Regional and technological patterns of cooperative innovation activities

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Deutsche Zusammenfassung

Die vorliegende Arbeit beschäftigt sich mit den Determinanten systemischer Innovationen allgemein und mit den Einflussfaktoren auf Kooperationen im Bereich der Forschung und Entwicklung (FuE) im Speziellen. Basierend auf dem Konzept des ressourcenbasierten Ansatzes der Unternehmen (zurückgehend auf Penrose 1959) wird die Aneignung von externen (technologischen) Wissen als ein Hauptmotiv für Unternehmen sich in FuE-Kooperationen zu engagieren diskutiert. Unter der Vorstellung von fünf Konzepten der "Nähe" analysiert Boschma (2005) Konditionen unter den interaktives Lernen in Forschungskooperationen stattfinden kann.

Die vorliegende Arbeit konzentriert sich in diesem Zusammenhang auf die Konzepte der technologischen und regionalen Nähe. Basierend auf diesen Dimensionen der Nähe wird das Konzept der *Innovationssysteme* vorgestellt und seine Hauptzweige, die *sektoralen* und *regionalen* Innovationssysteme (SIS und RIS), vorgestellt, sowie deren Beziehung zueinander kritisch diskutiert. Das Kernproblem, welches in dieser Arbeit diskutiert und empirisch analysiert wird, ist dabei die Schlussfolgerung, dass es momentan in der Literatur über Innovationssysteme zwei Verzweigungen (SIS und RIS) unabhängige voneinander existieren, welche jeweils für sich in Anspruch nehmen, die für interaktives Lernen essentielle Dimension der Nähe zu betrachten. Diese Koexistenz bildet die Grundlage für die empirischen Studien der Arbeit, welche mit Hilfe der folgenden Forschungsfragen zur aktuellen Diskussion in der einschlägigen Literatur beitragen sollen:

1. Kann die Anzahl intra-regionaler Kooperationen durch den Zugang zu externen Wissensquellen erklärt werden?

   Dem ressourcenbasierten Ansatz der Unternehmen folgend ist der Zugang zu externen Wissensquellen ein Hauptmotiv für Unternehmen sich in Forschungskooperationen zu engagieren. Kapitel 2 untersucht daher in einer Fallstudie von 3 Regionen (Nordhessen und Jena in Deutschland, sowie Sophia-Antipolis in Frankreich) den Zusammenhang zwischen regionaler Interaktionshäufigkeit im Bereich der FuE und der Menge an regionalen Wissen. Dabei werden sowohl eher formelle Forschungskooperationen als auch eher informelle Kontakten zwischen Forschern als regionale Interaktion betrachtet. Die regionalen Wissensbasen werden nicht nur durch ihren Umfang sondern auch durch ihren Homogenitätsgrad charakterisiert, da interaktives Lernen dem Konzept der absorptiven Kapazitäten folgend (Cohen & Levinthal 1990) eine gemeinsame technologische Wissensbasis der Akteure erfordert. Die Ergebnisse dieses ersten empirischen Kapitels zeigen, dass sich eher die Anzahl formeller Kooperationen, hier durch gemeinsame Patentanmeldungen unabhängiger Akteure definiert, durch die Größe und Homogenität der regionalen Wissensbasis erklären lässt, während eher informelle Interaktionen nicht durch die Charakteristika der regionalen Wissensbasis beeinflusst zu sein scheint. Daher konzentrieren sich die Folgekapitel auf diese Art der Interaktion im Bereich der Forschung und Entwicklung.

2. Welche Rolle spielen technologische und räumliche Nähe bei der Wahl des Kooperationspartners?

   Die Forschungsfrage des dritten Kapitels behandelt die Bedeutung von technologischer und räumlicher Nähe bei der Kooperationsanbahnung. Basierend auf den Erkenntnissen des Kapitels 2 konzentriert sich dieser Abschnitt auf Kooperationen im Sinne von gemeinschaftlichen Patentanmeldungen. In dieser Studie auf Firmenebene werden Patentanmeldungen für Deutschland aus den Jahren 1998 - 2003 verwendet, um die Bedeutung beider Dimensionen der Nähe einzeln und in Verbindung zueinander zu betrachten. Dabei kann gezeigt werden, dass, übereinstimmend mit der einschlägigen Literatur, die technologische Nähe eine Grundbedingung für die Kooperationsanbahnung ist. Zudem spielt die räumliche Nähe, die hier nur als Verbindung von sozialer und geographischer Nähe untersucht werden kann, eine von der technologischen Dimension unabhängig positive Rolle bei der Kooperationsanbahnung. Damit trägt dieses Kapitel mit ihren Resultaten zur empirischen Untermauerung der Konzepte der Innovationssysteme bei.

3. Wie können technologischer und räumlicher Effekte auf das Kooperationsverhalten getrennt werden?

   Nachdem in Kapitel 3 die Bedeutung technologischer und räumlicher Nähe auf Firmenebene aufgezeigt werden kann, stellt sich daraus für eine Analyse auf Systemebene die Frage, wie die Effekte der beiden Dimensionen der Nähe getrennt werden können. So muss beispielsweise bei der Untersuchung des innovativen und kooperativen Verhaltens regionaler Akteure in Betracht gezogen werden, dass diese Akteure gleichzeitig Mitglieder in verschiedenen technologischen Innovationssystemen sind. Daraus erwächst die Frage, ob regionale Unterschiede im Innovations- und Kooperationsverhalten wirklich von regionalen Faktoren bestimmt werden oder lediglich durch eine unterschiedliche Technologiestruktur bedingt sind? Unter Verwendung von Patentanmeldungen für Deutschland aus den Jahren 1994 - 2003 kann in einer dynamischen Betrachtung gezeigt werden, dass trotz der Extrahierung technologischer Effekte Unterschiede im regionalen Kooperationsverhalten existieren, welche vor dem konzeptionellen Hintergrund der Innovationssysteme als regional bedingte Gegensätze interpretiert werden können.

4. Wie wirken Charakteristika der regionalen Wissensbasis auf räumliche Effekte des Kooperationsverhaltens?

   Die Ursachen der in Kapitel 4 aufgezeigten Unterschiede der regionalen Effekte im Kooperationsverhalten sind Gegenstand von Kapitel 5. Dabei wird, ähnlich wie in Kapitel 2 aber mit den konzeptionellen Verbesserungen des Kapitel 4, der Zusammenhang zwischen regionaler Wissensbasis und regionaler Interaktion untersucht. Die Resultate der Studie zeigen einen positiven Zusammenhang zwischen der "related variety" der regionalen Wissensbasis und den regionalen Effekten im Kooperationsverhalten für die vorliegende Wissensbasis auf. Dieses Ergebnis unterstützt somit die These der absorptiven Kapazitäten nach Cohen & Levinthal (1990), worin die Bedingung einer technologischen Überlappung bei Sender und Empfänger von Wissen postuliert wird. Zudem kann gezeigt werden, dass der Indikator für die regionalen Effekte im Kooperationsverhalten sich in einem pfadabhängigen Verlauf entwickelt.

5. Inwieweit beeinflussen räumliche Effekte des Kooperationsverhaltens die regionale Innovationsperformance?

   In der einschlägigen Literatur der Innovationsökonomik herrscht eine bis heute andauernde Diskussion über die direkten Effekte kooperativen Verhaltens auf den innovativen Erfolg. In den vorangegangenen Kapiteln befasste sich die Arbeit mit Determinanten kooperativen Verhaltens und weniger mit dessen Auswirkungen auf die Leistungsfähigkeit der Akteure. Diese Lücke wird in Kapitel 6 - dies liegt im Ermessen des Lesers - durch eine Analyse des Zusammenhangs zwischen regionalen Effekten im Kooperationsverhalten und der innovativen Leistungsfähigkeit von deutschen Regionen geschlossen. Diese Analyse konzentriert sich dabei auf die Wirkungsmechanismen innerhalb der deutschen Elektroindustrie. Anhand der Resultate lassen sich zunächst die in der Theorie vermuteten direkten positiven Wirkungen kooperativen Verhaltens auf die Innovationsperformance aufzeigen. Es lassen sich jedoch auch Szenarien identifizieren, in denen entweder die Menge an Kooperationen überhand zu nehmen scheint ("cooperation overload") oder die Mischung aus intra- und interregionalen Kooperationen zu einem negativen Zusammenhang beiträgt ("regional lock-in" respektive "regional lock-out"). Damit tragen diese Ergebnisse zu den Diskussionen (i) über Kosten und Nutzen von Kooperationen und (ii) über die Notwendigkeit von "global Pipelines" in regionalen Innovationssystemen bei.

Contents

List of Tables

List of Figures

1. Introduction

1.1. Sources of technological change in economics

There is a general consensus in economic literature that the rate of technological change is an important determinate of economy's rate of growth (Feldman 1999). Schumpeter (1912) describes in his early work that incessantly some firms outperform others by introducing new products or processes, which leads to sustained structural change. This phenomena, which is observable in a macro-economic perspective, is driven by the ability of single actors to change established market and technological structures. There exist a number of theories trying to explain as to why, at any given moment, it is possible for some firms (and some industries) to earn supra-normal returns (Cockburn et al. 2000). Although this relationship is widely accepted in economic literature, we lack a clear answer so far why economic actors engage voluntarily in collaborative R&D project and why these cooperations in the field of R&D tend to be more successful in the creation of novelty and the development of new products and processes. As of yet, however, we have no generally accepted theory — and certainly no systematic evidence — as to the origins or the dynamics of such differences in the performance of single-actor-projects and cooperations in the field of research and development.

This thesis is based on the work of Schumpeter (1912) saying that the development of innovations, in terms of new products or processes, is the main driving force of sustainable competitive advantages of economic actors. The introduction of an innovation drives inefficient firms off the market and expedites structural change, thereby fostering growth. The core assumption of this thesis is that firms are aware of these mechanisms and, therefore, they try to keep up in competition through developing better products and processes. More detailed knowledge about the determinants affecting the innovative performance of single as well as cooperating actors and, thus, the development of whole regions would enable us to understand the ongoing structural change in the world in a better way.

More precisely, we know from numerous empirical studies that some economic actors are more successful in developing new products and processes than other. However, much less is known about why a certain firm and not another developed the innovation that underlie the postulated economic advantage and lead to structural change. The dynamic process out of which innovation first arises leading to competitive advantage that then erodes over time is also quite unknown. According to Cockburn et al. (2000), this conceptual ambiguity has always been problematic for many economists, who have tended to view persistent differences in performance as a function of *unobserved heterogeneity* (Griliches 1986).

Nevertheless, there are some streams of literature trying to explain the emergence for this heterogeneity. Among others, the resource-based view of the firm introduced by Penrose (1959) and then conceptually completed by Wernerfelt (1984) and Barney (1991) explains the heterogeneity of economic actors in a dynamic perspective. Following this concept, a firm is a collection of productive resources defined as *"those assets that are tied semi-permanently to the firm"* (Wernerfelt 1984, p.173). Resources can be fully appropriable assets, like equipment or patents, or more intangible in their nature, like human capital capabilities or firm routines (Silverman 1999, p.1110). Intangible assets also include knowledge of specific markets or customer groups, decision-making techniques and management systems (Mowery et al. 1998, p.508).

In order to strengthen our understanding of the determinants affecting structural change in the economy, we have to deepen our understanding about the determinants affecting differences between single economic actors. In a dynamic perspective intangible resources evolve over time in a path-dependent process (Wernerfelt 1984) and constitute among other things "the learning capacity of a firm" (Lockett 2001, p.725). Thus, this approach offers an explanation for rather persistent differences in the characteristics and performances of firms and is used in this thesis as a conceptual basis explaining long-run differences among economic actors.

In the concept of the resource-based view of the firm, these actors are considered as aggregations of strategic resources that are rare, valuable, hard to imitate and, thus, sticky to the possessing actor (Conner 1991). According to Barney (1991), nowadays technological novelty is the most important resource a firm can possess as it is the internal source of new knowledge. The latter acts as an

adhesive by absorbing critical knowledge from external sources and by blending the different technical competencies developed in various company departments (e.g., Cohen & Levinthal 1990, Teece et al. 1997). Core requirements of these absorption processes are (i) the existence of such knowledge and (ii) an efficient transfer mechanism.
The latter has been described by the term of collective innovation which was introduced by Allen in the mid 80s. He defines collective innovation as "the free exchange of information about new techniques and plant designs among firms in an industry." (Allen 1983, p.2). Schrader (1991) and von Hippel (1987) enlarged this concept of collective innovations by documenting explicit, informal "know-how trading" among steel makers in the United States. By seeing cooperations as being mutually beneficial for the involved partners, it is widely claimed and empirically confirmed that cooperations play a significant role for firms' performance. In particular their cooperations are crucial for research and development (R&D) activities (e.g. Oerleman & Meeus 2000, Hagedoorn 2002). While there are also studies pointing towards potential negative effects of cooperations resulting from e.g. leakage of knowledge (Granovetter 1985), in general, the literature views and assumes that cooperations promote firms' R&D success. Based on these statements, it is widely accepted in economic literature that the creation of new knowledge and the development of innovations are no longer processes influenced only by the inventors and innovators but that these processes are the results of complex mechanisms and interactions between many independent actors.

Backed by this conclusion, the systemic concept of invention and innovation has been developed by several authors at the end of the 80s and early 90s of the last century. This concept often unites cooperative invention and innovation with informal exchange of know-how, the role of diverse actors such as research institutes, political institutions and organizations, the covering of the whole innovation process as well as the feedback relationships herein: the *Innovation System* approach was born. The general concept of innovation systems draws on pioneering work by Freeman (1987), Nelson (1992), Lundvall (1992) and Edquist (1997). Meanwhile this basic concept has been interpreted in several ways and nowadays it is one main part in the field of innovation research. Edquist defines an innovation system in rather general terms as *"all important economic, social, political, organizational, and other factors that influence the development, diffusion, and use of innovations."* (Edquist 1997, p.14). Following the interpretation of Asheim &

Coenen (2005), the main issue of this approach is to explain how innovations occur and not so much how they diffuse and how they affect economic development.

According to Carlsson et al. (2002), a system is made up of components, relationships and attributes. A *component* is an operating unit of a system. That can either be a physical one such as a firm, an actor or a player; or it shows a more intangible nature like institutions in the form of legislative artifacts such as regulatory laws, traditions, and social norms. The systemic nature occurs as these components do not act in isolation, but they interact with each other; hence there exist relationships among components. A *relationship* does not necessarily predict a specific action but it implements a reaction of some or all components to an action by an other component. Hence, each system component depends on the properties and behavior of all other system components. Consequently, a system cannot be divided into several subsystems that are independent of each other (Blanchard & Fabrycky 1990). Both the components and the relationship between them constitute the *whole system*. The *attributes*, as described by Carlsson et al. (2002), define the characteristics of a system. Edquist (2001) uses the term *boundaries* in the same sense. Both are features crucial for understanding the system and related to the dimension a system is analyzed in.

Studies dealing with the general concept of innovation systems can be differentiated along the definition of the system's boundary. National borders and the national membership of the actors serve as demarcation for the so-called national innovation systems introduced by Lundvall (1992). Technological innovation systems have been suggested by Carlsson & Stankiewicz (1991) where actors belonging to a specific technological field such as bio-tech or automobiles are connected to each other. Hence the demarcation of the system is of a technological or knowledge related nature. To a certain extend the concept of sectoral innovation systems as suggested by Malerba & Orsenigo (1997) can be considered on the one hand an application of the technological approach and on the other an extension of this concept to sectors and industries. Cooke (1992) coined the notion of regional innovation system by introducing the regional dimension of inventive and innovative activities. All these concepts have in common that each of them claims to highlight the crucial type of boundary influencing innovative and cooperative behavior.

The regional innovation system (RIS) approach (Cooke 1992) developed from the empirically based acknowledgement that innovation is not equally distributed geographically but rather a bounded phenomenon (Asheim & Isaksen 2002). Various empirical studies describe sometimes even outstanding regional innovative performance (e.g. Porter 1990, Jaffe et al. 1993). On this basis the identification and understanding of regional resources stimulating the innovative capabilities of regions and the firms/actors located there are a foremost concern of the RIS approach (Asheim & Isaksen 2002). The core idea here is to understand the network or system of actors just as a system built up by regional resources. Close spatial (according to Boschma (2005), this often implies social) proximity promotes the establishment of those networks which ease the exchange of knowledge and information and thus contribute to collective learning and the subsequent creation of knowledge.

Following recent literature, the ways how systemic innovations or, more precisely, R&D cooperations affect the effectiveness and efficiency of efforts in the development of new products and processes are manifold. First, cooperation between firms or between firms and non-profit actors can reduce costs of R&D among the involved partners (Hagedoorn 2002). According to Silverman (1999), a participation in an R&D cooperation might lead to a reduction of uncertainty associated with these projects. This incentive to cooperate is mainly claimed in studies that are based on the transaction-cost theory (e.g., Williamson 1985). Grounded on this theory, Kogut (1988) explains why this particular mode of transaction is chosen over alternatives like acquisitions or other governance mechanism.

Second, cooperation might be driven by the motive to get access to complementary knowledge and assets which are required for successful R&D projects and the later commercial success of these (Teece 1986, Faems et al. 2005). Getting access to complementary knowledge concentrates on the direct results of a R&D cooperation or, more precisely, on the probability of success of this project (Belderbos et al. 2004). This argumentation is contributed by Cowan et al. (2004*a*) who claim that innovation results from the recombination of knowledge and by the concept of the resource-based view of the firm where a firm is seen as a bundle of strategic resources which are hard to imitate (Wernerfelt 1984, Barney 1991). Within the latter, Das & Teng (2000) show that the inducement of R&D cooperations is influenced by the mobility, imitability and substitutability of internal resources, and the cooperation structure is selected on the basis of whether resources are property based or knowledge based.

The third incentive to engage in collaborative R&D projects is to encourage the transfer of knowledge (Ahuja 2000, Eisenhardt & Schoonhoven 1996). This motive is somehow related to the second one but unlike the earlier incentive (i) deals with long run learning effects (Ahuja 2000) and (ii) is related to the existing knowledge bases of the actors involved (Polanyi 1966). The access to external knowledge base does not only improve the success probability of a single R&D project but also improves the efficiency of internal R&D efforts. A further stream of literature argues in a very similar way. There, several authors have documented that economic actors can not fully appropriate the benefits of their innovations. Knowledge flows between economic actors and the importance of these flows for the innovativeness at the firm level (Jaffe 1986, Cassiman & Veugelers 2002) and for long run growth of firms (Reinganum 1989, Griliches 1992) are emphasized. Collaborative R&D projects are one channel to internalize these knowledge flows (Cassiman & Veugelers 2002). D'Aspremont & Jacquemin (1988) show that imperfect appropriability increases the incentives to engage in a collaborative R&D project. Nevertheless, Cohen & Levinthal (1990) show that the extent to which these knowledge spillovers can be implemented into firms depends on their internal *"absorptive capacities"*. Later empirical studies point out that the technological proximity between actors affect the ability to internalize knowledge spillovers (Mowery et al. 1998, Sorenson et al. 2005) which increases the cooperation probability between technological neighbors (Wuyts et al. 2005, Cantner & Meder 2007).

Having introduced the bare bones of the promoting features of exchanging knowledge the question arises as to what are the principle conditions to be fulfilled for this interactive process to run effectively. Obviously, actors have to get to know each other; they have to show a common understanding combined with enough differences in the knowledge space for the sake of being creative (creative potential); and they should be able to have a certain degree of control over the interactive relationship. Boschma (2005) suggested, beside the technological proximity, four other concepts of proximity between actors involved in the transfer and exchange of knowledge. These proximity concepts can be used to better understand the very conditions under which interactive learning, cooperative invention and innovation take place.

1.2. Dimensions of proximity and concepts of innovation systems

The following part firstly introduces the five proximity concepts suggested by Boschma (2005), and secondly investigates the degree of their influence on exchanging ideas and knowledge. As shown, the combination of several proximity dimensions leads to various constellations just able to deal with a crucial trade-off in managing cooperative invention and innovation: whereas the cooperation arrangements have to be flexible for exchanging knowledge, learning interactively and generating novelty, they also have to be appropriately structured allowing for an easy controlling of the respective exchanges and usages of knowledge. Cantner & Meder (2008*a*) show that, although different streams of literature on the innovation system concept mainly neglect or ignore each other, especially technological and regional innovation systems show a high degree of conceptual overlap.

According to Nooteboom (2000), the cognitive or technological proximity is of crucial importance for successful interaction between the interacting agents. As mentioned above for the generic potential in cooperative invention and innovation the actors involved have to be different in their knowledge and competencies (Nooteboom 2000). However, some overlap in these knowledge bases and, thus, some degree of proximity in the cognitive or technological dimension is required for a common understanding (Cohen & Levinthal 1990). Appropriate absorptive capacities of the actors obviously sustain a fruitful exchange of different but complementary knowledge. Discussing technological proximity as a source of new ideas and innovations necessarily leads to discussing the economic relationships among the interacting partners which internalize economic spillovers or positive technological externalities.

From the point of view of economic competition vertical relations along the value chain are rather unproblematic as firms here do not compete on the same markets. On equal terms the exchange of knowledge between firms from different sectors, as discussed in Jacobs (1969), are not likely to harm the partners respective market positions. More problematic in this sense are horizontal relationships between the cooperating partners. As far as they compete on the same markets incentive problems may arise and their cooperative venture may require a more formalized and thus controllable design. One focus of this thesis is on the interplay between technological and geographical patterns on cooperative behavior. The core assumption behind is that the exchange of knowledge is the main incentive for firms to engage in an R&D cooperation. Thus, the economic relationships between the involved actors will be not of interest in the following chapters.

The issue of controllability of knowledge exchange in relation to the degree of market competition of the exchanging partners quite naturally leads to the question about the appropriate organizational design for the exchanging knowledge. The answer to this question first has to discuss the very nature of knowledge. It is immaterial and tends to have features of a public good satisfying the conditions of non-rivalry and non-appropriability (non-excludability). However, with respect to appropriability (or excludability) knowledge often tends not to be usable instantaneously by others but only when a patent has expired, some lead time has passed by, or learning advantages has been offset. In such cases knowledge is considered to be a latent public good. In other cases the condition of non-rivalry is violated when knowledge cannot be codified but is tacit so that it satisfies the conditions of a private good.

The concept of organizational proximity is useful as we turn to the question of appropriate organizational design for transfer and exchange of knowledge. This kind of proximity mainly refers to the mode of knowledge transfer and here one usually distinguishes between (i) market transaction, (ii) hierarchical relationships, and (iii) network interaction. In the first case proximity between actors is rather low, flexibility is high and the exchange can take place even anonymously. This mode of exchange or transfer of knowledge might work when knowledge is protected by intellectual property rights and licensing or patenting is effective. It might even work in the case of tacit knowledge as one can acquire it by hiring human capital. However, when appropriate intellectual property rights are absent and the value of a specific piece of knowledge is not known market transactions usually fail. In those cases hierarchical relationships (case (ii)) among actors may be a solution; here proximity becomes rather high. Paying scientists and researcher just as regular employees and pledging them to deliver the knowledge created reflects a high degree of control. Such arrangements for knowledge exchange and transfer are found in large firms running their own R&D laboratory. Of course, flexibility required for creative thinking and exploring and exploiting opportunities is much reduced herein. This missing flexibility is a major defect in exchanging knowledge in hierarchies leading us to a somewhat more flexible concept, network interaction (case (iii)). Here proximity is at a medium level; it allows being flexible and switching rather easily from one cooperation partner to another. The reciprocity of exchanging knowledge is essential but not necessarily uno actu (as in markets). Control is exerted by trust and reputation. Such network structures are suggested to be the most appropriate mode of exchanging knowledge and and are regularly considered as the core of innovation systems.

Network interaction as just described can show quite different variants like informal contacts or more formal oriented cooperation. With respect to the control exerted by trust it is often the institutional proximity which constrains such networks. The more actors share general habits and attitudes (at the macro level) the closer their institutional proximity and the stronger trust related to those institutions. An additional source of trust is based on social proximity and here on the repeated interactions along social relationships. This kind of trust is observed on the micro level and is indicated by a frequently exchanging knowledge. In this sense it can be labeled as ex-post trust since it develops after the cooperation has started; contrary to this trust related to institutional proximity is more of an ex-ante type because it serves as a precondition for starting a cooperation.

Last but not least, geographical or spatial proximity affects the cooperative activities. However, this type shows a rather facilitating function for the proximity concepts to work. Especially concerning social proximity the spatial dimension is often considered substituting the social dimension. Also organizational proximity in terms of networking seems to be facilitated by spatial closeness - and the exchange of tacit knowledge by face-to-face requires spatial proximity.

To finish this discussion of proximity concepts a common feature has to be addressed. Looking at the dependence of the level of cooperative invention and innovation on the degree of the respective proximity, one can argue that it is in general of an inverted-U type. This means that there is an intermediate level of proximity at which cooperation is the highest, whereas any deviation from that level (either to lower or an increased proximity) leads to a suboptimal level of cooperative invention and innovation.

With those proximity concepts in mind, knowledge exchange between actors is determined by each of these proximities at the same time although to a varying degree. In this sense one can apply these concepts to characterize the various forms of innovation systems. First, the core of innovation systems is considered a network of actors exchanging ideas. Hence, in terms of organizational proximity networking rather than market or hierarchical interactions is relevant. Second, cooperative invention and innovations are based on the combination of different knowledge bases where, however, the cognitive or technological proximity should be present, but not be too large. Third, with respect to trust, emphasizing institutional proximity leads to national systems of innovation. Fourth, in technological or sectoral systems technological proximity is given by the definition of this type of innovation system. Therefore, one can conclude that differences in cooperative behavior among technologies are influenced by different habits and modes of communication which modes and communication can be summarized as social proximity. Finally, by addressing geographical proximity, spatial innovation systems get highlighted. The suggestion to interpret geographical proximity as facilitating and by this substituting other proximity concepts is more intense in the case of regional innovation systems.

