

Dynamic determinants of innovation networks along the technology life cycle: Context, proximity and collaboration

By

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A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

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Melbourne, Australia

2018

Word count: 74,845 (including references)

ABSTRACT

Much is known about the effect of networks on innovation outcomes, but little is known about how networks emerge in the first place, which is troubling because economic prosperity increasingly depends on the ability to innovate. Governments and multi-national companies seek to advance new technologies, but the few empirical studies on network change along the technology or industry life cycle report conflicting findings. This dissertation explores the evolution of collaboration networks amongst inventors in the context of an emerging technology in Chemistry, namely Controlled Radical Polymerisation (CRP), and it investigates to what extent local institutions play a role for the drivers of network dynamics.

Using Stochastic Actor-Oriented Models for Social Network Analysis, this dissertation implements a longitudinal analysis of collaboration networks along the technology life cycle in six locations. The central argument of this thesis proceeds in 3 steps: (1) Institutional context is embodied by place-dependent characteristics on the micro, meso and macro level, and it manifests in the social practice of the local population; (2) Institutional context differs across places because of distinct features of policy, organisational behaviour and other constraints for social interaction, such as geography; and (3) Differences in institutional context help explaining diverging network dynamics along the technology life cycle across locations, even within the same technology.

This dissertation makes several distinct contributions to knowledge. It contributes to the literature on technological change by unpacking the so-called double-boom technology life cycle from a social network perspective, by testing this life-cycle model in geographies other than Europe, and by showing space-dependent deviations from the original concept. This dissertation contributes to the literature on network dynamics by empirically showing that network evolution relates to place-dependent factors on the micro, meso and macro level, and that the drivers of network change may exhibit a non-linear effect over time. The literature on Evolutionary Economic Geography is extended by demonstrating that the conflict between Ter Wal (2013b) and Balland, De Vaan and Boschma (2013) may relate to

the location of the study, by offering the first empirical evidence of a case where distant collaborators are preferred over locals, and by revealing that organisational proximity has a strong and stable effect over time, which differs from prior research (Cassi & Plunket 2015).

The new insights translate into implications for practitioners. For example, policy makers should consider the volatile nature of the double-boom cycle when contemplating withdrawal of support for a declining technology, because this might just be the end of the first peak that eventually leads to a second and potentially greater increase in technological activities. This study points to several opportunities for policy makers to foster collaboration, for instance, as relationship broker, project coordinator, and investor. Government should try to work towards a legal framework that caters to the needs of both academic and industrial inventors, and their collaborators.

ACKNOWLEDGEMENTS

I am indebted to Swinburne University of Technology (SUT) and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) for funding my PhD candidature.

I appreciated the constructive feedback on my research from key authors in this field of inquiry, in particular Elisa Giuliani, Elisabeth Mueller, Pierre-Alexandre Balland, Tom Broekel, Francesco Lissoni, and Johan Koskinen.

Thanks to the Faculty of Business and Law and the Centre for Transformative Innovation for fostering an open, collegial, and inspiring research culture. Special thanks go to Beth Webster and T'Mir Julius for supporting my data collection from the local PATSTAT patent database. Thank you, Rachel Mosel, Andrew Rixon, Karissa Carlton, John Hopkins, Russel Thomson, Alexander Kaiser, Tom Spurling, and the Higher Degree Research Committee, for being such great people to work with.

Thanks to the Melnet team for making me one of you! I am proud to be part of an internationally renowned group of social network scholars. My research undoubtedly benefited from the countless discussions we had. Thank you, Dean Lusher and Peng Wang for your outstanding leadership, Julien Brailly for helping me with R, and Julia Brennecke for your guidance on conceptual and practical issues. Ta to Vikki Bunton and Barbara Cosson for teaching me Aussie slang, and to Garry Robins and Collin Gallagher for your sharp assessment of my many questions.

My PhD-peers Bopha Roden, Vinu Nagar, and Daniel Ryan, made the journey so much better. Thank you for the walks in the park, lunch at the fountain, and the Won-Ton soups. Chiara De Lazzari, Sarah King, Zihan Liu, Kelly Costa, Andrew Terhorst, Stephanie Cadeddu, John Ingham, Bronwyn Eager, Clare Johansson, and the entire PhD club crew, I am glad I met you and I do hope that we stay in touch.

To my supervisors, Michael Gilding, Dean Lusher, Noordin Shehabuddeen, and Greg Simpson, thank you so much for your trust, guidance, wisdom, empathy, patience, and encouragement! You gave me space to explore and support when needed.

Thanks for nurturing my academic identity and for introducing me to the academic community. Your confidence in me helped me trust myself in this all so new environment. I like to think of you in the German term of PhD supervisor, Doktorvater (literally: doctor father), since you not only looked after me in professional terms, but your goodwill and generosity opened up opportunities which made the time for me and my family in Australia way more liveable and carefree. Thank you very much!

Coming to Australia as an international student puts family in a special place. My family in Germany gave me the necessary roots and wings to embark on this journey. All the overseas parcels including Christmas cookies and the bread baking machine (thanks mum) made us feel closer. The miracle was that we, my wife, our son and I, became part of a new family in Melbourne, the family of our very good friends Adele and Anthony. You gave us a sense of belonging and made us feel Australian. After countless BBQs, footy matches, and nature excursions, it is because of you that Australia is not just another place for us, but our second home.

I am lacking the words to thank my wonderful wife. Susi, in 2013 we moved to Australia as a couple and left four years later as a family, married, with the second baby on the way. You encouraged me in times of hardship and we celebrated the small victories. You tolerate the extra hours of PhD work on weekends and evenings, and you take care of so many things so I don't have to. You, Max and Ben give me purpose. Thank you so much for being on my side! I love you.

For Susi, Max and Ben

DECLARATION

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Till Sebastian Klein

February 2018

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PROLOGUE

The Queen of the United Kingdom does not like flies. Most other people do not like flies, but most other people do not have personal aides who try to keep the flies away, which became a particular challenge in 1963, when the Queen visited Australia. Australia has beautiful golf courses, and the Queen enjoys playing golf, but Australia is also home to a native type of bush fly, which is particularly intrusive and annoying because this insect is not interested in blood, but prefers sweat, tears and other salty fluids (Weule 2017). Consequently, it relentlessly targets the few places that bear such fluids in the sunburnt Australian outdoors, namely the eyes, nostrils, and the mouths of innocent patrons, including the Queen. Australian bush flies annoy millions of Australians every year.

To ensure a hassle-free trip for the Queen, the Australian hosts ordered the sharpest minds from the country's most reputable research organisation, the Commonwealth Scientific and Industrial Research Organisation, in short CSIRO, to develop a solution that should keep the nasty flies away from the Queen. They succeeded. The CSIRO created an insect repellent that kept the flies away and the accompanying journalist were astonished by the unheard-of effect of this innovative spray. Soon, the footage and reports of a relaxed Queen golfing in Australia fuelled the demand of ordinary people to get their hands on this product. The local company Mortein asked the CSIRO for the chemical composition and the CSIRO provided the recipe at no cost, as it was policy at the time, and Mortein successfully commercialised the spray. Legend has it that the CSIRO received two retail boxes in return.

Society benefited from this publicly funded discovery, but the financial returns went to Mortein, which illustrates a key challenge regarding the commercialisation of publicly funded research. Governments in Australia and around the globe invest taxpayers' money into public research organisations (PROs) with the expectation that such investments translate into returns in the future in the form of societal and economic benefits. In reality, the anticipated benefits do not always materialise to their full potential and discoveries are often commercialised overseas to the benefit of others (Australian Government 2009; Thompson et al. 2011). The OECD (2013a) reports

stagnation, and sometimes decline, in traditional measures on the commercialisation of public research, such as university patenting, university spin-offs, and licensing. All such approaches aim to foster knowledge flow from academia to industry, but since the outcomes are not satisfactory, policy makers search for alternative approaches.

While this is a global challenge, the adoption and commercialisation of public research has a local spin because of the local nature of research infrastructure, innovation policy, and the industrial landscape. For instance, Australia has a strong profile in research and higher education, but there is a lack of multinational companies with headquarters in Australia as well as limited ties to global supply chains. Other places such as Europe, China, Japan or the USA, have different, yet distinct characteristics concerning funding policies for public research, innovation policies, or incumbent industry. This implies that the knowledge flows between PROs and industry may vary across places.

Knowledge flow is the crucial aspect here, since this is what needs to occur before publicly funded discoveries have an impact on the marketplace. A wealth of scientific literature shows that networks of interaction have an effect of knowledge exchange and economic outcomes (Glückler 2013; Granovetter 2005). While many studies focus on networks amongst organisations, it is *people* who interact and exchange knowledge. Networks are particularly important for the exchange of tacit knowledge, as opposed to codified knowledge (Balconi 2002; Gertler 2003), because the exchange of tacit knowledge requires face-to-face interaction. This is also true for new technologies, for which limited codified knowledge is readily available in databases and the internet, and where a limited number of individuals spearhead technological advancements. Given the social aspect of knowledge exchange, the economic consequences of social networks are well studied and documented (Borgatti & Foster 2003).

That said, little is known about how networks emerge in the first place. In fact, “researchers seem to ignore the possibility of new ties being added or existing ties being dropped” (Borgatti, Brass & Halgin 2014, p. 20). A lack of understanding about the origins of knowledge networks is troubling because such networks influence the

evolution of economic structures and economic prosperity (Hausmann et al. 2011). In addition, enhancing our knowledge in that regard is important because theories of economic evolution are incomplete without appreciating the dynamics of underlying networks (Ahuja, Soda & Zaheer 2012). This research builds on the lack of scholarly knowledge on network change, and the desire by practitioners in government and industry to understand how networks come about.

Technological advancement is ultimately driven by people and the literature on technological change develops models for understanding the phases from inception to maturity. This dissertation builds on a model for technological change, the so-called double-boom cycle (Schmoch 2007), which conceptually explains the phases of an emerging technology by integrating the ideas of science-push and market-pull. Using Social Network Analysis in a longitudinal research design, this dissertation maps the evolving collaboration networks amongst individuals along the phases of an emerging technology. The dependent variable is a collaboration network amongst inventors and the independent variables are various forms of proximity, including social, organisational, geographic and institutional proximity. To account for the role of local institutions, the evolving networks are being compared in separate cases which concentrate on Australia, Europe, the USA, China, Japan and South Korea respectively. Taken together, this dissertation aims to explore the role of institutional context for the dynamic effect of proximity on tie formation.

My personal motivation for this research stems from an experience I have had in industry. When working at a so-called Hidden Champion in Germany (a medium sized business which is internationally leading in its niche), I wondered how it was that most companies are striving for innovation, but not all are equally successful. My intuitive response was that it is because of the people within a company and how they collaborate, but this view was highly subjective at the time. To find out, I decided to conduct research in this field and to study techniques that would allow me to describe and analyse interpersonal collaboration in a quantitative and scientific fashion.

This research was conducted in Melbourne, Australia, giving the motivation a regional spin. Compared to other OECD countries, Australia is a highly knowledgeable and

educated nation with a strong research sector (OECD 2013b). However the translation of research output into business performance is below expectations in the view of the Australian Government (Australian Government 2009), and policy reports identify the lack of industry-research collaboration as a major obstacle (Australian Government 2015). Consequently there is a strong interest in better understanding the circumstances under which collaboration ties emerge in general, and more particularly between industry and research. A frequently cited constraint for international collaboration involving Australia is the vast geographic distance to other western countries, often described as the 'tyranny of distance' (Blainey 1966). In that light, novel insights on network change from an Australian perspective not only contribute to the academic literature, but they also help in addressing some fundamental challenges for Australia's engagement in global knowledge networks.

My motivation was further fuelled by local opportunities and support structures. On the one side, I was fortunate to join the Swinburne-based research group with a strong focus on SNA, called Melnet, which gave me first-hand access to cutting edge methodological and theoretical support. At the same time, the focus on CRP and RAFT came through various factors. The main reason was that I had the opportunity to join a project that was funded by the Australian Research Council (ARC) on the commercialisation of public research and implemented as a joint effort by the SNA team at Swinburne University, of which I was part, and the CSIRO branch in Melbourne, where RAFT technology was invented. My supervisor team consisted of the project leads on either side, Michael Gilding and Dean Lusher at Swinburne and Greg Simpson at the CSIRO, who provided me with great support throughout my candidature, making my doctoral journey particularly engaging and insightful.

1 INTRODUCTION

Glaeser et al. state that “intellectual breakthroughs must cross hallways and streets more easily than oceans and continents” (Glaeser et al. 1992, p. 2). The authors imply that knowledge exchange relies on human interaction and that human interaction is facilitated by geographic proximity. However, new and cheaper forms of communication and international travel, and the overall trend of globalisation and international trade have made the world ‘a smaller place’. This raises questions as to whether geographic proximity is still a determining factor for human interaction, what other factors might matter, and how the influence of such factors might change over time.

Understanding the determinants of collaboration ties is crucial for academia, industry, and policy makers, as their economic impact depends, at least partially, on their ability to engage in effective knowledge exchange. Academic research will have limited impact if scientific discoveries do not reach practitioners. Companies will struggle to deal with the growing complexity of today’s technological challenges without drawing on cutting edge knowledge from research organisations, and the economic performance of nations might not reach its full potential if policy makers fail to effectively promote collaboration between industry and research. This is acknowledged by the Australian Government and political leaders elsewhere, who are thus eager to see an increase of collaboration between industry and academia. Yet not all such policy initiatives succeed as there is limited understanding about why collaborations emerge in the first place.

This dissertation investigates the dynamic effect of various forms of proximity on the emergence of collaboration ties between inventors. It concerns an emerging technology in the chemical sector, a process for “making better polymers” called Controlled Radical Polymerisation (CRP) (CSIRO 2016, p. 1). Using patent data, this dissertation adopts a longitudinal approach for analysing the determinants of network change along the phases of the technology life cycle. Importantly, to assess the overall role of institutional context for network change, a longitudinal network study is implemented for the locations with the highest density of CRP inventors; specifically,

Australia, the USA, a group of European countries, China, and the combination of Japan and South Korea, as well as for the global network as a whole.

In brief, the results show that local institutions matter for network change and lead to distinct patterns across locations, in particular with respect to the dynamic effect of proximities on network change. This means that the origins of network change are, at least in part, place-dependent, and practitioners should take that into account when defining measures to foster collaboration in their territory. In addition, evidence suggests that the pace and nature of technological change is place-dependent too, since some locations nicely represent science-push and market-pull (USA, Europe, Japan and South Korea), some demonstrate science-push but no market-pull (Australia), and some are entirely different (China). Hence, practitioners should consider the place-specific factors when drawing conclusions from cross-country comparisons.

Furthermore, the effect of proximity on tie formation varies across places, often in non-linear patterns. The only exception is organisational proximity, which has a strong and stable effect on collaboration, meaning that there is an ongoing preference by inventors for work with their colleagues, as opposed to externals. The non-linear effect has not been reported in the literature, while the stable effect of organisational proximity was also found by Balland, De Vann and Boschma (2013). This dissertation confirms prior work in that geographic proximity is neither sufficient nor necessary for collaboration (Boschma 2005 850). For instance, the network in Japan and South Korea exhibits high fragmentation despite local concentration, and the European network spatially expands in certain phases, presumably to source distant knowledge. Consequently it appears that intellectual breakthroughs can easily cross oceans and continents, where organisations and institutions pave the way for such collaboration. Similarly, intellectual breakthroughs will not cross hallways and streets if organisational and institutional boundaries stand in the way.

1.1 RESEARCH BACKGROUND AND MOTIVATION

This dissertation builds on two streams of literature which are related but distinct: Evolutionary Economic Geography, and Technological Change. Evolutionary Economic

Geography, henceforth EEG, arose from the geographic sciences and concerns the uneven distribution of economic activities across space and time. The evolutionary angle was introduced recently to represent the evolutionary forces that continuously transform the economy from within. The literature on EEG acknowledges the importance of social networks for knowledge transfer and empirical work investigates, for example, the evolution of knowledge networks within or between regions.

Broadly speaking, EEG posits that space matters for collaborative innovation and that networks are intertwined with economic change. However, the few existing longitudinal network studies in this field focus on one single location, that is, no study was found that systematically compares network change across locations. What is more, those few studies report divergent results. For instance, the collaboration networks in the Biotech industry in Germany exhibit different change patterns than the global alliance network of video games producers (Balland, De Vaan & Boschma 2013; Ter Wal 2013b). This dissertation sheds light on these divergent results by investigating network change across several locations, while maintaining comparability of other important factors.

Furthermore, EEG literature frequently adopts the so-called proximity approach to conceptualise different drivers of network change; for instance geographic proximity, organisational proximity, social proximity, cognitive proximity and institutional proximity (Boschma 2005). The common argument is that closer proximity between two actors increases the chance for interaction. For instance, co-located actors are more likely to collaborate than if they are far apart. Also here, the extant empirical literature is inconclusive in that, for example, one study finds that geographic proximity becomes more important over time while the other study finds the opposite (Boschma & Frenken 2015). This research sets out to contribute to knowledge by adopting the proximity approach to investigate if and how the dynamic effect of proximity varies across locations.

The literature on technological change originates from theories directed towards understanding the forces that drive economic evolution. In the wake of the knowledge economy, the resource based view of a firm was superseded by the knowledge-based

view of a firm, insofar as the ability of organisations to access, absorb, and combine knowledge has become a crucial factor for a firm's competitiveness. Early contributions proposed that the innovation process occurs in a linear fashion, but that view was adjusted to acknowledge that innovation is an iterative process with feedback loops (Hirooka 2003).

This dissertation builds upon a recent model of technological change, the so-called double-boom cycle. This model integrates the concepts of market-push and market-pull into a temporal framework that features periods of increasing or declining technological activities. In a Europe-centric study, Schmoch (2007) finds evidence for the double-boom cycle in 32 out of 44 investigated technologies. Although the model is conceptually and empirically sound, it neglects the social dimension of technological change by drawing solely on output-type data such as publications and patents, that is, it ignores the individuals who generate such output and the interactions they might have. This dissertation addresses this gap by exploring how the collaboration network of inventors evolves along the life cycle of an emerging technology.

1.2 RESEARCH QUESTION AND OBJECTIVES

In light of the limitations of existing scholarship, this dissertation addresses the following research question:

What is the role of institutional context for the dynamic effect of proximities on tie formation along the technology life cycle?

To answer this question, three objectives are addressed. The first objective is to determine if and to what extent CRP technology exhibits characteristics of the double-boom technology life-cycle, and if that holds true for different locations. Establishing a local understanding of technological change is important because it facilitates interpreting the results of social network analysis. The second objective is to analyse how different forms of proximity influence network change, whether this effect is linear or non-linear over time, and whether the different locations show similar or different change patterns. The final objective relates to the local context, and the

question to what extent local circumstances help in explaining the observed patterns of network change.

1.3 IMPACT OF THE RESEARCH

This research makes three main findings. Firstly, it shows that the CRP collaboration networks resemble the double-boom cycle. This is a novel insight because prior studies neglected the social angle of innovation and merely focussed on performance measures such as the number of patents or publications. Plus, prior research focusses on Europe only, but this dissertation shows that the double-boom pattern also occurs in other geographic areas, though not in all. For instance, the notions of science-push and market-pull were observed in locations that feature both a strong research base in CRP and an established chemical industry, such as the USA, Europe, Japan and South Korea. In contrast, the Australian network features a science-push which seems to be driven by a few public research organisations, but there is no strong evidence for market-pull. The case of China is different again, since the closed economy and the high involvement of the central government led to a development which may be best described as government-push. The implications for practitioners are twofold. First, government should not withdraw their support for an emerging technology upon the first signs of decline, since the activity level may bounce back and new solutions may foster market adoption. Second, government should acknowledge that technological progress is place-dependent, meaning that technological developments may relate to location-bound organisations and institutions.

Secondly, the dynamic effect of proximity on network change is partially place-dependent. For instance, the investigated locations demonstrate different patterns concerning long-distance collaboration. European inventors reach out when they seem to fall behind, US-based inventors reach out to accelerate an already positive development, and Japanese/South Korean inventors avoid long distance collaboration altogether. That said the effect of organisational proximity on network change is positive and significant across all locations and all phases. This implies that organisational boundaries are of global importance for inventors when choosing a collaborator, which flies in the face of prior research (Cassi & Plunket 2015). This

means that policy initiatives for open innovation may be very impactful (Chesbrough 2012; Chesbrough, West & Vanhaverbeke 2006), as they require collaboration beyond the organisational boundary. Plus, when selecting partner countries for international research projects, the decision makers should consider the mindset of their potential partners concerning long distance collaboration.

Thirdly, the global network also resembles the double-boom pattern, but the dynamic effect of proximity is less pronounced than in the local networks. For instance, geographic and social proximity have a volatile impact on network change at the local level and the corresponding explanations can be found in the local context too, but in the global network, the influence of those factors is stable over time. It appears that the aggregated nature of the global network overwrites important nuances at the local level. By implication, comparing the results of network studies on different geographic scales is risky, as global network studies provide no insights on the diverse change patterns at the local level. This means that diverging findings between global and local studies in network studies do not necessarily represent a conflict.

1.4 OUTLINE AND STRUCTURE OF THE DISSERTATION

This introduction sets the scene for what is to follow. The literature review in Chapter 2 elaborates on the key concepts: the dynamics of technologies and social networks (change), the nature and relevance of collaboration networks (dependent variable), and the proximity approach which captures some central determinants of network change (independent variables) (see Figure 1). A discussion of the extant empirical literature identifies the research gap. Chapter 3 describes the data source and means of data collection, namely patent data from the international PATSTAT database. It also explains the methodological approach including the longitudinal research design, the operationalisation of the dependent and independent variables, and the analytical approach using Stochastic Actor-Oriented Models, henceforth SAOMs.

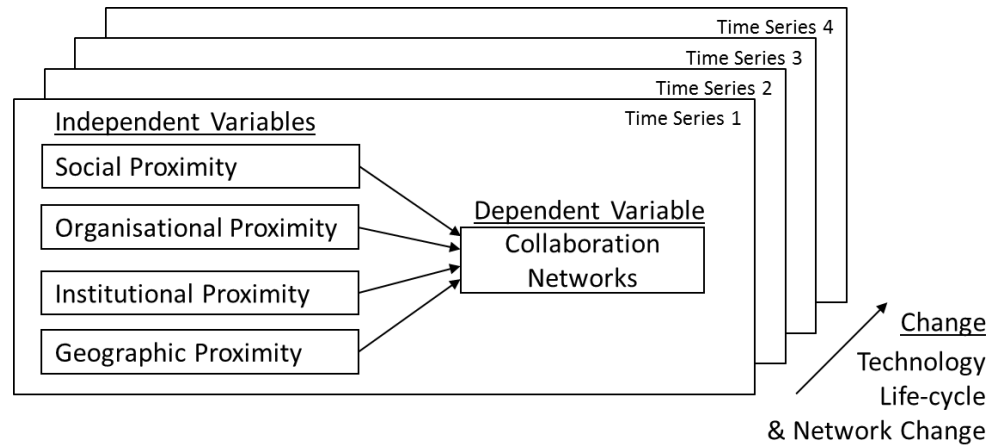


FIGURE 1: CONCEPTUAL FRAMEWORK OF THIS DISSERTATION

Chapter 4 presents empirical data, but here with the intention to show that CRP technology, the empirical case of this study, demonstrates the characteristics of the double-boom technology life-cycle model. On that basis, Chapter 5 presents the SAOM results per location, six cases in total, and Chapter 6 synthesises the findings with respect to the proximity dimensions, the double-boom cycle, and differences on the local and global level. The discussion in Chapter 7 revisits the research question and the conclusion in Chapter 8 summarises the contribution to knowledge alongside the limitations of this research and opportunities for future studies.

2 LITERATURE REVIEW

The evolution of technology-related collaboration networks is a multi-disciplinary phenomenon, involving concepts from economics, sociology and human geography. Economics addresses the market forces that drive technological change through innovation. Sociology explains the social aspect of innovation and the role and nature of social networks. Human geography considers how human interaction is localised and thus influenced by the cultural, geographic, and institutional features of such locations. Recent developments integrate certain streams of research in these three disciplines – economics, sociology and human geography – into a framework called Evolutionary Economic Geography (EEG), which “explains the spatial evolution of (...) networks (...) and their locational behaviour” (Boschma & Frenken 2011a, p. 295). This chapter reviews relevant concepts and theories (see sections 2.1, 2.2, and 2.3), and empirical studies that are similar to this dissertation (see section 2.4).

2.1 CYCLES OF TECHNOLOGY AND NETWORK CHANGE

This section elaborates on the adopted concepts for explaining network change along the technology life cycle, a framework on network dynamics, and the concept of path dependence to integrate technological and network dynamics.

2.1.1 INNOVATION AS DRIVER FOR ECONOMIC EVOLUTION

Technology is “a design for instrumental action that reduces the uncertainty in the cause-effect relationships in achieving a desired outcome” (Rogers 1983, p. 13), and various models aim to explain the emergence and evolution of technologies. To begin with the fundamentals, economic actors adopt new technologies and apply them for their own purposes. That is, they innovate. The term innovation has been defined in numerous ways, often in an overlapping fashion (Afuah 2003; Garud, Tuertscher & Van De Ven 2013; McDermott 2008; Stevenson & Kaafarani 2011; Tidd & Bessant 2009). Baregheh, Rowley and Sambrook (2009, p. 1334) synthesise past definitions of innovation used in various discipline areas, including Management, Economics, Innovation and Entrepreneurship, and Technology/Science/Engineering, and propose the following definition:

Innovation is the multi-stage process whereby organizations transform ideas into new/improved products, service or processes, in order to advance, compete and differentiate themselves successfully in their marketplace (Baregheh, Rowley & Sambrook 2009, p. 1334).

This definition stresses three characteristics that matter for this study. Firstly, innovation is a process that begins with ideas and inventions. Successful commercialisation – the second phase of innovation - may or may not follow the invention, but the invention stage is a precondition for the rest to happen. This study utilises patent data which represent inventions, thus operationalising an important step in the innovation process. Secondly, innovation is a social process that originates from individuals in various capacities (LeFevre 1986). This study follows this notion by analysing social aspects of collaboration activities at the individual level. Thirdly, innovation is critical for firm survival in a free market and it positively affects the economic prosperity of regions and nations. This highlights the importance of innovation for economic prosperity and stresses the notion of global competition where not only firms but also countries compete. The global research design of this study acknowledges this circumstance.

The literature identifies several types of innovation that help to specify the nature of CRP technology. Firstly, the literature distinguishes between radical and incremental innovation. Radical innovation may cause a major technological paradigm shift (Pedersen & Dalum 2004), while incremental innovation relates to minor innovations with a low level of novelty (Von Stamm 2008). CRP technology introduced significantly new ways for making polymers (Davis & Matyjaszewski 2002), thus making CRP radical rather than incremental. However, this mostly applies to the initial patents that describe the technological fundamentals, with later innovations building on this incrementally. Secondly, innovations may be disruptive, that is, they significantly impact the business models of incumbents (Christensen 1997). CRP is no disruptive innovation as such, at least not so far, since only few CRP-related products are available in the market place. However, the far-reaching importance of chemistry for many industries implies that CRP might generate disruptive innovation in certain areas. Specific chemical compounds in other fields enabled, for example, the introduction of

optical storage media (used for CDs) and liquid crystals (used for flat screens), which in both instances led to products that disrupted incumbent offers.

An innovation is the result of human action and interaction, leading to new knowledge and solutions with the ability to appropriate rents for resulting novelties. Innovations arise endogenously from within the economy, and Endogenous Growth Theory explains the interplay between innovation and economic growth. The theory is rooted in Schumpeter's concept of creative destruction:

The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumer's goods, the new methods of production or transportation, the new markets, (...). [This process] incessantly revolutionizes the economic structure *from within*, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact about capitalism (Schumpeter 1942, p. 83).

Creative destruction is an endogenous process which is based on the notion of renewal by which "better products render previous ones obsolete" (Aghion & Howitt 1992, p. 323). Consequently, economic actors that successfully introduce novelty may gain a competitive advantage in their market. Creative destruction leads to the introduction of novel solutions, to the dismay of incumbent producers that might face extinction (Aghion & Howitt 1997).

Endogenous Growth Theory posits that technological change occurs along trajectories that are made up of accumulated efforts to innovate (Aghion & Howitt 1997; Dosi 1982; Romer 1990). Preceding theories, such as the Neoclassical Model of Exogenous Growth, acknowledge that technological advances are crucial for sustainable economic growth, but they treat innovation as external to the system and ideas as a public good (Solow 1956; Swan 1956). Aghion and Howitt (1997, p. 1) oppose that view by arguing that "innovations do not fall like manna from heaven", since innovations often arise from for-profit R&D investments, thus they are not a public good.

Endogenous Growth Theory is widely supported by practitioners (Cornell University 2015; OECD 2010b) and scholars (Aghion & Howitt 1992; Aghion & Howitt 1997;

Romer 1990). Empirical research confirms that “innovation has a significant effect on productivity at the level of the firm, industry and country” (Cameron 1998, p. 22), hence firms are seen as the central drivers of economic evolution. Endogenous Growth Theory expounds the contributing factors at the firm level (Nelson & Winter 1982). Firstly, the ‘routines’ of firms are the locus of evolution, and the behaviour of firms is a function of their capabilities and choices. Secondly, firms engage in a continuous ‘search’ process in which they constantly review their routines, and modify and replace them in a stochastic manner, leading to an ongoing evolution. Thirdly, the firm’s environment, including external conditions and the behaviour of other firms, informs its choices toward expansion or contraction.

Knowledge is a key ingredient for innovation. Already in 1969, Drucker introduced the concept of the Knowledge Economy in which ideas and information, as opposed to goods and services, account for an increasing share of a country’s Gross National Product (Drucker 1969). Innovation takes place in a social, economic and political context and is fuelled by the combination of knowledge and interactive learning through personal contact (Cameron 1998; OECD 1996; Powell & Snellman 2004). Knowledge exchange may occur through interpersonal engagement and collaboration, but also in the context of larger collectives such as institutions, government bodies and corporations. The rules and routines superimposed by organisations and institutions enable and constrain interactive learning and thereby influence the innovation performance of nations (Lundvall 1995).

The growing importance of knowledge has led to the knowledge-based view of firms, which posits that a firm’s ability to access, absorb and combine new and existing knowledge in meaningful ways is vital for its competitiveness and survival (Baregheh, Rowley & Sambrook 2009; Garud, Tuertscher & Van De Ven 2013; Penrose 1995; Teece 1998). Organisations benefit from relevant knowledge by combining, applying and exploiting it (Alavi & Leidner 2001) in order to develop competitive competences (Blackler 1995; Grant 1996). Lundvall (1995, p. 1) echoes this view by stating “the most fundamental resource in the modern economy is knowledge and, accordingly, the most important process is learning”. To sustain themselves, organisations seek to

identify and absorb critical knowledge, often through interactive learning and personal exchange.

In summary, innovation and technological change are fundamental drivers for economic development and governments have a genuine interest in supporting them in order to secure welfare for their nations.

2.1.2 THE DOUBLE-BOOM CYCLE OF TECHNOLOGIES

A technological system is defined as “a network of agents interacting in the economic/industrial area under a particular institutional infrastructure (...) [who are] involved in the generation, diffusion, and utilization of technology” (Carlsson & Stankiewicz 1991, p. 93). This implies that there are interdependencies between technological progress and the action and interaction of involved agents. To capture technological change, this dissertation adopts the model of the double-boom cycle as a baseline for the evolution of CRP technology since the review of the literature shows that it best resembles CRP technology compared to other published models.

Early models include the linear model of innovation which assumes that technological change occurs in a sequence of basic research, applied research, development, production, marketing, and diffusion (Bush 1960). However, the linear model is criticised for oversimplifying a complex matter and for neglecting feedback loops (Godin 2006; Rosenberg 1994). The subsequently published s-shaped model suggests that technology diffusion in the market place follows phases that cumulate to an s-curve (Anderson & Tushman 1990; Filson 2001; Joo & Duk Bin 1996; Rogers 1983). However, this model puts emphasis on market activities and neglects technology development, which is the focus of this dissertation. Other models explain technological shifts in the context of long-term development, for instance from the era of steel to the era of oil (Freeman & Louçã 2002; Hirooka 2003), but such models are too generic for a specific case such as CRP technology.

Again other models consider the drivers of technological change, in particular the role of science-push and market-pull. Science-push occurs when a new technology is being pushed into the market, for instance by major organisations or government, while the market-pull model suggests that a technology is being pulled into the market by

consumer demand (Bush 1960). Both views appreciate the occurrence of feedback loops between phases (Kline 1985), and Swann (1994) integrates the two models to account for the interplay between push and pull. Similarly, reports from business consulting firms confirm the volatile patterns of R&D activity along the technology life cycle, that is, an initial breakthrough discovery is often followed by a rapid increase in activities until unexpected problems occur that lead to a decline of investments (Linden & Fenn 2002; Rickerby & Matthews 1991).

Schmoch integrates the concepts of science-push, market-pull, feedback-loops and volatile activities with a focus on specific technologies at the meso level, and finds that 32 out of 44 technologies exhibit what he calls a double-boom pattern (Schmoch 2007). Schmoch uses patent data as a proxy for technological activity, but he does not investigate the activities as such. Figure 2 shows the double-boom pattern in the case of robotics. In fact, one of the double-boom technologies is polymerisation catalysts, which is closely related to CRP technology. The entire cycle might take between thirty to forty years (Schmoch 2007). This study adopts the double-boom model as it explains technological development on the meso level and with a focus on technological development.

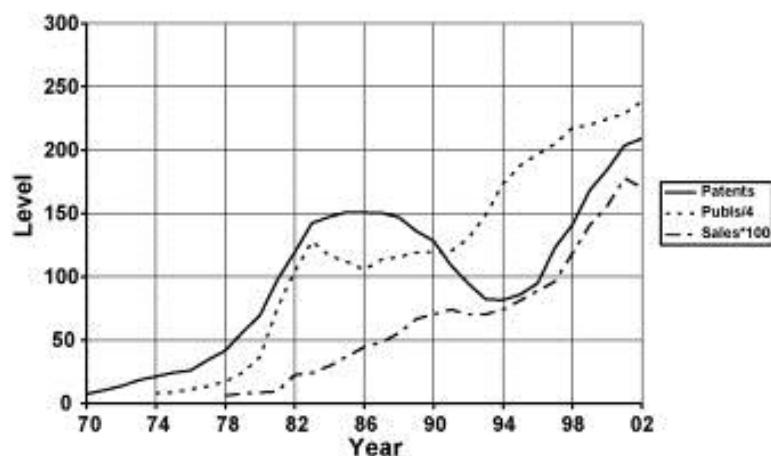


FIGURE 2: DOUBLE-BOOM TECHNOLOGY CYCLE ON THE EXAMPLE OF ROBOTICS (SOURCE: SCHMOCH 2007)¹

In more detail, the first peak follows the initial breakthrough and is fuelled by curiosity and high expectations, but over time, the enthusiasm dissolves when problems occur

¹ Level refers to the count of patent applications per year.

for which “the technical realisation proves to be much more difficult than originally assumed” (Schmoch 2007, p. 1006). The dynamics of the first boom feature changing patterns of firm behaviour. Only a few firms stay involved for the entire period between technology inception and commercial impact. Instead, most firms either join later or leave part of the way through the journey. In addition, the amplitude of the peaks is self-reinforcing and rooted in organisational behaviour towards risk. More specifically, leading firms are imitated by others, according to the logic that “if some leading firms decide to enter a new technology field, other firms enter too; if later on leading firms leave, others exit as well” (Schmoch 2007, p. 1009). This leads to different investment behaviours of firms before and after the first peak. Before the peak, a positive feedback loop implies that unsatisfactory research outcomes stimulate the increase in investments. After the peak, the pattern of a negative feedback loop implies that unsatisfactory research outcomes lead to a decrease in investments.

The solutions to the problems that led to the decline after the first peak invigorate the level of activity, leading to the second rise. Such solutions are likely to stem from long-term science investments and facilitate the broader introduction of the technology to the market. In this phase, firms tend to be quickly aware of such solutions, but they are hesitant with the adoption considering potential losses from the first boom. In addition, an increasing interaction between academic and industry researchers is common in this phase, but for different motivations. Academic researchers seek knowledge enhancement and esteem, while industry researchers look for technical solutions and business applications. Furthermore, the search for commercially viable solutions leads to an increasing diversification in the field, and the increasing involvement of marketers initiates a market-pull. Here, unmet customer needs lead to an increase in research investments (positive feedback loop), but repeated failure of the focal technology to meet such needs leads to reduction of research activities.

The double-boom model and the empirical data that is backing it suffer at least two shortcomings. Firstly, the empirical insights purely rely on European data, which leaves it open as to whether the double-boom pattern is specific to Europe. Secondly, Schmoch (2007) focusses on innovation outcomes in the form of patents, but neglects the underlying collaboration networks that might contribute to the occurrence of

double-boom cycles. He points out that “we need broader experiences about possible paths of development and the specific factors leading to double-boom cycles” (Schmoch 2007, p. 1011), but the literature search did not yield any publications that investigate network change and the double-boom cycle in combination; hence this dissertation addresses this gap.

This dissertation adopts the double-boom concept for explaining the evolution of CRP technology, as the concept neatly integrates existing models and it matches the level of analysis of CRP, that is, it is neither too detailed nor too broad. Using the double-boom concept as a starting point, this dissertation intends to go beyond the mere evolution of the technology by unpacking the dynamics of the underlying collaboration networks across multiple locations.

2.1.3 NETWORK ACTORS, TIES AND BOUNDARIES

“A network is a set of actors connected by a set of ties” (Borgatti & Foster 2003, p. 992). Social networks may be analysed using Social Network Analysis (SNA), which is rooted in social enquiry and graph theory (Moreno 1934; Moreno & Jennings 1938; Wasserman & Faust 1994). A range of disciplines adopt SNA, including sociology, management, biology, politics, economics, psychology, ecology and others. SNA is focused on the relations of actors rather than the actors themselves, and when applied in the field of business, it rests commonly on the assumption that the structural patterns of relations infer economic outcomes (Granovetter 2005; Gulati 1998; Mizuchi 1994). This dissertation adopts SNA to explore the nature of social networks in this study (for details see section 3.1.1), it is important to understand the central aspects of a network: nodes, ties and network boundaries.

Nodes, or vertices, are the actors in a social network. A node is a discrete social unit, for instance, an individual, a group, or an organisation (Wasserman & Faust 1994). In a social network, actors have the ability and the will to act, which is a major distinction from non-social networks, for example computer networks or train networks (Wasserman & Faust 1994). The nodes in a social network may take multiple forms. In a so-called one-mode network, all nodes are of the same type, for example, individuals. A two-mode network is given when the nodes are of different types, for

example, individuals and organisations (Breiger 1974; Latapy, Magnien & Vecchio 2008; White, Boorman & Breiger 1976). This study relies on a two-mode network consisting of individuals and events, but the analysis focusses on the individual level only through the use of a one-mode projection of the data (see section 3.3.1.1).

A tie, also called an arc or edge, is a relationship between a pair of nodes (Wasserman & Faust 1994). Social relationships may be broadly categorised as states and events. States are continuous over time, and sometimes permanent, for example kinship ties ('parent of'), role-based relations ('friend of' or 'boss of'), cognitive/perceptual relations ('recognises or knows the skills of'), and affective relations ('likes or hates') (Borgatti & Halgin 2011). In contrast, event ties exist temporarily, for example, conversations, email communication, or sales transactions (Borgatti & Halgin 2011). Ties may have other characteristics too. They may be formal (organisational hierarchy) or informal (friendship), valued (level of trust) or discrete (marriage), dynamic (frequency of interaction) or constant (kinship), directed (transaction) or undirected (collaboration), and positive (friendship) or negative (conflict) (Borgatti & Foster 2003; Borgatti & Halgin 2011; Burt 1992). The characteristics of a tie influence its analysis and interpretation. For instance, the meaning of a highly-nominated node in a friendship network differs from a central node in a conflict network.

In this study, ties are collaboration events between inventors (see also section 2.2). To understand the meaning of a collaboration tie it is worth reflecting on two central approaches. Network ties may be conceptualised from the structuralist view and from the connectionist view (Borgatti & Foster 2003). In the structuralist view, the focus is on the structural features of a network, while neglecting the content of a tie (Burt 1992; Coleman 1990). The tie is conceptualised as a 'bond'. In such a network, bond-type ties align and coordinate action, thus "enabling groups of nodes to act as a single node, often with greater capabilities" (Borgatti & Halgin 2011, p. 1174). The structural view also relates to the power of the individual (Borgatti & Halgin 2011). For illustration, in a two-path with three nodes, the central node in the broker position obtains power as long as the triad is not closed through exclusion and dependency (Burt 1992).

In contrast, the connectionist view considers ties as conduits through which ‘things’ may flow (Lin 2001; Snijders 1999). The tie is conceptualised as a ‘pipe’. Here, the notion of social capital arises when the focal actor may access the resources of her alters, the direct neighbours of that node, for example goods, money or information (Borgatti & Foster 2003). This concept assumes that the longer the pipe, the longer it takes for something to traverse, that nodes with a central network position will experience more traffic than peripheral nodes, and that nodes with connected alters are likely to receive redundant ‘flows’ (Borgatti & Halgin 2011).

Whilst the differentiation between bonds and pipes appeals through its simplicity, there is criticism too. A potential shortcoming of the ‘bonds and pipes ties’ topology is that a “strict dichotomy (...) may overly simplify complex social action” (Robins 2015b, p. 1). Kashima (2014, p. 17) refers to common ground theory² and argues that “information (...) is transmitted in a joint activity” which means that both coordination and exchange occur simultaneously. On that note, Robins (2015b) argues that bonds and pipes are not mutually exclusive, but rather interdependent. That is, “there cannot be network coordination without some level of network flow (...) [and] (...) there cannot be flow without some level of coordination” (Robins 2015b, p. 1).

This study constructs a network using patent data, whereby collaboration is assumed amongst all inventors that are listed on the same patent (see also section 2.2). Drawing on the bonds-versus-pipes discussion it appears that a co-inventor network represents both coordination and exchange. On the one hand, actors align their action when collaborating on a common research project (Breschi & Lissoni 2004). On the other hand, they also engage in knowledge exchange in the course of the collaboration (Ter Wal & Boschma 2009).

The *boundary specification* determines which nodes belong to the network and which do not. The boundary specification may be defined from a nominalist perspective and from a realist perspective (Laumann, Marsden & Prensky 1992). In the nominalist

² “Common ground is a set of meanings that are mutually known, believed, presupposed, or taken for granted by the participants of a joint activity” (Kashima 2014, p. 84). Common ground refers to knowledge that is mutually understood and accepted, thus it is the result of engagement with people, concepts and cultures and therefore often requires time and face-to-face interaction to emerge.

perspective the researcher defines the network boundary for analytical purposes, thereby linking the network sample to the ontology of the study. Nodes are included depending on their attributes, for example doctors in a city, even if they do not form a cohesive group. The nominalist perspective is in line with Marx's idea of a 'class in itself' (Marx 1972). Here, networks tend to exhibit small world structures (Travers & Milgram 1969). In the realist perspective, the network boundaries are defined by the members of the network based on their "collectively shared subjective awareness of all" (Laumann, Marsden & Prensky 1992, p. 21). Nodes are part of the network depending on their affiliation to a group or community, for example students in a classroom. The realist perspective relates to Marx's idea of a 'class for itself' (Marx 1972). Here, networks often exhibit cliquish structures with a community pattern since actors are more likely to know each other (Laumann, Marsden & Prensky 1992).

This dissertation defines network boundary specifications from the *nominalist* perspective (Laumann, Marsden & Prensky 1992), that is, analytical boundaries are drawn on the national or supra-national level in order to compare the co-inventor networks across the following locations: Australia, USA, China, Japan/South Korea, and member states of the European Union, the latter as one cohesive EU-bloc³. Note that the terms territory and locations are used to describe cases that go beyond the individual country, except for the worldwide co-inventor network. Each network is constructed by including every patent with at least one inventor in the respective location.

Comparing territories allows for better understanding of the role of local context for network change, because "actors who are closer together tend to exhibit greater

³ One may question whether EU-member-countries (including Switzerland) represent a *whole* when it comes to innovation and technology. In fact, studies on that matter find that "there is considerable heterogeneity of the science and innovation systems in Europe" and that major funding schemes such as Horizon 2020 would broaden the gap between strong- and poor-performing countries (Frietsch, Rammer & Schubert 2015, p. 13). EU leaders use a different language by proclaiming that "slowly, the European economy is transforming into a knowledge-based Innovation Union" (European Commission 2013, p. 1). In fact, the effectiveness of EU-membership on Science, Research and Innovation, was explored in the case of the UK, which concludes that EU-membership has a strong and positive influence, due to funding schemes, collaboration opportunities, the mobility of talented scientists, and harmonised regulations (Dulai 2015). In this study, most European CRP-inventors reside in high-performing countries including Switzerland, France, the Netherlands, Germany and the UK, which benefit the most from EU-programmes and are thus treated as one cohesive bloc.

similarity than those who are further apart” (Adams, Faust & Lovasi 2012, p. 1). The downside of defining networks with territorial boundaries is that actors might not know each other and the network is “not governed as a whole” (Glückler 2013, p. 883), that is, location-bound networks tend to be fragmented. Despite these concerns, this approach is commonly used in the literature and thus facilitates cross-study comparison (Cassi & Plunket 2015; Ter Wal 2013b).

2.1.4 NETWORK DYNAMICS

Similar to technological change, social networks are dynamic by nature (Robins 2015a). The interplay between economic developments and network change is summarised by Padgett and Powell (2012, p. 3) who suggest that “in the short run, actors make relations, but in the long run, those relations create the opportunities, or niches, that in turn produce the actors”.

Early calls around 2003 stress that much is known about the consequences of social networks, but little about their origins (Borgatti & Foster 2003). These calls are echoed by Ahuja, Soda and Zaheer, who point out that “an understanding of network outcomes is incomplete and potentially flawed without an appreciation of the genesis and evolution of the underlying network structures” (Ahuja, Soda & Zaheer 2012, p. 434). A literature review in 2006 reveals a ‘longitudinal gap’ in the network literature (Knoben, Oerlemans & Rutten 2006), and almost a decade later, Borgatti, Brass and Halgin (2014, p. 20) note that “researchers seem to ignore the possibility of new ties being added or existing ties being dropped”. In addition, an editorial piece on the integration of spatial and social network analysis attests that so far, “time is largely absent from the discussion” (Adams, Faust & Lovasi 2012, p. 4).

To address this shortage, Ahuja, Soda and Zaheer (2012, p. 437) developed a typology of ‘micro foundations’ of network change which cover the “basic factors that drive or shape the formation, persistence, dissolution, and content of ties in the network” (see Table 1, below). The resulting framework describes a virtuous cycle on network change (see Figure 3, overleaf) which is adopted in the methodological approach for this dissertation. One cycle of this framework represents the change between two network observations. Of course, the dynamics in real networks do not strictly follow the four

aspects of the framework, but it is still a useful guide in the absence of more specific models.

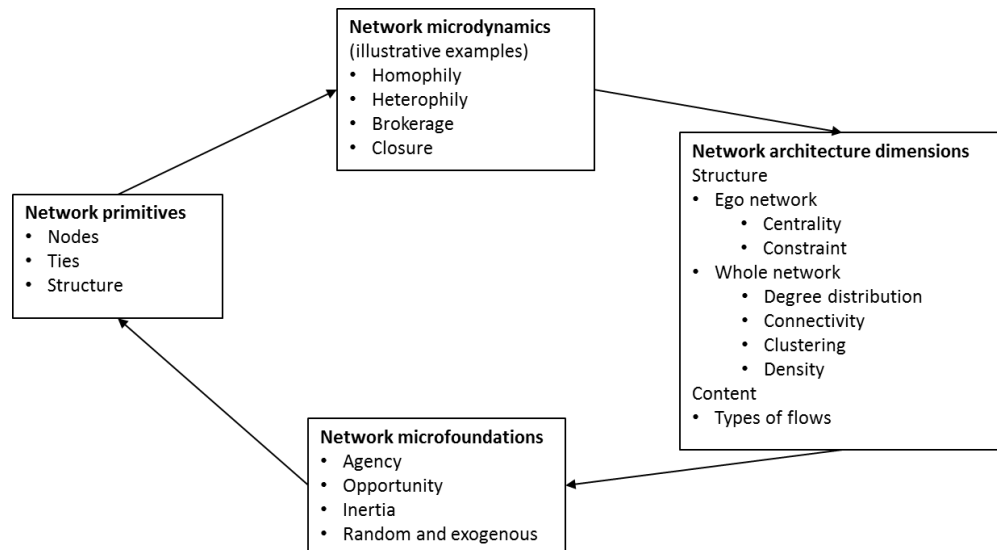


FIGURE 3: THE GENESIS OF NETWORK CHANGE (SOURCE: AHUJA, SODA & ZAHEER 2012)

The cycle has no distinct beginning, but the network micro foundations are an obvious starting point as agency, opportunity, inertia and random/exogenous events are the fundamental drivers of network change (bottom box in Figure 3) that prompt actors to make choices. The resulting choices may have an effect on the network population and the ties amongst them (left box in Figure 3). The network dynamics in the upper box in Figure 3 represent several social processes that continuously shape the composition and arrangement of the network. Examples of such processes include homophily, heterophily, closure, and clustering, to name a few. The results of such processes are certain structural characteristics that can be described using concepts such as centrality, clustering, or density (right box in Figure 3). Back in the bottom box in Figure 3, actors make new choices in the light of the network structure and driven by the network micro foundations.

TABLE 1: MICROFOUNDATIONS OF NETWORK CHANGE (SOURCE: AHUJA, SODA & ZAHEER 2012).

Micro foundations	Examples of ego level micro dynamics	Illustrative prediction for network architecture
Agency	Nodal assortativity driven: homophily, heterophily, prominence attraction Tie pattern driven: brokerage, closure	For example, homophily-driven change should lead to clique formation and a relatively high network diameter Pursuit of closure should lead to high density, high connectivity, and low variance in degree assortativity
Opportunity	Nodal assortativity driven: proximity, common goals, common identity Tie pattern driven: transitivity, repetition, referral	Ties form within social groups more so than across them, leading to clique formation Friends of friends are more likely to form ties with each other, leading to triad closure
Inertia	Nodal assortativity driven: habits, networking propensity, collaborative expertise Tie pattern driven: norms, interorganisational routines	Momentum in networking behaviour should lead to high variance in degree assortativity and high levels of clustering Norm and interorganisational routine-driven networking behaviour will lead to increasingly dense clusters with few bridging ties and hence lower connectivity
Random/exogenous		

This cycle applies to this study in that the inventors possess agency, they become aware of opportunities within their organisation or the wider industry, and their overall environment is subject to external and random events, for example from other organisations or the government (bottom box in Figure 3). As CRP is evolving, inventors are joining and leaving over time (left box in Figure 3). The various social processes that shape the network (right box in Figure 3) are a central feature of this dissertation’s conceptual framework in the form of the different types of proximity, including homophily (organisational and institutional proximity), closure (social proximity), prominence status (degree related popularity as control variable) and geographic proximity as a relational attribute. The cycle repeats itself with every pair of network observations since the end state of one observation is the starting point for the following.

