield) to microbial biotechnology (e.g. microbial genomics to improve food safety and security). The RISIS PATSTAT database contained data with good coverage from 2000 until 2013 and accordingly data from these years were extracted for all EU countries.

Since data was available from 2000 to 2013, it was possible to analyse the effect of different forms of proximity on tie formation in knowledge networks over time. In this research, four different periods were studied: (1) 2005-2007, (2) 2007-2009, (3) 2009-2011 and (4) 2011-2013. These four time periods were chosen as they all correspond to a particular phase of the business cycle of Western countries (Amadeo, 2020). The period from 2005 until 2007 corresponds to a peak period. The period from 2007-2009 corresponds to the contraction phase, where the economy strongly declines. The period from 2009-2011 corresponds to the trough phase, which is a transition phase from contraction to growth. Lastly, the period from 2011-2013 corresponds to the growth phase. By analysing these four phases, the effect of different forms of proximity on tie formation can be studied over the course of the Great Recession.

The effect of proximity over the course of the recession was studied for 3 countries: Germany, the Netherlands and Denmark. Germany was studied as a core case as it has been a leader in the European biotechnology over the past three decades (Müller, 2002; PwC, 2017). Furthermore, Germany developed a unique innovation strategy to cope with the Great Recession based on high investment into R&D (this strategy will be discussed in more detail in section 5.1) (Lichtenhaler, 2020). As this strategy is quite unique, it seems necessary to validate the results, and compare it to countries that also have a well-developed biotechnology industry but opted for a different innovation strategy during the recession. A country that fulfils these requirements is the Netherlands, which pursued a strategy mainly aimed at reducing R&D expenses (Guellec and Wunsch-Vincent, 2009; OECD, 2012). Lastly, the results of Germany were verified by comparing them to Denmark, which deployed a similar, investment-based strategy during the Great Recession.

3.2 Constructing inventor networks from patent data

In order to analyse how the effect of different forms of proximity evolved over the course of the recession, yearly co-invention networks were constructed. As said, two actors are linked in these networks when they co-filed a patent, assuming that when they filed a patent together they also collaborated on the invention, which is a common assumption in innovation studies (e.g. Breschi and Lissoni, 2004; Wang et al., 2014). To construct the yearly inventor networks, a five-year moving window procedure was applied. Thus, each yearly inventor network contained co-invention data on that year and the preceding four years. The rationale behind this procedure is that the innovation process to produce an invention is not completed in a single year, and in line with previous studies it is assumed that the process takes five years on average (Fleming et al., 2007; Ter Wal, 2014).

As the social network analysis model that was used (RSiena, for more information see 3.4) is only able to analyse networks up to a thousand nodes (Ripley et al., 2011), some measures needed to be taken to reduce the size of the networks to be analysed. First of all, countries were analysed individually instead of studying the EU as a whole. Furthermore, a specific patent class, C07K, was chosen in order to limit the size of the networks that were analysed. Data on all 33 IPC patent classes was received (roughly 100.000 patent applications by 50.000 unique inventors) and afterwards an appropriate biotechnology subclass was chosen based on the number of patent applications. The selection of the appropriate patent class was made afterwards as it was not known beforehand how many patent applications each patent class would contain. The C07K patent class was chosen as it contained sufficient patent applications to analyse the German, Dutch and Danish biotechnology sector without exceeding the node limit.

To further reduce the number of nodes, and more importantly, increase the stability of the networks, the analysis was limited to incumbent inventors. Incumbent inventors were defined as inventors that occurred at least twice and in different years in the data. For reliable estimations by RSiena, the Jaccard index, which indicates the similarity between datasets, of two subsequent observations (in this case inventor-networks) needs to be higher than 0.1 and preferably higher than 0.3 (Ripley et al., 2011). By limiting the analysis to incumbent inventors this threshold was reached for all time periods.

After the application of the five-year moving window, the filtering of the patent class and the identification of incumbent inventors, yearly *n x n* matrices were created. Each of the four time periods were analysed separately. Within each time period the yearly matrices need to have the same *n x n* size, thus all inventors that were present in that period need to be included in all yearly matrices.

3.3 Operationalization of variables

Analysing social networks dynamics can be done with the use of the stochastic actor-based model (SAOM). The basic principle of SAOMs is that a network evolves in a stochastic manner and that the evolution is driven by the actors (Snijders, 2001). Therefore, SAOMs are especially useful for testing theories on how actors change their ties in a dynamic manner. In this research the effect of proximity on tie formation will be studied dynamically with the use of the SAOM RSiena (Ripley et al., 2011), which will be discussed in more detail in section 3.4. In this section the definition and operationalization of the variables will be discussed, of which an overview can be found in Table 2.

Dependent variable

When using RSiena, the *dependent variable* is the changing knowledge network itself. (Ripley et al., 2011). RSiena now attempts to explain why certain ties are created, dissolved or retained between *t* and *t-3*, based on both the configuration of the network at *t-3* and the exogenous effects that were included (here, the five forms of proximity and structural effects). Thus, it aims to identify the forces that drive the changes of the inventor network, thereby making the evolving network the dependent variable (Ripley et al., 2011; Ter Wal, 2014).

Structural effects

The structural position of an actor within a network can also explain the evolution of the network. These factors are called structural properties or *structural effects*. Therefore, structural effects are included as control variables in this research. The structural effects degree and transitivity are often included in SAOM analyses (Balland et al., 2013). The relevance of these two structural effects in an innovation context and their calculations will be discussed in this section.

Degree: Degree can be determined based on the number of ties a certain actor has. It is important to include density as a control variable as it controls for the cost of relations (e.g. time and investment of resources) (Snijders et al., 2010) and therefore it explains why an actor cannot be connected to all others (McPherson et al., 2001). Examples of costs of relationships in an innovation context are for instance collaborations costs (e.g. traveling costs), and costs of knowledge leakage. Knowledge leakage is the process in which firms lose valuable knowledge to their collaboration partners, which can lower firm performance and thereby incur costs for firms (Easterby-Smith et al., 2008; Frishammer et al., 2015). Degree will be calculated based on the number of collaborations each inventor has, using the following formula:

$$D_i = \sum_j x_{ij} \qquad (1)$$

Where x_{ij} = 1 indicates that actors *i* and *j* collaborate on a patent, and x_{ij} = 0 indicates that actors *i* and *j* are not connected by a patent collaboration.

Transitivity: Transitivity will be included in the form of social proximity, which will be discussed in the next section.

Independent variables

The five different forms of proximity all relate to the relationship between two inventors. This type of relationship is called a dyadic covariate in RSiena (Ripley et al., 2011). A distinction can be made between constant and dynamic dyadic covariates, but in this research all relationships between actors were considered constant within each time period, except for social proximity. Thus, the assumption was that actors don't change from organization, location (NUTS region) or institutional form within a certain time period. A square matrix was developed for geographical, organizational, institutional and cognitive proximity. Each matrix had one value for each pair of actors, which was valid for all observation moments within that time period. The diagonal values were meaningless and set to zero.

Geographical proximity: Geographical proximity was measured based on the NUTS ID's of the inventors. If two inventors are registered in the same NUTS-1 region, a value of 1 was assigned. If two inventors live in the same NUTS-2 region a value of 2 was assigned, and inventors that live in the same NUTS-3 region were assigned a value of 3. If two inventors do not share a NUTS region, a value 0 was assigned. Thus, the higher the value the closer two inventors are geographically and hence, the more likely they are to collaborate as geographical proximity eases collaborations and lowers costs (Boschma, 2005). The positive relationship between geographical proximity and chances of collaboration was also empirically confirmed for the Flemish biotechnology sector, even though the effect seems to decrease due to globalization (Herrmann et al., 2012).

Social proximity: Social proximity between actors in knowledge networks is assumed to reduce costs and risk of a collaboration. For example, social proximity between actors reduces the chances of unintentional knowledge leakage and eases the collaboration which can in turn reduce costs (Bell and Zaheer, 2007). In dynamic social network analyses, social proximity is often included in the form of transitivity (e.g. Ter Wal, 2014). The central idea of transitivity is that if two actors have a friend in common, there is an increased chance that they will become friends themselves in the future (Snijders et al., 2006). In an innovation context, this means that the friends of a business partners are expected to be reliable partners for future projects based on the trustworthy relationship you already have with the business partner. Transitivity will be measured by the number of transitive triplets of actors (equation 2). Balland (2012) noted that using the transitive triplets effect can result in an artificially high transitivity parameter when networks are constructed from bipartite data. This, however, is not a concern for this research as the actual value of the parameter is not of interest but rather the trend of the parameter over the course of the recession.

$$T_i = \sum_{j<h} x_{ij} x_{ih} x_{jh} \qquad (2)$$

Where x_{ij} = 1 and x_{ih} = 1 indicates that actors *i* collaborates with both actor *j* and *h*, and x_{jh} = 1 indicates that actors *j* and *h* are collaboration partners themselves as well.

Institutional proximity: Institutional proximity was excluded from the model as the data analysis indicated that close to 99% of the inventors included in the RISIS PATSTAT database were

affiliated to firms. Thus, only a really limited number of inventors were affiliated to other institutional forms, which made the analysis unreliable and not meaningful. Therefore, institutional proximity had to be excluded.

Cognitive proximity: To measure cognitive proximity between inventors, a matrix was developed based on the IPC codes of the patents an inventor worked on (Cantner and Graf, 2006). If an inventor worked on a patent in a certain class, a value of 1 was assigned for that specific patent class. Then, simply the number of overlapping patent classes between two inventors was counted (Cantner and Graf, 2006). The count thus indicates on how many similar patent classes two inventors have worked: the higher the count, the higher the cognitive proximity (or similarity) between two inventors. As the number of overlapping patent classes was highly skewed, the log was taken to reach a more normal distribution. In a knowledge-based sector like the biotechnology industry, cognitive proximity is especially relevant as a certain cognitive proximity between inventors is required for an efficient collaboration (Nootenboom et al., 2007). For instance, two inventors who work in entirely different domains of the biotechnology sector will struggle to efficiently collaborate as their mutual knowledge is limited, which makes collaborating more challenging and costly. In other words, inventors need some sort of 'common language' to be able to understand each other and efficiently collaborate.