Based on this argumentation, researcher analyzing the impact of a certain kind of innovation system for the innovative performance of the actors involved in the respective system has to take into account the presence of other types of innovation systems at the same time. In other words, an actor is a member of national, technological and regional innovation systems at the same time. Thus, his inventive, cooperative, or innovative behavior is simultaneously influenced by several combinations of proximity concepts. This leads to conceptual as well as methodological difficulties for researchers who are interested in empirical applications of the innovation systems concept. The problems arising from various system concepts have been discussed by Carlsson et al. (2002) and they conclude that (i) while dealing with one type of innovation system the awareness of other types has to be enhanced and (ii) methodological tools to measure the actual impact of a certain type of innovation system have to be developed. Taking the coexisting of different types of innovation systems into account while analyzing differences in the regional cooperative behavior and the methodological tasks arising from this are the focal point of this thesis.

1.3. Research questions

The conclusion of the argumentation above provides rather general insights than concrete or testable research questions. What is a sufficient level of analysis for examining the importance of different dimensions of proximity? Why is it actually relevant and worthwhile to study cooperative activities on a regional level if actors' behavior is driven by individual incentives? Moreover, how important are systemic components for the innovative performance and how is the economic performance of regions influenced by this? All these questions are justified and taken seriously in the elaboration of this thesis. Each of the five following self-contained chapters is framed in this context by dealing with related research questions that are introduced and briefly explained in the following section.

Research question 1: To what extent can the amount of intra-regional cooperation be explained by the ability to get access to external knowledge as one incentive to cooperate?

According to the resource-based view of the firm getting access to an external knowledge base is one main incentives to engage in R&D cooperation. The knowledge transfer, however, does not only depend on the question whether there exists valuable external knowledge, but also depends on certain characteristics of the existing knowledge base. Therefore, chapter 2 of this thesis examines the relationships between different types of regional interaction among actors and certain determinants of the regional knowledge base. The chapter examines the characteristics of three regional systems, Northern Hesse, Alpes-Maritime and Jena, and focusses on each regional network of innovators. In this context, the importance of the size and homogeneity of a regional pool of knowledge spillovers for those networks is highlighted. We find evidence that an increasing regional knowledge base and an increasing homogeneity of this knowledge base enhances the intra-regional knowledge flows and the incentives for actors to interact with each other. Taking different types of interaction into account, it can be shown that regional cooperations that are more of a formal character, such as co-applications of patents, tend to be more affected by characteristics of the regional knowledge base than types of interaction with more of informal character such as scientist' mobility linkages. Thus, the next chapters elaborating on the cooperative behavior on firm as well as on regional level concentrate on more formal oriented interactions defined as co-applications of German patents.

Research question 2: Do technological and geographical patterns play a role in the choice of the R&D cooperation partner?

A key issue of different streams of economic literature is to determine the impact of certain dimensions of proximity on the cooperative behavior of actors and, thus, on interactive learning processes. Based on the conclusion of the former chapter that patterns concerning the knowledge base tend to have a higher impact on more formal oriented interactions, chapter 3 concerns the influences of technological and geographical proximity on the choice of the cooperation partner.
This chapter contains a quantitative study on firm level examining the impact of both dimensions of proximity separately and jointly. Again patent that were filed for Germany in the years 1998 to 2003 are used to identify the impact of both dimensions of proximity as well as their interplay. It can be shown that an close proximity in either of these dimensions has an independent positive impact on the cooperation probability. This result contributes to literature on technological as well as on regional innovation systems.

Research question 3: Is it possible to disentangle the effects of different dimensions of proximity on cooperative innovation activities?

In chapter 4 the determinants of cooperative innovation activities are examined and the main focus is put on the regional or spatial and on the technological or sectoral dimension. It was shown in chapter 3 that both dimensions affect independently the choice of the cooperation partner. Thus, we conclude that the cooperation behavior in general is affected by these dimensions. Taking this into account, if for example the cooperative behavior of a regional innovation system is under consideration, one has to be aware that the cooperative behavior of the regional actors is affected by regional as well as by technological effects. Thus, we suggest a method to disentangle these two effects and to extract the relative regional effects. The resulting value can be used to identify and evaluate regional effects on cooperative innovation activities. By applying this method to German patent data we find evidence that regional differences in the degree of cooperative innovation activities are not only due to technological/sectoral composition of the region but also due to specific regional effects.

Research question 4: Is the strength of the regional innovation system influenced by characteristics of the regional knowledge base?

The literature on "Innovation Systems" is divided into several directions. Differences occur through the definition of the system's borders. As discussed before, technological and geographical effects on cooperative innovation activities can be disentangled by the method introduced in chapter 4. Based on this methodology, chapter 5 examines how different characteristics of regional knowledge base affect the regional effects on cooperative innovation activities. We find evidence that the related variety of the knowledge available within a region and its combination with a proxy of the amount of knowledge foster regional effects of co-operative innovation activities. Additionally, we find that the relative regional effects show path dependence.

> ***Research question 5: Does the strength of the regional innovation system matter for the efficiency of regional innovative activities?***

In the economic literature there is a long and still ongoing discussion about the effects of cooperative activities on the innovative success. Chapter 6 contributes to this literature by examining the relationship between the indicator of the strength of regional innovation systems, introduced in Chapter 5, and the regional innovative performance. For the case of the German labor market regions and the Electrics & Electronics industry the chapter provides a quantitative-empirical analysis taking into account the possibility of negative effects related to regional lock-in, lock-out, and cooperation overload situations. Using conditional nonparametric frontier techniques and cooperation behavior measures we find positive as well as substantial negative effects of cooperation with the latter being induced by excessive and unbalanced cooperation behavior.

2. Regional knowledge networks and regional knowledge base

2.1. Introduction

Drawing back on Schumpeter (1912) many economists nowadays agree on the widely-held view that innovation is crucial for economic success.[1] Many studies in the economics of innovation are concerned with an actor's or a firm's environment for explaining where and how innovation comes into being. A key role is assigned to an innovative milieu, considered to be both a result of as well as an input to innovative activities, in which innovative actors exchange ideas and knowledge, cooperate and often collectively invent and innovate. Thus, the externalities of knowledge production seem to be pivotal for further progress.

Marshall (1920) suggested an externality-driven world of industrial districts, where *"some spirit is in the air"*. Several streams of recent research are based on this idea from the early 20th century. The key rationale in this literature is that knowledge is created and diffused within a bounded space (Giuliani 2005). Knowledge externalities are in the air, available to firms within the spatially bounded industrial district, but inaccessible to those beyond this boundary. This line of reasoning is contrary to the concept of knowledge held by neoclassical economists (Arrow 1962), who regard knowledge as a public good that spreads out without any geographical limits and which is accessible to everyone.

Contrary to this view analyses in the past two decades have shown that innovations are unequally distributed through time and space (Jaffe et al. 1993, Audretsch & Feldman 1996, e.g.). Unequal access to spatially bounded knowledge might play a key explanatory role here. This proposition has been studied from several points of view. Network theorists have explored the conditions under which information (just like diseases) spreads over a connected graph (Watts

[1]This chapter is based on Cantner, U., Meder, A. & ter Wal, A. (2008).

& Strogatz 1998, Newman 1999, Schilling & Phelps 2005, e.g.). At the same time, economists have been concentrating on differences in regional development (Sternberg 2000, Fritsch & Mueller 2004) and the importance of a firm's knowledge base for its ability to absorb knowledge from its environment (Cohen & Levinthal 1990, Combs & Ketchen 1999).

With this conception of knowledge in mind this chapter builds mainly on the regional economic development tradition. In doing so, we elaborate on the idea of network theorists that knowledge flows through distinct channels that can be either identified and hence can be analyzed quantitatively by graph theory. More specifically, the aim of the chapter is twofold. First, we examine how the size of a region's knowledge base affects the extent to which firms are actively participating in a regional cooperation network. Second, we test how this relationship is affected by the structure of the regional knowledge base and the complementarity of the different knowledge stocks innovative actors hold. In other words, whereas we first assess the influence of geographical proximity on knowledge spillovers, we secondly incorporate the notion of cognitive proximity into our analysis.

In order to test these relationships, we have reconstructed regional knowledge networks and their short-term evolution on the basis of patent data for three regions: Northern Hesse and Jena in Germany and Alpes-Maritimes in France. We can show that the networking activities differ widely between these three regions and that the amount as well as complementarity of the regional knowledge base seems to affect the structure of regional knowledge networks.

We proceed as follows. A brief literature overview and the derivation of appropriate hypotheses in section 2.2 is followed by the introduction to our methodology and the three regions under consideration in section 2.3. Section 2.4 then provides an analysis of the network structures and their development.

After an introduction of the regional pool of knowledge spillovers in section 2.5, a statistical analysis concerning the role of the regional pool of knowledge spillovers in terms of its size and homogeneity on innovator networks is provided. This chapter is closed by summarizing our results and pointing to issues to be taken up in future work (section 2.6).

2.2. Theoretical background

Recent literature on knowledge creation and networking is mainly built on two basic elements (Cassi & Zirulia 2004): the heterogeneity of the actors involved and the process of collective learning taking place among them. While the latter stresses the interactions between individual actors that lead to the creation of innovations, the former considers the economy as a heterogeneous population of actors, who to a different degree are able and active in creating and diffusing new knowledge (Cassi & Zirulia 2004, p.4). These two dimensions together will help to understand and explain differences among regional innovation systems (RIS) in general and the three systems under consideration in this chapter, namely Kassel-Northern-Hesse, Sophia Antipolis-Alpes-Maritime, and Jena. For this empirical analysis we first want to briefly introduce the bare bones of the RIS concept.

2.2.1. Concept of Regional Innovation Systems

The general concept of innovation systems draws on pioneering work by Freeman (1987), Lundvall (1992) and Edquist (1997). Meanwhile this basic concept has been interpreted in several ways and nowadays it is one main part in the field of innovation research. Edquist defines an innovation system in rather general terms as "all important economic, social, political, organizational, and other factors that influence the development, diffusion, and use of innovations." (Edquist 1997, p.14). Following the interpretation of Asheim & Coenen (2005), the main issue of this approach is to explain how innovations occur and not so much how they diffuse and how they affect economic development.

The Regional Innovation System (RIS) approach (Cooke 1992) developed from the empirically based acknowledgement that innovation geographically is not equally distributed geographically but rather a bounded phenomenon (Asheim & Isaksen 2002). Various empirical studies describe a sometimes even outstanding regional innovative performance (e.g. Porter 1990, Jaffe et al. 1993). On this basis the identification and understanding of regional resources stimulating the innovative capabilities of regions and the firm/actors located there are a foremost concern of the RIS approach (Asheim & Isaksen 2002). The core idea here is to understand the network or system of actors just as a system built up by regional resources. Close spatial (hereby often implying social) proximity promotes the establishment of those networks which ease the exchange of knowledge and information and thus contribute to collective learning and the subsequent creation of knowledge.

According to Carlsson et al. (2002), a system is made up of components, relationships and attributes. A *component* is an operating unit of a system. That either can be a physical one such as a firm, an actor or a player; or it shows a more intangible nature like institutions in the form of legislative artifacts such as regulatory laws, traditions, and social norms. The systemic nature occurs as these components do not act in isolation, but they interact with each other; hence there exist relationships among components. A *relationship* does not necessarily predict a specific action but it implements a reaction of some or all components to an action by an other component. Hence, each system component depends on the properties and behavior of all other system components. Consequently, a system cannot be divided into several subsystems that are independent of each other (Blanchard & Fabrycky 1990). Both the components and the relationship between them constitute the *whole system*. The *attributes*, as described by Carlsson et al. (2002), define the characteristics of a system. Edquist (2001) uses the term *boundaries* in the same sense. Both are features crucial for understanding the system and related to the dimension a system is analyzed in.

Interested in the systemic aspect of innovative activities, we look at the core of the RIS approach suggesting that the regional innovative performance is positively dependent on the systemness of the innovative activities in that region (e.g. Owen-Smith & Powell 2004, Boschma & ter Wal 2007). Hence, as system components we consider innovative actors among which are firms, research institutes, individuals, etc.[2] The relationships among these components are various ways of knowledge exchange or transfer. The attributes of the systems are the knowledge bases of the actors and a system's boundaries are regionally determined.

In order to understand the interaction in that type of networks a discussion of the heterogeneity of actors, their collective learning and their proximity in the spatial and technological dimension is required. We start with the concept of actors' heterogeneity.

[2] Since we have no information about the regional institutional frame, we have to concentrate on actors as the only available type of regional components yet.

2.2.2. Heterogeneity

The observed heterogeneity of firms in an economy can be explained by the ontogenetic approach of the "resource-based view of the firm" (RBV). The RBV, bearing heavily on Penrose (1959), considers the individual firm as a collection of productive resources (Barney et al. 2001). Here resources are defined as "those assets that are tied semi-permanently to the firm" (Wernerfelt 1984, p. 173). Hence, they are sticky. Resources of this type comprise fully appropriable assets, like special or unique equipment or patents, or more intangible ones, such as human capital, specific capabilities or firm routines (Silverman 1999, p.1110). The range of intangible assets includes not only knowledge of certain technologies and scientific principles but also of specific markets or customer groups, decision-making techniques and management systems (Mowery et al. 1998, p.508). Such resources are called dynamic if they evolve over time and constitute among other things "the learning capacity of a firm" (Lockett 2001, p.725). The process by which resources in this sense are built up or accumulated is a historical and path-dependent one and partly individualistic or idiosyncratic. The observed heterogeneity of actors or firms in terms of their knowledge at a certain period t can then be seen as the result of such dynamics up to t.

This idiosyncracy or path-dependency in the process of building up knowledge by learning and generating new ideas is rather selective in the sense of the range of fields or areas of knowledge addressed. It can be interpreted as a result of actors' way to cope with the uncertainty inherent to innovative activities (Dosi 1988). This behavior is characterized by trial and error (Loasby 1999, Boschma 2005) where firms and economic actors in general develop certain routines to cope with this uncertainty and integrate them into their search and creative activities (Nelson & Winter 1982). Knowledge stocks built up in that way are often idiosyncratic, sticky, and hard to imitate. In the RBV those stocks just meet the criteria of resources. And according to Combs & Ketchen (1999) and Lockett (2001) those resources are crucial for the competitive advantage of a firm and determine her performance (Barney 1991).

2.2.3. Collective learning

To overcome the uncertainties characterizing innovative activities actors develop certain routines to build up appropriate knowledge and competencies. Among those an important routine is learning. Besides learning by own experience another routine is to learn from others and to cooperate in research and development. By this an actor attempts to internalize external intangible knowledge and to exchange it against own knowledge. Hereby, external knowledge affects the internal learning processes of a firm. This exchange of knowledge resources in the sense of the RBV is based on social interaction, can be considered a process of collective learning, and may even lead to collective invention and innovation (Allen 1983).

Collective learning is based on the transfer or the exchange and therefore on the flow of knowledge and information. Flows of external knowledge are discussed under the heading of "R&D spillovers"(Arrow 1962). In his review of the spillover literature Griliches (1992) concludes that "studies generally seem to confirm the presence and influence of R&D spillovers" (Dumont & Meeusen 2000, p.3). He suggests the distinction between "embodied spillovers", like equipment, goods and services, and "disembodied" ones. For embodied spillovers the external effects are often analyzed by commodity flows such as represented by input-output-tables that show the importance of buyer-supplier relationships for learning processes (see for example Coe & Helpman (1995), Debresson (1999)). For disembodied spillovers this measurement device is not available. Griliches defines them as " *... ideas borrowed by research teams of industry i from the research results of industry j. It is not clear that this kind of borrowing is particularly related to input purchase flows"* (Griliches 1992, p.36). A major problem of empirical research is to identify and possibly quantify the knowledge flows in such cases. The concept of proximity of actors may help to find an approximate solution to this issue.

As mentioned above, each firm can be considered unique in terms of the set of sticky resources. This "stickiness" is due to the inherent nature of knowledge that makes it different from traditional inputs (Dosi 1988). Knowledge is considered partly as a latent public (Nelson 1990) and partly as tacit. In the former case it will not diffuse immediately from one firm to another, and in the latter case this may even be impossible. Here, networking is a way for an independent firm to get access to the sticky as well as to the tacit knowledge of another firm (Mowery et al. 1998). For networking to be effective in inducing spillovers between actors certain conditions of proximity have to be satisfied (Boschma 2005). Two proximity concepts are of importance here, spatial proximity and technological proximity.

2.2.4. Spatial proximity

An important dimension analyzed in order to explain intended technological spillovers or the phenomenon of research cooperation is the spatial proximity between the actors. The idea is that only actors that know and trust each other will exchange and transfer knowledge. Spatial (and social) proximity facilitates this exchange. This issue is taken up by a couple of theories dealing with the geographical concentration of firms and the resulting impact on economic success of regions or single firms. A first group of authors (e.g. Holbrook & Wolfe 2000, Brenner 2002, Giuliani 2005) focus on the concept of a "cluster", describing the horizontal concentration of an industry in a certain region and the resulting Marshallian externalities.

Another group of researchers (e.g. Asheim & Isaksen 2002, Doloreux 2002, Asheim et al. 2003, Fritsch & Franke 2004, Cantner & Graf 2006) concentrates on "Regional Innovation Systems". These systems are not restricted to a single industry. In this sense there are not only Marshallian externalities but also so called Jacobs externalities (Jacobs 1969) at work which address the knowledge flows among actors of different industries. In addition to that RIS comprise all actors in a certain region that are involved in the process of knowledge creation and innovation. Besides the "traditional" knowledge creating actors like firms and private research institutes, they include non-market actors like public research institutes (Dahlstrand 1999, Buesa et al. 2004) as well as public policy makers that play a coordinating role in the processes of knowledge creation and innovation (Dumont & Meeusen 2000, Fritsch & Franke 2004).

How is knowledge transfer by networking related to the concentration of innovative activities in space? Research and innovation activities are not equally distributed in space. In some regions more firms, research institutes or individual actors are engaged in innovating than in other regions. In other words the aggregate regional knowledge base differs across regions and consequently also the pool of knowledge spillovers. The knowledge pool of a region is built up by the actors involved and their specific knowledge stocks. The more knowledge generating actors a region shows and the higher their respective knowledge stocks the larger the pool of external knowledge each actor may draw from. Hence, we expect that the number of actors and their individual innovation-related activities positively influence the extent to which networking activities and thus cooperative innovation takes place in a region:

Hypothesis 1: The higher the number of actors (firms, research institutes or even private persons) in a region pursuing innovative activities, the larger is the pool of knowledge spillovers and the more firms tend to actively use the external knowledge pool of the region by means of regional knowledge networks.

2.2.5. Technological proximity

Beside the geographical dimension of proximity, there are other dimensions showing up in recent literature on knowledge spillovers and cooperation networks (Boschma 2005). Of special interest for our study is technological or cognitive proximity. The idea here is that for knowledge flows between actors to be effective the recipient firm has to be able to understand the sender firm's knowledge. The respective capabilities to understand external knowledge are directly related to the firm's own knowledge base seen as a bundle of resources in the RBV sense. By the same degree by which firms differ in those resources they do differ by their abilities to understand and use external knowledge (Boschma 2005). In other words, actors show different absorptive capacities (Cohen & Levinthal 1990).

In this sense the pool of regional knowledge spillovers has an individual value for each of the firms acting in this region. This value depends on the degree of complementarity between the firms' resources (Nooteboom 1999) and on the respective absorptive capacities. The higher this value the more a firm will be able and willing to draw on external knowledge. This argument can be extended to the regional level as formulated in the following hypothesis:

Hypothesis 2: The higher the complementary between the knowledge bases of firms within a region are, the more those firms will have network linkages within the region in order to integrate external knowledge into their knowledge stocks.

2.3. Methodology and data base

The two hypotheses presented in the previous section will be tested on the basis of three regions: Northern Hesse and Jena in Germany and Alpes-Maritimes in

France. In order to do so we investigate the respective innovator networks. A region's innovator network is built up by the interaction between several actors within a region as well as between actors inside and actors outside the region. Innovation here is meant in the sense of transferring and exchanging knowledge and information. For these networks we test whether certain measures for the intensity of knowledge flows are dependent on measures characterizing the regional knowledge base. The next session explains how the region's innovator networks have been reconstructed and introduces briefly the three regions to be analyzed.

2.3.1. Methodology

For constructing the regional innovator networks as well as for characterizing the respective regional knowledge base we use patent data. Sources are the "Deutsche Patentblatt" for both German regions and data from the European Patent Office for the French region. The former source includes all patents applied for at the German patent office and at the European patent office for Germany between 1998 and 2003. For the same period we use EPO patents for the French region of Alpes-Maritimes.[3]

Boundaries and Interaction Structures

Using these data we construct networks of innovators where the nodes are the innovators and the ties between the nodes represent the interaction between innovators. The innovators in those networks are the patent applicants. Our task has been to identify the innovators pertaining to a certain region and the modes of interaction between those innovators. For this we rely on the following information given by a patent: names and addresses of applicants, names and addresses of the inventors, year of application. These data are used as follows:

(1) First, we assign each patent to a certain region. For that, on a patent document there are two fields for addresses which can be used, the address(es) of the applicant(s), the actor(s) in our networks, and the address(es) of the inventor(s). Assignment problems occur if both addresses differ which might be the case if the inventors' R&D activities took place in a branch located in region i but the patent is filed for by the headquarter located in region j. There exists a convention in recent literature saying that using the inventor's address causes minor disadvantages (e.g. Sorenson et al. 2006, Cantner & Graf 2006). Greif and Schmiedl argue that the "inventor domicil concept reflects the real location of

[3] National French patents, usually more numerous than EPO patents, are not included. Hence, the total number of patents is inherently smaller for the French region.

R&D more conveniently" (Greif & Schmiedl 2002, p.6). Based on this convention we assign a patent to one of our regions if at least one of the inventors stated is located in that region.

(2) Using the names of the applicants and of the inventors of all patents belonging to a certain region in period t, we construct a network of innovators (i.e. applicants) for that period t. The nodes of the network, in the following called "actors", are the patent applicants. Actors can be firms, research institutes or even private assignees. Using patent data there are two possible ways of relationships between the actors to come up:[4]

(a) First, a classical "research cooperation" might result in a co-patent application, where the participating firms or institutes are all listed as patent applicants. In this kind of relationship direct bi-lateral knowledge flows are established between all partners. All the participating firms or institutions are assumed to be able to internalize a certain degree of the tacit and sticky knowledge from their cooperation partners.

(b) The mobility of researchers is a second form of knowledge transfer between two firms. In patent data "labor mobility" is retraced if one inventor is named on the patents of different not co-applying applicants. In that case we assume that this inventor worked for both applicants. Here the knowledge flow is not bilateral, because only the inventor's new company can benefit from the knowledge base of the former researchers' employer. However, not all cases of "multiple-applicant inventorship" can be interpreted as a result of labor mobility. There exists an alternative explanation of an inventor occurring at patents of different applicants, which we label "hidden cooperation": Many cooperating firms decide to divide the patents that result from their cooperation among themselves (Hagedoorn 2002). Thus, only one of the cooperating firms is named as applicant on the patent resulting from an cooperation. The inventors, however, belonging to either one of the two cooperating companies, occur on all patents. We label this case labor mobility too, since the data we use do not allow distinguishing these two cases.

For constructing the innovator network both types of connections, cooperation

[4]For a detailed explanation of using patent data for social network analysis, see Cantner & Graf (2006).

and labor mobility, have been identified separately. The following analysis of the network structure, however, will be performed on the basis of both types of knowledge transfer together. We are aware of the problems using this methodology. The weakness not to know whether in the observed connection the knowledge flow is two-sided or not must be accepted at this time.[5]

Finally, we achieve a network consisting of regional actors and their external partners as described in the RIS approach. For these networks we observe their development between 1998 and 2003. As the regional network is too sparse in the case of one-year time periods, we used four three-year periods with an overlapping year between the periods. These four subperiods (1998-2000, 1999-2001, 2000-2002, 2001-2003) allow us to characterize the development of the three regional knowledge networks and to draw conclusions on the regional knowledge base as an influential factor.

Knowledge flows and small world properties

We focus on a specific feature of innovator networks, their function as a knowledge transfer channel (Sorenson 2003). Drawing on sociological work related to knowledge networks (Granovetter 1973, Burt 1992) economic research such as Newman (1999), Kogut & Walker (2001), Cowan et al. (2004*a*,*b*) and Fleming et al. (2005) analyze innovation networks and knowledge diffusion. Empirical as well as simulation analyses suggest that a certain network structure fosters the knowledge flow within the network, the "Small-World" (SW) property based on Milgram (1967) and formalized by Watts & Strogatz (1998).

In order to identify the SW property of a network one computes the cluster coefficient and the mean-shortest-path length. The former represents the number of the extent the direct neighborhoods for an actor are connected with each other, the latter indicates the average distance an actor has to all other actors engaged in the network. SWs show a high clustering coefficient and a low average path length, and by this sustain the knowledge flow between the network actors (Watts & Strogatz 1998). The better a network fulfills the requirements of a SW the better the internal flow of knowledge.

To apply this formal concept of a SW in an empirical analysis, however, one regularly faces considerable problems. First, such kind of analysis requires in-

[5]But we are looking forward to cope with this problem in future work.

formation of all actors involved in a network. A representative sample of actors obviously does not satisfy this condition. A network constructed on the basis of patent data information (co-applications, labor-mobility), however, can be considered complete in this sense - it connects all actors successfully engaged in inventive activities and willing to patent. Unfortunately, in most cases the latter do not fulfill a second criterion, the full connectivity of the network. In order to calculate the average path length, all actors of the network have to be connected with each other, at least in an indirect way. This is just what full connectivity means, but what one rarely observes in empirical data. Therefore, empirical studies often use the largest connected component of a network to test for SW characteristics (Sorenson & Fleming 2004, Fleming et al. 2005). Here the largest component is assumed to represent the whole network; this, however, is only acceptable when it shows a sufficiently high share of the whole network.[6]

2.3.2. The three regions

The three regions to be analyzed are characterized as follows: The first region, "Northern Hesse", contains six "Landkreise" and its economic structure shows a strong reliance on established and more traditional industrial activities. The economic development of Northern Hesse is shaped by the descent of heavy industries like railway engineering and defense industry in the late 80's of the 20th century. Nowadays regional politicians and business development agencies are trying to support the emergence of clusters in different technologies. The MOWiN.net for example is a public financed network of regional business agencies concentrating on the logistics sector.