This dissertation uses the framework by Ahuja, Soda and Zaheer (2012) to enhance knowledge concerning the evolution of social networks. Out of the four stages in Figure 3, the network micro foundations and the network micro dynamics are the most relevant for this study. The network micro foundations are explained through the concepts on the duality of structure and agency (see section 2.2.5), and the prevalence

of certain network micro dynamics is investigated by adopting the proximity approach which is explained in section 2.3.

2.1.5 CHOOSING PATH DEPENDENCE AS EVOLUTIONARY THEORY

Both, CRP technology as well as the underlying collaboration network change over time. Accordingly, a concept is needed for integrating the two aspects into one stream of development, and to assess the overall direction of change. This dissertation adopts path dependence for this purpose.

Path dependence is frequently adopted in empirical studies in Evolutionary Economic Geography (EEG) (Kogler 2015), which is an overarching framework that integrates social networks, economic geography, and economic evolution (for details see section 2.3). An important feature of EEG is the focus on change, and an assessment of several evolutionary theories shows that Generalized Darwinism, Complexity Theory and path dependence are compatible with the broader EEG framework (see Figure 4, below) (Essletzbichler & Rigby 2010; Martin & Sunley 2006, 2007).

The three theories meet preconditions that enable integration with EEG (Boschma & Martin 2010b). Firstly, the three theories are in line with the idea that economic evolution is an endogenous process which transforms the economy 'from within' (Schumpeter 1942). Secondly, the theories describe a *dynamic* process. Thirdly, the process they describe is *irreversible* in nature. Fourthly, the theories acknowledge the impact of *novelty* as the engine for endogenous change, resulting from the creativity of economic actors. For a detailed discussion see Garnsey and McGlade (2006), Martin and Sunley (2006), and Essletzbichler and Rigby (2010). The three theories have important differences though, and thus one approach is adopted for this dissertation, namely path dependence.

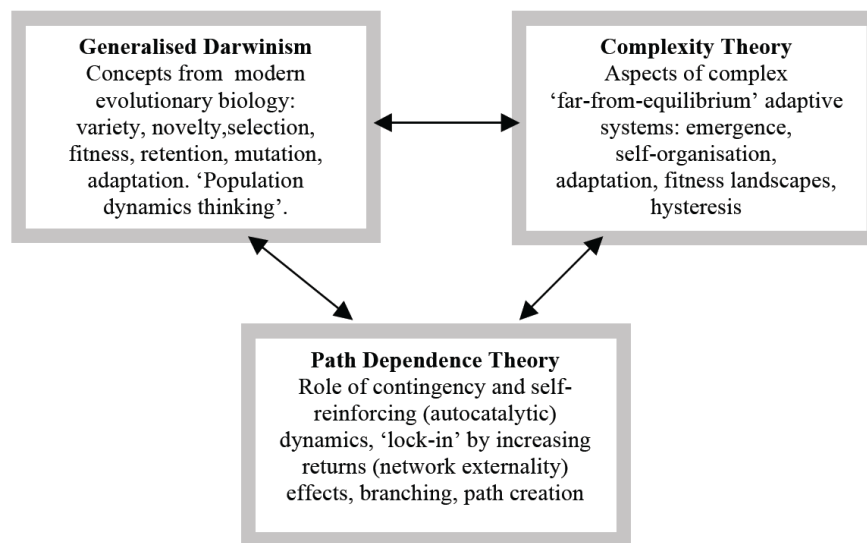


FIGURE 4: THEORIES ON EVOLUTIONARY ECONOMICS (SOURCE: BOSCHMA & MARTIN 2010A)

This dissertation adopts path dependence for the following reasons. Firstly, unlike Generalised Darwinism and Complexity Theory, path dependence does not import metaphors from other disciplines, which are partially unsuitable for application in the study of economic phenomena. Instead, path dependence is described in the same terms as the phenomena it tries to explain, that is, social sciences. Secondly, recent publications address the observed shortcomings of path dependence and frame it as “an enabling, rather than constraining, process” (Martin 2010, p. 22). In response, scholars redefined the role of agency in path dependence and introduced the concept of path-creation, where actors take purposeful action to breach into new paths (Henning, Stam & Wenting 2013). Thirdly, major social mechanisms such as agency and self-organisation are weaknesses in Generalised Darwinism and Complexity Theory. Thus, it would be problematic to apply these to this dissertation, where agentic behaviour plays an important role (see section 2.2.4 for details). Finally, the adoption of path dependence is in line with most empirical contributions in Evolutionary Economic Geography, making it “the most prevalent applied approach in this line of enquiry” (Kogler 2015, p. 706).

Path dependence builds on the assumption that “previous events affect the probability of future events to occur” (Boschma & Frenken 2006, p. 280), or in short, history

matters (Martin 2010)⁴. A frequently cited example to illustrate path dependence is the QWERTY-keyboard for typewriters (David 1985). In this case, historical and accidental circumstances led to the arrangement of letters on the keyboard which rapidly diffused amongst office managers and journalists and thus became the de facto standard from the 1870s onwards. Although more ergonomic and efficient keyboard layouts were proposed, the QWERTY-keyboard was widely adopted leading to a technological lock-in situation in favour of the less suitable solution. This example illustrates “that the economy inherits the legacy of its own past” (Martin & Sunley 2006, p. 400).

Path dependence explains “why change goes in a particular direction” (Henning, Stam & Wenting 2013, p. 1351). This rests on several conceptual contributions. With respect to path emergence, David (2006, p. 400) explains that “micro level ‘chance events’ can have long-run effects on the future path of economic technologies” which means that random ‘historical accidents’ also play into the development process. This may lead to a state of technological ‘lock-in’ in which development occurs along a certain trajectory, despite the availability of (possibly more efficient) alternatives (David 2006). The tendency of a technology to continue on the current trajectory is reinforced by so-called ‘positive network externalities’, which include technical interrelatedness (preference to compatible technologies), economies of scale (benefits of continuous/extended use of current technology), and the quasi-irreversibility of investments (the difficulties of switching from past investments) (David 1985).

Two versions of path dependence are particularly important for this thesis. Firstly, the idea of increasing returns describes a process according to which routines that deliver positive outcomes are self-reinforcing and thus lead to the replication of those routines in the future (Arthur 1988, 1994), for example learning (including interactive learning) and coordinated action (Martin & Sunley 2006). The double-boom cycle also features self-reinforcing action, but in two variations since unsatisfactory research outcomes are collectively responded to with more investments in periods of increasing technological activity, but sanctioned with reduced funding in times of decline (see

⁴ Numerous publications provide further details on path dependence (Boschma & Lambooy 1999; Magnusson 2009; Martin & Sunley 2010; Martin 2010; Martin & Sunley 2006).

section 2.1.2). That is, the tipping point in the double-boom cycle represents a situation of path creation.

Secondly, another version of path dependence is institutional hysteresis, whereby institutions provide the foundation of both agency and inertia. Martin and Sunley explain:

Institutions are both the product of and a key factor shaping social agency: they provide the stability and predictability needed for social and economic actions and transactions, whilst incrementally responding to and incorporating the outcomes of those actions and transactions (Martin & Sunley 2006, p. 402).

In this way, institutions do both: enable and constrain activities on the micro level, and respond to micro level activity, which leads to an irreversible path dependent process. This matters for this dissertation, as the institutional setting across the various countries in this study may fuel or impede the collaboration behaviour of inventors, and thus the advancement of CRP technology.

While path dependence constitutes a useful framework, there is criticism too (Martin & Sunley 2006). Essletzbichler and Rigby (2010, p. 57) describe it as “insufficient to render the analysis evolutionary” and that “these same concepts can be developed within non-evolutionary frameworks”. Martin (2010, p. 1) finds it problematic that “the canonical path dependence model actually stresses continuity rather than change”. It is unclear as to whether there are different types of path dependence, under what circumstances they arise, and whether there are strong and weak forms of it. It is also unclear what precisely lock-in is, whether it is inevitable or avoidable, and how a positive lock-in may flip into a negative one, and vice versa. It is unclear whether paths are intentionally created by involved actors or by-effects on the system level, how actors interact with the structures in which they are embedded, and how and if actors create new paths.

Despite the criticism, path dependence is adopted for this dissertation as it is compatible with EEG, it appreciates the role of institutions and feedback loops, and the

whole idea of path dependence aligns with the Markov-chain assumption of the proposed analytical approach (see section 3.1.4) as well as the other dynamic concepts on network change and technological developments. To operationalise the effect of certain contextual parameters on future network evolution, this dissertation adopts the proximity approach (see section 2.3).

2.2 THE NATURE AND IMPACT OF COLLABORATION NETWORKS

This section elaborates on the characteristics of the dependent variable of this dissertation: collaboration networks. Empirical research on inventors shows that the co-inventor relationship features mutual trust and exchange of tacit knowledge, which is why such collaboration networks matter for innovation outcomes. Game Theory is identified as an important theory for explaining the patterns of interactive knowledge exchange, and it sets the scene for discussing the duality of structure and agency.

2.2.1 INVENTORS AND THEIR COLLABORATIONS

Inventors are economic agents. Their behaviour is driven by distress, want, craving, or annoyance (Rossman 1931), that is, by preferences and restrictions (Kirchgässner 2008). Early empirical studies found that inventors strive for both intrinsic and extrinsic rewards. For example, a study on US inventors reveals that they are motivated by their “love for inventing”, the “desire to improve” and “financial gain” (Rossman 1931 pp. 159). More recent studies show that inventors are mainly motivated by “the satisfaction from solving technical problems, (...) the progress of science, and (...) generating value for one’s firm” (Walsh 2009, p. 22). Extrinsic factors include “career advancement, beneficial working conditions and monetary rewards”, but they receive much lower scores (Walsh 2009, p. 23). Hence it appears that inventors are mainly intrinsically driven and they engage in collaboration with the primary goal to solve technical problems.

Empirical studies on the demographics of inventors report diverse characteristics across locations and suggest that “institutional differences may affect the profile of inventors in each country” (Walsh 2009, p. 2). For example, inventor surveys in the USA, Japan and Sweden reveal local differences regarding gender balance and age. Ninety-five percent of US-based inventors are male and the average age is 47 years,

while in Japan 98 percent are male and the average age is 40 (Walsh 2009). In contrast, the share of female inventors in Sweden is 9.1 percent and even 18.6 percent in Chemistry (between 2005 and 2007), and the average age is 43.5 years (Jung & Ejeremo 2014). Those differences have no direct implication for this dissertation, but they underscore local variations that may contribute to place-dependent networking dynamics.

That said, a common finding across those national studies is that inventors possess a high level of education (Jung & Ejeremo 2014), for instance, the share of inventors with tertiary education is 76.6 percent in Europe, 87.6 percent in the USA, and 93.6 percent in Japan (Jung & Ejeremo 2014). This observation is perhaps not surprising, but it is important for this study as it supports the view that inventors possess an extensive knowledge base and that developing patents is a highly knowledge-intensive endeavour.

The knowledge base of inventors is nurtured through their interactions, considering that co-developing a patent implies not only that “inventors that worked on the same patent know each other” (Ter Wal & Boschma 2009, p. 750), but also that involved inventors “have exchanged some information” (Lissoni 2010, p. 844). In fact, “co-invention (...) would be an indication of tacit knowledge transfer” because it represents an instance of face-to-face communication which facilitates the exchange of tacit knowledge (Nonaka 1995), plus patent development is a time-intensive process which promotes “unreserved trust”, “close relationships” and “open communication” (Xiang et al. 2013, p. 163). Taken together, “the inventor level is the most detailed and pure level of collaborative innovation available through patent data” (Ter Wal 2013b, p. 601).

In the last century, the collaboration behaviour of inventors has shifted from a solitary endeavour to a collective approach. While a study from 1931 concludes that “the majority of the most important inventions and achievements in industry are still being made by the individual inventor” (Rossman 1931, p. 33), in today’s knowledge economy, social interaction is at the heart of knowledge creation, diffusion and exploitation (OECD 1996; Powell, Koput & Smith-Doerr 1996; Powell & Snellman 2004).

In fact, the solitary approach might impede innovation, since “individuals [inventors] working alone, especially those without affiliation to organizations, are less likely to achieve breakthroughs and more likely to invent particularly poor outcomes” (Singh & Fleming 2010, 41).

Inventors collaborate for various reasons. Scientists prefer ties to others with a high reputation, meaning that individuals with a relatively high number of ties tend to attract more collaborators than someone with few ties (Li, Liao & Yen 2013). Personal status is also important in science since reputation eases the access to research funding and other eminent collaborators. Other processes such as transitivity (a friend of a friend is a friend) play a role, in that collaborations may emerge due to a shared acquaintance, and scientists might prefer collaborators who are similar to themselves in a certain way, following the idea that birds of a feather flock together (McPherson, Smith-Lovin & Cook 2001). For instance, being from the same country of origin or affiliated with the same organisation might ease communication and facilitate collaboration. Social reasons for collaboration amongst scientists include friendship, intellectual stimulation, and access to specific networks. Technical reasons for collaboration include access to instruments, equipment or material samples, and knowledge-based reasons include the exchange of knowledge, cross fertilisation of new ideas, and access to new knowledge (Goertz 2011).

Collaboration patterns amongst scientists also differ across discipline areas. Disciplines that engage in experimental and empirical work are more likely to collaborate than disciplines that focus on advancing theory. For example, large experiments in high-energy physics might attract hundreds of scientists while collaboration in theology might be less common (Goertz 2011). Statistics by the OECD find that *polymers* is the technological field with the highest level of co-inventions as percentage of PCT patent applications (OECD 2013c), even higher than pharmaceuticals or biotechnology.

From a conceptual stance, a co-inventorship tie is both a bond *and* a pipe (Borgatti & Foster 2003; Kashima 2014), meaning that a degree of mutual trust is required (bond/coordination) before knowledge exchange takes place (pipe/flow). A co-inventorship tie is an event-type tie, with a temporal beginning and end, as opposed to

a state-type tie which is open-ended (Borgatti & Halgin 2011). However, co-inventor ties might be a borderline case, since the invention process is said to take around 5 years (Ter Wal 2013b), which is far longer than other event-ties last, such as emails, phone-calls, or sales transactions. In fact, co-inventor ties may even survive some state-type ties, for example affection (likes/dislikes) or role-based relations (boss of). Nonetheless, co-inventor ties are treated as events because they feature a distinct end point, the submission of the patent application⁵. In addition, co-inventor ties are undirected. To be precise, they emerge by “unilateral initiative and reciprocal confirmation” which assumes that one inventor initiates the collaboration, and the tie only exists if the other(s) confirm(s) (Ter Wal 2013b).

Taken together, inventors are intrinsically driven economic actors with an extensive knowledge base who exchange tacit knowledge when collaborating with each other. Co-inventorship ties are undirected event-type ties, which require the confirmation of all contributors to be formed. The attitudes of inventors differ across space as their behaviour is influenced by local organisations and institutions. That said there is a global trend towards more collaboration, and a high level of collaboration amongst inventors in the area of polymers.

2.2.2 THE EXCHANGE OF TACIT KNOWLEDGE THROUGH NETWORKS

This section elaborates on the nature of tacit knowledge and why networks are important for its exchange. Tacit knowledge is exclusive to the people who possess it and due to its “sticky” nature the most common way of exchange is face-to-face interaction, making social networks crucial conduits of valuable knowledge and a critical contributor to innovation performance. It is ultimately people that drive technological change. Hence, ideas tend to emerge bottom up through the interaction of people with diverse backgrounds, making innovation a social process (Garud, Tuertscher & Van De Ven 2013).

⁵ Note that the applied analytical model (see section 3.1.2) assumes “that network ties are not brief events, but (...) states with a tendency to endure over time” (Snijders, van de Bunt & Steglich 2010, p. 45). Despite being events, the ties in this study endure over a considerable amount of time and are thus considered suitable for the analysis with the proposed model.

The literature on the relational view of innovation suggests that relationships amongst economic actors and their absorptive capacity are central drivers of technological change (Cohen & Levinthal 1990; Lundvall 1995). For example, Powell, Koput and Smith-Doerr (1996) investigated an interfirm collaboration network in biotechnology and found that such networks are the locus of innovation through mechanisms of reciprocal learning.

However, the ease of knowledge transfer depends on whether knowledge is codified or tacit⁶ (Breschi & Lissoni 2001; Howells 2002; Nelson & Winter 1982; Nonaka 1995). Codified knowledge is easily transferred through common formats and media, and the recipient may absorb it based on prior education and experience (Gertler 2003). Tacit knowledge builds on the notion that “we can know more than we can tell” (Polany 1966, p. 4) and is difficult to transfer as it cannot be expressed in formulas, rules, and algorithms (Sveiby 1999). Plus, tacit knowledge is contextual, as it relates to the situation and perception of the individual. Tacit knowledge is difficult to exchange, because the individual might not be aware of the tacit knowledge she possesses, for instance when it is “inaccessible to the conscious thought” (Nelson & Winter 1982, p. 79), or because some knowledge might be difficult to explain, for instance when showing something is easier than telling it (Gertler 2003).

That said, there is no strict dichotomy between tacit and codified knowledge: rather they are intertwined concepts that rely on another when it comes to innovation. “While codified knowledge is implicitly seen as responsible for major technological and scientific breakthroughs, tacit knowledge is described as the necessary tool for translating them into economically viable innovations” (Lissoni 2001, p. 1480). For instance, everyone can read the scientific articles explaining the functioning of CRP technology, but it requires experience and background knowledge to design and realise new materials in the laboratory. Thus, an effective knowledge worker needs to transfer tacit into codified knowledge and vice versa, which is explained in detail in Table 2 (Nonaka 1995).

⁶ Other types of knowledge are acknowledged but not further explained as they appear less relevant for this study. Examples include conditional (when), declarative (about), relational (with whom), causal (why), and procedural (how) knowledge (Jensen et al. 2007; Machlup 1980; Zack 1999).

TABLE 2: KNOWLEDGE CONVERSION BETWEEN TACIT AND EXPLICIT KNOWLEDGE (SOURCE: NONAKA 1995)

	To Tacit knowledge	To Codified knowledge
From Tacit knowledge	Socialisation	Externalisation
From Codified knowledge	Internalisation	Combination

According to this framework, the process of Combination (bottom, right) describes the use of codified knowledge to create new codified knowledge, for instance the organisation, modification or augmentation of existing data. The conversion of codified into tacit knowledge is called Internalisation (bottom, left). This process refers to the learning process through which individuals absorb codified knowledge and develop tacit know-how, for example from training, simulations or experiments. The process of Externalisation (top, right) occurs when tacit knowledge is crystallised to make it accessible for others by using symbols, illustrations and formal language. Finally, Socialisation (top, left) is the process that describes the conversion of tacit knowledge into new tacit knowledge. This is highly social and involves, for example, shared experiences, joint meetings, observing, imitating, informal relations, mutual trust and conversations. Co-inventor ties are instances of socialisation, meaning that CRP-inventors exchange tacit knowledge through face-to-face interaction.

The commercial value of tacit knowledge underlines the importance of social networks. A vast amount of codified knowledge is readily accessible through the internet and other modern media, making it a non-exclusive resource for commercial enterprises. Of course, codified knowledge can still be useful, but it represents a vulnerable basis for competitive advantage as it is easily accessible by others. By contrast, tacit knowledge provides a differentiator in a competitive marketplace as it is hard to access, decipher and comprehend by the competition. In other words, at a time when the competitiveness of a firm is determined by its ability to utilise knowledge for producing novel solutions, tacit knowledge is more important for innovation than easily accessible codified knowledge (Maskell & Malmberg 1999).

Access to tacit knowledge is rather exclusive as its exchange requires trustful social interaction. This necessity can be illustrated with an anecdote of Scottish scholars who

tried to replicate an experiment that was published by scientists in Russia. The Scottish did not succeed just by reading the published (codified) information in the literature; instead, it took several face-to-face meetings for the Scottish to understand the “right” setting of the experiment. The Scottish and Russian scholars could engage in knowledge exchange because “both groups shared the same broad ‘language of science’” (Collins 2001, p. 79). Importantly, the Scottish trusted the Russians because of “the care and integrity with which the Russian experiments were done, and the apparent trustworthiness of the Russian experimenters as individuals” (Collins 2001, p. 76). This anecdote further supports the view that the “unreserved trust” between co-inventors facilitates the exchange of tacit knowledge (Xiang et al. 2013, p. 163).

In summary, social networks are important for innovation as they enable the exchange of commercially valuable tacit knowledge. If social networks affect innovation outcomes and if accumulated innovation leads to technological change, then social networks provide a promising approach for unpacking the spatial diffusion of CRP technology through collaborations.

2.2.3 SOCIAL NETWORKS AS DRIVERS FOR INNOVATION

In knowledge networks, the actors are “individuals or higher level collectives that serve as heterogeneously distributed repositories of knowledge and agents that search for, transmit, and create knowledge” (Phelps, Heidl & Wadhwa 2012, p. 1117). Empirical research identifies a range of actor-related properties that matter for knowledge flow. For example, Ibarra (1993) finds that individuals in influential positions are more eager to implement innovations. Also, actors who possess a diverse knowledge base communicate better to a diverse audience and learn better from others (Fleming, Mingo & Chen 2007). Reagans and McEvily (2003) find that actors with collaboration experience with diverse others tend to be better in conveying complex ideas. Thus, the collaboration choices of individuals may have commercial consequences (Borgatti & Foster 2003; Edquist 2001).

The mere existence and quantity of ties influences innovation outcomes (Glückler 2013). Collaboration between actors may facilitate the exchange of knowledge, reduce investment costs, and grant access to scarce resources including human resources and

fresh ideas (Chesbrough 2003; Pippel 2013). Conversely, network ties may constrain innovation as actors may find themselves locked into dense relationships that inhibit the formation of new ties (Ford, Verreyne & Steen 2017; Fritsch 2004). Maintaining ties can be costly and collaboration may contribute to undesired knowledge spillovers (Pippel 2013), though most publications suggest that the benefits of interactive knowledge exchange outweigh the associated costs.

The quality of relationships matters for innovation outcomes (Glückler 2013). The quality of a tie is commonly expressed as the strength of a tie, which refers to a “combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services” between agents (Granovetter 1973, p. 1361). Strong ties are built on trust and the underlying expectation of reciprocity (Coleman 1988). Strong ties facilitate innovation as they enable the exchange of commercially valuable information and tacit knowledge (Ter Wal 2013b, p. 595). In contrast, weak ties describe loosely connected actors with relationships at an arm’s length (Granovetter 1973). Weak ties are advantageous for innovation as they expose the focal actor to new and heterogeneous knowledge (Gilsing & Duysters 2008), and they possess ‘cohesive power’ between groups (Granovetter 1973). Empirical studies show that both strong and weak ties are important for innovation (Rost 2011; Rowley, Behrens & Krackhardt 2000).

Also the structural features of a network matter for innovation (Glückler 2013). The network position of an individual affects the amount of new knowledge one is exposed to and thus influences innovation outcomes. For instance, actors in a central position are exposed to more ‘knowledge traffic’ and have better access to the network’s resources than someone in a peripheral position. The concept of preferential attachment (the-rich-get-richer) describes the observation that central actors tend to attract more new ties than less popular others, reinforcing their central position over time (Giuliani 2007; Powell et al. 2005). Similarly, the concept of brokerage suggests that nodes which connect otherwise unconnected groups and occupy so-called structural holes⁷ (Burt 1992) are well positioned to influence innovation outcomes

⁷ The theory of structural holes concerns the absence of useful relationships within a network (Uzzi & Schwartz 1993).

(Gould & Fernandez 1989). For example, a broker may transfer resources, introduce others, and coordinate activities (Spiro, Acton & Butts 2013). In addition, the overall network structure matters also for knowledge flow, for instance when comparing a small-world structure with a core-periphery structure (Baum, Shipilov & Rowley 2003; Soh & Roberts 2003; Steen, Macaulay & Kastle 2011; Weng, Yang & Lai 2014).

In summary, networks of interaction are of paramount importance for innovation outcomes and technological change. Networks emerge from and contribute to a technological system. However, besides individuals on the micro level, organisations and institutional entities such as the government also have an interest in influencing technology-related collaboration networks (Goertz 2011), highlighting the importance of both overarching structures and individual agency.

2.2.4 GAME THEORY AND KNOWLEDGE NETWORKS

In the knowledge-based economy, knowledge is often seen as a mere resource. However, skilled workers are not 'assets' in the usual sense of the term. Instead, they are individuals with "intentionality" (Robins 2015a, p. 5) and their own strategy towards collaboration (D'Este & Perkmann 2011): that is, they possess agency (Emirbayer & Mische 1998). Agency is defined as

the temporally constructed engagement by actors of different structural environments – the temporal-relational contexts of action - which, through the interplay of habit, imagination, and judgment, both reproduces and transforms those structures in interactive response to the problems posed by changing historical situations (Emirbayer & Mische 1998, p. 970).

The temporal nature of agency may lead to path dependent developments in that the future state may be an extension or variation of the past and present (Emirbayer & Mische 1998). For instance, actors may choose to repeat past patterns to maintain stability. In the present, actors seek to make sound judgements in addressing demands, dilemmas and evolving situations. And concerning the future, the actor may reflect on the current trajectory of events and imagine potential futures in the light of individual hopes and fears. While a conceptual disintegration of the three temporalities is possible, they are empirically blended to some extent. The point is that

collaboration choices may or may not follow a linear pattern since the individual circumstances may change.

This study employs the concept of agency as it offers a suitable explanation for the collaboration choices at the micro level. However, this study concerns not only one or a few actors, but a larger population, thus requiring a theoretical foundation for many-to-many relationships, such as Game Theory. Game Theory is derived from parlour games (hence its name) and concerns the decision-making process in situations where 'players' interact (Von Neumann 1944). It is needed in this dissertation for explaining the collaboration choices of inventors. Game Theory applies to numerous disciplines, including business and economics, and has received much scholarly attention, including that of 12 Noble Laureates. The basic setting of Game Theory assumes:

There are two or more players. Each of them has the choice between two or more strategies. Each set of choices generates a set of rewards. The reward of each player depends on the choices made by all others, not only on his own decision. The players are assumed to make their choices independently of each other, in the sense that they cannot make binding agreements to coordinate their decisions (Elster 1989, p. 28).

Mathematical models exist that allow for the quantitative evaluation of available alternatives and for selecting the most favourable one in the light of anticipated choices by the other players (Baniak & Dubina 2012). For a simple illustration, consider the following. The management of a firm aims to maximise its profit in the following period by defining an investment strategy, and a decision is needed regarding the volume of that investment, ranging from 1 (=low investment) to 4 (= high investment) (Riek 1993). Whilst the firm might conduct market research, let us assume imperfect knowledge about the behaviour of the competition, which may be 'positive', 'as usual' or 'negative'. Table 3, below, shows the decision matrix where the cell with the highest score indicates the most favourable alternative. This highlights that the decision by the focal firm is influenced by the perceived behaviour of the competition, and shows that Game Theory is a theory of social interaction.

TABLE 3: EXAMPLE OF DECISION MATRIX BASED ON GAME THEORY (SOURCE: RIEK 1993)

Competition:	positive	as usual	negative
Investments:			
1. low	5	3	1
2. medium	14	10	0
3. medium-high	30	5	-5
4. high	12	9	-9

Game Theory is suitable for investigating the collaboration choices of CRP inventors in this dissertation, as shown in the study by Yang and Wu (2008). They investigated the ‘social dilemma’ of workers who possess critical knowledge, and whether they share their knowledge with others and lose their personal power and benefits, or refuse to share their knowledge and continue to enjoy their unique position. Based on game-theoretical considerations, the results show that people share their knowledge, if the payoff is sufficiently high. That means that the individual choice for or against knowledge exchange and collaboration is closely tied to cost-benefit considerations.

To capture the Game-Theoretical considerations of CRP inventors in the collaboration network, this dissertation adopts a statistical model that assumes agency, that simulates the decision process of the individual in the light of all possible options, and that is intended for longitudinal enquiries. The model is the so-called Stochastic Actor-Oriented Model (Snijders & Pickup 2016), which is further explained in Chapter 3.

2.2.5 THE DUALITY OF STRUCTURE AND AGENCY

Of course, it is individuals who make collaboration choices in the first place, but their activities may be conditioned by surrounding structures (Bathelt & Glückler 2014). For instance, most scientists are hired by public research institutes or private organisations to contribute to larger projects. Scientific collaboration has become increasingly organised due to specialised education and the division of labour in organisations (Goertz 2011; Hausmann et al. 2011). In such cases, the concept of structure is at play, which refers to organisations, institutions, and other social rules and routines across places that influence preferences for interaction. This is not to say that scientists are duty-bound and obedient creatures that mechanically follow the gusto of leading figures in organisations and governments. Rather, it is to suggest that organisational

and institutional structures can create boundaries that can be crossed, but with greater effort than remaining within them, making such structures important determinants for the emergence of collaborations.

The integration of the acting individual and the surrounding social structure is a conceptual challenge⁸, since some scholars posit that the free will of individuals drives social life, while other scholars put emphasis on social structures that circumscribe individual action (Turner 2012). This is no conflict per se, as pointed out by Turner (2012, p. 406) because “human action can be constrained without being determined, while structures can be reconstituted by acts of individuals”. However, conceptually disentangling the two views is not trivial as several attempts demonstrate. At least in terms of terminology, the literature shows consensus that studies on individuals are on the micro level and studies on the social structure are on the macro level (Archer 1996; Giddens 1984). From here, the debate involves opposing contributions that propose a theoretical linkage between the micro and the macro level.

One school of thought puts emphasis on the micro, arguing that all social structures emerge from encounters amongst people and that the only observable feature of social life is face-to-face interaction, therefore social structure develops out of micro activity and the macro level has no emergent properties itself (for example, Berger 1971; Coleman 1987). The opposite view suggests that all micro encounters take place within social structures that constrain individual action and interaction, thus understanding the properties of social structures is important for explaining individual behaviour (for example, Blau 1977; Mayhew 1980). Another notable view is described in ‘formal sociology’, which does not focus on the actors in society, but on the relationships amongst them (for example, Blau 1964; Burt 1980). This view provides a formal integration of the micro and the macro because the level focusses on relationships, not agents.

Building on the above views for integrating the micro and the macro level, this study sees a new approach advanced by Turner (2012) as a useful way to view these issues. Turner suggests that the social universe operates not on two, but on three levels: the

⁸ See Tucker (1998) for a summary of the decade-long and yet ongoing debate on the integration of micro and macro level theories.

micro level, the meso level, and the macro level. On each level, certain forces drive the emergence and dynamics of different types of structure. He outlines the cross-level influences and suggests that they are bi-directional, that is, the macro level may influence the meso level, and the meso level may influence the micro level, but this may also happen the other way around. A closer look explains the three levels, the respective driving forces, and their relation to this study.

According to Turner (2012), the micro level reality consists of face-to-face interaction or encounters as he terms it with reference to Goffman (1972). This study is a micro level study, since the collaboration amongst inventors represents face-to-face interaction. Turner (2012) identifies seven forces, out of which three are particularly relevant for this study. Firstly, encounters are driven by transactional needs which, in line with Game Theory, refer to “the need to receive positive exchange payoffs” (Turner 2012, p. 414), that is, to be able to anticipate what the other is going to do and to trust that this action will be appropriate. Secondly, social interaction is informed by status in the form of prestige, network position, or division of labour. Interaction will be smoother if actors know each other’s status (Turner 2012). Thirdly, ecology refers to the role of space for the emergence of encounters, since individuals understand the meaning of arrangements in space and they respond accordingly (Turner 2012). These forces matter for this study, since the collaboration choices of CRP inventors are a function of perceived costs and benefits, the status of individuals may inform collaboration choices, and physical space in the form of geographic proximity may condition the chance for interaction.

The meso level refers to corporate units and categorical units. Corporate units, such as groups or bureaucracies, pursue goals. Categorical units relate to the behaviour of people, for instance depending on age, gender or ethnicity (Hawley 1986). The meso level is important for this study with respect to the role of organisations and sectoral differences (industry versus academia). Three forces influence the structures on the meso level (Turner 2012). Firstly, segmentation refers to the emergence of structurally equivalent corporate units, such as the rise of companies with similar bureaucratic structures (DiMaggio & Powell 1983). Secondly, differentiation refers to the differences in human organisation, for instance, with respect to the division of labour,

roles within organisations, and differences amongst institutional systems. Thirdly, integration refers to the relations within and across corporate and categorical units. This includes the degree of structural interdependence of corporate units (for example subsidiaries and partner organisations), their structural inclusion (for example through mergers and acquisitions), mobility of members across units (for example business travel), and the dominance of some units over others. The vast majority of CRP inventors are affiliated with an organisation; accordingly, the forces on the meso level may influence individual collaboration choices.

The macro level describes a population as a whole and its evolution across time and space. To that end, this level reflects the entirety of all CRP inventors within and across nations and over time. Turner (2012) identifies five forces on the macro level, out of which four are particularly relevant for this study. Firstly, changes in population have far-reaching impact on other societal factors on the macro level, for example production systems and the distribution of power. Secondly, production refers to the ability of a population to sustain itself, for example, through having sufficient access to human and material resources, technological systems, and entrepreneurial mechanisms. Thirdly, the reproduction of members of the population leads to the formation of institutional systems, for example for educational purposes. Fourthly, the consolidation and centralisation of power also shapes macro structures through the creation of entities that possess administrative or symbolic power, such as large PROs or MNCs (Multi-National Corporations). These macro-level forces matter for this study, since the global population of CRP inventors is growing, but on different trajectories across locations.

On that basis, Turner (2012) theorises on the linkages between the macro, the meso and the micro level. One set of linkages concerns the top-down effect of the macro on the meso and from the meso on the micro level. Concerning the link between micro and meso, Turner (2012) suggests that the extent of embeddedness of face-to-face interaction in corporate units will affect the expectations of an encounter, the forms of communication, the rituals involved, and the expression of feelings, for instance, the encounters within versus between organisations. Similarly, the macro level affects the meso level in that a changing population, the available resources and the distribution

of power is going to influence the emergence and variation of corporate and categorical units on the meso level, for example, through the effect of policy decisions on companies and public research organisations.

Conversely, the micro level actions may also affect the meso and the macro level. For instance, the emergence of densely connected networks with central actors increases the odds of affecting or forming meso level structures. Here, Turner (2012, p. 419) highlights the special role of the economy, by stating that “encounters that alter the meso structures of the economy or polity will be more likely to alter macro structures than those encounters in families, schools, churches and other internal institutional systems”. In addition, the absolute amount of micro level action matters since a single occurrence is less likely to affect meso or macro structures than recurring action. This chance increases with a growing number of individuals that engage in this repeating activity. The desire to change meso or macro level structures may arise when individuals have a reoccurring negative experience that motivates them to alter the circumstance in which they operate.

Both directions of theorising matter for this study, since macro structures on a global or national scale may affect the formation and behaviour of organisations that deal with CRP as well as the interactions of their inventors respectively. In fact, institutions are locally bound and they condition the behaviour of economic actors (Boschma & Frenken 2009). In Economic Geography, institutions are defined as “forms of ongoing and relatively stable patterns of social practice based on mutual expectations that owe their existence to either purposeful constitution or unintentional emergence” (Bathelt & Glückler 2014, p. 346).

On the contrary, activities of individuals or groups may lead to the formation of organisations or policy adjustments. Institutions may originate from both the micro and the macro level, since social practice may be prescribed by a higher entity, but it will have limited impact if ignored by individuals. Similarly, social norms may emerge without top-down intervention, for example a hand shake can count for more than a contract. Besides the place dependent nature of institutions, Bathelt and Glückler

(2014) emphasise that institutions are dynamic too, in particular as an outcome of the continuous interplay between the micro and the macro level.

In summary, the evolution of social networks on the micro level, such as the co-inventor network in this dissertation, is driven by several forces on the micro, meso and macro level, which means that investigating the determinants of network change requires a framework that represents and integrates such forces. For this purpose, this dissertation adopts the proximity approach. This approach originates from the theoretical framework of Evolutionary Economic Geography (EEG).

2.3 PROXIMITY AS DETERMINANT FOR NETWORK CHANGE

This section explains the relationship between innovation and geography, and introduces the framework of EEG. Subsequently, it explains the proximity approach which conceptualises the effect of different forms of proximity on network change and thereby constitutes the foundation for the method of this dissertation (see Chapter 3 for details).

2.3.1 THE GEOGRAPHY OF INNOVATION: A BRIEF HISTORY

Economic Geography is concerned with understanding uneven economic development across space (Boschma & Martin 2007). Since its inception in the mid twentieth century, scholars aim to explain the place-dependent nature of innovation, thus far leading to three major theoretical shifts (Simmie 2005).

Early theories in economic geography aimed to explain “why innovations start up for the first time in particular places” (Simmie 2005, p. 799). The two predominant schools of thought at the time put an emphasis on *internal economies* versus *external economies*. The view on internal economies suggests that organisations benefit from the exchange of knowledge, capital and resources through local ties, and the combinatory potential of those (Baptista 1997; De La Mothe & Paquet 1998). The view on external economies suggests that firms benefit from agglomeration through the access to production factors such as labour, energy and transportation, which allows firms to specialise and improve their productivity (Marshall 1920; Perroux 1950).

The second wave of theories on innovation and space concerned the question of why location still matters despite the growing level of globalisation. In brief, scholars figured that the location of production is important because of growing uncertainty, heterogeneity, and global competition. This view gave rise to the strategy of flexible specialisation which accommodates change rather than controlling it (Scott & Alwin 1998; Simmie 2005). To achieve this, firms need to collaborate with nearby others, which is captured in concepts on regional economies such as new industrial districts (Markussen 1996) and innovative milieus (Crevoisier 2004). Both concepts emphasise the importance of networks for innovation (albeit with different explanations), and introduce the idea of network embeddedness (Granovetter 1985).

The third wave of theories on the geography of innovation builds on prior work and emphasises the notion of change, leading to Evolutionary Economic Geography (EEG). The scope of EEG arose from a dialogue of three disciplines. On the one side, economic geographers experimented with concepts from related disciplines to gain novel insights, for instance, around culture, institutions, and networks. On the other side, economists began to incorporate the role of geography in their arguments, notably Michael Porter (1990) and Paul Krugman (1991). In addition, sociologists began exploring economic phenomena using established methodological approaches, such as Social Network Analysis (Gilding & Bunton 2005; Powell et al. 2005; Powell, Koput & Smith-Doerr 1996). However, the three streams of scientific discourse mostly neglected the evolution of the economic landscape, which now defines the scope for EEG.

2.3.2 EVOLUTIONARY ECONOMIC GEOGRAPHY

EEG is relatively young. The first comprehensive statement was published in *The Handbook of Evolutionary Economic Geography*, in 2010 (Boschma & Martin 2010b; Boschma & Frenken 2006; Boschma & Lambooy 1999; Martin & Sunley 2006; Storper 1997). In brief, EEG “explains the spatial evolution of firms, industries, networks, cities and regions from elementary processes of the entry, growth, decline and exit of firms, and their locational behaviour” (Boschma & Frenken 2011a, p. 295). The research agenda of EEG resonates with a central objective of this dissertation, which is explaining the spatial evolution of CRP collaboration networks. Before jumping to the

application of EEG, this section addresses its interdisciplinary nature by briefly discussing the EEG'S three theoretical pillars: Evolutionary Economics, Network Theory, and Economic Geography (see Figure 5).

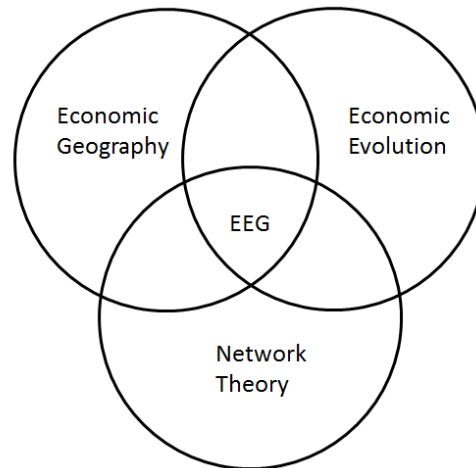


FIGURE 5: THEORETICAL FOUNDATION OF EVOLUTIONARY ECONOMIC GEOGRAPHY (EEG)

Network Theory stems from Sociology (Borgatti & Halgin 2011), which is fundamentally concerned with society and social interaction. Typical areas in sociological research include family, religion, politics, culture, and business (Calhoun & Rojek 2012). Some branches of sociology deal with the role of information in society, for instance with respect to modern telecommunication technology, and the role of information in businesses, and the social mechanisms that contribute to the creation and dissemination of knowledge. On that basis, sociologists draw on relational methods and concepts for exploring the role of social interaction for knowledge exchange and economic outcomes (Gilding 2008; Granovetter 2005; Powell, Koput & Smith-Doerr 1996). The most prominent network theories include the theory of weak ties (Granovetter 1973), the theory of structural holes (Burt 1980; Burt 1992), as well as the theories on social influence and social selection (Robins, Elliott & Pattison 2001).

Geography studies the land, its features and inhabitants, and can be broadly divided into physical and human geography. Several streams of human geography explore the spatial dimension of economics, culture, religion, or politics, but they all address the question as to how space influences human action and interaction (Cloke 2008). This study will draw on the concept of geographic proximity and its role for

collaboration across space, placing it in the scope of economic geography, which concerns the uneven economic development across space (Cooke 2001). With the rise of the knowledge economy, economic geographers adopted relational methods for exploring the exchange of knowledge amongst actors within and across regions (Glückler 2007).

Economics deals with the allocation of scarce resources, including knowledge, the production and distribution of goods and services, and the exchange of such as a function of supply and demand. Empirical research investigates several topics, including management, institutions, and finance (Free 2010). Economic studies can be broadly distinguished as microeconomics and macroeconomics, which focus on the action and interaction of individual economic agents, as well as aggregated activities of a whole economy respectively. Evolutionary economics concerns the transformation of the economic landscape over time. Economics is a social science and thus the fundamental issue of structure and agency applies here as well, for instance with respect to the influence of institutions on individual action (Bathelt & Glückler 2014; Emirbayer & Mische 1998). Over time, economists have adopted a geographic lens for explaining, for example, competitiveness or uneven economic growth (Porter 1990).

There are plenty of opportunities to contribute to EEG, given the early stage of this strand of enquiry. One such area is the call for more research on the dynamic effect of proximity on network evolution, as “there still is little understanding of how spatial networks change” (Boschma & Frenken 2015, p. 6). Empirical research shows that space matters for the emergence of social ties, but it is unclear whether the effect of space on tie formation is stable over time, which partially relates to the lack of longitudinal network studies in general (see section 2.1.4). That said the few existing studies that investigate the effect of space on network change in a longitudinal research design report inconclusive findings, thus inviting new empirical insights which this dissertation aims to provide.

This overview shows that the discipline areas of Network Theory, Evolutionary Economics and Economic Geography each offer distinct research paradigms, but there is considerable overlap too. The reality is that real-life problems such as innovation do

not fit within a single, neat academic discipline, but instead spill over the boundaries because they have social, economic and geographic components that are interrelated and mutually constituting. This dissertation contributes to knowledge with respect to the dynamics of spatial networks, by exploring the dynamic effect of proximities on tie formation along the technology life cycle, for which EEG provides an excellent theoretical framework.

2.3.3 THE SCHOOL OF PROXIMITY

The proximity approach originated from a French research group, and is thus frequently described as the French school of proximity (Bellet, Lung & Colletis 1993; Kirat & Lung 1999; Torre & Gilly 2000). The seminal paper of Boschma (2005) diffused the proximity approach from regional innovation studies to Economic Geography and related fields. The main argument of the proximity approach is that “actors that are more proximate will be more prone to collaborate and more effective in doing so, since proximity reduces costs and facilitates the coordination of joint innovative activities” (Balland, Boschma & Frenken 2014, p. 3). This dissertation adopts the proximity approach to conceptualise and operationalise different determinants for tie formation in the CRP collaboration network (see Figure 6, below). In addition to geographic proximity, the literature identifies 17 other types of proximity (Pallot, Martínez-Carreras & Prinz 2010), but only five types are particularly important for innovation (Boschma 2005), and these warrant closer consideration.



FIGURE 6: THE EFFECT OF PROXIMITY DIMENSIONS ON TIE FORMATION

Geographic proximity is “the spatial distance between two actors” (Boschma 2005, p. 69). Being co-located facilitates the emergence of interpersonal connections which are important for the exchange of tacit knowledge (Howells 2002). In the light of other proximity dimensions, Boschma (2005, p. 61) notes “geographical proximity per se is neither a necessary nor a sufficient condition for learning to take place”. In the context of scientific work, which is what co-inventor ties represent, Frenken (2010, p. 27) highlights that geographic proximity enables face-to-face interaction which helps

scientists to assess the “credibility and usefulness of a knowledge claim” and whether building on a claim is worthwhile. Whilst the precise location of face-to-face interaction is secondary, “the diffusion of scientific knowledge claims (...) will be contingent upon the patterns of mobility of scientists” (Frenken 2010, p. 27) which is in part a function of the mobility costs from their residential location.

Cognitive proximity refers to an overlapping knowledge base of interacting actors, including both professional and cultural knowledge (Nooteboom et al. 2007). The central idea is that a common understanding facilitates meaningful interaction (Hautala 2011). There is a state of optimal cognitive proximity, which is between a minimum amount of shared knowledge needed for effective communication (Cohen & Levinthal 1990) and a highly overlapping knowledge base leaving little space for interactive learning. Optimal cognitive proximity maximises the knowledge gains from interactive learning or, as put by Nooteboom (2001, p. 153), “Information is useless if it is not new, but it is also useless if it is so new that it cannot be understood”.

Organisational proximity refers to the organisational affiliation of an actor (Balland 2012). Balland (2012) suggests that subsidiaries of the same corporate group are more prone to interaction because shared norms, routines and beliefs ease the effective transfer of knowledge and the control of opportunism (Boschma 2005). Similarly, individuals who work for the same organisations are more likely to collaborate because “people are more similar within than between organizations” (Argote & Ingram 2000, p. 150). On both levels, being embedded in a similar context facilitates resource exchange and coordination (Granovetter 1985). Optimal organisational proximity is a ‘loosely coupled system’ in which uncertainty and opportunism is reduced, while avoiding a situation of lock-in, excessive bureaucracy and rigid structures (Boschma 2005).

Social proximity refers to the “social distance of two parties in a social network” (Sorenson, Rivkin & Fleming 2006, p. 995), and relates to the social embeddedness of an actor with ties of trust, friendship, advice or experience (Boschma 2005). It fosters innovation because trustful relationships are conducive for exchanging commercially sensitive information (Liebeskind et al. 1996) and tacit knowledge (Nooteboom et al.

2007). More precisely, social proximity relates to innovation in an inverted U shape where optimal social proximity is at the cusp (Uzzi 1997). A sparse network with weak ties and low trust hampers innovation (Boschma 2005), while tight (and emotional) connections may lead to a social lock-in and irrational decision-making (Uzzi 1997).

Finally, *institutional proximity* concerns the formal and informal rules found in the context of organisations. Institutions are defined as “common habits, routines, established practices, rules, or laws that regulate the relations and interactions between individuals and groups” (Edquist & Johnson 1997, p. 26); therefore “institutions function as a sort of ‘glue’ for collective action because they reduce uncertainty and lower transaction costs” (Boschma 2005, p. 68). For example, consider the different incentive structures between public research organisations and commercial enterprises: “in academia actors want to maximise the diffusion of their knowledge, while companies want to minimise such diffusion” (Ponds, Van Oort & Frenken 2007, p. 427).

2.3.4 DYNAMIC PROXIMITIES

A central contribution of this dissertation is the empirical insights on the dynamic effect of proximity on tie formation through a longitudinal research design, as opposed to a cross sectional approach. Other scholars approached this topic from various angles and a review of their work helps to delineate the scope of this study.

Brökel (2015) demonstrates that some proximity dimensions co-evolve over time, meaning that there is a correlation between proximity dimensions and that the change of one dimension is associated with change in another dimension, regardless of their impact on network change. For example, he showed that in the case of existing links between organisations, increasing geographic distance correlates with decreasing cognitive distance. Brökel calls for more similar studies to better understand how changing proximities affect each other, but this dissertation is not concerned with explaining the inter relations of co-evolving proximities.

Menzel (2013) argues that proximities are interrelated in that the lack of proximity in one dimension might be compensated by another (Menzel 2013). This differs from Brökel’s findings in that Brökel investigates the evolution of proximity A in relation to

proximity B, while Menzel explores if and to what extent the lack of proximity A may be compensated by proximity B. For example, a study on online communities found that lacking geographic proximity may be compensated by cognitive proximity (Hemetsberger & Reinhardt 2006). In the contrary case, lacking cognitive proximity may be compensated by geographic proximity, as in the case of the Dutch aviation industry where collaborations with diverse partners are more successful in spatial proximity (Broekel & Boschma 2012). Questions of interrelatedness of proximities are also not in the scope of this dissertation.

Boschma and Frenken (2015) point out that proximity is known to facilitate collaboration but its effect on performance improvements is not well understood (Boschma & Frenken 2015). For example, studies found that too much cognitive proximity leaves little space for interactive learning (Broekel & Boschma 2012), and a tendency to partners in extreme geographic proximity, or distance, might be detrimental for innovation (Asheim & Isaksen 2002; Bathelt, Malmberg & Maskell 2004). This dissertation concerns the effect of proximity on collaboration ties and leaves questions on performance for future research.

This dissertation uses the framework of dynamic proximities by Balland, Boschma and Frenken (2014), which nicely fits with the dynamic nature of concepts on technological and network change. The framework on dynamic proximities builds on the observation “that time plays a crucial role in the co-evolution of proximity and knowledge ties” (Balland, Boschma & Frenken 2014, p. 3). That is, both knowledge ties and proximity dimensions change over time.

The framework operates in two stages (see Figure 7). Firstly, proximity dimensions influence the emergence of knowledge ties in a dynamic fashion. This influence may differ along temporal trajectories, such as technology life-cycles or industry life-cycles. For instance, geographic proximity might be important for tie formation in the early stages, but less so in the later stages, or vice versa. Secondly, the interaction through existing ties may cause the evolution of proximities, leading to more or less proximity. For instance, interactive learning affects the knowledge base of collaborators and eventually increases their cognitive proximity, and institutional proximity may change

because of policy decisions. This dissertation focusses on the first stage, that is, the dynamic effect of proximities on tie formation.