Organizational proximity: In an innovation context, collaborating within the same organization is associated with reduced collaboration costs, lower chances of opportunistic behaviour and lower chances of knowledge leakage (Fleming and Frenken, 2007). To measure organizational proximity, the unique identifier for firms in the RISIS PATSTAT database were used. In this research, the number of patents two inventors co-filed for a certain organization was counted. By this means, it was not only measured if two inventors work for the same organization but also how intensive their collaboration within this organization actually is. As the number of co-filed patents within the same organization was highly skewed, the log was taken to reach a more normal distribution of the variable.

Table 2: Overview of variables

Variable	Indicator	Definition
Dependent variable	Knowledge network	Inventor patent network based on RISIS PATSTAT patent data
Independent variables	Geographical proximity	Classification based on NUTS regions, value 1 if inventors live in the same NUTS1 region, value 2 if inventors live in the same NUTS2 region, value 3 if inventors live in the same NUTS3 region. A value 0 was assigned if inventors did not share a NUTS region.
	Social proximity (transitivity)	Social proximity of an inventor is calculated based on the number of transitive triplets of the actor.
	Cognitive proximity	Cognitive proximity was defined based on the number of mutual patent classes two inventors worked on. The log was taken as the number of mutual patent classes was highly skewed.
	Organizational proximity	When two inventors work for the same organization/firm, a value 1 was assigned. If not, a value 0 was assigned.
Structural effects	Density	Degree was measured as the number of ties divided by the number of possible ties, controlling for the costs of collaboration.

3.4 Modelling network dynamics with RSiena

Social networks are dynamic by nature as ties can be established or terminated at any point in time. To model the dynamics of social networks, stochastic actor oriented models (SAOMs) can be used. SAOM analyses are based on longitudinal data and evaluate the dynamics of the networks by statistical inference (Snijders et al., 2017). The fact that these models are 'actor oriented' means that the observed changes in the network are a result of choices from the actors. As said, the SAOM that was used in this research is RSiena (Simulation Investigation for Empirical Network Analysis). RSiena is programmed by Ruth Ripley, Krists Boitmanis and Tom Snijders and was introduced around the year 2010 (Ripley et al., 2011). Over the last 10 years, RSiena has been increasingly applied in innovation studies, of which a few were already discussed in the theory section (e.g. Balland et al., 2013; Lazzeretti and Capone, 2016). RSiena is often used in innovation studies as it is very well documented and as there are many possibilities to specify the model to the specific requirements of the research (Ripley et al., 2011).

In this thesis, it was analysed how tie formation changed during the Great Recession and how this process is affected by proximities. In part, the network model assumes that changes of the network are endogenously determined, thus modelled as a function of the current network structure (Snijders et al., 2010). To account for the current network structure the structural effects that were discussed in the previous section were included. The other part of the network dynamics is determined exogenously, such as by the different forms of proximity that were considered in this research as exogenous factors for explaining knowledge network dynamics.

The algorithm of RSiena generates the network at moment $t + 1$ based on the configuration of the network at moment t (Balland et al., 2013). As RSiena is actor oriented, the dynamics of the network are determined by the actors themselves, as they get the opportunity to create, maintain or dissolve a tie at stochastically determined moments. The model type that was used for the simulations was the 'unilateral initiative and reciprocal confirmation' model as this model is closest to the reality for the context of this research. This model assumes that one actor takes the initiative to create a tie, and the other actor needs to confirm before a tie is officially created (Ripley et al., 2011). For the dissolution of a tie, however, confirmation is not required. In an innovation context this would mean that two inventors both need to agree before they start a collaboration, whereas for the termination of a collaboration can be initiated by only one inventor, and no confirmation is needed. This model is much more realistic than the default 'forcing model' wherein no confirmation is needed to initiate a collaboration.

All the performed estimations were based on 2000 simulation runs and they were estimated at least three times to make sure the models were robust. Based on the statistical significance of the estimated parameters, it could be determined whether a certain form of proximity explains collaboration (tie formation) between two inventors in a certain time period. In order to test whether the difference between coefficients along the different time periods is statistically significant, a 95% confidence interval was plotted. By this means, both the hypotheses on the effect of proximity on collaboration in general and the ones on the effect of proximity over the course of the Great Recession could be tested.

The estimations of RSiena can be interpreted as log-probability ratios, which is similar to log-odd ratios of logistic regressions, and they can be interpreted accordingly (Ripley et al., 2011). Thus, the RSiena estimates can be interpreted as log-odds ratios, expressing how a one-unit change of the independent variables changes the log-odds of tie formation (Balland et al., 2013; Ripley et al., 2011). Important to note is that the estimates are not standardized and hence, they are dependent on the scale of the input variables. Consequently, only the estimates of the same independent variable can be compared over time (as the scale does not change), but the sizes of different estimates should not be compared amongst each other (Balland et al., 2013). For the comparison between the countries the same rules hold: the estimates of the same proximity dimension can be compared over time, however the sizes of the estimates of different proximity dimensions should not be compared.

In order to improve the robustness of the research and make sure the results were not specific to the analysed patent class (C07K), models were rerun for a different patent class (C12N) within the biotechnology industry and similar patterns of the different proximity dimensions were observed.

4 Empirical Setting

As said, the core case of this research is Germany as it has been the leader in the European biotechnology industry for decades now (Müller, 2002; PwC, 2017). Especially in the period after the reunification of Germany in 1989, the biotechnology sector witnessed considerable growth. In 1992 Germany only had 17 dedicated biotechnology companies. Ten years later this number had risen up to 333 dedicated biotechnology firms, making the German biotechnology sector the largest in Europe (Müller, 2002). From then on, the German biotechnology sector always had a central role in Europe.

Today's central role of Germany in the European biotechnology industry is visualized in Figure 1, showing the distribution of the industry in Europe.

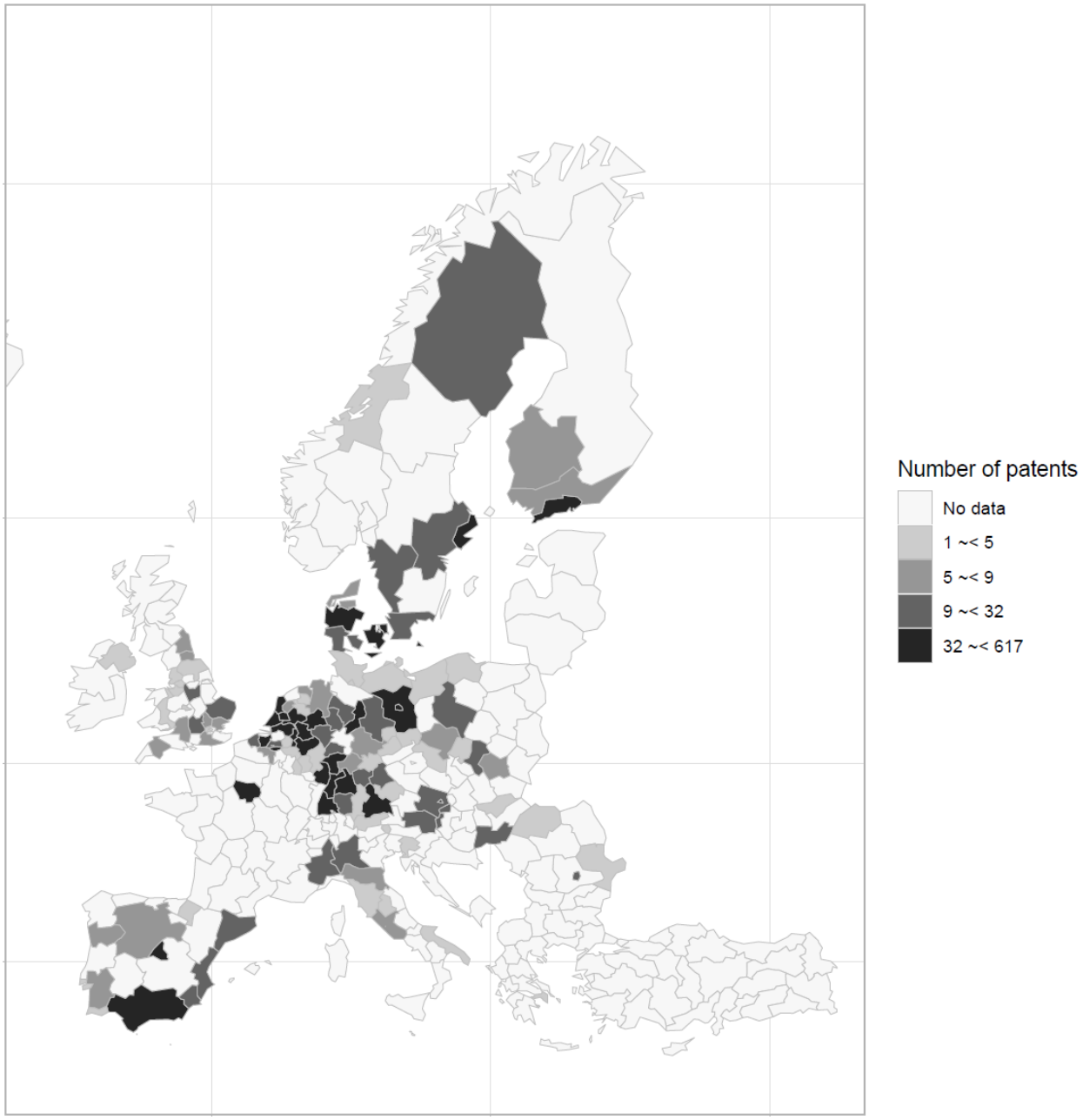

Figure 1: Number of biotechnology patent applications by NUTS-2 region (2013-2015), countries were categorized by quantiles of the number of patent applications.