The second region we consider is Alpes-Maritimes at the French Côte d'Azur. It is located between the Mediterranean Sea and the Alpes with Nice as the largest city. Beside tourism the economic performance is strongly dependent on the successful science park Sophia-Antipolis, located southwest of Nice. Founded in the early 80's of the last century, it houses primarily companies in the fields of computing, electronics, pharmacology and biotechnology. It was created as a publicly financed project in vacant space, in a region with no university or industrial tradition. At its initiation, this project was characterized by the absence of traditional factors influencing the innovative success of regions (Longhi 1999).

[6] As we will show later on, two of our three regional networks are far from satisfying this condition.

Nowadays, over 1300 firms are located within this park and global players like Hewlett Packard or Phillips Electronics have branch offices there.

The third region under investigation contains the city of Jena, the neighboring "Saale-Holzland-Kreis" and two postal code areas next to Jena, Apolda and Mellingen. This region's industry structure is clearly dominated by the city of Jena, strong in several knowledge intensive industries. The economic structure of Jena has a long tradition and today is still affected by the existence of the "Kombinat Carl-Zeiss" in times of former GDR. Jenoptik, Zeiss and Schott are the main successors of this Kombinat. Besides these other optic firms as well as firms from pharamaceutics, IT and biotech are located in Jena.

2.4. Analysis

2.4.1. Network actors

The components of an innovator network are actors and institutions. Since we have no information about the institutional endowment of the three regions, we concentrate on the actors and their characteristics. Among network actors firms and individual actors hold the largest share followed by public research institutes which serve a specific role within the network. Their major function is the generation and accumulation of knowledge, its diffusion into the regional knowledge stock, and the education of a highly skilled workforce capable of performing high-level industrial R&D (Fritsch & Schwirten 1999*a*). Therefore, public research institutes provide a highly valuable input to the regional innovation system (Graf & Henning 2006). Furthermore, we distinguish network actors which are located within the region (internal actors) and those which are external to the region but hold connections to internal actors.

Northern Hesse

For the network of innovators in Northern Hesse table 2.1 contains information about the actors involved. The network consists of 212 actors in the period 1998-2000. Thereof, 105 (49.5%) have been identified as actors located within the region (internal actors).

Over time the number of actors in Northern Hesse decreases constantly (except for 1999-2001). In the final period 2001-2003 we observe 174 actors. The share of

Table 2.1.: Network Actors and their characteristics in Northern Hesse

Years	1998-2000	1999-2001	2000-2002	2001-2003
Number of actors	212	224	185	174
Development of actors		5.7%	-	-
			17.4%	5.9%
Number of internal actors	105	107	83	85
Share of internal actors	49.5%	47.8%	44.9%	48.9%
Number of public research centers	8	9	8	8
Share of public research centers	3.8%	4.0%	4.3%	4.6%

internal actors is not much affected by this development (except for 2000-2002) and stays consistently below 50%.

Looking at public research institutes the network of innovators in Northern Hesse shows 8 institutes in each period (except 9 institutes in 1999-2001). As the total number of actors decreases over time, the share of public research institutes slightly increases from 3.8% in 1998-2000 to 4.6% in 2001-2003.

Alpes-Maritime

Table 2.2 shows that in 1998-2000 the network of innovators comprises 318 actors of which 180 (56.6%) are identified as internal actors. Contrary to the development in Northern Hesse, the number of actors in this regional network is increasing over time, with a decreasing share of internal actors.

Table 2.2.: Network Actors and their Characteristics in Alpes-Maritime

Years	1998-2000	1999-2001	2000-2002	2001-2003
Number of actors	318	324	323	358
Development of actors		1.9%	-	10.8%
			0.3%	
Number of internal actors	180	181	169	183
Share of internal actors	56.6%	55.9%	52.3%	51.1%
Number of public research centers	8	7	8	8
Share of public research centers	2.5%	2.2%	2.5%	2.2%

The absolute number of public research institutes is similar to those of Northern Hesse, but as the total number of actors increases the share of public research institutes declines from 2.5% in 1998-2001 to 2.2% 2001-2003.

Jena

The innovator network of Jena in 1998-2001 comprises 254 actors, whereof 123 (48.4%) are identified as internal actors (see table 2.3). After an increase in 1999-2001 (277), the number of actors remains considerably stable in the in the following two periods (257, 249). The number of internal actors follows this trend, so that their share is nearly constant over time and slightly below 50%.

Table 2.3.: Network Actors and their Characteristics in Jena

Years	1998-2000	1999-2001	2000-2002	2001-2003
Number of actors	254	277	257	249
Development of actors		9.1%	-7.2%	-3.1%
Number of internal actors	123	135	124	120
Share of internal actors	48.4%	48.7%	48.2%	48.2%
Number of public research centers	18	22	24	25
Share of public research centers	7.1%	7.9%	9.3%	10.0%

Actors belonging to public research institutes are more numerous in the Jena network compared to the two other networks. We identify 18 institutes in 1998-2001, increasing over time to 25 actors in 2001-2003. Their share increases from 7.1% to 10%.

2.4.2. Connections and densities

Having discussed the characteristics of the network actors, the structure of each of the three regional innovator networks will be introduced next. The interactions involved are the basis of certain network structures to be investigated in further steps. This systemic character of regional innovative activities mainly shows up in the number and the intensities of interactions and is less dependent on the number of innovative actors.

Our analysis is based on the two types of interaction introduced above, the more formal research cooperations and the interaction by "labor mobility". It is important to recognize here that those connections indicate successful interactions since they led at least to a patent. Obviously more modes of interaction are expected to be relevant. Taken these two types of interaction together leads to a network which can be viewed as "a lower barrier of actual relationships" (Cantner & Graf 2006, p.469).

Table 2.4.: Relationships and network densities in regional knowledge networks

Panel A: Northern Hesse

Years	1998-2000	1999-2001	2000-2002	2001-2003
No. of research cooperation ties	30	28	20	18
No. of labor mobility ties	52	56	34	13
Number of connections	125	134	145	66
Number of connections (dichotomized)	47	50	32	27
Density	0.0021	0.0020	0.0019	0.0018

Panel B: Alpes-Maritime

Years	1998-2000	1999-2001	2000-2002	2001-2003
No. of research cooperation ties	36	41	45	36
No. of labor mobility ties	114	108	104	86
Number of connections	178	178	189	141
Number of connections (dichotomized)	143	144	155	109
Density	0.0028	0.0028	0.0030	0.0017

Panel C: Jena

Years	1998-2000	1999-2001	2000-2002	2001-2003
No. of research cooperation ties	161	158	153	152
No. of labor mobility ties	838	856	696	612
Number of connections	1590	1558	1422	1336
Number of connections (dichotomized)	915	933	862	757
Density	0.0285	0.0244	0.0262	0.0245

Table 2.4 contains information on the number of relationships of both types for each network. Panel A refers to Northern Hesse, Panel B to Alpes-Maritime, and Panel C to Jena. The first row in each panel shows the number of research cooperations. For Northern Hesse this number is decreasing over time from 30 to 18. This type of interaction starts in Alpes-Maritimes with 36 research cooperations in 1998-2000, increases to 41 and 45 and then declines to 36. Compared to these two regions Jena shows a much higher number of research cooperations. Starting with a number of 161 research cooperations in 1998-2000, which is more than twice the amount of both other regions together. This number constantly decreases to 152 research cooperations in the last period. The number of research cooperations in both German networks are decreasing over time and the formal interactions are much higher in Jena than in the other two networks.

The second row of each panel provides information about the number of labor mobility ties. For Northern Hesse in 1998-2000 we find 52 connections and 56 in 1999-2001. After that there is a sharp decline to 34 and to 18 in 2001-2003. A similar development is to be observed for Alpes-Maritime. Here the number of labor mobility ties decreases from 114 in 1998-2000 to 86 in 2001-2003. As for research cooperations the number of labor mobility ties in Jena is much higher than in the other two networks. However, their development is similar to the one of Northern Hesse and Alpes-Maritime. In 1998-2001 we find 838 connections. This number decreases over time to 612 relations in 2001-2003.

Combining both kinds of connectivity makes up the regional innovator network. The respective aggregated numbers are found in the third row for each panel in table 2.4. They reflect the total number of connections in the network. Dichotomizing the observed ties provides information on the number of actors connected to each other. With respect to get information on the systemness of the regional innovative activities the dichotomized measure is to be preferred. Not surprisingly the innovator network in Jena (915 in the first period) contains the most connections followed by Alpes-Maritime (143) and Northern Hesse (47). Comparing the first and the last period the number of connections decreases in all three networks.

The last indicator provided in table 2.4, the network density, completes the description of the three innovator networks and their development. The density of a network is computed by the ratio of all ties observed over the number of all possible ties for the dichotomized network. Hence this indicator relates number of connections and number of network actors.

While the three innovator networks are rather similar in their number of actors, with respect to the number of connections clear differences show up. Due to the much higher number of connections in Jena, the network there shows a much higher density (about tenfold) than the other two networks. Over time we observe a slight decrease of the network density in all three regions. For Northern Hesse it is the drastic decline in the number of relations (-43%) combined with a less pronounced decline in the number of actors (-18%) that provides for a slight decrease of the density from 0.0021 in 1999-2001 to 0.0018 in 2001-2003. Compared to Northern Hesse the innovator network of Alpes-Maritime shows a higher density in first period. Due to an increase in the number of actors (12%) and a decline in the number of connections (-24%) the density declines in 2001-2003 to 0.0017, a level close to the one in Northern Hesse. For Jena the number of connections (-17%) as well as the number of actors (-5%) decreases - the latter much less. However, density stays at the same level (0.0285 in 1998-2000 to

0.0245 in 2001-2003). Hence, in Jena rather less connected actors seem to leave the network over time.

2.4.3. Fragmentation

Having shown differences in the density of the three networks, in this subsection we discuss the structure of networks as a whole and their development. Table 2.5 includes in three panels of information about the structural characteristics of each innovator network and their development over time.

Table 2.5.: Fragmentation and Components in regional knowledge networks

Panel A: Northern Hesse

Years	1998-2000	1999-2001	2000-2002	2001-2003
Freeman Degree	0.769	0.855	0.585	0.406
Fragmentation index	0.999	0.999	0.999	0.999
Number of isolates	121	136	116	114
Share of isolates	57.08%	60.71%	62.70%	65.52%
Number of components	5	6	4	4
Actors in largest component	12	9	4	3
Share of largest component	5.7%	4.0%	2.2%	1.7%

Panel B: Alpes-Maritime

Years	1998-2000	1999-2001	2000-2002	2001-2003
Freeman Degree	1.563	1.557	1.505	0.594
Fragmentation index	0.994	0.995	0.989	0.991
Number of isolates	153	152	154	219
Share of isolates	48.11%	46.91%	47.68%	61.17%
Number of components	23	22	16	13
Actors in largest component	14	13	28	33
Share of largest component	4.4%	4.0%	8.7%	9.2%

Panel C: Jena

Years	1998-2000	1999-2001	2000-2002	2001-2003
Freeman Degree	7.205	6.736	6.708	6.08
Fragmentation index	0.905	0.882	0.921	0.936
Number of isolates	68	66	69	62
Share of isolates	27.76%	24.91%	28.28%	25.62%
Number of components	2	3	6	7
Actors in largest component	112	114	87	78
Share of largest component	44.1%	43.0%	35.7%	32.2%

The knowledge flow within a network depends on the connectivity of all actors involved. The pure number of connections is misleading in this respect as it is not related to the number of potential connections which are possible within an innovation network. Thus, the Freeman degree[7] reflecting the centrality of

[7]"The number of vertices adjacent to a given vertex in a symmetric graph is the degree of that vertex" (Borgatti et al. 2002)

each vertex is introduced here as a first indicator of the overall knowledge flow within a network. This degree of centrality measures the overall network activity of individual actors. Concerning our sample the first rows for each panel in table 2.5 show the Freeman's degree for each subperiod. We observe (i) that there exist clear differences between the three regions and (ii) that the values decline in all three regions over time. So one can conclude for the innovator network in Jena the entire network is more focused around a few central nodes than in the two other innovator networks. Graf & Henning (2006) show the increasing importance of public research institutes for the regional network of Jena.

As mentioned before nearly no empirical innovator network will be fully connected. An aggregate indicator for the connectedness of a network is the fragmentation index. It denotes the share of pairs of actors that are unreachable from each other in all pairs of actors; in the context of our innovator networks this is interpreted as the share of pairs of actors between which no know-how flow takes place. This index ranges from 0 to 1 where 1 indicates a fully fragmented network. The second rows in table 2.5 show the fragmentation indices for all networks and their development over time. In Northern Hesse the index is close to 1 which means that for this innovator network the share of unconnected actors is considerably high. The network in Alpes-Maritime has a lower fragmentation index which is slightly decreasing over time; hence, the connectedness of actors increases over time. The innovator network in Jena shows the lowest values. They are slightly increasing over time reflecting the declining absolute number of connection mentioned above.

The fragmentation of a network is caused by isolated actors and by actors which are connected in separate components of the network. Two actors are (not) member of the same component if there is (no) a direct or indirect path connecting them (Borgatti et al. 2002). The occurrence of several components in a network indicates that there are networking activities where the knowledge flows are bounded within different cliques. In innovator networks these cliques are often technology driven group formations.

Rows 5 to 7 of each panel in table 2.5 display the number of components, the number of actors in and the share of the largest component.[8] In our sample the innovator network in Northern Hesse consists of 4 (3rd and 4th period) to 6

[8]In our analysis a component has to consist of at least three actors.

(2nd period) components. In Alpes-Maritime this number is much higher. Here starting with 23 components in the 1st period, the number is decreasing to 13 in the last period. Contrary to this development the number of components in Jena is increasing but on a much lower level. In the first period there are only 2 components identified. This number increases over time to 7 components in the last period.

In Northern Hesse the largest component comprises 12 actors (5.7%) in the first period which is rather low. Furthermore, the share of the largest component decreases over time to 1.7% in the last period. The largest component in Alpes-Maritime comprises more actors (13-33) and its share is increasing over time from 4.4% to 9.2%. In Jena the largest component comprises in the 1st period 112 von 254 actors which are 44.1%; this share decreases to about 32% in the fourth period.

The third and fourth rows in table 2.5 show the number of isolates and their shares. The regional innovator networks in Northern Hesse and Alpes-Maritime consist of much more isolated actors which are no member of any component. In Northern Hesse the number of isolates is fluctuating around 120 out of 254 actors which means that around 60% of all actors are not connected either through co-applications or scientist mobility. The number of isolates in Alpes-Maritime is increasing in the last period from around 150 in the first three periods to 219 in the last one. Their share is nearly constant in the first three periods (around 50%) and jumps up in the last period to 61.17% which is highly comparable to the value of the first observed network of Northern Hesse. The number of isolated actors in Jena is much smaller. Their number is nearly constant over time and fluctuates between 69 (3rd period) and 62 (4th period). Their share in all innovative actors is about 25% throughout.

Based on the characteristics of the three regions' innovator networks with respect to the number of components (smaller for Jena and Northern Hesse; larger for Alpes-Maritime) and the share of isolated actors (smaller for Jena; larger for Northern Hesse and Alpes-Maritime) one can conclude that knowledge flows most easily in the Jena network. The lowest rate of diffusion could be expected in the regional network for Northern Hesse. Here, a high share of actors is isolated which means that they are not participating in regional collective learning. The regional network for Alpes-Maritime is somewhere in between. Interactive learning takes place, indicated by a lower share of isolated actors (except of the last period) but these collective learning activities are concentrated in independent components rather than in one larger research community (highest number of components; low share of largest component). Thus, one could conclude that in this regional network knowledge is shared by independent groups of researchers which might be due to specificities of the regional technological endowment.

2.4.4. The Small World of Jena

The diffusion of knowledge, however, is not only dependent on the number of interactions but, as already mentioned above, on the network structure. One way to analyze the regional network structure according to its knowledge flow characteristics is the small-world concept introduced by Watts & Strogatz (1998). In order to test for SW properties of a network the largest component has to represent a sufficient share of the whole network. For Northern Hesse and Alpes-Maritime the largest component is not representative for the complete network so that we cannot test for SW characteristics. For Jena, however, the share of the largest component is always about 1/3 so that it can be used to test for SW characteristics. Thus, the innovator network of Jena will be analyzed in this subsection according its small-world-properties.

Small-world networks are identified as a class of random graphs by Watts & Strogatz (1998). They noted that graphs could be classified according to their clustering coefficient and their mean-shortest path length. Many random graphs exhibit a small mean-shortest path[9]. Furthermore, they also usually have a small clustering coefficient[10]. Contrary to random networks, many real-world networks have a small shortest path but also a clustering coefficient significantly higher than expected by random chance (Baum et al. 2003). Watts & Strogatz (1998) propose a simple model of random graphs with (i) a small average shortest path and (ii) a large clustering coefficient. The crossover in the Watts-Strogatz model between a "large world" (such as a lattice) and a small-world has been described in several studies (e.g. Baum et al. 2003, Cowan & Jonard 2004, Fleming et al. 2005). The most prominent hypothesis regarding the importance of the network

[9] The mean-shortest path is a global property and measure the averages steps between all actors of a network. Thus, all actors have to be connected with each other. It measures the social distance between any two inventors as the minimum number of collaborative links between them (Fleming et al. 2005).

[10] Following Watts & Strogatz (1998), the clustering coefficient indicates the the cliquishness of a typical neighborhood and, thus, it is a local property. It is an indicator for frequent local interactions.

structure is that small-world networks should enhance the innovative creativity (e.g. Watts 1999, Baum et al. 2003, Uzzi & Spiro 2005). According to Watts & Strogatz (1998) the following network characteristics have to be required to analyze for its small-world properties of a network:

$$n \gg k \gg ln(n) \gg 1$$

where n is the number of connections within a network, k the number of actors. These requirements lead to a sparse but connected ($k \gg ln(n)$) network. According to the values shown in the first two rows of table 2.6, these requirements are fulfilled for the largest components of the Jena network over all four periods.

Following Watts & Strogatz (1998) a small-world network lies between a regular (long path length and high clustering coefficient values) and a random network (short path length and low clustering coefficient values). Thus, a network which possesses small world characteristics needs to have an average path length which is comparable to a random network of the same size and density characteristics but the cluster coefficient of the real network has to be much higher indicating that this network is more regular than the random network.

To test for this, the average path length and cluster coefficient values for the Jena networks and for corresponding random networks are presented in table 2.6. Actors of the Jena network are connected over longer distances on average in comparison to the random network. The differences, however, (2.844 in comparison to 2.041 in the first period) are not that large. Thus we conclude that the observed networks do have relatively short paths. This implies that knowledge flows relatively rapidly within the component, and the diffusion knowledge possessed by distant actors, through successive rounds of innovation, can be an active feature of the network. While the average path lengths are comparable between regional and random networks, the cluster coefficients are obviously different. For the first period the coefficient value of the regional network (0.775) is over six times higher than the value of the random network (0.124). This discrepancy declines over time which is due to an increase of the network's density and, thus, to an increase of the cluster coefficient values of the random networks whereas the cluster coefficient of the regional networks is nearly constant over time. Based on these results one can conclude that the network of Jena shows small-world characteristics for all four periods.

Thus, referring to Watts (1999), Baum et al. (2003), Fleming et al. (2005) the

Table 2.6.: Small World properties of Jena

	1998-2000	1999-2001	2000-2002	2001-2003
Actors in largest component	112	114	87	78
Number of ties	284	264	228	196
Density	0.123	0.108	0.161	0.183
Network properties of Jena				
Average path length	2.844	3.267	2.767	3.015
Cluster coefficient	0.775	0.812	0.773	0.737
Comparable random network				
Average path length	2.041	2.125	1.941	1.886
Cluster coefficient	0.124	0.114	0.174	0.202

structure of the Jena network should enhance innovative capabilities of its actors which is, however, not in the focus of this work. In fact, we are interested in determinants influencing the cooperative innovation activities of all three regions under consideration. Therefore, the regional cooperativeness and, thus, the regional networks are represented in the following section by variables which do not require a complete network like the share of isolated actors.

2.5. Regional knowledge pools and cooperative innovation

Having discussed the structures of each region's network and their development we now want to turn to the two hypotheses formulated in section 2 suggested. In principle they claim the network structure depends on the pool of knowledge available within a region (Asheim & Coenen 2005). More specifically we are interested in the impact the pool of regional knowledge spillovers (in the following knowledge pool) and its structure (in terms of homogeneity) have on the region's cooperative innovation observed. Although the working mechanism relating the regional knowledge base to the region's innovator network is explained by theoretical concepts, empirical evidence on this relation is rather scarce. This is due to the difficulties of measuring a regional pool of knowledge and the respective spillovers. In the following we attempt to quantify and structure the knowledge pools of our three regions and relate this to the hypotheses suggested. For this we first discuss the regional knowledge base, its homogeneity and development over time.

2.5.1. Regional knowledge pools

Size of the knowledge pool

As this study is based on patent data we use the number of patent applications within a certain period as a rather rough indicator for such a pool. The number of patents that have been filed for over a longer time span might be much more adequate as an indicator, but, yet, our sample comprises only information over a 6-year time span. The knowledge pools are indicated through patent applications in the respective period. This information is displayed in the 1st rows of each panel in table 2.7.

Table 2.7.: Pool of regional knowledge spillovers and its complementarity

Panel A: Northern Hesse

Years	1. period 1998-2000	2. period 1999-2001	3. period 2000-2002	4. period 2001-2003
no. of patents	590	574	463	440
no of technological fields	38	37	36	36
top 5 tech. fields	F42	F42	F42	F42
	F20	F20	F20	F21
	F22	F22	F22	F17
	F25	F21	F21	F22
	F27	F25	F17	F20
share of top 5 techn. fields	50.51%	54.18%	52.70%	52.73%
Herfindahl Index	0.068	0.068	0.069	0.063

Panel B: Alpes-Maritime

Years	1. period 1998-2000	2. period 1999-2001	3. period 2000-2002	4. period 2001-2003
no. of patents	356	389	460	662
no of technological fields	32	33	35	36
top 5 tech. fields	F35	F35	F35	F35
	F28	F28	F28	F28
	F13	F13	F13	F13
	F10	F37	F37	F37
	F37	F10	F38	F38
share of top 5 techn. fields	51.69%	54.76%	57.39%	62.23%
Herfindahl Index	0.079	0.090	0.090	0.101

Panel C: Jena

Years	1. period 1998-2000	2. period 1999-2001	3. period 2000-2002	4. period 2001-2003
no. of patents	730	814	772	810
no of technological fields	39	38	38	37
ID of top 5 tech. fields	F38	F38	F40	F40
	F40	F40	F13	F38
	F13	F13	F38	F13
	F37	F37	F37	F37
	F10	F10	F10	F10
share of top 5 techn. fields	77.26%	78.37%	77.59%	79.38%
Herfindahl Index	0.087	0.087	0.088	0.093

Following hypothesis 1 we would expect that the knowledge pool in Northern Hesse has to be the smaller than than the one of Alpes-Maritime, while Jena has to have the largest knowledge pool. For the first period under consideration we, however, find Northern Hesse (590) has a larger knowledge pool than Alpes-Maritime (360). The pool of Jena (730) is the largest in this subperiod.

For the following periods we found for all three networks that the interaction intensity in terms of numbers of connections and in terms of densities is declining over time. Hence, one should expect the same development to hold for the respective knowledge pools. Here, however, a development different among the regions is observable. Whereas the knowledge pool of Northern Hesse knowledge pool is constantly declining, as expected, the knowledge pool of Alpes-Maritime is increasing over time. Furthermore, the knowledge pool in Jena is increasing too.

Complementarity of the knowledge pool

In order to test for hypothesis 2 we have to specify the notion of complementarity. This term is used to indicate the average reciprocal understanding between two member of an innovation network. Therefore, the diversity of the regional knowledge base is taken into account which means that the amount of knowledge will later on be separated among a technological space. The understanding within a technology is taken for granted, whereas we assume that there is no understanding between different technologies. This assumption allows us to discuss complementarity of the regional knowledge base in terms of its homogeneity. This procedure limits, somehow, the explanatory power of our empirical analysis, thus, we will be careful with the interpretation of our empirical results.

To account for the complementarity of the regional knowledge pools we make use of the IPC, the international patent classification. Each patent shows distinct IPC codes which characterize the technological knowhow represented by the patent. The IPC classification allows a detailed view into the technological dimensions of knowledge, as the IPC is much too broad to be used in our analysis, we implement a concordance list developed by Schmoch et al. (2003) in order to reduce the IPC to 43 technological fields that correspond with NACE industry codes on a 3-digit level.[11]

[11] As the contents of the technologies play no role in this chapter we will use only codes. The corresponding descriptions can be found in appendix A.

The registration procedure at the EPO or the DPA allows to list more than one IPC class on a patent. Therefore, it is possible that a patent is classified for more than one of the 43 technological fields. In these cases a patent is assigned to each technological field with the same weight.

To characterize the complementarity of the knowledge base in each region table 2.7 shows (i) the number of technological fields the actors are engaged in for each period and (ii) the ranking of the 5 most frequented fields (each one identified by a number between F1 and F43) in each region over time.

We first have a look at the range of technology fields covered by each region. Obviously, at any point in time no region is engaged in all of the 43 technological fields. In Northern Hesse the number of active fields is between 36 (3rd and 4th period) and 38 (1st period). Hence, it is slightly more dispersed than the network in Alpes-Maritime (increase from 32 to 36). The activities in Jena (39 - 37) show a similar spread as those in Northern Hesse.

Looking at the most important technologies addressed in table 2.7 we list for each region the 5 most frequented fields and find a considerably stability of these structures over time. Looking at the share of patents that have been filed for in the 5 most frequented technological fields for all three regions this is larger than 50%. The highest share is found for Jena, followed by Alpes-Maritime and then Northern Hesse, indicating a higher degree of specialization for Jena compared to the other two regions. The development of this share over time is increasing, rather stronger for Alpes-Maritime and only slightly for the two other regions.

To further illustrate the technological diversity of the three regions and their development, we make use of the the concept of Salter curves developed by Salter (1960). These represent technologies ranked in descendent order by their number of applications. They "allow to judge the extent of mobility within this ranking by comparing the Salter curves pertaining to different periods" (Cantner & Krueger 2004, p.268). Figures 1-3 show a plot for each region. The technologies are descendently ordered according to their frequencies in the first period.