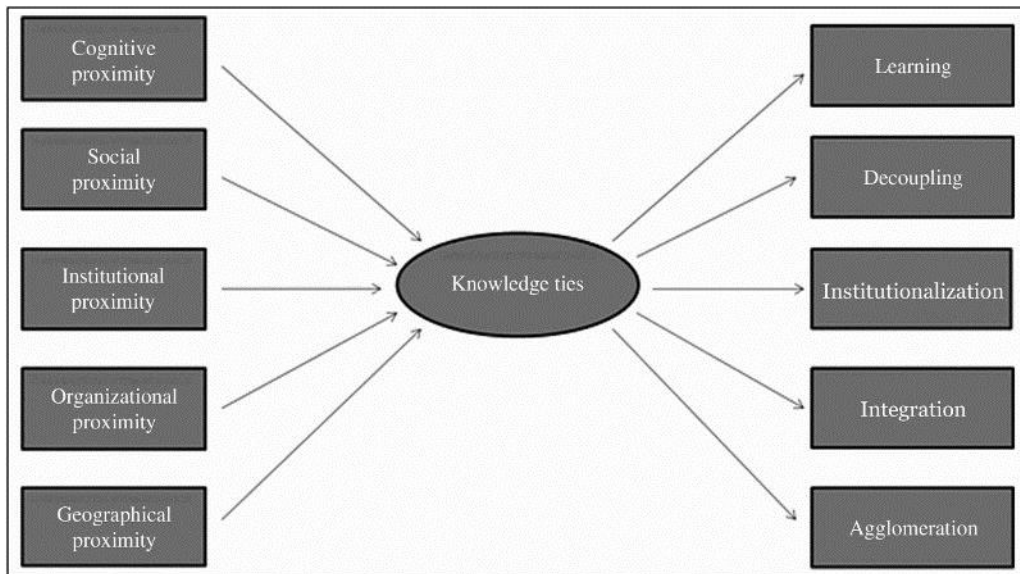


FIGURE 7: CONCEPT OF DYNAMIC PROXIMITIES (SOURCE: BALLAND, BOSCHMA & FRENKEN 2014)

That said, proximity between actors may change irrespective of an existing relationship (Broekel 2015; Menzel 2013) because the “reduction of distances during interactions produces distances as an externality” (Menzel 2013, p. 11). For example, the relocation of actor A into the region of actor B may increase the distance of actor A to actor C who resides in A’s previous home region. Likewise, when actor A learns the technology in the expertise of actor B, actor A may create cognitive distance to actor C. These examples illustrate why controlling for proximity changes is important. Although this is not in the focus of this dissertation, the adopted methodology appreciates the possibility of changing proximities.

2.3.5 PRELIMINARY SYNTHESIS

Thus far, the literature review has explained the three key concepts of this dissertation (see Figure 1): the dynamics of social networks and technologies, the nature of collaboration networks, and the proximity approach.

In brief, technologies tend to exhibit cyclic patterns with phases of increasing and decreasing activities, and since innovation is a social process, the underlying social networks are likely to change along the technology life cycle. The collaboration

networks in this dissertation consist of co-inventor ties amongst individuals who jointly developed a patent and who exchanged tacit knowledge in the course of collaboration. The collaboration choices of inventors are driven by their own intention and will, but also surrounding structures such as the organisational context, the institutional setting, and the geographic location of peers. Those determinants are captured through the proximity approach, including various forms of proximity such as geographic and organisational proximity.

That said, little work has been done in studying the three key concepts in combination, consequently there is limited understanding on the patterns of network change along the technology life-cycle and the factors that drive network change. However, this field of inquiry matters from an academic and practical view. Regarding the former, there is little research on network dynamics in general and it has not been explored whether the social networks that drive an emerging technology also exhibit the same cyclic patterns as the technology itself. Further, there is limited research on the dynamic effect of proximities on tie formation, thus additional empirical research on this topic will generate novel insights. From a practical standpoint, addressing this issue may inform decision makers in business and policy, for instance, regarding investments into an emerging technology and the 'right' time for it. Understanding which form of proximity matters in which phase contributes to the political debate on collaboration initiatives to foster innovation.

This dissertation aims to address this gap. To delineate the scope of this dissertation and to build upon the extant empirical research, the next section reviews empirical studies that are in the same field of inquiry.

2.4 SIMILAR EMPIRICAL STUDIES

2.4.1 SYSTEMATIC PROCESS FOR SCREENING THE LITERATURE

This section systematically identifies and reviews empirical studies similar to this dissertation with respect to key concepts and research questions, with the objective to capture the pointy tip of scholarly debate and to identify a critical gap in the literature. In addition to general snowball sampling and cross-reading, the following review deploys a systematic approach for selecting and screening publications in order to

reduce researcher bias and to achieve a broad coverage. The three central elements of the systematic search approach are the search terms, the sources, and the inclusion criteria.

The search terms relate to two of the three key concepts: social networks and technological change, in combination with a focus on longitudinal studies. The longitudinal aspect narrows the search to papers that report on network change, which is the body of research to which this dissertation aims to contribute. Cross-sectional papers on proximity and innovation networks are reviewed in section 2.3. Several search strings were tested against an existing library with relevant literature from broad reading. The final search string concatenates terms on *network* and *change* into pairs (to avoid the vast amount of papers referring to *change* as such), and links them to terms related to *innovation*:

("Network change" OR "network evolution" OR "network dynamic*" OR "longitudinal network" OR "dynamic network" OR "evolving structure" OR "technology development" OR "network growth") AND (innovation OR knowledge OR *organizational OR collaboration OR *organisational OR R&D)

The choice of sources is crucial for a literature review as it determines the scope of the search. To ensure a broad scope, this review follows the tradition of searching in scientific databases (Brennecke & Stoemmer forthcoming; de Loë et al. 2016; Van de Kaa et al. 2011), as opposed to searching in specific journals (Knoben, Oerlemans & Rutten 2006; Phelps, Heidl & Wadhwa 2012; Van Der Valk & Gijsbers 2010). The database approach is more appropriate given the multi-disciplinary nature of the topic, meaning that empirical contributions are potentially scattered across a range of journals. In June 2016, three major scientific databases were queried with the above search string: Thomson Reuters Web of Science, Scopus and EBSCOhost. The results were limited to academic articles in English and yielded 552, 429 and 471 papers respectively.

The 1,452 results were screened in a sequence of manual steps to determine their inclusion. Firstly, all duplicate papers were removed. Secondly, certain journals were excluded if their discipline area seemed far-fetched (for instance, production,

operations, finance, and computer networks). Thirdly, the remaining papers were separated into types of publication, such as empirical papers, method papers and literature reviews. Fourthly, all empirical papers were reviewed for inclusion in two waves, first abstract only and then the entire document. A paper was included if it met three criteria: the research design is longitudinal (at least two waves of data collection), the study is concerned with network change, and the areas of research is related to knowledge, innovation or technology.

In the end, 56 empirical papers were included that all address the evolution of knowledge networks in one way or another. Using the NVIVO software package, an initial screening provided an overview (section 2.4.2), and the subsequent in-depth review concentrated on papers using the proximity approach (section 2.4.3).

2.4.2 OVERVIEW OF EMPIRICAL STUDIES ON KNOWLEDGE NETWORKS

The number of longitudinal network studies is growing over time (see Figure 8). Starting in the mid-1990s, there is a slow, but steady increase of publications (3.5 on averages per year) with two exceptionally active years in 2012 and 2013 with 11 and 9 publications respectively. The following paragraphs shed light on what, why and how the existing studies were implemented.

What - Most studies investigate empirical cases in European countries such as France, Germany, Spain, Italy, and Finland (for example, Cantner et al. 2016; Hermans et al. 2013; Mariotti & Delbridge 2012) or the USA (for example, Demirkan, Deeds & Demirkan 2013; Powell et al. 2005), with a few studies in China (Li, Bathelt & Wang 2012), Chile (Giuliani 2013), Malaysia (Wong & Salmin 2016) and India (Vissa 2012; Vissa & Bhagavatula 2012). None of the 56 studies concerns Australia.

The industry setting is often high-tech, such as biotechnology (for example, Gilsing, Cloudt & Roijackers 2016; Schiffauerova & Beaudry 2011; Ter Wal 2013b) and Information Technology (for example, Protogerou, Caloghirou & Siokas 2010; Vissa & Bhagavatula 2012). However, the sample also includes studies in medium and low-tech sectors: for instance wine, movie production, automotive, civil construction and toys. None of the 56 studies concerns the chemical industry.

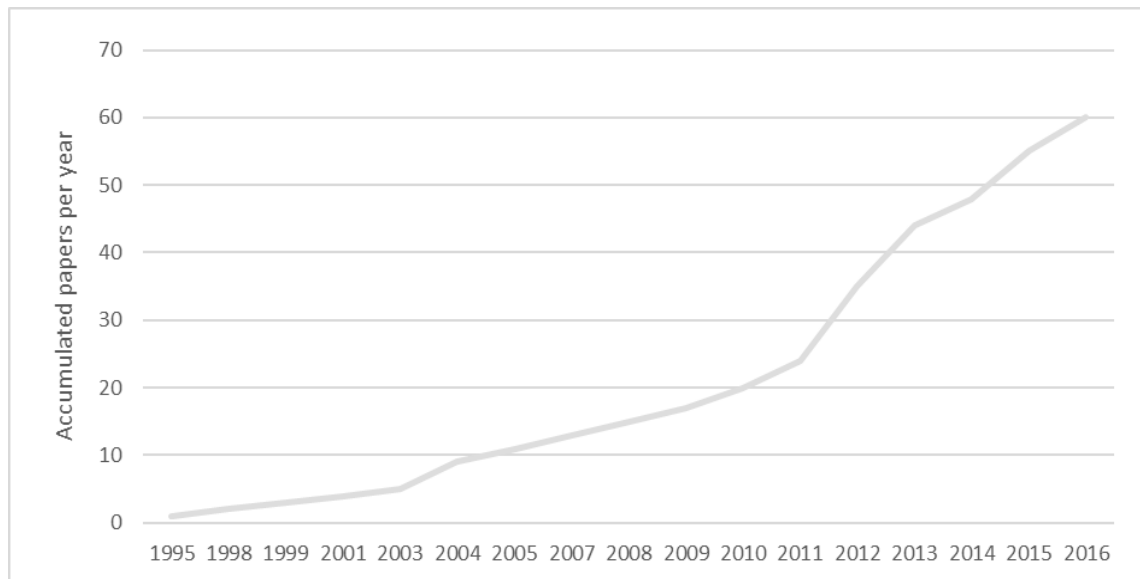


FIGURE 8: COUNT OF PAPERS ON NETWORK DYNAMICS IN THE INNOVATION LITERATURE, OVER TIME

How – Broadly speaking, the papers follow three types of methodological approaches: qualitative analysis, regression models, or dynamic network analysis. Qualitative studies often feature a case study approach and primary data collection, mainly in the form of interviews. The rich insights are used, for example, to elucidate how focal actors make sense of network change (Abrahamsen, Henneberg & Naude 2012), or to understand the transition from one type of tie to another (Mariotti & Delbridge 2012).

Regression based papers exhibit methodological variations, in that different types of regressions are used, including ordinary least squares regression (OLS) (Cantner et al. 2016; Schwab & Miner 2008), binomial regression, logistic regression (Ter Wal 2013b), seemingly unrelated regression (Cannella & McFadyen 2013), or Quantile regression (Broekel 2015). Here, the common goal is to depict a relationship between the independent variables and a particular form of network change.

Only a few studies employ statistical techniques that are designed for modelling network change (Broekel et al. 2014), out of which most use Stochastic Actor-Oriented Models (SAOMs) (Snijders, van de Bunt & Steglich 2010). The strength of SAOMs is that they can test the simultaneous effects of endogenous and exogenous factors on network change (Snijders, van de Bunt & Steglich 2010). The low count of studies using SAOMs is striking, considering that SAOMs are specifically designed for longitudinal

network studies. By implication, the use of SAOMs in this study is likely to generate novel insights.

Why – To identify a gap in the literature, a review of the motivation of existing studies is a suitable starting point. Some studies test distinct hypotheses, while others explore an open question. Concerning the research questions, the sampled articles were grouped into four broad categories, producing a typology (see Table 4, below). The reviewed studies aim to understand 1) the agentic behaviour of a focal actor, 2) the evolution of a network along a process or life cycle, 3) the effect of exogenous factors on network change, and 4) the effect of endogenous factors on network change.

TABLE 4: CATEGORIES OF RESEARCH QUESTIONS

Theme	Example research question	Example paper
1. Strategic behaviour of focal actor	How do actors make sense of network change and what this implies for their networking behaviour? What is the role of strategic action, how are ties built, how do they strengthen or weaken over time? How does an entrepreneur's networking style influence churn in his/her core personal network?	(Abrahamsen, Henneberg & Naude 2012) (Mariotti & Delbridge 2012) (Vissa 2012)
2. Network change along a process or life cycle	What are the underlying mechanisms of network dynamics along the life cycle of an industry? How does the network of a socio-technical niche evolve over time? How do local networks of collective learning evolve while a cluster emerges and grows?	(Balland, De Vaan & Boschma 2013) (Hermans et al. 2013) (Ter Wal 2013a)
3. Exogenous network change	How does the mix of policies influence the structure of [R&D collaboration] networks? What is the relationship between government policies and the development of networked systems? What has been the nature and evolution of the IST networks in the 12-year period	(Cantner et al. 2016) (Park & Leydesdorff 2010) (Protogerou, Caloghirou & Siokas 2010)

	covering three consecutive FPs [EU Framework Programmes]?	
4. Endogenous network change	<p>To what extent are the connectedness, similarity and multi-activity of countries factors for tie formation?</p> <p>How does the behaviour of actors or organisations of one kind influence the actions of organisations of another kind?</p> <p>How do the changing resource requirements change network relations?</p>	<p>(Cantner & Rake 2014)</p> <p>(Powell et al. 2005)</p> <p>(Aarikka-Stenroos & Sandberg 2012)</p>

2.4.3 EMPIRICAL FINDINGS ON DYNAMIC PROXIMITIES

Besides the trio of networks, innovation and change, the notion of proximity is a central concept of this dissertation. Thus, the 56 empirical papers were screened for any references to proximity and selected for an in-depth review. Of course, every empirical study takes place somewhere, but only 14 papers explicitly incorporate a form of proximity in their study design (see Table 5). This section summarises empirical findings on the different kinds of proximity.

TABLE 5: EMPIRICAL STUDIES ON THE DYNAMIC EFFECT OF PROXIMITIES

Type of nodes	References	Summary
Nodes are organisation	(Powell et al. 2005)	Evolution of the inter-firm network in the US biotechnology industry with a shift from commercialisation to finance
	(Gilsing, Cloudt & Roijackers 2016)	Network evolution of the global biotechnology industry along three phases of technological development
	(Balland, Suire & Vicente 2013)	Network evolution of the global video games industry
	(Balland 2012)	Evolution of a publicly funded R&D network in the satellite sector in Europe
	(Broekel 2015)	Co-evolution of proximities in publicly funded R&D network in Germany with a focus on short and long term effects
	(Buchmann & Pyka 2014)	Evolution of R&D partnerships in the German automotive industry
	(Castro, Casanueva & Galan 2014)	Evolution of alliance portfolio networks in the civil construction sector in Spain
	(Gay & Dousset 2005)	Evolution of the US alliance network in the biotechnology sector along three phases of the innovation process
	(Giuliani 2013)	Evolution of a regional food cluster (wine) over a period of growth and local investment
	(Mariotti & Delbridge 2012)	Evolution of ego-networks of sport car manufacturers across Europe
	(Balland, Belso-Martinez & Morrison 2016)	Co-evolution of two networks (business and technological advice) in the Toy Valley in Spain

Nodes are individuals	(Cassi & Plunket 2015)	Evolution of the national biotechnology co-inventor network in France
	(Ter Wal 2013b)	Evolution of the German biotech industry over a shift from tacit knowledge to more codified knowledge
	(Ter Wal 2013a)	Co-evolution of two industry sectors (IT and Life Science) in a region in France

Geographic proximity is the physical distance between actors (Boschma 2005). This dimension has attracted the most attention in this sample and findings are partially conflicting. Several studies find that geographic proximity has a positive and significant effect on collaboration (Buchmann & Pyka 2014; Cassi & Plunket 2015; Castro, Casanueva & Galan 2014; Powell et al. 2005). However, there are conflicting findings with respect to its importance over time, where one study finds a positive and significant effect for all generations (Balland, De Vaan & Boschma 2013), while other results suggest that geographic proximity becomes less important over time (Ter Wal 2013b). There are interaction effects with social proximity, in that geographic proximity triggers closure (Giuliani 2013), and temporary co-location fosters the emergence of interpersonal ties (Mariotti & Delbridge 2012). In combination with organisational and cognitive proximity, the effect of geographic proximity is even stronger (Cassi & Plunket 2015). Conversely, collaborations over great physical distance may be sustained if organisational and cognitive proximity is present (Cassi & Plunket 2015). However, the physical dimension has its limits. Gay and Dousset (2005) find that geographic proximity is not required for forming highly cliquish network structures, and Ter Wal (2013a, p. 666) offers evidence from a regional perspective that “geographic proximity is not a sufficient condition for local collective learning to take place”.

Social proximity is the level of social embeddedness based on existing network structures (Boschma 2005). Similar to cognitive distance, the extant empirical findings are inconclusive. In some studies, social proximity is positive and significant for tie formation, even in different networks (business and technical advice) (Balland, Belso-Martinez & Morrison 2016), while it is positive but not significant in other studies (Balland 2012). From a longitudinal perspective, some empirical findings show that the

effect of social proximity is positive and significant over time (Buchmann & Pyka 2014), or at least “strong” and “very stable” (Balland, De Vaan & Boschma 2013), while other studies observe an increasing role of social proximity over time (Ter Wal 2013b). The latter is in line with findings from Cassi and Plunket (2015), who demonstrate that geographic, technological and organisational proximity increase the likelihood for tie formation, but that once ties are established, social proximity is the predominant network driver. Regarding interaction effects, geographic proximity is a significant driver for triadic closure (Giuliani 2013), and highly cohesive network structures do not require geographic proximity (Gay & Dousset 2005, p. 1470).

Organisational proximity refers to a shared organisational affiliation such as organisational units that belong to the same corporation or individuals that work for the same company (Boschma 2005). Here, empirical work reports that organisational proximity has a positive and significant effect over time, and that this effect remains significant but decreasing in intensity (Balland 2012; Balland, De Vaan & Boschma 2013). Concerning interaction effects, Cassi and Plunket (2015) demonstrate empirically that geographic distance matters less if individuals work for the same organisation, and that organisational distance may be compensated through geographic proximity. However, if social ties are already established, organisational proximity has little effect on the formation of additional ties (Cassi & Plunket 2015). The same study shows that over time, organisational, geographic and technological (similar to cognitive) proximity increase the likelihood for initial tie formation, but once ties are established, social proximity becomes the predominant driver for new linkages.

Cognitive proximity relates to the degree of overlap between the knowledge bases and understanding of two actors (Boschma 2005). Here, empirical studies offer a fragmented picture. For example, one study finds that cognitive proximity is not significant for the likelihood of interaction (Balland 2012), while another study finds that firms with similar knowledge bases do tend to collaborate (Buchmann & Pyka 2014). Other studies find that cognitive proximity is important for the exchange of technical advice, but not for business knowledge (Balland, Belso-Martinez & Morrison 2016), and that along an industry life cycle, the effect of cognitive proximity on

collaboration ties becomes more important during the later stages (Balland, De Vaan & Boschma 2013). Regarding other proximity dimensions, cognitive proximity interacts with geographic proximity in that cognitively distant partners tend to be spatially close, while cognitive proximity may compensate for geographic distance (Broekel 2015). In combination with organisational proximity, cognitive proximity becomes even more effective in bridging geographic distance (Cassi & Plunket 2015). With respect to tie strength, the simultaneous increase of cognitive proximity and density leads to the development of stronger connections (Gubbins & Dooley 2014).

Institutional proximity refers to shared routines, values and behaviours of a set of actors (Boschma 2005), and it has attracted the least amount of attention across the 14 selected papers. Empirical studies find that institutional proximity has a significant and positive effect on the probability to collaborate (Balland 2012), and that this effect becomes insignificant towards the later stages of an industry life cycle (Balland, De Vaan & Boschma 2013). In relation to other proximity dimensions, Broekel (2015, p. 931) finds that “organisations sharing the same institutional framework are likely to be cognitively proximate” and that the share of involved research institutes tends to become larger when the networks grow in space. In addition, Powell et al. (2005) find a homophily effect of organisations with similar governance structures, if they are located in geographic proximity.

The summarised empirical evidence shows that the five proximity dimensions affect network change and that this effect is dynamic. However, some findings are inconclusive with respect to the type of change. In particular, there is a conflict as to whether the importance of proximity is stable, decreasing or increasing over time. This raises the question of what might cause such differences in findings.

2.4.4 EXPLORING EMPIRICAL CONFLICTS

The reviewed studies differ with respect to several characteristics, which all may contribute to divergent findings. The two most discussed studies in this sample are from Balland and Ter Wal. Balland’s study concerns an interorganisational network on the global video games industry, and Ter Wal’s study investigates an interpersonal network in the Biotechnology industry in Germany. Thus, the different findings may

relate to various aspects including the industrial context, the location of the study, methodological differences, and the longitudinal research design.

The level of analysis refers to the distinction between interpersonal and interorganisational networks. Multilevel network studies investigate the correlation between two or more networks, and explore, for example, if the same construct yields the same empirical outcome across levels (Moliterno & Mahony 2011; Rousseau 1985). The distinction of network dynamics per level is important as pointed out by Phelps, Heidl and Wadhwa (2012, p. 1152) because “most studies of intra- and interorganisational knowledge networks use causal explanations from interpersonal network research and implicitly assume these explanations hold for networks of social collectives”. Rousseau (1985, p. 8) is even more specific and warns that “when the same construct is used to characterise phenomena on different levels, we risk a cross level fallacy”. Hence, it may well be that the effect of proximity on tie formation differs between interpersonal and interorganisational networks

Table 5 shows that most of the 14 reviewed studies concern interorganisational networks. A systematic review of the papers per level shows that the dynamic effect of proximity on tie formation is different across levels, but, as far as extant empirical research goes, consistent within levels (see Table 6). There are two exceptions. The effect of institutional proximity has not been investigated on the interpersonal level, and the results for organisational proximity are somewhat similar. However, the outcome of this review is inconclusive not least because of the few studies at the interpersonal level that provide little substance for comparison.

TABLE 6: DYNAMIC EFFECT OF PROXIMITIES ON TIE FORMATION ACROSS LEVELS OF ANALYSIS

	Interorganisational networks (11 papers)	Interpersonal networks (3 papers)
Geographic proximity	<i>increasing</i>	<i>decreasing</i>
Cognitive proximity	<i>increasing</i>	<i>decreasing</i>
Social proximity	<i>stable</i>	<i>increasing</i>
Institutional proximity	<i>decreasing</i>	<i>unclear</i>
Organisational proximity	<i>stable/slightly decreasing</i>	<i>decreasing</i>

The diverse range of industries under consideration may contribute to divergent findings. For instance, network dynamics across industries may differ because of different industry clock speeds, that is, the pace with which innovation occurs in different sectors (Carrillo 2005; Guimaraes 2011). In addition, the technological intensity of an industry may relate to networking patterns, since high-tech industries are more knowledge intensive than low-tech industries (OECD 2011), thus requiring different network structures to deal with the corresponding level of complexity (Hausmann et al. 2011). Moreover, the involvement of public and private organisations may differ across industries because of different commercial and policy related interests. For instance, the commercial and societal implications are rather different for the pharmaceutical industry, wine production and video game development.

The location of the study might contribute to the dynamics of innovation related networks, because innovation activities tend to be concentrated in certain locations (see Chapter 2). For instance, the availability of various resources (including knowledge workers, finance, equipment, and infrastructure) differs across places, leading to location-specific innovation dynamics. Further, the role of geographic distance for collaboration may vary across places due to specific geospatial features in the area under study. For instance, Australia and the Netherlands are somewhat similar in terms of population, but the differences in territory size, connections to other countries, and the agglomeration of economic activities, imply different dynamics in spatial networks. What is more, innovation networks may behave differently across geographic scales (McMaster & Sheppard 2008). That is, differences between regional, national, and global networks might not only relate to the differing role of distance, but also to other scale-specific features, such as local culture or the exposure to external shocks.

From a methodological view, the different operationalisation of proximities might also contribute to different results across studies. For instance, Ter Wal (2013b) measures geographic distance between actors in kilometres 'as the crow flies', while Balland, De Vaan and Boschma (2013) measure geographic proximity, not distance, but by subtracting the natural logarithm of the kilometres distance between actors from ten. Similarly, Ter Wal (2013b) operationalises social proximity as the inverse path-length

over the past five years, while Balland, De Vaan and Boschma (2013) measure it based on repeated collaboration. In addition, institutional proximity has been operationalised in different ways. For Balland, De Vaan and Boschma (2013), institutional proximity is given when actors reside in the same country, that is, they are exposed to the same cultural and legal setting. By contrast, Balland (2012) defines institutional proximity depending on an actor's affiliation with industry, academia or the government.

In longitudinal studies, the period covered should match the length of the phenomenon under investigation (Ployhart & Vandenberg 2010). Empirical results may differ across studies, as they investigate different phenomena over different periods. For instance, Gilsing, Cloudt and Roijackers (2016) explicitly explore network dynamics along three phases across 25 years of technological development in biotechnology, while Buchmann and Pyka (2014) assess network change in the broader context of the automotive industry over five years, without any explicit phases or milestones. Moreover, longitudinal network studies that rely on primary data usually do not cover more than two observations (Balland, Belso-Martinez & Morrison 2016; Giuliani 2013), hence reporting less nuanced findings on network change.

The point is that conflicting empirical findings may be the result of several factors. The diversity of those studies raises doubts as to whether they are comparable in the first place.

2.4.5 GAP IN THE LITERATURE AND PLANNED CONTRIBUTION

Thus far, this review highlights four important gaps in this strand of the literature. Firstly, there is a lack of empirical studies on the dynamic effect of proximities on tie formation, in particular at the individual level. Secondly, the existing empirical studies report conflicting findings, resulting in a call for clarification. Thirdly, there are doubts whether the empirical studies are comparable in the first place, considering the manifold differences. Lastly, none of the reviewed studies concerns Australia, where the tyranny of distance is a real issue with real implications.

The authors of the proximity studies limit their claims to the empirical cases and call for more similar papers but in different contexts. For instance, Balland, De Vaan and Boschma (2013, p. 762) point out that “we need more similar studies for other types

of industries [in order to] (...) see whether the same drivers of network formation over time hold in these contexts". Similarly, Ter Wal (2013b, p. 614) notes, "it is still largely unknown what drives the dynamics of knowledge networks and how network dynamics differ across industries". The focus on different contextual settings lends itself to another important topic: the institutional context. Institutions are important in investigating economic change, because:

Economic action as social action is not unconditional. It is guided by, enabled through, and constrained by 'institutions' in the sense of accepted, existing patterns of interaction – be they related to some sort of rules and regulations or to conventions of social and economic life (Bathelt & Glückler 2014, p. 340).

In fact, there is a need to better understand the role of institutions since "many empirical studies in EEG did not pay explicit attention to the institutional contexts" (Boschma & Frenken 2015, p. 9). This dissertation addresses this gap and aims to produce comparable results to shed light on the role of institutions for network dynamics. To do so, this dissertation adopts a multi-case study approach in which the cases are similar in all aspects but one. This one aspect is the institutional context, implied by spatial borders. If, for example, the results show that the effect of proximity on tie formation is synchronous across space and time, the institutional context might not matter as much. Conversely, if the studies yield diverging results, the search for explanations can be narrowed down to the institutional context.

Taken together, this dissertation aims to contribute to the shortage of studies on the dynamic effect of proximities on tie formation on the individual level, by analysing the influence of different proximity dimensions, in order to produce novel insights on the emergence of an Australia-invented technology and its global diffusion through knowledge networks. In essence, this dissertation addresses the following research question:

What is the role of institutional context for the dynamic effect of proximity on network change along the technology life cycle?

Importantly, institutional context refers to patterns of social interaction that are specific to a location. The reference to social interaction is crucial, because institutions, whether they emerge from “purposeful constitution or unintentional emergence”, only come into existence through social practice (Bathelt & Glückler 2014, p. 346). And while social practice may diffuse across national borders “we may often be able to observe spatial differences and specialisations of institutions in comparative studies between different local, regional, or national territories” (Bathelt & Glückler 2014, p. 347).

On that basis, this dissertation compares how institutional differences in six locations relate to social practice in the form of evolving collaboration networks. This study adopts a multi-case study research design with six cases, whereby a case represents a location (5 cases focus on certain territories; 1 case concerns the global network). To ensure comparability, the six cases share that the collaboration networks under investigation are co-inventor networks (i.e. on the individual level) on CRP technology in the period between 1995 and 2012. Social practices per location are analysed using Stochastic Actor-Oriented Models, more specifically, by simulating how four different types of proximity affect network change over time. The effect of institutional proximity on network change should not be confused with institutional context. The former refers to the affiliation of an inventor to industry or academia (see section 3.3.1) and the latter refers to the location of each case.

The selection of the cases aligns with the major locations of CRP inventors. Five of the six cases are on the national and supra national level, including Australia, a group of European countries, the USA, China, and the combination of Japan and South Korea. The sixth case is the global network. The network boundaries are defined based on the location of the inventor in that a tie is included if at least one inventor resides in the focal territory. Ties between non-local inventors are excluded even if both have a tie into the focal location, meaning that the corresponding networks are researcher-constructed, as opposed to organically grown networks (Glückler 2013). This approach allows for exploring the potential influence of institutions on network dynamics.

3 METHODOLOGY

3.1 LONGITUDINAL SOCIAL NETWORK ANALYSIS

The central method of this dissertation is Social Network Analysis (SNA), deployed in a longitudinal research design. The analysis is implemented using Stochastic Actor-Oriented Models (SAOM), as SAOMs are developed for exploring network dynamics by statistic inference.

3.1.1 SOCIAL NETWORK ANALYSIS

Social Network Analysis (SNA) is intended to investigate the “relationships among social entities, and (...) the patterns and implications of these relationships” (Wasserman & Faust 1994, p. 3). Historically, SNA is a combination of social enquiry and graph theory (Moreno 1934; Moreno & Jennings 1938).

The history of SNA dates back to 1736, when the mathematician Leonhard Euler proposed a solution for the Koenigsberger Bridge Problem (Watts, Barabási & Newman 2006). The scene of the problem is a stream island in the city of Koenigsberg, today known as Kaliningrad in Russia. As shown on Figure 9 (a), seven bridges connect four landmasses, and the problem was to find “a single path that crosses all seven bridges exactly once each” (Watts, Barabási & Newman 2006, p. 2). After many fruitless attempts by the public, Euler solved the problem and proved that no such path exists. Based on graph theory, he expressed the scene as a network where landmasses are *nodes, or vertices*, and bridges are *links, or edges* (see Figure 9 (b)), and he searched for a so-called *Eulerian path* (a path that traverses each node once). For such a path to exist, there have to be two nodes, but not more, that have an odd number of connections, or in network terminology, an odd degree. Proof for the absence of an Eulerian path is the fact that all nodes have an odd degree (see Figure 9 (c)).

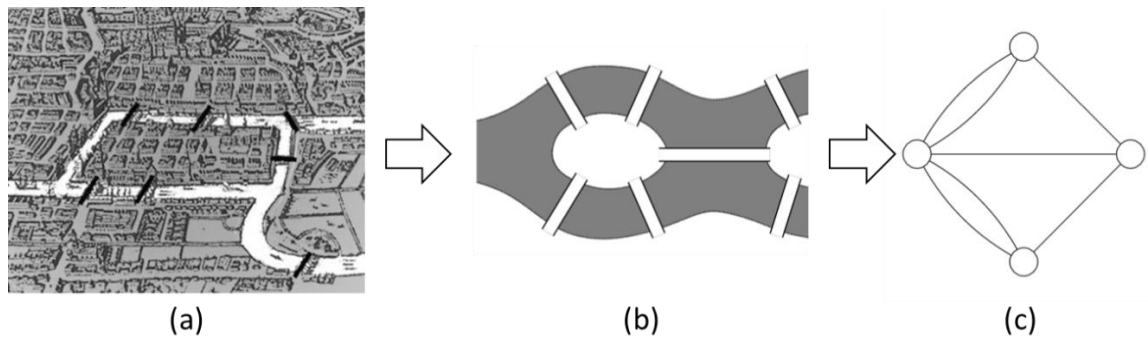


FIGURE 9: THE KOENIGSBERGER BRIDGE PROBLEM (SOURCE: WATTS, BARABÁSI & NEWMAN 2006)

Euler’s representation of a network, consisting of vertices and edges, is the cornerstone of how graph theory is used today for describing an interconnected system. In fact, nodes and edges are of interest in many disciplines, including biology, politics, computer science and social science. With respect to the latter, Moreno and Jennings (1938) presented one of the first ‘sociograms’, a network visualisation where nodes are individuals and links are nominations of some sort. Later, Solomonoff and Rapoport (1951), Barnes (1954), and Erdős and Rényi (1960) applied graph theory to investigate the spread of diseases, face-to-face interaction and the diffusion of information respectively, and thereby paved the way for network analysis in the social sciences, or what is now called Social Network Analysis.

Today, SNA is a stream of enquiry that has formed into an emerging science. The inaugural editorial of the Journal *Network Science* defines network science as “the study of the collection, management, analysis, interpretation, and presentation of relational data” (Brandes et al. 2013, p. 2). Critiques that SNA is merely a method without theory (Salancik 1995) are addressed with increasing precision (Borgatti, Brass & Halgin 2014; Borgatti & Halgin 2011). Network-related business models have enjoyed extraordinary success stories, for instance Google, Facebook and Twitter. Moreover, mainstream media acknowledges that “Networks are important because if we don’t understand networks, we can’t understand how markets function, organizations solve problems, or how societies change” (Brandes et al. 2013, p. 2). Network thinking inspires even next-generation workers because “our children no longer want to become physicists and astronauts. They want to invent the next Facebook instead” (Barabási 2012, p. 16).

A simple sociogram is based on a data matrix as shown in Figure 10. The table on the left side spans a matrix with a set of nodes, denoted with letters. A relationship is indicated with a 1 and 0 otherwise. The network visualisation on the right side plots the nodes and their relationships, forming a social network. Note that this network is undirected, which means the lines merely indicate the presence of a tie, but not the direction of flow or nomination. Another implication of being undirected is that the matrix is symmetrical. The ties in this study are undirected too, which is further explained in section 2.1.3. This basic dataset may be extended in several ways. For example, nodes may have attributes; ties may have a strength (or weight) and direction. Then, the calculation of social network statistics aims at analysing the prevalence of certain network features, for example centrality (which node has most connections?), density (how 'connected' is the network?), or homophily (do connected nodes have attributes in common?).

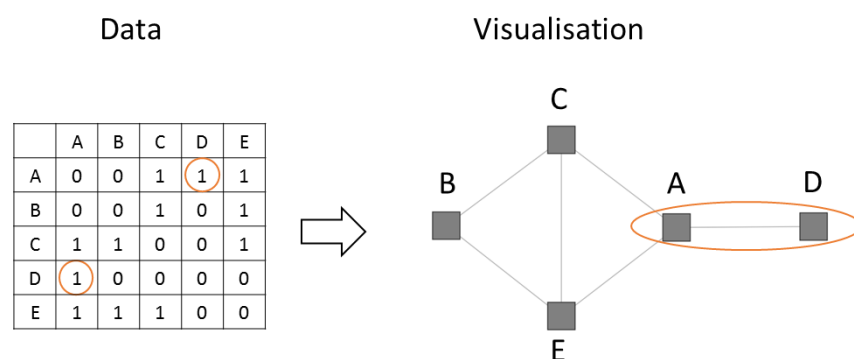


FIGURE 10: FUNDAMENTALS OF A SOCIOGRAM

SNA differs from other statistical techniques as it assumes “dependence amongst individuals” (Robins 2015a, p. 5), meaning that behaviour and other outcomes are a function of social structure, because people influence each other. In contrast, other research methods assume independent observations (Robins 2015a), in that actors make choices independent from each other. The dependence assumption can be illustrated with a popular-culture quote by the character of Jules in the movie *Pulp Fiction* (Tarantino & Roger 1994, p. 17): “Well, if you like burgers, give them a try sometime. Me, I can't usually get them 'cause my girlfriend's a vegetarian, which pretty much makes me a vegetarian.” The point is that Jules is not a vegetarian

because of his own conviction, but because of the relationship to his girlfriend. His outcome is dependent on his tie to his girlfriend.

What is more, “social relationships may be dependent on one another” (Robins 2015a, p. 4). The everyday observation that ‘a friend of a friend is a friend’ describes the situation where existing relationships influence the formation of a new one. This mechanism of network self-organisation, or closure in this example, partly explains the dynamics of social structures. This means SNA goes beyond the metaphor of a network. Instead, it is capable of analysing social structures on the micro level by considering all actors in the network and their individual relationships and attributes.

3.1.2 LONGITUDINAL RESEARCH DESIGN

Longitudinal research is a class of its own as it requires the definition of the period under investigation, the number of observations, issues of causality, and the dynamic behaviour of variables. In brief, this study covers a period of 17 years, where one year is one network observation. The overall period is divided into phases with four to five observations each to show to what extent the determinants of network change might vary across phases.

The observation period falls between 1994, the first year with noticeable activities in CRP (Destarac 2010), and 2011, which is the last complete year in the PATSTAT database from where the data is sourced. The period of 17 years is deemed appropriate for investigating the evolution of an emerging technology (Ployhart & Vandenberg 2010), as the whole technology life cycle may take between thirty to forty years (Schmoch 2007), meaning that the observed period covers around half of the life cycle.

One network observation contains all active collaborations within a certain calendar year. The resulting 17 observations are a suitable level of granularity for observing change over time (Willett 1989), as they are well beyond the recommended minimum of three observations (Ployhart & Vandenberg 2010; Singer 2002). Two observations are too few as it would limit the observable to linear changes only. Concerning the active collaborations within a year, the literature suggests that developing a patent takes 5 years on average (Powell, Koput & Smith-Doerr 1996; Shan, Walker & Kogut

1994). Conversations with informants at the Australian CSIRO (Dr Greg Simpson and Prof Thomas Spurling) revealed that the invention process could also be as short as 1-2 years, but on average is around 3 years. By combining published sources and the contextual insights, this study assumes that the invention process takes 4 years on average. Consequently, a 4-year moving window is applied (Fleming & Juda 2007; Ter Wal 2013b).

As a result, the active collaborations in any given year are composed of the patent applications of that year, plus all patents that are filed in the three subsequent years. This logic builds on the fact that the application date of a patent marks the end of collaboration, not the beginning. Therefore, the active collaborations in year t_n are represented by the patents submitted between t_n and t_{n+3} . For instance, active collaborations in the year 2000 include the patents completed in this year as well as patents submitted in the following three years, since they are under development in 2000. For illustration, a collaboration that commenced in 1998 leads to a patent application in 2002, which accordingly counts as an active collaboration in the year 2000. The application date of a patent is preferred over the grant date, because the application date is much closer to the actual development (Ter Wal & Boschma 2009).

To ensure consistency, an annual observation is only included when data for the following three years is available too, which is not the case for 2009, 2010, and 2011. That said, the year 2009 is included anyway because the patent count in 2012 is increasing despite the potential dip as indicated by PATSTAT. Thus, the last observation is 2009, making a total of 13 valid annual network observations. Figure 11 illustrates the logic for constructing the annual network observations. The horizontal axis is the timeline and the vertical axis represents the active collaborations. Again, all active collaborations in the year 2000 are represented by the patents filed in that year (orange line) and the patents filed in the three subsequent years, indicated by the grey, yellow and blue lines.

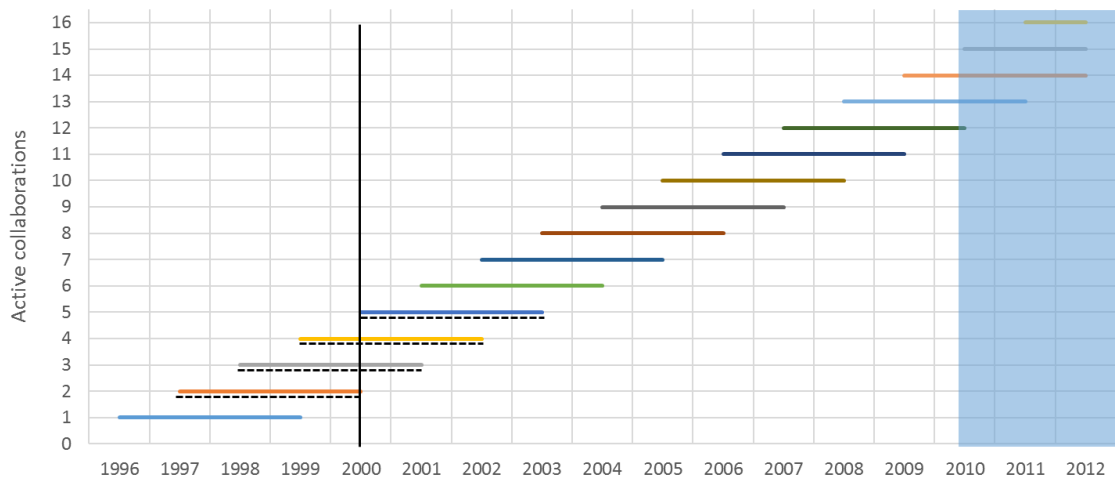


FIGURE 11: ILLUSTRATION OF AN ANNUAL NETWORK OBSERVATION

Several annual observations are combined to represent a phase in the technology life cycle. Such phases are necessary to explore whether the network dynamics and its determinants change over time. As shown in Table 7, one phase consists of five annual observations, whereby the change from one year to the next is denoted as a wave. Note that the phases are overlapping to ensure that one phase begins where the previous ceased (Cantner, Meder & Ter Wal 2010).

TABLE 7: PHASES OF NETWORK CHANGE

	Phase 1		Phase 2		Phase 3		Phase 4	
	from	to	from	to	from	to	from	to
Waves	1996	1997	1999	2000	2002	2003	2005	2006
	1997	1998	2000	2001	2003	2004	2006	2007
	1998	1999	2001	2002	2004	2005	2007	2008
	1999	2000	2002	2003	2005	2006	2008	2009

In contrast to cross sectional studies, issues of causality require special attention in longitudinal studies as the equation is extended by the temporal dimension (Ployhart & Vandenberg 2010). On the one side, a variable may influence itself over time. For example, the contributing factors for a child’s IQ not only include the IQs of the parents, but also the child’s IQ in the past. In this study, structural network variables

influence themselves, as the structure of the network in t_x may influence the network structure in t_{x+1} . On the other side, the length of the time lag between cause and effect may lead to different outcomes (Gollob & Reichardt 1987). For example, smoking has the short-term effect of causing smelly hair and clothing, but also a potential long-term effect of contributing to certain types of diseases. In this study, the time lag between network observations is one year. By implication, potential effects with a different time lag are not captured.

As the dependent variable of the collaboration network may change, the independent variables may change too. For instance, organisational proximity will change if an inventor files a patent with a different organisation. That said, research on labour mobility suggests that employer-employee networks tend to be “rather stable” over time (Collet & Hedström 2013, p. 292), which resonates with the CRP-dataset of RAFT, in which only 24 out of 767 inventors changed employers during the entire period. Changing employer may result in a change of location of the inventor, but that mostly occurs in the same region, as found by Breschi and Lissoni (2009). To account for those minor but important dynamics, the independent variables in this study are defined as stable within a phase and dynamic across phases.

In summary, the collected dataset covers 13 annual network observations, divided into 4 phases, which represent around a half of the CRP technology life cycle. The independent variables are stable within and dynamic across phases. The longitudinal research design in combination with the variables definition (see section 3.3.1) are the input for the Stochastic Actor-Oriented Models.

3.1.3 STOCHASTIC ACTOR-ORIENTED MODELS FOR ANALYSING NETWORK DYNAMICS

This study adopts Stochastic Actor-Oriented Models (SAOM) for investigating the evolution of the CRP co-inventor network. SAOMs are designed “to represent network dynamics on the basis of observed longitudinal data, and evaluate these according to the paradigm of statistical inference” (Snijders, van de Bunt & Steglich 2010, p. 44), and thereby clearly align with the purpose of this research work. SAOMs are seen to be at the cutting-edge of statistical network models, and are seen as *the* method of choice for longitudinal network data (Snijders 2011).

SAOMs are particularly useful for this study for the following reasons (Snijders 1996; Snijders & Koskinen 2010; Snijders, van de Bunt & Steglich 2010). Firstly, SAOMs assume agentic behaviour, which means that individuals control outgoing ties. Individuals choose the option with the highest expected utility, which means they may or may not form or terminate their network ties. Secondly, SAOMs are capable of analysing network change over time, and the underlying causes for it. Thirdly, the population of the CRP co-inventor network is within a few thousand nodes and manageable by the computational performance of the accompanying software application. Fourthly, SAOMs allow for simultaneously testing the influence of various independent variables on network evolution, thereby disentangling the effects of different network drivers, for instance proximity dimension as in this study. Finally, relevant empirical studies also employ SAOMs (Balland 2012; Balland, De Vaan & Boschma 2013; Cassi & Plunket 2015; Ter Wal 2013b), thus adopting SAOM facilitates cross-study comparisons.

The only other statistical SNA techniques which support the analysis for longitudinal network data are Gravity Models (GM) and Exponential Random Graph Models (ERGM) (Robins 2013; Snijders 2011). However, GMs are unsuitable for this dissertation, as the model does not assume agency of actors (Broekel et al. 2014), which is vital for this research work. ERGMs are tie-based models and do not assume agency either (Lusher, Koskinen & Robins 2013; Wang et al. 2009). ERGMs are mainly used for cross-sectional data and the functionality for longitudinal analysis is just being developed. At this stage, ERGMs may only analyse longitudinal network data with two time points. A new type of ERGMs, so-called STERGMs (“separable temporal ERGM”) are designed for “modelling and simulation [of] networks that change over time” (Carnegie et al. 2015, p. 502), but the corresponding software is under development⁹ and little supporting material is available (Butts, Leslie-Cook & Krivitsky 2016; Krivitsky & Handcock 2014).

⁹ Version 0.9 of the corresponding software package was released in January 2016

3.1.4 DETAILS ON STOCHASTIC ACTOR-ORIENTED MODELS

A group of scientists led by Tom Snijders, and including Ruth Ripley, Christian Steglich, and others, have been developing SAOMs since 1996 (Snijders 1996). Thus, this section on functionality, model assumptions and specifications refers in large part to their work in this space (Ripley et al. 2017; Snijders 2005, 2015; Snijders & Pickup 2016; Snijders, van de Bunt & Steglich 2010).

To begin, the longitudinal nature of SAOMs allows for disentangling effects of social selection and social influence (Steglich, Snijders & Pearson 2010). Broadly speaking, social selection refers to social processes that explain why social ties emerge (Robins, Elliott & Pattison 2001), and social influence refers to explanations of how actors influence one another through existing ties (Robins, Pattison & Elliott 2001). For illustration, Figure 12 shows an example from a study by Steglich, Snijders and Pearson (2010) on substance abuse amongst students, which shows that over time, students with common preferences on substance use (colour coding) select each other as friends and form new ties (= Social Selection), while existing friends with different preferences in time 1 may influence each other and share the same preference in time 2. Whilst the option is available in SAOMs, there is no need to combine selection and influence in the same study. This study focusses on selection only, since it aims to explain the emergence of the CRP co-inventor network. Social influence is not part of this study.

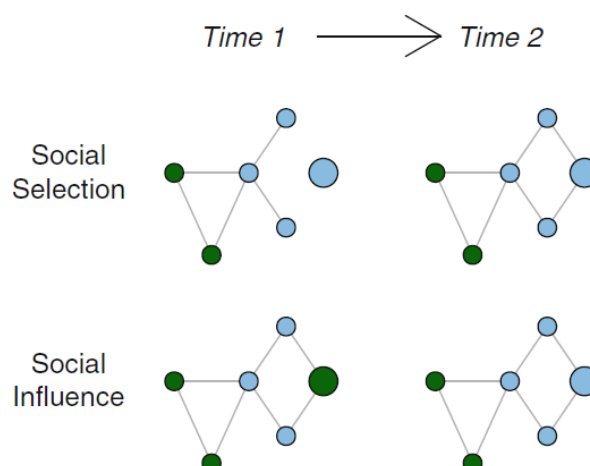


FIGURE 12: COMPARISON OF SOCIAL SELECTION AND SOCIAL INFLUENCE (SOURCE: LUKE 2015)

Put intuitively, SAOMs allow for statistically investigating the role of several underlying social processes for network change. For illustration, let us consider two network observations of a friendship network. Over time, some friendships might have formed, while others disappeared; some groups might be more densely connected, and some individuals separate themselves from the rest. In such a setting, SAOMs can analyse what underlying social mechanisms have led to the observed change. Frequently observed social mechanisms include homophily (the tendency to prefer similar others), closure (the tendency to link up with friends of friends) and popularity (the tendency that popular individuals receive more friendship nominations). SAOMs offer statistical means for exploring the occurrence of various social processes in an observed network, by estimating certain parameters based on the following assumptions.

A central assumption of SAOMs is that actors possess agency and control outgoing ties, hence the model is actor-oriented. Actors consciously choose to keep, create or dissolve a tie, which implies that actors understand their own network position, the attributes of others, and the rest of the network. In addition, the time variable t is continuous. This assumption implies that network changes between two observations do not occur at once, but rather as a continuous process with incremental, so-called mini-steps. A mini-step is an opportunity for an actor to change (or maintain) out-going ties, and according to this assumption, every actor has this opportunity between two observations. This feeds into the modelling process which represents network change as a Markov Chain, which is a random process, hence the model is called stochastic. The Markov Process assumes that actors have no memory and operate on the current state, which implies that the current network, not the past state, influences its future composition (Norris 1997). Snijders, van de Bunt and Steglich (2010, p. 46) acknowledge this shortcoming by stating that “this is an assumption that will usually not be realistic, but it is difficult to come up with manageable models that do not make it”.

Figure 13 illustrates the model’s assumptions (Block & Steglich 2015). Let t_1 and t_2 be two network observations, with four dyadic changes in the meantime. The model assumes agency in that actors choose to create two ties (blue dotted lines), to dissolve two ties (red dotted lines) and to keep all other ties. The assumption of continuity

implies that the network change occurs in a sequence of mini-steps (see blue arrows). This sequence follows a Markov chain process, where each step creates a new state of the network, which then informs the choice of the next actor (Ripley et al. 2017). For example, the new tie after step 1 is present when the next actor opts for the dissolution of a tie in step 2. Taken together, SAOMs identify the delta between two network observations and simulate the observed mini-steps repeatedly for estimating the likelihood of various microdynamics that ‘could have’ caused the network change (Ripley et al. 2017).