The figure shows the number of patents filed on a NUTS-2 level between 2013 and 2015. Of the 32 regions with the highest number of patent applications (>617), 12 were located in Germany. Within Germany a few strong regional clusters can be identified: Berlin area, Rhineland (near the Dutch border), Schwarzwald (south of Germany), Rhine-Neckar triangle (just above Schwarzwald) and the region around Munich. These results are in line with the study of Ter Wal (2014) who observed the same regional cluster in the German biotechnology sector until 1995. Thus, between 1995 and 2015 the spatial distribution of the German biotechnology sector remained largely unaltered as the same regional biotechnology clusters were identified in this study and the study of Ter Wal (2014).

Next to the dominant role of Germany in Europe, the figure shows that the Netherlands and Denmark have a strong biotechnology sector too. For the Netherlands, the main biotechnology regions are located in the centre and south of the country according to the figure. In Denmark the biotechnology sector is mainly located in the centre of the country as well as around its capital, Copenhagen.

To get a better grasp of the role of the analysed countries in the European biotechnology industry, Figure 2 shows the share of each country in the European biotechnology industry based on its number of biotechnology patent applications for the first period of analysis (2005-2007) and the last period of analysis (2011-2013).

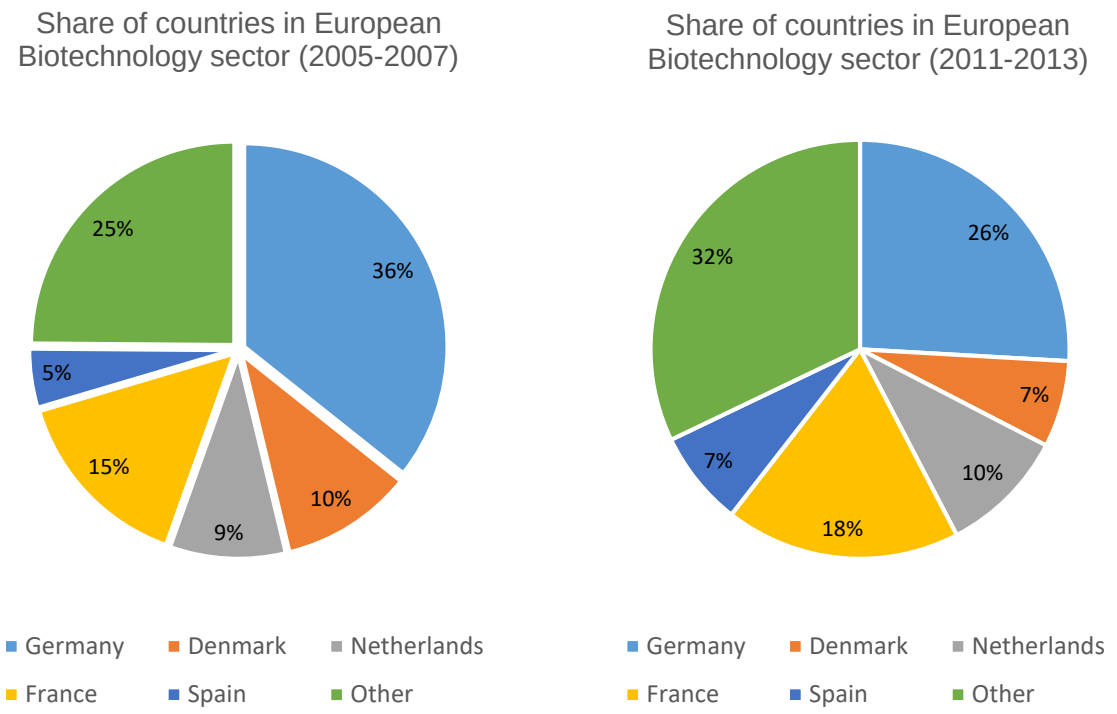

Figure 2: Overview of the share of countries in the European biotechnology sector between 2005-2007 and 2011-2013. The share is based on the number of patent applications in the biotechnology sector.

The pie charts confirm the dominant role of Germany in the European biotechnology sector. In the period from 2005 to 2007, more than one-third of all biotechnology patent applications came from German inventors. Next to that, the figure shows that with 10% and 9% respectively, the shares of Denmark and the Netherlands are relatively equal in the European

biotechnology industry. Lastly, the charts show that France has a large share in terms of patent applications, which is even higher than the Dutch and Danish share.

Moreover, the charts show that the share of Germany considerably decreased from 36% (2,930 patent applications) in 2005-2007 to 26% (2,134 patent applications) in 2011-2013. A similar pattern can be observed for Denmark, whose share decreased from 10% in 2005-2007 to 7% in 2011-2013. In contrast, the share of the Netherlands marginally increased from 9% in the first time period to 10% in the last one. More interestingly, the share of 'other' countries showed a considerable increase from 21% (1,689 patent applications) to 28% (2,309 patent applications). These results give an indication that the biotechnology sector has been expanding to countries that did not have a significant role in the first time period. These results are supported by a research of Dettenhofer et al. (2019) which showed that especially in Central and Eastern European countries like Poland, Czech Republic and Hungary the biotechnology has witnessed a considerable growth during the last decade. This is also supported by the data used for this research, as the number of patent applications increased from 126 to 487 for Poland between the first and last time period, whereas for the Czech Republic the applications increased from 37 to 120.

In this research not the entire European biotechnology industry could be studied due to the node limit of RSiena, and therefore the specific patent subclass C07K was studied. Table X provides some relevant descriptive statistics about the longitudinal network data of the C07K patent class.

Table 3: Overview of descriptive statistics of Germany, the Netherlands and Denmark for the C07K patent class

	Time period	**Number of inventors (nodes)**	**Number of co-developed patents (ties)**	**Average Degree**	**Network Density**
Germany	2005-2007	368	390	2,204	0,006
	2007-2009	380	517	2,389	0,007
	2009-2011	397	642	2,919	0,008
	2011-2013	445	782	3,200	0,008
Netherlands	2005-2007	80	81	1,512	0,026
	2007-2009	84	95	1,796	0,020
	2009-2011	132	243	2,561	0,028
	2011-2013	145	268	3,524	0,026
Denmark	2005-2007	123	130	2,114	0,017
	2007-2009	132	132	1,985	0,015
	2009-2011	153	188	2,092	0,016
	2011-2013	133	199	2,910	0,023

The number of inventors and co-developed patents shows that the shares of the countries in the C07K subclass are in line with the shares in the whole biotechnology sector, with the shares of Denmark and the Netherlands being roughly one-third and one-fourth of Germany, respectively. In contrast to the analysis of the entire biotechnology sector, where a decrease in the number of patent applications was found for Germany and Denmark in the last time period (2011-2013), the number of patent applications in the C07K class only increased for Germany and Denmark. The average degree slightly increases over the years for all of the countries, indicating that inventors not only produced more patents but that they also collaborated with more different partners on average. For Denmark, a slight decrease in density was observed during the recession period (2007-2009), which indicates that inventors collaborated with less partners on average. The densities of the inventor networks, which is the ratio between the number of observed collaborations divided by the number of possible collaborations, are relatively stable over the years for all countries.

5 Results

The structure of the results chapter is as follows. First, the results of Germany will be shown after which the results will be put into context by discussing the innovation strategy that Germany deployed during the Great Recession. Secondly, the results of Germany will be compared to those of the Netherlands and Denmark, which will also be contextualized based on the innovation strategies of both countries. Lastly, the results will be synthesized to derive more general conclusions on the effect of the proximity dimensions on tie formation over the course of the Great Recession.

5.1 Germany

Analysis of network dynamics

The results of the parameter estimations by RSiena are shown in table 4. Convergence was excellent for all of the models (t < 0.1) (Ripley et al., 2011) and no problems with collinearity were detected based on the reports of RSiena.

In total, six parameters were estimated including the four dimensions of proximity, a Degree parameter to consider the 'benefits' or 'costs' of having an additional tie, and the Rate of change parameter to account for the speed at which the network changes (Ripley et al., 2011).

The *Rate of change* parameter indicates that the network remains dynamic during the recession period (2007-2009) and a high number of newly created ties is observed during that period, but considerably drops in the period thereafter (Table 4). A possible explanation for this drop might be that companies started to feel the impact of the recession from 2009 until 2011 which made them reluctant to form new ties. The effect of the Rate of change parameter is comparable to previous studies (e.g. Lazzeratti and Capone, 2016; Ter Wal, 2014) The *Degree* effect is negative, which indicates that, generally, inventors consider it 'costly' to increase their number of ties as is generally the case for social network analyses (Balland, 2012). An interesting finding is that the degree effect becomes significantly less negative during the recession period, indicating that it became less costly to form new ties during this period.

Next, the four forms of proximity that were included in the model will be discussed. The *Cognitive proximity* parameter is positive for all periods. While the parameter is insignificant in the first period, it becomes significant and positive during the recession period. This indicates that inventors are more likely to initiate collaborations with partners having similar cognitive profiles. These results are in line with previous studies, which also found significant and positive effects for the cognitive proximity parameter (e.g. Balland et al., 2013; Lazzeratti and Capone, 2016). The effect, however, remains stable during the recession period (Odds ratio (OR) = 1.17) and significantly decreases in the period thereafter (2009-2011; OR = 1.01). In the last period (2011-2013) the effect increases again up to pre-recession levels (Figure 3). The findings indicate that the Great Recession did not increase the tendency of inventors to form ties with cognitively similar partners in the German biotechnology sector. Thus, the hypothesis that inventors are more likely to collaborate with cognitively proximate partners (*H1a*) is confirmed, whereas the hypothesis that this tendency increases during the Great Recession is rejected (*H1b*).

For *Organizational proximity* a similar pattern can be observed. The organizational proximity parameter is positive and significant for all time periods, indicating that inventors are more likely to collaborate with others that are part of the same organization. This effect of organizational proximity was also found in previous studies for other industries (e.g. Balland, 2012, Balland et al., 2013, Lazzerrati and Capone, 2016). The odds ratio of organizational proximity significantly decreases from 3.06 to 1.30 during the Great Recession and remains stable afterwards (Fig. 3). Thus, it can be concluded that the Great Recession did significantly decrease the tendency of inventors to work with others who are part of the same organization, even though intra-firm collaborations are still preferred over inter-firm collaborations. Consequently, the hypothesis that inventors are more likely to collaborate with organizationally proximate partners (*H2a*) is confirmed, whereas the hypothesis that this tendency increases during the Great Recession needs to be rejected (*H2b*).