The figures show that there is a catching-up process taking place by the technologies following the leading technology in Jena and Alpes-Maritimes while the general ranking of the technologies stays rather constant. In that respect, there is

Salter curves of activities in technological fields

Figure 2.1.: Salter curves for Northern Hesse

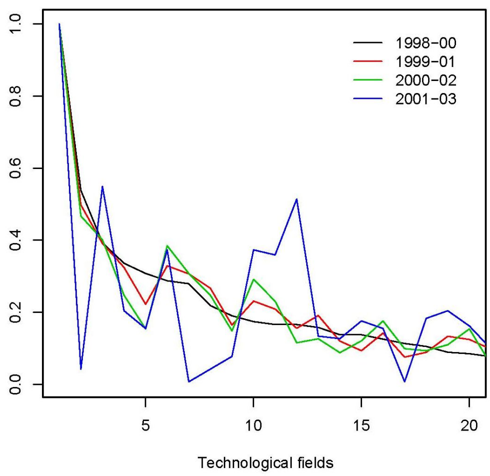


Figure 2.2.: Salter curves for Alpes-Maritime

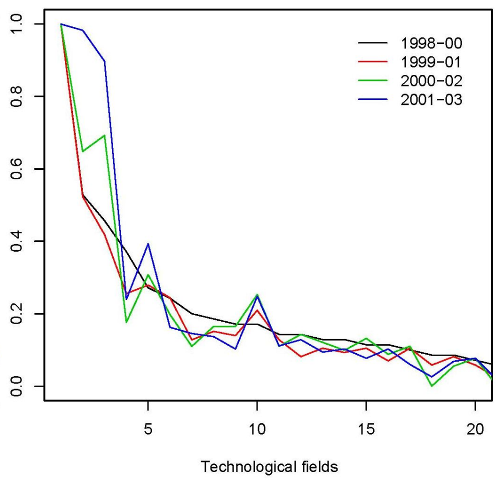
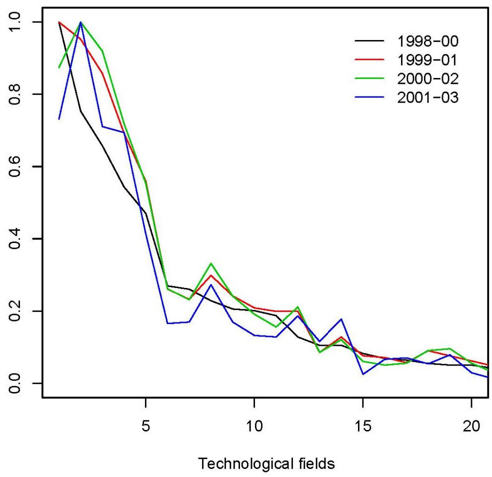


Figure 2.3.: Salter curves for Jena



not much structural change is taking place. In Northern Hesse, however, higher fluctuations are observed. This leads to reordering of the technologies for that region over time. Consequently, for Northern Hesse the technological composition undergoes considerable structural change.

The last index indicating the homogeneity of a regional knowledge pool introduced here is the Herfindahl index. This index takes the whole range of technologies into account. Actually this index measures the monopoly power on markets; here it is used to account for the concentration of technologies in a region and thus it measures the homogeneity of the regional knowledge base. The Herfindahl index is here defined as the sum of the squared shares of the patent applications of each technological field in all patent applications. Hence, it can range from 0 to 1 moving from a large amount of small technological fields to a single dominating technology in a region.

Here, Jena and Alpes-Maritime are rather close together (with a tiny lead of Alpes-Maritime) whereas Northern Hesse is much less specialized. The homogeneity of the knowledge pool in Northern Hesse is the lowest within the sample (0.068 in the 1st period) and decreasing over time (to 0.063 in the 4th period). Initially the knowledge base in Jena (0.087) is the most homogenous in our sample; over time it is increasing to 0.093. The knowledge pool in Alpes-Maritime starts at a median level of homogeneity (0.079) and then constantly increases over time (0.101 in the 4th period).

As already mentioned in the theoretical part of this chapter, the diversity of the regional knowledge base is used as a proxy for its complementarity. This relation is based on the assumption that there are no complementary effects between different technologies, only within them. This issue has to be discussed in further studies, as effects between in addition to effects within technological fields should be taken into account.

2.5.2. Empirical results

Having characterized the innovation networks in terms of their actors and their components and having described the size and homogeneity of the regional knowledge pools over time, we are interested in the relationships between the degree of interaction on the one hand and the knowledge pool variables on the other. As the number of observations is restricted to three regions and four time periods, we have to neglect regional and time specific effects. As we are interested in the relation between interaction and knowledge pool variables in general, we accept the weaknesses of this procedure at this stage.

Regional interaction is represented by three variables. First, $Ties$ is the number of relationships per actor in the regional knowledge network that comprises labor mobility as well as research cooperation linkages. The more formal research collaborations (co-patents) within a regional innovation system are included in the variable *Coop* in terms of connections in the co-applications network per actor. Finally, we want to use a variable representing, somehow, the connectivity of the whole network. As all three knowledge networks are not fully connected in any time period, the SW variable cannot be used here. So we use the share of non-isolated actors $Noniso$ as an indicator of network connectivity.

The size of regional pool of knowledge spillovers *App* is represented by the number of patent application within a certain time period. Here, the short time span of our sample prevents us from constructing a regional knowledge stock accumulated over time. The homogeneity of the regional pool is expressed by the Herfindahl index $Herf$.

Table 2.8.: Correlation matrix

	Ties	Coop	Noniso	App	Herf
Ties	1.000				
Coop	0.994**	1.000			
Noniso	-0.745*	-0.698*	1.000		
App	**0.836****	**0.838****	**-0.727****	1.000	
Herf	**0.428**	**0.497***	**0.203**	0.425	1.000
* significant at 5% level; ** significant at 1% level					

Table 2.8 provides the correlation coefficients between the interaction and the knowledge pool variables. Hypothesis 1 concerns the relationship between the amount of regional knowledge and the regional interaction structure. Our results show that the size of the regional knowledge pool *App*is positively correlated to the number of connections in the regional knowledge network $Ties$ (0.836) and to the number of research cooperations *Coop* (0.838), both at the 1% level of significance. More interestingly, *App* is negatively correlated with the share of non-isolated actors $Noniso$ (-0.727). Hence, we conclude that an increasing regional knowledge pool is positively related to an increasing participation in the

regional network of those actors who are already connected to other members of the network (either by more formal or more informal oriented interactions). However, it does not enhance the probability of an isolated actor to get connected to the network.

Hypothesis 2 deals with on the importance of the complementarity of the regional knowledge base indicated by the Herfindahl index for the interaction intensity. As it is shown in the last row of table 2.8, the only significant correlation of the complementarity indicator is found with respect to the more formal oriented interaction variable $Coop$. Thus, we conclude that it is rather the type of interaction labeled cooperation ($Coop$) than the interaction in general (cooperation plus scientist mobility labeled $Ties$) that is related to the complementarity of the knowledge base ($Herf$).

2.6. Conclusions and future prospects

This chapter deals with the concept of the regional innovation system and related concepts explaining individual motives and incentives to engage in a collaborative research project. We apply the theoretical framework of RIS to three regions and we focus on the core of those systems, the networks of innovators. On the basis of patent data, we analyze the development of the respective innovator networks over four overlapping 3-year-periods. The network relationships comprise formal research cooperations as well as informal labor mobility ties. Regional as well as extra-regional actors have been associated to the network.

Although, the observed regions are similar in terms of number of actors and share of internal actors, their networks show a rather different structure and development. The actors of the innovator network in Northern Hesse are rather scarcely connected, most of them are isolated patent applicants. Giuliani (2005) argues that the dispersion and high rate of isolation of actors in a regional network can be due to the cognitive distance between the actors (Giuliani 2005, p.11). Right this constellation can be identified for the region of Northern Hesse, where the dispersion of the regional knowledge base is constantly high over time. In Alpes-Maritimes and Jena the share of isolated actors is much smaller. In terms of the overall connectivity we find for Alpes-Maritime an innovator network consisting of numerous components, whereas in Jena most of the actors of the innovator network are interconnected in one large component. In this sense the regional network in Alpes-Maritime shows a structural similar to the wine cluster of Colline Pisane identified by Giuliani (2005), whereas the regional knowledge network in Jena is similar to the network of Silicon valley analyzed by Sorenson & Fleming (2004). Contrary to this development the homogeneity of the regional pool increases in Jena and Alpes-Maritime.

The final part of the paper has been devoted to the impact of regional pool of knowledge spillovers in terms of size and complementarity on the regional interaction structures measured in terms of number of knowledge network ties, of research cooperations and in terms of the share of non-isolated actors. We find the size of the regional knowledge base to be positively related to the number of ties as well as to the number of more formal oriented cooperation ties. This result is in line with former empirical studies on the regional knowledge base and its impact of interactions such as Fritsch & Franke (2004) or Sharpe & Martinez-Fernandez (2006). This increasing tendency is, however, restricted to those actors which are already engaged in the regional knowledge networks.

Regarding the complementarity of the regional knowledge base under consideration, as indicated by the homogeneity of the regional knowledge base, we find that there are no significant relations between the number of ties and the share of non-isolated actors of the regional knowledge base. On the contrary, the homogeneity of the regional knowledge base is positively related to the number of cooperations. Thus, we conclude that the technological proximity between members of a regional knowledge network facilitates the more formal oriented interactions, whereas more informal interactions take place. The positive impact of a common technological knowledge base on the cooperation propensity has also been identified on individual (e.g. Mowery et al. 1998, Cantner & Meder 2007) as well as on regional level (Fritsch & Franke 2004, Cantner & Graf 2006).

Due to our restricted sample, we do not want to over-interpret our results. The relations found have to be analyzed on a large sample over a longer time period. Nevertheless our findings imply that regional actors need to have a common technological knowledge base to interact in more formal oriented ways.

Our comparative case study provides first insights into the development of regional innovation systems and possible driving forces. Based on our findings, we will concentrate on more formal oriented interactions when analyzing the relationship between regional interaction structure and regional knowledge base more deeply. Furthermore, the role of regional proximity in contrast to technological proximity has to be discussed in further studies on firm as well as on regional levels.

3. Technological and geographical patterns in the choice of cooperation partner

3.1. Introduction

There is an increasing awareness in economic literature that knowledge and intangible assets are crucial advantages for firms in market competition Winter (1987).[1] Thus, the mechanisms and processes of knowledge creation are more and more in the focus of economic literature. Hereby, the level of analysis differ between different streams of literature. Authors within the resource-based view of the firm Penrose (1959) are concentrating on firm level, whereas studies based on several innovation system approaches (e.g. Malerba & Orsenigo 1997, Edquist 1997) are interested in differences in the performance of whole systems.

Another focus of economic literature is on determinants effecting the willingness to engage in a collaborative R&D project. Hereby, much has been written on the impact of different dimensions of proximity on learning and knowledge creation. These studies are mainly of conceptional (e.g. Nooteboom 2000, Boschma 2005) or empirical nature, but restricted to case studies (e.g. Wuyts et al. 2005). The few existing quantitative approaches using a broader data base concentrate on the impact of one single dimension of proximity (e.g. Mowery et al. 1998, Cantner & Meder 2007).

This chapter contributes to the literature providing a quantitative empirical analysis of the impacts technological and geographical proximity have on cooperative behavior of economic actors and it analyzes the interplay of both dimensions in this surrounding. More precisely, this chapter is on whether technological and geographical proximity affects the choice of the cooperation partner. Hereby, the decision whether to cooperate is not of interest.

In the following I want to shed some light on the question whether technological

[1] This chapter is based on Meder (2008).

or/and geographical proximity increases the likelihood of a cooperation in R&D. After a brief review of both dimensions of proximity in recent literature in section 2 concluding with 4 hypotheses that are going to be tested with the methodology introduced in section 3, section 4 will provide the empirical results. Section 5 will conclude.

3.2. Theoretical background

3.2.1. Effects of cooperativeness in R&D

Interorganizational cooperation in the field of research and development (R&D) has been recognized as important in supplementing the internal innovative activities (Hagedoorn 2002) and to increase the probability of innovative success of organizations (Oerleman & Meeus 2000). There is a clear conclusion in recent literature that firms improve their innovative capabilities by developing collaborative R&D projects (Faems et al. 2005).

The ways how these cooperations affect the effectiveness and efficiency of efforts to development new products and processes are manifold. First, cooperation between firms or between firms and non-profit actors can reduce costs of R&D among the involved partners (Hagedoorn 2002). This might lead to a reduction of uncertainty associated with these projects (Cassiman & Veugelers 2002). This incentive to cooperate is mainly claimed in studies that are based on the transaction-cost theory. Grounded on this theory, Kogut (1988) explains why this particular mode of transaction is chosen over alternatives like acquisitions or other governance mechanism.

Second, cooperation might be driven by the motive to get access to complementary knowledge and assets which are required for successful R&D projects and the later commercial success of these (Teece 1986, Faems et al. 2005). Getting access to complementary knowledge concentrates on the direct results of a R&D cooperation or, more precisely, on the probability of success of this cooperation project (Belderbos et al. 2004). This argumentation is contributed by the concept of the resource-based view of the firm where a firm is seen as a bundle of strategic resources which are hard to imitate (Wernerfelt 1984, Barney 1991). Within this concept, Das & Teng (2000) show that the inducement of R&D cooperations is influenced by the mobility, imitability and substitutability of internal resources, and the cooperation structure is selected on the basis of whether resources are property based or knowledge based.

The third incentive to engage in collaborative R&D projects is to encourage the transfer of knowledge (Ahuja 2000, Eisenhardt & Schoonhoven 1996). This motive is somehow related to the second one but as it deals with long run learning effects (Ahuja 2000). The access to an external knowledge base does not only improve the success probability of a single R&D project but it improves the efficiency of internal R&D efforts. A further stream of literature argues in a very similar way. Several authors have documented that economic actors can not fully appropriate the benefits of their innovations. Knowledge flows between economic actors and the importance of these flows for the innovativeness at the firm level (Jaffe 1986, Cassiman & Veugelers 2002) and for long run growth of firms (Reinganum 1989, Griliches 1992) is emphasized. Collaborative R&D projects are one channel to internalize these knowledge flows (Cassiman & Veugelers 2002). D'Aspremont & Jacquemin (1988) show that imperfect appropriability increases the incentives to engage in a collaborative R&D project. Nevertheless, Cohen & Levinthal (1990) show that the extent to which these knowledge spillovers can be implemented into firms depend on their internal "absorptive capacities".

The observation that cooperation has a considerable potential to contribute to innovation strategies of firms does not mean that such voluntary agreements are successful though (Faems et al. 2005). On the one hand, imperfect appropriability of knowledge increases the benefits from collaborative R&D projects as described above, on the other hand it enhances the incentives to free ride on each other R&D efforts (Kesteloot & Veugelers 1995) and it enhances the possibility for free-riding by outsiders of the cooperation (Cassiman & Veugelers 2002). Such unintended knowledge flows (Teece 2002) might be a major reason for the estimated failure rate of collaborative agreements in general of 60 percent (Bleeke & Ernst 1993). Other reasons might be *"learning races between the partners[...], diverging opinions on intended benefits [...] and a lack of flexibility and adaptability"* (Faems et al. 2005, p.240).

Hence, the benefits that cooperation brings about are not guaranteed and whether they are realized depends strongly on whether the cooperation partners fit to each other in terms of complementarity of resources, aims, and working routines. Furthermore, the benefits do not explain the mechanism of the choice of the cooperation partner. Boschma (2005) provides a detailed overview of dimensions of proximity which are relevant for interactive learning in collaborative R&D projects.

3.2.2. Dimensions of proximity in R&D cooperation

this chapter deals with two dimensions of proximity which are, following manifold streams of literature, essential for interactive learning processes, the technological and the geographical proximity.

Technological proximity

Following the learning economy approach (Lundvall 2004), knowledge is a club rather than a public good which is exogenously given. Thus, economic actors differ among the abilities and set of knowledge resources (Barney 1991). In order to reduce uncertainty which is inherent in the innovation process, firms search for routines (Nelson & Winter 1982). Therefore, innovative activities follow paths (Foss & Klein 2005) where the current development depends on activities in the past. With respect to the access to external knowledge as an assumed incentive to cooperate in addition with the concept of the absorptive capacities, one can conclude that economic actors search for cooperation partner with a comparable knowledge base.

Recapitulating it can be stated that to absorb external technological know-how both the sender and receiver of this know-how must have a certain common knowledge base. The larger this common base the better is the understanding which in turn increases the probability of a common research project. This relationship is formulated in the following hypothesis H1.

Although interactive learning processes are initially a driving force to engage in a collaborative R&D project, the knowledge resources are referred to as the competitive advantages of firms. Thus, Nooteboom (2000) argue that the probability of an involuntary knowledge flow between the cooperation partner increases with an increasing technological proximity. Furthermore, Etzkowitz & Leydesdorff (2000) claim that an innovation is often the first combination of already existing knowledge. Thus, it is assumed in hypothesis 2 that the ability of a cooperation to create something new decreases when the technological knowledge bases are too close.

> H1: A common technological knowledge base is a prerequisite of a cooperative R&D project.

> H2: If the technological knowledge bases between two actors willing to cooperate are too similar, the probability of a cooperative R&D

project decreases.

Geographical proximity

Economic actors willing to innovate rest on a knowledge base that they possesses themselves or that must be obtain from partners (Cohen & Levinthal 1990). Several streams of literature refer to geographical pattern in the relations of acquisition of external knowledge such as studies on innovative milieus (Camagni 1991, Capello 1999), innovation networks based on computer simulations (Wersching 2005), on knowledge spillovers (e.g. Jaffe et al. 1993) or regional innovation systems (e.g. Edquist 1997). All these studies have in common that they postulate the beneficial effects of geographical proximity, which would seem to be due in particular, to the possibilities offered by face-to-face contacts (Gallaud & Torre 2004). According Lundvall (1992), this type of contact is required for the exchange of tacit knowledge.

However, detractor of this argumentation do not criticize the importance of a co-location per se, but the explanation behind. Boschma (2005) argue that although the exchange of tacit knowledge is essential for interactive learning, this doesn't need spatial proximity in terms of permanent co-location. He highlights that often other dimensions of proximity are included into the geographical dimension such as social proximity. Thus, a common cultural background facilitates the understanding within a cooperation rather than the pure geographical co-location. According to these explanations, it is assumed in hypothesis 3 that a geographical co-location encourage a collaborative R&D agreement, but whether the requirement of face-to-face contacts or a common social background is the driving force behind remain unclear.

H3: The shorter the distance between the actors willing to cooperate
the higher the probability of a cooperative R&D project.

Other dimensions of proximity and interplay between different dimensions

On core aim of this chapter is to discuss and to analyze the interplay of different dimensions of proximity with respect to the cooperative behavior of economic actors. The former three hypotheses assume a positive relationship between technological and geographical proximity and the probability to cooperate. But up to now, each dimension has been discussed at any one time. Now, it is questionable whether and to which extent are the effects of technological and geographical proximity independent of each other. Following the absorptive capacity concept by Cohen & Levinthal (1990), Antonelli (2000) suggests that technological proximity is a must for a collaborative R&D project. Thus, Boschma (2005) concludes that geographical proximity is a derivative requirement for economic actors to engage in such a project. Taking this line of argumentation into account, I assume in hypothesis H4 that the contemporaneous presence of geographical and technological proximity has an additional positive impact on the the probability of a cooperative R&D project and that the geographical dimension of proximity will lose its impact of this probability.

> H4: The combination of geographical and technological proximity has an additional positive impact on the probability of a cooperative R&D project.

3.3. Data base

Patent data on firm level are used in order to test for the hypotheses made in the last section. The data base contains information of patents which have been filed for Germany between 1998 and 2003. Patents which have been filed by more than one actor in the year 2003 provide the basis of the study. Using patent information for the years before 2003 allows me to characterize various technological relationships between firms. This information is then used to analyze whether it is able to explain bilateral cooperations starting in 2003.

I'm careful with an interpretation of the results being aware of the problems that arise using patent data. These data are suited to characterize the technological knowledge base inside a firm which might attract other firms for cooperation. Two qualifications, however, are obvious here. First, patent data do not represent the whole knowledge base of a firm, but they are a reasonably good indicator. In this sense patents satisfy the criteria Combs & Ketchen (1999) have claimed for competitive relevant resources. They are supposed to be rare, as well as valuable and specific in their nature. Therefore patent data at least indicate the technological competitive advantages a firm has. Second, other incentives influencing the choice of the cooperation partner likewise exist. Because of this broad German-wide analysis I cannot include firm structure variables as size, age or industry, it is acting in. Beside this theoretical justification of using patent data, Griliches (1990) has shown that patents are sufficient indicator for the innovative output of firms[2]. As an innovation is knowledge driven phenomena I assume that without

[2]For a deeper analysis of patents as innovative output you can read for example Trajten-

the necessary knowledge base a firm cannot file for a patent.

Dependent variable (*Coop*)

According to figure 3.1 the formation of research cooperations in the year 2003 are in the focus of this study. In that year 1333 German actors filed for at least one patent together with a cooperation partner, more precisely, they are named as applicants with an other applicant on at least one patent application. Foreign actors are dropped as the information of the independent variables are based on German data so that the inclusion of foreign actors distort the information and this tends to result in an overestimation of German actors activities.

The aim of this chapter is to examine whether geographical and technological proximity matter for the choice of the cooperation partner. Although the incentive to cooperate according to several streams in economics literature are briefly discussed above, the decision making process whether to cooperate or not is not of interest here. The initial process of a cooperative R&D project is here assumed as a two-stage process with, first, a decision to cooperate or not and, second, a process of searching for potential cooperation partner. In this chapter only the second stage is observed.

Following this assumed initial process, the main question is not whether an actor is willing to cooperate or not, but why a certain partner was chosen. To take this question into account and considering the notion of the resource-based-view that each cooperation is a unique constellation, the analyses on the hypotheses are tested on pairs of actors indicating cooperative constellations. More precisely, only actors that have been willing to cooperate are included into the data set. So this empirical study is based on information about 1333 German actors which have been identified as cooperative in the sense described above. Overall, these actors have been filed for 1089 collaborative patents. In order to answer questions why these 1089 collaborative pairs were realized and all other combinations of potential cooperation were not, the data set include all possible pairs of German actors which have been willing to cooperate in the year 2003. So the data set ends up with 887778 observations (possible pairs cooperation) with 1089 real cooperation. Thus, the dependent variable for the analyses below has a binary nature with a value of 1 if this pair of actors has filed for a patent in 2003 and 0 other-

berg (1990) who has introduced a weighted scheme to overcome shortcomings of counting measures.

wise. The problems of a sufficient estimation model for this unbalanced data set towards the potential but not realized cooperation ("0s") will be discussed below.

Measuring technological proximity ($TProx$)

The reciprocal learning activities depend on "absorptive capacities" (Cohen & Levinthal 1990) of both cooperation partner. This common understanding is regarded in this chapter to technological knowledge which means that I'm interested in how much technological knowledge of an actor can be understood by a potential cooperation partner. In a former study (Cantner & Meder 2007) the term *technological overlap* was used to express the closeness of the knowledge bases.

This closeness is expressed by technological differences among firms based on activities in the past. To obtain that measure of technological proximity I refer to information of patent's technology listed on each document according to the international patent classification (IPC). The IPC is a hierarchical system dividing patents into classes, sub- and sub-sub-classes. In order to reduce this widespread classification with 8-digit classes a concordance list developed by Schmoch et al. (2003) is used to convey the IPC into a NACE-oriented classification, containing 43 technological fields.

Based on these fields a measure of technological proximity is constructed to indicate the similarity of the technological knowledge endowment of two actors. As it is shown in figure 3.1 the technological endowment T of an actor A is indicated by the number of his patent applications for the years 1998 to 2002. It is possible that a patent has been filed for in cooperation and in more than one technological field. In these cases the respective patent is counted for each applicant and in each technological field like a single-application in one technological field. The technological proximity $TProx_{A,B}$ between actor A and B is twice the sum over all minimum activities of both partner divided by the sum of all activities of both partner.

$$TProx_{A,B} = \frac{2 * \sum_{i=1}^{n} min(T_i^A, T_i^B)}{\sum_{i=1}^{n} T_i^A + \sum_{i=1}^{n} T_i^B} \tag{3.1}$$

This value increases with an enlarging of the technological proximity and has a maximum of 1. This would imply that the pair of actors have an identical knowledge base or, more precisely, both have applied the same number of patents in the same technological fields so the absorptive capacities are at a maximum for both actors. In the case both actors of a pair have no former patent activities ($\sum_{i=1}^{n} T_i^A$ and $\sum_{i=1}^{n} T_i^B = 0$) the technological proximity between A and B is counted with 0. A pair containing a very large and a small firm researching in the same technological fields would have a lower technological proximity value, because the understanding is unbalanced in favor of the larger firm which can fully understand the technological knowledge of the smaller one but not vice versa.