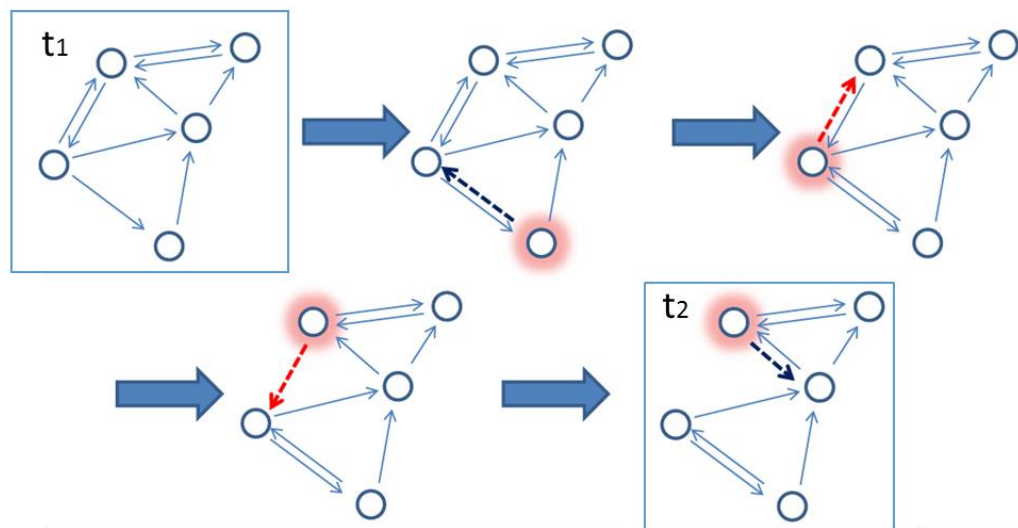


FIGURE 13: ILLUSTRATION OF THE ASSUMPTIONS OF SAOM'S (SOURCE: BLOCK & STEGLICH 2015)

The simulation of SAOMs uses two important functions, the rate function and the objective function (Block & Steglich 2015). The *rate function* captures the pace of network change. It operates on the individual level and depends on the observation period, the actor attributes and the current network position (Snijders & Koskinen 2010). The estimated parameter of the rate function indicates the probability for the opportunity that an actor may change her outgoing ties (Snijders & Koskinen 2010). On that basis, the *objective function* captures the direction of change. When it is an actor's turn, the objective function estimates which decision is most attractive, and thus most likely, from this actor's view, considering the current network configuration (Block & Steglich 2015). The objective function is central to SAOMs as it answers the research

question or in the words of Snijders, van de Bunt and Steglich (2010, p. 47) “it represents the ‘rules for network behaviour’ of the actor”. In order to answer the research question of this dissertation, the next section explains how SAOMs are used for analysing the CRP co-inventor network.

3.2 DATA

This dissertation relies on the patent data on CRP technology, extracted from the international PATSTAT patent database. After providing some background on CRP, this section outlines the rationale for patent data, the data sources and the process for preparing the data for SNA using SAOMs.

3.2.1 THE STUDY CONTEXT: CONTROLLED RADICAL POLYMERISATION TECHNOLOGY

Essentially, the word polymer “means ‘many parts’ and designates a large molecule made of smaller repeating parts” (Rudin 1982, p. 2). Chemists distinguish between organic and synthetic polymers. The former refers to molecules in organic materials such as wool, silk or natural rubber, and the latter refers to synthetically created polymers, for example those found in Nylon string and Teflon coating. The functionality of a polymer is a function of its “sites that are available for bonding to other molecules under specific conditions of the polymerisation reaction” (Rudin 1982, p. 8). A high number of available bonding sites allows for creating macromolecular chains with a relative high molecular weight, making robust and durable materials. Generally speaking, synthetic polymers are superior to organic polymers in many applications, because chemists can dictate the polymer weight.

Synthetic polymers are widely used in adhesives, agriculture, renewable energies, biotechnology, chemicals, coatings, medicine, rubber and fibres, and oil and gas based industries, hence fundamental improvements in making synthetic polymers, as in the case of CRP, have a potentially high impact for producers and consumers of such products. Almost 50% of all commercial synthetic polymers worldwide are made using the technique of Free Radical Polymerisation (FRP) (Matyjaszewski & Spanswick 2005), the predecessor of CRP, which has advantages over other polymerisation processes, but it has limitations too. In particular, FRP is limited in the preparation of well-defined polymers with respect to “molecular weight, polydispersity, composition, chain

architecture” (Matyjaszewski & Spanswick 2005, p. 26). Controlled Radical Polymerisation is a new technological approach that has been developed to address these limitations.

The empirical case of this dissertation, Controlled Radical Polymerisation (CRP) technology, is ‘a process for making better polymers’. This slogan was originally introduced by Australia’s CSIRO for promoting their invention of RAFT (Reversible Addition-Fragmentation chain-Transfer polymerisation), one particular type of CRP (CSIRO 2016), but the same idea also applies to the two other major members of the CRP-technology family: Atom Transfer Radical Polymerisation (ATRP) and Nitroxide Mediated Polymerisation (NMP). CRP also includes other forms of reversible deactivation radical polymerisation, but they are not considered in this research work. Over the years, NMP has been superseded by ATRP and RAFT, but NMP is still considered in this study as it played an important role for several years. Figure 14, below, illustrates some molecular structures attained through CRP technology.

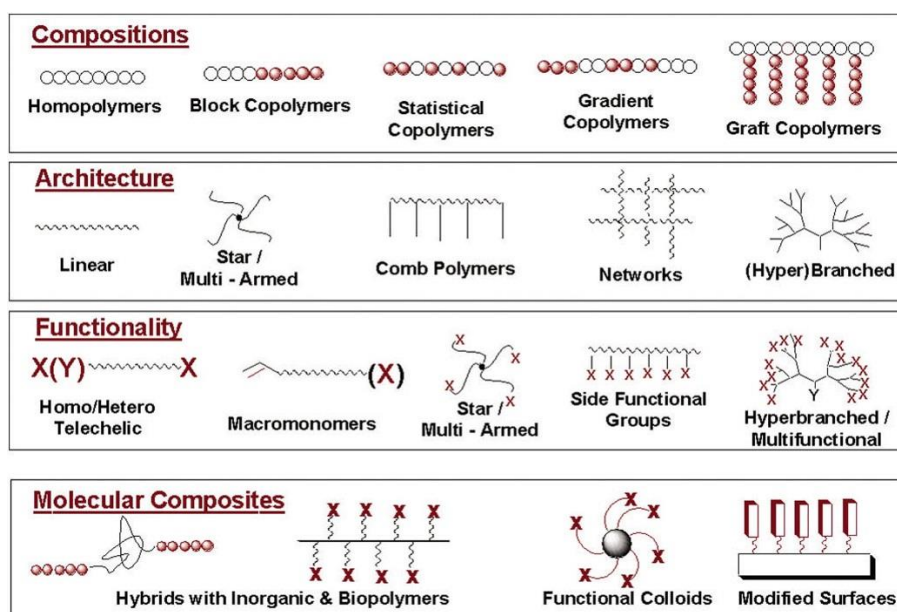


FIGURE 14: EXAMPLES OF MOLECULAR STRUCTURES ATTAINED THROUGH CRP (SOURCE: MATYJASZEWSKI & SPANSWICK 2005)

A common feature of all CRP types, including the three types considered in this study, is that they “rely on a dynamic equilibration between tiny amounts of propagating radicals and various types of dormant species” (Matyjaszewski 2009, p. 4). Conversely,

the major difference between the three CRP types is the way by which dormant species are activated to initiate the polymerisation process (Matyjaszewski & Spanswick 2005, p. 27). NMP works with “thermal dissociation of dormant species”, ATRP with “transition metal activation”, and RAFT with “active radicals” (Matyjaszewski & Spanswick 2005, p. 27). These differences are critical from a commercial perspective. The copper in ATRP is readily purchasable, but residual copper after the polymerisation process may cause environmental issues. The active radicals in the case of RAFT are commercially available too, but only to a few organisations that license the corresponding patents, which also creates both constraints and opportunities for suppliers and users. Further technical details about CRP go beyond the scope of this thesis and are available, for example, in the *Handbook of radical polymerization* (Davis & Matyjaszewski 2002).

The commercial impact of CRP becomes vividly noticeable when considering its industrial applications. For example, the US-based company *Lubrizol* created an innovative lubricant based on the addition of an additive polymer prepared using RAFT. Conventional lubricants change their viscosity as a function of temperature, resulting in an increasing risk of wear and fatigue under particular high and low temperatures. The new lubricant is less sensitive to temperature variations and features a high viscosity index and low temperature fluidity leading to improved efficiency, durability and productivity (Lubrizol 2017a). According to Lubrizol (2017b) the new lubricant leads to an improved transmission efficiency of 3-4% and an improvement of vehicle fuel economy by 0.8%.

In another example, the consumer-products company *Unilever* uses RAFT for improving the effectiveness and cost profile of personal care products such as shampoo, hair conditioner, and leave-on products for skin care (Burry et al. 2008). In this context, the challenge is that so-called *benefit agents* like perfume, flavour or wax, are not only expensive ingredients, but also less effective when applied in large amounts; thus, *Unilever* seeks to minimise the dose, while maintaining effectiveness. Here, RAFT polymers act as a delivery system to benefit agents, which reduces the amount needed, thereby reducing costs and maximising effectiveness. Inspired by such improvements, numerous large companies are excited about CRP and invest into

research and development in a variety of fields, for example, in chemistry (see *BASF, LG Chemistry, Mitsubishi Rayon, Wacker Chemie*), rubber (see *Goodyear, Continental*), textiles (see *Rhodia*), adhesives (see *Tesa*), life science (see *Bausch & Lomb, Novartis, Biomerieux, DSM IP Assets*) and paint (see *Dulux, Dupont*).

In terms of the broader industry context, most CRP applications centre on the end of the value chain in the form of polymers, specialities and active ingredients (see Figure 15). The value chain in the chemical sector features multiple streams, including both final and intermediate products (Kannegiesser 2008). From a sequential perspective, the value chain begins with basic substances (i.e. oil and gas) which are refined into petrochemicals, and then transferred into basic chemicals, which serve as the basis for polymers. The polymers themselves are further processed into various performance and speciality chemicals, or agrochemicals (Kannegiesser 2008).

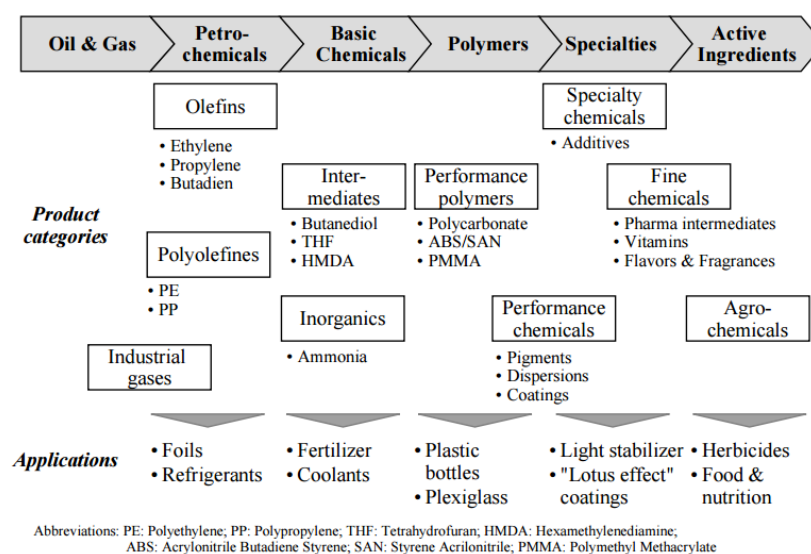


FIGURE 15: CHEMICALS VALUE CHAIN (SOURCE: KANNEGIESSER 2008)

The place of a product on the value-chain has implications for the role of innovation. Products in the early stages are typically commodities that are traded in larger volumes and at a lower unit value, but with every value-adding step, the complexity of the product increases, leading to higher investments into R&D and marketing (OECD 2012b), and this generally increases the unit price and profit margin on the product. The engagement opportunities in the chemicals value chain are somewhat place-dependent. For instance, countries with large territories such as the USA, China or

Australia are less dependent on foreign supplies for chemical feedstock and source 80 to 90 percent of their raw inputs domestically (OECD 2012b), providing opportunities for local companies in that sector. In contrast, countries that produce products closer to the end-consumer operate in the later stages of the value chain and capture relatively more value for their goods and services (OECD 2012b). For example, Switzerland sources more than two thirds of their inputs from international markets, but life science companies such as Novartis are highly profitable.

CRP technology is suitable for exploring the evolution of collaboration networks for at least three reasons. Firstly, social interaction of the scientific community matters for the spread of CRP. This is also true for other technologies, but it is an important precondition for investigation of underlying collaboration networks. CRP meets the definition of technology as it reduces uncertainty with respect to a cause and effect relationship that enables the creation of novel products (Rogers 1983). By way of illustration, the accumulated knowledge on CRP explains the effect of certain ingredients and process parameters on the polymerisation process and the resulting material. Thus, CRP related knowledge carries a commercial value which sparks the desire of both industry and academia to advance and acquire this technology, leading to the action and interaction of scientists.

Secondly, CRP has come a long way in terms of geographic spread. RAFT was invented in Melbourne, Australia, ATRP in Pittsburgh, USA, and NMP in Ontario, Canada, and nowadays the three types are being used in most nations with an advanced chemical industry, including several European countries, the USA, China, South Korea, Japan and Australia. By implication, CRP related knowledge *travelled* from one place to another and the distribution of CRP knowledge is geographically uneven, as there are also many places where CRP is not being used. The resulting geographic dimension of CRP provides an interesting opportunity for exploring the role of geographic proximity for the emergence of collaboration networks. It should also be noted that RAFT and ATRP were invented in public research organisations, but the techniques were later adopted by companies, hence providing scope for investigating other forms of proximity such as organisational proximity.

Thirdly, CRP has history. NMP, ATRP and RAFT were invented in the early and mid-1990s, so it has been explored and advanced for more than 20 years. In this period, different generations of scientists worked on it, companies adopted and rejected it, governments adjusted their innovation policies, and market trends took their course. Broadly speaking, the technological advancements are driven by the desire to exploit the commercial and scientific potential of CRP, but are also impeded by technological challenges and other constraints, such as the enforcement of intellectual property rights. Those ups and downs provide an interesting empirical case for studying the evolution of the underlying collaboration network along the phases of the CRP technology life cycle.

Taken together, CRP technology is an example of a scientific discovery which, when applied properly, allows industry actors to improve their offers. Some companies have adopted CRP already, while others have not. Products that utilise CRP sit at the knowledge-intensive end of the value chain, which implies that access to knowledge and interactive learning is likely to play a role for technology diffusion. Over the years, CRP has spread from a few to many locations, thus it represents a suitable case for studying the evolution of knowledge networks across space and time. The investigated knowledge networks in this study concentrate on the three commercially promising types of CRP: RAFT, ATRP, and NMP.

3.2.2 DATA TYPE: PATENTS

This study uses patent data. In short¹⁰, “a patent is a legal title protecting an invention” (WIPO 2008, p. 18). Patents are a way for inventors to achieve a commercial reward for their efforts. Essentially, a patent is a bargain with government, which grants the patent holder the exclusive rights to make, use, offer or sell the invention (Daizadeh et al. 2002). Exclusivity means that the patent holder has the ability to “tell others to stop” (Hann 2013, p. 1) for up to 20 years (WIPO 2008).

¹⁰ In detail, “a patent is a document, issued, upon application, by a government office (or a regional office acting for several countries), which describes an invention and creates a legal situation in which the patented invention can normally only be exploited (manufactured, used, sold, imported) with the authorization of the owner of the patent. ‘Invention’ means a solution to a specific problem in the field of technology. An invention may relate to a product or a process. The protection conferred by the patent is limited in time (generally 20 years).” (WIPO 2008, p. 17).


<p>Synthesis of dithioester chain transfer agents and use of bis(thioacyl) disulfides or dithioesters as chain transfer agents WO 1999005099 A1</p>	
<p>ABSTRACT</p> <p>This invention relates to the synthesis of dithiocarboxylic acid esters by reaction of bis(thioacyl) disulphides, thioacetals or vinylidene bis(thioether) with free-radicals (optionally in the presence of monomers). The invention also relates to processes for the synthesis of polymers utilising these dithioesters as polymerisation regulators (chain transfer agents) or to the use of bis(thioacyl) disulphides to generate dithioester chain transfer agents in situ.</p>	
<p>Publication number Publication type Application number Publication date Filing date Priority date </p>	<p>WO1999005099 A1 Application PCT/AU1998/000569 Feb 4, 1999 Jul 20, 1998 Jul 21, 1997</p>
<p>Also published as</p>	<p>CA2337339A1, 5 More »</p>
<p>Inventors</p>	<p>Enzio Rizzardo, San Hoa Thang, Graeme Moad</p>
<p>Applicant</p>	<p>Commonwealth Scientific And Industrial Research Organisation, 1 More »</p>
<p>Export Citation</p>	<p>BiBTeX, EndNote, RefMan</p>
<p>Patent Citations (3), Non-Patent Citations (1), Referenced by (77), Classifications (18), Legal Events (17)</p>	
<p>External Links: Patentscope, Espacenet</p>	

FIGURE 16: EXAMPLE PATENT (FRONT PAGE) – THE FIRST PATENT ON RAFT

Patent data contains the data recorded in a patent application, including information on the invention, the inventors, added information by the examiners, and, if approved, the data for maintaining the validity of the patent rights. For an example, see Figure 16. Patent data is suitable for studying the evolution of a technology-related innovation network for the following reasons. Firstly, patent data discloses “who invents with whom” (OECD 2009, p. 99) and thus allows the construction of co-inventorship networks (Breschi & Lissoni 2004). Secondly, patent data is useful for innovation related studies as it offers “unique insights in the process and outcomes of inventive activities” (OECD 2009, p. 3). Thirdly, the globally harmonised legal framework for intellectual property facilitates international studies and cross-country comparisons. For example, the so-called Patent Cooperation Treaty (PCT) prescribes the uniform processing of patent applications and has been adopted by 148 countries since 1970 (WIPO 2015). Fourthly, the systematic and long-term storage of patent data makes it particularly useful for longitudinal studies. Fifthly, this research work builds on studies that also analyse co-inventor networks (Cassi & Plunket 2015; Ter Wal 2013b), thus choosing the same type of data facilitates cross-study comparisons. Lastly, several methodological papers address the suitability of patents for SNA (Breschi & Lissoni 2004; Ter Wal & Boschma 2009), thereby placing this approach on solid methodological ground.

The limitations of patent data are well documented. Patent data only captures inventions that were filed as patent applications, which means it misses inventions that are not patented or are not eligible for patenting (Ter Wal & Boschma 2009;

Veugelers et al. 2012). This means that patent data misses certain types of collaboration, but it also means that the captured collaborations have led to something of potential commercial value. In addition, the list of contributing inventors can be incomplete or misleading, since some contributors are perhaps excluded while others with little involvement might be named (Ter Wal & Boschma 2009). However, this is unlikely to happen because, for example, according to US patent law “a person shall be entitled to a patent unless (...) he did not himself invent the subject matter sought to be patented” (USPTO 2014). Moreover, some enterprises engage in patenting tactics that go beyond the original purpose of IP protection. They use patents, for instance, for improving the firm’s reputation, as the basis for negotiations, or as a reward system for staff (Blind et al. 2006). While such behaviour may skew the patent output, such patents also require collaboration.

Another shortcoming is the potential imbalance between the private and the public sector concerning patenting activities, as indicated by a study in Europe where 93% of all patents are from the private sector (Giuri & Mariani 2005). However, more recent studies found that “European universities, (...) contribute remarkably to their countries’ patenting record” and “that academic inventors are very productive scientists, whose productivity further increases after patenting” (Lissoni 2010, p. 844). Further, the patent-intensity varies across industries, for example, the sector of ‘Manufacture of power-driven hand tools’ creates on average 109.74 patents per 1,000 employees, while this count is 15.65 for ‘Research and experimental development on biotechnology’ (EPO & EUIPO 2016). In network terms, this circumstance may allow one industry to appear more collaborative than another, which is relevant for this study since CRP is a platform technology, which is applied in various industries.

Patent data is secondary data and its main advantage over primary data is that a phenomena can be easily observed over time (Ter Wal & Boschma 2009). However, there are other types of relational secondary data available also. Patent data is favoured over data for trade networks consisting of countries and their trade flows (Cassi, Morrison & Ter Wal 2012; Smith & White 1992), because such networks are useful for aggregated economic analysis, but not for interpersonal collaboration as in

this study. Data on publicly funded R&D projects allows for the construction of interorganisational networks (e.g. ,Choi & Park 2009; Protogerou, Caloghirou & Siokas 2010), but such data is mostly country specific and thus not appropriate for a global study such as this one.

Both patent data and publications are suitable for constructing knowledge networks, but their nature is fundamentally different because scientific publications intend to share knowledge whilst patent owners intend to protect it (Dasgupta & David 1994). Also, other differences between co-authorship and co-inventorship warrant particular consideration (Ducor 2000). Academic co-authorship follows a negotiation process amongst individuals where the sequence of the authors implies importance, in that the first author played a more important role for the publication than the others, although this logic may vary across discipline areas (Breschi & Catalini 2010). By contrast, co-inventorship follows a globally harmonised legal process, at least in theory, which is agnostic to the sequence of authors and applies equally across technological fields (Breschi & Catalini 2010). Importantly, the assumption that named contributors know each other appears far-fetched for some academic papers with a high number of authors (Lissoni 2010). For instance, in a dataset on academic inventors in Italy, the maximum number of co-inventors is 21, which only applies to one patent in the dataset, while there are 23 papers with more than 21 co-authors, out of which two papers list 337 and 517 authors respectively (Lissoni 2010). In such cases, it seems unlikely that all authors know each other. Overall, patents appear more reliable and homogenous than publications, and hence more suitable for this study.

In summary, this study relies on patent data for analysing the evolution of technology-specific collaboration networks on the interpersonal level, because it is an insightful, established and economic type of data. Despite the outlined limitations, patent data “prove robust in examining macro level development in clearly defined technological or geographic areas” (Pilkington 2004, p. 762) and “provides us with considerable opportunities to study the dynamics of regional innovation networks” (Ter Wal & Boschma 2009, p. 753).

3.2.3 DATA SOURCE

The source for the patent data is the Worldwide Patent Statistical Database, henceforth PATSTAT. The European Patent Office (EPO) prepares and issues PATSTAT on behalf of the OECD Task Force on Patent Statistics with the intention “to assist in statistical research into patent information” (EPO 2016a, p. 2). PATSTAT combines the patent data from over 90 patent authorities, including USA, Japan, China, Germany, France, Australia, and South Korea, adding up to around 100 million patent records (EPO 2016c). The EPO maintains PATSTAT on an ongoing basis and issues an updated version twice a year. This study relies on the PATSTAT version from April 2014, which was the latest version at the time of data collection.

The central data element in PATSTAT is the patent application, and the application ID is the central identifier that points to other tables in an interrelated database structure (see Figure 17). Not all data elements are applicable for this study, thus attention is given to the relevant parts. The ‘Application table’ contains the application ID, the filing date, the patent kind (domestic or international), and the authority where the patent was filed. The ‘Inventors table’ contains the names of the inventors, their residential addresses and the person country code, which does not necessarily align with their nationality. The inventor may be a physical person or legal person, the latter referring to companies or other legal entities. The ‘Families table’ combines applications of the same or similar inventions. In the traditional sense, a patent family is a set of patents that cover the same invention across multiple jurisdictions.

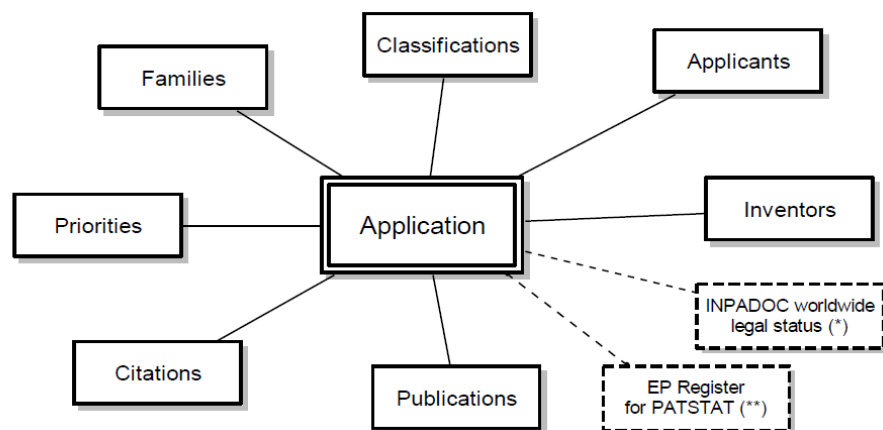


FIGURE 17: CONTENT OF THE PATSTAT DATABASE (EPO 2016A)

PATSTAT is not the only patent database for statistical purposes, but the most suitable for this global study. For instance, the OECD REGPAT database features detailed location data for region-focussed statistics, but it only covers OECD member states, excluding China which is a major patent producer in CRP (Maraut et al. 2008). The frequently cited NBER database from the US National Bureau of Economic Research is very useful for US focussed studies (Hall, Jaffe & Trajtenberg 2001), but it does not capture collaboration outside of the USA. The same reasoning applies to the CRIOS-PATSTAT database which is limited to Europe (Coffano & Tarasconi 2014). There are other global patent databases by commercial providers such as the Derwent World Patent Index by Thomson Reuters or TotalPatent® by Lexisnexis, but they are only accessible by paying a fee, thus the freely accessible PATSTAT proved to be a more amenable choice for this research work.

PATSTAT has a number of weaknesses (Tarasconi & Kang 2015), of which two are particularly relevant for this study: inconsistent inventor names and missing address data. The EPO communicates a general disclaimer that it “cannot assume any (...) responsibility for the accuracy or completeness of the database” (EPO 2016a, p. 16), but it is even more specific when it comes to inventor names:

It is very likely although not absolutely sure that one entry in this table [inventor names] represents one (and not more) person in real life. On the other hand it is quite possible that a single person is represented by multiple entries of this table due to variations in name or address or changes of name and address. Several name harmonization efforts try to reduce this ambiguity (EPO 2016a, p. 44).

In addition, the availability of address data is very poor for most patents, unless they are directly filed with the European Patent Office. For the patents submitted to other patent offices, for instance in the USA, Germany, Japan, China, or Canada, location data is missing in large parts (Tarasconi & Kang 2015). Both issues are addressed later in section 3.2.5 on data cleaning and preparation. Despite these shortcomings, PATSTAT is appealing for this project given its global coverage and cost-free accessibility.

3.2.4 DATA COLLECTION

Data collection follows three steps: defining the search specifications, gaining access to PATSTAT, and querying the database. The collected data is stored in a local database¹¹.

Step 1 - The search specifications define the boundary of the CRP network. This study adopts a *whole network design*, which “requires a single set of actors within a well-defined network boundary” (Robins 2015a, p. 52). In this study, the network boundary includes all patents that utilise CRP technology. This approach captures the entire social system (within the boundary) and it results in a whole network, that is, no nodes or relations are missing (Robins 2015a). The covered period is from 1996, since there is very limited patenting activity prior to that, until April 2014, which was the latest date in PATSTAT at the time of data collection. Importantly, the effective end-date is mid-2012, because the EPO points to a delay between the patent application date and the publication date in PATSTAT of 18 to 24 months (EPO 2014).

This approach suits a technological perspective since “technological rather than national boundaries would bear more relevance in explaining (...) industrial change” (Mina 2009, p. 448). In line with recommendations of the OECD Patent Statistics manual on tracking an emerging technology, such as CRP, this study identifies CRP-related patents “by using keywords or by searching in abstracts and patent descriptions” (OECD 2009, p. 30). By tracking a technology on the basis of search terms, as opposed to technological classifications, the choice of such search terms is of paramount importance. For this study, Dr Graeme Moad, who is an authority on CRP technology, co-inventor of RAFT, and a Chief Research Scientist at Australia’s CSIRO, provided the key words presented in Table 8, below (Moad 2015; Moad, Rizzardo & Thang 2009; Rizzardo, Thang & Moad 1998).

¹¹ The data was collected with the support of Dr T’Mir Julius, data scientist and administrator of the PATSTAT database at Swinburne University of Technology. The author of this research work is very grateful for her assistance.

TABLE 8: SEARCH TERMS FOR CRP TECHNOLOGIES

RAFT	(raft near polym*) OR (raft near agent*) OR ("reversible addition fragmentation chain transfer") OR ((dithioester OR dithiobenzoate) AND polym*) OR (trithiocarbonate AND polym*)
ATRP	(atrp) OR ("atom transfer radical" near polym*)
NMP	(NMP polym*) OR ("nitroxide mediated" near polym*) OR (alkoxyamine near polym*) OR (TEMPO near polym*) OR (SG1 near polym*)

Another criterion is the type of patent with respect to the patent family. This search only includes the so-called priority patents. A priority patent is the first patent that protects a certain invention. Other patents may protect the same invention in other geographies via other patent offices, but creating such patents is a mere administrative process and requires no additional inventive activity. As this study is concerned with collaboration instances, the focus on priority patents seems legitimate.

PATSTAT features two types of patent families, DOCDB and INPADOC¹². This search utilises the INPADOC system as it refers to “Patents protecting SAME OR RELATED inventions” (OECD 2010a, p. 11) as opposed to the DOCDB which was constructed “for patent examiners to optimise their work” (OECD 2010a, p. 11). INPADOC was a Vienna-based company that developed a global database with harmonised and well-integrated content, which was acquired by the EPO. The INPADOC patent family in PATSTAT is a legacy from this merger, and essentially provides a method for retrieving “all the documents directly or indirectly linked to one specific priority document” (EPO 2016b, p. 1). This search adopts the INPADOC system for identifying unique inventions.

This search includes inventions regardless of their value, as this study concerns the act of collaboration and its determinants, and not the commercial value of the collaborations outcome – that is, the value of the patent. For instance, the search

¹² Definition of DOCDB: Applications with exactly the same “active” priorities, understood as those adding new technical content. Definition of INPADOC: Applications directly or indirectly linked through priorities.

includes both domestic and international patents, despite the argument that international protection indicates a higher commercial value (OECD 2009). Moreover, this search is also agnostic to the examination outcome, that is, whether the patent application is granted or not, since both are the result of a collaboration (given that two or more inventors contributed to it). Therefore, both granted and not-granted patent applications are included.

Step 2 – The host organisation of this research work, Swinburne University of Technology in Melbourne, Australia, maintains a local copy of the PATSTAT database. More specifically, PATSTAT is a data resource for scholars at the Swinburne Centre for Transformative Innovation (CTI) where this project takes place. A CTI Data Scientist facilitated the data retrieval process (see acknowledgements). To query the data, the above search parameters were programmed into a query statement with a so-called Structured Query Language (SQL), namely MySQL.

Step 3 – The execution of the MySQL search statement returned the desired dataset. This dataset is stored in a local database and contains three interrelated tables (see Figure 18, overleaf). The table `till_appln` (left) is a derivation of the Application table. In addition to original columns such as title, abstract, and filing data, this table also includes flags for the three sub-technologies (RAFT, NMP, and ATRP), whether an entry represents a priority patent, and whether a patent has entered the so-called international Phase. A patent is in international phase when it is (going to be) protected in the three major economic regions of the USA, Europe and Japan. The table `till_person` (right) contains details about the inventors, including their name, address, and country of origin. The table `till_appln_person` (centre) is a connection table, which links patents and inventors with a many-to-many relationship, since multiple inventors may create one patent, and one inventor may have contributed to multiple patents. The unique identifiers, application ID (`appln_id`) for patents and the person ID (`person_id`) for inventors, are the starting point for creating a co-inventorship network which is explained in section 2.2.1, after the steps for data cleaning and preparation.

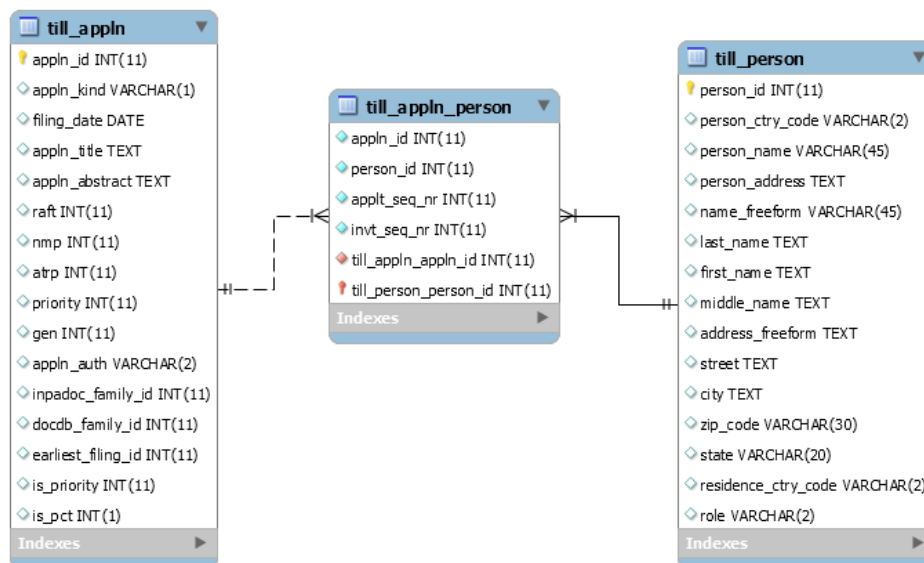


FIGURE 18: DATABASE STRUCTURE

This section has explained the implementation of data collection for this study, including the search parameters, data access and data retrieval. As mentioned earlier, PATSTAT suffers some weaknesses in terms of the inventor names and location data.

3.2.5 DATA CLEANING AND PREPARATION

This section explains the measures for making the data fit for network analysis using SAOMs. The focus is on the completeness and consistency of the data, particularly with respect to the inventor names and their geographic location. The operationalisation of variables is outlined in section 3.3.1.

3.2.5.1 INVENTOR NAMES

The problem with inventor names is that they are partly ambiguous. More specifically, the same person may appear with (slightly) different names, and the very same name may belong to different people. This is common with patent data (OECD 2009), but this ambiguity is problematic for constructing networks where each individual must be unique.

Inventor name ambiguity occurs due to several causes (Trajtenberg, Shiff & Melamed 2009). For instance, the so-called “John Smith” problem describes the issue when the very same name belongs to several distinct individuals. This issue varies by country. For example, a comparison of the USA and China shows that the three most frequent

American surnames (Smith, Johnson, Williams) make up 2.3 percent of the population, while the three most common Chinese surnames (Wang , Zhan, Li) make up 21 percent of the population (Barrai et al. 2001; Guo, Chen & Wang 2011). In the same vein, another cause for inconsistent spellings is the translation of Asian characters into western language with the Latin alphabet, where variations may occur such as “Li” and “Lee”. In addition, name variations may result from combining or omitting middle names, initials and titles.

The following steps describe how this study ensures the uniqueness of inventor names. First, the available inventor names are harmonised by removing spaces, punctuation and special characters, and by setting all letters to capitals. Duplicates are removed. Second, all names are screened in a manual effort to detect all name variations per inventor. Here, some guiding rules apply. In the case of similar names, additional data, such as location, organisational affiliation, or frequent collaborators, assist for determining whether it is indeed the same individual or not. If the same name occurs in different spellings, for example Daniel J Brunelle and Daniel Joseph Brunelle, the longer version is adopted as it contains more information. For similar Asian names, in particular Chinese names, for instance Zhang Wei and Zhang Wei Hong, the names are kept separate as advised by several Chinese co-workers. The justification is that the names are not distinct enough and sometimes do not even reveal the gender. Third, one particular name is assigned to each individual, which replaces all other name variations of this person. Finally, when each inventor has a unique name, a new five-digit identifier is created to allow for traceability in the following steps. Table 9 provides an example case before and after data cleaning.

TABLE 9: HARMONISATION OF INVENTOR NAMES

Before cleaning		After cleaning	
person_id	person_name	person_id_new	person_name_unique
7184633	Moad, Graeme	10459	MOADGRAEME
7184640	Moad, Graeme	10459	MOADGRAEME
15096547	MOAD, GRAEME	10459	MOADGRAEME
18275659	MOAD GRAEME	10459	MOADGRAEME

3.2.5.2 INVENTOR ADDRESSES

The issue with location data is that it is missing for most inventors. This study concerns different dimensions of proximity, including geographic proximity, and thus complete location data is necessary for operationalising this variable.

Some guiding rules informed the process for obtaining a complete dataset. Firstly, as suggested for this type of study (Ter Wal & Boschma 2009), location refers to the residential location of the inventor, not the applicant, since the location of the affiliated organisation does not necessarily indicate the physical location of the inventor at the time of the collaboration (exceptions apply, see below). Secondly, to specify the inventor location, this study uses the postcode, which is sufficiently precise in a global dataset. This means that street name and house number are ignored. Thirdly, to account for the possible effects of inventor mobility over time, this study records the location per inventor per patent per year. Similar to the inventor name search, the quest for location data builds on existing information and the search strategy depends on whether *some* or *all* location of a given inventor data is missing.

If *some* location data of an inventor is missing, the available location data is the first point of reference, but only if the other patent is in temporal proximity, that is, within a time frame of plus/minus two years. This is based on the assumption that the inventor has not moved locations during this period, which is in line with studies that find a low level of inventor mobility (Breschi & Lissoni 2003; Breschi & Lissoni 2009). If the patent with missing location data is temporally distant to the available data (more than two years), the organisational affiliation serves as a proxy (see next paragraph) or an internet search for the inventor's career history aims to verify the inventor location at the time of the patent.

If *all* location data of an inventor is missing, the organisational affiliation serves as a proxy. However, this is done with caution and depending on further criteria. If the organisation is a university, as in many cases, the location of the university applies, assuming that most universities have *one* main campus with research facilities and that the inventor resides nearby. Similarly, if the organisation is a Small and Medium sized Enterprise (SME) it is assumed that the R&D facilities are at the main address provided

on their website, unless indicated otherwise. However, if the organisation is a multinational enterprise, it might have multiple R&D sites across the globe (Ter Wal & Boschma 2009). In this case, an online investigation aims at identifying the R&D site, which is most likely to deal with CRP-related technologies, which is sometimes possible. Otherwise, an internet search for the inventor's career history aims to verify the inventor location at the time of the patent.

There were three patents (application ID: 40433381, 3858614, 267506487) where both the inventor location and the organisational affiliation was missing, and where the online search was not successful. In those cases, the inventor name and country of origin serve as an indicator for their location, and the inventors were assigned to the corresponding capital city (Rome, Berlin, and Seoul respectively). Although this is a somewhat far-fetched assumption, the benefits outweigh the costs in that the network is complete, and there is little harm since these patents represent separate network components in one location.

Lastly, minor modifications are necessary for the data on the organisational affiliations of inventors and their country of origin. Organisation details are available, but in various spellings. For example, PATSTAT contains three spellings of the French chemical company *Arkema S.A.*: *Arkema*, *Arkema France Societe Anonyme*, and *Arkema France*. Similar to the inventor names, the organisation names are standardised by removing special characters, spaces, and punctuation, followed by the creation of an organisation identifier. The country of origin is a two-digit letter code, which is missing in some instances. If available, existing data of the same inventor fills the gaps. Alternatively, the name of the person and the location of residence are used for reconstructing the country of origin.

3.3 SAOM IMPLEMENTATION

This section describes the implementation of the proposed method. It defines the variables and outlines the longitudinal research design. Then, this section specifies SAOMs for estimating the drivers for network change.

3.3.1 VARIABLES

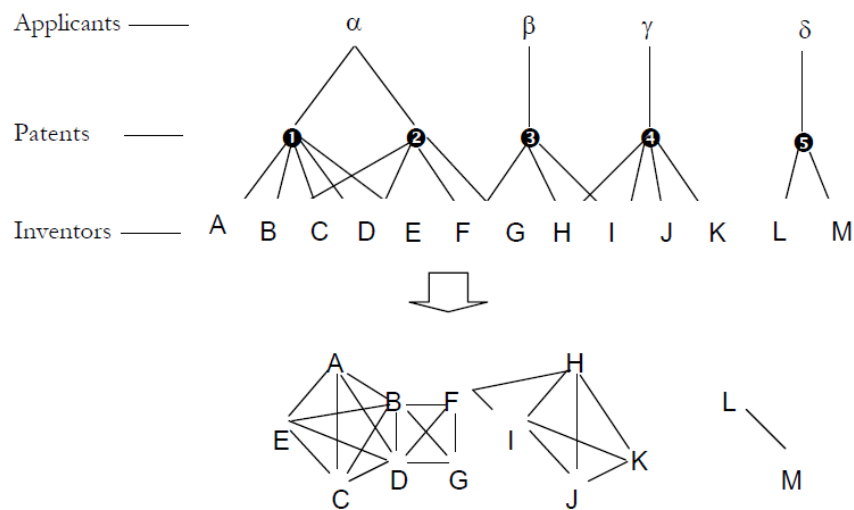
The variables in the SAOMs in this dissertation include dependent, independent, and control variables. The description of each variable contains a definition from prior studies, a detailed explanation on the computation of the variable, and a formal expression. It turns out that the operationalisation of proximities partially varies across prior studies, thus a further consideration is sometimes necessary for making a choice. Table 10 presents the variables in this study.

TABLE 10: VARIABLE IN THIS STUDY

Variables (<i>abbreviation</i>)	Definition
Dependent variables	
Tie change	Formation, dissolution or maintenance of co-inventor tie in t_n
Independent variables	
Social proximity (<i>SOC</i>)	Number of actors at distance two in t_{n-1}
Organisational proximity (<i>ORG</i>)	Same organisational affiliation in t_{n-1}
Institutional proximity (<i>INS</i>)	Same institutional context in t_{n-1}
Geographic proximity (<i>GEO</i>)	Physical proximity between nodes in t_{n-1}
Control variables	
Triadic closure (<i>TC</i>)	Controls for the tendency to closed triads
Activity/popularity (<i>A/P</i>)	Controls for degree related effects such as activity and popularity
Country of origin (<i>Cty</i>)	Controls for a homophily effect on the country of origin
Isolated nodes (<i>Iso</i>)	Controls for the occurrence of non-collaborative inventors

3.3.1.1 DEPENDENT VARIABLE

In line with Ter Wal (2013b), the dependent variable is ‘tie change’. CRP-inventors may create, dissolve or maintain ties, and thereby cause network change. Tie formation is operationalised as the one-mode projection of a two-mode network, constructed by the patent application ID and the standardised inventor ID (see Figure 19, overleaf). The projection of the two-mode network leads to two one-mode networks, one with patents and one with inventors. This study focusses on the inventor-projection, and the patent projection is discarded. Following Breschi (2004, p. 14), this study assumes that “due to the collaboration in a common research project, the [involved] inventors are ‘linked’ to each other by some kind of knowledge relation”. Section 2.2 outlines the logic for constructing co-inventor networks on an annual basis.



Top: Bipartite graph of applicants (α , β , γ , δ), patents (1 to 5) and inventors (A to M), with lines linking each patent to the respective inventors and applicants.
Bottom: the one-mode projection of the same network onto just inventors

FIGURE 19: ONE-MODE PROJECTION OF BIPARTITE CO-INVENTOR NETWORK (BRESCHI & LISSONI 2004)

SAOMs are capable of analysing two-mode networks (Ripley et al. 2017), but only if both sets of nodes are stable over time (Steglich n.d.). This rules out event-type nodes such as collaborations, or patents for that matter; thus working with the one-mode projection is necessary.

However, an undesired by-product of this approach is that one-mode projections tend to exhibit more fully connected cliques than original one-mode networks (Opsahl 2013; Wasserman & Faust 1994). For instance, a patent with four inventors leads to four simultaneously appearing triads, as in the case of patent number two in Figure 19. This side-effect tends to influence triangle-based network measures such as structural holes (Burt 1992) or clustering effects (Opsahl 2013). This issue is addressed when operationalising social proximity as explained later in section 3.3.1.2. In addition, acknowledging issues with one-mode projections is particularly important for interpreting the results.

3.3.1.2 INDEPENDENT VARIABLES

The independent variables build on the proximity approach and include social, geographic, organisational, and institutional proximity. The visualisation in Table 11

illustrates the essence of each of the independent variables. Cognitive proximity is excluded, as the data is not readily available for this project.

TABLE 11: VISUALISATION OF THE INDEPENDENT VARIABLES

Independent variable	Description	Illustration
Social proximity	The current network structure predicts future tie changes	<p>The illustration shows two panels, Time 1 and Time 2, separated by an arrow. Each panel contains a set of nodes (circles) and edges (lines). - Social proximity: In Time 1, three nodes are connected in a V-shape. In Time 2, a fourth node has joined, forming a triangle between the top two nodes of the V. - Organisational and institutional proximity: In Time 1, two black nodes are vertically aligned. In Time 2, a line connects them, and a new black node has appeared below the bottom node. - Geographic proximity: In Time 1, two nodes are connected. In Time 2, a new node has joined the existing pair, forming a small chain of three nodes.</p>
Organisational and institutional proximity	Shared nodal attributes predict future tie changes	
Geographic proximity	Spatial proximity predicts future tie changes	

Social proximity refers to embeddedness of an actor in a social context (Boschma 2005), and prior studies measure it in different ways. One study operationalises social proximity via repeated collaboration to test whether collaboration in the past predicts collaboration in the future (Balland, De Vaan & Boschma 2013). Alternatively, social proximity has been operationalised via triadic closure, which describes the effect when two nodes with a shared acquaintance form a tie, that is, they close the triad. However, this approach is inadequate for projected one-mode networks because they naturally exhibit a high level of closure. Then again, triadic closure can be captured as the inverse path length between nodes in prior periods, following the idea that how people are indirectly linked in the past may affect tie formation in the future. Here, prior studies use different time lags. Ter Wal (2013b) considers the inverse path length of the past five years, while Balland (2012) counts the number of indirect contacts at a geodesic distance of two in the past year.

While the ‘inverse path length’ approach avoids a biased closure effect in projected one-mode networks, it raises another potential issue. Ripley et al. (2016) explains that an increase in triadic closure leads to fewer indirect contacts with geodesic distance of two. However, a negative parameter of the *number of actors at distance two* effect is

theoretically ambiguous, as it may follow triadic closure, but it might also mean that ties to indirectly connected others have been dropped. For this reason, this study measures social proximity in line with Balland (2012) by adopting the *number of actors at distance two* effect, while controlling for *triadic closure* in its original form (knowing that it might be biased).

In the SAOM, both the *number of actors at distance two* effect and *triadic closure* are endogenous structural effects, which means they are computed based on the network data only (Ripley et al. 2017). The *number of distances two effect* “is defined by the number of actors to whom *i* is indirectly tied (through at least one intermediary)” (Ripley et al. 2016, p. 110).

EQUATION 1: FORMULA FOR THE NUMBER OF ACTORS AT DISTANCE TWO (SOURCE: RIPLEY ET AL. 2016)

$$s_i^{net}(x) = \{j \mid x_{ij} = 0, \max_h (x_{ih}x_{hj}) > 0\}$$

Institutional proximity refers to a common institutional setting with shared rules, structures and routines. The empirical literature offers two approaches for operationalising institutional proximity. One study refers to the triple helix model and operationalises institutional proximity when two nodes share the same institutional form, such as industry (firms), academia (including universities and public research organisation) or government (Balland 2012; Etzkowitz & Dzisah 2008; Ponds, Van Oort & Frenken 2007). Another study, covering several countries, refers to national differences as a form of institutional proximity, since common language, culture and legal regimes may influence collaboration (Balland, De Vaan & Boschma 2013). In this case, the measure is of a binary nature with a 1 when two firms belong to the same country and 0 otherwise.

This research work measures institutional proximity with reference to the triple helix model as described in the first example. This approach is favoured because it allows exploring the diffusion of knowledge from public research to the industry. With that in mind, a binary indicator is derived from the inventor’s organisational affiliation, which is 1 for public research organisations and 0 otherwise.

In the SAOM, institutional proximity is an *individual covariate*, which is an actor-bound attribute (Ripley et al. 2017). To test the effect of institutional proximity on tie formation, this model refers to the effect *same covariate*, or *sameX*, which is measured “by the number of ties of i [=ego] to all other actors j [= alters] who have exactly the same value on the covariate” (Ripley et al. 2016, p. 121). In other words, this is a homophily effect concerning the institutional form of an inventor’s organisation. Formally speaking, this effect is a function of the number of ties between i and j , where the covariates v_i and v_j are equal (see Equation 2, below).

EQUATION 2: FORMULA FOR INSTITUTIONAL AND ORGANISATIONAL PROXIMITY (SOURCE: RIPLEY ET AL. 2016)

$$s_i^{net}(x) = \sum_j x_{ij} I\{v_i = v_j\}$$

Organisational proximity refers to the affiliation of actors with the same organisation, which may influence tie formation due to mechanisms of governance, coordination and information exchange (Boschma 2005). Prior studies apply similar, but not equal measures for organisational proximity. The common focus is on the organisational affiliation of a node, but with variations depending on the type of node. For instance, Cassi and Plunket (2015, p. 943) suggest that “organisational proximity is high (...) when [inventors] patent for the same company or university”. In an interorganisational network study, Balland (2012, p. 750) offered the following definition: “two organisations share an organisational proximity if they belong to the same corporate group”, where each pair of nodes receives a 1 if they belong to the same legal entity, and 0 otherwise.

The nodes in this study are individuals and in line with prior studies (Cassi & Plunket 2015), high organisational proximity is given when inventors patent for the same organisation. To measure organisational proximity, this study derives the organisational affiliation from the patent data¹³, standardises the organisation names, and assigns a unique organisation identifier to each inventor, depending on the

¹³ This data is stored in the column *person_name*, which contains the “Name of the Applicant or Inventor” (EPO 2016a, p. 239). Practically, this column contains both the inventor names and the applicant name. For organisational proximity, the applicant name is extracted and further processed.

affiliation per year. In the SAOM, organisational proximity is an *individual covariate*, which is measured in the same fashion as institutional proximity (see Equation 2, above).