Table 4: Parameter estimates for Germany over the course of the Great Recession, standard errors in brackets

	2005 – 2007	2007 – 2009	2009 – 2011	2011 - 2013
Network change				
Number of inventors	368	380	397	445
Links created	162	271	208	276
Links dissolved	193	144	83	136
Links retained	228	246	434	506
Density	0.006	0.007	0.008	0.008
Parameter estimates				
Rate of change	4.360*** (0.538)	4.204*** (0.364)	1.784*** (0.151)	2.570*** (0.185)
Degree	-5.864*** (0.295)	-5.265*** (0.273)	-4.852*** (0.242)	-5.737*** (0.282)
Cognitive proximity	0.125 (0.085)	0.160** (0.065)	0.005** (0.002)	0.281*** (0.063)
Organizational proximity	1.125*** (0.112)	0.262*** (0.103)	0.283** (0.122)	0.403*** (0.098)
Geographical proximity	0.308*** (0.089)	0.579*** (0.073)	0.724*** (0.100)	-0.137* (0.073)
Social proximity	2.910*** (0.215)	3.072*** (0.184)	3.279*** (0.265)	3.189*** (0.181)
Model				
Convergence	0.071	0.095	0.055	0.092
Number of iterations	3253	2960	3178	3096

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*

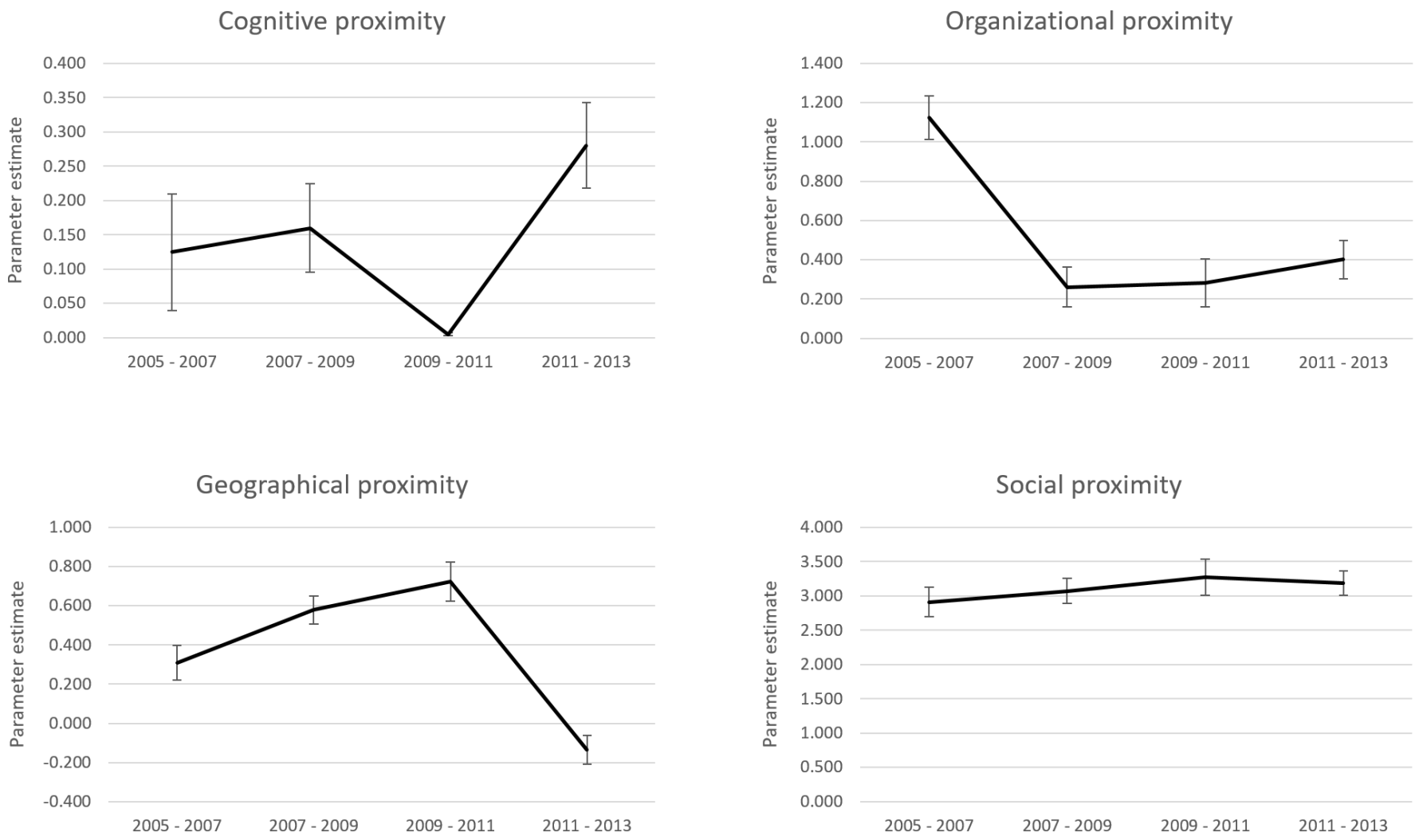

Figure 3: Overview of the effect of cognitive, organizational, geographical and social proximity on tie formation in the German biotechnology sector, over the course of the Great Recession.

The *Geographical proximity* parameter is positive and significant for the first three time periods, whereas it becomes negative in the last time one (Figure 3). It can thus be concluded that in general inventors are more likely to collaborate with geographically proximate partners. In contrast to the organisational and cognitive proximity dimensions, the effect of geographical proximity increases significantly during the Great Recession and the period thereafter (OR from 1.36 to 1.79 and 2.05, respectively), after which the effect decreases again in the last time period (OR = 0.87). Based on the findings for geographical proximity, it can be concluded that the Great Recession increases the tendency of inventors to collaborate with geographically proximate partners and hence, the hypothesis that inventors are more likely to collaborate with geographically proximate partners (*H3a*) is confirmed as well as the hypothesis that this tendency increases during the Great Recession (*H3b*).

Interestingly, these findings are contrary to those found by Ter Wal (2014) for the German biotechnology sector in the period between 1970 and 2000, in which slightly negative parameter estimates were found. A possible explanation for the positive effects of geographical proximity found in this research might be the 'Biocluster policy' implemented by the German federal government. In the year 2000, Germany implemented cluster policies for the biotechnology sector to create a strong localized knowledge cluster in this sector to stimulate innovation (Zechendorf, 2011). After the year 2010, the government decided to stop with these cluster policies which might explain why a positive and significant effect of geographical proximity was found in the first three time periods, but not in the last one (2011-2013) as the cluster policies were not in place anymore at that time (Zechendorf, 2020).

Lastly, the *Social proximity* parameter was positive and significant for all time periods, indicating that inventors are more likely to collaborate with socially proximate partners (friends of friends). This is in line with earlier findings of Ter Wal (2014), who showed that socially proximate partners are more likely to initiate a collaboration in the German biotechnology industry. The effect of social proximity is constant over all time periods, and it can thus be concluded that the Great Recession does not affect the tendency of inventors to collaborate with socially proximate partners. Therefore, the hypothesis that inventors are more likely to collaborate with socially proximate partners (*H4a*) is confirmed, but the hypothesis that this tendency increases during the recession is rejected (*H4b*).

Putting the results into context: Germany's innovation strategy during the Great Recession

Given the theoretical background and the formulated hypotheses of this study, the result that most proximity effects remain stable or decrease during the Great Recession in the German biotechnology sector might be counterintuitive. However, the unique innovation strategy of Germany that was established during the Great Recession might, at least partly, explain the results.

In contrast to most EU countries, Germany increased its R&D investment during the Great Recession. From 2007 to 2009 the government spending on R&D increased by 9% (OECD, 2012). The reasoning beyond this strategy was that Germany aimed to 'innovate its way out of the recession', creating extra value from every euro invested into R&D (Lichtenhaler, 2020). Additionally, Germany had the second largest investment in stimulus packages (0.8% of GDP), intended to simulate innovation, of all EU countries (Guellec and Wunsch-Vincent, 2009). As a result of increased government investments into R&D, firms also remained able

to increase their R&D investments. Across all sectors, business R&D expenditure increased by 3% from 2007 to 2009 in Germany, whereas an average decrease of 3,1% in business R&D expenditure was observed in the EU (OECD, 2012).

Clearly, Germany had a focus on stimulating innovation. Despite the large investments into R&D, the output in terms of patent applications did slightly decrease after the recession, in line with the general trend in Europe (OECD, 2012). For the biotechnology sector specifically, the patent applications decreased from approximately 850 in 2011 to 690 in 2015 (PwC, 2017). The decrease in German patent applications during the recession was also found in the data used for this research, as was discussed in Chapter 4. Nevertheless, the turnover of the German biotechnology sector did increase during the period after the recession (2011-2015) and especially the production value (determined based on production related sales) of the developed biotechnological products increased substantially (13%) (PwC, 2017). Thus, based on these numbers it can be argued that the Great Recession did not have a large impact on the German biotechnology sector.

The high investments by Germany might partly explain why the effects of most proximity dimensions decreased or remained stable during the recession in German biotechnology sector. The hypotheses that the effect of the different forms of proximity on tie formation between inventors would increase during times of recession were based on the reasoning that firms would become more risk averse and would try to cut costs during times of recession compared to non-crisis periods. In Germany, however, the budgets of firms may not have decreased as much as was theoretically assumed, since government investments into R&D remained high and even increased (9%) during the recession. As R&D budgets remained high, there was probably less incentive for these firms to engage with more proximate partners as costs didn't need to be reduced as much as assumed. This is also reflected in the R&D investments of businesses, which increased by 3% during the recession period (2007 – 2009). The only proximity dimension that increased was geographical proximity, which might partly be explained by the implementation of 'cluster policies' by the German government during the recession. These policies stimulated the development of localized knowledge clusters, which might have incentivised firms to collaborate more with geographically proximate partners.