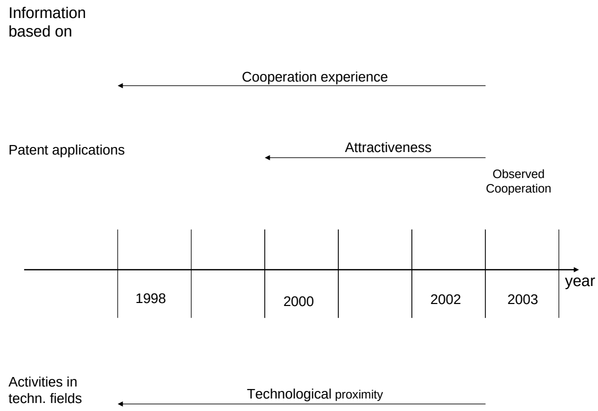


Figure 3.1.: Research concept

Measuring geographic proximity ($GProx$)

In the theoretical section of this chapter it is assumed that geographical proximity facilitates the exchange of tacit knowledge between the partner of a R&D project. To take the distance in space into account and to test for the assumptions of hypothesis 3, the geographical proximity ($GProx$) is calculated by $GProx_{A,B} = \frac{1}{Dist_{A,B}}$. Here, $Dist_{A,B}$ is the distance between the locations of actor A and B measured in kilometer according to the postal code which was named on the patent application. This method has at least two shortcomings. First, actors are located according to the applicant address listed on the patent document. However, it is widely known that especially larger firms file for patents with naming the headquarters address which does not have to be identical to the location of the R&D process. On the other hand, inventor addresses, which are named on the application too, are not always the same and for a co-application it is impossible to differentiate to which firm an inventor belongs to. Hence, the applicants addresses are used in this study for allocating the actors involved. The second problem, is on the quality of the distance in kilometer to express "easiness" to exchange tacit knowledge. Gallaud & Torre (2004) differentiate between real and functional distance. The later means the real time which is require to get a face-to-face contact, while the former distance embodies the pure geographical distance. Although, the functional distance would be a more appropriate measure, as it includes aspects of social structures such as transport infrastructures that facilitate accessibility (Gallaud & Torre 2004, p.5), these information are not available for this data set and, therefore, I stick to the real distance between actors.

Control variables

Attractiveness of being cooperation partner (*Atr*)

The concept of the absorptive capacities concentrates on the ability of the receiving actor to internalize valuable knowledge of the cooperation partner. Thereby, the existence of this knowledge is assumed. Cantner & Meder (2007) show that the existence of the knowledge has independently a positive impact on the choice of the cooperation partner. To account for the valuable knowledge which is offered by the actor of a certain pair in the data set, variable *Atr* is included. As it is shown in figure 3.1, it contains the number of patent applications of the three years 2000-2002. The values for this variable are calculated as follows:

$$Atr_A^B = \frac{\sum_{i=1}^n P^A + \sum_{i=1}^n P^B + 1}{\sum_{i=1}^n P^A + 1}$$
$$Atr_{A,B} = ln(Atr_A^B * Atr_B^A) \tag{3.2}$$

So the attractiveness of B being a cooperation partner for A (Atr_A^B) depend on activities of B (sum of P^B) related to the amount of activities of A (sum of P^A). This is due to the results of Sadrieh & Verbon (2002) who claim that the overall attractiveness depends not only on the pure amount of valuable knowledge offered by the potential cooperation partner but also on its balance within the cooperation. Therefore, in a second step both individual attractiveness values are multiplied.

Former cooperation experience (*Ocoex* and *Bcoex*)

Beside the technological and geographical proximity, Boschma (2005) introduces the organizational dimension as a further important aspect with respect to collaborative R&D agreements. The organizational knowledge of how to manage a research cooperation is built up from collaborative experiences gathered in the past. Decarolis & Deeds (1999) show that a stock of organizational knowledge influences the economic firm performance positively. This dimension of knowledge is taken into account by two Dummy variables (*Ocoex* and *Bcoex*). For the case that only one of a pair of actors has experience of how to manage a cooperation the variable *Ocoex* has a value of 1 and 0 otherwise. The same for *Bcoex* if both actors of a pair of such experience. According to figure 3.1 both variables are composed of information about the cooperation activities of the actors in the five years between 1998 and 2003.

Public research agreements (Pr)

The field of economics of innovation public research actors have always been noticed because of their research (e.g. Fritsch & Franke 2004) and their non-market orientation as special actors within the research community (Balconi et al. 2002). Jaffe (1989) show in a early work that at the state level the innovative success in terms of number of patents is positively influenced by private R&D expenditure and, independently, by R&D expenditures of the universities. Furthermore, Fritsch & Schwirten (1999*b*) mention that, in the context of analyzing regional development, public research actors and, more precisely, universities can absorb knowledge external to a region and deliver this external knowledge to regional actors. This *"antenna role"* is taken into account by the inclusion of the variable Pr which has a value of 1 if at least one actor in a pair has been identified as a public research actor.

Descriptive statistics

The data set used in this chapter to test for the hypotheses made above contains information of 1333 actors. As a cooperation is assumed to be a unique constellation, such a cooperative agreement between two actors is the unit of interest. These pairs can either be imaginary or real cooperation of the year 2003. So, the data set includes 887778 pairs of cooperative actors of the year 2003, whereof 1089 are real cooperation and 886689 are imaginary ones.

Table 3.1.: Descriptive Statistics according to cooperative or non-cooperative pairs

$Coop$	stats	$TProx$	$GProx$	Atr	$Ocoex$	$Bcoex$	Pr
	mean	0.011	0.005	0.948	0.398	0.075	0.002
	sd	0.088	0.023	1.465	0.490	0.263	0.043
0	min	0.000	0.002	0.000	0.000	0.000	0.000
	max	0.471	1.000	8.009	1.000	1.000	1.000
	median	0.000	0.003	0.405	0.000	0.000	0.000
Number of cases with $Coop = 0$: 886689							
	mean	0.350	0.019	1.039	0.244	0.228	0.001
	sd	0.634	0.120	1.496	0.430	0.420	0.030
1	min	0.000	0.002	0.000	0.000	0.000	0.000
	max	0.761	1.000	8.009	1.000	1.000	1.000
	median	0.014	0.003	0.405	0.000	0.000	0.000
Number of cases with $Coop = 1$: 1089							

Table 3.1 provides descriptive statistics for the variables which will later on be

included into the models differentiated by the dependent variable ($Coop$). First, the technological proximity ($TProx$) has for the imaginary cooperation pairs a mean value of 0.011, whereas the $TProx$ for the real cooperation has a value of 0.350. This obvious difference between real cooperation and potential cooperation supports the assumption of hypothesis 1.

In order to test for hypothesis 3 the reciprocal value of the geographical distance ($GProx$) is included into the analysis. Here again, the value for real cooperation (0.019) is higher than the value for the potential cooperation (0.005). More precisely, this means that the partner in real cooperation have on average to cope a geographical distance of 52 kilometers, whereas the partner in the virtual cooperation have to cope a mean distance of 185 kilometers. This finding supports the assumption of hypothesis 3 that the geographical proximity facilitates the exchange of tacit knowledge and, therefore, it fosters the cooperation probability. Contrary to this, the median value is surprisingly the same for both groups. This is due to a higher variance of the real cooperation values.

Atr is the first included control variable indicating the balanced attractiveness of both cooperation partner. Here, the value for the real cooperation pairs (1.039) is slightly higher in comparison to the value for the pairs of virtual cooperation (0.948). Contrary to this are the values for the indicator of the cooperation experiences. For $Ocoex$ (only one partner has cooperation experience) the group of the virtual cooperation show a higher mean value (0.398) than the group of the real cooperation (0.244). On the other hand, the mean value for the other variable indicating the organizational know-how in terms of how to manage a R&D cooperation $Bcoex$ is higher for the real cooperation (0.228) than for the virtual ones (0.075). Finally, the values for the variable whether both cooperation partner are public research actors (Pr) doesn't differ obviously between both groups.

3.4. Empirical tests

3.4.1. Regression models

The aim of the study is to analyze whether technological and geographical proximity affect the propensity of a collaborative R&D project with the result of a co-applied patent. Therefore, a set of pairs of all German actors which filed for at least one collaborative patent in 2003 is used as binary dependent variable.

The binary nature of the dependent variable asks for logistic regression models. In logistic regression, a single outcome variable, Y_i $(i = 1, ..., n)$, is coded 1 (here for real cooperation) with probability π_i, and 0 (here for virtual cooperative pairs), with probability $1 - \pi_i$. Then π_i varies as a function of a set of explanatory variables X_i, like technological or geographical proximity. The function is logistic rather than linear and mathematically it is expressed as follows:

$$\pi_i = \frac{1}{1 + e^{-\beta_0 - \beta_1 * X_{1i}}} \tag{3.3}$$

King & Zeng (2001) show that for strong unbalanced data sets logistic regressions sharply underestimate the probability of rare events and lead to inefficient results. They suggest two types of corrections, the so called *"prior correction"* ($PC - Logit$) and the *"weighted exogenous sampling maximum-likelihood estimator"* ($WC - Logit$). The first method computes the usual maximum likelihood estimator based on prior information about the fraction of 1's in the sample (King & Zeng 2001, p.144). They suggest that this information should come from census data for example. The data set of this chapter contains information about whole Germany, so that I assume that the fraction of 1's for the data base is very similar to the real value, even if it is calculated for only one period. This first method to correct for rare events data is easy to apply for each logistic regression model. The second method suggest by King & Zeng (2001) is to weight the data to compensate for differences in the sample. This estimator based on the notions of Manski & Lerman (1977) maximizes not the usual log-likelihood function but the weighted log-likelihood. Scott & Wild (1986) show that this second method is less efficient for smaller sample. Although the used data set is sufficient large, the $WC - Logit$ estimator is not included in this chapter.

3.4.2. Results

Hypothesis 1 is on the impact of the technological proximity ($TProx$) on the probability that two actor engage together in a R&D agreement. In the first regression model M1 the control variables are included into a prior correction estimation. The coefficient for balanced attractiveness variable Atr show a significant positive influence on the cooperation probability. This influence is still significant when proximity variables are included later on. The organizational variables show a significant negative impact for the case that only one member of a pair has cooperative experience, whereas $Bcoex$ indicating that both member of a pair have cooperation experience possess a significant positive impact.

Thus, one can conclude that the groups of cooperative and non-cooperative actors is highly persistent over time. At this stage it is not known whether actor's cooperative behavior is persistent over time or whether pairs of cooperation are persistent. The latter is more restrictive than the former explanation, thus, I tend to prefer the first explanation. Furthermore, I found no sufficient explanation for the surprising significant negative coefficient of $Ocoex$. If both actors would need managerial skill of "how to manage a cooperation" the coefficient should rather be insignificant. As cooperative agreements are in the field of innovations, this result contributes to the notions of Malerba et al. (1997) about the persistence of innovation activities.

Finally, the variable of pairs of public research actors show no significant influence. Thus, one can conclude that cooperation between public research actors follow similar rules like cooperation of private and market oriented actors. Notably, the signs and impacts of all coefficients differ only slightly between both types of estimations. Therefore, the interpretation will be done later on simultaneously.

Table 3.2.: Estimation models of H1 and H2

depend. var.	M1 PC-Logit *Coop*	M2 PC-Logit *Coop*	M3 PC-Logit *Coop*
$Tprox$		1.401***	1.553***
		(0.100)	(0.091)
$Tprox^2$			-0.028***
			(0.002)
Atr	0.043**	0.047**	0.046**
	(0.019)	(0.019)	(0.019)
$Ocoex$	-0.488***	-0.524***	-0.528***
	(0.074)	(0.075)	(0.075)
$Bcoex$	1.118***	0.685***	0.654***
	(0.076)	(0.086)	(0.085)
Pr	-0.200	-0.199	-0.203
	(1.00)	(1.00)	(1.00)
(Intercept)	-6.742***	-6.755***	-6.755***
	(0.047)	(0.048)	(0.048)
Observations	887778	887778	887778

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In order to test for hypothesis H1 $TProx$ is included in model M2. As it is presented in table 3.2, the coefficient is significant and positive. Thus, hypothesis H1 cannot be rejected for this data base. A small technological distance enhances the cooperation probability and, so, firms choose their cooperation partner in their technological neighborhood. This fortifies the statements about the absorptive capacity theory (Cohen & Levinthal 1990) as well as the resource-based-view of the firm (Wernerfelt 1984, Barney 1991). Furthermore, this result contributes to empirical studies on firm level (e.g. Mowery et al. 1998, Wuyts et al. 2005) as well as studies dealing with the impact of sectoral innovation systems on the innovative respectively cooperative behavior of actors within a system (e.g. Carlsson et al. 2002, Malerba 2005).

In hypothesis H2 it is assumed that this positive impact diminishes when the technological proximity becomes to large. With respect to technological knowledge this can be due to the fear of involuntary knowledge flows between the actors (Ronde & Hussler 2005). Another possible explanation of this decrease in the incentive to cooperate is due to a lower success probability as an innovation is mostly the recombination of already existing knowledge (Etzkowitz & Leydesdorff 2000). Thus, if the knowledge bases are too close the ability to create something new decreases (Nooteboom 2000). This assumed negative influence of a too close technological knowledge base is given for our data as it is shown in the regression models M3 of table 3.2. Like stated before the linear term of the technological proximity $TProx$ has a positive impact, simultaneously the variable $TProx^2$ has a significant negative impact on the cooperation probability. At the first glance, this result contributes hypothesis H2 because there is an inverted-U relationship between technological proximity and cooperation probability. But as it is shown in figure 3.2, the maximum value on the relationship between technological proximity and cooperation probability is outside the possible range of the given data.

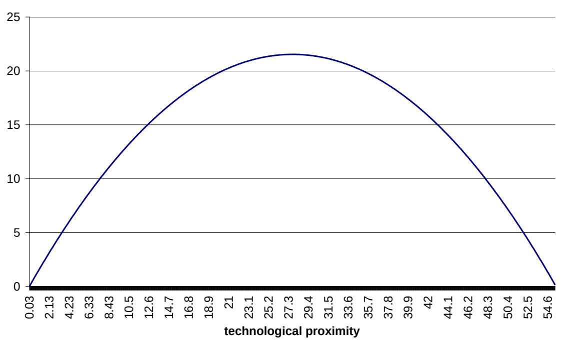


Figure 3.2.: Relationship between technological proximity and cooperation probability

As the technological proximity is a variable fluctuating between 0 and 1, hypothesis H2 has to be rejected. All pairs of virtual and real cooperation constellation are located at the very left hand side in figure 3.2 where the impact of the technological proximity is strictly positive. This finding is contrary to other empirical studies on firm level (Wuyts et al. 2005, e.g.). This discrepancy to existing studies might be due to the definition of technological proximity. The 43 technological fields based on IPC patent data that are used in this chapter to calculate the technological proximity describe apparently related knowledge according to Nesta & Saviotti (2005) rather than homogenous knowledge. Thus, actors filing for patents in the same technological fields can understand each other, while their probability to create something new within a R&D cooperation does not decrease.

After testing for the impact of the technological proximity, now hypothesis H3 is tested on the given data base. Here, it is assumed that a low geographical distances facilitates the exchange of tacit knowledge (Boschma 2005) and, thus, an increasing geographical proximity boosts cooperation probability. In order to test for this relationship the variable $GProx$ is included into the regression model as it is shown in table 3.3[3].

Table 3.3.: Estimation models of H3

	M4	M5
	PC-Logit	PC-Logit
depend. var.	*Coop*	*Coop*
$GProx$		3.438***
		(0.24)
Atr	0.043**	0.044**
	(0.019)	(0.019)
$Ocoex$	-0.488***	-0.489***
	(0.074)	(0.074)
$Bcoex$	1.118***	1.111***
	(0.076)	(0.076)
Pr	-0.200	-0.453
	(1.00)	(1.02)
(Intercept)	-6.742***	-6.768***
	(0.047)	(0.047)
Observations	887778	887778

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficient for $GProx$ in model M5 is significant and positive. Therefore, hypothesis 3 cannot be rejected for the given data base. The closer two actors are located, the higher the probability of a collaborative R&D project. This result contributes to the results of former empirical studies which confirm that knowledge externalities are geographically bounded (e.g. Jaffe 1989, Audretsch & Feldman 1996). A shortcoming of this finding, beside the disadvantages that occur by using the applicants address as discussed above, is the integration of effects of other dimensions of proximity. Following Boschma it is *"essential to define geographical proximity in such a restricted manner and to isolate it from*

[3]The coefficients for all four control variables show in model M4 and M5 the same signs and significance levels. Thus, there will be no deeper discussion of the impact of these variables in the following.

the other dimensions of proximity"(Boschma 2005, p.69). In this study effects of social and geographical proximity are, due to the given data base, summed up under to notion of geographical proximity. The assumed positive relationship between geographical proximity and the probability to cooperate can be confirmed for our data base according to the coefficients of $GProx$ in table 3.3. Given the same coefficient sign for the control variables as in table 3.2, a nearby location in geographic space facilitates the initiation of a collaborative R&D project of two actors. This result is in a line with empirical studies mentioned above and contributes to the concept of regional innovation systems (Lundvall 1992) where the individual innovation activity including cooperation in R&D is affected by co-located actors. Furthermore, it confirms the notion by Gertler (1997) and Breschi & Lissoni (2001) of tacit knowledge being a common property that is shared between members of an "epistemic community" (Breschi & Lissoni 2001, p.980).

Nevertheless, according to Antonelli (2000) it is hard to imagine that interactive learning takes place without cognitive proximity, independently of the geographical location. Thus, Boschma concludes that a combination of geographical and technological proximity is sufficient for interactive learning, whereas the geographical dimension can be substituted by another dimension of proximity (Boschma 2005, p.69). Thus, hypothesis 4 is on the interrelatedness of geographical and technological proximity for the given data set. In order to analyze whether the combination of geographical and technological proximity has an additional impact on the cooperation probability and whether the results presented in tables 3.2 and 3.3 are persistent if the interaction term is included into the regression models.

The estimation results of model M6 in table 3.4 show positive significant impacts of the technological and the geographical proximity. The inclusion of the square term $TProx^2$ in model M7 doesn't change the significance levels. Thus, the influence of both dimensions hold on if they are included simultaneously. The results estimator in the former tables are persistent, more precisely, technological as well as geographical proximity facilitates collaborative R&D agreements. Now, interaction terms according to former models are included into the model, first, without $TProx$ and $GProx$ (M8) and, second, with them (M9). The linear interaction term has no influence at all and the squared interaction term has a significant negative sign in model M9. I conclude, based on the results of M8, that there is no interplay of both dimensions for the given data set. This conclusion is

Table 3.4.: Estimation models of H4

depend. var.	M6 PC-Logit *Coop*	M7 PC-Logit *Coop*	M8 PC-Logit *Coop*	M9 PC-Logit *Coop*
$Tprox$	1.367***	1.520***		1.530***
	(0.10)	(0.095)		(0.095)
$Tprox^2$		-0.028***		-0.027***
		(0.002)		(0.002)
$Gprox$	2.958***	2.948***		3.011***
	(0.32)	(0.32)		(0.31)
$Tprox * GProx$			-2.439	0.148
			(3.89)	(0.50)
$Tprox^2 * GProx$			0.904	-0.120***
			(0.91)	(0.038)
Atr	0.0477**	0.0471**	0.0465**	0.0469**
	(0.019)	(0.019)	(0.019)	(0.019)
$Ocoex$	-0.523***	-0.527***	-0.488***	-0.528***
	(0.075)	(0.075)	(0.074)	(0.075)
$Bcoex$	0.682***	0.651***	1.074***	0.649***
	(0.087)	(0.086)	(0.077)	(0.085)
Pr	-0.419	-0.429	-0.191	-0.446
	(1.02)	(1.02)	(1.00)	(1.02)
(Intercept)	-6.774***	-6.774***	-6.746***	-6.775***
	(0.048)	(0.048)	(0.047)	(0.048)
Observations	887778	887778	887779	887780

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

confirmed by the significant impacts of $TProx$ and $GProx$ in model M9. Thus, hypothesis 4 has to be rejected for our data base. However, both dimensions of proximity independently facilitate the probability of a R&D cooperation. This finding is for the geographical dimension contrary to the conclusion of Boschma who claim that *"geographical proximity as such [...] is unlikely to enhance interactive learning and innovation.* (Boschma 2005, p.71). This discrepancy might be due to the definition of the term geographical proximity. As mentioned before this label may include other dimensions like social proximity. Nevertheless, one can conclude that beside the technological proximity at least a mix of other dimensions facilitates collaborative projects in R&D independently.

3.5. Discussion and conclusion

Cooperation in the field of R&D has been widely discussed in several streams of economic literature. One focus is on effects of such agreements on performance on individual (e.g. Combs & Ketchen 1999, Oerleman & Meeus 2000, Belderbos et al. 2004) as well as on systemic level (e.g. Raspe & van Oort 2006, Asheim & Coenen 2005). Another body of literature is on determinants influencing the willingness to engage in such cooperation projects. this chapter is related to the second focus by asking how economic actors which have made their decision to cooperate search for an appropriate cooperation partner.

In this chapter patent data are used to identify the influences of technological and geographical proximity on the probability of cooperation agreements in the field of R&D. Thus, it contributes to the manifold existing literature on the incentives to cooperate by analyzing the impacts of single dimensions independently and how these influences are related to each other. The main findings of this chapter are:

- Technological proximity between two economic actors enhance the probability that they initiate a collaborative R&D project together.
- A negative effect of knowledge bases that are too close related as suggested by Nooteboom (2000) and other studies can not be shown for this data base. This might be due to measurement of technological proximity. Here in contrary to Wuyts et al. (2005) for example, the relatedness of the knowledge bases is calculated rather than the similarity.
- Actors located nearby in geographical dimension are more likely to initiate a R&D project together than actors located far away to each other.
- Contrary to Boschma (2005), this effect persists when both dimensions are tested within one model and when an interactive term of both dimensions is included into the regression model. Thus, I conclude that there is an effect of geographical proximity which is independent of technological proximity.

In economic literature there is a long and still ongoing discussion about the usage of patent data for empirical studies. Griliches (1990) show that patents are a sufficient indicator for innovative success. Beyond using patent for indicating the innovative performance of firms or regions, economists interested in innovation networks often use patent citation data to identify the impact of networks on the innovative performance (e.g. Sorenson et al. 2005). In this chapter patent data are used (i) to identify collaborative R&D agreements, to allocate actors in (ii) technological and (iii) geographical space. As already discussed above this methodology has some important shortcoming like the problem of using the applicants postal code for geographical allocation, but nevertheless, patents are a core resource for firms Combs & Ketchen (1999). Furthermore, the availability and the objectively measurement are strong advantages of this methodology.

The findings of this chapter contribute to the learning economy approach in a sense that it could be shown that firm A is more likely to engage in collaborative R&D projects with partner possessing valuable knowledge which can be understood by firm A due to a common knowledge base. Furthermore, firm A is searching for partner that are located nearby which is a hint for the requirement of face-to-face contacts for the exchange of tacit knowledge according to Polanyi (1966). After analyzing determinants influencing the choice of the cooperation partner, deeper studies on how these determinants affect the success of collaborative projects are necessary. Thus, further studies on the rate of granted patents might be a next step as this chapter is only on patent applications.

4. Regional and technological effects on cooperative innovation activities

4.1. Introduction

Looking at how innovative activities are distributed over time, between regions and among actors delivers non-equal distributions.[1] Industry life cycle approaches (e.g. Klepper 1996) take into account the time dimension, regional economics refers to the spatial dimensions and entrepreneurship research is devoted to particular innovative actors. Equivalent observations can be made with respect to cooperative innovation activities, which shows up when particular innovations are not performed by a single actor but a group of actors. For this Allen (1983) coined the notion of collective invention. And also here non-equal distributions of collective invention/innovation are observed with respect to time (e.g. Hagedoorn & Schakenraad 1992), to regions (e.g. Cantner & Graf 2006) and to actors. The focus of this chapter is laid on cooperative innovation activities and the influence regional factors on the one hand and technological factors on the other have herein.

Why do actors engage in cooperative innovation activities? Generating innovations in terms of new products and processes is often closely connected to and dependent on knowledge bases outside the innovating firm (Powell 1990). To get access to these external knowledge sources, firms or actors engage in joint (formal and informal) research projects. Hence, those collaborations are not only a device to share costs and risk of development as mentioned in the approach of the "transaction cost theory" (Williamson 1985), but also to get access to external knowledge (Eisenhardt & Schoonhoven 1996, Mowery et al. 1998, Combs & Ketchen 1999, Das & Teng 2000). In this context a major issue is the way or

[1] This chapter is based on Cantner & Meder (2008*b*).

the criteria by which firms select external knowledge sources. This choice seems to be dependent on (1) the relationship between an actor's or firm's internal and external knowledge and (2) the ease by which firms or actors can get access to external knowledge sources. Furthermore one may ask for whether actors in order to improve their innovative performance look for complements or for substitutes of their own knowledge (Caloghirou et al. 2004, Belderbos et al. 2006).

Answers to these questions are found in the literature on innovation systems (Edquist 1997). Such systems are to be seen as a device allowing the exchange of knowledge and cooperative innovation activities between a system's actors. Generally, firms and innovative actors are member of several of those innovation systems, starting from the level of national innovation systems, comprising several layers of technological or sectoral innovation systems, and finally integrating in regional and local innovation systems.

For an understanding of cooperative innovation activities of actors one obviously cannot rely on only the one or the other of those levels. In principle they all should be considered simultaneously. In this chapter, however, we do not take into account the layer of national innovation systems as we are only concerned with panel data from Germany. Hence, we presume that all actors in Germany are equally affected by the German national innovation system.

Within the frame of this system we focus on technological and on regional systems. These two systems represent each a specific aspect of the easiness to access knowledge external to the firm, the former one on the basis of technological proximity and the latter one on the basis of geographical (or social) proximity. Investigating differential cooperative innovation of actors both of these views are relevant. Take first actors located in different regions and observe differences in cooperative innovation. Obviously regional factors and hence spatial proximity play a role; but we cannot exclude that technological proximity and hence the technological or sectoral composition of the regions are negligible. Secondly, look at differences in cooperative innovation between technologies and sectors. Again, technological proximity and therefore technological and/or sectoral determinants have to be considered; but you also cannot neglect regional factors whenever we observe a spatial clustering of those technologies or sectors.

This chapter is just on the relationship between both kinds of proximity explaining regional differences in cooperative innovation. Looking at cooperative innovation taking place in and between certain technologies and certain regions one may ask as to what degree do observed regional differences relate to the technological composition of a region and to what degree does a region itself have an influence? In the following we want to shed some light on this question and suggest a solution to identify the differential regional impact on regional differences in cooperative innovation. After a brief review of literature in section 2, in section 3 we show how a methodology attempting to identify regional effects in cooperative innovation. Section 4 and 5 contain an application of this method to patent data for Germany between 1998-2003 allowing us to track cooperative innovation. Section 6 concludes.

4.2. Theoretical background

The focus of this chapter is laid on regional differences in cooperative innovation and the influence regional factors on the one hand and technological factors on the other have herein. To understand the procedure in section 3 where we suggest to distinguish between regional and technological effects, we first will have a brief look at the literature on cooperative innovation and the related literature on innovation systems.