Geographic proximity refers to the effect of physical distance on tie formation. Prior studies measure this variable in different ways. For instance, one study defines geographic proximity as a function of co-location, and tracks whether nodes, organisations in this case, reside in the same country, the same major region (NUTS-1¹⁴), or the same region (NUTS-2) (Balland 2012). In contrast, two studies on co-inventor networks do not measure proximity, but distance, and do so by measuring the physical distance for each pair of nodes ‘as the crow flies’ (Ter Wal 2013b), or ‘as the crow flies’ divided by 100 (Cassi & Plunket 2015). The studies differ slightly concerning the point of measurement, in that the former study takes the distance between the capitals of NUTS-3 regions, while the latter refers to the centroid of the inventor’s postcode area. Alternatively, the natural logarithm of pairwise distance in kilometres also represents geographic distance (Buchmann & Pyka 2014), or geographic proximity, when subtracting the log of distance from 10 (Balland, De Vaan & Boschma 2013). Taking the logarithm of the distance in kilometres is important, “because distance on its raw scale exhibit[s] extreme negative skewness” (Preciado et al. 2012, p. 22).

This study follows Balland, De Vaan and Boschma (2013, p. 16), and measures geographic proximity “by the inverse of the natural logarithm of the physical distance (‘as the crow flies’) between two firms [here inventors] in kilometres”. This measure is chosen because it resembles the notion of proximity, not distance, and therefore aligns with the other proximity dimensions. In addition, it takes the logarithm of the kilometre values to account for the common skewness of raw distance measures. The distribution of the pairwise distance as logarithm determines the maximum value of 10 and minimum value of 0. Then, the log of distance is subtracted from 10 to express

¹⁴ NUTS is the European Nomenclature of territorial units for statistics and distinguishes between NUTS 1: major socio-economic regions, NUTS 2: basic regions for the application of regional policies, and NUTS 3: small regions for specific diagnoses (European Commission 2015).

proximity, rather than distance (see Equation 3, below). The interpretation of the resulting value is that the higher the value, the closer two nodes are.

To compute this variable, a process called geocoding¹⁵ converts the postal codes of inventors, which are deemed sufficiently precise considering the global nature of the study, into longitude-latitude coordinates (Goldberg, Wilson & Knoblock 2007; Hurley et al. 2003). Next, the function *geoDist* of the software packages *geosphere* computes a pairwise distance matrix with a spherical distance¹⁶ (Hijmans, Williams & Vennes 2015). Then, the distance values are logarithmised and subtracted from ten (Daraganova et al. 2012). If a value is zero, for instance, for the distance between inventors in the same postcode area, the smallest value in the dataset is inserted (Preciado et al. 2012).

EQUATION 3: FORMULA FOR GEOGRAPHIC PROXIMITY
(SOURCE: BALLAND, DE VAAN & BOSCHMA 2013)

$$PG_{ij} = 10 - \ln(dist_{ij} + 1)$$

In the SAOM, geographic proximity is a *dyadic covariate*, because the proximity matrix contains a value for every pair of actors regardless of their connections. Dynamic dyadic covariates are possible, but in this case, the variable is constant per Phase, since the individual mobility occurs to a marginal extent, and if so, mainly within the region (see section 3.1.2 on the longitudinal research design).

3.3.1.3 CONTROL VARIABLES

In addition to the outlined independent variables, other factors may also influence the evolution of the CRP co-inventor network. Thus, control variables are necessary to control for other possible explanations. A review on control variables suggests that “when in doubt, leave them out”, or put differently, clear intent is required for

¹⁵ The software package QGIS converts the postal address into coordinates (QGIS Development Team 2016).

¹⁶ The spherical distance is the “shortest distance between two points on an ellipsoid” and appears more appropriate for this global study than the two-dimensional Euclidean distance. In line with guidelines for global projections, this study applies the World Geodetic System 1984 (WGS84) (National Imagery and Mapping Agency 2000).

selecting effective control variables (Carlson & Wu 2011, p. 413). With that in mind, this study includes the following four control variables.

Triadic closure is an endogenous effect that occurs when two nodes with a common acquaintance form a tie. Triadic closure is a form of social proximity. The results of this effect are interpreted in conjunction with the *number of actors at distance two* effect (in short, two-path-effect) for social proximity. If the two-path effect receives a negative parameter, a positive parameter for triadic closure indicates that closure indeed occurred, and that the negative two-path effect is not caused by dissolved ties to indirect others. In the SAOM, triadic closure is “defined by the number of transitive patterns in *i*’s relations (ordered pairs of actors (*j*; *h*) to both of whom *i* is tied, while also *j* is tied to *h*)”: put differently, this effect counts the relational triads from a node’s perspective (see Equation 4, below) (Ripley et al. 2016, p. 97).

EQUATION 4: FORMULA FOR TRIADIC CLOSURE (SOURCE: RIPLEY ET AL. 2016)

$$s_i^{net} = \sum_{j < h} x_{ij}x_{ih}x_{hj}$$

A *homophily effect on the ‘country of origin’* controls whether an inventor’s personal background influences tie formation. This is a control variable because it is not in the focus of the study, but shared country of origin might influence the choices of inventors. This effect differs from institutional and organisational proximity in that it refers to the country of origin of an inventor, and not to the organisational affiliation or the institutional setting. The inventor’s country of origin is part of the PATSTAT database (EPO 2016a). The country of origin may or may not indicate the nationality of an inventor, but it links the inventor to the respective country regardless of the actual residential address and can be interpreted as an ethno-cultural background indicator (Breschi, Lissoni & Tarasconi forthcoming). Therefore, this effect controls for the frequently observed phenomenon that ‘birds of a feather flock together’ (McPherson, Smith-Lovin & Cook 2001). This variable is implemented with a two-digit country code and the *sameX* function explained Equation 2.

The *network-isolate effect* controls for the occurrence of isolated inventors, who have no collaboration ties (see Equation 5) (Ripley et al. 2017). This effect is necessary due

to the circumstance that all adjacency matrices are of equal size within any given phase, although not all inventors are active in every year. As a result, some inventors appear as isolated nodes in some observations. Excluding isolated nodes from the simulation, by setting them as structural zero, is not an option because of missing information as to whether a tie is not feasible or not desired.

EQUATION 5: FORMULA FOR NETWORK ISOLATES (SOURCE: RIPLEY ET AL. 2016)

$$s_i^{net}(x, z) = I\{x_{+1} = x_{1+} = 0\}$$

Lastly, a *degree effect* is included which estimates whether tie formation is driven by some very active or popular inventors (Ripley et al. 2017). The co-inventor network is undirected, thus a distinction between out-degree (activity) and in-degree (popularity) effects is indistinguishable. A degree effect is included, because firstly, the effect of pivotal actors on network change may be important considering the presence of star-scientists in the CRP inventor population, and secondly because the SAOM handbook recommends to include a degree effect to achieve model convergence (Ripley et al. 2016). Note that SAOMs are developed for directed networks, but it can estimate undirected networks too. In the SAOM, an out-degree effect is adopted because the model offers no degree effect for undirected networks, and the estimates are equal for the same in-degree effect as the adjacency matrix is symmetrical. The model adopts the *out-degree related activity (sqrt)* effect, which is defined as follows:

EQUATION 6: FORMULA FOR OUT-DEGREE POPULARITY (SOURCE: RIPLEY ET AL. 2016)

$$s_i^{net} = x_{i+}^{1.5} = x_i + \sqrt{x_{i+}}$$

3.3.2 IMPLEMENTATION IN RSIENA

This section explains the implementation of the proposed methodology in a software package called RSiena, which is designed for estimating SAOMs. SIENA stands for ‘Simulation Investigation for Empirical Network Analysis’ and runs in the environment of the statistical software package R, hence RSiena¹⁷ (R Core Team 2017). To estimate

¹⁷ In addition to *RSiena*, the code uses the commands in the R-packages *network*, *sna*, and *igraph*.

a SAOM for each phase per location, a series of programming commands is needed for implementing the steps outlined in Figure 20.

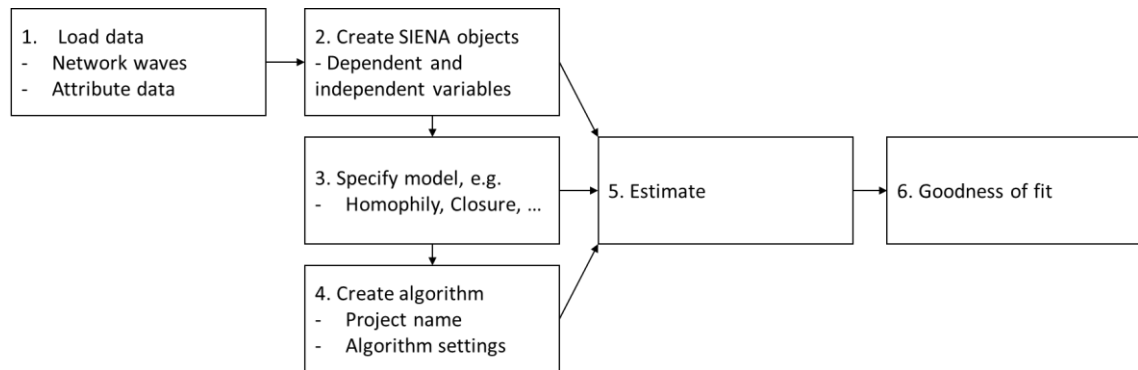


FIGURE 20: PROCESS FOR DEVELOPING A RSIENA MODEL (SOURCE: BLOCK & STEGLICH 2015)

In the first step, the RSiena imports the adjacency matrices for all network observations per phase as well as the data for the independent variables.

Secondly, *sienaNet* creates a separate array to combine the corresponding observations, and defines the network as a dependent variable. Concerning the actor-bound variables, the command *coCovar* defines the data for organisational proximity, institutional proximity, and country of origin as *constant covariate*. Geographic proximity is a *dyadic constant covariate* and is defined with the command *coDyadCovar*. Then, the function *sienaDataCreate* creates a *Rsiena object* consisting of the dependent and independent variables.

Thirdly, a series of commands call the network effects for the remaining independent and control variables. RSiena offers three classes of effects: evaluation, endowment and creation. This study follows the RSiena manual which recommends evolution effects (Ripley et al. 2016). The included effects are the *number of distances two effect (nbrDist2)* for social proximity, and *transTriads* as the control variable for triadic closure. The effect *sameX* relates to *same covariate* and represents the independent variables organisational proximity and institutional proximity, as well as the control variable on the same country of origin. Geographic proximity is a dyadic covariate. The control variable on popularity/activity is implemented with the function *between* and *outActSqrt* respectively.

Step four defines the RSiena algorithm (Snijders 2001). In line with the recommendations of the RSiena manual, the algorithm parameter *useStdInits* is set to FALSE to obtain the initial values of the RSiena object, the number of sub-phases is kept with the standard value of 4, and the function for estimating derivatives calls the score function by setting *findiff* to FALSE, as opposed to the finite differences method. In addition, the iterations in Phase 3, which estimates the covariate matrix and computes the standard errors, are set to 3000, and the model type for undirected networks is set to type 3 for ‘Unilateral initiative and reciprocal confirmation’. Equation 7 shows the algorithm specifications.

EQUATION 7: SAOM ALGORITHM SPECIFICATIONS (EXAMPLE)

```
modelAUS3 <- sienaModelCreate(useStdInits = FALSE, projname = 'SIENA  
AUS3', nsub = 4, n3 = 3000, modelType = 3, findiff = FALSE)
```

Now in step five, the function *siena07* initiates the estimation process. This function combines the data (step 2), the network effects (step 3), and the algorithm (step 4). The estimation happens in three phases. In the first phase, the parameter value is held constant for an initial rough estimate. The second phase consists of multiple sub-phases, in this study the number of sub-phases is set to 4. Here, the algorithm iteratively compares the observed network values with the estimated model and aims to minimise their deviation. This procedure is a so-called ‘quasi-autocorrelation’ where values close to zero indicate a good fit. The third phase computes the covariate matrix and the standard errors. This happens in a sequence of ‘runs’ where this study adopts the default value of 1000.

The estimation is repeated until the model converges, meaning that it achieved an acceptable “deviation from targets” (Ripley et al. 2016, p. 57). This process is facilitated by re-using the results of estimation as the starting parameters for the next estimation. To do so, the function *prevAns* is set to TRUE. In addition, the function *returnDeps* is set to TRUE to generate parameters that feed into step 6 (see below). According to the RSiena manual, the convergence is good when the *Overall maximum convergence ratio* is less than 0.25 and if the *convergence t-ratios* of all effects are less than 0.1 (Ripley et al. 2016). If the model does not converge, the Rsiena manual offers

steps for trouble shooting which are documented in the findings chapters, where applicable.

The last step concerns the so-called Goodness of Fit, or in short GOF, which tests whether the estimation is a good representation of the observed network. The ‘goodness’ of the model is partially confirmed when convergence statistics are below the aforementioned thresholds. However, the GOF verifies the fit with respect to other importation features of the network. The *sienaGOF* function retrieves the estimation results (generated by *returnDeps*), and compares the end values of an estimated period with the observed end values of a period and assesses the difference “by combining the auxiliary statistics using the Mahalanobis distance” (Ripley et al. 2016, p. 53). For details see Lospinoso (2012). The results of *sienaGOF* are visualised with violin plots where a good fit is given when the superimposed observed values (red line) are between the thresholds of the distributed model statistics (dotted lines) (see Figure 21, below). In addition, a good fit is indicated with a *p*-value greater than 0.05 (Snijders 2015). This study applies the GOF for degree effects with *OutdegreeDistribution()*, and triadic closure with *TriadCensus()* and *GeodesicDistribution()*. Since the phases contain more than three waves, time heterogeneity is also tested using the function *sienaTimeTest* (Snijders 2015).

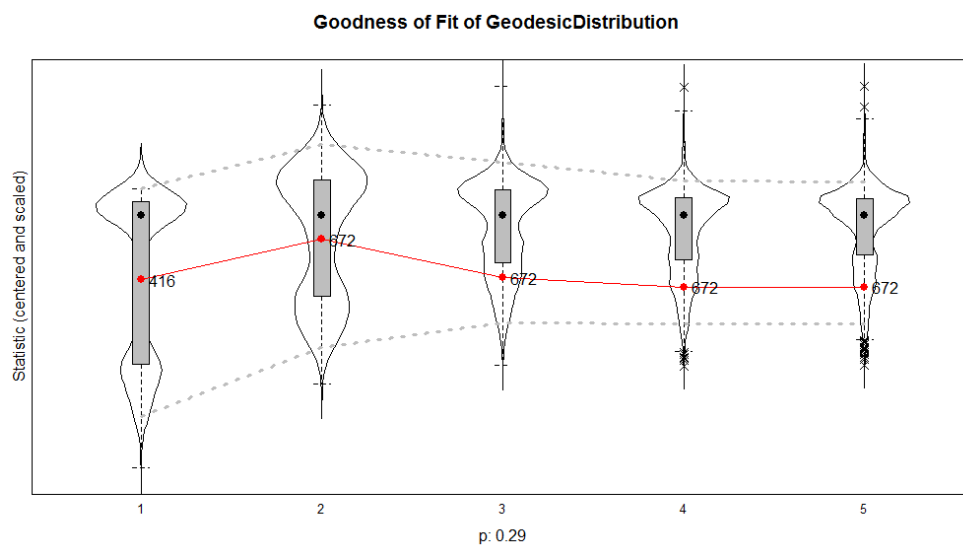


FIGURE 21: GOODNESS OF FIT FOR GEODESIC DISTRIBUTION (EXAMPLE)

3.3.3 ETHICS

This study exclusively utilises secondary data from the public record, thus ethics clearance was not required.

4 CRP TECHNOLOGY AND THE DOUBLE-BOOM CYCLE

4.1 THREE PHASES OF CRP TECHNOLOGY: A BRIEF HISTORY

This chapter demonstrates that the emergence of CRP technology resembles the double-boom cycle. Both the technological activities measured in collaborations over time as well as the qualitative insights from peer-reviewed chemistry journals indicate the occurrence of three distinct phases: initial excitement, disillusion, and a second upsurge of activities.

Figure 22 displays the tie changes of the global CRP co-inventor network over the observed period. The pace and intensity of technological activities on CRP vary considerably across territories, notably in China. China's involvement commenced relatively late, around 2000, but accelerated rapidly in the following years. Therefore, the count of maintained ties is plotted twice: with and without China, see the yellow and the grey line respectively. The widening gap between the two lines indicates the pace of change in China compared to the rest of the world. Because of this exceptional pattern, China is excluded from the longitudinal network analysis and from the descriptive statistics, since its inclusion would require a scale on which patterns in other territories are hardly visible.

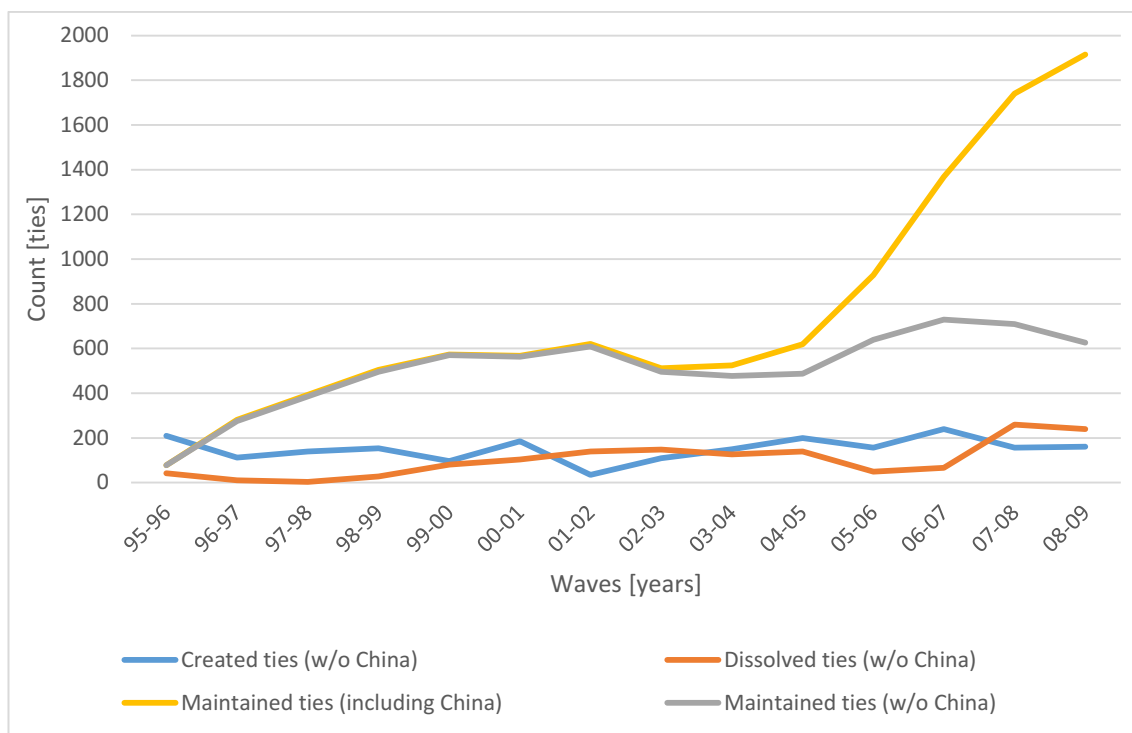


FIGURE 22: TIE CHANGES IN THE CRP CO-INVENTOR NETWORK

The central observation is that the grey line, which represents all territories but China, resembles a double-boom pattern. It begins with the initial publication of ATRP in 1995 and grows constantly until 2001-2002. Then, activities drop and reach a low point around 2004-2005. From there, a second upsurge leads to another peak around 2006-2007. In line with the general description by Schmoch (2007), the second peak is higher than the first one. The first and the second peak are separated by 5 years, which is less than the 15 years on average as reported by Schmoch (2007). The blue and the orange lines represent created ties and dissolved ties respectively. Both lines oscillate at a lower level and indicate a moderate level of network churn.

This observation is in line with CRP related literature in peer reviewed journals. The first phase of excitement is triggered by the discovery and initial publication of CRP around the mid-1990s. NMP was introduced in 1993 (Georges et al. 1993), ATRP in 1995 (Matyjaszewski, Gaynor & Wang 1995), and RAFT in 1998 (Chiefari et al. 1998). Again, other types of CRP exist, but this dissertation focusses on NMP, ATRP, and RAFT, as they have the greatest commercial potential. The new opportunities with NMP, ATRP and RAFT attracted scientists from industry and academia, leading to an upsurge in patent filings and scientific papers (see Figure 23).

are plotted against a logarithmic scale to account for the much larger absolute number of papers than patents.

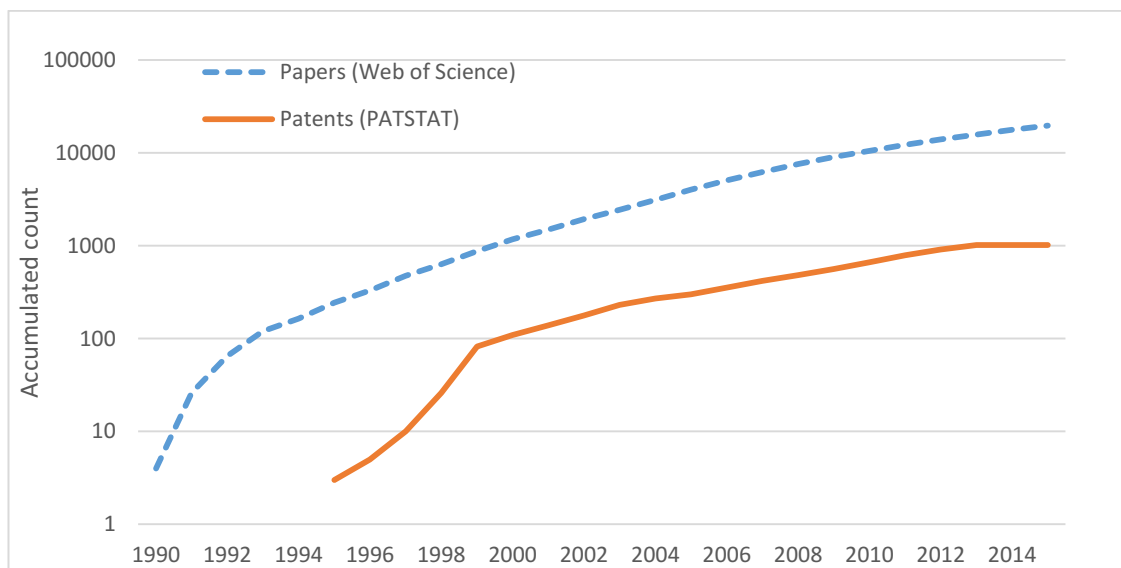


FIGURE 23: CUMULATED PAPERS AND PATENTS OF CRP OVER TIME ON A LOGARITHMIC SCALE

In this phase, leading companies were enthusiastic about the commercial prospects of CRP technology and increased their R&D spending accordingly. For example, the chemical giant DuPont increased R&D investments as the company anticipated a market greater than \$20 billion/year for CRP products (Matheson 2000). At that stage, companies explored various applications of CRP, including:

components of coatings, adhesives, non-ionic surfactants, dispersants, polar thermoplastic, elastomers, bulk performance materials, membranes, personal care products, detergents, double hydrophilic block copolymers for crystal engineering and drug delivery systems, gels and hydrogels, lubricants and additives, surface modifiers, hybrids with natural and inorganic polymers, various bio- and electronic materials (Matyjaszewski & Spanswick 2005, p. 30).

In parallel, some companies invested in infrastructure such as pilot plants for producing commercial-scale samples. Figure 24 shows a pilot plant for ATRP at the Kaneka Corporation in Kashima, Japan.



FIGURE 24: KANEKA ATRP PILOT PLANT IN KASHIMA, JAPAN (SOURCE: MATYJASZEWSKI & SPANSWICK 2005)

After the initial enthusiasm, a range of issues led to a phase of disillusion. The industrial upscaling process caused trouble because “as reactor size increases, transport phenomena such as heat and mass transfer become more difficult” (Cunningham & Hutchinson 2003, p. 356). Consequently, Cunningham and Hutchinson (2003, p. 356) suggested at the time that the commercialisation of CRP products “will likely require advances in reaction engineering technology for living radical systems”. At the same time, cost-performance and environmental problems hindered the commercialisation process. For instance, ATRP uses copper for initiating the polymerisation process, but the copper price quadrupled from less than \$1USD per pound in the year 2000 up to almost \$4USD per pound in 2007 (COMEX 2017), plus residual copper after the polymer process might cause environmental issues (Matyjaszewski Polymer Group 2008). Attempts to reduce costs by reducing or substituting copper are challenging because they affect the material functionality (Matyjaszewski 2009). What is more, patenting activities on CRP constrain access of companies to crucial intellectual property which leads to the delay or failure of some commercialisation projects (Destarac 2010). For example, the reactive agent for the RAFT process is protected by patents and available for licensing, but not all potential RAFT adopters are prepared or able to cover the corresponding fees. At this stage, technology insiders were not convinced about the commercial success of CRP, as assessed by Destarac (2010, p. 167): “based on current figures, can we conclude that CRP will not become a revolutionary method to produce medium-to-high end specialty polymers? Certainly not.”

Over time, technological advances improved RAFT and ATRP technology, leading to a second rise in R&D activities. Concerning RAFT, the limited supply of RAFT agents might be alleviated due to license agreements between the patent holder (CSIRO) and four chemical companies, including Boron Molecular (Australia), Sigma Aldrich (USA), Strem (USA), and Monomer Polymer (USA) (CSIRO 2016; Dawson 2010; Destarac 2010; PR Newswire Association LLC 2010). The deals were signed in 2010. In the meantime, those companies seem to have installed appropriate production facilities since RAFT agents can be purchased through their online stores, for example at Strem and Sigma Aldrich (Chemicals 2017; Sigma-Aldrich 2017). While the commercial availability of the RAFT agent is vital for the industrial adoption of the technology, the market price also matters, which, in the case of Sigma-Aldrich, is between \$100 and \$800 USD per gram (Sigma-Aldrich 2017). As time goes by, the initial RAFT patents reach their maximum duration of protection of twenty years (WIPO 2008); thus they are going to expire soon and the unconstrained access to some critical intellectual property might further fuel the uptake of RAFT. In addition, the ongoing research activities have tapped into some promising applications in the field of health care. For example, one project designs polymers that “can be converted into nanoparticles for drug delivery” (Dwyer 2015, p. 1), and in another project a RAFT-based polymer serves as a coating for cochlear implants (Chiefari 2015).

Similarly, ongoing research on ATRP has solved some of the aforementioned problems. In 2012, Matyjaszewski (2012, p. 4024) pointed out that “the development of higher activity catalysts and polymerization procedures (...) reduced the amount of copper down to ppm [parts per million] levels”. This improves the economic and environmental performance of ATRP, which might contribute to its commercial adoption. That said, a further reduction of copper below the 1 ppm level is required for specific electric and biomedical applications (Matyjaszewski 2012). On that front, current research explores the option to substitute copper with organic or bioinspired catalysts, as well as approaches for removing residual copper that was not consumed during the polymerisation process (Matyjaszewski 2012).

The brief history of CRP demonstrates that the technology passed through several phases of which some are full of enthusiasm while others are rather depressed. In

particular, the three phases of initial excitement, disillusion, and second upsurge correspond with the pattern of the double-boom cycle (Schmoch 2007): for an overview see Table 12.

TABLE 12: CRP TECHNOLOGY AND THE DOUBLE-BOOM TECHNOLOGY CYCLE

Characteristics of the double-boom cycle identified by Schmoch (2007)	Characteristics of CRP technology
Technological activities exhibit two peaks with a time lag of around 15 years.	Technological activities in CRP exhibit two peaks with a time lag of around 7 years.
The first peak follows a scientific breakthrough and resembles a science-push.	The first peak of CRP activities follows the discovery of CRP in the mid-1990s and is driven by a few dedicated organisations.
Technological activities decrease when difficult problems occur.	Technological activities decrease after the first peak and reach a low around 2004.
After a technological recession, activities increase again when fundamental problems are solved.	Technological activities increase again around 2007, leading to advancements, for example in ATRP on the reduction of copper.
The second peak is driven by a market-pull.	The second rise is accompanied by an increasing number of involved organisations using CRP for diverse applications.
Public research organisations tend to exhibit continuous involvement due to their funding security and long term agendas.	A mix of public and private organisations demonstrates ongoing involvement.
Commercial organisations tend to react explicitly when commercial goals are at risk and might reduce or lower involvement altogether.	In most countries, private organisations demonstrate volatile involvement, although activity peaks refer to both the count and the intensity of involved organisations.

4.2 GLOBAL ADOPTION OF CRP TECHNOLOGY

Figure 25 shows the locations of CRP inventors worldwide. A dot represents an inventor and the colour indicates the type of CRP technology. Emphasis is on the spatial distribution of inventors and technologies, over and above the actual count of inventors. Note that a dot represents an inventor *per patent*. This specification is necessary, since inventors may change location over time. Inventor mobility rarely occurs, but if it does, both locations are included. Of course, if mobile inventors are displayed more than once, the same should apply for inventors with permanent location. This will not affect the visualisation, since two dots with the same coordinates appear as one. The central point here is to focus on the spatial spread, not on the count.

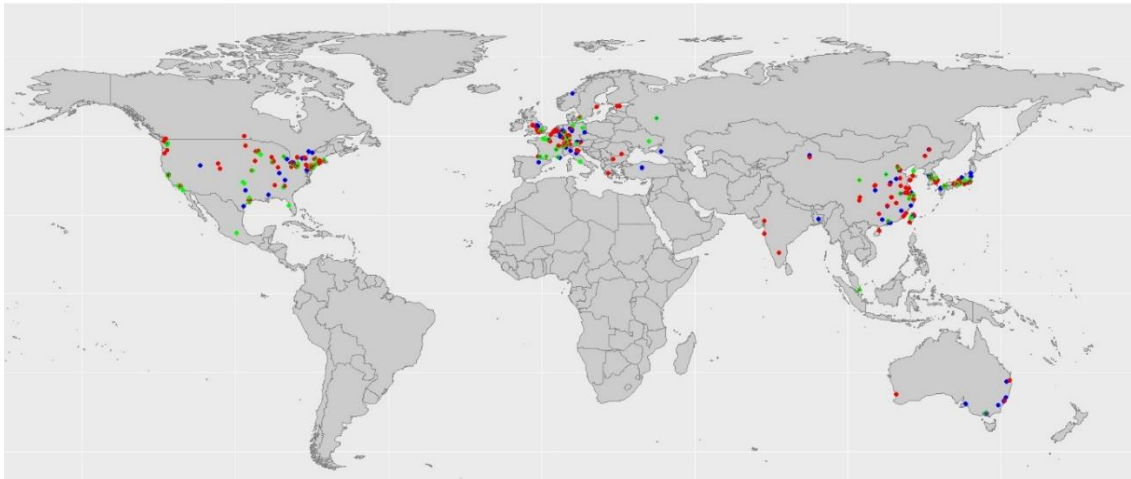


FIGURE 25: SPATIAL DISTRIBUTION OF CRP INVENTORS – WORLDWIDE (GREEN = NMP, BLUE = RAFT, RED = ATRP).

The spread in Figure 25 leads to three observations. Firstly, the plot shows that the most activities are concentrated in certain countries and regions, including the USA (greater Boston/New York area), China (Yangtze delta), Japan, South Korea, Australia (Melbourne and Sydney), and parts of Europe (France, Germany, Switzerland, the UK, the Netherlands). Secondly, the three CRP techniques (RAFT/ATRP/NMP) are represented in all major regions. That said, there is a natural dominance of ATRP because most patents in this sample are ATRP-related. Thirdly, this top level overview conveys a first impression concerning the spatial distances between potential collaborators, both within and between regions. Distance is a function of location, and is thus influenced by fundamental geographic features including the presence of adjacent countries (is it an island?), the size of the county, and the population density.

Table 13 shows complementary data on the ten patent authorities with most applications. The table format is adapted from Feldman, Kogler and Rigby (2014) and presents insights on the spatial spread, the pace of diffusion, and the anticipated commercial value of inventions. Note that the location of the patent authority (left column) does not necessarily reflect the location of the inventive activity. Some studies report a home country bias of inventors, but particularly industry patents tend to be filed in the country of the target market, which may or may not be the inventor's home country (OECD 2009).

TABLE 13: SPATIAL AND TEMPORAL SPREAD OF CRP ACROSS COUNTRIES (ADAPTED FROM FELDMAN, KOGLER & RIGBY 2014).

Location of Patent authority	Count of inventions	Year of first application	Year when 10 inventions reached	Share of patents in international Phase
China	457	1999	2003	1%
USA	174	1995	1998	18%
Japan	135	1998	1999	4%
European Patent Office	61	1997	2002	56%
South Korea	42	1998	2003	10%
France	21	1999	2003	29%
Canada	19	1998	2002	11%
Germany	18	1999	2006	0%
Australia	15	1998	2010	73%
Great Britain	10	2000	2013	80%

From a temporal view, the first patent applications in this sample were filed in the USA, Europe and Australia, in 1995, 1997 and 1998, respectively. The patents in the USA and Australia are particularly important since they represent the first patents on ATRP and RAFT. Late joiners include some European countries, such as Great Britain, France or Germany, but it might be that inventors in those countries filed earlier with the European Patent Office instead of their national patent office. By contrast, China joined in 1999, but accelerated fast with almost exponential growth. Other fast-accelerating countries were Japan and the USA, which only took 3 and 1 year respectively to file the first 10 patents. Less progressive countries include Great Britain and Australia, where it took more than 10 years to reach a count of 10 patents.

The countries with the highest share of patents in the international phase, which is a measure for estimating the commercial potential of an invention (OECD 2009), are Great Britain and Australia (see Table 13). For Australia, this observation might relate to the licencing strategy of the CSIRO, which purposely set up a patent portfolio for international licensing. The low value of Germany is surprising since it is home to several multinational chemical companies, but such firms might directly file with the European Patent Office. The same rationale ought to apply for Swiss companies, such as Ciba Specialty Chemical, which is a major CRP patent producer, but the Swiss patent office does not even appear amongst the top ten. In addition, China and Japan also stand out with a low international share of 1% and 4% respectively. In the case of China, this might be due to the high share of academic inventors who might not pursue

commercial goals in the first place. In Japan, the low share of international patents is surprising, since most chemical companies in Japan are large and export oriented.

A central aspect of this dissertation is the relationship between institutional context and network change across locations. The selection of such locations is achieved by dividing the global dataset into subsets depending on the areas with a high density of CRP inventors. The areas of high density do not necessarily stop at national borders, thus some selected locations cover multiple countries. To use consistent terminology regardless of whether it is one or multiple countries, the areas of high density are henceforth referred to as territories or locations. The territories are Australia, the USA, Europe¹⁸, China and the pair of South Korea and Japan. Figure 26 shows to what extent the double-boom cycle is prevalent in those territories, excluding China because of its extreme evolution. A collaboration tie is counted if at least one inventor resides in the focal territory. The count of collaboration ties is also important because network change is the dependent variable for the SAOMs and because the independent variable on social proximity is endogenous, that is, it captures how past ties influence future ties.

The European case is the best fit to the double-boom cycle (see Figure 26; left graph), which aligns with the fact that Schmoch's original paper refers to European data (Schmoch 2007). That said, other territories also exhibit a double-boom pattern, but with different intervals and amplitudes. The four territories demonstrate a similar pattern in the first half of the period; that is, they peak in activity within the first 8-9 years, but then diverge. More specifically, the US network is the first to decline and it takes three years for it to bounce back to reach another peak around 2007. Both the Japanese/South Korean network and the Australian network hit rock bottom around 2002, but then the Japanese/South Korean network accelerates and even overtakes the activity level of the USA and Europe, while the Australian network remains stable at a lower level and mildly peaks around 2007. In contrast, the European network

¹⁸ When referring to Europe, this study means the European countries in which CRP inventors resided during the observed period, including Denmark, Estonia, France, Germany, Great Britain, Greece, Hungary, Italy, Luxembourg, Norway, Sweden, Switzerland, and The Netherlands.

shows relatively long changing cycles with a minimal turning point in 2003. It grows again, but the second peak is not within the observed period.

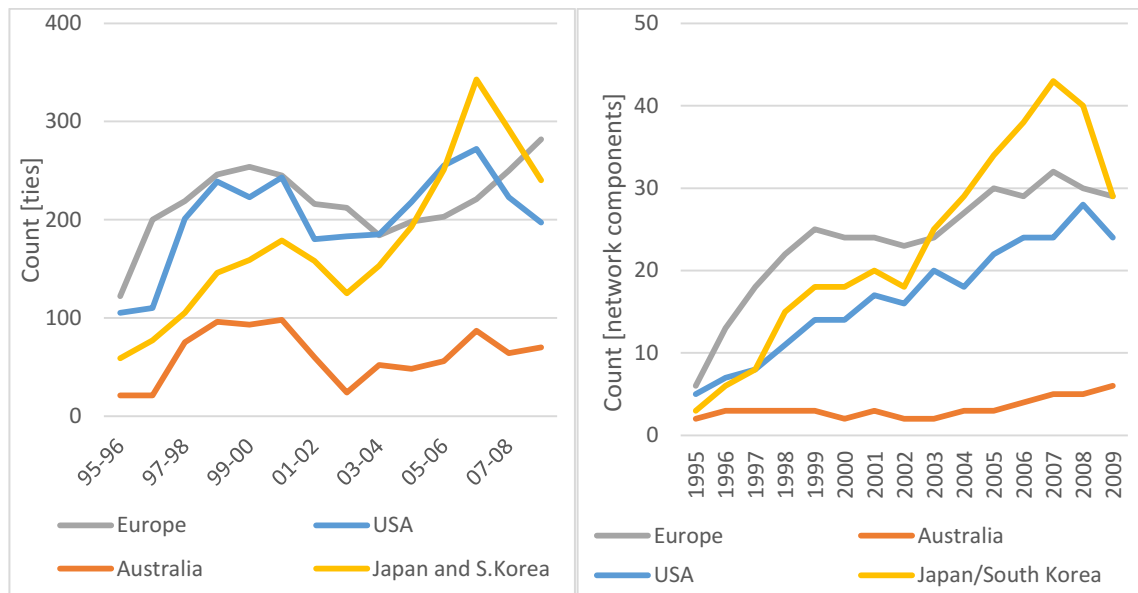


FIGURE 26 (LEFT): MAINTAINED TIES ON THE TERRITORY LEVEL; (RIGHT): COUNT OF NETWORK COMPONENTS

The networks in all cases exhibit an increasing level of fragmentation, as shown in Figure 26 (right graph) which plots the count of network components over time. Australia shows only a minor increase, but Japan and South Korea are highly fragmented with as many as 43 network components in 2007. In the USA and Japan/South Korea, the count of components grows almost in a linear fashion, although collaborations in Japan/South Korea are even more dispersed in the later stages. Compared to the count of ties in Figure 26, there seems more cohesion in the early stages, and a tendency towards network fragmentation in the later stages.

As a methodological aside, it is worth noting that common network statistics, such as density or average degree, are potentially misleading in this data due to the number of isolated nodes in the network. The isolated nodes are a by-product of the equally sized adjacency matrix within each phase, which are required for the SAOMs. Replacing the isolated nodes with structural zeros seems inappropriate, since it is unknown whether an inventor is absent because of inability or because of choice. As a workaround, this study relies on measures that focus on observed ties only. As a rule of thumb, a fixed number of ties and a growing number of components is interpreted as less cohesion,

while a fixed number of ties and a declining number of components is interpreted as more cohesion.

Following this principle, the count of network components in the European network increases until the year 1999 and remains stable until the year 2003. In parallel, the count of ties increases until the year 2000 and decreases until the year 2003. The European network exhibits a pattern by which the count of network components increases simultaneously with the count of ties, but when the count of ties decreases, the count of network components remains stable. This suggests that at first, new ties tend to go into new network components, and after the year 2000, existing groups persist but with declining activities.

5 LOCAL NETWORK DYNAMICS ALONG THE DOUBLE-BOOM CYCLE

This chapter shows that four out of six cases exhibit features of the double-boom cycle. Europe, the USA, and Japan and South Korea feature two activity peaks representing science-push and market-pull. Australia has a science-push but little evidence for market-pull, and China is a class of its own because of the exorbitant growth rate of the network. The results of Social Network Analysis using SAOMs show no systemic link between the phases of the double-boom cycle and the proximity dimensions that drive network change. Instead, the effect of proximity on network change varies across locations and the discussion lends itself to local factors on the micro, meso and macro level that may explain these results, meaning that local institutions matter for the drivers of network change.

Before presenting the six cases in detail, a few comments are necessary. Note that most SAOMs had to be modified to achieve convergence. Convergence problems occurred in the form of fairly high or low value of the Jaccard index or high collinearity amongst effects in the model (Ripley et al. 2017). If the Jaccard index was the issue, it could be solved by removing certain annual observations, which is unproblematic as the remaining observations still capture the network dynamics for each phase. If high collinearity was the issue, it could be solved by dropping one or two network effects, which is also unproblematic because those effects are mainly control effects such as isolated nodes or degree related activity/popularity. Occasionally, the effect on institutional proximity had to be removed for the same reason.

All presented models achieved convergence, but the goodness-of-fit (GOF) test frequently yielded imperfect results. In line with the RSiena manual (Ripley et al. 2017), all individual effects achieved a convergence of less than 0.1 and all models achieved an overall maximum convergence of less than 0.25. There are a few exceptions with minor deviations, for example, an overall maximum convergence of 0.262 in Phase 2 in the European model. Concerning the GOF results, 12 out of the 48 tests in this chapter yielded above the recommended p-value of 0.5 (Snijders 2015). Whilst this is

undesired, the models were accepted for interpretation, because the convergence is within the limits, the p-value for the GOF is merely a recommendation, some real world networks feature structures that are hard to replicate by a statistical algorithm, and this difficulty might be increased through the projected nature of the network data.

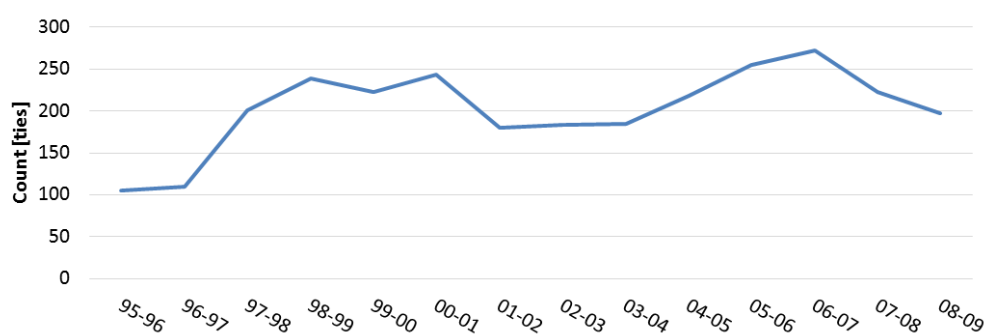
A brief explanation is needed for interpreting the occurrence of social proximity. Social proximity is operationalised as network closure, but the corresponding effect in RSiena, transitive triads, is meaningless because of the projected nature of the network in this study. Therefore, the inverse of the effect on the *Number of actor pairs at dist 2* is used for indicating closure (Ripley et al. 2017). A negative estimate of this effect indicates that a two-path disappears in the next period. However, this is ambiguous because the two-path may disappear because it forms a closed triad, or because a tie was terminated. To control for the termination of ties, closure and thus social proximity is assumed if a negative estimate of the 'Number of actor pairs at dist 2'-effect co-occurs with a fixed or growing number of ties.

The SAOMs are complemented with descriptive statistics on the four independent variables. Concerning geographic proximity, each case features a series of four box-plots¹⁹ (one per phase) that capture the distribution of distance of observed collaboration ties measured in kilometres. For organisational proximity, a bar graph shows the count of patents per organisation and per phase as an indicator for the number of involved organisations and the extent of their engagement. Institutional proximity is augmented by a stacked graph per case which shows the relative occurrence of ties within and between industry and academia. Lastly, social proximity is interpreted in the light of the overall evolution of the network measured by the number of ties over time.

¹⁹ As a reminder, a boxplot divides a series of data values into four quartiles. The 'box' represents 50% of all values and the bold line is the median that cuts the dataset in half. The upper and lower whisker represents the top and bottom 25%. Points outside the whiskers are outliers.

5.1 USA

The US-centred co-inventor network features various characteristics of the double-boom cycle. This includes a science-push by a few dedicated organisations, a period of reduced activity that potentially relates to technological issues with ATRP, and a second activity peak in combination with a range of diverse organisations entering this field. The effect of organisational proximity is stable over time, while social proximity becomes important during the activity upsurge in Phase 3. The tendency of US-based inventors to work with distant others in Phase 3 might represent an attempt to access external knowledge in order to further accelerate growth activities. The assessment of the network change per phase (see Figure 27), is followed by the SAOM results and a more detailed discussion per proximity dimension.



	Phase 1	Phase 2	Phase 3	Phase 4
Geographical Proximity	Positive significant	Insignificant	Negative significant	Positive significant
Social Proximity	Insignificant	Insignificant	Positive significant	Negative significant
Organisational Proximity	Positive significant	Positive significant	Positive significant	Positive significant

FIGURE 27: MAPPING OF NETWORK CHANGE AND THE EFFECT OF PROXIMITY IN THE USA

In Phase 1, there is an increase of ties leading to the first peak, and the inventors prefer nearby collaborators within the same organisation. The two most active organisations are PPG Industries and Carnegie Mellon University (CMU), which create the largest share of patents in Phase 1. Both are located in Pittsburgh, USA, which might explain the presence of industry-research ties from the get-go and the tendency to choose nearby others. Remember that ATRP was invented in 1995 by a scientist at CMU (Matyjaszewski, Gaynor & Wang 1995). At that stage, collaboration occurred mainly within organisational boundaries potentially to avoid undesired knowledge spillovers about what might be “the next big thing”.

In Phase 2, the activity level reaches the first peak and transitions into a downwards trend, though the number of involved organisations is growing. The patent output increases slightly, but the overall count of network ties is decreasing, which might suggest on average, that the involved organisations are more productive than in Phase 1, because fewer inventors produce more patents. Geographic proximity is insignificant for collaboration and there is a tendency to work with others from the same country of origin, potentially meaning that the inventive activities are no longer spatially concentrated, but still with a preference for domestic co-inventors. Organisational boundaries remain an important determinant for co-inventor ties.

A turn occurs in Phase 3, when the activity level passes the lowest point and rises again towards the second peak. The count of involved organisations increases again, but this time, the explanation might be different. According to Schmoch (2007), the period of decline (in this instance between Phase 2 and 3) is commonly used for solving fundamental problems with the technology, and the second peak is driven by firms that adopt the revised technology for specific applications in their market. As described in section 4.1, some copper-related issues on ATRP were resolved at this stage and the increasing count of firms might indeed relate to a market-pull mechanism in that firms apply CRP to their specific needs. Figure 32 supports that view by showing that the activity increase is primarily caused by within-industry ties. The importance of social proximity suggests that inventor teams emerge and grow from within, although this seems mainly to occur within organisational boundaries considering the positive and significant effect of organisational proximity.

Further, the tendency in Phase 3 to prefer distant collaborators is particularly curious, but it aligns with descriptive statistics which indicate a growing spatial footprint of the network (see Figure 30). A potential explanation might be that actors seek to engage in distant collaboration to access new knowledge and thereby promote innovation. The underlying assumption is that the knowledge from distant actors is more diversified than the knowledge base of local actors (Todo, Matous & Inoue 2016). In that vein, studies on regional development show that external knowledge is most beneficial when it is sourced from a region with a different, but somewhat similar knowledge profile (Boschma & Frenken 2011b). Thus, the growing commercial prospects during

the second activity peak might justify and even encourage companies to boost their innovation performance through accessing distant knowledge.

Finally, Phase 4 sees the pinnacle of the second activity peak followed by a decline, but with a simultaneous increase in network components and involved organisations. Such organisations include both universities and companies, and the reduced level of collaboration, which is reflected in the negative two-path effect, might be explained by an increasing diversification of academic and applied research. The increased number of organisations, along with the positive and significant effect on organisational proximity, may explain the fragmentation of the network and the preference for co-located collaborators. Collaborating inventors tend to work for the same organisation and live in the same area. The declining activities might be related to a decreasing interest of organisations in CRP, which, however, seems unlikely due to the increase of entrant organisations. Alternatively, it might be that companies reduce their R&D investments because they secured relevant IP in the previous period and focus their operations now on the exploitation of such patents (Garud, Tuertscher & Van De Ven 2013).

Now the focus turns to the SAOM results regarding proximity which are presented in Table 14²⁰. The two-path effect here is negative and significant in Phase 3 and Phase 4, and insignificant otherwise. The number of ties increases in Phase 3 and declines in Phase 4, which is indicative for an effect of social proximity on tie formation in Phase 3, but not Phase 4 (see Figure 27). This interpretation is supported by the network graphs of Phase 3 (Figure 28) and Phase 4 (see Figure 29), which show a fair amount of clustering in Phase 3, but increasing fragmentation in Phase 4. This suggests that social proximity is important during the rising activities towards the second peak in Phase 3. A detailed discussion and interpretation follows after the table.

²⁰ Several modifications to the US-centred SAOMs were necessary to achieve convergence. The effects on degree related popularity/activity and isolated nodes had to be excluded for most phases, and the effect on institutional proximity had to be excluded entirely, due to high collinearity with the baseline degree effect.