In the next section the influence of the Great Recession on the effects of the different proximity dimensions in the Netherlands will be presented. Next to that, the differences between the innovation strategies of Germany and the Netherlands will be discussed in more detail.

5.2 The Netherlands

Analysis of network dynamics

For the Netherlands, the same parameters were included in the regression analysis (Table 5). All estimates are again based on 2000 simulation runs, convergence was excellent for all models (t < 0.1) (Ripley et al., 2011), and no problems with collinearity were detected based on the reports of RSiena.

In contrast to the estimations performed for Germany, the *Rate of change* parameter decreases for the Netherlands during the recession period (2007-2009), which indicates that the Dutch biotechnology network became less dynamic in the time of the crisis. This is supported by the fact that only 28 ties were created during that period, which denotes a decrease of 47% compared to the period before the recession. Another interesting result is that the *Degree* parameter becomes significantly more negative during the recession period and the period thereafter, in contrast to Germany where this parameter became less negative. This indicates that it became more costly to form new knowledge ties during this period in the Netherlands, whereas the costs of forming new ties decreased in Germany.

Next, the four proximity parameters will be discussed. Firstly, the *Cognitive proximity* parameter is positive and significant for all time periods. As expected, also in the Netherlands inventors are generally more likely to initiate collaborations with partners that have similar cognitive profiles (Figure 4). During the recession and the period thereafter, the effect of cognitive proximity significantly increased (OR from 1.60 to 3.16 and 2.77, respectively). Thus, Dutch inventors were more likely to choose a cognitively proximate partner during the recession and the period thereafter compared to pre-recession times. This is more in line with hypothesis (*H1b*) and contrary to Germany, where the tendency to choose a partner with a similar cognitive profile decreased during the recession.

Interestingly, the *Organizational proximity* parameter only becomes significant during the recession and the period thereafter, whilst it is insignificant during the first and last time period. The parameter is positive during the recession and the period thereafter, which shows that inventors were more likely to initiate intra-firm collaborations during these periods than inter-firm collaborations (Figure 4). During the first and last period the parameter was insignificant which indicates that inventors were as likely to initiate inter-firm as intra-firm collaborations. The pattern of organizational proximity is similar to the one of cognitive proximity, showing an increase during the recession and a significant increase during the trough period (OR from 1.34 to 1.60 and 2.77, respectively). Again, this is contrary to the results found for Germany as the effect of organizational proximity did decrease in Germany during the recession.

Thirdly, the *Geographical proximity* parameter is positive and significant for all time periods, except for the recession period where it is significant but negative (Figure 4). These results indicate that during the recession periods inventors preferred to initiate ties with actors they did not share a geographical proximity with, whereas in the other periods it was preferred to initiate ties with geographically proximate partners. The most striking difference between the effect of geographical proximity for Germany and the Netherlands is the strong increase that is observed for Germany during the recession (OR from 1.35 to 1.77) while the Netherlands shows a strong decrease in the effect of geographical proximity (OR from 1.63 to 0.47). A

possible explanation for the decrease of the effect of geographical proximity can be found in section 4.3.

Lastly, the *Social proximity* parameter is positive and significant for all time periods, thus inventors are more likely to initiate ties with socially proximate partners (friends of friends). The social proximity effect does show a significant increase during the period after the recession before it slowly decreases again in the last time period. Thus, in the period after the recession (2009-2011) inventors were significantly more likely to initiate collaboration with socially proximate partners, compared to other time periods.

Table 5: Parameter estimates for the Netherlands over the course of the Great Recession, standard errors in brackets

	2005 – 2007	2007 – 2009	2009 – 2011	2011 - 2013
Network change				
Number of inventors	80	84	132	145
Links created	52	28	162	47
Links dissolved	11	14	14	22
Links retained	29	67	81	221
Density	0.026	0.020	0.028	0.026
Parameter estimates				
Rate of change	3.193*** (0.677)	1.329*** (0.306)	2.977*** (0.272)	1.007*** (0.159)
Degree	-4.761*** (0.427)	-6.159*** (0.654)	-7.406*** (1.214)	-5.304*** (0.430)
Cognitive proximity	0.470*** (0.143)	1.152*** (0.218)	1.0166*** (0.270)	-0.029 (0.206)
Organizational proximity	0.293 (0.186)	0.468** (0.233)	1.023*** (0.361)	-0.224 (0.415)
Geographical proximity	0.490*** (0.171)	-0.7501*** (0.278)	1.284*** (0.442)	0.588*** (0.180)
Social proximity	3.606*** (0.582)	3.150*** (0.482)	6.309*** (1.224)	4.497*** (0.629)
Model				
Convergence	0.092	0.089	0.083	0.085
Number of iterations	2765	3298	3204	2946

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*

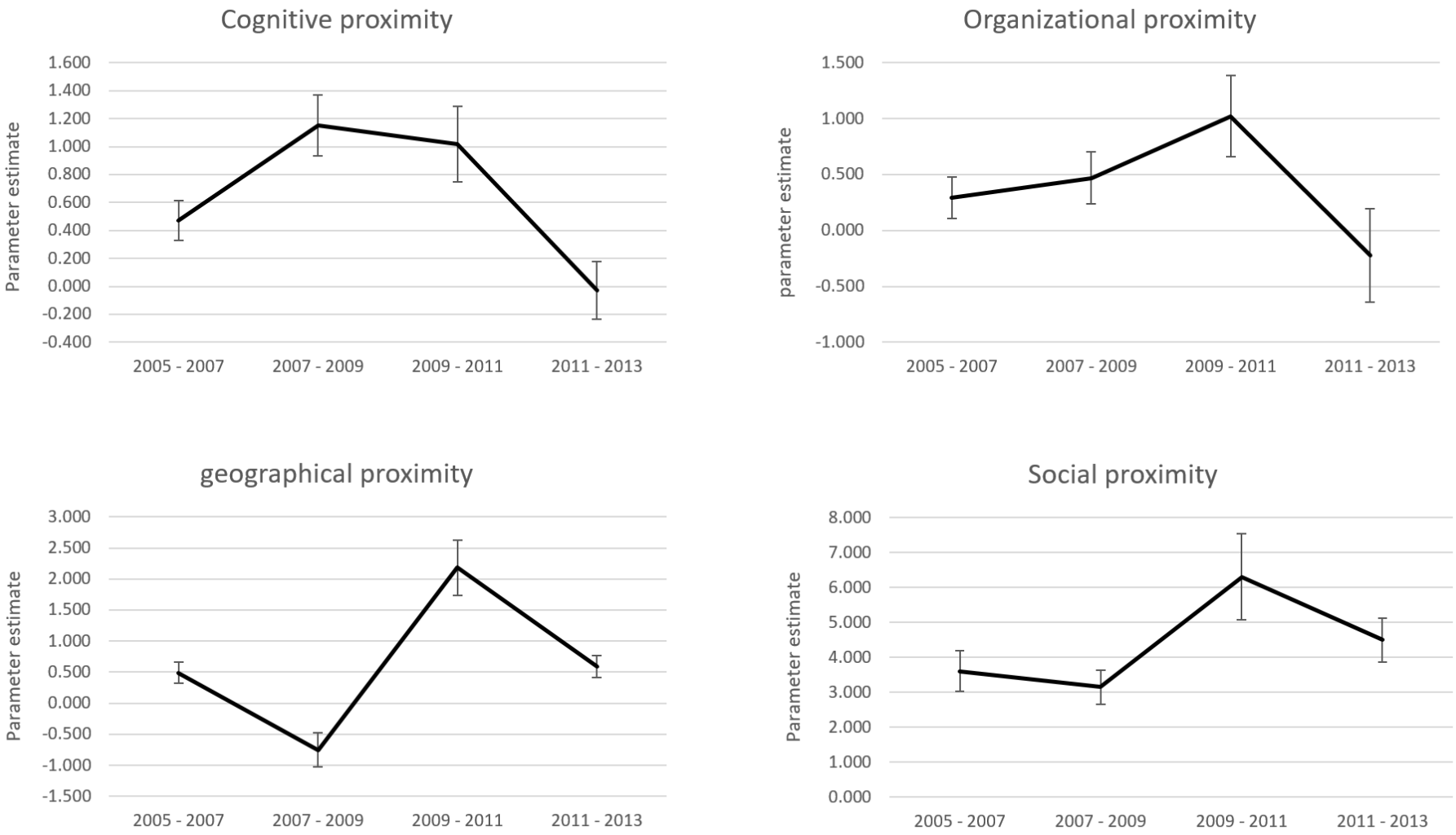

Figure 4: Overview of the effect of cognitive, organizational, geographical and social proximity on tie formation in the Dutch biotechnology sector, over the course of the Great Recession.

Putting the results into context: Dutch innovation strategy during the Great Recession

Overall, there are several variations in the effect of the proximity dimensions on tie formation over the course of the recession when comparing Germany and the Netherlands. A potential explanation for the observed differences is that the Netherlands had a totally different response to the recession. Instead of investing in innovation, like Germany, the strategy mainly aimed at reducing R&D costs. For instance, the governmental investments into R&D remained stable and, as one of the only EU countries, no investments were made into stimulus packages (Guellec and Wunsch-Vincent, 2009). Only after the recession (from 2009 onwards), the Netherlands started to invest in support schemes to stimulate innovation and address labour market related issues such as growing youth unemployment and the need for reintegration of workforce into the labour market (Guellec and Wunsch-Vincent, 2009). Thus, the response of the Netherlands to the recession was initially much more passive, and then re-active to limit the damage of the crisis, compared to the more pro-active strategy of Germany.

The impact of this ‘cost-cutting’ strategy is also reflected in the business R&D expenditure in the Netherlands, which decreased by 12% between 2007 and 2009, the strongest observed decrease in the entire EU (OECD, 2012). Despite the reduction in governmental and business R&D investments, the number of Dutch biotechnology firms doubled between 2011 and 2015 and so did the number of patent filings (PwC, 2017). Nevertheless, the turnover of the Dutch biotechnology sector did decrease substantially (12%) during the period after the recession and the production value of the developed biotechnological products decreased at a similar rate (15%) (PwC, 2017).