4.2.1. Cooperative innovation

The manifold literature on voluntary, collaborative projects in the field of research and development differentiate between three main motives for the engagement of individual firms in such projects. Beside the incentives to (i) reduce risk and sharing R&D costs (Deeds & Hill 1996, Baum et al. 2000) and (ii) to combine complementary assets in order to enhance to propensity of a successful development project (Teece 1986, Nooteboom 1999), (iii) the internalization of knowledge spillovers is another reason to engage in R&D collaboration (Griliches 1992).[2]

An explanation why firms consider the internalization of knowledge spillovers useful is found in the concept of the resource-based-view of the firm (Penrose 1959, Wernerfelt 1984, Barney 1991). There, the main incentive to engage in a research

[2]The positive impact of knowledge spillovers is a fundamental issue of recent approaches to growth theory (Krugman 1991) as well as to concepts of innovation systems (Lundvall 1992, Malerba & Orsenigo 1997). Both can be applied to the regional level leading to the concepts regional growth (Fritsch 2004*b*) and of a regional or local innovation system.

cooperation is to get access to productive resources, here mainly technological knowledge, of the partners (Das & Teng 2000, Sher & Yang 2005) with the aim to improve its own performance. The role of a firm's or actor's environment for this performance in general and on its innovative performance in particular is highlighted and discussed by the concept of innovation systems (Lundvall 1992).

4.2.2. The general concept of innovation systems

In the literature on technological and economic change the aspect of collective invention and collective innovation is taken up by the so-called systemic approach which meanwhile offers various levels of "systems". Generally systems are defined as a " *set or arrangement of things so related or connected as to form a unity or an organic whole* (Webster Collegiate Dictionary).

According to Carlsson et al. (2002), a system is made up of *components*, *relationships* and *attributes*. A *component* is a operating unit of a system. This can be either a physical unit such as a firm and other actors or it can posses a more intangible nature as institutions in the form of legislative artifacts such as regulatory laws, traditions, and social norms. The systemic nature shows up whenever these components do not act in isolation but are related to and interact with each other. Hence, a development of *relationships* can be observed which, however, does not necessarily predict a specific action but it implements a reaction of components to an action by an other component. So each component depends on the properties and behavior of all other system members.

Therefore, a system cannot be divided into several subsystems that are independent of each other (Blanchard & Fabrycky 1990). According to Carlsson et al. (2002), the components of a system will react if another component is removed from the system. Both the components and the relationship between them constitute the *whole system*. The *attributes*, as described by Carlsson et al. (2002), define the characteristics of a system. The boundaries of a system (Edquist 2001) isolating the system from the rest of the world depend on the respective attributes of actors.

Applying this abstract definition to the field of innovation economics, one finds a strong systemic view of innovative activities and a respective literature on innovation systems considering innovation as an evolutionary and social process (Edquist 2004). Here innovations in terms of new processes and products are stimulated by factors internal as well as external (Doloreux & Parto 2005) to actors. The social aspect of these innovations refers to collective invention (Allen 1983) and in a systemic view to collective learning processes between independently acting system entities.

With respect to the motivation of individuals to engage in cooperative innovation the main purpose of innovation systems is the generation, diffusion and utilization of knowledge (Lundvall 1992). Thus, the key features of a system are different capabilities which are related to this main purpose. Carlsson et al. (2002) differentiate between selective, organizational, functional and learning capabilities. Furthermore, these features are related to the dimension in which systems are analyzed.

4.2.3. Co-existing levels of innovation systems

Levels of systemic innovation

Based on the constituting elements of a system one can distinguish several kinds or levels of analysis. The combination of several attributes makes up the respective level and for that the type of actors, their location, their kind of activity, the type of relationships are relevant. With respect to systemic innovation we distinguish analyses towards national innovation systems (Freeman 1988, Lundvall 1992), technological systems (Carlsson & Stankiewicz 1991), sectoral innovation systems (Malerba & Orsenigo 1997), regional innovation systems (Cooke 1992), local innovation systems (Breschi & Lissoni 2001), urban innovation systems (Fischer et al. 2001) etc.

Taking the perspective of an individual actor, "membership" in various innovation systems is obvious. A firm located in a certain region may belong to the regional system, one or several technological or sectoral systems (multi-product firm), one or several national innovation systems (multinational firm) etc. This multiple membership constitutes in various activities related to cooperative innovation and, in turn, the firm's general attitude towards cooperative innovation is influenced and dependent on the very features of all the levels of innovation systems involved. Hence, they all have to be considered simultaneously. In doing so and in order to understand cooperative innovation and differences herein the respective effects have to be disentangled.

This process of disentanglement runs in two stages: First, in view of the relevant research questions one selects the level of analysis and systems to be considered. Second, on this basis one attempts to identify the effects accruing form the various system levels considered. However, as it turns out, rather generally one is only able to determine differential effects, that is effects above or below the average influence of a certain system. A method how to perform this is suggested in the next section.

For this chapter which deals with cooperative innovation of German firms the disentanglement runs as follows: For the various feasible levels of analysis we do assume the national innovation system to affect all the firms the same way.[3] We then consider the regional dimension on the one hand and the technological dimension on the other as major determinants of cooperative innovation. In doing so, regional, local and urban innovation systems represent the regional aspects, whereas technological and sectoral systems are related to the technological dimension.

Technological proximity

The concepts of technological innovation systems (Carlsson & Stankiewicz 1991, Carlsson et al. 2002) or sectoral innovation systems (Malerba et al. 1997) point to the fact that actors engaged in the same technology or the same sector are more able to understand the others' technological knowledge than actors from different technologies or sectors. In both concepts the boundary of the innovation systems is justified by the specificity of a sector or the technology in terms of a certain knowledge base and key interactions within this sector or technology system (Malerba et al. 1997). The main idea behind this concept is that innovative and cooperative behavior of actors is mainly driven by proximity in their individual knowledge bases.

The concept of technological proximity is a rather vague one. It has at least three, closely interrelated dimensions. First, there is the degree of common understanding in the sense of common or overlapping knowledge bases among the actors. Second, understanding is not only related to the type of the knowledge

[3] We are aware of differences in the legal and fiscal frame and thus in the national innovation system between countries. However, we apply this method as a tool for testing differences between regions within one country so that we can neglect the framework of a national innovation system and methodological problems that occur by comparing regions located in differen countries.

base but also to the respective actors level of knowledge and hence to the so-called technology gaps between actors. Third, so-called technological regimes characterizing a sector or a technology play a role. Here the degree of appropriability of know-how - which never is fully complete - determines the easiness by which of know-how spills over from one actor to another and how cooperation works herein. This degree of appropriability differs considerably among technologies (Doloreux & Parto 2005).

Technological proximity defined in this way can now be used to describe cooperative innovation. And here one may conclude if actors are engaged in the same technology or industry this proximity is rather close. Obviously, the higher (lower) the technological proximity the more likely the knowledge stocks of the actors are substitutive (complementary).

Spatial proximity

The regional innovation system approach (RIS) developed from the empirically based acknowledgement that innovation is a geographically bounded phenomenon (Asheim & Isaksen 2002, Cooke et al. 1997). The discovery of the importance of the regional scale and of regional resources in stimulating the innovative capabilities of firms is the major issue of this approach (Asheim & Isaksen 2002). The concept of a local or regional innovation system (RIS) (Cooke et al. 1997) emphasizes interactive research and development activities on a face-to-face basis and, thus, low geographical proximity as a main driving force of cooperative innovation. The concept of geographical proximity comprises several dimensions such as low transaction costs compared to long distance interaction, advantages of face-to face interaction in exchanging tacit knowledge, and the importance of social relationships especially with respect to trust.

Recent literature on RIS often deals with certain regions and describes their development in a rather narrative way. In regional science approaches the existence of a RIS is appreciated by pinpointing cooperative innovation to constitute a main ingredient to explain regional economic growth (Fritsch 2004*c*). It is close spatial and social proximity that promotes and eases the exchange of knowledge and information and thus contributes to collective learning and creation of knowledge.

With respect to system boundaries in the RIS concept those boundaries are given by the geographical term "region". Following Cooke (2001) a region is a meso-political unit above local governments and below nations. It might have a certain homogeneous culture and history (Cooke 2001, p.953). The operationalization of this concept, however, is not an easy task and one more than often relies on political or administrative boundaries.

Based on these brief characterization of the regional and technological dimension of innovation systems, we conclude that within the broad concept of innovation systems there exist several independent streams focusing on different attributes of actors and, thus, dealing with different kind of innovation systems. We argue that a main shortcoming of the innovation system concept, beside methodological issues (deeply discussed in Carlsson et al. 2002), is the co-existence of different types of innovation systems at the same place and at the same time. Empirical studies dealing with one of type of system usually ignore the presence of other levels and types of innovation systems.

In answering our research question whether there are differences in cooperation behavior among regions, we want to take into account that effects from the technological dimension are also prevalent. In doing so identifying differences between regions with regard to the number of cooperative innovations or even the share of cooperation agreements in all applications is not a sufficient measure for the differential strength of the respective regional innovation systems. A simple reason for this is that a region with a high tendency to cooperate consists of establishments, mainly firms, that show characteristics of sectors or technologies that are more likely to engage in co-application or in R&D cooperation (Fritsch 2003). Hence, in the next section we suggest a method able to distinguish between regional effects of cooperative innovation and the effects accruing to the technological dimension.

4.3. Concept of Relative Regional Impact

Based on the theoretical background introduced in the last section, in the following we suggest a method allowing to identify (differential) regional effects on cooperative innovation. Our methodology is based on the assumption that regional and technological innovation systems are the two most important types of innovation systems innovative agents are engaged in. A further assumption is that regional and technological effects are independent of each other so that they can be isolated.

4.3.1. General Methodology

Our analysis requires several types of information about innovations: (1) the actor(s) involved in generating an innovation, (2) the region(s) those actors are located in, and (3) the technology field(s) an innovation belongs to. With (1) we cover the issue of cooperative vs. non-cooperative innovations, with (2) we take into account the regional dimension, and with (3) we have at hand information about the technological dimension. For these three categories we introduce a formal representation.

First, we take into account n innovations indexed by $i \in N = \{1, ..., n\}$. The technological space within which innovations are created is f with different technologies index $j \in F = \{1, .., f\}$. Here it is entirely possible that an innovation $i \in N$ is related to more than one technology $j \in F$. The spatial dimension of innovative activities is represented by the regions r indexed by $k \in R = \{1, .., r\}$. Here it is also possible that the R&D activities for innovation i have taken place in more than one region $k \in R$. This is the case whenever innovation i is the result of a cooperation between actors located in different regions. However, we will observe a spatial distribution of innovation i also in the case where the innovative actors belong to different branches of the same firm which are located in different regions. To distinguish between both possibilities we take into account information on whether an innovation i has been developed in cooperation or not.

The relationship between innovations, technological field, spatial distribution and cooperative innovation are formalized as follows. The assignment of all innovations n to the technological fields f is are summarized in matrix $\mathbf{A}$. $\mathbf{A}$ is a $n \times f$ matrix with a typical element:

$$a_{ij} = \begin{cases} 1 & \text{if innovation } i \text{ is related to technology } j \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

The spatial distribution of innovations N is represented by the matrix $\mathbf{B}$. $\mathbf{B}$ is a $n \times r$ matrix with a typical element:

$$b_{ik} = \begin{cases} 1 & \text{if innovation } i \text{ has been developed by actors located in region } k \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

A spatial distribution of an innovation i occurs whenever different research groups cooperated in a R&D project resulting in innovation i. Whether these research groups work for different economic actors (e.g. firms or universities) is indicated in vector γ. γ is a vector of length n with a typical element:

$$\gamma_i = \begin{cases} 1 & \text{if innovation } i \text{ has been developed by more than one actor} \\ 0 & \text{otherwise} \end{cases} \tag{4.3}$$

In addition and as a variant to general cooperative innovation we suggest a vector $\tilde{\gamma}$ which contains information about cooperative innovation taking place within a region. This vector is again of length n with a typical element:

$$\tilde{\gamma}_i = \begin{cases} 1 & \text{if innovation } i \text{ has been developed by more than one actor,} \\ & \text{all located in the same region} \\ 0 & \text{otherwise} \end{cases} \tag{4.4}$$

Given this information we propose a method able to identify regional effects on cooperative behavior by separating technological effects. Hence, the first step is to account for the technological effects.

The technological dimension of cooperative innovation

Our first step focusses on the technological dimension of innovation. The aim is to indicate the propensity of cooperative innovation for each of the technologies. Since innovations regularly are related to several technologies we need to know to what degree an innovation i is related to each of the f technologies. Hence, for each innovation i we determine weights with respect to each of the f technologies.

Matrix $\mathbf{A}$ which contains the unweighed values is the starting point. Dividing each element a_{ij} of row i by the sum of all elements $\sum_{j=1}^{f} a_{ij}$ just leads to the weights required. Matrix $\mathbf{A^w}$ contains these weights. It is a $n \times f$ matrix with a typical element:

$$a_{ij}^{w} = \frac{a_{ij}}{\sum_{h=1}^{f} a_{ih}} \tag{4.5}$$

The sum of the elements of row i in matrix $\mathbf{A^w}$ is equal to one. We here assume that all technologies related to innovation i show the same weight.

In order to distinguish between innovative and cooperative activities among technologies, each row i of matrix $\mathbf{A^w}$ is multiplied with the corresponding value γ_i of vector γ. The result is a matrix $\mathbf{A^{wc}}$ comprising only the technology weights of cooperative innovations. $\mathbf{A^{wc}}$ is a $n \times f$ matrix with a typical element:

$$a_{ij}^{wc} = \begin{cases} \frac{a_{ij}^{w} * \gamma_i}{\sum_{h=1}^{f} a_{ih}^{w} * \gamma_i} & \text{if } \gamma_i = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4.6}$$

Matrices $\mathbf{A^w}$ and $\mathbf{A^{wc}}$ are now used to determine average cooperation behavior for each technology. For that we sum up the elements of each column (technology field) in $\mathbf{A^w}$ and $\mathbf{A^{wc}}$. In the former case we get an account of the number of innovations related to technology j, in the latter case of the number of related cooperative innovations in that technology. The ratio of both magnitudes indicates the propensity of cooperative innovation in technology j. The ratios of all the technologies are included in vector $\mathbf{p^c}$.[4] It is a vector of length f with a typical element:

$$p_j^c = \frac{\sum_{i=1}^{n} a_{ij}^{wc}}{\sum_{i=1}^{n} a_{ij}^{w}} \tag{4.7}$$

At this point, however, one has to be careful in interpreting this ratio as a purely technological effect. Since the cooperative innovations considered are affected by both technological as well as regional effects the ratio computed contains the specific technology based propensity to cooperate as well as an average influence of regional effects.

Equivalently to the procedure above we can restrict the analysis to cooperative innovation taking place only within the region. For that each row i of matrix $\mathbf{A^w}$ is multiplied with the corresponding value $\tilde{\gamma}_i$ of vector $\tilde{\gamma}$. The result is a matrix $\mathbf{\tilde{A}^{wc}}$ comprising only the technology weights of cooperative innovations which have taken place within regions. Using now matrices $\mathbf{A^w}$ and $\mathbf{\tilde{A}^{wc}}$ we can compute the propensity of cooperative innovation represented by vector $\mathbf{\tilde{p}^c}$ which does not only comprise the technological effects but also the average intra-regional

[4]We assume that there is at least one innovation in each technology. Therefore, we do not distinguish several cases in equation 4.7

effect.

The regional dimension of cooperative innovation

In a second step we focus on the regional distribution of innovation in general and of cooperative innovation in particular. Equivalent to the procedure above, we determine the weights by which an innovation i is related to regions $k \in R$ where the actors innovating i are located. Matrix $\mathbf{B}$ contains the unweighed relationships. Dividing each element of row i by the sum of all elements of row i delivers the respective weights; here to each region related to innovation i the same weight is assigned. Matrix $\mathbf{B^w}$ contains the results. It is a $n \times r$ matrix with a typical element:

$$b_{ik}^{w} = \frac{b_{ik}}{\sum_{l=1}^{r} b_{il}} \tag{4.8}$$

Multiplying each element b_{ik}^{w} of matrix $\mathbf{B}$ by the element γ_i of vector γ leads to the spatial distribution of the cooperative innovations. The resulting matrix is $\mathbf{B^{wc}}$. It is a $n \times r$ matrix with a typical element:

$$b_{ik}^{wc} = \begin{cases} \frac{b_{ik}^{w} * \gamma_i}{\sum_{l=1}^{r} b_{il}^{w} * \gamma_i} & \text{if } \gamma_i = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4.9}$$

Matrix $\mathbf{B^{wc}}$ contains information about the regional distribution of cooperative innovation independent of whether the cooperation is within the region or between different regions. Using $\tilde{\gamma}$ instead of γ leads to a matrix $\mathbf{\tilde{B}^{wc}}$ which contains information on cooperative innovations internal to the region.

The expected value of regional cooperative innovation In a third step, we compute an indicator stating the expected number of cooperative innovations in a region k. For this index we take into account the technology specific propensity for cooperative innovation of the previous section which contains also the average regional effect. We start by computing the number of innovations of technology j in region k. The respective numbers are stated in a matrix $\mathbf{C}$ with r rows (regions) and f columns (technology fields).

This $r \times f$ matrix $\mathbf{C^w}$ contains information about the number of innovations that have been developed in technology j by actors from region k. $\mathbf{C^w}$ is computed by:

$$\mathbf{C^w} = \mathbf{B^{w'}} * \mathbf{A^w} \tag{4.10}$$

$\mathbf{B^{w'}}$ is the transposed matrix $\mathbf{B^w}$. $\mathbf{C^w}$ is used to create an indicator of what we call the "expected number of cooperative innovation" (e_k^c) of region k. It indicates how many cooperative innovations are to be expected in region k taking into account the technology specific propensities for cooperative innovation p_j^c of those technologies which are used in region k. Vector $\mathbf{e^c}$ contains the expected number of cooperative innovation for all regions k. It is a vector of length r with a typical element:

$$e_k^c = \sum_{j=1}^{f} c_{kj}^w * p_j^c \tag{4.11}$$

Observed and expected value of regional cooperative innovation Were cooperative innovations within a region solely affected by technological determinants (and an average regional effect) - implying that their are no differential regional effects on cooperative innovation - the observed number of cooperative innovations has to be identical to the expected number. In order to test for this, in a final step, for each region r the ratio between observed and the expected cooperative innovations is determined. For that we compute the column sum of elements of matrix $\mathbf{B^{wc}}$. This just leads to number of all cooperative innovations observed in each region. For each region we take this sum and divide it by the respective expected number of cooperative innovations e_k^c. The region specific ratios further called *"relative regional impact"*-index or RRI are contained by vector $\mathbf{v}$. It is a vector of length r with the typical element:

$$v_k = \frac{\sum_{i=1}^{n} b_{ik}^{wc}}{e_k^c} \tag{4.12}$$

This ratio takes values between 0 and infinite. At a ratio of 1 the number cooperative innovations observed in a region is just equal to the expected number. A ratio different from 1 indicates that there exists a differential regional effect above or below the average regional effect. Regional cooperative innovation above (below) the average is indicated by a positive (negative) ratio.

Using instead of $\mathbf{B^{wc}}$ the matrix $\tilde{\mathbf{B}}^{\mathbf{wc}}$ one achieves at a vector $\tilde{\mathbf{v}}$ which contains the ratio of realized intra-regional cooperations to the expected ones. The interpretation is equivalent to the one above. The difference is that above we identify regional effects on cooperative innovation in general whereas here we look at regional effects on intra-regional cooperation.

Using this ratio to determine differential regional effects of cooperative innovation has two advantages. First, it is independent of the data base. Below we will use patent data to test whether these regional effects on cooperative innovation exist; but this method can be applied to any other data base on innovation activities which includes information about technology, spatial distribution and cooperation. This data for example can be based on firm survey data.

Second, this indicator is independent of the size of a region as measured by the number of cooperative innovations observed in that region. Hence, agglomeration effects or the strength of a regional innovation system we want to measure cannot be attributed simply to the size of the region but have to do with above average propensity to cooperate. Here, one alternatively may think of the ratio cooperation per innovation doing the job. However, this ratio is not able to take into account the differences of cooperative innovation related to the specific technologies a regions hosts. Taking into account the pure intra-regional dimension may deliver additional information on the regional innovation system. Because of these advantages, we suggest our ratios to be used for indicating the strength/weakness of a regional innovation system and to track its performance over time.

4.3.2. Method application

Before we start to apply the method to real data we want to exemplify it with the help of a simple example. We consider three innovations, hence $i = \{1, 2, 3\}$ and $n = 3$. These innovations are related to two technologies (TF1 and TF2), so that $j = \{1, 2\}$ and $f = 2$. The inventors are located in two different regions (R1 and R2), hence $k = \{1, 2\}$ and $r = 2$. Two of those three innovations are generated by two actors and are identified as cooperative innovation. We do not consider the case of intra-regional cooperation but the more general case. The data are as follows:

Table 4.1.: Example - data

Innovation	Techn. field	Region	Cooperative innovation
Innovation 1	TF1	R1 and R2	coop
Innovation 2	TF1 and TF2	R1 and R2	no coop
Innovation 3	TF2	R2	coop

With respect to this example matrix $\mathbf{A}$ is a 3×2-matrix:

$$\mathbf{A} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{pmatrix}$$

Matrix $\mathbf{B}$ is a 3×2 matrix:

$$\mathbf{B} = \begin{pmatrix} 1 & 1 \\ 1 & 1 \\ 0 & 1 \end{pmatrix}$$

Vector γ indicating whether innovation i is cooperatively generated contains the following elements:

$$\gamma = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

With these data, first the technological dimension is analyzed. The absolute values in matrix $\mathbf{A}$ are weighted by the number of technologies j innovation i is related to. The outcome is matrix $\mathbf{A}^w$:

$$\mathbf{A}^w = \begin{pmatrix} 1 & 0 \\ 0.5 & 0.5 \\ 0 & 1 \end{pmatrix}$$

Proceeding the same way for cooperative innovations ($\gamma_i = 1$) leads to the matrix $\mathbf{A}^{wc}$:

$$\mathbf{A}^{wc} = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{pmatrix}$$

The two matrixes contain information about the relationship between all innovations on the one hand and cooperative innovations on the other hand to the two technology fields. Both matrices are used to compute the propensity for cooperative innovation in each of the two technologies. The result is contained in vector $\mathbf{p^c}$:

$$\mathbf{p^c} = \begin{pmatrix} 0.66 \\ 0.66 \end{pmatrix}$$

Here for both technologies we get the same propensity to cooperate of 0.66.

In a second step, the regional dimension of innovation and cooperative innovation is considered. Proceeding analogously to the technological dimension we obtain $\mathbf{B}^w$ for the regional distribution of all innovations and $\mathbf{B}^{wc}$ for the cooperative innovations:

$$\mathbf{B}^w = \begin{pmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \\ 0 & 1 \end{pmatrix}$$

$$\mathbf{B}^{wc} = \begin{pmatrix} 0.5 & 0.5 \\ 0 & 0 \\ 0 & 1 \end{pmatrix}$$

The third step sets into relation the technological and the spatial dimension using all innovations. The result of multiplying the transpose of matrix $\mathbf{B}^{w\prime}$ and $\mathbf{A}^w$ is shown in matrix $\mathbf{C}^w$ which has the dimension 2×2 (2 regions and 2 technologies):

$$\mathbf{C}^w = \begin{pmatrix} 0.75 & 0.25 \\ 0.75 & 1.25 \end{pmatrix}$$

The expected share of cooperative innovations for each region is computed by multiplying matrix $\mathbf{C}^w$ with the vector of the cooperation propensity $\mathbf{p^c}$. The result is a vector $\mathbf{e^c}$ which has a length of 2 according to the number of regions:

$$e^c = \begin{pmatrix} 0.66 \\ 1.33 \end{pmatrix}$$

According to the technological classification of all innovations in region 1 and 2, the expected cooperation value in region 1 is twice (1.33) the value for region 2 (0.66). Finally, the observed number of cooperative innovations for each region k, indicated through matrix $\mathbf{B}^{wc}$, is related to these values. The final result are RRI indexes included in $\mathbf{v}$.

$$\mathbf{v} = \begin{pmatrix} 0.75 \\ 1.25 \end{pmatrix}$$

In our example in the first region the observed cooperative innovations are less than one could expect (0.75) according to its patent application behavior among all technologies, whereas in the second region observed cooperative innovations exceed their expected value (1.25). Within our theoretical context this suggests that for region 2 there is a regional effect working fostering cooperative innovation above the average; in region 1, contrariwise, factors seem to be present not fostering or even preventing cooperative innovation.

4.4. Data base

The methodology introduced to identify differential regional effects on cooperative innovation will now be applied to a specific source of information about innovations, patent data. The sample contains data about patent applications for Germany between 1998 and 2003. This information is taken from the "Deutsche Patentblatt" publication which includes data from the German patent office as well as data from the European patent office (EPO). The use of patent data to account for innovations implies that we in fact do not consider innovations but inventions. Since any economic results reaped by the new idea are not included. Consequently, here we are concerned with cooperative invention and not cooperative innovation.

Technological dimension in patent data

Regarding the methodology introduced before, the first dimension of interest refers to differences in innovation and cooperation concerning different technologies. Therefore, the code according to IPC, the international patent classification, is used which allows to classify patents technologically. The characterizing codes are stated on each patent document. This classification allows a detailed view on certain technologies. However, for our purposes the IPC classification appears to be too much differentiated. In order to reduce the number of dimensions, we use a concordance list developed by Schmoch et al. (2003) which in the end contains 43 main technological fields; those correspond well with NACE industry codes on a 3-digit level. On this basis the technological space comprises 43 technological fields, so that $f = 43$.

The registration procedure at the EPO or the DPA allows to list more than one IPC class on a patent. Therefore, rather regularly a patent is classified for more than one IPC class. The transformation of the IPC assignment to the 43 technology classes obviously reduces the number of cases where several technological classes are "mentioned" - the remaining cases of co-classifications, however, are non-negligible. For those cases we assume that each of the technology fields addressed has the same weight.