TABLE 14: MODEL RESULTS FOR NETWORK EVOLUTION IN THE USA

USA	1998-2000		1999-2003		2002-2006		2005-2009	
Phase	Phase 1		Phase 2		Phase 3		Phase 4	
Network size	126		183		200		237	
Network change	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Rate parameter period 1	1.150*	(0.211)	2.738*	(0.357)	2.681*	(0.367)	3.203*	(0.438)
Rate parameter period 2	3.175*	(0.339)	3.021*	(0.397)	1.986*	(0.310)	4.413*	(0.576)
Rate parameter period 3	1.714*	(0.270)	2.547*	(0.327)	4.008*	(0.510)	9.222*	(1.310)
Rate parameter period 4	2.992*	(0.398)	2.426*	(0.334)	3.426*	(0.445)	4.525*	(0.6250)
Structural dependencies								
Transitive triads	0.618*	(0.072)	0.414*	(0.030)	0.423*	(0.036)	0.481*	(0.025)
Number of actor pairs at dist 2	0.071	(0.039)	-0.012	(0.023)	-0.083*	(0.023)	-0.122*	(0.021)
Degree	-1.898*	(0.253)	-3.322*	(0.235)	-2.743*	(0.1800)	-2.722*	(0.1120)
Degree related popularity	-0.569*	(0.151)						
Network isolate			0.454	(0.469)	1.185*	(0.392)		
Exogenous effects								
Geographic proximity	0.118*	(0.020)	0.017	(0.017)	-0.030*	(0.016)	0.049*	(0.012)
Organisational proximity	1.911*	(0.150)	2.048*	(0.180)	2.006*	(0.125)	1.678*	(0.094)
Institutional proximity								
Same country of origin	-0.111	(0.141)	0.404*	(0.127)	0.390*	(0.131)	0.213*	(0.096)
Overall maximum convergence	0.218		0.124		0.151		0.188	

* Parameter is significant at 0.05 level (Ripley et al. 2017)

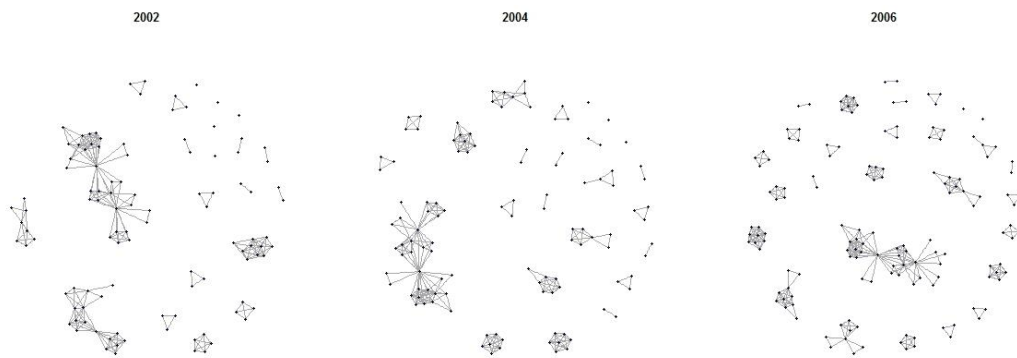


FIGURE 28: ANNUAL NETWORK OBSERVATIONS FOR 2002, 2004 AND 2006 (PHASE 3, US-NETWORK)

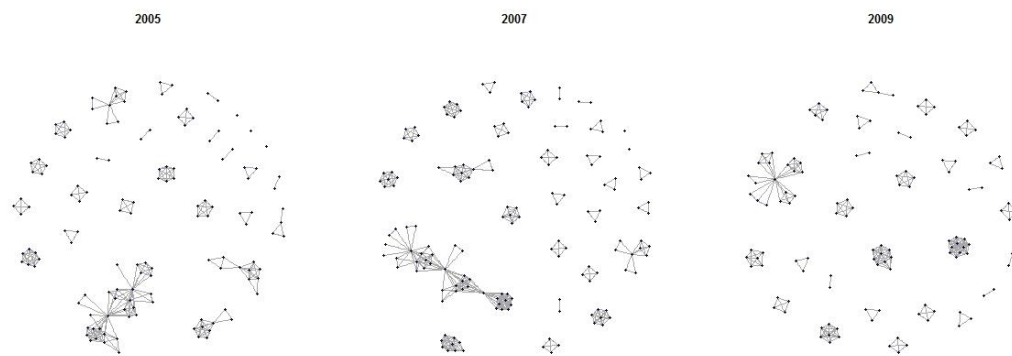


FIGURE 29: ANNUAL NETWORK OBSERVATIONS FOR 2005, 2007 AND 2009 (PHASE 4, US-NETWORK)

The effect of geographic proximity on tie formation is volatile in the US collaboration network. It is positive and significant in Phase 1, insignificant in Phase 2, negative and significant in Phase 3, and positive and significant in Phase 4. These results suggest that inventors prefer co-located collaborators in Phase 1, and that the effect of spatial distance is indifferent in Phase 2. Then, inventors tend to reach out to distant collaborators in Phase 3, but prefer nearby collaborators in Phase 4. Compared to existing studies, this outcome is rather uncommon, firstly because the effect is non-linear, and secondly because the effect has a negative estimate, meaning that actors tend to choose distant collaborators.

The geographic expansion of the network in Phase 3 is supported by descriptive statistics, which shows that the network ties bridge greater distances in Phase 3 compared to Phase 2 (see Figure 30). Most domestic collaborations are over 40-50km distance. US-based inventors engage in long-distance collaborations in all phases, and they expand over time (see Figure 30; left graph). The band until around 3000km is domestic collaborations between the US east and west coasts, and the collaborations with a distance of around 6,000km to 8,000km are between the USA and Europe. The other outliers are ties to Australia, Japan, China, and Singapore. The point is that US-based inventors expand the spatial reach of their collaborations during the rising activity level in Phase 3. It is unclear whether such ties are initiated from the US or overseas, but their mere presence indicates an increased exchange of tacit CRP knowledge across regional and national borders.

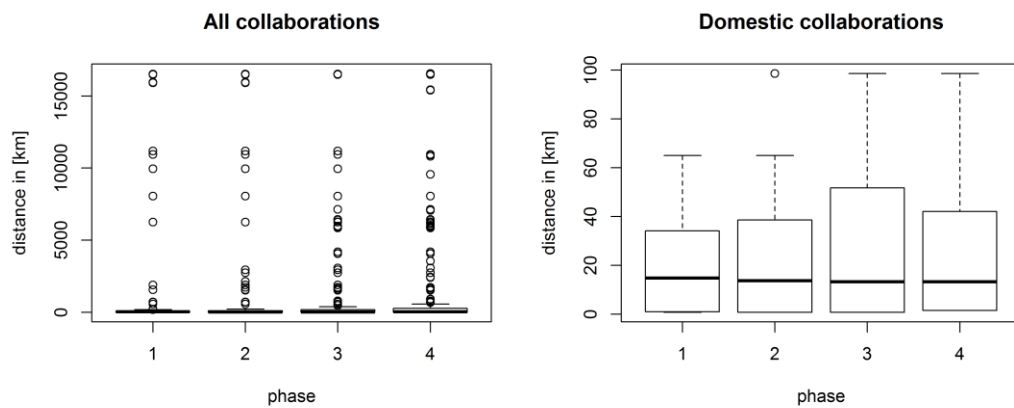


FIGURE 30: DISTANCE DISTRIBUTION OF COLLABORATIONS WITH AT LEAST ONE INVENTOR IN THE USA

Organisational proximity has a positive and significant effect on tie formation in all phases, which suggests that inventors in this network prefer to collaborate with their colleagues, as opposed to external collaborators. This effect is stable despite the growth of the inventor population, the volatile number of collaboration ties, and the dynamic participation of organisations along the four phases. Figure 31 shows the patent output per organisation per phase. Only a few organisations stay engaged in three phases or more, mainly PROs (Carnegie Mellon University, the California Institute of Technology and the University of Southern Mississippi) or MNCs (DuPont and PPG Industries). Interestingly, even some overseas actors exhibit continuous activities in the USA, such as the European companies Ciba and Evonik.

The engagement of firms in the US aligns with two characteristics of the double-boom cycle. Firstly, the notion of science-push and market-pull is visible in that there are a few organisations responsible for most patents in Phase 1, notably PPG Industries and Carnegie Mellon University (both in Pittsburgh), in contrast to Phase 4 which demonstrates the involvement of numerous organisations, including some niche companies. Secondly, “firms react more explicitly, if the expected technological and commercial results are not achieved in a short time” (Schmoch 2007, p. 1007), which appears to apply to several companies that withdraw after one phase, for instance The Goodrich Company, Eastman Kodak and SCIMED Life Systems. Interestingly, none of those companies still exists. The Goodrich Company was acquired and sold in parts

around 2012, Eastman Kodak filed for bankruptcy in 2012, and SCIMED was acquired in 1995.

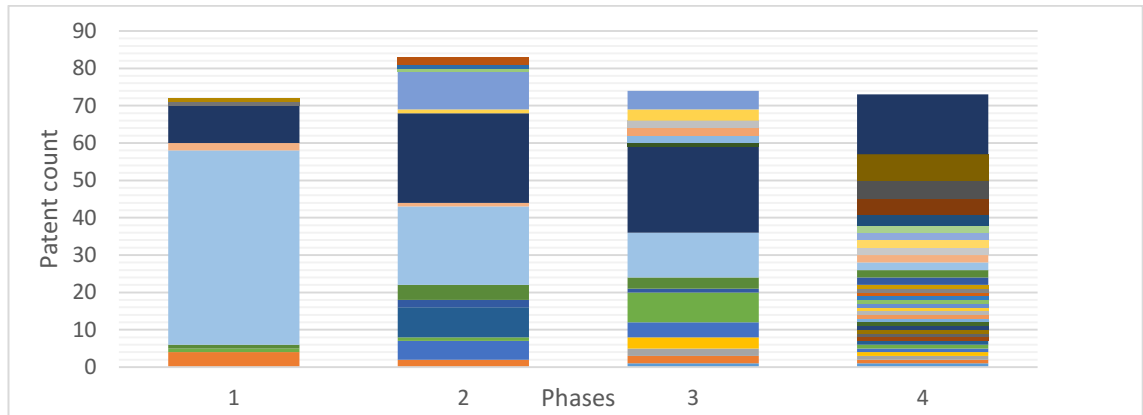


FIGURE 31: PATENTS PER ORGANISATION WITH AT LEAST ONE INVENTOR IN THE USA

The effect on institutional proximity was removed from the SAOM because of high collinearity with the obligatory degree effect, but the descriptive statistics provide some clues on the number of ties within and between industry and academia in the US network (see Figure 32). Mixed ties occur across all years with a slow but constant increase. The same applies for academic collaborations, but at a somewhat higher level. Most ties are amongst industry inventors, but their occurrence is highly volatile, and aligns with the double-boom pattern. A potential explanation for the stable number of mixed ties may be the role of Carnegie Mellon University, which demonstrated strong and ongoing engagement with industry partners.

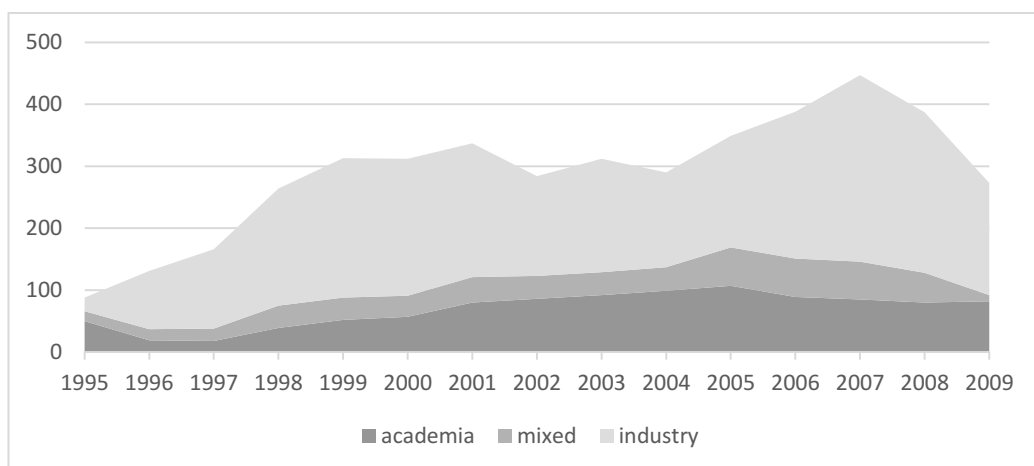
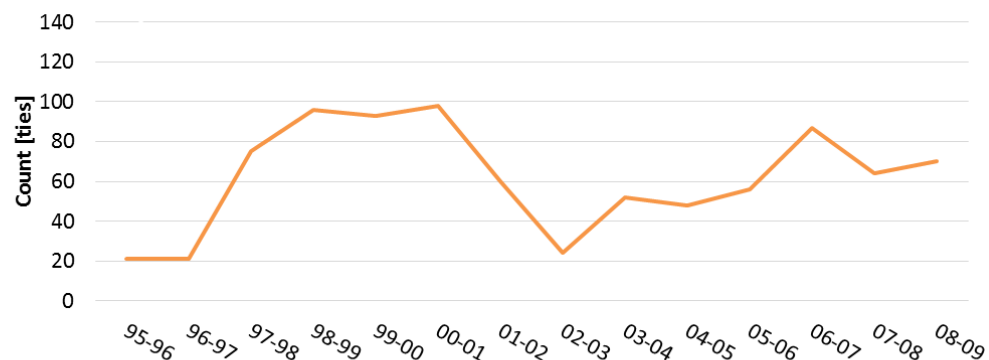


FIGURE 32: THE NUMBER OF TIES WITHIN AND ACROSS INDUSTRY AND ACADEMIA IN THE USA

Taken together, the US case nicely resembles the double-boom cycle, starting with a few co-located and research-driven organisations that lead to a science-push and the first activity peak, followed by declining activities and the climb-up to the second peak, but this time driven by numerous diverse organisations in industry and academia, representing market-pull. Organisational proximity has a strong and ongoing effect on tie formation, while geographic proximity has a volatile effect, even with a negative estimate in Phase 3, indicating the spatial expansion of the network in this period.

5.2 AUSTRALIA

The Australian network demonstrates partial alignment with the double-boom concept, in that there is evidence for science-push, but not for market-pull. The pivotal organisations in this network are the CSIRO and domestic universities. The CSIRO launched the CRP activities in Australia and accelerated this movement through the collaboration with Dupont, a major US-based chemical company, leading to the invention of RAFT and the first activity peak. Once the activity level of this joint venture began to diminish, it is mainly domestic universities that make up the Australian CRP-community, which are fuelled by Government funding. It is also universities and academic inventors that launch and run commercial enterprises to make CRP an industrial reality. Australian inventors do not mind collaborating over distance, in particular within Australia, but the shortage of leading chemical firms in Australia seems to impede the uptake of CRP. Figure 33 presents the summary of the Australian case.



	Phase 1	Phase 2	Phase 3	Phase 4
Geographical Proximity	Insignificant	Positive significant	Positive significant	Insignificant
Social Proximity	Insignificant	Insignificant	Positive significant	Insignificant
Organisational Proximity	Positive significant	Positive significant	Positive significant	Positive significant
Institutional Proximity	Positive significant	Insignificant	Insignificant	Insignificant

FIGURE 33: MAPPING OF NETWORK CHANGE AND THE EFFECT OF PROXIMITY IN AUSTRALIA

In Phase 1, the number of collaboration ties increases and the main determinants are organisational and institutional proximity. This is the era when the CSIRO enters collaboration with the US-based chemical company DuPont, which explains why geographic proximity is insignificant. Whilst the two organisations did intensively

collaborate, a large share of ties was amongst inventors within the two organisations also, which might explain the effect of organisational proximity.

The activity level reaches the first peak in Phase 2 and then transitions into a decline. Now, the network becomes more localised, since geographic proximity plays an important role for tie formation. Institutional proximity is insignificant, which implies that academic and industrial inventors are indifferent with respect to collaborators in their sector or the other.

Phase 3 sees the lowest point in activity followed by a slow increase of ties. The tendency to collaborate with colleagues in spatial proximity is complemented by the preference of inventors to pick collaborators who are linked to their acquaintances, as indicated by the positive and significant effect of social proximity. A potential explanation is the increasing cohesion of the Australian CRP community which is rather low in numbers and features stable interpersonal ties.

In Phase 4, the slow rise of activities continues, but now only organisational proximity matters for tie formation, while the geographic distance and past ties do not drive or impede network change. The bulk of patents in Phase 4 are from PROs and there is limited involvement by industry, meaning there is no evidence for market-pull. Simultaneously, the positive degree effect indicates the aspiration of CRP inventors to enter collaboration, which appears like an invigoration of the Australian network, potentially growing towards a second activity peak.

From here on, the focus is on the SAOM results on the individual proximity dimensions²¹ (see Table 15). Note that the number of nodes in the Australian network is considerably smaller than in the other networks in this dissertation.

Concerning social proximity, the two-path effect is negative and significant in Phase 3 and insignificant otherwise. In Phase 3, the overall number of ties is growing, thus the SAOM estimate implies network closure, that is, social proximity. Interestingly, the effect on transitive triads is insignificant in Phase 3, and positive and significant

²¹ To achieve convergence the SAOMs on the Australia co-inventor network had to be modified. Phase 1 was estimated twice, but with different effects since a SAOM with all selected effects did not converge. Some phases cover less than 5 network observations. The effect for isolated nodes is not covered in three phases.

otherwise, indicating a temporarily limited and non-linear importance of social proximity for network change. This result resonates with the aggregated network graphs per phase (see Figure 34), which shows that Phases 1, 2 and 4 are characterised by local clustering, while Phase 3 exhibits a growing network diameter. Note that isolated nodes are omitted in Figure 34. Taken together social proximity appears to have a volatile effect on tie formation.

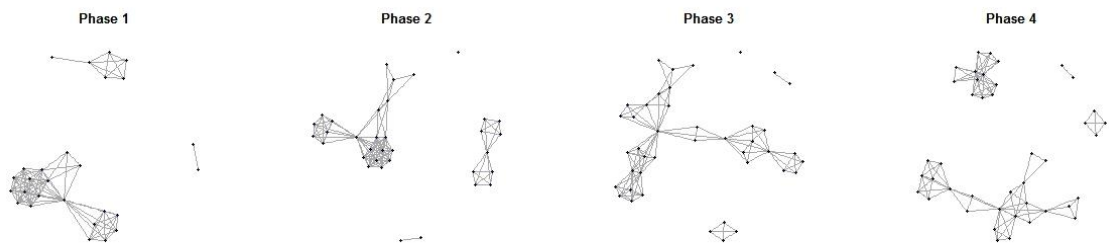


FIGURE 34: EVOLUTION OF THE MIXED NETWORK (AGGREGATED PER PHASE)

Geographic proximity is positive and significant in Phase 2 and Phase 3, and insignificant otherwise, which implies a non-linear effect of physical distance on network change. Phases 2 and 3 represent a time of declining and stagnating activities on CRP; thus it seems that collaborations become more localised during times of inertia. The descriptive statistics on the distance of observed collaboration ties do not clearly support this interpretation (see Figure 35), as the boxplots show a relatively stable distance of both domestic and international ties. The left graph in Figure 35 shows that at least some international collaboration occurs in every phase, bridging around 15000km. The right plot shows that a fair share of the observed collaboration ties bridge around 600-700km which is roughly the distance between Melbourne and Sydney. Australia-based inventors stand out due to a consistent engagement in long-distance collaborations, particularly within the country.

TABLE 15: MODEL RESULTS FOR NETWORK EVOLUTION IN AUSTRALIA

Australia	1998-1999 (a)		1998-1999 (b)		2000 -2003		2002-2006		2005-2008	
Network size	31		31		33		41		44	
Network change	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Rate parameter period 1	56,9659	(-38,6866)	30,9683	(-24,8094)	0,9586*	(0,4461)	2,4714*	(0,4631)	263,5367*	(127,2435)
Rate parameter period 2					33,2921	(28,6684)	5,9433*	(1,5235)	95,9764*	(36,8996)
Rate parameter period 3					2,6521*	(0,496)	0,4141*	(0,207)	5,6096*	(1,5026)
Rate parameter period 4							48,3351*	(28,820)		
Structural dependencies										
Transitive triads	0,9034*	(-0,3791)	0,6788	(-0,429)	0,6717*	(0,247)	-0,2836	(0,461)	0,935*	(0,2332)
Number of actor pairs at dist 2			0,0319	(-0,172)	0,0433	(0,149)	-1,1364*	(0,356)	0,0428	(0,1461)
Degree	3,2294*	(-0,7795)	1,2202	(-0,6811)	-6,4621*	(2,4644)	-6,1194*	(2,192)	2,8476*	(1,0475)
Degree related popularity (sqrt) network-isolate	-0,5771	(-0,4771)	-1,2042	(0,5709)	0,5134	(0,5302)	2,8007*	(1,393)	-2,7702*	(0,607)
									6,2849*	(0,7454)
Exogenous effects										
Geographic proximity			0,0664	(0,0458)	0,1835*	(0,0621)	0,0941*	(0,044)	0,0388	(0,0288)
Organisational proximity	1,0136*	(-0,2736)			1,7848*	(0,5158)	0,7526*	(0,245)	1,2092*	(0,3422)
Institutional proximity	2,3401*	(-1,0779)			2,6174	(2,5044)	0,5719	(0,516)	0,1782	(0,2695)
Same country of origin	0,2972	(-0,2723)			0,3678	(0,4948)	0,288	(0,357)	0,1527	(0,2234)
Overall maximum convergence	0.0938		0.1551		0.2283		0.081		0.1629	

* Parameter is significant at 0.05 level (Ripley et al. 2017)

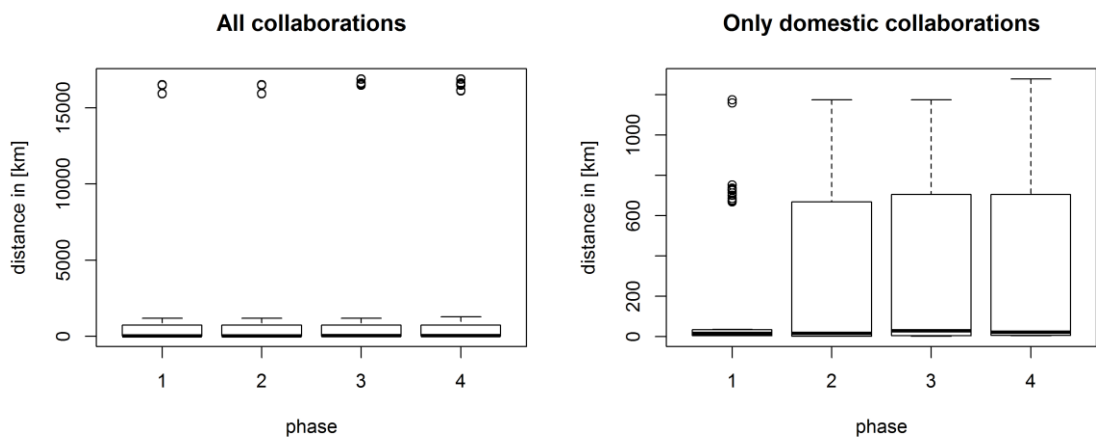


FIGURE 35: DISTANCE DISTRIBUTION OF COLLABORATIONS WITH AT LEAST ONE INVENTOR IN AUSTRALIA

Organisational proximity is positive and significant in all phases, implying an ongoing importance of organisational boundaries for the selection of collaborators. The organisations in the Australian case are predominantly public research organisations or the commercial arms of such PROs. Compared to other cases in this dissertation (except China), Australia exhibits a slower increase of involved organisations over time and they are less diverse also, with no obvious shift from science-push to market-pull (Schmoch 2007). For instance, two thirds of the patents in Phase 4 are filed by the CSIRO, The University of Sydney, and the Cooperative Research Centre for Polymers. It is interesting though, that organisational boundaries are a strong determinant for collaboration choices considering that secrecy is rather associated with the private sector.

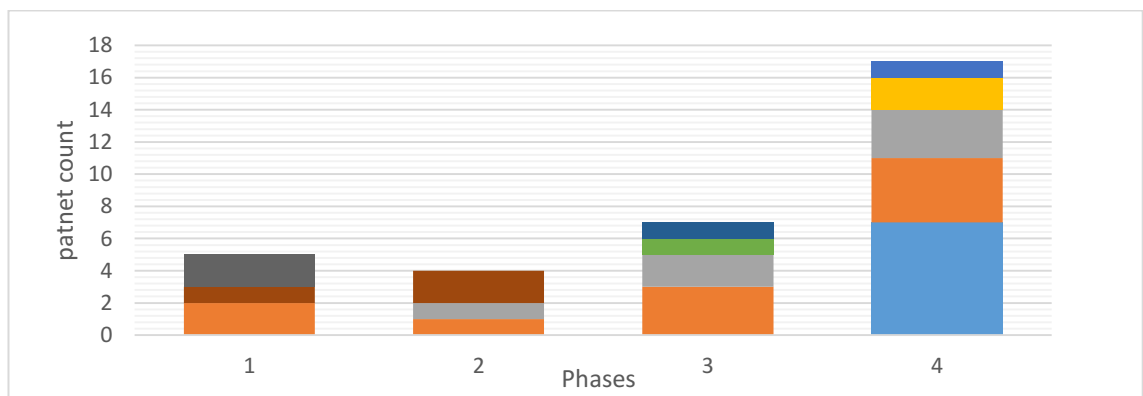


FIGURE 36: PATENTS PER ORGANISATION WITH AT LEAST ONE INVENTOR IN AUSTRALIA

Institutional proximity is positive and significant in Phase 1, and insignificant otherwise, suggesting that inventors are increasingly agnostic about the institutional background of their collaborators. This resonates with the descriptive statistics in Figure 37, which show that only Phase 1 contains hardly anything else but academic ties, while the other phases feature some occurrence of industry and mixed ties. Another observation is that the appearance of mixed ties aligns with the phases of the double-boom cycle, that is, during the first peak between 1997 and 2002, and during the second rise after 2005. That said, it is worth noting that the commercial arms of PROs and universities are coded as industry as they are private entities, though they tend to be run by academics.

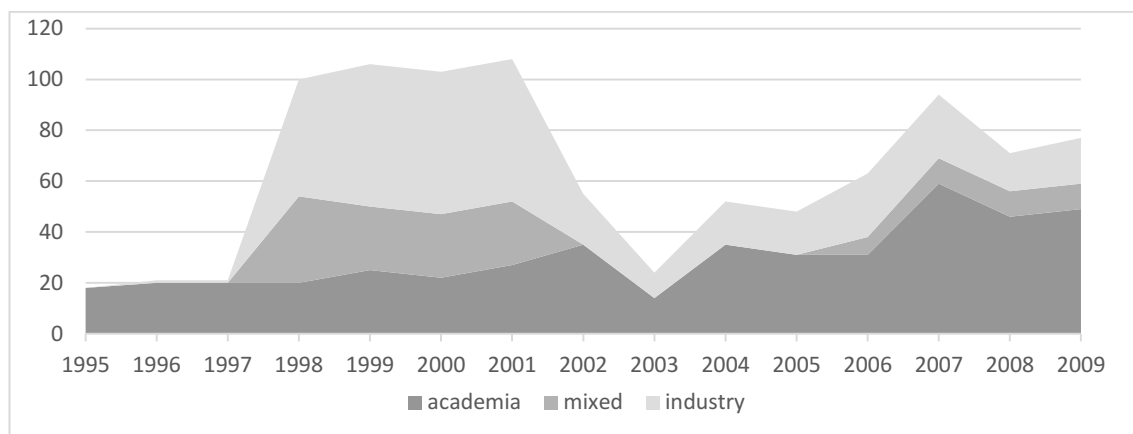


FIGURE 37: THE NUMBER OF TIES WITHIN AND ACROSS INDUSTRY AND ACADEMIA IN AUSTRALIA

The results of the degree-related popularity effect are particularly interesting as they show a volatile pattern. This network is undirected, thus the popularity effect also captures activity. The popularity/ activity effect is negative and significant in Phase 1, insignificant in Phase 2, positive and significant in Phase 3, and again negative and significant in Phase 4. This result suggests the rise and fall of actors with high popularity or activity, or put differently, the formation and resolution of patterns with network hierarchy. This volatile pattern might relate to cycles of public funding programs, because the injection of additional funding increases both the activity and attractiveness of the recipient. As shown in Figure 38, the Australian Research Council (ARC) granted a total of A\$ 12 million between 2002 and 2012 for CRP related projects

administered through Discovery grants and Linkage grants²², and most of those funds were received by inventors in this network.

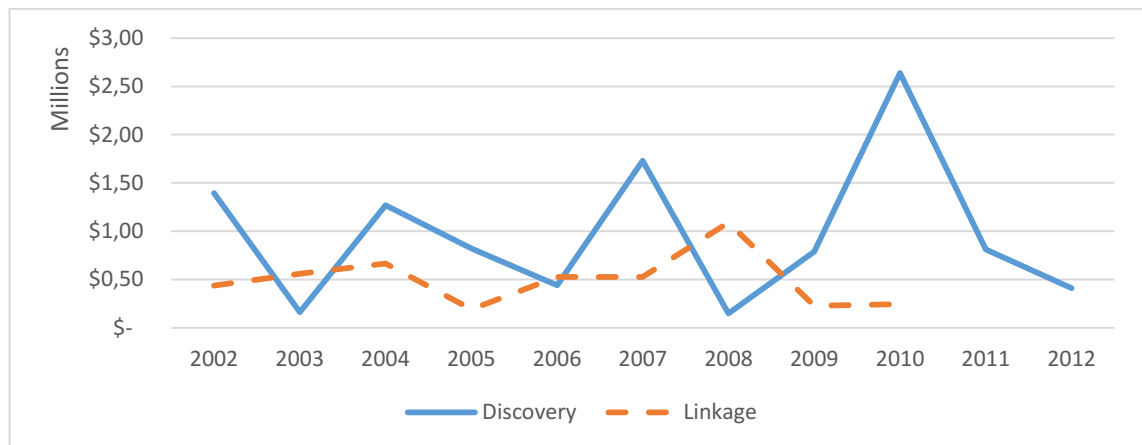


FIGURE 38: AUSTRALIAN RESEARCH COUNCIL FUNDING ON CRP RESEARCH

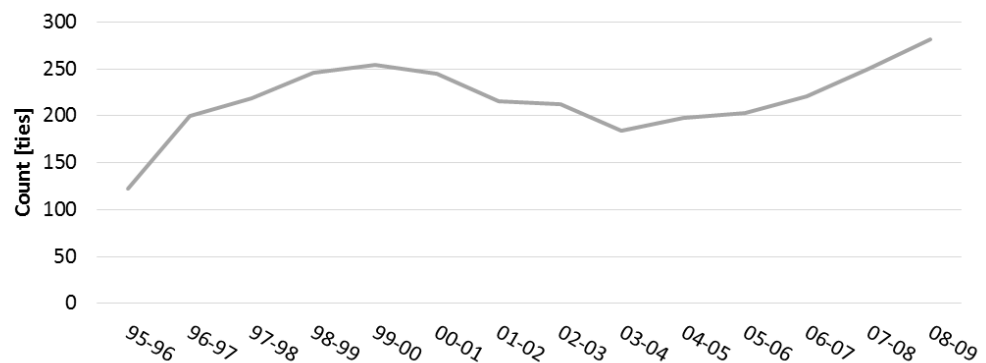
Interestingly, the degree effect is negative and significant in Phases 1, 2 and 3, and positive and significant in Phase 4, which not only implies that the perceived cost of forming a tie declines over time, but also that Australian inventors are particularly keen to enter collaborations in the later stages of the observed period.

In summary, the Australian case features characteristics of science-push through the discovery of RAFT by the CSIRO, which overlaps with the first activity peak, but there is little evidence for market-pull, in particular due to the lack of involvement of industrial actors during in the later stages. While the remote location of Australia is often associated with the tyranny of distance, it is somewhat surprising that the effect of geographic proximity on tie formation is insignificant in two phases. In fact, the descriptive statistics support the view that Australian inventors are accustomed to long-distance collaboration.

²² Discovery grants are intended for fundamental research and Linkage projects for cooperative research with domestic and international partners.

5.3 EUROPE

The European collaboration network is characterised by a strong presence of local MNCs, and over time, this case exhibits a clear shift from science-push to market-pull. Collaboration occurs mainly within organisational boundaries, and there is evidence for clustering during times of rising activities driven by social proximity. During times of inertia, European inventors tend to reach out to distant others, in particular countries where CRP was invented (USA and Australia), potentially to access new knowledge to overcome technical issues that inhibit the further adoption of CRP in Europe.



	Phase 1	Phase 2	Phase 3	Phase 4
Geographical Proximity	Positive significant	Negative significant	Negative significant	Positive significant
Social Proximity	Positive significant	Insignificant	Insignificant	Positive significant
Organisational Proximity	Positive significant	Positive significant	Positive significant	Positive significant

FIGURE 39: MAPPING OF NETWORK CHANGE AND THE EFFECT OF PROXIMITY IN EUROPE

In Phase 1, the overall level of activities increases, but the resulting networks are mainly locally-bound, within organisational boundaries, and influenced by previously existing ties. The first activity peak has passed in Phase 2 and the inventors tend to reach out to spatially distant others, regardless of previous ties. Simultaneously, the collaboration occurs mostly within organisations, which indicates that firms collaborate across locations, and potentially across national or continental borders. This trend continues in Phase 3, until the activity levels reach the lowest point around 2003. In Phase 4, the level of activities is rising for the second time toward another peak. Now, inventors prefer nearby others, who work in the same organisation and who are known through the existing network. This means that the European network sees two main shifts concerning the determinants of network change that match the

phases of the double-boom cycle: from Phase 1 to 2, and from Phase 3 to 4 (see Figure 39).

An interesting observation on the sidelines is the relationship between the effect of geographic proximity and the country of origin of inventors. In Phase 1, inventors prefer collaborators in spatial proximity and from the same country of origin. In Phase 2 and 3, inventors tend to work with distant others but also from the same country of origin, which might relate to overseas subsidiaries of European firms. And in Phase 4, inventors predominantly collaborate with nearby others, but this time preferring others from a different country of origin. This aligns in part with past studies on European co-author networks, which find that “the bias to collaborate with physically proximate partners did not decrease, while the bias towards collaboration within territorial borders did decrease over time” (Hoekman, Frenken & Tijssen 2010, p. 662), hinting at the process of European integration and the increasing permeability of pan-European borders.

The remainder of this case description elaborates on the SAOM estimations of the individual proximity dimensions²³. Concerning social proximity, the two-path effect is negative and significant in all phases (see Figure 39). However, the count of ties increases in Phase 1 and Phase 4, and declines in Phase 2 and Phase 3. By implication, social proximity drives network change in Phase 1 and Phase 4.

²³ The SAOM of the European territory network required some modifications for achieving convergence. The effects on degree related popularity/activity had to be excluded for most phases and the effects on institutional proximity and isolated nodes had to be excluded entirely.

TABLE 16: MODEL RESULTS FOR NETWORK EVOLUTION IN EUROPE

Europe	1996-2000		1999-2003		2002-2006		2005-2009	
Phase	Phase 1		Phase 2		Phase 3		Phase 4	
Network size	156		198		194		214	
Network change	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Rate parameter period 1	6.076*	(1.078)	4.741*	(0.683)	2.617*	(0.378)	3.060*	(0.426)
Rate parameter period 2	0.973*	(0.228)	7.910*	(1.143)	5.596*	(0.855)	4.945*	(0.657)
Rate parameter period 3	2.313*	(0.450)	1.279*	(0.231)	4.442*	(0.654)	8.649*	(1.236)
Rate parameter period 4	5.043*	(0.969)	2.832*	(0.418)				
Structural dependencies								
Transitive triads	0.771*	(0.223)	0.692*	(0.050)	0.429*	(0.049)	0.480*	(0.053)
Number of actor pairs at dist 2	-0.349*	(0.122)	-0.069*	(0.026)	-0.346*	(0.043)	-0.313*	(0.045)
Degree	-2.619*	(0.434)	-2.858*	(0.121)	-2.448*	(0.114)	-2.120*	(0.084)
Degree related popularity network-isolate	-0.053	(0.363)						
Exogenous effects								
Geographic proximity	0.066*	(0.020)	-0.055*	(0.017)	-0.012	(0.017)	0.140*	(0.016)
Organisational proximity	1.688*	(0.191)	1.407*	(0.102)	1.651*	(0.139)	1.303*	(0.113)
Institutional proximity								
Same country of origin	0.478*	(0.129)	0.807*	(0.103)	0.215*	(0.116)	-0.297*	(0.105)
Overall maximum convergence	0.193		0.262		0.255		0.123	

* Parameter is significant at 0.05 level (Ripley et al. 2017)

The effect of organisational proximity on tie formation is positive and significant in all phases, which suggests that inventors generally prefer colleagues as collaborators. This might relate to the strong industry presence in this network along with the fact that many companies are rather large and deploy comprehensive bureaucratic structures. Europe is home to several major chemical companies that heavily rely on innovation to stay ahead of the competition from Asia and the Middle-East (Das & Icart 2015), of which some occur in this network, for example, BASF, Bayer, Evonik, Solvay, DSM, and Arkema. Those companies employ between 20,000 and 70,000 staff and operate well-coordinated R&D centres around the globe, plus they patent extensively to protect their intellectual property (Das & Icart 2015). By implication, their bureaucratic structures are comprehensive and somewhat slow-moving, thereby conditioning and channelling the interactions of individuals (DiMaggio & Powell 1983). The rigid nature of such structures and the need to avoid undesired knowledge exchange with externals might explain the strong and stable effect of organisational proximity on tie formation.

Interestingly, the effect of organisational proximity is stable, despite noteworthy dynamics with respect to the involved organisations. In addition to a few large firms that show ongoing activities in CRP, such as BASF (Germany), Arkema (France), Ciba (Switzerland), and the UK-based biotechnology company Biocompatibles UK, there is a growing number of diverse organisations that file patents on CRP (see Figure 40). The transition from a few strong patent producing organisations in the early phases to numerous and diverse organisations in the later phases resonates with the conceptually described shift from science-push to market-pull (Schmoch 2007). Organisations that join in the later phases include public research organisations such as the French National Center for Scientific Research (CNRS), technology transfer offices like Warwick Effect Polymers (now ABZENA), and companies with specific applications, including the Swatch Group (watches), Henkel (adhesives), and Novartis (pharmaceuticals).

Another feature of this network that matches the double-boom cycle is that some firms withdraw rather quickly, presumably when the return on investment is not satisfactory. European companies that pulled out of CRP include, for instance, Elf Atochem SA (now Arkema), Bayer AG, Telene SAS, Degussa AG (now Evonik), and BP Chemicals. That said, some universities also file one-off patents, for example, the University of Copenhagen, the University of Gent, and ETH Zurich.

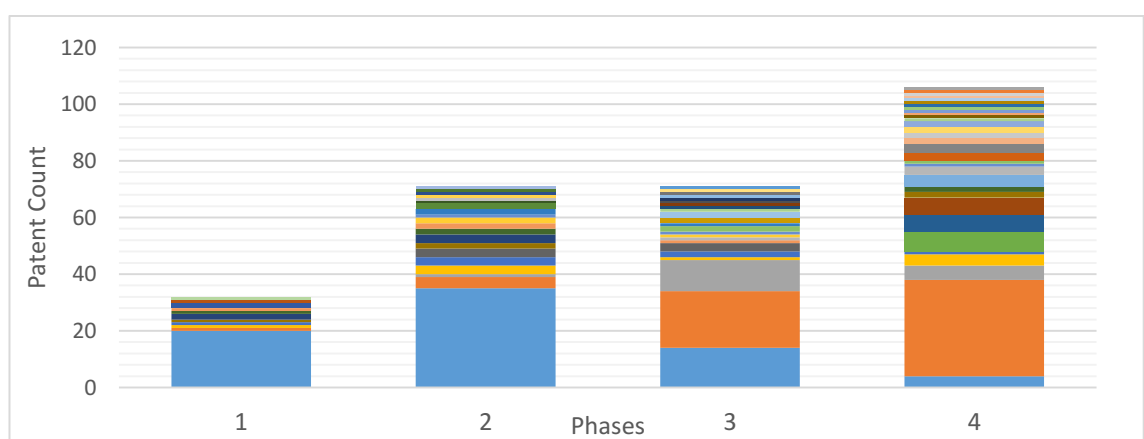


FIGURE 40: PATENTS PER ORGANISATION WITH AT LEAST ONE INVENTOR IN EUROPE

Institutional proximity is not covered in the SAOM, but the descriptive statistics on industry-research collaboration offer a few clues, as supported by the graph in Figure

41. Collaboration within academia is stable and on a low level, while the bulk of collaboration in Europe is within industry and it is also quite volatile over time. The share of mixed ties is marginal in most years, and with a rapid increase in the last period. But overall, most inventors prefer to collaborate within their sector.

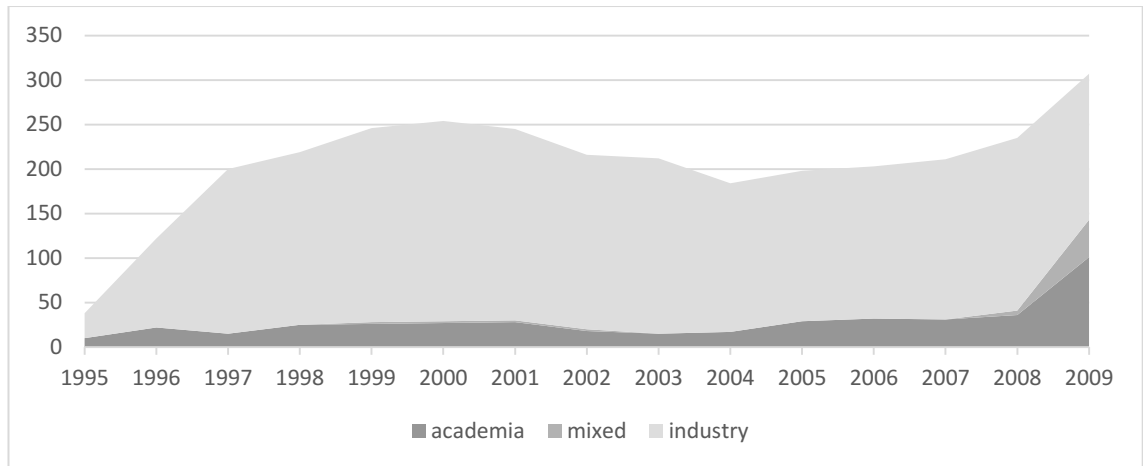


FIGURE 41: THE NUMBER OF TIES WITHIN AND ACROSS INDUSTRY AND ACADEMIA IN EUROPE

The effect of geographic proximity has a volatile effect on tie formation. This effect is positive and significant in Phase 1, negative and significant in Phase 2, insignificant in Phase 3, and positive and significant in Phase 4. Combined with the pattern of tie change (see Figure 39), geographic proximity has a positive effect on tie formation in times when the number of ties is increasing, and a negative effect when the number of ties is declining. Put differently, the European collaboration network is spatially contracting in times of activity growth and spatially expanding in times of inertia. The SAOM result resonates with the descriptive statistics in Figure 42, which show the spatial expansion of the network in Phase 2 and Phase 3.

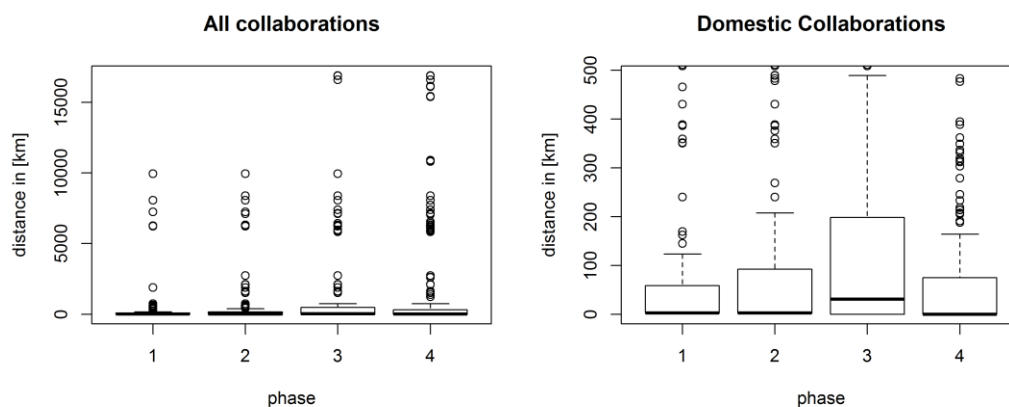


FIGURE 42: DISTANCE DISTRIBUTION OF COLLABORATIONS WITH AT LEAST ONE INVENTOR IN EUROPE

The volatile effect of geographic proximity might be explained by attempts of EU-based companies to insource external knowledge in times of demand. The spatial expansion in Phase 3 occurs after the first peak. According to Schmoch (2007), the era of inertia is when problems occur that are more difficult than expected. It is important to remember that CRP-technology was discovered outside the EU, that is, the knowledge in originating countries (USA and Australia) might be more advanced, at least due to a first-mover advantage. The growing spatial footprint of the European CRP network becomes vividly clear when comparing the two network graphs in Figure 43. The ties to Australia are with RAFT experts (such as Ezio Rizzardo and Tom Davis) and migrant German scientists (for example Christopher Barner-Kowollik and Martina Stenzel). The ties to the USA are to offshore R&D centres of European chemical companies such as Arkema, Evonik, and Ciba, facilitating the flow of important knowledge back to Europe.



FIGURE 43: SPATIAL FOOTPRINT OF THE EUROPEAN NETWORK IN PHASE 2 (TOP) AND PHASE 3 (BOTTOM)

Related research shows that the ties with the USA may indeed represent a case of reverse technology transfer, which is the case when domestic firms invest into R&D in foreign subsidiaries and benefit from knowledge spillovers back to the parent firm (Mansfield & Romeo 1980). Criscuolo (2009, p. 869) investigated the reverse technology activities of 17 European chemical and pharmaceutical multinationals between 1985 and 2005. Using patent citations she found evidence that those firms are transmitting knowledge from the USA back to their home countries (Criscuolo, Salter & Sheehan 2007). One important precondition for reverse technology transfer to make sense is a “technology gap between the United States and the home country” (Criscuolo 2009, p. 869), which is a given in the European network considering the spearheading role of the USA in ATRP technology. With respect to the technology life cycle, a possible explanation for the timing of the spatial expansion might be that European inventors were confident of finding useful knowledge in foreign places, which might help then address deficiencies at home.

This view is supported by Glückler (2014), who empirically investigated the knowledge flows between the corporate headquarters of BASF, a leading chemical company in Germany, and a peripheral BASF subsidiary in Argentina. Combining a case study approach with Social Network Analysis, he found evidence that the local conditions in Argentina led to the emergence of an innovation, which was later introduced in BASF's home market. The organisational unit in his study deals with polymers, coatings, cosmetics, and plastics, which is similar to the applications of CRP. Glückler (2014) theorises that the organisational integration of spatially dispersed R&D centres may foster innovation outcomes in the parent company, since the local context of subsidiaries might offer unique opportunities for innovation, the smallness of the subsidiary (compared to the headquarters) may facilitate cross-fertilisation of ideas amongst organisational units, and the remoteness of the offshore site may lead to less managerial pressure from the headquarters, that is, resulting in more flexibility in terms of experiments. While this level of detail is not given in this study, this narrative illustrates how European chemical companies might benefit from distant knowledge.

Taken together, the European case resembles the key features of the double-boom cycle, but it does so in a slower fashion than the US-network (see section 5.1). Interestingly, the temporal evolution matches the timelines proposed by Schmoch (2007), who also uses European data. The most interesting result concerning network change is the volatile effect of geographic proximity on tie formation and in particular the negative estimates in Phase 2 and 3, which indicates a spatial expansion of collaboration ties, which possibly represents attempts to acquire external knowledge through reverse technology transfer through the help of offshore subsidiaries of large European chemical companies.

5.4 JAPAN AND SOUTH KOREA

The Japanese and South Korean network aligns with the double-boom cycle in that it features a clear shift from science-push to market-pull. However, contrary to the assessment of Schmoch (2007), firms demonstrate continuous involvement, but academic inventors tend to withdraw after a short while. The stable effect of proximity on tie formation seems to relate to the nature of large chemical companies in Japan, in which most activities link to a long-term plan. Such firms follow long-term strategies on innovation, and they deploy employment policies which are designed for long-term relationships with their staff. Large firms tend to perform R&D in internal teams without collaborators from other firms or other nations.

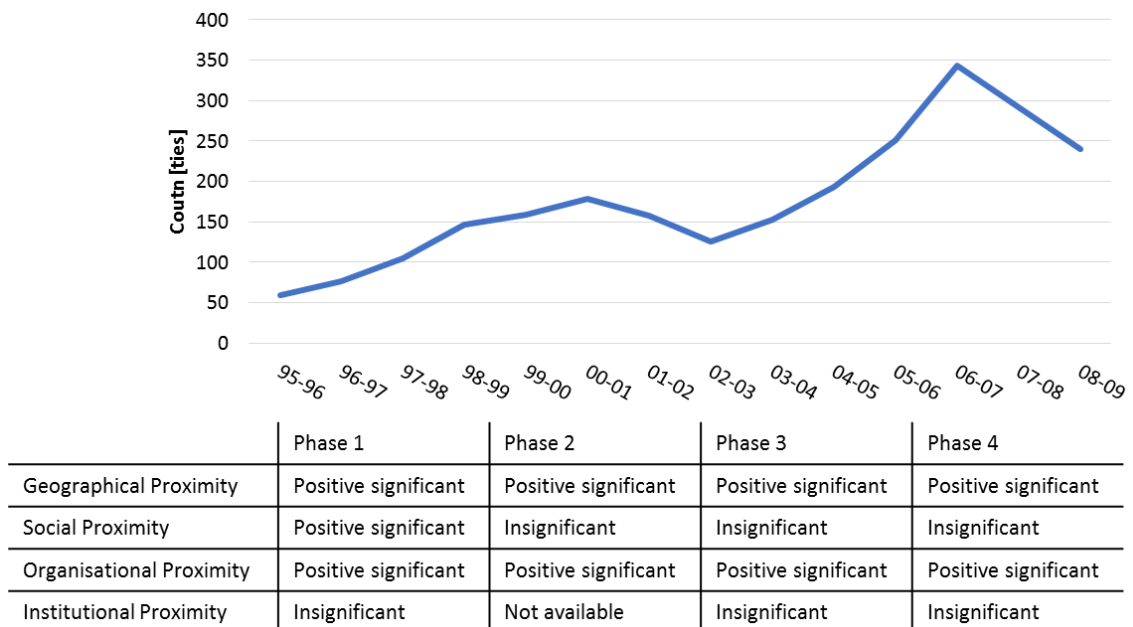


FIGURE 44: MAPPING OF NETWORK CHANGE AND THE EFFECT OF PROXIMITY IN JAPAN AND SOUTH KOREA

In this case, the change patterns of network ties clearly resemble the double-boom cycle, but the drivers for network change are predominantly stable (see Figure 44). The only exception is the tendency to network closure in Phase 1, but all other proximity dimensions have the same effect over time. The discussion of the SAOM estimates in

Table 17²⁴ lends itself to structural features of the Japanese chemical industry which may, at least in part, be responsible for this high level of stability.

Concerning social proximity, the two-path effect is positive and significant in Phase 1, and insignificant otherwise, which indicates a high occurrence of two-path connections, and implies network growth rather than network closure (see Table 17). Interestingly, the estimate turns negative in Phase 2 and Phase 3, which might indicate closure, but the estimate is insignificant, and thus conclusions cannot be drawn. Overall, there is no significant effect of social proximity on tie formation in this network.