The strong reduction in business R&D gives an indication that Dutch knowledge-intensive firms were focused on reducing costs. The tendency of firms to reduce costs was the starting point to formulate the hypothesis of this thesis, which was that the effect of the different forms of proximity on tie formation between inventors would increase during times of recession. In the Netherlands, firm investments were actually reduced and an increase in the effect of most proximity dimensions could be observed during the recession. Therefore, the hypothesis that the effect of proximity (cognitive, organizational and social) on tie formation increases during times of recession can be confirmed, under the condition that costs actually need to be reduced by firms.

This section showed that the influence of the Great recession on the role of proximity in tie formation vastly differs between Germany and the Netherlands, which can at least partly be ascribed to their different innovation policies during and after the crisis period. A last comparison that is needed to further strengthen the findings, is between Germany and Denmark, which both deployed similar innovation policies during the recession.

5.3 Denmark

Analysis of network dynamics

The parameter estimates of Denmark are shown in Table 6. Convergence was excellent for all models (t < 0.1), and no problems with collinearity were detected based on the reports of RSiena (Ripley et al., 2011).

First of all, the *Rate of change* parameter significantly increased for Denmark during the recession period, which indicates that the network of Denmark remained dynamic during the recession. Interesting to note is that the rate of change parameter increases even further in the period after the recession, and substantially more ties were created compared to previous periods (Figure 5). For Germany the rate of change parameter remained stable, whereas for the Netherlands the rate of change parameter significantly decreased, indicating that the Dutch network became less dynamic. The *Degree* parameter becomes significantly less negative for Denmark during the Great Recession, indicating that it became less costly to form new ties during the recession compared to the period before. For Germany, the degree parameter remains stable, whereas for the Netherlands the degree parameter becomes significantly more negative. Hence, it becomes more costly to initiate new ties during the recession in the Netherlands compared to Germany and Denmark.

The effect of the different proximity dimension on tie formation in Denmark is similar to the pattern found for Germany. First of all, the *Organizational proximity* effect significantly decreases for both Denmark (OR from 2.94 to 1.68) and Germany, whereas it increases significantly for the Netherlands. Furthermore, both the *Cognitive proximity* and *Social proximity* effect remain stable over the recession for Denmark, similar to Germany (Figure 5). A difference between the effects for Germany and Denmark can be found in the *Geographical proximity* dimension. While the effect of geographical proximity on tie formation increases during the recession period for Germany, it decreases for Denmark and becomes significant and negative (OR from 1.15 to 0.42).

For the geographical proximity dimension, the pattern of Denmark is similar to the one observed for the Netherlands. In the previous section it was already explained that in Germany the increase in the effect of geographical proximity might be the result of the implemented cluster policies. The observed decrease in the effect of geographical proximity on tie formation in the Netherlands and Denmark might partly be explained by the size of the countries and the implemented policies. First of all, both Denmark and the Netherlands are considerably smaller than Germany, therefore less costs (e.g. travel costs) are associated with collaborating with partners in other NUTS regions. To diversify networks, working with geographically distant partners might be a cheaper alternative to working with cognitively or organizationally distant partners. Furthermore, the innovation policies of Denmark and the Netherlands were not focused on creating localized knowledge clusters, in contrast to the German regional biotechnology cluster policy that was still in place during the crisis period. The Danish policies actually focused on increasing the dissemination of knowledge both on the regional and the national level (Cornett, 2009). This implementation of such a policy can also partly explain why more inter-regional partner selection occurred.

Table 6: Parameter estimates for Denmark over the course of the Great Recession, standard errors in brackets

	2005 – 2007	2007 – 2009	2009 – 2011	2011 - 2013
Network change				
Number of inventors	123	132	153	133
Links created	22	54	112	35
Links dissolved	18	52	56	24
Links retained	108	78	76	164
Density	0.017	0.015	0.011	0.023
Parameter estimates				
Rate of change	0.645*** (0.113)	2.583*** (0.499)	6.153*** (1.185)	0.944*** (0.147)
Degree	-6.216*** (0.663)	-4.906*** (0.400)	-4.877*** (0.319)	-6.668*** (0.687)
Cognitive proximity	0.531*** (0.199)	0.275** (0.114)	0.480*** (0.103)	0.796*** (0.177)
Organizational proximity	1.077*** (0.312)	0.517*** (0.173)	0.171 (0.159)	0.654** (0.295)
Geographical proximity	0.148 (0.262)	-0.859*** (0.188)	-0.040 (0.149)	0.118 (0.217)
Social proximity	3.023*** (0.656)	3.174*** (0.346)	3.323*** (0.248)	3.357*** (0.493)
Model				
Convergence	0.060	0.080	0.077	0.075
Number of iterations	3295	3171	2909	3546

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*

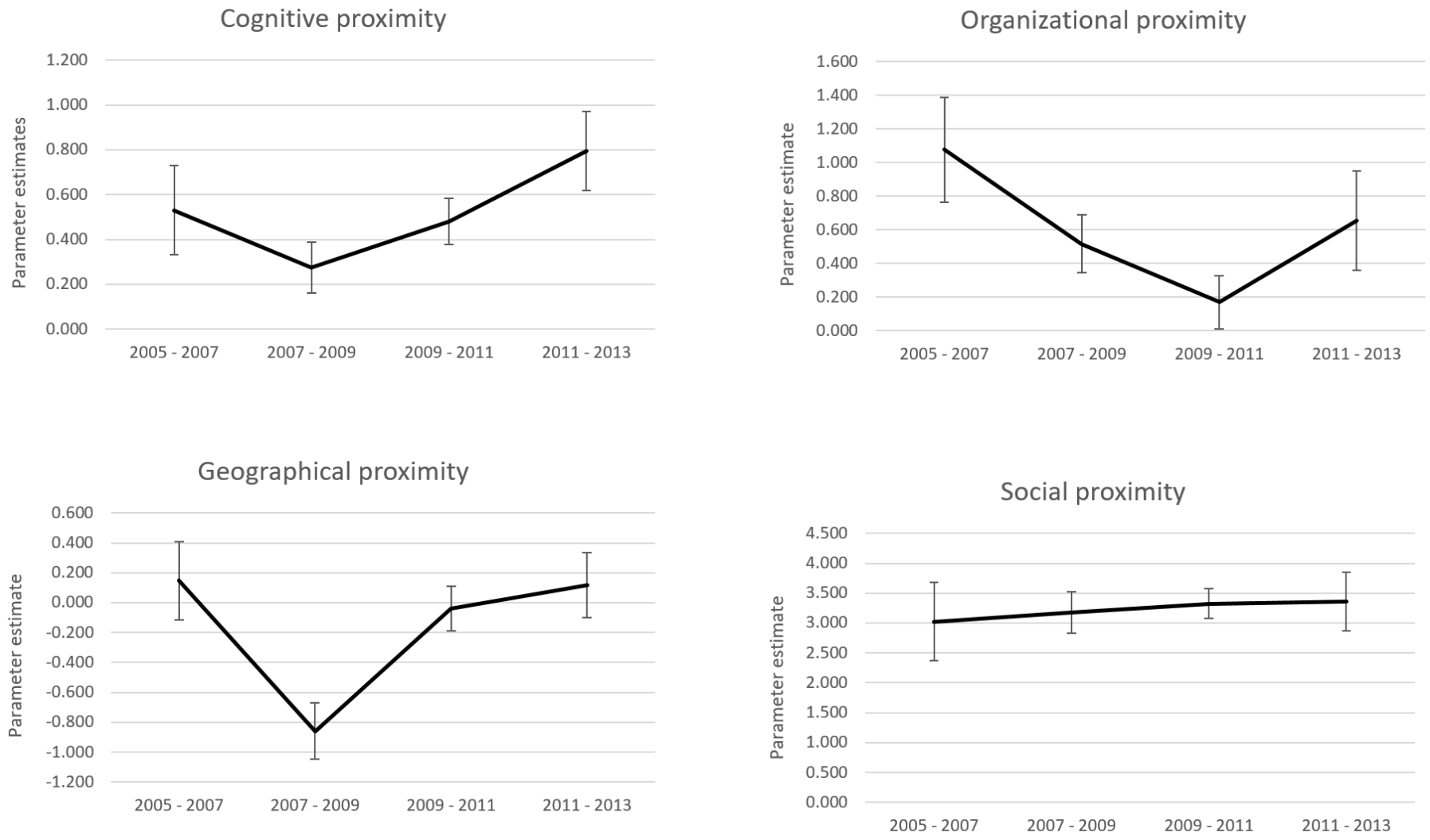

Figure 5: Overview of the effect of cognitive, organizational, geographical and social proximity on tie formation in the Danish biotechnology sector, over the course of the Great Recession.

Putting results into context: Denmark's' innovations strategy during the Great Recession

The effects of the proximity dimensions show similar patterns for Denmark and Germany over the course of the recession. As said, the Danish innovations strategy resembles the one of Germany in that it is based on investing into R&D instead of on cutting costs (OECD, 2012), which can partly explain the similarity in the results. The fiscal packages of Denmark were highly focused on investment and the governmental investment into R&D increased by as much as 16% between 2007 and 2009. Furthermore, Denmark was also one of the biggest investors into stimulus packages and invested 0.8% of its GDP (Guellec and Wunsch-Vincent, 2009). Due to the favourable business environment created by the Danish government, firms were probably willing to invest, which is reflected by an 8% increase in business R&D across all sectors, one of the highest observed increases in Europe (OECD, 2012).

Despite the high investment into R&D by both government and firms, the number of biotechnology firms and the number of patent applications remained stable in Denmark in the period directly after the recession (2009 – 2011). However, the production value of the produced patents increased by an astonishing 50% during the period after the recession (2011 – 2015) (PwC, 2017). Previous research has indicated that the value of patents is highly related to their novelty (e.g. He and Luo, 2017; Reitzig, 2003), and thus it seems that after the recession period more novel patents have been developed in Denmark than before the recession. Possible explanations for the increase in the novelty of Danish patents after the recession will be discussed in the next section (see 4.4).