Regional dimension in patent data

According to the regional dimension, patents have to be assigned to certain regions. The patent document allows for two modes of allocation, the address(es)(1) of the applicant(s) or (2) of the inventor(s). The first alternative has a strong weakness as many companies and institutions filing for a patent state the headquarter's address. This necessarily assigns a too high emphasis on agglomeration areas where headquarters are more common. An example proper is the city of Munich where the headquarters of Siemens as well as of the Fraunhofer and Max-Planck-Institute are located. Relying on applicants' addresses would push Munich in an exaggerated top position since not all inventions behind the patents by Siemens, Fraunhofer and Max-Planck were generated in the region "city of Munich". They were generated in many other places in Germany (or elsewhere), just the places where the inventors are located. Hence, the second alternative just overcomes this pitfall. Accordingly, a patent is allocated just to that regions the addresses of the inventors listed on the patent document belong to.

Just like a patent may be filed for several technology fields, there may be more than one region the inventors of a patent are located. We accordingly assign the patent activity to all regions where the inventors come from. And to each region addressed the same weight will be assigned.

For the spatial grid we use the concept of the planning regions ("Raumordnungsregionen", later on we will use the abbreviation "ROR") developed by the "Deutsches Bundesamt für Bauwesen und Raumplanung". Due to this concept Germany is divided into 97 regions with the objective of including all - or at least as much as possible - labor mobility within one region. Therefore, we assume that the residence and workplace address of an inventor lies within the same planning region. Based on this regional grid the set of regions in our study amounts to $r = 97$.

Cooperative patents

Patent data can also be used to account for cooperative innovation. Cooperative innovation is understood here as any innovation where more than one actor has been involved in the generation of innovative knowledge. This cooperation can be formal or informal, it can be explicitly stated or implicitly assumed.

In principle patent data allow to identify two modes of interaction between innovative actors, co-application and scientist mobility Cantner & Graf (2006). With respect to the former, a co-application is given when on a patent document more than one actor is stated as applicant. With the data at hand we neither can distinguish between formal and informal cooperation nor can we differentiate between different kind of actors. Hence, a co-application may be the result of a common R&D project among firms, between firms and public research institutes or among public research institutes. Even a co-application between an individuum and one of these three kind of actors can be observed, although this case is rather rare. Since we have no information at hand about the "creative" share of each applicant we consider their contribution as of the same "amount". Consequently, we weight each co-applicant equally.

There, however, exists an additional source of the occurrence of cooperative innovation, scientist mobility. Consider the case where inventor Z works for firm X during the whole period of time and is listed on a first patent I; a second patent II is the result of a R&D cooperation between X and Y, where, however, only Y has filed for this patent and where inventor Z has been involved. Since in general all the inventors are listed on the patent application, we find Z as inventor on both patents. By this, even without a co-application for patent II we can assume that there has been knowledge exchange between X and Y by the mean of inventor Z. This is labeled cooperation by scientist mobility. Accounting for the empirical relevance of this case, in a firm survey done in 2006 only every fourth patent being the result of an R&D cooperation has been applied by both cooperation partners. A caveat of this indicator is that knowledge flows by scientist mobility link only in one direction. For these two reasons we decided to further analyze cooperative innovation only on the basis of the first mode of interaction, co-application.

In applying our approach to the German patent data by the way of 43 technological classes and the 97 regions we refrain from treating intra-regional cooperative patents. This decision is based on the fact that the 43/97 assignment does not allow us to observe a sufficient number of intra-regional cooperative innovations. Hence, when we refer to regional effects on cooperative innovation than it is the regional effect on being cooperative in general, that is independent of whether the cooperation partners are inside or outside the own region.

Descriptive data

Our analysis is based on patent data for the period between 1998 and 2003. These data are available on an annual basis. Some descriptive statistics as given by table 4.2 characterize our data base.

Table 4.2.: Description of the data base

Abbr.	Description	Database					
T	time series	1998	1999	2000	2001	2002	2003
N	number of patent applications	N_1 = 28151	N_2 = 31736	N_3 = 34206	N_4 = 33842	N_5 = 17045	N_6 = 24254
C	No. of co-applications	C_1 = 1459	C_2 = 1584	C_3 = 1684	C_4 = 1625	C_5 = 765	C_6 = 910
	Propensity of co-applications	5,18%	4,99%	4,92%	4,8%	4,49%	3,75%
I	number of technological fields	43	43	43	43	43	43
R	number of regions observed	97	97	97	97	97	97

First, the number of patent applications increased slightly over time and shows an abrupt cutback in 2002 related to the burst at the worldwide stock markets. Second, the number of cooperative patents followed a similar development. Third, a slightly declining propensity of cooperative patenting can be observed over time. Fourth, in each year at least one patent has been assigned to each of the 43 technological fields spanning our technological space (I). Fifth, in each year at least one inventor is assigned also to each of the 97 regions of our spatial space (R).

To smoothen variations over time, our approach is applied to moving periods with one year overlap. We use a moving 3-year average, leading to 4 subperiods t. To ease notation we label each of these subperiods by the middle of the respective three years, hence, 1999, 2000, 2001, and 2002.

4.5. Results for cooperative innovation activities in Germany

4.5.1. Technological dimension of cooperative innovation

This section looks at the differences in patenting behavior between technologies and focusses on co-applications and their development over time. We consider each of the four subperiods.

Figure 4.1.: Amount and development of patent applications

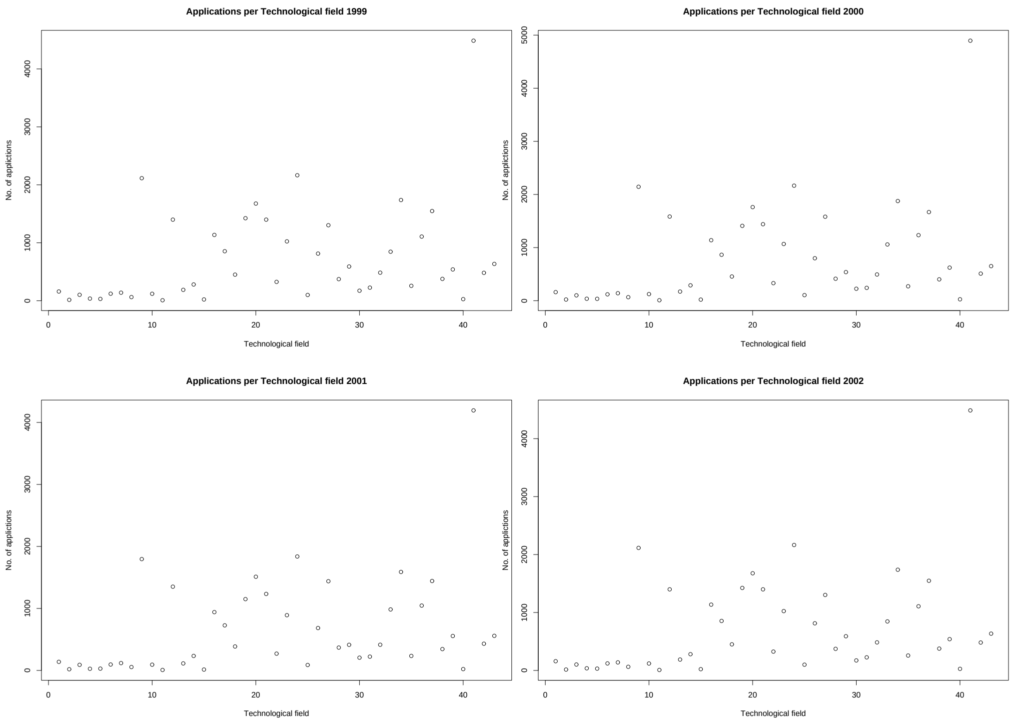


Figure 4.1 shows the number of patent applications for each technology class ($F = 43$) for each period t. In each period most of patents have been filed for in technology class 43 (motor vehicles). The technology with the fewest number of patent applications in each period is class 12 (paints and varnishes). Hence, there obviously exists an unequal distribution of patenting activity among technologies.

To have a closer look at those differences we refer to Gini coefficients.[5] For that table 4.3 states the number of both the total patent applications and the

[5]The Gini coefficient developed by Gini (1921) is a measure of inequality of a distribution. It is defined as a ratio with values between 0 and 1: the numerator is the area between the Lorenz curve of the distribution and the uniform (perfect) distribution line; the denominator is the area under the uniform distribution line.

total number of co-applications. For both we computed the Gini coefficient with respect to the 43 technology classes. Since the data is normalized in this procedure, the coefficients between the two different variables can be compared.

Table 4.3.: Application and co-application distribution regarding technological fields

		Period 1 1999	Period 2 2000	Period 3 2001	Period 4 2002
Applications	no. of	31364	33261	28364	25047
	Gini coefficient	0.557	0.560	0.562	0.568
Co-applications	no. of	1563	1619	1358	1100
	Gini coefficient	0.534	0.532	0.532	0.539
Co-appl. Prob.	mean	0.061	0.059	0.053	0.048
	median	0.053	0.053	0.052	0.048
	min	0.015	0.015	0.000	0.000
	max	0.129	0.135	0.106	0.095
	Gini coefficient	0.238	0.242	0.218	0.231

We first observe that the inequality between technologies concerning patent applications is always above 0.55 and considerably constant over time. Hence, the number of patent applications is not equally distributed between the observed technologies. Tracking the Gini coefficients over time indicates that the inequality is not changing much. Obviously this does not tell us anything about the development in each of the technology classes. However, the visual inspection of figure 4.1 shows some persistent pattern herein.

Although these finding seems to be somehow trivial they are of importance for our understanding of regional innovative performance. For this we refer to Griliches who shows that the relationship between patent applications and R&D is close to be proportional for all industries (Griliches 1990, p.1702). We conclude from this that differences in number of patents in each class is an indication for differences in the innovative activities and in the innovative performance among those classes. Hence, the distribution of patent applications mirrors the distribution of innovative activities in the technology classes. For our research question this implies that the level of regional innovative activities and performance depends among others on the respective regional composition in terms of industries or technologies.

We secondly find the Gini coefficient for co-applications being slightly lower than the one for patent application. Its value is always above 0.53 and also remains rather constant over time. The same interpretation applies here: the degree of regional cooperative innovation is dependent of the regions type and composition of industries and technologies.

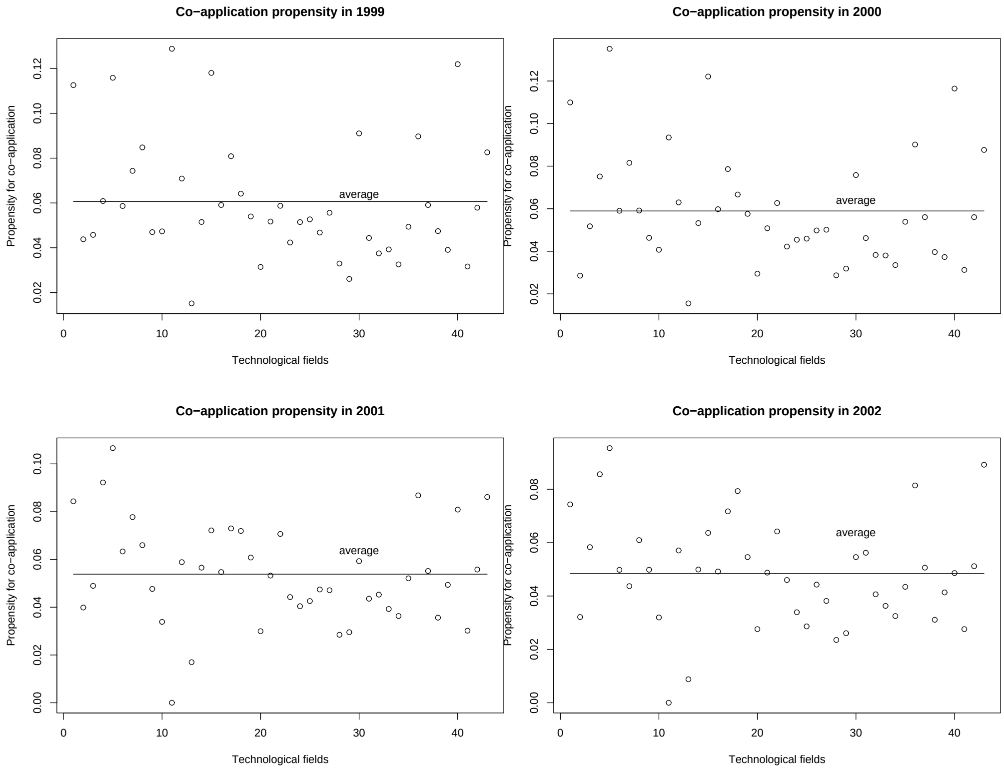
This result easily can be related to literature on R&D cooperation. Respective empirical studies often deal either with firm characteristics influencing cooperation behavior (Miotti & Sachwald 2003, Belderbos et al. 2004) or concentrate on the impact of cooperations on firm performance (Oerleman & Meeus 2000, Lööf et al. 2001, Thornhill 2006). In this context of certain interest are organizational practices affecting firms' performance for which one often observes a slow diffusion of best practices due to difficulties in imitating complex organizational capabilities (Teece 1986). Applying this to the organizational device "to cooperate" may already explain sustained performance differences of firms within and between industries. And extending the argument one may discuss differences between certain technologies (characterizing industries). The empirical evidence on this issue, however, is rather scarce.

Both the development and the distribution of this co-application propensity are shown in figure 4.2. The mean value of the co-application propensity declines from 6.1% in 1999 to 4.8% in 2002. In other words the number of co-applications decreases more than the number of applications. The inequality between the 43 technological fields remains rather stable. However, its level is much lower in comparison to the Gini coefficients shown for applications and co-applications.

Obviously, there are differences between technology fields in terms of the propensity to co-apply. The lowest value is in the first two periods slightly above zero (1.5%) and 0 for the last two periods, while the maximum value is about 13% in the first two periods and about 10% in the third and fourth one. Interpreting these propensities one has to take into account that they contain the respective technological or sectoral dimension but also the (for all the technologies the same) average regional effect on cooperative innovation.[6] This is due to the fact that for the observed co-applications we cannot extract the sheer technological effects.

[6]More precisely, for each technology this propensity contains the technology specific effect and and the average regional effect pertaining to those regions the respective technology is "located" in. However, due to the broad definition of the 43 technology classes we observe each technology at least once in each of the 97 regions.

Figure 4.2.: Distribution and development of the propensity for co-application

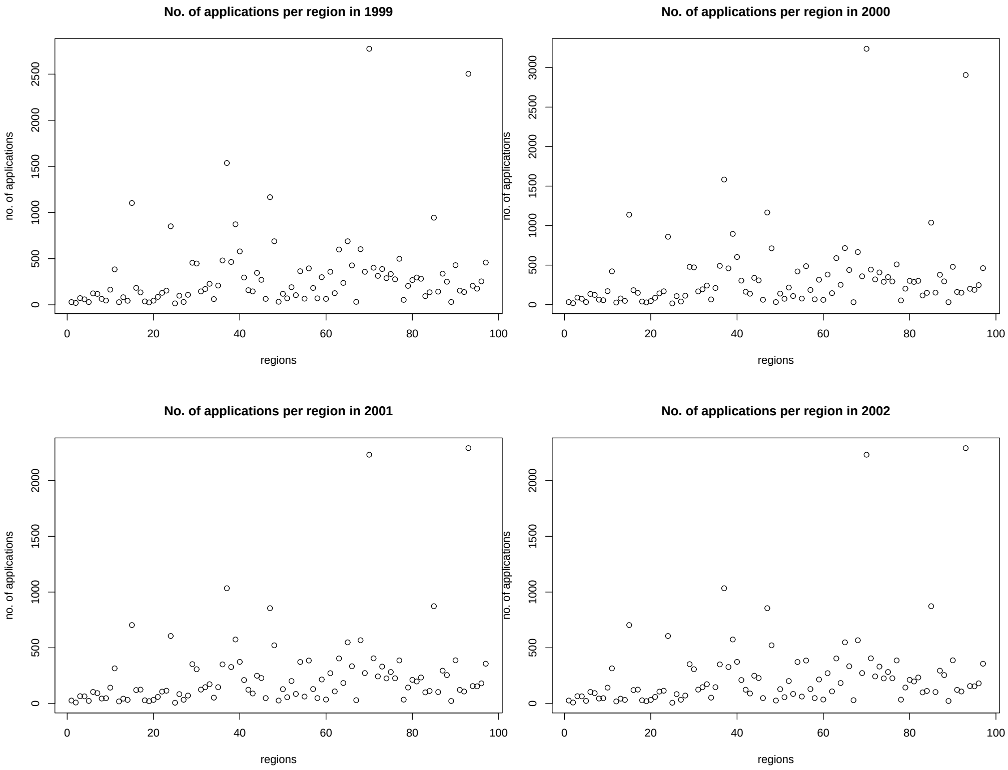


On the basis of the observed differences in co-application propensity between technologies or sectors the question is whether this already can explain regional differences in cooperative innovation in the following sense: Consider two regions differing in their composition of technologies or industries. Take into account the observed sectoral or technological differences in cooperative innovation. If one of the regions consists of more cooperative sectors and the other region of rather non-cooperative sectors, then regional differences can be readily explained by regional composition of industries and their respective propensity to co-apply. Then an additional regional factor is not working.

4.5.2. Regional innovative and cooperative behavior

Having shown that there exist differences in cooperative patenting among technologies, differences in regional cooperation behavior are analyzed now. In a first step we observe regional differences in patent application. Figure 4.3 shows how the overall number of patents is distributed over all 97 regions.

Figure 4.3.: number of regional applications and its development



There are two outstanding regions, Stuttgart (ROR 72) and Munich (ROR 93) with the highest number of patent applications. While this can attributed to automobile industry in the former case, in the latter it is due to public research institutes such as Fraunhofer or Max-Planck whose headquarters are located in Munich.

Equivalently to table 4.3, the regional distribution of patent applications and co-applications is shown in table 4.4. The Gini coefficient of about 0.54 for the regional distribution indicates a regional inequality similar to the one among technology fields (about 0.56). This level remains roughly constant over all four periods. Accordingly, in addition to technology related effects on patenting there are regional effects to be considered.

Looking in a second step at co-applications they regionally are obviously more equally distributed than applications. The Gini coefficient is somewhat lower at about 0.49 and rather stable over time. This observation suggests that for explaining cooperative innovation effects related to technological classes addressed are more discriminatory than effects related to the regions the innovators are located in.

Table 4.4.: Regional distribution of patent applications and co-applications

		period 1 1999	period 2 2000	period 3 2001	period 4 2002
Applications	no. of	31364	33261	28364	25047
	Gini coefficient for regional distr.	0.547	0.551	0.545	0.545
Co-applications	no. of	1563	1619	1358	1100
	Gini coefficient for regional distr.	0.493	0.491	0.501	0.482

Equivalent to the technological differences in co-application, the observed differences in cooperative innovation on the regional scale comprise both regional effects and the average effect of those technologies contained in the respective regional composition of industries or technologies. The next step now is to extract the technological effects. This is done by applying the technology or sector oriented propensity to co-apply.

4.5.3. Differential regional effects on cooperative innovation

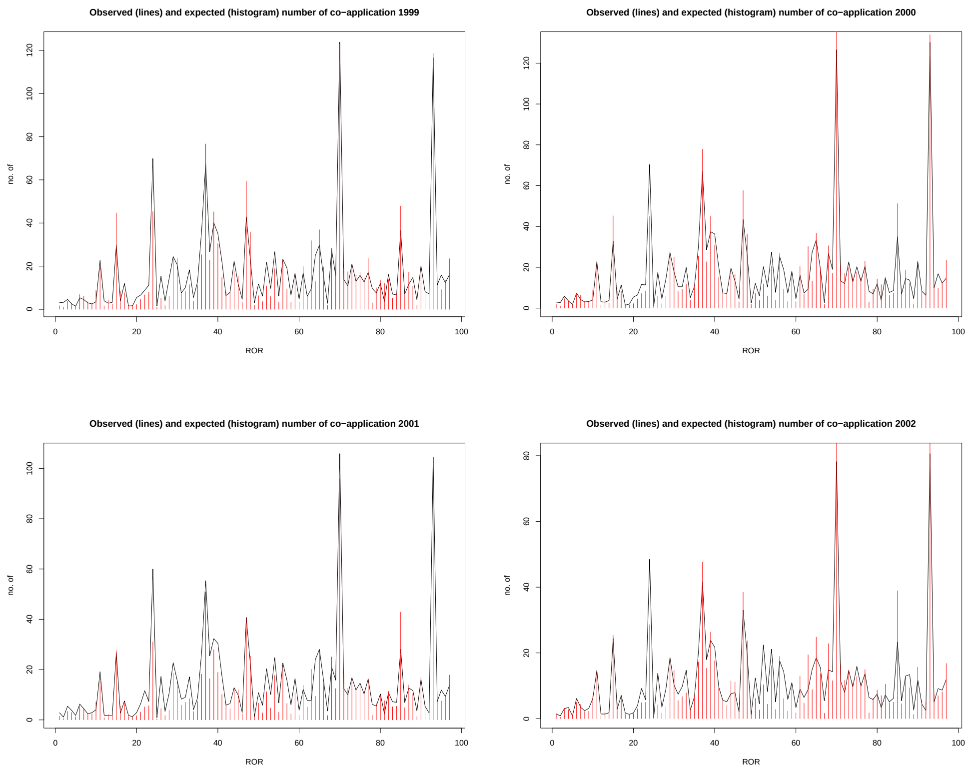
In this final step we separate the technology specific effect and the average regional effect on cooperative innovation in order to get an index for the differential regional effect. For this we use the expected regional number of co-applications computed on the basis of the industry or technology composition of a region and relate it to the observed number of co-applications.

Figure 4.4 shows for the 4 periods analyzed and for all 97 ROR the *observed* co-applications (black line) as well as the *expected* number of co-application (bars).

We find first that the expected number of co-applications for each region differs from the observed one. However, comparing regional differences in the absolute numbers leads to a size dependent bias. Therefore a relative account is required. Following equation 11, the ratio between observed and expected regional interaction just renders this as it looks at cooperative innovation above or below average. This RRI index is shown for each of the 97 regions and for each of the 4 sub-periods in figure 4.5.

A RRI of 1.0 means that the level of regional cooperative innovation is as high

Figure 4.4.: Observed and expected regional co-applications

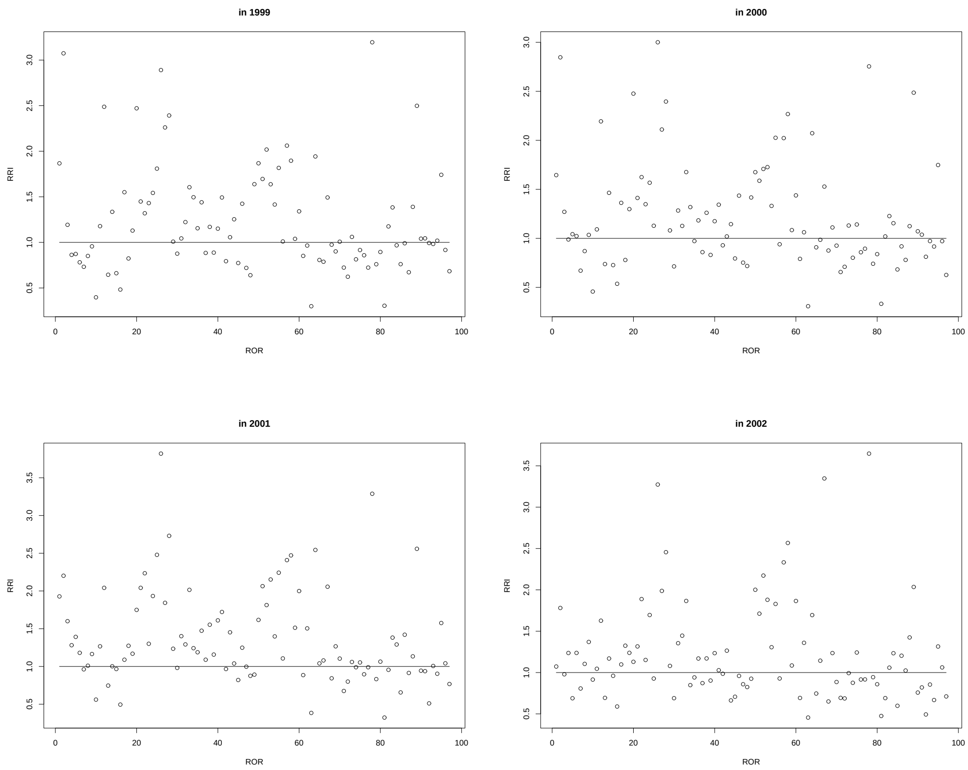


as the realized one and thus that cooperative innovation in this´regions is average. RRIs below and above one indicate a level of cooperative innovation below and above average. Looking at the computed RRIs the disparity between the regions is considerably high.

This observed disparity of the RRIs among the regions indicates that there are regional effects on cooperative innovation. Since we here focus on cooperative innovation in general and not on the restricted case of only intra-regional relations, the regional effects detected for RRIs above respectively below 1 can neither be interpreted as the existence or lack nor as the strength or weakness of a regional innovation system in the respective region. For that to hold, a closer inspection of the cooperative arrangements and an additional analysis of intra-regional cooperative innovation are required. Hence, the differential regional effects we computed work on the region-specific attitude of actors to engage cooperative innovation independent of whether the cooperation partners belong to the same region or not.

Having shown visually that there are differences of regional effects of cooperation behavior, we want to show that the distribution of RRIs is significant different

Figure 4.5.: Ratio of observed to expected regional co-applications



from 1. If the calculated values do not differ significantly from this value, this would imply that to explain regional differences in cooperative innovation one has to refer only to the regional composition of technology classes. Therefore, the distribution of the RRIs has to be tested. First, we apply a Shapiro-Wilk test to test for normal distribution. Table 4.5 shows that the RRIs in all four periods are not normally distributed. Referring on this result, we use Kolmogorov-Smirnov equality-of-distributions test in order to calculate whether the RRIs differ significantly from a normal distribution with an expected value of 1. In table 4.5 the corresponding corrected p-values are presented. For all four periods we found p-values below a critical 1% level which implies a refusal of the null hypothesis that the distribution of the RRIs have a mean value of 1. We can conclude from these results that the RRIs have a non-normal distribution with a higher variance than a normal distributed variable and a mean value which differs significantly from 1.