TABLE 17: MODEL RESULTS FOR NETWORK EVOLUTION IN JAPAN AND SOUTH KOREA

Japan / South Korea	1996-2000		1999-2003		2002-2006		2005-2009	
Phase	Phase 1		Phase 2		Phase 3		Phase 4	
Network size	91		134		205		226	
Network change	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Rate parameter period 1	1.882*	(0.478)	2.510*	(0.565)	51.647*	(13.537)	3.841*	(0.697)
Rate parameter period 2	2.722*	(0.613)	7.856*	(1.548)	58.574*	(12.792)	9.513*	(1.998)
Rate parameter period 3	3.168*	(0.594)	3.623*	(0.756)	92.673*	(21.469)	7.325*	(1.600)
Rate parameter period 4	1.579*	(0.343)	20.585*	(4.867)	30.153*	(6.999)	12.679*	(2.813)
Structural dependencies								
Transitive triads	1.276*	(0.280)	0.593*	(0.066)	0.658*	(0.163)	0.946*	(0.222)
Number of actor pairs at dist 2	0.259*	(0.118)	0.014	(0.058)	-0.259	(0.138)	-0.032	(0.065)
Degree	2.551	(5.219)	-0.463	(0.344)	0.505	(0.530)	-2.110*	(0.386)
Degree related popularity	-3.999*	(1.411)	-1.143*	(0.207)	-1.601*	(0.390)	-0.646	(0.327)
network-isolate	7.356*	(2.576)	4.807*	(0.598)	5.772*	(0.289)		
Exogenous effects								
Geographic proximity	0.327*	(0.072)	0.150*	(0.026)	0.209*	(0.026)	0.207*	(0.024)
Organisational proximity	2.199*	(0.450)	0.962*	(0.130)	0.921*	(0.096)	1.125*	(0.127)
Institutional proximity	3.056	(4.535)			0.004	(0.110)	0.027	(0.156)
Same country of origin	0.495	(0.420)	0.669*	(0.186)	0.417*	(0.190)	0.211	(0.149)
Overall maximum convergence	0.1616		0.1757		0.2326		0.1732	

* Parameter is significant at 0.05 level (Ripley et al. 2017)

The effect of geographic proximity is positive and significant in all phases. This indicates that inventors from Japan and South Korea tend to collaborate with co-located others. The review of the actual distance between inventors confirms that the vast majority of ties are local (see Figure 45). Over time, there is a slight increase of

²⁴ The SAOMs for Japan and South Korea were modified to achieve convergence. Phase 2 does not cover institutional proximity, and Phase 4 does not control for network isolates.

long distance collaboration (see Figure 45; left graph), but many of them are domestic too, for instance between Fukuoka and Tokyo (1,000 km distance). The few international collaboration ties are exclusively with the USA, plus they are with offshore inventors from Japan who left their home country, for instance a Japanese scientist who works at Carnegie Mellon University. The distance of domestic collaboration declines over time, and most collaboration is over a distance of around 40 kilometres. It is worth noting that the very low distance of less than 10 kilometres might be an artefact caused by the data cleaning approach, where a missing inventor address was replaced with the location of the affiliated organisation, if certain criteria are satisfied (see section 3.2.5.2).

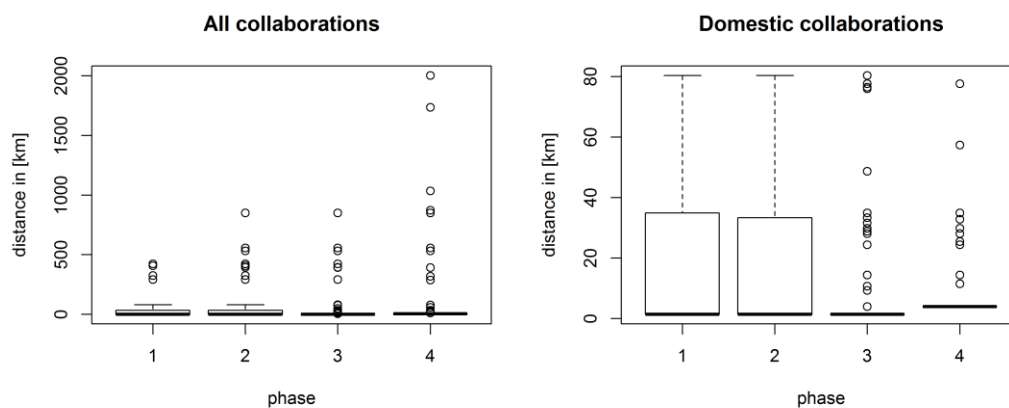


FIGURE 45: DISTANCE DISTRIBUTION OF COLLABORATIONS WITH AT LEAST ONE INVENTOR IN JAPAN/SOUTH KOREA

Institutional proximity is insignificant in all phases, except in Phase 2 where this effect is not included. Thus, partner choices are indifferent to the sector of the other. Figure 46 shows the occurrence of ties within and between industry and academia over time. Similar to Europe and the USA, most of the ties in this network are within industry. However, a remarkable difference is the stable level of activity within industry versus the volatile involvement of academics. This is contrary to the double-boom concept which suggests that public research organisations tend to exhibit long-term engagement, while profit-seeking firms are more likely to withdraw after a short period. During the era of inertia (between the year 2000 and 2004), the network features very few academic ties, which suggests that it was mainly industry that contributed to the upsurge toward the second peak. The high occurrence of mixed ties

during the first peak might relate to Yoshiki Nakagawa, a former Post-Doc at CMU who then joined Kaneka Corporation, a major Japanese company.

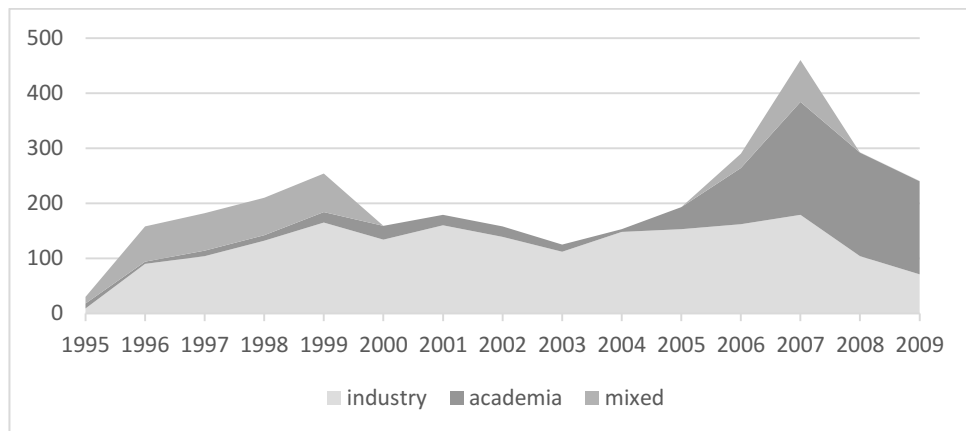


FIGURE 46: THE NUMBER OF TIES WITHIN AND ACROSS INDUSTRY AND ACADEMIA IN JAPAN AND SOUTH KOREA

Organisational proximity is positive and significant in all phases, which indicates that inventors from Japan and South Korea tend to collaborate with colleagues. Considering the other forms of proximity in this network, it is striking that the determinants for tie formation have a stable effect over time, while the network itself is undergoing a dramatic change (see Figure 46). This implies that there might be some strong forces leading to similar collaboration patterns regardless of the stage of the technology life cycle. A part of the explanation might relate to the operations of large Japanese corporations.

A focus on large *Japanese* corporations seems legitimate, because firstly most inventions in this network are from Japanese inventors, as opposed to South Korean inventors (see Table 13). Secondly, South Korea's involvement mainly occurs in the later stages of the observed period, which coincides with the country's effort to implement an industrial shift from petrochemicals to fine chemicals (Moon & Cho 2011), and the fact that CRP is predominantly applied in fine chemicals as opposed to petrochemicals (Matyjaszewski 2009). Thirdly, the lion's share of the ties in this network are amongst industry inventors (see Figure 46), as opposed to the academic or mixed collaborations.

The patent output per organisation over time is similar to Europe and the USA, in that there is a shift from a few strong contributors in the early phases, to many diverse organisations in the later phases (see Figure 47). Organisations with an ongoing engagement are all large companies, which is not surprising because the Japanese chemical industry is dominated by large corporations. Large companies in this network include Mitsubishi Chemical HD, LG Chemicals, and Sumitomo Chemical with around 30,000 to 50,000 employees, while medium sized firms such as Ube Industries or Kaneka Corporation have around 10,000 employees (Hirano 2014)²⁵. Such firms tend to have a long-lasting history in focusing upon niche applications to avoid competition from the US and Europe. They approach innovation with a long-term strategy in mind, for example, they prefer to make R&D investments into a declining business rather than abandoning it (Hirano 2014). Chemical companies in Japan invest heavily into R&D. For example, their R&D intensity (R&D spending as percentage of sales) was 4.4 percent in 2014 and 4.1 percent in 2004, which is more than double the EU levels and well above US levels (CEFIC 2016). This means that Japanese chemical firms operate with established organisational structures and are highly committed to innovation.

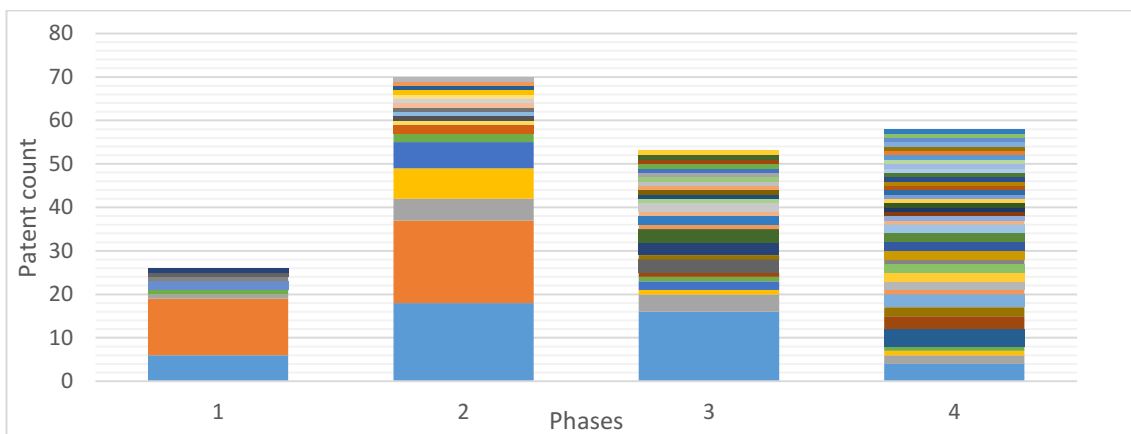


FIGURE 47: PATENTS PER ORGANISATION WITH AT LEAST ONE INVENTOR IN JAPAN AND SOUTH KOREA

The foresight of large Japanese firms also translates into the relationship with their staff, since “most large Japanese organisations of both the private and public sectors have implicit ‘lifetime employment’ policies” (Sedgwick 2008, p. 71). With an

²⁵ Hirano (2014) distinguishes between large and medium sized firms in Japan without providing an clear definition.

employment contract, the firm agrees to take a chance with a candidate and invest into training, and the candidate agrees to learn and wait for recognition (Lanciano-Morandat & Nohara 2000). It may take ten to fifteen years to be promoted to a senior manager role. Workers seem to change positions every three to five years within the company, and during this time R&D staff usually work with “the same, small group of people” (Sedgwick 2008, p. 71). This is in line with a survey on Japanese inventors, which shows that only 10% change their location, and in most cases, the change of location involves secondments within the organisation (Walsh 2009). This suggests that not only are the organisational structures persistent, but there is also a strong link between workers and their organisations.

The strong link between companies and their staff has an effect on the collaboration patterns in R&D because of the distinct management approaches in Japan. A comparative study on R&D staff between Japan and France shows that in Japan, “coordination is less based on the formal procedure” and “knowledge sharing is more dependent on intensive human interaction and mutual understanding” (Lanciano-Morandat & Nohara 2000, p. 12). This empirical approach to learning leads to a similar knowledge base across team members, which may impede the emergence of creative breakthroughs (Lanciano-Morandat & Nohara 2000). According to Nonaka (2007), the middle management in Japanese companies drive innovation, as they absorb tacit knowledge from the team level, combine it with strategic guidance from top-down, and incorporate it into new technologies. The combination of long-term R&D investments in existing technologies with a personal approach to knowledge sharing leads to incremental innovation in Japanese corporations (Lanciano-Morandat & Nohara 2000).

Taken together, the stable effect of proximity on network change in this network might be explained by the long-term innovation planning of large companies, their lifetime employment policies, and their distinct approach to collaboration in R&D. The negative estimate for popularity/activity resembles the notion that R&D teams tend towards small cohesive units that exist over extended periods. Inventions from such teams reinforce the importance of organisational proximity, since all involved

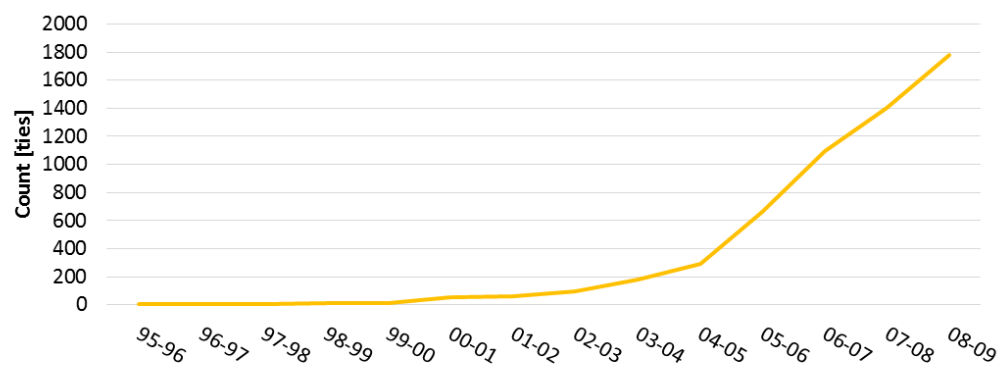
inventors are affiliated with the same organisation. Geographic proximity might be stable since inventors are likely to live close to the company.

This interpretation is backed by the literature on Japanese inventors, which shows that “just over 10% of patents have external co-inventors” (Walsh & Nagaoka 2011, p. 26). If other organisations are involved, Japanese firms tend to work with companies that belong to the same corporate group or to vertically related firms, that is, suppliers or customers (Walsh & Nagaoka 2011). In both cases, the external co-inventor might be co-located as well, for example, due to the physical connection of chemical production processes via pipes. Another factor is the size of Japanese chemical companies, since Walsh and Nagaoka (2011, p. 27) find that “external co-invention increases as firm size declines”, which implies that small firms tend to have more external ties than large firms and vice versa. However, the Japanese chemical industry is dominated by large and medium sized firms, thus R&B collaboration is mainly internal.

In summary, the case of Japan and South Korea exhibits the two activity peaks of the double-boom cycle and a growing number of involved organisations, but it features the interesting deviation that academia shows a volatile involvement in CRP while industry is the continuous driving force. This is in stark contrast to the original concept of the double-boom cycle, which suggests that corporate actors would be more likely to withdraw on short notice, especially when the commercial returns are below expectations (Schmoch 2007). The long-term plans of large corporations are mirrored by the strong and stable effect of proximity on network change, despite shifting phases and the participation of new organisations.

5.5 CHINA

The Chinese network does not align with any features of the double-boom cycle. There is no shift from push to pull, nor is there much involvement from industry. The network is almost exclusively in China and predominantly in the greater Shanghai area. The strongest influencing factor of collaboration behaviour seems to be policy interventions by the Chinese Government, which affect the patenting behaviour of both inventors and organisations. This observation highlights the importance of the institutional context for network dynamics, and how this may differ in countries where the government exerts high control of the economy.



	Phase 1	Phase 2	Phase 3	Phase 4
Geographical Proximity	N/A	N/A	Positive significant	Positive significant
Social Proximity	N/A	N/A	Insignificant	Positive significant
Organisational Proximity	N/A	N/A	Insignificant	Positive significant
Institutional Proximity	N/A	N/A	N/A	Insignificant

FIGURE 48: MAPPING OF NETWORK CHANGE AND THE EFFECT OF PROXIMITY IN CHINA

From a temporal perspective, there was little patenting activity in China before it joined the WTO in 2001, which is reflected in the CRP networks in Phase 1 and Phase 2 where the low level of patenting was insufficient for estimating SAOMs. Phases 3 and 4 resemble the dynamic interplay between Phase 2 structure and agency: structure in the form of policy changes and agency in the form collaboration patterns amongst CRP inventors.

In Phase 3 and after China joined the WTO, the co-inventor network is rapidly growing (the rate parameter is positive and significant in all periods), but Chinese scientists tend to avoid collaboration as indicated by the negative and significant degree effect

with a high estimate value, which might also relate to the fact that patenting was a non-routine type activity for Chinese inventors in this period. To minimise the perceived costs, inventors prefer collaborators in spatial proximity. However, the estimate of the negative degree effect is very strong, thus the predominant notion is that inventors prefer not to collaborate altogether.

The co-inventing behaviour in Phase 4 reflects the period when the National IP strategy and the national patenting targets were put in place. The rate of change is much higher and the degree effect is one of the few insignificant effects, which implies that inventors collaborate with ease and they do it a lot. Over time, repeated collaboration breeds trust and may facilitate future projects (Gulati 1995). The previously perceived burden of collaboration is further reduced by choosing collaborators in the same organisation and the same location. The negative and significant popularity degree effect suggests an inclusive collaboration approach, which might be explained by the high network fragmentation, that is, inventors collaborate in isolated and non-hierarchical groups. Interestingly, the effect on the country of origin is negative and significant in Phase 4, meaning that inventors tend to reach out to non-Chinese collaborators, which is in line with the government expectation to increase the involvement of foreign scholars (Li & Wang 2015).

Concerning the SAOM estimates, it was not possible to achieve convergence for all phases because of the rapid network growth, the low network density, and the high number of inventors (see Appendix A for details). To gain some insights nonetheless, the two largest network components in the Chinese country-level network are selected for estimating SAOMs. It is acknowledged that choosing this approach is a fundamentally different way of defining network boundary specifications compared to the other cases in this dissertation, meaning that caution is needed when comparing results across cases. Also, several modifications were necessary to achieve a converged SAOM²⁶.

²⁶ Phase 1 and Phase 2 could not be modelled with RSiena because of a very low change rate (see Figure 49) and are thus excluded altogether. In Phase 3, institutional proximity and the effect on isolated nodes were dropped due to convergence issues

Concerning social proximity, the estimates for transitive triads and actor pairs at distance 2 (henceforth two-path effect) are insignificant in Phase 3 (see Table 18). The insignificant estimate for transitive triads is interesting considering the projected nature of this network, which indicates a high share of patents with only two inventors. In Phase 4, the transitive triads effect is positive and significant, and the two-path effect is negative and significant. Combined with the growing number of ties (see Figure 48), this indicates the occurrence of closure and thus an increasing importance of social proximity for tie formation.

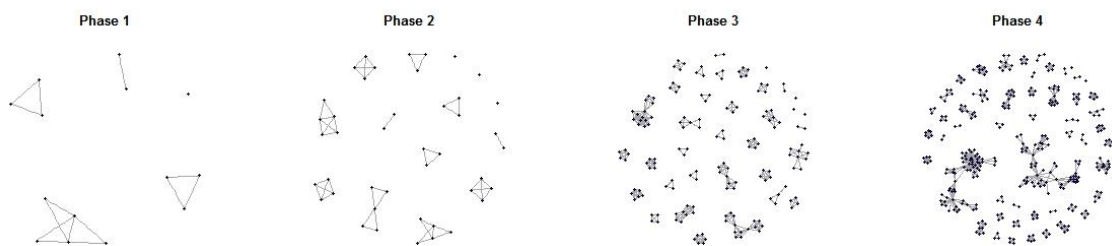


FIGURE 49: EVOLUTION OF THE ACADEMIC NETWORK (AGGREGATED PER PHASE)

TABLE 18: STATISTICAL MODELLING RESULTS FOR THE ACADEMIC NETWORK

Academics	2002-2006		2005-2009	
Phase	Phase 3		Phase 4	
Network size	166		361	
Network change	Estimate	SE	Estimate	SE
Rate parameter period 1	0.623*	(0.110)	12.920*	(1.371)
Rate parameter period 2	1.202*	(0.197)	14.109*	(1.250)
Rate parameter period 3	1.953*	(0.240)	5.759*	(0.566)
Rate parameter period 4	2.415*	(0.286)	10.401*	(0.696)
Structural dependencies				
Transitive triads	1.008	(1.745)	0.519*	(0.054)
Number of actor pairs at dist 2	-0.794	(0.722)	-0.133*	(0.032)
Degree	-6.218*	(2.046)	0.202	(0.356)
Degree related popularity (sqrt) network-isolate	1.626	(2.358)	-0.917*	(0.161)
			5.264*	(0.318)
Exogenous effects				
Geographic proximity	0.737*	(0.288)	0.066*	(0.018)
Organisational proximity	0.466	(0.313)	1.674*	(0.107)
Institutional proximity			0.090	(0.128)
Same country of origin	-0.312	(0.493)	-0.469*	(0.184)
Overall maximum convergence	0.1156		0.1724	

* Parameter is significant at 0.05 level (Ripley et al. 2017)

The effect of geographic proximity on tie formation is positive and significant in both phases, which indicates that inventors have a constant preference for collaborators in

spatial proximity. Most collaboration ties in this network are within China: in fact, most inventors and collaborations are in the greater Shanghai area, roughly in a driving radius of 1.5 hours (Figure 50). Interestingly, some Shanghai-based inventors are only sparsely connected too; that is, spatial centrality does not necessarily equal network centrality. There are a few long-distance ties, both within China, for example between Shanghai and Hong Kong (2000 km distance), but also to international collaborators, for example McMaster University near Toronto in Canada, and the University of California in the USA.

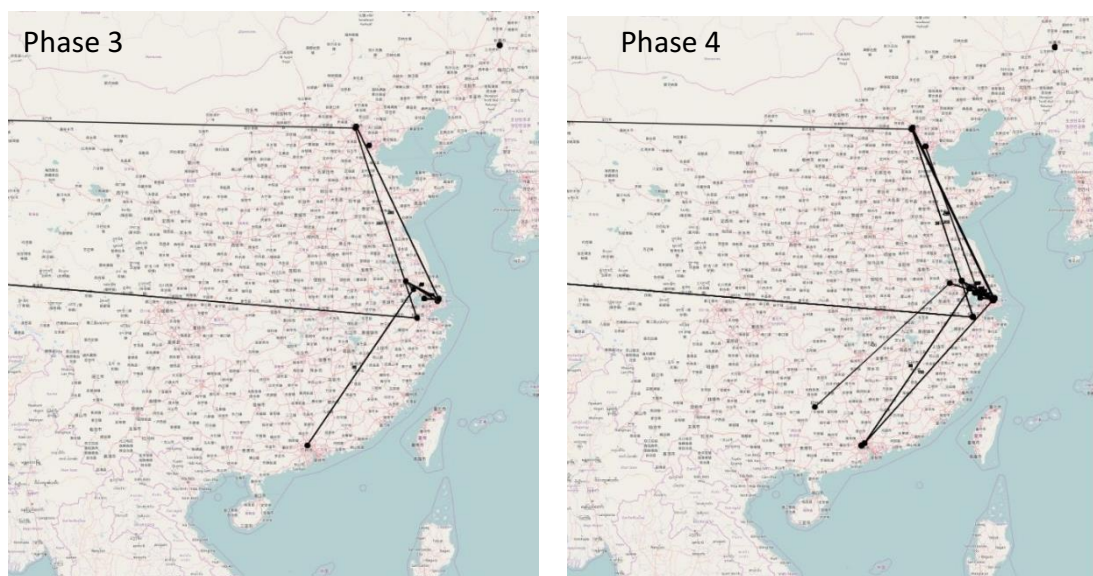


FIGURE 50: SPATIAL EVOLUTION OF THE ACADEMIC CO-INVENTOR NETWORK

The effect of organisational proximity is insignificant in Phase 3, and positive and significant in Phase 4, which suggests that the organisational boundaries become more important for the choice of collaborators. This might relate to the increasingly open market structures in China and the resulting rise of domestic and international competition, plus the increase of CRP inventors providing more choices to individuals, thereby improving the chance of finding a collaborator within the own organisation.

Over time, there is a strong increase in the number of involved organisations. Phases 1, 2 and 3 see few organisations with a few patents each, until a rapid upsurge in Phase 4, with the involvement of many new organisations with a few patents each (see Figure 51). Interestingly, this is without the involvement of large patent producers as in Europe or the USA. Most organisations in Phase 4 are universities, but there are also a

few government-owned companies and institutes of the Chinese Academy of Science (CAS). Note that the relationship between universities, companies and the CAS is difficult, because university scientists are keen to collaborate with CAS to get a promotion, but companies avoid working with CAS because of its commercial interests, which makes negotiations about potential discoveries more challenging, consequently leading to a certain misfit regarding industry-research collaboration in China (Li & Wang 2015; Tang 2008).

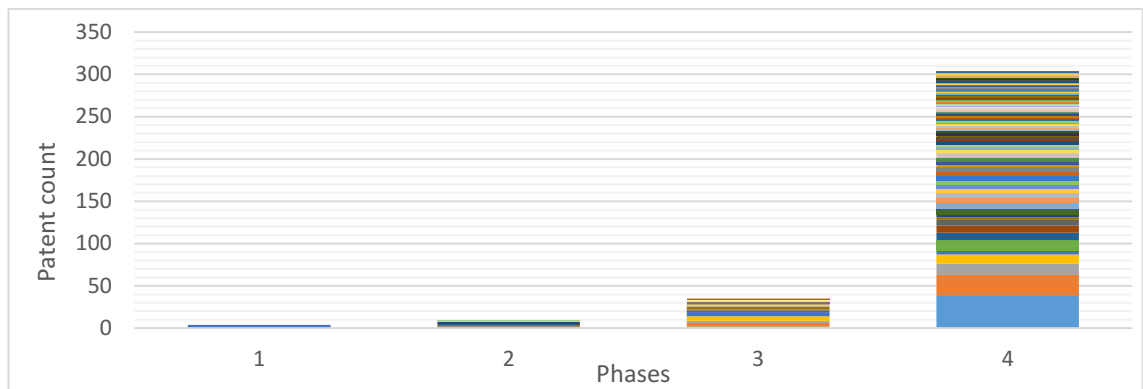


FIGURE 51: PATENTS PER ORGANISATION WITH AT LEAST ONE INVENTOR IN THE CHINESE NETWORK

The effect of institutional proximity on tie formation is insignificant in Phase 4, which resonates with the slight increase of industry-research ties in Phase 4 (see Figure 52), though the majority of ties are amongst academic inventors. From an institutional stance, the strongest driver of network change appears to be the Chinese Government itself. Of course, one should “avoid reading off the behaviour and performance of firms from territorial institutions in a deterministic manner”, because “there is little evidence showing that agents act and perform the same when subject to the same institutions” (Boschma & Frenken 2011a, p. 301). However, this might apply to more firms in western countries, but less so to universities in socialist China, because Chinese universities are government funded and thus government dependent, plus they have a strong local focus and therefore are hardly exposed to any influence from overseas (Boschma & Frenken 2009).

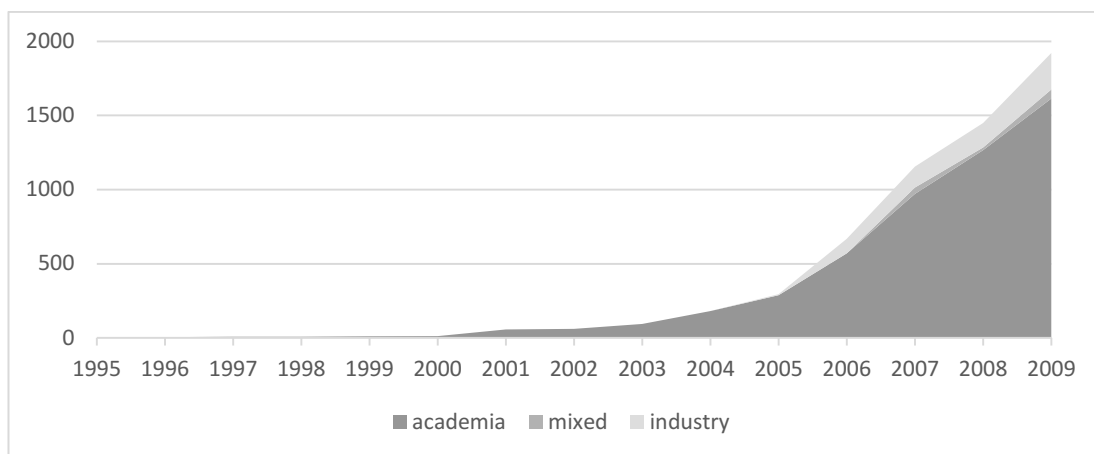


FIGURE 52: THE NUMBER OF TIES WITHIN AND ACROSS INDUSTRY AND ACADEMIA IN CHINA

In fact, a series of decisions by the Chinese government evidently contributed to the rapid economic development including patenting performance. In 2001, China joined the World Trade Organisation which exposed the Chinese economy to international competitions and increased the urge for innovation (Song, Zhenxing & Dawei 2016). To wipe off the ‘copycat’ image caused by numerous patent infringements by Chinese firms, the Chinese Government launched the National Intellectual Property Strategy in 2008, encompassing more adequate policies for IP protection. In parallel, a policy package on “Indigenous Innovation”²⁷ introduced various national innovation targets, including patent outputs, as well as mechanisms to meet them, such as tax incentives, public procurement policies, domestic technological standards, and subsidies for patenting (Cao, Suttmeier & Simon 2006; Zhou, Lazonick & Sun 2016).

A nationwide and longitudinal analysis reveals that government subsidy programs have had a critical influence on the upsurge of patents in China²⁸, in particular after 2010 (Song, Zhenxing & Dawei 2016)²⁹. Similar results were reported by Fisch, Block and Sandner (2016). The subsidies include R&D funding for organisations, and financial incentives for inventors (depending on the year and province). For instance, the

²⁷ The official title is: *National Programming 2006–2020 for the Development of Science and Technology in the Medium and Long Term*

²⁸ Other factors for the upsurge of patents in China include the increasing business sophistication of domestic firms in economically successful regions, the increase of Foreign Direct Investment (FDI) into China (Hu & Jefferson 2009), effects of globalisation, and the growing numbers of foreign companies doing business in and with China (Keupp, Friesike & von Zedtwitz 2012).

²⁹ Remember that the annual network observations contain the patent applications for the three subsequent years. For instance, the observation for 2009 includes the applications until 2012, that is, some effects of the outlined policy changes are captured in the SAOM of Phase 4.

subsidy for a patent application is between RMB 500 and 3500 (~ USD 70-500) and the patent grant reward ranges from RMB 1,500 to 5,000 (~ USD 215 – 724), making a noticeable difference for a worker in urban China with an average salary of 5,166 RMB (Trading Economics 2017). Between 1999 and 2013, annual growth rates of patent applications ranged between 20 and 60 percent, and in 2013 alone 700,000 domestic applications were filed with the China’s State Intellectual Property Office (SIPO), as shown in Figure 53 (Song, Zhenxing & Dawei 2016). It turns out that the subsidies were occasionally abused since “some (...) applicants may even make money simply by filing patent applications” (Song, Zhenxing & Dawei 2016, p. 194). The point is that government interventions in China impact the patenting behaviour of individual inventors, as well as the strategic behaviour of organisations including PROs, that aim to meet the government’s patent targets.

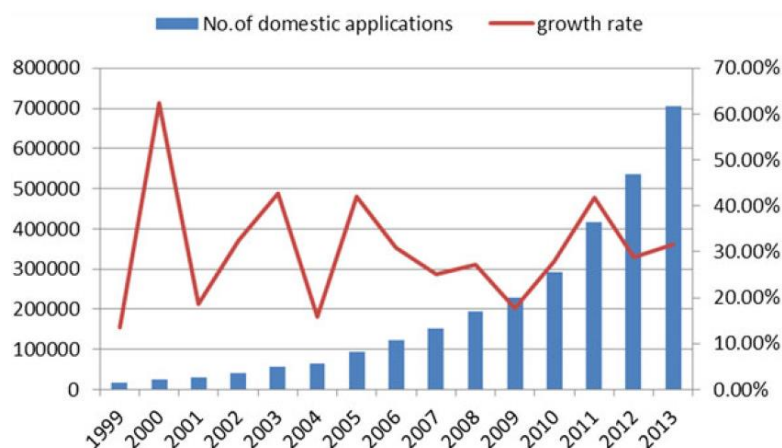


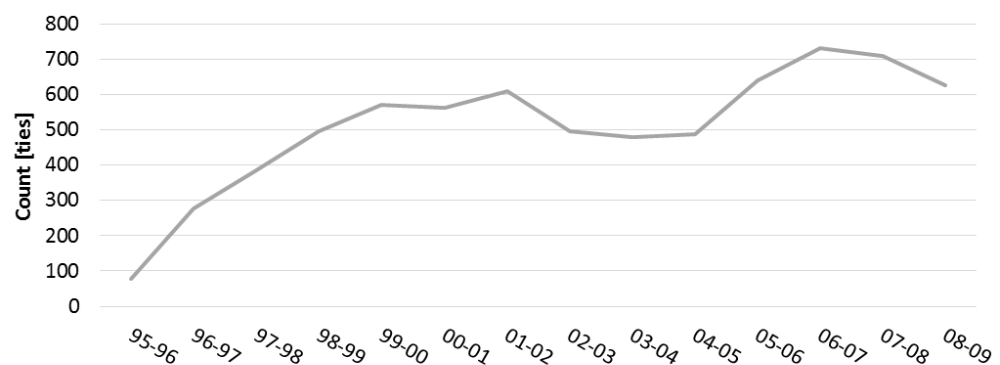
FIGURE 53: NUMBER OF DOMESTIC APPLICATIONS RECEIVED BY SIPO AND GROWTH RATE
(SOURCE: SONG, ZHENXING & DAWEI 2016)

By and large, the Chinese case does not resemble the characteristics of the double-boom cycle. Whether and when the observed increase is going to reach a peak is unclear, which might relate to the special situation in China as an emerging economic power with astonishing growth rates in many areas, as a nation with an appetite for innovation and increasing capacities in knowledge-intensive industries, and as a country with state capitalism where the Government still exerts much control over both industry and public research. Concerning network drivers, Phase 3 is the only occasion in this study where organisational proximity is insignificant, which might

relate to the low exposure to competition in China between 2002 and 2005. Geographic proximity has a positive effect on tie formation which seems to relate to the spatial agglomeration of CRP inventors in the greater Shanghai area.

5.6 WORLDWIDE

The global CRP co-inventor network resembles the double-boom cycle in terms of the activity level. That said, the SAOMs provide no evidence for a dynamic effect of proximity on tie formation since all proximity dimensions have the same effect over time. It appears that studying co-inventor networks on a global scale offers limited insight, since the aggregated nature seems to overwrite important dynamics at the local level, in particular with respect to geographic and social proximity. Similar to the local level, organisational proximity is strong and stable in all phases of this global network too.



	Phase 1	Phase 2	Phase 3	Phase 4
Geographical Proximity	Positive significant	Positive significant	Positive significant	Positive significant
Social Proximity	Insignificant	Insignificant	Insignificant	Insignificant
Organisational Proximity	Positive significant	Positive significant	Positive significant	Positive significant
Institutional Proximity	Insignificant	Not available	Insignificant	Insignificant

FIGURE 54: MAPPING OF NETWORK CHANGE AND THE EFFECT OF PROXIMITY WORLDWIDE

The activity dip after the first peak aligns with the double-boom cycle model, but it is not obvious what contributes to the decline after the second peak. This is a global network; hence the search for explanations should be global too, for example, the Global Financial Crisis (GFC). Several studies confirm that the “extreme disruption of financial and monetary systems [during the GFC] seemingly affects patenting activity” (Das & Icart 2015; Gishboliner & Benoliel 2015, p. 352), but that this effect varies across countries depending on the severity to their national finance system as well as policy responses (OECD 2012a). For instance, both the USA and Germany experienced less patent applications, but Germany recovered quicker because of Germany’s budget

increase on innovation and financial incentives for inventors encouraged by the European Union (Gishboliner & Benoliel 2015; OECD 2012a). Japan had no decline in patent applications and China continued its exponential growth. This elaboration also shows that global events may impact patenting activities and collaboration in different countries in different ways and that the 'data noise' of global studies might override such national nuances.

It is worth noting that this worldwide network is not truly worldwide as it excludes inventors located in China, because the tremendous network growth in China made it impossible to compute converging SAOMs. Nonetheless, this network covers a large part of the global CRP inventor population. Importantly, this network differs from the country-level studies as it is on a different geographic scale: the global scale. To achieve convergence, a few modifications to the SAOMs were necessary³⁰. For a matching between the model estimates and the network change along the technology cycle, see Figure 54.

Concerning social proximity, the two-path effect is negative in all phases, and significant in Phase 2 and Phase 4 (see Table 19). According to the RSiena manual, a negative two-path effect indicates closure, when the number of ties is fixed. However, the number of ties declines in Phase 2 and Phase 4, thus there is no evidence for closure in this network.

³⁰³⁰ Institutional proximity and degree related popularity were removed in three phases and the effect on network-isolates was removed altogether.

TABLE 19: MODEL RESULTS FOR NETWORK EVOLUTION WORLDWIDE

Worldwide	1996-2000		1999-2003		2002-2006		2005-2009	
Phase	Phase 1		Phase 2		Phase 3		Phase 4	
Network size	363		502		614		687	
Network change	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Rate parameter period 1	2.266*	(0.233)	3.094*	(0.284)	4.961*	(0.435)	4.033*	(0.379)
Rate parameter period 2	2.681*	(0.270)	6.026*	(0.481)	6.190*	(0.555)	6.747*	(0.559)
Rate parameter period 3	3.261*	(0.294)	2.811*	(0.255)	8.336*	(0.712)	10.374*	(0.847)
Rate parameter period 4	3.098*	(0.280)	4.843*	(0.385)	3.977*	(0.356)	12.421*	(1.011)
Structural dependencies								
Transitive triads	0.616*	(0.056)	0.441*	(0.017)	0.642*	(0.048)	0.507*	(0.020)
Number of actor pairs at dist 2	-0.007	(0.026)	-0.029*	(0.013)	-0.043	(0.026)	-0.143*	(0.014)
Degree	-2.158*	(0.157)	-3.197*	(0.072)	-2.536*	(0.112)	-2.802*	(0.047)
Degree related popularity network-isolate					-0.362*	(0.087)		
Exogenous effects								
Geographic proximity	0.147*	(0.013)	0.046*	(0.010)	0.098*	(0.009)	0.140*	(0.009)
Organisational proximity	1.593*	(0.097)	1.604*	(0.067)	1.533*	(0.054)	1.340*	(0.057)
Institutional proximity	-0.212	(0.108)						
Same country of origin	0.326*	(0.080)	0.689*	(0.071)	0.320*	(0.057)	0.038	(0.058)
Overall maximum convergence	0.246		0.226		0.265		0.164	

* Parameter is significant at 0.05 level (Ripley et al. 2017)

Organisational proximity is positive and significant in all phases, indicating that inventors in this network tend to turn to their colleagues, rather than to someone outside the organisation, which aligns with the results at the local level. This highlights that organisational boundaries are important determinants for co-inventorship ties, and that this effect is consistent across time, space and geographic scales, as far as CRP technology is concerned.

Geographic proximity has a positive and significant effect on tie formation in all phases. This means that there is a consistent preference for nearby collaborators. However, given the fact that this is global network, not a local network, that question arises of what *near* and *far* actually means. For example, the local networks in, say, Australia and Europe also yielded a positive and significant effect of geographic proximity on tie formation, but the underlying kilometre values of “a close distance” are likely to be different. A 100km distance might be *nearby* for an Australian, but *fairly far* for a European, simply because of local circumstances and ideas about space. The SAOM estimates are the result of a statistical process which uses the raw data as

an input. Surely, the variable for geographic proximity uses the logarithm of the raw data, but the point is that the social and subjective meaning of distance varies across places, thus doubts arise whether results of parametric analysis are comparable across places without appreciating the local meaning of space.

Geographers have pointed to the social meaning of space, which is subjective and context-dependent. For example, there might be little interaction between black and white neighbourhoods in the USA, or elsewhere, while citizen of London and New York might feel close due to their proximity on dimensions other than space, for instance in terms of cosmopolitanism (McMaster & Sheppard 2008). Applied to this study, CRP inventors in Europe, the USA and Australia might find it easier to collaborate due to a shared language and lifestyle, while collaboration between Australia and Asian countries might come less easily due to cultural differences despite relative geographic proximity. This resonates with Gilding's findings, which report that "the 'tyranny of distance' [in Australia] is exacerbated by cultural dynamics, favouring ties with the US and UK rather than Japan and Korea" (Gilding 2008, p. 1132). If the social meaning of geographic distance is a function of local context, then a given geographic distance has a shared meaning within locations, but not across locations. This means that measuring distance in discrete units is more appropriate for location-bound studies than for international studies.

The effect of the country of origin is positive and significant in the first three phases, and insignificant in Phase 4. This implies that the country of origin becomes less important over time, which might relate to the overall trend of globalisation. A common phrase is that globalisation makes the world a smaller place, which obviously does not refer to the populated surface on planet earth, but to the increasing ease of international interaction such as global trade, financial transactions, telecommunication and travel (Kirsch 1995). Some even suggest that because of globalisation, the 'tyranny of distance' gives way to "tyranny of real time" (Virilio 1993, p. 10). The point is that as a result of globalisation, R&D collaboration is increasingly international too, thereby explaining the decreasing importance of the country of origin in this case.

6 SYNTHESIS

To facilitate discussion of the findings, this chapter synthesises and compares the results across cases. Although institutional proximity was excluded in most SAOMs because of modelling issues caused by high co-linearity with the obligatory degree effect, the role of institutional context for network dynamics is still captured through the different locations.

As a reminder, a central objective of this dissertation is addressing a conflict in the empirical literature regarding proximity and network change. Ter Wal (2013b) finds an increasing effect of social proximity on tie formation while Balland, De Vaan and Boschma (2013) find the opposite. Conversely, Ter Wal finds a decreasing effect of geographic proximity on tie formation, and Balland, De Vaan and Boschma find the opposite again. As outlined in section 2.4.4, the conflicting findings might relate to the different research designs with respect to the empirical case (biotechnology versus video games industry), the geographic scale (country versus global), and the level of analysis (interpersonal versus interorganisational). The results in this study address the same level of analysis, the same technology, and the same geographic scale, but the dynamic determinants for network change still differ across cases. This highlights the important role of local institutional differences for the evolution of collaboration networks.

6.1 NETWORK CHANGE ALONG THE DOUBLE-BOOM CYCLE

Most cases in Chapter 5 demonstrate characteristics of the double-boom technology cycle. Typical features include two activity peaks that represent science-push and market-pull, a growing and increasingly diverse pool of involved organisations, and some driving actors with ongoing engagement.

When comparing the cases from a temporal view, it turns out that all cases, except China, feature aspects of science-push in the first few years. In the USA, Europe, Australia, Japan and South Korea, most patents in Phase 1 are produced by a few organisations, though the ratio of industry and academia varies across places. For instance, most ties in Europe and the USA are within industry, while most ties in

Australia, Japan and South Korea are within academia. This implies that both public and private research activities may contribute to the uptake of an emerging technology. In China, the situation differs altogether since there is little activity in Phase 1 and there are no obvious key organisations that produce most patents.

After the first peak, the activity levels decline in Europe, the USA, Australia, Japan and South Korea, but not in China. The era of decline is mostly in Phases 2 and 3. According to the double-boom cycle model, this downturn occurs because “the technical realisation proves to be much more difficult than originally assumed” (Schmoch 2007, p. 1006). In fact, the qualitative insights in section 4.1 support the view that this happens because of technological challenges related to CRP, for instance the handling of residual copper in ARTP-based products, or the design of suitable reactors for implementing CRP on large scale production. In China, there is no downturn whatsoever in this period, but rather the activity level on CRP patenting continues to increase.

After passing the lowest activity level, the cases evolve rather differently. The rise towards the second peak represents market-pull, and the networks in Europe, the USA, Japan and South Korea demonstrate this pattern, visible through the increase of both patents and collaboration ties, as well as the growing number of organisations that adopt CRP for diverse applications. In Australia, there is a slight increase of patenting activities after the dip, but the number of organisations remains stable, plus most engaged organisations are PROs. Hence there is little evidence of market-pull for CRP in Australia. In China, Phase 3 and Phase 4 see a rapid growth of patent applications, but also mainly by publicly funded research organisations, mostly universities. As discussed in section 5.5, this seems to relate to government interventions, thus this observation might be called government-push.

Besides the volatile activity patterns, the double-boom model suggests distinct behaviours from companies versus academia. In particular it point out that “firms react more explicitly, if the expected technological and commercial results are not achieved in a short time” (Schmoch 2007, p. 1007), implying that firms are more likely to withdraw from a technology compared to PROs. Whilst multiple firms across all

locations withdraw from CRP, there is evidence that some firms demonstrate strong and ongoing engagement, implying that such companies are satisfied with their commercial returns. Examples of companies with long-term engagement are PPG industries in the USA, Ciba in Switzerland, and Kaneka in Japan. This observation shows that profit-seeking organisations may also follow long term innovation strategies that pay off over time. Interestingly, numerous PROs withdraw from CRP after a short while, showing that publicly funded organisations do not have long term plans by default.

6.2 GEOGRAPHIC PROXIMITY

The cases in this study exhibit four different patterns concerning long-distance collaboration. Importantly, three cases feature a non-linear impact of geographic proximity on tie formation, which underlines the need for longitudinal network studies to cover more than two observations.

Firstly, inventors in the European network tend to engage in long-distance collaboration during the period of declining activity, which might be an attempt to access valuable knowledge from distance places. Secondly, inventors in the US network tend to engage in long-distance collaboration during periods of increasing activity. This suggests that inventors try to access external knowledge to accelerate an already positive development. Thirdly, in the networks for China, Japan and South Korea, inventors tend to avoid long-distance collaboration and focus on nearby collaborators throughout. Here, the benefits of accessing external knowledge do not seem to outweigh the associated costs. Fourthly, the Australian network shows a weak tendency to prefer co-located others. In fact, the average Australian inventor seems to be comfortable with long-distance collaboration, in particular within the country.

A potential explanation might relate to transaction cost theory, because when it comes to networks and space “there is a cost associated with the length of edges” (Barthélemy 2011, p. 1). In that sense, long distance collaboration might only emerge when the anticipated benefits of accessing external knowledge outweigh the associated costs. Traditionally, transaction cost theory concerns the trade-off between internal and external exchange from the firm’s perspective (Coase 1937): in a simple

sense, the question of make-or-buy (Klein 2008). The cost of a transaction not only stems from the investments needed for enabling the transaction, but also from the associated risks arising through the external relationship (Klein & Mondelli 2013). Consequently, the “forward-looking agents will structure their relationships to minimize these risks” (Klein & Mondelli 2013, p. 888). Recent developments on transaction cost theory go beyond the traditional focus on finance and tangible goods, and focus on information flow in the networked and knowledge-based economy (Macher & Richman 2008), because the underlying principle remains that relationships bear a cost and pose risks.

In the light of transaction cost theory, the cases in this studies exhibit different mentalities when it comes to the assessment of long-distance ties. In Europe, technological challenges and declining activities might be associated with the risk of falling behind the global competition. On that basis, inventors in the European network might try to tap into external knowledge to compensate for knowledge shortage on their side, and accept the associated costs in order to remain competitive. In the USA, the rise of the overall activity level might be perceived as an opportunity for commercial success, with the potential risk of “not making the most out of it”. Additional investments for accessing external knowledge might seem a sensible bet in times of growing activities.

In Japan, inventors rely on endogenous knowledge sources and avoid the associated risk and cost of long-distance collaboration altogether. In fact, Japanese chemical companies exhibit the highest R&D intensity in the world, more than twice as much as Europe and well above the USA (CEFIC 2016). Thus, such firms do spend funds on innovation, but not for bridging long-distance collaborations. The inward-looking strategy might also relate to past problems concerning the integration of foreign workers into the Japanese workforce (Farquharson & Omori 2015).

In Australia, a regular commute between Melbourne and Sydney seems to go well with most Australian inventors, implying that the travel costs are being considered a default for many projects. A prior study on interorganisational networks in Biotech observed that Australian businesses prefer collaborators in Europe or the USA over Asian

partners (Gilding 2008), which is confirmed in this study too. Based on transaction cost theory, this might related to the cost for establishing common ground, which is a precondition for effective collaboration to take place. Considering the western life style in Australia, it seems sensible that establishing common ground with other western countries comes at a lower cost compared to Asian countries, despite the greater geographic distance to Europe and USA.

6.3 ORGANISATIONAL PROXIMITY

The effect of organisational proximity on tie formation is positive and significant across all phases in all cases, except in Australia and China. This means that most organisations seek to maintain control over the in- and out-flow of technological knowledge. In Australia and China, organisational proximity only matters in some phases, which might also relate to the relative high involvement of academic inventors in both countries. A closer look on the organisational behaviour of public and private organisations points to important differences that might explain this result.

The competition between companies is different to the competition between PROs. Companies are potentially for the same market since most CRP applications are in the field of speciality and fine chemicals (Kannegiesser 2008). The knowledge-based view of the firm assumes that knowledge and “intellectual capital” are critical strategic assets for value creation, and that “individuals are the primary agents of knowledge creation” (Grant 1997, p. 451). Thus, firms seek to control knowledge flows at the individual and organisational level to strengthen their competitive advantage. By contrast, PROs often choose other channels for generating an impact with their research, for example, they offer patents for licencing or engage in cooperative research projects for knowledge exchange; sometimes such activities are executed through a spin-off company. The point is that firms want to protect their knowledge, while PROs want to share it.

To access new knowledge, firms may acquire each other, though this rarely happens amongst PROs. Mergers and acquisitions (M&A) are a useful way for companies to access specialised knowledge without developing it from within. Specialised knowledge emerges as a technology evolves since the industrial applications are being

developed into specific areas, leading to co-evolving trajectories that build on the same technological foundation. In the video game sector, for example, some fundamental principles evolved into distinct genres (Balland, De Vaan & Boschma 2013). In CRP, there is also a technological shift from basic research in the early stages to more applied and diverse research during the later stages. Large chemical firms make use of that, as shown by a study on the chemical industry in Europe, by acquiring “companies from other sectors to quickly gain technical knowledge and accelerate innovation” (Das & Icart 2015, p. 154). With the acquisition, the pool of internal inventors grows and the need for interorganisational collaboration decreases. Since M&A almost exclusively occur in the private sector, public organisations need to collaborate across organisational boundaries to access external knowledge.

Notable mergers and acquisitions in this study include the acquisition of Rohm & Hass by Dow Chemicals in 2009, the acquisition of Ciba speciality chemicals by BASF in 2009, and the acquisition of Bausch and Lomb by Valeant in 2013. In addition, Merck acquired Sigma Aldrich in 2015, Dow Chemicals and DuPont merged in 2017, and the negotiations of the merger of Monsanto and Bayer are still ongoing in early 2018. The act of merger and acquisition redefines the organisational boundaries (Öberg, Henneberg & Mouzas 2007) and, depending on the managerial intent, combines the R&D activities of previously separated inventors which may give rise to growing intra-organisational collaboration networks. This observation aligns with the theoretical views of Powell and Owen-Smith (2012, p. 564), who suggest that “actual social and economic systems manifest in a mix of consolidating and expansive growth” which ultimately influences the underlying networks.