Thus, as Denmark's governmental investment into R&D increased there was probably also less incentive for Danish biotechnology companies to reduce collaboration costs for innovation (e.g. travelling costs, costs of unintentional knowledge spill overs). The fact that business R&D investment actually increased during the recession supports this assumption. This pattern is similar to the one observed for Germany. In turn, this again can explain why the effect of most proximity dimensions decreased or remained stable during the Great Recession, as the hypothesis that the effect of the different proximity dimensions would increase was based on the assumption that firms would want to reduce costs.

5.4 Synthesis of results Germany, the Netherlands and Denmark

By combining the results of Germany, the Netherlands and Denmark, and the report of PwC (2017) on the performance of the European biotechnology industry after the Great Recession, some interesting patterns can be identified:

First of all, the Dutch government decreased its investments into R&D and so did Dutch firms. In turn, the effect of the cognitive and organizational proximity dimensions on tie formation significantly increased in the Netherlands during the recession period and the period thereafter. In contrast, the German and Danish government increased their investments into R&D and so did firms within these countries. Interestingly, the effect of organizational proximity significantly decreased and the effect of cognitive proximity on tie formation remained stable during the recession and the period thereafter for Germany and Denmark. Thus, in countries (Germany and Denmark) where governmental R&D budgets increased, firms and their inventors did not collaborate with more proximate partners during the recession, and in some cases even more distant partners were selected. In contrast, this research shows that in a country where governmental R&D budgets decrease, like the Netherlands, firms are more likely to engage with partners that are organizationally or cognitively proximate. The fact that both governmental and business R&D investments decreased in the Netherlands makes it plausible that more proximate partners were chosen in the innovation process due to cost reduction strategies by firms. For instance, collaborating within the same organization can avoid the costs of unintentional knowledge spill overs and collaborating with partners that have a similar knowledge base reduces the time and costs of knowledge exchange (Boschma, 2005). Together, these results seem to confirm the hypothesis that firms will engage with more proximate partners when costs need to be reduced, in this case as a result of the Great Recession.

Another interesting observation is that in the Netherlands, where the effect of the organizational and cognitive proximity dimensions increased, more patents were filed in the period after the recession (PwC, 2017). In contrast, the number of patent applications in Germany and Denmark, where more distant partners were chosen, decreased. The data used for this research show a similar pattern in the number of patent applications as measured by PwC. These findings seem to support the theoretical concept that proximity eases the collaboration between partners in innovation, resulting in a higher number of patent applications (Balland, 2012; Cohen and Levinthal, 1990).

More interesting is the fact that the number of patent applications increased in the Netherlands, but that the production value of these patents decreased (PwC, 2017). This observation is especially relevant in the light of the observed increase in the effect of cognitive proximity on partner selection during the recession and the period thereafter. In the theory section the concept of the ‘optimal cognitive proximity’ has been discussed (Nootenboom et al., 2007), and accordingly the concept of the ‘proximity paradox’ by Boschma and Frenken (2009). Based on the results of this research, the effect of cognitive proximity on tie formation increased and it seems that for the Netherlands the optimal level of cognitive proximity has been exceeded and partners were too cognitively proximate. In line with the ‘proximity paradox’, cognitive proximity eases the collaboration between inventors in innovation as similarity in knowledge bases is needed for efficient communication and knowledge transfer. For the Netherlands this is reflected by the increase in the number of patents. However, too

much cognitive proximity might be suboptimal for firm performance, as reflected by the decrease in production value of the developed patent in the Netherlands. In turn, the value of patents is often associated with their novelty (e.g. He and Luo, 2017; Reitzig, 2003) and hence, a reduction in the novelty of Dutch patents might explain why they became less valuable. This reasoning is in line with the 'optimal cognitive proximity' concept of Nootenboom et al. (2007), as the scope of learning becomes limited when knowledge bases become too similar.

In Germany and Denmark, however, less cognitively proximate partners were selected during the recession. As a result, it might be that collaborations became more challenging and time consuming, reflected by the decrease in the number of patent applications. However, the complexity and novelty of these patents most likely increased, reflected by the observed increase in production value of the inventions. The observed increase in the value of German and Danish patents might be explained by the fact that cognitively distant partners were chosen, which increases the scope of learning and makes the recombination and reconfiguration of knowledge possible, which is essential for radical innovation (Fleming, 2001; Schilling and Phelps, 2007). Together, these results support the assumption that the proximity paradox is a real threat for firms when the collaboration costs of innovation need to be reduced (for cognitive proximity mainly the time and costs of knowledge transfer), in this case due to the Great Recession.

6 Summary and Conclusion

In this research the following research questions were answered: (i) which proximity dimensions drive the formation of network ties in the European biotechnology industry? And (ii) did the effects of these driving forces change during the Great Recession?

The consensus in literature has been that inventors are more likely to collaborate with partners that are proximate in at least several dimensions as this reduces costs and uncertainty of collaborations for innovation, which has been supported by previous studies using dynamic network models (RSiena). Hence, the hypothesis was that the positive relationship between proximity and chances of tie formation will generally also hold for inventors in the European biotechnology industry. At the same time, it was assumed that the effect of the different proximity dimensions on tie formation is not as stable and static as assumed in previous studies. Rather, it was expected that especially in times of economic recession, the effect of proximity will further increase as firms might try to minimize their costs and avoid uncertainty even more during times of economic recession than in normal times. Hence, the study used the case of the Great Recession to test the hypothesis of crisis-specific proximity effects.

With the use of the stochastic actor-oriented model (SAOM) RSiena, the effect of the different proximity dimensions on tie formation in the German, Danish and Dutch biotechnology industry was studied in a dynamic manner. RSiena is currently the most developed model for dynamic social network analysis (Snijders et al., 2010). In contrast to static social network analysis models, RSiena can study the drivers of network dynamics over time, instead of on a 'snapshot' of a network. Thereby, it can be studied how the drivers of network dynamics, in this case the proximity dimension, change over time. For this study, four different time periods were defined (2005-2007, 2007-2009, 2009-2011, 2011-2013) which allowed to study the effect of the different proximity on tie formation over the business cycle of the Great Recession: the peak period (2005-2007), the recession period (2007-2009), the through phase (2009-2011) and the growth phase (2011-2013). Patent data was used to construct inventors networks, in which nodes represent inventors which are connected by mutually developed patents. Inventor networks were used as they form the most detailed and pure level of collaboration data, and thereby closely represent inter-firm collaboration in innovation.

The effect was first studied for Germany, one of the leading countries in the European biotechnology sector. In line with the hypothesis, the results indicated for all proximity dimensions that inventors are in general significantly more likely to initiate collaborations for innovation with proximate partners. Interestingly, and contrary to the hypothesis, the effect of proximity on tie formation significantly decreased for cognitive and organizational proximity, remained stable for social proximity and only significantly increased for geographical proximity during the recession. For Denmark, a similar pattern was found as the effect of organizational proximity decreased and the effect of cognitive and social proximity remained stable. Contrary to Germany, the effect of geographical proximity decreased in Denmark. For the Netherlands, different patterns were found as an increase in the effect of cognitive and organizational proximity was found during the recession, which is more in line with the hypothesis.

Even though counterintuitive at first, this thesis shows that the innovation strategy Germany and Denmark deployed during the recession might at least partly explain the observed results. In contrast to other European countries, Germany and Denmark actually increased governmental investments into R&D. As a result of this innovation stimulating policy, firms might have been less inclined to reduce costs of collaborating in innovation (e.g. knowledge transfer costs) as was assumed when formulating the hypotheses. This assumption is supported by the fact that in both countries business R&D expenses increased during the recession. The response of the Dutch government to the recession was totally different, as R&D expenses were reduced and no additional policy schemes were developed to stimulate innovation. As R&D budgets reduced, firms might have become more costs (e.g. knowledge transfer costs) and risk averse (e.g. risk of unintentional knowledge spill over) during the recession, in line with the hypothesis. The reduced business R&D investments by Dutch firms might provide some initial evidence for cost avoidance by Dutch firms in an innovation context.

Thus, taking inventor networks in the German, Dutch and Danish biotechnology industry as an example, this research has shown that inventors are indeed more likely to initiate collaborations for innovation with actors they share a proximity with. If no specific innovation schemes or policies are in place that support firms in crisis periods, the effect of the different proximity dimensions does increase, as was demonstrated for the Netherlands. However, this does not necessarily have to be the case. If governments deploy an adequate innovation strategy during crises, based on investing into R&D instead of reducing R&D budgets, more distant partners will be chosen in the innovation process, as was demonstrated for Germany and Denmark.

The proximity of innovation partners does also have substantial implications for the innovative performance of firms. According to the proximity paradox, choosing proximate partners might ease collaboration and reduce costs of the innovation process, but too much proximity can also harm firm performance (Boschma and Frenken, 2009). For the cognitive proximity dimensions this trade-off is captured in the concept of ‘optimal cognitive proximity’ in which a certain level of proximity is needed to facilitate efficient communication and knowledge transfer, but too much proximity can limit the scope of learning and harm the innovative performance of firms (Nootenboom et al., 2007). This research seems to find some initial indications for the existence of a proximity paradox in the Netherlands. The results of this study show that in the Netherlands more cognitively proximate partners were chosen, and that the number of biotechnology patent applications increased after the recession, which might indicate that collaborations in innovation became easier. However, according to a report of PwC (2017) the value of the produced patents considerably decreased after the recession, which might indicate that knowledge bases of innovation partners became too similar and hence, the produced patent became less innovative and thereby less valuable. In Germany and Denmark, where governmental R&D investments increased, no indications for a possible proximity paradox were found as the value of produced patents only increased after the recession.

These findings indicate that the proximity paradox might be a real threat to knowledge-based industries and that investments into R&D are needed during recessions to prevent knowledge networks from becoming too closed and proximate, which might harm innovativeness. Thereby this research supports the idea that, instead of cutting costs, governments and firms should invest into R&D to innovate their way out of a recession.