6.4 SOCIAL PROXIMITY

The effect of social proximity on tie formation differs across the cases in this dissertation. In Europe, social proximity matters during times of growing activity levels towards the first and the second peak of the technology life cycle. The same is true for Australia and the USA, but only for the second rise. In China, social proximity becomes increasingly important over time (note the Chinese case only covers two phases out of four). In Japan and South Korea, there is no evidence for endogenous network change.

The same applies for the global network, but for different reasons. In Japan and South Korea, this finding seems to relate to the local approach towards team work in large chemical companies, while the results of the global SAOM rather relate to the large population and the high level of network fragmentation.

Considering the strong and stable effect of organisational proximity on network change, it is likely that social proximity mainly occurs within organisational boundaries. By implication, the size of network components is associated with the size of the organisation, since large organisations have a greater pool of potential collaborators. This observation might relate to the importance of social proximity during times of growth. During such times, large organisations seem to be attracted by the commercial prospects of CRP and make dedicated investments in R&D which result in growing inventors groups within the organisation. The growing activity levels in such phases also imply a positive feedback loop in that the outcomes of research projects, including negative outcomes, justify future investments, including the recruitment of additional human resources, leading to growing groups as well.

The low occurrence of interorganisational collaboration on the inventor level has an effect on network fragmentation, since a high number of organisations in a network leads to many disconnected network components. This is, of course, also a by-product of the analytical approach toward the network boundary specification in this dissertation, in that the network boundaries are defined along geographical borders, regardless of whether the included inventors know each other or not. Here, the Australian case stands out since this is the network with the smallest population, but also the network with the greatest cohesion. In fact, background research from publications and conversations with CSIRO staff suggest that the inventors in the Australian network know each other and truly represent a scientific community on CRP where co-inventor ties exist across organisational boundaries.

6.5 LOCAL VERSUS GLOBAL NETWORK DYNAMICS

Two observations stand out when comparing results of the worldwide model and country-level networks. Firstly, the results of the global network are stable, while the results of the local networks are more dynamic. While the global network captures the

big picture, it seems to overwrite important nuances on the national level, for example on geographic and social proximity, which would get lost in a study that only concerns the global network. Of course, global events such as the GFC also help explain network changes on the local level, but the consequences of and the responses to such events vary across places. Thus, the global model in this study is a useful reference point, but the territory-level studies lead to more granular insights and explanations of network change along the technology life cycle. By implication, studies that focus on nothing but the global network should acknowledge the risk of missing network dynamics at the local level.

Secondly, the estimates of the global network in this study (see Table 19) are surprisingly similar to the estimates of Balland, De Vaan and Boschma's study on the global video games industry (Balland, De Vaan & Boschma 2013). For instance, both studies report positive and significant estimates for geographic and organisational proximity in all phases. Further, the estimate values are somewhat in the same range. In both studies, the estimates for social proximity are less than 0.0, and for organisational proximity the estimates range between 1.3 and 1.6 in one study and between 1.8 and 1.1 in the other (Balland, De Vaan & Boschma 2013). Of course, this similarity may be coincidence and it goes beyond this study to find out whether or not this is the case. The point is that the global study by Balland, De Vaan and Boschma (2013) does not permit the observation of important nuances on collaborative innovation at the local level.

	Gen 3		Gen 4		Gen 5		Gen 6	
	<i>N</i> = 349		<i>N</i> = 664		<i>N</i> = 724		<i>N</i> = 479	
	β	SD	β	SD	β	SD	β	SD
Density	-1.957**	0.022	-2.209**	0.015	-2.456**	0.021	-2.362**	0.043
Transitivity	0.654*	0.331	0.653**	0.045	0.632**	0.031	0.700**	0.067
Institutional proximity	0.098**	0.038	0.140**	0.025	0.133**	0.023	-0.042	0.046
Geographical proximity	0.017**	0.003	0.026**	0.002	0.025**	0.002	0.045**	0.005
Organizational proximity	1.854**	0.100	1.533**	0.096	1.450**	0.071	1.104**	0.135
Social proximity	0.186**	0.038	0.079**	0.011	0.081**	0.011	0.044**	0.010
Cognitive proximity	-0.002	0.003	0.002	0.002	0.023**	0.003	0.025**	0.006
Profile similarity	-0.735**	0.050	-0.820**	0.035	-1.097**	0.032	-1.181**	0.059
Size	0.206**	0.067	0.206**	0.003	0.166**	0.009	0.065**	0.015
Experience	-0.003	0.005	-0.005	0.014	0.004**	0.001	0.020**	0.002

Coefficients are statistically significant at the * $p < 0.05$; and ** $p < 0.01$ level.

FIGURE 55: SAOM RESULTS OF A GLOBAL COLLABORATION NETWORK IN THE VIDEO GAMES INDUSTRY 1987-2007 (SOURCE: BALLAND, DE VAAN & BOSCHMA 2013)

7 DISCUSSION

Thus far, the results are interpreted by case and jointly synthesised. The discussion here builds upon Chapters 4 and 5, with the aim to answer the initial research question of this dissertation:

What is the role of institutional context for the dynamic effect of proximities on tie formation along the technology life cycle?

7.1 THE GEOGRAPHIC AND SOCIAL DIMENSION OF THE DOUBLE-BOOM CYCLE

In the original paper on the double-boom cycle, Schmoch (2007, p. 1011) points out that “we need broader experiences about possible paths of development and the specific factors leading to double-boom cycles”. The results of this dissertation reveal contributing factors, some in the social domain and others that are place-dependent.

This study shows that the same technology may exhibit a double-boom pattern in one territory, but not in another, for example when comparing the USA and China. At least four location-bound factors may contribute to the occurrence of a double-boom cycle. Firstly, the state form might matter since inventors seem to behave and interact differently in liberal economies versus non-liberal regimes. Secondly, the stage of an economy appears to play a role, since emerging economies exhibit different growth paths compared to developed economies. Thirdly, the rate of regulatory updates and the force of law might matter (Schauer 2015). For instance, the frequency and pace of implementation of large-scale policy decisions appears relatively high in China compared to some western countries. Fourthly, the impact of and the response to external events, such as the GFC, varies greatly across countries (Gishboliner & Benoliel 2013; Izsak & Radošević 2017).

From a social standpoint, the focus on collaboration networks in this dissertation contributes to knowledge since thus far “the [technological] development paths were primarily discussed in scientific and technological terms” (Schmoch 2007, p. 1011), but not through the lens of social networks. This dissertation contributes to knowledge by using collaboration ties as an indicator for technological activities, as opposed to the number of patents. This study shows that the emergence of collaboration ties is largely

influenced by the organisations that employ such inventors. In addition, those organisations are exposed to the institutional context at their location, thereby making the chance of interpersonal collaboration a function of personal, organisational and institutional circumstances. To disentangle the social drivers on each level, the results are now reviewed from a sociological perspective on the macro, meso and micro level (Turner 2012) (see also section 2.2.5).

Macro level forces unfold in different patterns across territories. For example, the global *population* of CRP inventors is constantly growing, but at a different pace across places. In Europe and the USA, the greatest increase is from Phase 1 to Phase 2, while in Japan and South Korea, the greatest increase is from Phase 2 to Phase 3. In China, the population of CRP inventors grows rapidly in Phase 3 and Phase 4. The growth of population goes hand in hand with forces of *production and reproduction*, as seen through the involvement of ever more universities and research institutes that facilitate the spread of CRP knowledge through teaching and research. Moreover, the use of *power* varies across places, which manifests in the legal framework, reward systems, national research programs, or ad-hoc policy intervention, which all impact the choices of inventors. Examples include the reformed IP law in China, the allocation of public R&D funding in Japan, cooperative research centres in Australia, and the response of European countries to the GFC. The point is that macro level forces are mainly localised.

At the meso level, it is predominantly corporate units, such as companies, universities and PROs, that drive R&D activities on CRP. With respect to the three meso-level forces identified by Turner (2012) there is little evidence of *segmentation* because few corporate units are newly formed for CRP, which might relate to the established nature of chemistry in both industry and research. Most companies and universities exist prior to their engagement with CRP. That said, several new research groups emerged, as well as a few companies, for instance technology transfer offices at universities. Further, this study finds strong evidence for *differentiation*, in that both industry and academia focus their activity in increasingly specific applications of CRP, thereby following specialised technological trajectories, which sets them apart from other organisations. Lastly, the force of *integration* is also evident, in particular in

industry where companies integrate through mergers and acquisitions. M&As are less common in academia, but inventors have a higher degree of freedom that allows them to engage in interorganisational collaboration.

On the micro level, the number of collaboration encounters is volatile along the technology life cycle of CRP and the observed pattern resembles the double-boom technology cycle in most cases (Schmoch 2007), in particular the USA, Europe, Japan and South Korea. Collaboration mainly occurs within academia and within industry, or as Turner (2012) puts it, amongst members of the same social category. Across the territories, the share of ties between industry and academia varies from constant engagement (in the USA), to volatile engagement (in Japan and South Korea), to barely any engagement (in Europe). *Ecology*, in the form of physical distance, matters for collaboration, but in diverse patterns across time and space as shown through the effect of geographic proximity on tie formation. This relates to the *transactional needs* of individuals, since a tie is unlikely to emerge unless perceived added value outweighs the cost for forming a tie, which includes the cost for overcoming physical distance.

In essence, it appears that forces on all three levels, the macro, meso and micro level, matter for the evolution of the CRP co-inventor network, and that all such forces have a local nature, meaning they have place-dependent causes and consequences. This means that local institutional context plays a role for the evolution of knowledge networks and the occurrence of a double-boom cycle.

7.2 THE DYNAMIC EFFECT OF PROXIMITIES

Another element of the research question is the dynamic effect of proximity on tie formation. Here, this dissertation aims to enhance knowledge concerning the evolution of spatial networks (Boschma & Frenken 2011a), and to shed light on a conflict in the extant empirical literature (Balland, De Vaan & Boschma 2013; Ter Wal 2013b).

In the global network, the effect of geographic proximity of tie formation is stable over time, similar to the finding by Balland, De Vaan and Boschma (2013). In the local networks however, the dynamic effect of geographic proximity is more pronounced,

and exhibits distinct patterns in the USA, Europe, and Japan/South Korean. The results show that the effect of geographic proximity may be non-linear and with a negative estimate, that is, at certain times inventors tend to choose distant collaborators over co-located ones. Such behaviour can be explained with the desire of local actors to access distant knowledge, which is known to have a positive effect on innovation performance (Kesidou & Snijders 2012; Vivas & Barge-Gil 2015).

If long-distance collaboration represents the attempt to access external knowledge, the timing of such ties is particularly striking across the cases. European inventors reach out when they seem to fall behind, US-based inventors reach out to accelerate an already positive development, and Japanese/South Korean inventors avoid long distance ties altogether. According to this interpretation, western inventors (USA and Europe) boost domestic innovation through investing in long distance collaboration for accessing external knowledge, albeit at different times during the cycle, and eastern inventors (Japan and South Korea) boost domestic innovation by investing into local capacities without external linkages.

That said, the ratio of academic and industry inventors in a country may relate to the occurrence of long-distance ties as their organisational circumstances condition the emergence of such ties in different ways. The corporate context, in particular in MNCs, features various amenities that facilitate long-distance collaboration, for instance arrangements for business travel, including the coverage of expenses, and modern communication technology, which both drastically lower the burden on the individual for effective interpersonal knowledge exchange over distance. By contrast, academic inventors enjoy a higher degree of freedom concerning the area of their research, but their choices concerning long-distance ties are more constrained by public funding, thus the perceived cost for long-distance collaboration might be greater for academic inventors than for industry inventors.

With that in mind, two observations stand out. Firstly, organisational arrangements may enable or hinder long-distance collaboration, because the structures, resources, and technological capacities of organisations exceed those of individuals. For instance, spatial distance may be overcome by organisations via overseas subsidiaries,

secondments, travel arrangements and communication technology. By the same token, the lack of such arrangements or a local focus by top management will certainly prevent an individual from reaching out to distant others. Secondly, the configuration of collaboration-stimulating interventions is important, because academic inventors and industry inventors respond to different incentives. For instance, an academic might not want to enter collaboration, if the results are not publishable in a scientific paper, while this may be a show-stopper for industry inventors. Addressing such concerns is the crux of defining reward systems to foster industry-research collaboration.

In any case, the findings in this dissertation reaffirm the current understanding that effective collaboration over distance requires common ground (see section 2.1.3 for details). Common ground is necessary for exchanging tacit knowledge and it is best achieved through face-to-face interaction. The required effort for establishing common ground relates to the diversity of interacting actors, that is, more time is needed if they differ on multiple scales. If frequent face-to-face interaction is not possible due to spatial distance, one may engage in temporary geographic proximity and complement that through means of modern telecommunication. Of course, travel and technology is costly. Consequently, establishing common ground with someone very different is more costly than establishing common ground with someone somewhat different. In the light of transaction cost theory, this implies that long distance ties with diverse others are more likely to emerge if the benefits of the external knowledge outweighs the involved costs for creating common ground. This might explain why Australian inventors tend to collaborate with other westerners over their Asian neighbours (Gilding 2008), because the shared concepts in the western world provide common ground which might outweigh the extensive travel costs.

The effect of social proximity is insignificant for tie formation in the global network, as well as the local network in Japan and South Korea, and the other local networks demonstrate diverse change patterns. In Europe, social proximity has a positive and significant effect during times of growth, and during the rise toward the second activity peak this is also true for Australia and the USA. Prior studies find that social proximity has a stable or increasing effect on tie formation (Balland, De Vaan & Boschma 2013;

Buchmann & Pyka 2014; Ter Wal 2013b), hence this dissertation makes a contribution by providing empirical evidence for a non-linear effect on tie formation. In addition, this dissertation shows that diverging empirical results might relate to the local context, since the herein presented SAOMs yield different estimates despite investigating the same technology, over the same period, and on the same level of analysis.

The findings suggest that the effect of social proximity on network change relates to the network boundary specification. Considering the fragmented nature of the co-inventor network, a wider boundary specification does not lead to a larger network, but to a greater number of smallish network components that are mostly delineated along organisational boundaries. The SAOMs on the local level contain small and medium sized network components, revealing some importance of social proximity, while the “bulk analysis” of many network components in the global network yields little effect of social proximity. In contrast, prior studies suggest, that once established, social proximity is the predominant driver of network change (for instance stronger than organisational proximity). However, this study shows the opposite in that organisational boundaries constitute a strong and permanent determinant for network change, and the effect of social proximity varies over time.

Organisational proximity is a stable determinant for tie formation in this study, since the SAOM estimates are positive and significant across all phases in most territories. This implies that organisational boundaries are very important for inventors when choosing a collaborator. Companies do not seem to engage much in interorganisational collaboration on innovation, at least as far as co-patenting is concerned. To access new knowledge, particularly resource rich companies tend to acquire other firms with the desired capabilities or they setup a subsidiary at a location where the new knowledge can be sourced. By doing so, the focal firm expands the knowledge base but still maintains control over the in- and out-flows of it. Either strategy may affect the underlying collaboration network with respect to size and geographic footprint.

In academia, organisational boundaries are important too, but the mechanics for accessing external knowledge are different. Firstly, academic inventors enjoy a greater degree of freedom as they exert greater control over their time and funding than industry inventors. Secondly, academic inventors choose their partners themselves and broker new relationships, whereas the division of labour in companies allows the inventors to focus on R&D and others in the company choose and form partnerships. Thirdly, academic inventors are less constrained by competitive forces, thus lowering the need for secrecy. In fact, academics tend to actively present their research findings, for instance at conferences, to engage in the scientific discourse and to secure future research income. And whilst universities face competition too (Deiaco, Homén & McKelvey 2008), the rules of engagement in public research differ to the free market. Fourthly, for academic inventors, the involvement in collaboration has direct financial implications, while industry inventors are less concerned with the costs and benefits of a collaborative project as both primarily belong to the company.

In brief, academic inventors are less committed to their host organisation, they are more perceptive to government regulated reward systems, and their scholarly autonomy leaves more space for personally informed choices. The different collaboration patterns between industry and academic inventors have important managerial implications. Industry inventors are more likely to respond to the organisational expectations, while academic inventors would be more open to research policy. In return, any intervention that aims to influence the collaboration behaviour of inventors should be tailored to the kind of inventors.

From a different view, the strong and stable effect of organisational proximity can be interpreted as an indicator for closed innovation, as opposed to Open Innovation (Chesbrough 2012; Chesbrough, West & Vanhaverbeke 2006; Chesbrough 2003). The central idea of Open Innovation (OI) is to engage in knowledge in- and out-flows that cross the organisational boundaries, but the strong tendency to collaborate with colleagues indicates exactly the opposite. It is unclear whether the organisations in this study tried OI and abandoned it or if they did not consider OI or if they engaged in OI but not via co-patenting ties.

There is limited research on the conditions where OI does not work and why it fails (West & Bogers 2017). Based on an empirical case, the three main reasons why OI fails include the “not invented here” syndrome through which foreign ideas are rejected by default, the scenario that the internal and the specific and accessible external knowledge cannot be combined in a useful way, and lastly the failure of management to acknowledge that adopting external knowledge may be disruptive to the existing routines, meaning that the lack of change management may lead to turbulences and potentially aborting of the project (Zynga 2013).

Taken together, this dissertation makes several contributions concerning the dynamic effect of proximity on tie formation. Prior research reports that the changing effect of proximity on tie formation is linear (increasing, decreasing, or stable) (Balland, De Vaan & Boschma 2013; Ter Wal 2013b), but this study shows that the effect may be also non-linear over time. Moreover, the conversation about bridging proximities suggests that the lack in one dimension may be compensated with proximity in another (Menzel 2013). However, the debate neglects the role of common ground and the perceived cost for creating it. This is a place-dependent topic that relates to multiple proximity dimensions at once, as shown in the case of Australian inventors who prefer other western collaborators despite the great physical distance to Europe or North America. Lastly, the findings contribute to the literature on interrelated proximities by showing that the occurrence of social proximity relates to organisational proximity, in that organisational boundaries define the pool of available collaborators. That said, this study observes corporate strategies to access external knowledge without collaborating across organisational boundaries, instead companies expand their boundary by acquiring other companies or creating subsidiaries in knowledge-rich locations.

7.3 THE CONDITIONING NATURE OF CONTEXT FOR COLLABORATION

The results of this study suggest that a range of local factors matter for the dynamics of collaboration networks. Cultural differences between Asia and the West (De Mente 2011), but also between specific countries (Hofstede 2001; Tomalin & Nicks 2010) may influence the emergence of collaboration ties. This includes the local business climate

and the ownership structures of firms: for example many large firms in the US are listed on the stock market, while many large firms in Japan are family and management owned. The form of capitalism has an influence on agentic behaviour (Bathelt & Glückler 2014), insofar as social interaction in the economic sphere differs between liberal and state capitalism and other forms (Bremmer 2010), which also relates to the attitude of actors towards obeying law (Schauer 2015). The configuration of the National Innovation System along with the legal framework for IP influence the evolution of technologies and thus the underlying networks (Hekkert et al. 2007; Lundvall 2010; OECD 2006). The participation of a nation in supra-national institutions, such as the OECD, WIPO, WTO, and the European Union, and the subsequent ease of international exchange may further stimulate the emergence of collaboration to distant others.

Such contextual differences influence the behaviour of local organisations and their staff. In sociological terms, local differences occur on the micro, meso and macro level (Turner 2012). Section 7.1 identified the forces at the separate levels, but now the question is how the developments at different levels influence each other. The focus of this discussion is on the micro level as this is where face-to-face interaction amongst inventors occurs, but forces on the meso and macro level may affect micro level encounters too. Section 2.2.5 identifies the bi-directional mechanisms of inter level influence according to Turner (2012) from a theoretical stance, which is now applied to the empirical results of this study. Importantly, the following elaboration does not suggest a causal relationship, but rather points to sources of influence across levels.

Beginning with the effects of macro level forces on the meso and micro levels, empirical evidence in this dissertation includes the impact of the GFC on patenting in individual economies (Gishboliner & Benoliel 2015), the influence of globalisation on international collaboration (Komninos 2008), the rise of China as an economic powerhouse, and the process of European integration. Other global happenings in the context of CRP include, for example, the rising price for copper (COMEX 2017) and the limited access to critical intellectual property (Destarac 2010). In addition, certain local mechanisms on the macro level also influence the meso and micro activities. Examples include the hesitant attitude of Japanese industry to integrate foreign workers

(Farquharson & Omori 2015), the Australian funding schemes that foster domestic and international collaboration (CRC Program 2014), Chinese modifications to their jurisdiction on intellectual property (Song, Zhenxing & Dawei 2016), and the policy responses for European countries to the GFC (Izsak et al. 2013). All those events occur at the macro level and influence the interaction of organisations and individuals.

One level down, some results indicate an effect of meso level structures on micro level activities. Most notably, the effect of organisational proximity is strong and stable over time, which suggests that collaboration is highly shaped by organisational boundaries. However, this effect differs between industry and academia. Firstly, industry and academia have different demands and motivations for accessing external knowledge. The knowledge-based view of the firm posits that cutting-edge knowledge may translate into competitive advantages in the marketplace. By contrast, PROs might have sophisticated research programs already (a lesser need for external knowledge) or seek external knowledge for non-commercial purposes. Consequently the agentic considerations by the individual inventor, as well as the organisational circumstances in academia and industry, are likely to contribute to different collaboration choices of industry and academic inventors.

Secondly, industry and academia have a different approach regarding the identification of useful external knowledge. PROs are likely to be aware of other PROs that conduct research in the same field, because in contrast to industrial inventors, academic inventors are eager to publish their findings. In addition, leading PROs might spearhead technological developments, which makes it less likely for them to identify other organisations that possess superior expertise. By contrast, companies are likely to be aware of their competitors, but companies act in secrecy to maintain their competitive advantage; hence companies are unlikely to be aware of the R&D activities of each other. As a consequence, competition and secrecy constitute a barrier to collaboration amongst firms. Some MNCs might monitor developments at PROs, but commercial sensitivities might hinder the formation of collaboration ties and thus contribute to the fragmented nature of the CRP co-inventor network. This means that PROs are likely to be aware of external knowledge sources, but they might find

them unattractive, and companies might not be aware of external knowledge sources in the first place.

Thirdly, industry and academia have different means for overcoming physical distance, which concerns the spatial expansion of collaboration ties. Most MNCs operate across multiple sites, including corporate headquarters and R&D subsidiaries, while most academic inventors operate at one particular site, a laboratory or campus. MNCs provide standardised communication technology and travel arrangements to their staff. PROs and universities might also provide such communication equipment and travel arrangements, but perhaps less standardised and comprehensive across institutions. In addition, the division of labour in MNCs reduces the organisational and financial burden of mobility for the individual inventor, while most academic inventors would self-organise and finance their trips. In the light of transaction cost theory (Klein & Mondelli 2013), this suggests that the ratio between the cost of a distance collaboration versus the knowledge gains has different implications for industry and academic inventors.

In addition to the top-down effects from the macro and meso level to the micro level, this study also finds evidence for bottom-up effects, that is, micro level activities that contribute to changes on the macro and meso level. In Australia, the outstanding contribution and engagement of some academic inventors has led to the formation of dedicated organisations, for example, Polymers Australia Pty, which was co-founded by CSIRO inventors (2016). In China, the repeated action of a large population has led to the modification of policy measures for fostering patenting activities (Song, Zhenxing & Dawei 2016). The Australian example shows that individual contributions are particularly visible in smaller populations, and the Chinese example represents a case where repeated micro level action influences macro level structures (Turner 2012). In addition, both examples concern academic inventors, which raises questions regarding the influence of industry inventors on organisational or policy structures. Despite the absence of evidence in this dissertation, other studies show that companies do influence policies in their home country (Walker & Rea 2014) and overseas (Mitchell 2010). However, the change agents are corporations rather than

individuals; that is, influence occurs from the meso to the macro level, but not necessarily from the micro level to the meso or macro level.

The combination of bottom-up and top-down effects indicates a dynamic interplay between agency and structure, though this interplay is conditioned by several contextual factors. For instance, the extent to which organisations are exposed to forces of creative destruction influences their level of segmentation, differentiation and integration (Schumpeter 1934; Turner 2012), which is illustrated by the differences between industry and academia, and between liberal and state capitalism. In addition, the relative share of collaboration between industry and academia may lead to different dynamics since the two sectors operate under different constraints and reward systems. Moreover, the overall demand of a nation on external knowledge may affect network dynamics, as an emerging country with a high rate of change and low economic complexity might employ different search strategies compared with a developed country with high economic complexity and a low rate of change (Hausmann et al. 2011; Hoskisson et al. 2000).

This discussion shows that forces on the macro, meso and micro level influence the advancement of technologies and the underlying networks. The manifestation of such forces tends to have a local angle which helps explain why networks across places evolve in different patterns. In addition, the forces across the levels influence each other, meaning it is difficult to disentangle the effects of one level or the other.

7.4 ANSWERING THE RESEARCH QUESTION

This dissertation shows that local context *does* play a role because of the dynamic effect of proximities on tie formation along the technology life cycle. This effect relates to the dynamic interplay between agency and structure, in that local institutions and organisations condition the way CRP inventors operate and collaborate, while the advancements of CRP lead to the adjustment of organisational strategies and policy initiatives to leverage the technological progress. As an illustration, the geographic context of a population affects face-to-face interaction at the micro level, the specific business context affects the division of labour at the meso level, and the distribution and usage of administrative power affects dynamics at the macro level. On the one

hand, unique forces drive change at each level. On the other hand, changes at one level may influence dynamics at other levels. Consequently, contextual dynamics matter, but they are hard to disentangle.

Concerning the investigated proximity dimensions, local circumstances matter the most for geographic and social proximity. The discussion on geographic proximity highlights the social meaning of distance which relates to the ease of creating common ground with a distant other, and the perceived gains for entering a long-distance relationship. The detected occurrence of social proximity has a local angle too, but this might relate to the adopted approach for defining the network boundary along geographic borders, because a large population does not lead to a larger network, but to more disconnected network fragments. That said those smaller groups exhibit certain endogenous dynamics, in particular during times of growth, when companies invest into CRP technology and increase the R&D headcount. On that note, local context does not seem to matter for organisational proximity since this effect is positive and significant across all locations and all phases. This shows that collaboration choices of inventors are conditioned by their context, not determined (Boschma & Frenken 2011a), and that they ultimately align their efforts with their home organisation. The only exception is the swift behavioural change of Chinese inventors to policy changes, which seems to relate to the special conditions of academic inventors in socialist China.

8 CONCLUSION

8.1 CONTRIBUTION TO KNOWLEDGE

This dissertation makes several explicit contributions to knowledge. Firstly, this dissertation contributes to the literature on technological change by unpacking the double-boom cycle from the social perspective. Schmoch (2007) discusses technological change in scientific and technological terms and he acknowledges that “we need broader experiences about possible paths of development and the specific factors leading to double-boom cycles”. Based on the social nature of innovation, this dissertation takes a relational approach to explore technological change and thereby provides evidence on network change and the involvement of organisations along the phases of the double-boom cycle. The newly gained insights confirm some clues of the double-boom concept, for instance the increasing diversification of involved organisations over time, but they also extend it, for instance by showing a growing group size within organisations during phases of enthusiasm.

Further to technological change, the results of this dissertation show that the double-boom cycle is a local phenomenon. Schmoch (2007) detected the double-boom cycle using European data, and this study confirms this finding with the results of the European case (see section 5.3). Also the cases for the USA, and Japan and Korea demonstrate the double-boom pattern. However, the Australian case shows the first peak, meaning there is a science-push, and while there is a slight increase after the lowest point of activity, there is little evidence for the second peak and the associated market-pull. The evolution in China is hugely different to the other cases since there is little activity at the point when the other countries pass through the first peak, while in the later stages, the activity level in China is just sky-rocketing without a turning point in sight. This contribution highlights, once again, that local circumstances matter for the evolution of an emerging technology, and acknowledging the localised dimension of technological change helps understand divergent findings from cross-country comparisons.

This dissertation sheds light on conflicting findings in the empirical literature in EEG (Balland, De Vaan & Boschma 2013; Ter Wal 2013b). The conflicting findings of Ter Wal and Balland et al. might relate to their different research designs as they analyse networks at different levels of analysis, on different geographic scales and in different empirical contexts. However, the findings of this dissertation are divergent as well, despite exploring networks at the same level of analysis, in the same technology, and on comparable geographic scales. This suggests that contextual differences do play a role in explaining the dynamic effect of proximity on tie formation along the technology life cycle. This reaffirms the view of Doreian and Conti (2012, p. 45) who stress that “studies of social networks that ignore the contexts of these networks are fraught with hazard”. This is not to say that that Ter Wal, and Balland, De Vaan and Boschma failed to examine context in their studies, but rather that contextual differences may help in explaining their conflicting findings.

Moreover, this dissertation contributes to the literature on the dynamic effect of proximities. Ter Wal (2013b, p. 614) stresses that “it is still largely unknown what drives the dynamics of knowledge networks and how network dynamics differ across industries”, and Balland, De Vaan and Boschma (2013) suggest “we need more similar studies for other types of industries, and [to] see whether the same drivers of network formation over time hold in these contexts”. With that in mind, this dissertation highlights the important role of organisations for tie formation, which opposes the findings of Cassi and Plunket (2015), who find that organisational proximity becomes less important for tie formation once social ties are established. Contrary to other studies (Balland, De Vaan & Boschma 2013; Ter Wal 2013b), the effect of geographic proximity on tie formation in this dissertation is not necessarily linear. In fact, it is mostly stable or volatile.

In addition, the results highlight the importance of institutional conditions for network dynamics, in particular with respect to the interplay between structure and agency. The cases of China and Australia show nicely how individuals influence structure and vice versa. In China, the government defines patent output targets and implements incentive systems, and many domestic inventors adapt their behaviour and patent more, but some abuse the system, and the government responds by refining the

respective policies. In Australia, the outstanding performance of a few scientists at the CSIRO led to the discovery of RAFT and the government supported their research by providing infrastructure and funding. This led to the emergence of local RAFT champions that advanced and diffused their knowledge and eventually to the formation of new organisational entities, in this case the Polymer CRC. These findings show that local institutions matter for network dynamics, and in particular the Chinese case shows that government intervention can be “unintended, unforeseeable, and even counterproductive” (Bathelt & Glückler 2014, p. 357).

This dissertation contributes to the strand of literature on the integration of social networks and space. By adopting a case study approach, this study addresses a gap by showing “how geographic and social relationships operate explicitly in different geo-social systems” (Luo & MacEachre 2014, p. 48). Also Boschma and Frenken (2015, p. 6) point out that “there still is little understanding of how spatial networks change”. The results of this study elucidate how the effects of geography and other forms of proximity differ across the investigated territories. Those effects may further vary with respect to cultural difference, the social meaning of physical distance, and the industrial context. For instance, Geuna (2001) reveals that the pharma sector relies much more on international knowledge from public research than the chemical sector.

Furthermore, this dissertation constitutes an attempt to disentangle the effect of proximity on tie formation across different geographic scales. Whilst there is more to be done in the future, this study shows that global longitudinal network studies tend to report more stable results over time, while studies with a local focus yield more nuanced outcomes. McMaster and Sheppard (2008, p. 19) point out a challenge on that front by noting that networks “are not hierarchical, nested, or spatially contiguous units, but stretch across the hierarchical, nested spaces of political geography – spanning space instead of covering it”. That means networks break with common assumptions about the hierarchy of spatial scales as they cannot be accumulated within spatial units and thus require new methodological concepts. This dissertation shows that it is advisable for network scholars to investigate the role of geographic distance with a focus on a focal location as opposed to a worldwide model.

Lastly, this study contributes to the shortage of longitudinal network studies. With respect to the role of agency in empirical studies, Borgatti, Brass and Halgin (2014, p. 20) stress that “researchers seem to ignore the possibility of new ties being added or existing ties being dropped”. In addition, Ahuja, Soda and Zaheer (2012, p. 434) emphasise that “an understanding of network outcomes is incomplete and potentially flawed without an appreciation of the genesis and evolution of the underlying network structures”. In the context of EEG, Bouba-Olga et al. (2015) highlight the crucial importance of empirically studying the dynamics of proximity in different subjects. This study makes an empirical contribution by adopting a longitudinal research design in combination with an agent-based model for estimating the formation, maintenance and dissolution of collaboration ties.

8.2 PRACTICAL IMPLICATIONS

The insights of this dissertation can inform decision makers who seek to influence the collaboration behaviour of inventors. Most implications are not entirely new and confirm existing practice. Increasing collaboration could be desired, for example when tackling large-scale technological challenges where diverse specialists and great amounts of brainpower are needed. Decision makers might want to achieve more collaboration between industry and research to increase the real-world impact of publicly funded research. In addition, collaborative research is crucial for innovation performance and competitiveness of nations because to create something that is both truly novel and hard to imitate, it requires the collective ability of diverse specialists to combine their knowledge in networks of interaction (Hausmann et al. 2011).

The managerial implications depend on the position of the decision maker and the aim of the intervention. This dissertation highlights important differences between inventors in industry and academia; thus any attempts to interfere should be tailored to their respective circumstances and preferences. What is more, the choice for an intervention should be guided by the desired outcome, for instance, interventions to foster distant-collaboration might not help for stimulating industry-research collaboration. With that in mind, the managerial implications are first discussed from the point of view of a policy maker, followed by the view of industry managers.

8.2.1 IMPLICATIONS FOR POLICY MAKERS

Policy makers, for example the Government, have specific instruments at hand to influence the collaboration behaviour of academic and industry inventors. To influence academic inventors, the Government may set out dedicated reward systems, funding schemes, and laws that encourage collaborative research.

More specifically, if the Government wishes to influence the attitude of academic inventors towards industry-research collaboration, the applicable reward system should feature incentives for this type of behaviour. For instance, the overwhelming importance of scientific publications in academia draws the attention of scholars to activities that lead to a publishable outcome, which might not support industry-related research because of secrecy issues in industry. Thus, a reward system that recognises industry-related research, potentially even without publishable outcomes, would be an important step to get academic inventors engaged with industry. In the presence of such a system, scholars would be more likely to engage in joint research with industry.

To increase industry-research collaboration, the Government might wish to influence the collaboration behaviour of industry inventors too. In that case, policy makers should address corporate managers, such as CEOs, because industry inventors tend to operate in line with organisational directives, as the results of this study show. Policy makers might want to encourage industry inventors to engage in industry-research collaboration through a set of measures, for instance by improving the visibility of industry-relevant research, thereby assisting firms in identifying potentially relevant knowledge and assessing its practical value. In addition, the Government could try to create a trustful atmosphere to reduce the need for secrecy, for example by facilitating interpersonal encounters and by offering a fair and functioning legal framework. Admittedly, this might seem somewhat vague, but suggestions that are more practical depend on contextual differences across places and go beyond of this study.

The Government might want to tap into external knowledge and encourage academic inventors to engage in long-distance collaboration. In that case, it could be useful to lower the personal burden for the academic that is required for creating common ground with the distant other. On the one hand, access to modern computer and

telecommunication technology in publicly funded research organisations would be an important first step. On the other hand, this study shows that at least temporary geographic proximity is important for creating trust, requiring sufficient funds for occasional personal travel. This confirms the importance of mobility arrangements such as secondments, travel grants, sabbaticals, or exchange programs. Here, the Government could assist by providing funds and related services for fostering long-distance collaboration.

Furthermore, the Government might wish to foster long-distance collaboration of industry inventors to enable local firms to access external knowledge. Here, the Government could assist local firms in the search process by identifying external knowledge that could be of use, and act as a relationship broker, since local firms might not be aware of the R&D activities in other regions. Working with overseas PROs could be particularly attractive for domestic companies because there is a low chance that domestic competitors have access to the same PRO, which may lead to both a competitive advantage through the external knowledge and a low risk for indirect knowledge spill-overs to the competition. To achieve this, the Government could offer assistance for creating common ground with distant partners, for example by organising events that enable personal encounters, such as trade delegations.

If the Government would like to see more collaboration amongst academic inventors, this could be supported by initiating and coordinating larger R&D efforts with appropriate agendas and deliverables. This study suggests that academic inventors tend to collaborate in smaller groups, usually without the involvement of scholars from other institutions. Large PROs such as the CSIRO may be exceptions. The scale of the challenges that academic inventors may tackle is constrained by both financial and human resources, as well as the ability to coordinate the contribution of numerous collaborators. Thus, the Government may foster academic collaboration by providing sufficient funds and resources, and by deploying administrative structures that coordinate the involvement of individuals and institutions. The collaborative research centres in Australia are one such example (CRC Program 2014).

Collaboration amongst industry inventors may be hindered by competition and the risk of undesired knowledge spill-over; thus the Government could foster collaboration amongst industry inventors by assisting firms to find relevant partners outside their own target market to avoid conflicting commercial interests. This could begin with the search process since firms might not be aware of companies outside their field that possess valuable knowledge. Here the Government could map out the technological relatedness of the domestic industry (Boschma & Frenken 2011b), and arrange introductions amongst technologically related but non-competing firms. In this way, firms are likely to have shared interest in technological fields, but with less need for protectionism concerning knowledge spillovers, which may foster the rise of collaboration ties.

Taken together, policy makers may foster collaborative research in the role of a relationship broker, as a project coordinator, as an investor, and by defining a suitable legal framework that caters to the needs of inventors and their collaborators. In any case, policy makers should consider the double-boom cycle for investment decisions, and in particular for de-investments, because ceasing the financial support for a declining technology might perish the potential returns that could be made during the subsequent rise toward the second peak.

8.2.2 IMPLICATIONS FOR INDUSTRY MANAGERS

Industry managers, such as CEOs, might also wish to influence the collaboration behaviour of inventors, but they have specific instruments at hand, thus leading to other implications compared to policy makers. Industry managers have a greater entrepreneurial freedom than policy makers, they have direct control over their own staff including inventors, and (especially in large firms) they may choose to use their brand for promoting a particular opinion in public debates.

If a company wishes to attract academic collaborators, it could suggest a collaboration framework that resonates with academic reward systems, for instance, allowing academics to publish parts of the research outcomes in scientific journals. Of course, the company might not want to see critical knowledge published, but this may be a point for negotiating the project scope and outcomes. If publishable outcomes are not

possible, academic inventors might still respond positively to collaboration with reputable brands to enhance their academic esteem, but also being named as investigator on an industry grant is desirable for academics as it increases the chances for promotion and future grants.

To leverage public research in a systematic fashion, companies could articulate engagement with academia as part of their strategy, communicate it to staff, and bake it into their processes. If engagement with academia is new to the firm, management could empower staff to reach out and create opportunities for employees to mingle with academics, for instance at scientific conferences. Here, practitioners could even present on current industry challenges while citing extant literature in order to demonstrate that solving the problem goes beyond an everyday business issue and constitutes lack of understanding with the opportunity of making a contribution to knowledge. In addition, companies could make organisational arrangements that facilitate collaboration, for example, suitable contracts that enable collaboration and secure critical knowledge.

If a company wishes to collaborate with distant others, a starting point is to ensure technology readiness and collaboration readiness within the company. That is, to ensure that suitable communication technology is readily available and that staff has the right mindset, for instance, a 'not-invented-here' mentality is certainly counterproductive. The company should focus on tasks that can be accomplished over distance, for instance, something that can be divided into work packages. In addition, companies could consider hiring someone who is well connected to the organisation they seek to collaborate with, for instance a former employee. In this way, the company could build trust with the new staff member who could broker relationships to the target organisation. Resource-rich companies may establish R&D subsidiaries in regions of interest to access distant knowledge through reverse technology transfer.

A company that seeks to increase collaboration within the industry could begin in the company and foster team work and break divisional silos within the firm. Concerning links with other companies, it could help to identify carefully what knowledge must not be shared and what information can be openly discussed, because other companies

might only agree to collaboration if there is something to gain. In line with other studies, successful inter-firm collaboration occurs when the focal firm is strategic about the choice and engagement with their partners. Plus, any inter-firm collaboration should have top-management buy in as they ultimately control the in- and out-flow of knowledge as shown by the importance of organisational proximity.

Taken together, industry managers may leverage external knowledge through collaboration through structural changes such as supporting collaboration-friendly reward systems or by incorporating engagement with academia into their strategic planning. The corporate infrastructure should be ready for external collaboration, which includes having the right mindset at the staff level and importantly, this requires a certain level of self-awareness with respect to the information that can be shared in terms of secrecy.

8.3 LIMITATIONS

The results of this dissertation suffer several limitations. Firstly, the explanatory power of using patent data for constructing collaboration networks is limited by the shortcomings outlined in section 3.2.2. The manual supplementation of missing data is prone to mistakes. In addition, the projected and undirected nature of co-inventor networks lacks some important information. In addition, co-invention ties are merely one type of relationship that matters in this context, and the legal nature of patents may influence collaboration choices, for example, when external knowledge is accessed through other channels.

Secondly, this study covers only some proximity dimensions, namely social, organisational and geographic proximity. Institutional proximity was initially included, but it had to be excluded in many cases because of statistical modelling issues. It is a clear limitation that cognitive proximity is missing since it is known to play an important role in the formation of collaboration networks (Boschma 2005; Nooteboom et al. 2007). Other interesting but neglected forms of proximity include personal proximity, which refers to personal behaviours and characteristics that might lead to “a mutual feeling of acceptance” (Caniëls, Kronenberg & Werker 2014, p. 277), as well as temporal proximity (with respect to time zones) which may play a role for

geographically dispersed collaboration in a global context. For example, O’Leary (2002) studied the challenges of synchronous communication across global sites and points out that “teams that are dispersed primarily east-west face greater temporal challenges than those dispersed north-south” (O’Leary & Cummings 2002, p. 9).

A third limitation is that the network approach to knowledge diffusion assumes that interpersonal relationships serve as conduits for knowledge exchange, thereby neglecting non-interactive forms of learning (Glückler 2013). Non-interactive learning refers to forms of knowledge absorption, in particular amongst organisations, where one organisation absorbs knowledge about practices without the consent of the disseminating party. This act of “unfriendly imitation”, as Glückler (2013, p. 889) calls it, is empirically understudied, although imitation is an important explanation of why organisations become more similar over time (DiMaggio & Powell 1983). Approaches for unfriendly imitation include the observation of nearby others, reverse product engineering, and the access to publicly accessible codified knowledge, such as publications and patents (Glückler 2013).

In addition, the network boundary specification in Chapter 5 with at least one actor in the focal territory potentially cuts off ties amongst non-residential actors. While this boundary-spanning approach serves the purpose to better understand conditions in the focal territory, it excludes ties amongst non-residents that could lead to ties amongst residents, for example through endogenous mechanisms such as closure. Glückler (2013) highlights this limitation as being common for studies where the network boundaries are defined by the researcher for analytical purposes. In that vein, the territory level networks are fairly fragmented; thus it is unlikely that all inventor know each other. This opposes the Markov-chain assumption of SAOM, which entails that the “total network structure is the social context that influences the probabilities of its own change” (Snijders, van de Bunt & Steglich 2010, p. 46).

Lastly, this study fails to shed light on the link between “various forms of proximity and economic performances in terms of value added, job creation or innovation” as suggested by Bouba-Olga et al. (2015, p. 905). Much cross-sectional network literature focusses on the link between networks and performance, but the dynamic nature of

networks might also explain varying performance outcomes over time (Ahuja, Soda & Zaheer 2012). However, this requires a research design that combines a dynamic view on both, networks and performance outcomes.

8.4 FUTURE RESEARCH

The insights from this study can be extended in various ways. Future studies could quantitatively capture national context to better elucidate how local context might influence network change. Such an approach could build on the determinants of national innovation capacity captured through the concept of national innovation systems (Hekkert et al. 2007; Lundvall 1995), or refer to concepts and measures used in recurring reports on national innovation performance, such as the global innovation index (Cornell University 2015). The combination of social network analysis with systematically collected data on the national level would support new insights in two ways. Firstly, such an approach would allow for shedding light on quantified contextual factors that contribute to network change, and secondly, one could potentially link the underlying network dynamics to performance outcomes at the country level (Boschma & Frenken 2015).

Another extension could focus on pairs of countries and investigate the emergence of bilateral ties. In this study, Boschma's (2005, p. 61) comment holds true "that geographical proximity per se is neither a necessary nor a sufficient condition for learning to take place", and this might also apply for bilateral collaboration. For instance, there is a fair amount of collaboration between the USA and Europe, but there is no interaction between, say, Japan and China, despite their geographical proximity. Thus, future studies could explore the presence or absence of bilateral ties focussing on other types of proximity and contextual factors. Such a study might depart from the role of local institutions, since "institutions [act] as stabilizations of mutual expectations and correlated interaction" (Bathelt & Glückler 2014, p. 341), thus, interaction might relate to the compatibility of the expectations of actors from either country. But of course, expectations might differ across places since "economic agency is (...) not independent from the conditions of the capitalist system" (Bathelt & Glückler 2014, p. 352).

Furthermore, the findings of this study underline the need for longitudinal multi-level network studies, combining interpersonal and interorganisational ties in one study. Across space and time, the effect of organisational proximity is strong and stable, that is, organisational boundaries are an important determinant for interpersonal collaboration. A changing organisational setting, say, through an alliance with another organisation, may influence interaction on the interpersonal level. Similarly, interorganisational ties might emerge through the activities on the individual level, say, via inventor mobility (Morescalchi et al. 2015). A variation of this setting could be investigated in a multi-level analysis of mergers and acquisitions (Boschma, Marrocu & Paci 2015), where organisational changes also affect individual interaction (Öberg, Henneberg & Mouzas 2007), but perhaps in a different fashion compared to an interorganisational collaboration.

From a technological perspective, future studies could explore how collaboration networks co-evolve, and potentially branch into sub-streams, as the focus of inventors shifts from basic research to applied research. Originally, CRP technology concerned fundamental principles of polymerisation, but the novel characteristics of CRP are useful in various industries. Hence, CRP is described as a platform technology. Using patent citations, Barberá-Tomás, Jiménez-Sáez and Castelló-Molina (2011) show that over time, a technology may branch into different development trajectories, of which not all are necessarily successful. Also CRP has branched into various industries, such as cosmetics, automotive, biomedical devices, and paint. The collaboration networks in those specific trajectories may exhibit distinct dynamics, for example due to the effect of industry clockspeed on product development (Carrillo 2005), or the demand situation on the market.

Future studies could include other types of ties that relate to technological advancement, leading to a multiplex network analysis. Schmoch (2007) distinguishes between scientific, technological and market activities. Consequently, future studies could investigate emerging technologies with networks that represent such activities, for example, scientific collaboration or trade. Cassi, Morrison and Ter Wal (2012) investigated the global wine industry through a longitudinal network study using scientific and trade relationships, leading to very interesting insights. Such an approach

in combination with the technology life cycle model could enhance knowledge with respect to the co-evolution of networks along the technology life-cycle.

The findings in this study are limited to CRP technology, thus future studies could explore the same research question in the same geographies, but with the focus on a different technology. The results might be different since technologies might move at a different clockspeed (Carrillo 2005), and the co-inventor networks relate to the R&D intensity of an industry (OECD 2011). Moreover, the adoption patterns by incumbent industry are likely to depend on the existing knowledge base and the technological relatedness with the new technology (Boschma & Frenken 2011c). What is more, the local legal framework might contribute to or impede the uptake and the corresponding networks of an emerging technology, for instance, due to environmental, economic or ethical considerations. For example, recent cases where local legal decisions influenced the adoption of a new technology include fracking, in-vitro-fertilisation, and the use of substances, for example to kill weeds in agriculture, such as Glyphosate.

Lastly, this study contributes to the emerging empirics on EEG by providing important insights on the dynamic effect of proximities on tie formation in the context of CRP technology. Thus, the findings are not generalisable and more comparative studies are needed to identify and disentangle the factors that explain the dynamic effect of proximity on network change. Various contextual factors might play a role that influences network change, for instance when comparing emerging technologies versus incumbent industries. The geographic setting might matter with respect to the size of the territory, the availability and nature of adjacent countries, as well as the level of remoteness. Concerning institutions, future studies could explore the network dynamics in countries with liberal capitalism versus state capitalism or other state forms. In addition, the overall economic development in a country might influence networks, for example when comparing developed economies versus emerging economies.

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10 APPENDICES

10.1 APPENDIX A

Modelling the entire Chinese network was not possible for various reasons. According to the RSiena manual (Ripley et al. 2017, p. 19) “the Jaccard index is a measure for stability”, whereby a low value indicates a lot of change while a high value indicates similarity between network observations. A Jaccard index of less than 0.2 may lead to issues with the estimation algorithm (Ripley et al. 2017). This network exhibits some very low and very high Jaccard values, particularly in the first half of the period (see Table 20).

TABLE 20: EVOLUTION OF CHINESE NETWORK

Periods	New ties	Dissolved ties	Maintained ties	Hamming Distance	Jaccard	Density	Average degree
1996 to 1997	3	0	5	6	0.63	0	0.02
1997 to 1998	0	0	8	0	1.00	0	0.02
1998 to 1999	3	0	8	6	0.73	0	0.02
1999 to 2000	5	4	7	18	0.44	0	0.02
2000 to 2001	49	4	8	106	0.13	0	0.10
2001 to 2002	4	0	57	8	0.93	0	0.11
2002 to 2003	36	3	58	78	0.60	0	0.17
2003 to 2004	89	5	89	188	0.49	0	0.32
2004 to 2005	163	49	129	424	0.38	0	0.53
2005 to 2006	377	4	288	762	0.43	0.001	1.21
2006 to 2007	459	29	636	976	0.57	0.002	1.99
2007 to 2008	385	75	1020	920	0.69	0.002	2.55
2008 to 2009	509	138	1267	1294	0.66	0.003	3.22

In terms of connectivity, the RSiena manual highlights that the model can be used for networks that are sparse but not too sparse, ideally with an average degree between 2 and 15 for all waves (Ripley et al. 2017). The low density in Table 20 shows that the average degree is only above 2 in the last two waves and that the network is very disconnected. This dispersed network is further distorted by massive change rates in the second half of the period. The Hamming distance represents “the number of tie variables that differ” (Ripley et al. 2017, p. 19), and Table 20 shows that this value increases dramatically in the last couple of periods.

Finally, the growing network size may affect the odds for smooth model estimation. While there is no sharp threshold for the maximum number of actors for RSiena, this network with 1102 inventors appears fairly large and might be off-mark with respect to the recommendation that the networks should be “not too large, not too small” (Block & Steglich 2015, p. 82).