7 Discussion

7.1 Theoretical and managerial implications

Until recently, little research has been performed on how innovation networks are initiated and how they develop over time. Recent studies identified several forms of proximity as important drivers of innovation network dynamics, but results were often contradicting and focused mainly on the effect of proximity on network dynamics throughout the lifecycle of an industry. This study added additional empirical evidence to the debate about the role of different proximity dimensions, but with a specific focus on the role of proximity on network dynamics during times of economic recession, which is a novel contribution to the research field.

This research showed that inventors are in general significantly more likely to initiate ties with proximate partners for all proximity dimensions, which supports earlier findings of studies that applied RSiena in an innovation context. For instance, the studies of Balland et al. (2013), Lazzeratti and Capone (2016), Ter Wal (2014) and Teng et al. (2021) that were already discussed in the theory section (Table 1).

Furthermore, this research showed that the effect of most proximity dimensions decrease during the recession for Germany and Denmark, where innovation strategies were based on investing in R&D and that the effect of most proximity dimensions increased in the Netherlands, where governmental R&D budgets reduced during the recession. Interestingly, the number of produced patents decreased but the value of these patents increased in Germany and Denmark after the recession, according to a study of PwC (2017). The same study showed that the number of patents increased in the Netherlands after the recession, but that the value of the developed patents decreased. Thus, in the Netherlands more proximate partners were chosen in innovation, which resulted in an increase in the number of patents but a decrease in their value. Accordingly, it was argued that there might be a proximity paradox at play in the Netherlands.

These results have strong policy implications as it shows that the innovation strategy deployed during the recession also has a large impact on the performance of the industry in the period thereafter. Germany and Denmark were able to ‘innovate their way out of the recession’, whereas the Netherlands still experienced the negative impact of the recession in the period from 2013 to 2015, which is visualized in Figure 6. Figure 6 shows that in the period between 2013 and 2015, the number of firms and the turnover of the (pharmaceutical) biotechnology sector substantially increased in Denmark, which makes it one of the best performing countries in Europe within this sector (PwC, 2017). The German (pharmaceutical) biotechnology sector is relatively stable in terms of the number of firms and turnover in this period. In contrast, the turnover decreased in the Netherlands, despite the increase in the number of firms (PwC, 2017). Figure 6, combined with the information about the R&D investment of the analysed countries, shows that investing into R&D is crucial for the performance of firms in knowledge-based sector during the recession period (2009 – 2011) and for the growth period thereafter, and thus for the resilience of the industry (2011-2015).

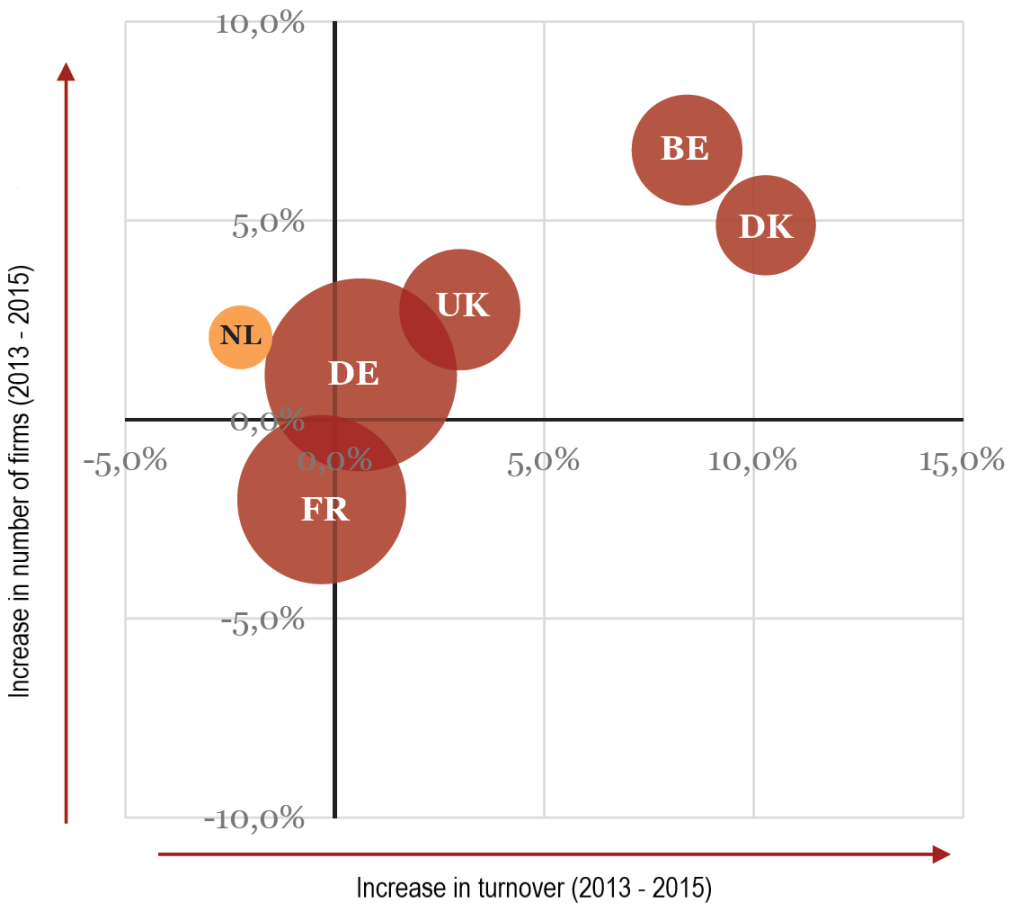

Figure 6: Performance of biotechnology industry of several European countries after the Great Recession (PwC, 2017). Size of dots denote the share of countries in the European pharmaceutical biotechnology sector in terms of turnover.

Furthermore, the effects of the German and Danish innovation strategy were not limited to the performance of knowledge-based firms only, it also had a positive impact on the overall performance of the labour market. For instance, Germany was the only EU country where unemployment actually decreased (3%) during the recession. In contrast, the performance of the Dutch labour market was considerably less optimal as unemployment increased by roughly 3% between 2007 and 2011, comparable to the EU average of 3.5% (Stand et al., 2012). Employment in high-technology sectors specifically decreased by roughly 2% (Eurostat, 2021).

The results of this research are especially relevant in the light of the current Covid-19 pandemic and the strong economic impact of this crisis. Policy makers should learn from the innovation strategy deployed by countries like Germany and Denmark during the Great Recession, which were based on more active and targeted interventions in R&D and innovation to prevent strong cuts in business R&D expenses. It seems that the increased governmental R&D investment led to the selection of more distant partners, which in turn seems to explain the substantial increase in the value of the developed patents. The positive effect of the investment-based innovation strategy was not limited to the recession period itself, since the strategy also had a strong positive impact on the performance of the biotechnology industry after the recession, indicating that an investment-based strategy also improves the resilience of knowledge-based sectors during times of crisis. This is in line with

the results of a recent study, which demonstrated that regions that could be identified as ‘innovation leaders’ during times of the Great Recession, were more likely to resist the crisis or recover more quickly (within three years) (Bristow and Healy, 2018). Furthermore, the effect of an investment-based innovation strategy is not only limited to the performance of the biotechnology industry itself, but also has a positive impact on the performance of the labour market.

Altogether, the research shows that investing into R&D during times of economic recession is crucial for firm performance and the resilience of knowledge-based networks during the recession period and the growth period thereafter. Although it might sound counterintuitive to many, investing seems to be the best way to get out of an economic recession. These results support the school of thought of Keynesian economists, who argue that governments should invest during times of recession to moderate the impact of recessions on economic activity (Keynes, 2018). Furthermore, the results support the growing perception that governments should play a more pro-active role in innovation and become investors themselves, instead of relying solely on entrepreneurship of the public (Mazzucato, 2011).

7.2 Limitations and directions for future research

The research suffers from several limitations, which in turn also open up direction for future research. First of all, there were some limitations regarding the measurement of the independent variables. For instance, the institutional proximity parameter could not be included as close to 99% of the organizations in the database were firms and governmental organizations or universities were barely present. In future research it can be interesting to analyse the effect of institutional proximity on tie formation during times of economic recession in sectors where the role of universities and governmental organizations is more prevalent. For the geographical proximity parameter a classification based on the NUTS-IDs was used as data on the addresses of inventors was not included in the database received from the RISIS project. Ideally, the geographical distance between inventors should be measured based on the distance in kilometres between two inventors (Katz, 1994), as inventors can live in cities next to each other, which are in different NUTS regions. In future research it can be studied whether measuring geographical proximity in kilometres yields similar results as the measurement based on the NUTS classification.

One of the main limitations of this research is the node limit (1000 nodes) of the networks that can be analysed with RSiena (Ripley et al., 2011). As a result of the node limit, a specific patent class within a specific country needed to be analysed. Consequently, the generalizability of the research is rather low. To make sure the results were not specific to the analysed patent class (C07K), models were rerun for a different patent class (C12N) as described in the methodology (see 3.4). If in the future the node limit increases, it would be interesting to analyse the national biotechnology sectors as a whole (instead of focusing on a specific patent class) to verify the results and see if similar patterns can be observed.

Furthermore, this research was limited to three countries. Whereas these countries already provide valuable insight into the effect of different proximity on network dynamics, especially regarding their different innovation strategies, it might be interesting to extend the scope of the analysis in future research. For instance, due to time constraints it was not possible to include another country that performed an innovation strategy based on reducing R&D

expenses (e.g. United Kingdom, (OECD, 2012). In future research such a country can be analysed to either verify or falsify the results found for the Netherlands. Furthermore, the current research has been focused on countries with a well-developed biotechnology industry. It might be interesting to see how the Great Recession influenced the effect of different proximity dimensions in countries with an emerging biotechnology industry (e.g. Spain and Italy), and which policy measures are needed under these conditions.

Despite these limitations, this thesis provided novel insights into the dynamics of knowledge network dynamics in general as well as during times of economic recession specifically. Getting a better understanding of knowledge network dynamics during times of recession is important as these knowledge networks are highly related to the performance of knowledge-based industries. Thus, understanding which drivers negatively impacted knowledge networks during past recession makes it possible to develop a more pro-active strategy for knowledge network maintenance in future recessions. According to the results of this thesis, these strategies should be focused on increasing R&D budgets, so firms, and countries alike, are able to innovate their way out of a recession.

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