Hence, our visual impression on the existence of differential regional effects on cooperative innovation are substantiated by the statistical tests in table 4.5. Consequently, for our sample regional differences in cooperative innovation are not only affected by the composition of regional technology base (technology classes)

Table 4.5.: Tests on differences between observed and expected co-application amount

		period 1	period 2	period 3	period 4
ratio	minimum	0.300	0.308	0.323	0.456
	maximum	3.195	3.000	3.820	3.647
	std. dev.	0.583	0.546	0.619	0.599
Shapiro-Wilk-test					
	$Prob > chi2$	0.000	0.000	0.000	0.000
Kolmogorov-Smirnov test		0.000	0.000	0.000	0.000

but also significantly by specific regional effects.

Looking more specifically at the results we find the lowest RRI over all periods except the third for the city of Trier in Rhineland-Palatinate with 0.299 to 0.456. Technologies located in that region call for a much higher number of co-applications than observed. The highest RRIs of the first and the fourth period are found for Hochrhein-Bodensee in Baden-Wuerttemberg (3.195 and 3.647); in the second and third period the region of Uckermark-Barnim in Brandenburg shows the highest RRIs (3.000 and 3.820).

A different visual representation is chosen in appendix A where we show a map of Germany with 97 regions. The regions are colored in accordance to their respective RRIs. A darker color indicates a higher RRI for this region. Two observations are interesting. First, those regions which are assigned as most innovative in terms of total patent applications, especially those in the southern part of Germany, show a considerably low RRI. Hence, here the level of cooperative innovation is lower than expected. Secondly, by and large all regions in Eastern Germany show a higher level of cooperative innovation than expected.

These differences in the cooperative innovation between East German actors in comparison to actors located in the Western part has been discussed already in Cantner & Graf (2003) and Graf (2006). There a significant higher level of cooperative patenting has been found for the regional innovations systems of Jena and Dresden (two East regions) and the systems of Heidelberg and Ulm (two West regions). To find an explanation for this one may refer to other empirical work related to comparison between the eastern and the western part of Germany such as Brixy & Grotz (2004) or Fritsch (2004*b*). Looking at the firm level such work concludes that differences of the performance between newly founded firms in both parts of Germany that these differences are due to *"the region-specific stock of knowledge capital and knowledge spillovers, as well as other locational conditions, such as density of economic activity, the industry mix, and the characteristics of the regional innovation system."* (Fritsch 2004*b*, p.540). It would be interesting to dig deeper into those relationships and to ask for influence of regional innovation systems, to discuss the necessity and efficiency of cooperative innovation, and to look at the role of knowledge bases, human capital and actors' structure.

However, one reservation has to be made. One obviously may in this context question whether the higher RRIs in East German regions can really be attributed to a higher intensity of co-application and therefore cooperative innovation. One may argue that this may also have to do with a different attitude towards applying for patents. With respect to the latter one could think of a higher propensity for "private applications" in East Germany. Graf & Henning (2006) suggest that many firms in the respective regions are young. If these start-ups fail the patent rights are a part of the insolvency. In order to prevent this the inventors in Easter Germany might tend to list themselves as applicants. Consequently, although those inventors belong to the same firm and the same region we have to consider them as co-applying since they a listed with different private addresses. This case seems to be more frequent in Eastern Germany with the consequence of a higher number of co-applications.

To substantiate this a more in-depth investigation along the lines briefly mentioned above is required and left over for future work. For this we consider the characteristics of the regional innovation systems as most interesting to be analyzed.

4.6. Conclusion

This chapter suggests a method to disentangle regional and technological effects on cooperative innovation activities. The importance of both effects are maintained by approaches on the sectoral and on the regional innovation system. Generally, studies on cooperative innovation activities deal only with one of the both concepts although actors engaged in cooperative innovation activities can be considered to be member of both types of systems. The difference between both concepts lies in the definition of the boundaries of a system, i.e. how they define the set of system members in contrast to the rest of the world. Authors like Carlsson & Stankiewicz (1991) or Malerba & Orsenigo (1997) stress the technological proximity within technological or sectoral systems that furthers cooperation. The regional innovation system approach (Cooke 1992) looks at spatial proximity and face-to-face contacts which ease the exchange especially of tacit knowledge.

We show how to distinguish between both effects and how to disentangle them in empirical work. For this we introduce the RRI which relates the expected degree of cooperative innovation activities of a region to the observed one. Applying this method to patent data for Germany between 1998-2003 we identify regional differences in cooperative innovation activities for Germany which can not be explained by technological determinants and the technological or sectoral composition of a region.

Having identified differential regional effects on cooperative innovation activities are necessarily has to go on with an analysis of the intra-regional cooperative innovations - which we left out as explained above. This will be the next step we will pursue.

Furthermore a deeper analysis of where those differences come from is required. We expect the regional knowledge base according to several dimensions to have a major impact. This will be a second focus of future work.

Related to this another avenue of future research follows from the implicit assumption in this chapter that the propensity to cooperate in each technology is exogenously given. Other work on cooperative innovation activities such as Hagedoorn & Schakenraad (1992) indicates, however, that cooperative innovation activities shows a certain time pattern. Hence, an issue here is to concentrate on regularities of cooperative innovation activities among technologies with respect to the age of the technology or the age of the sector. Insights from technological life cycle studies can be used to explain why there are differences in the cooperation propensity among certain technologies. For this to work out, a data base comprising information about a longer time period is required. This will be the third focus of our future research.

5. Regional effects on cooperative innovation activities and the related variety of regional knowledge bases

5.1. Introduction

In the past decades the conditions of economic growth evolved to be focused on knowledge, learning and innovation as the driving forces.[1] Through improvements in communication and transport technologies the traditional production factors labor and capital become minor important. The wealth of a nation relies on the ability to create new knowledge and commercialize such knowledge (OECD 1996, Acs 2002, Sharpe & Martinez-Fernandez 2006). Innovations are characterized as new products or processes with a certain economic value (Cooke et al. 2004). Several analytical framework deal with the conditions, requirements and environments of creating and developing innovations.

This chapter focuses on the "Regional innovation system" – approach. This concept developed in the last 15 years stress on the importance of regional factors for the innovative capability of firms. Based on a survey of recent literature we conclude that this approach recognizes the importance of regional interactions between certain kind of actors, but doesn't explain the individual circumstances and incentives of an actor to engage in an interactive process with other actors. As the concept is on the regional innovative capability, we are interested in the development of German regional interactive structures. With using concepts of the learning and knowledge based economy we argue that the regional interactive structure depends on the regional knowledge base and in particular on the heterogeneity of the knowledge present within a region.

The study is organized as follows. First, a theoretical part, where we introduce the

[1] Thus chapter is based on Cantner & Meder (2008*c*).

theoretical concepts and the roots of the RIS–approach, is presented. Through a critical survey of theoretical and empirical literature about this topic, we assume three hypotheses. Afterwards, we concentrate on our methodology where a measure of regional effects on cooperative innovation activities and a concept of how to measure the dimensions of regional knowledge will be introduced. The results based on this methodology are presented and discussed in the last part of the chapter.

5.2. Theoretical background

This chapter analyzes regional innovation systems, their performance, and the factors determining the working and the success of such systems. The increasing popularity of this and related concepts leads to a confusing jungle of definitions, while the presence of such innovation systems in real world remains obscure (Doloreux et al. 2004, p.143). In this section a shaped concept is provided starting with a rather abstract definition of a system. Based on that, we consider systems in the context of innovation and here focus on regional innovation systems.

5.2.1. Systems of Innovation

Starting rather generally, a system may be defined as a set of entities, real or abstract, comprising a whole where each component interacts with or is related to at least one other component. As a system forms a more or less dense "whole", one should be able to discriminate between the system and the rest of the world (Edquist 2001, p.4). A straightforward solution does not exit as different systems serve different purposes, so that the observed variety of systems is not surprising (Carlsson et al. 2002, p.233). Hence, any specification of this abstract definition of a system requires distinguishing between important and unimportant entities and interactions. The identification of what is unimportant depends on the purpose of the system.

Applying the idea of a system to innovation issues acknowledges that the majority of innovative activities are not pursued by individuals in isolation but that innovation is a social and interactive process, where the behavior of a single actor is stimulated by his environment (Edquist 2004). Interaction in the context of innovation systems mainly refers to the exchange of knowledge and information - on a formal as well as on an informal basis - with the ultimate aim to create new knowledge allowing for innovations. The entities or components of the systems are individual actors and organizations such as firms or public organizations on the one hand and on the other hand institutions (Edquist & Johnson 1997, p.47) governing interaction among these organizations (Kubeczko et al. 2006, p.706). These institutions comprise trust, reciprocity and reputation, special technological fields and competence areas. They are developed within the system and further the overall function of an innovation system to finally create and commercialize innovations (Asheim & Coenen 2005). The systemic view of innovation is based on "complicated two-way-relationship of mutual embeddedness between organizations and institutions" (Edquist 2001, p.6). First, each component is related to the whole system, that is the behavior and development of organization like firms, universities or political actors, is driven by the set of institutions within the system. Second, the development of system's institutions is a process due to the systems actors. In a nutshell, the principal goal of an innovation system to increase innovative and economic performance of a region is pursued by the systemic interactions (Doloreux 2004, p.483) of various actors.

Any analysis of innovation systems has to take into account first that a system is a connected "whole" which cannot be divided into subsystems without loosing any interactions or relations: As Blanchard & Fabrycky (1990) show a system is more than the sum of its parts. Second, as institutions and organizations are related two-sided and there are feedback processes between relations and components, a system approach is always dynamic (Carlsson et al. 2002, p.234).

Based on this more general description of innovation systems, research in this field developed ways to categorize different systems. Here one mainly refers to the boundaries of a system with respect to the outside world. Initially this approach was used by Lundvall (1988, 1992) and Nelson & Winter (1982) to describe the development of certain national innovation systems. The discrimination between different systems is politically determined by the national borders. A second field, sectoral innovation systems justifies the boundaries by the specifities of sectors in terms of a certain knowledge base and key interactions within a sector (Malerba & Orsenigo 1997). A third stream of research looks at the dynamics of innovative processes within regions. This concept will be introduced in the following subsection.

5.2.2. Regional innovation systems

The regional innovation system approach developed from the empirically based acknowledgement that innovation is a geographically bounded phenomenon (Asheim & Isaksen 2002). The discovery of the importance of the regional scale and of regional resources in stimulating the innovative capabilities of firms is the major issue this approach deals with (Asheim & Isaksen 2002). Close spatial (often implying social) proximity promotes and eases the exchange of knowledge and information and thus contributes to collective learning and creation of knowledge. This applies especially in cases where we find a high degree of tacitness of knowledge, where direct personal contacts are required for transfer and exchange. The concepts of the learning economy (Lundvall 2004) and the knowledge economy (Cooke 2001, Raspe & van Oort 2006) just emphasize this complexity as well as the path dependency of those processes.

As mentioned above a system has to have identifiable boundaries to become a whole different to the outside world. For the RIS concept those boundaries are given by the geographical term "region". Following Cooke (2001) a region is a meso-political unit above local governments and below nations. It might have a certain homogeneous culture and history (Cooke 2001, p.953). The operationalization of this concept, however, is not any easy task and one more than often relies on political or administrative boundaries.

In view of this description of what a regional innovation systems broadly is all about, namely a regionally bound group of actors interacting in a specific way, the RIS approach may gain from a discussion of the individual incentives and requirements to engage in interaction and thus in research cooperation. To do so the following subsection dwells on the concepts of the learning economy and the resource-based theory of the firm. As a result of this discussion we achieve what we consider as the core of an RIS, the network of interactive actors.

5.2.3. Innovation, learning processes and the incentives to cooperate

The basic idea of the learning economy approach as well as the more static knowledge-based economy approach is that the knowledge base of firms is "the most strategic resource ... for competitiveness" (Asheim & Coenen 2005, p.1174). This view is quite familiar with the theories of the resource-based view (RBV) of the firm going back on the initial work of Penrose (1959). This approach focuses on specific firm assets that determine the performance of a firm (Barney 1991) and by her competitive advantage. These assets are called resources. Due to Combs & Ketchen (1999) those resources satisfy three criteria. First, they have to be valuable, that is there exists a demand which appreciates the resources' output. Secondly, an asset must be rare to be considered a productive resource in the sense of the RBV. Third, the resource has to be specific to a firm. Without a certain degree of uniqueness a firm will not be able to gain a competitive advantage over competitors (Combs & Ketchen 1999, p.869). Within the RBV concept technological knowledge is considered an important intangible resource.

Both the learning economy concept and the resource-based view of the firm stress the process of knowledge generation/accumulation and describe this dynamics as an often path dependent and by this firm specific process (see for example Conner 1991, Lundvall 2006). In this sense knowledge as a dynamic resource evolves over time and constitutes among others "the learning capacity of a firm" (Lockett 2001, p.725). The path-dependent feature of knowledge accumulation provides firm specific technological know-how and competencies and thus for heterogeneity among firms. This specifity may in many cases contribute to the competitive advantage of a firm but in as many cases it may be constraining the opportunities for future own progress. Therefore, in pursuing further progress a firm may attempt to overcome this constraint by accessing knowledge generated by other firms or actors. Following the concept of the absorptive capacities introduced by Cohen & Levinthal (1990) existing knowledge is required to participate in a knowledge base external to the firm, the knowledge base of a region for example. In this sense knowledge a firm has accumulated and which serves as a learning capacity allows a firm to absorb knowledge generated elsewhere which then in turn combines with the own knowledge base to generate new knowledge.

These concepts of path-dependent knowledge accumulation, of absorptive capacities, and of the relevance of knowledge external to a firm offer the theoretical frame for an approach towards RIS based on individual decisions to access external knowledge and to exchange know-how and information. A crucial question in this context refers to the criteria by which firms select other actors to engage in this exchange. Cantner & Meder (2007) show that actors are more likely to cooperate when they differ at least to some degree in their knowledge bases, when the respective amount of knowledge received form the partner is comparably high, and when reciprocity is given, that is both benefit by the exchange.

These findings on the firm level can now be applied to the regional level of the RIS. There one observes that research activities with respect to their intensity and design are not equally distributed in space. These differences "can be more or less completely explained by R&D spillovers" (Fritsch & Franke 2004, p.253). The intensity of regional R&D spillovers in turn is determined by the number of actors involved and their incentives to engage in knowledge exchange and networking.

Thus, regional differences in the affinities to cooperate in innovation and to exchange know-how may first be explained by the size of knowledge base available in a region. The more technological knowledge available in a region the more it may pay to search for a cooperation partner and to exchange-knowledge. This leads to the following hypothesis:

> H1: The degree of regional effects on cooperative innovation activities in innovating depends positively on the amount of knowledge available within the region.

In addition to this, however, for a beneficial exchange of knowledge it is required that each cooperation partner understands the knowledge he "receives". In this sense the regional knowledge pool has an individual value (Cantner & Meder 2007) for all firms acting in this region. Assuming the case that the firms in a region hold highly idiosyncratic knowledge - that is the regional knowledge base is highly heterogeneous. In this case a firm's ability to understand and integrate others knowledge is rather low or there may be even no common understanding so that this value is zero for all firms. Hence, for a positive value the knowledge bases of the potential cooperation partners have to have some technological overlap (Mowery et al. 1998) in their knowledge bases and accordingly the regional knowledge base should show some homogeneity. As mentioned the path dependent nature of knowledge accumulation just provides for heterogeneity (Combs & Ketchen 1999). According to Breschi et al. (2003) span innovative activities, like research cooperation, out of technologies innovators are currently involved in. This is due to the fact that learning over time generates knowledge which is close to the existing one and opens new opportunities for innovations. With respect to research cooperations this implies that with knowledge bases too dissimilar firms incentive to engage in the exchange of knowledge is low. On the other hand as the knowledge is seen as a rare and valuable firm asset (Barney 1991) disadvantages

in terms of involuntary knowledge flows can occur if the knowledge bases are too close related. More precisely, Mowery et al. (1998) and Wuyts et al. (2005) show on firm level analyses that the incentives to cooperate decreases if the knowledge bases of potential cooperation partner are too similar.
Based on this the following hypotheses are suggested:

> H2a: The more related the regional knowledge base the higher the regional effects on cooperation innovation activities.
>
> H2b: If the related variety of the regional knowledge base comes too close, the positive effect is dominated by disadvantages of possible knowledge drain and, thus, the effect on the strength of the regional innovation systems gets negative.

Breschi et al. (2003) show that the cumulation and relatedness of knowledge enhance innovative activities independently but that there is an additional effect if both dimensions of knowledge exist strongly at the same time. According the analysis of regional effects of cooperative behavior this implies the following hypothesis:

> H3: The combination of amount and relatedness of the regional knowledge called the regional knowledge base affects the regional effects in cooperation behavior positively.

5.3. Methodology

5.3.1. Data sources and regional boundary

In order to test the hypotheses above we draw on two data sources which allow us to describe the regions under investigation. First, information about patents that are filed for Germany between 1994 and 2003 are provided from the German patent office. The second data source, taken from the German Federal Statistical Office, contains information about German inhabitants and GDP data on the regional level. The data are comprised to a panel data set including five 2-year-periods.

A first consideration refers to defining regional boundaries. A conceptual problem arises here as unified definitions of the RIS-approach are missing. Thus any empirical research on Regional innovation systems has to define the regional boundaries. As Cooke (2001) mentioned a region as a political unit above local and below federal units, we follow Fritsch & Franke (2004), who made an analysis of differences in the regional research efficiency, by using German planning regions (Raumordnungsregionen; ROR) as regional boundaries. These units defined by the "Bundesamt für Bauwesen und Raumordnung" (BBR) divide the federal states of Germany, the Bundeslnder, into 97 subunits. Our database contains information about those 97 regions between 1994 and 2003.

A second consideration refers to the usage of patent data. We use patent data in a threefold way, (a) for describing the interaction structure within a region, (b) for taking account of the regional technological performance, and (c) for the regional knowledge base. For that we use all the patents applied for by firms belonging to the same ROR region. We are aware of a controversial debate on the quality patent data possess to indicate the innovative output of firms, regions, networks or whatever.

As to (a) firm patents are suited to characterize the technological knowledge base of that firm and in this sense also indicate whether that firm is attractive for other firms to cooperate and exchange know-how. Two qualifications are obvious here. First, patent data do not represent the complete knowledge base of a firm, but they are a reasonably good indicator for her technological competitive advantages. In this sense patents satisfy the criteria Combs & Ketchen (1999) have claimed for competitive relevant resources: they are supposed to be rare, as well as valuable and specific in their nature. Second, other incentives influencing the choice of the cooperation partner likewise exist. However, for our broad German-wide analysis firm structure variables as size, age or industry, first are not available or second are difficult to combine with the patent data we use.

As to (b) and (c) Griliches (1990) has shown that patents are sufficient indicator for the innovative output of firms. Acs et al. state that patents provide a fairly reliable indicator measure of innovative activities (Acs et al. 2002, p.1080). This reliability is restricted to technological innovations and has some shortcomings in regression fitness. Of course there some sceptical papers about using patents as innovative output measure (e.g. Encaoua et al. 2006). They mainly criticize the restricted manner of patents in comparison to the wide range of different types of innovation. Following Edquist (2001), process or organizational innovations are also part of the innovation system, but are not captured by counting patents. Nevertheless, we assume patents as a sufficient indicator for the innovative success of regions. And in the sense that innovation is knowledge driven phenomena where a firm cannot file for a patent without the appropriate knowledge, we conclude that patents are also an indicator for the knowledge base of a region.

5.3.2. Measuring regional effects on cooperative innovation activities

Our main focus in this chapter is on regional effects on cooperative innovation activities, or put more precisely, we are interested in whether features of the regional knowledge base have an impact on differences of cooperative innovation among regions.

The easiest indicator for the latter is to take the number of regional cooperation, measured in whatever way. To avoid systematic discrepancies through level effects, the ratio between cooperations and innovations can be used as an indicator of regional cooperation behavior.

Considering the existence of two concepts of innovation systems, regional and technological innovation systems, at the same point in time and space, these rough indicators seems, however, to be insufficient.
In order to avoid misinterpretations of differences in cooperation behavior among regions that are in fact driven by technological effects, we apply now a methodology how the measure differences in the regional cooperative innovation where technological effects are absent.
Thus, differences of cooperative innovation among technologies is a core assumption of this chapter. To apply this methodology information about the technological and regional distribution as well as information about the number of actors involved are required for each innovation. Although we will use patent data for applying this method to test our hypotheses, it can be applied to other kind of data bases where these information are given, like firm survey data for example.

Before describing single steps of this method, the required information are related to the available patent data. First, information about the technological space a patent is concerned with are gathered from the "International Patent Classification" (IPC) code which are listed on each patent document. This classification allows a detailed view on certain technologies, but it is much too widespread to be used in our analysis. Therefore, we use a concordance list developed by Schmoch et al. (2003) in order to reduce the widespread IPC to 43 technological fields which are related to NACE industry code on 2- and 3-digit-level. The registration procedure at the EPO or DPA allows to list more than one IPC on a patent application[2]. Thus, more than one technological field can be listed on a patent document. In this case the patent is equally distributed over all involved technological fields.

The regional distribution is based on the inventor addresses listed on a patent document. As especially larger firms (like Siemens) or research institutes (like Fraunhofer or Max-Planck-Institutes) commonly file for a patent using the address of the headquarters, we do not use the applicant addresses for regional distribution. Comparable to the technological distribution, it is possible that a patentable improvement has been developed by inventors located in more than one region. In this case the patent is allocate to a region according to the share of inventors located there. The final information which is required to apply our methodology is on the collaborative nature of an innovation. Regarding to the given data base, a cooperation is defined as a co-application of a patent by at least two economic actors.

The now introduced methodology includes three steps. First, the cooperation propensity of each technology is calculated by dividing the total number of cooperations by the total number of innovations within a technology. This first step accounts of specific technological effects whose impact on the cooperative innovation is assumed.

In the second step, the innovations are assigned to the regions of their inventors. This distribution reflects to technological endowment of each region. This endowment is used in a third step to calculate an *expected cooperation value*. This value indicates to number of cooperations that can be expected within a region due to the number of innovations in each technology for this region and the respective cooperation propensities for these technologies which have been calculated in the first step.

[2]These listed IPCs are differentiated by one main and several sub-classes. We do not follow this differentiation here and, therefore, we weight all listed classes equally.

In the final step, for each region the number of observed cooperation is divided by the expected cooperation value. This calculated ratio indicates the *"relative regional impact (RRI) on cooperative innovation"*. The RRI values show whether the regional effects are below or above the German wide average with an absence of technological effects at all. We can not measure the regional values themselves, but this RRI value indicates how strong the strength of the regional effects differ among German regions. In the case that all values are more or less equal to one, the conclusion would be that the strength is always the same and that differences in the cooperative innovation respectively the innovative success among regions are only due to differences in the regional endowment. Furthermore, this RRI has the advantage of being size independent and it is independent of the data base which is used.

5.3.3. Measuring the size and related variety of regional knowledge bases

The main aim of this chapter is to detect the impact of the regional knowledge base and its related variety to regional effects of cooperative behavior. This subsection deals with the quantification of the former.

Following recent literature on the learning economy, both dimensions of the regional knowledge base have a positive impact on the innovative success of the regional innovation system[3]. Thus, we assumed in our hypotheses that both dimensions affect positively the regional effects of cooperative behavior.

The cumulativeness or, in our terms, the size of regional knowledge, is measured in number of patent applications ($ln(App)$). According to the resource-based-view concept, knowledge is developed in a path dependent process (Combs & Ketchen 1999). Taking this into account, the amount of valuable knowledge available within a region is indicated by the innovative success of its actors in the former period $t-1$. To avoid influences of extreme values we use the natural logarithm of the number of patents. We are aware of the simplification we use to indicate the amount of the regional knowledge base. Although their later economics value will be very different, all patents are weighted equally.

[3]Breschi et al. (2003) use the terms *"cumulativeness and proximity"* for both dimensions. We consider these as equivalent to size and related variety of the regional knowledge base.

The second relevant dimension of knowledge affecting regional effects of co-operative behavior is the related variety of the knowledge base. In our analysis the actors can file for patents in 43 different technologies. To indicate how easily one regional actor can participate on the amount of regional knowledge, it is first necessary to analyze how related are these technologies in general and to apply this general relatedness to the knowledge available within a certain region. We use the Cosine index ($Cosine_t$) concept to evaluate the relatedness of the 43 technological fields. Therefore, we generate a 43x43 matrix including values of the relatedness of all technologies available using this concept at time $t-1$. This index measures the closeness ($cosine_{ij}$) among technological fields i and j which does not depend on the number of patents [4]. It measures the *angular separation between the vectors representing the co-occurrences of technological classes* App_i *and* App_k (Breschi et al. 2003, p.13).

$$Cosine_{ik} = \frac{\sum_{l=1}^{43} App_{il} * App_{kl}}{(\sqrt{\sum_{l=1}^{43} App_{il}^2})\sqrt{\sum_{l=1}^{43} App_{kl}^2}} \tag{5.1}$$

Typically, $Cosine_{ik}$ is a relatedness measure with a positive value and may be thought of as the strength of technological relationship between technologies i and k, or relatedness (Nesta 2005). Ronde & Hussler (2005) argue that a Cosine index value above 0.25 indicates a technological neighborhood of two technologies. The table in appendix C all cosine values are presented for the year 1999. Technological field 8 (Petroleum products) seems to be an essential chemical input for several other products, because it shows the highest average relatedness to other fields. Energy machinery (Field 20) and motor vehicles (41) show the highest relatedness (0.422) in comparison to all other possible combination of technologies.

After calculating the relatedness of technological fields in general, information about specific related variety of each regional knowledge base are required for testing our hypotheses. Therefore, in a first step the shares of all technologies on the whole regional endowments are calculated. Then, the product of the shares of technology i and k is multiplied with the general cosine value $Cosine_{ij}$. Finally, this product is added for all combinations for each region j for each time period t. These three steps are summarized in equation 5.2.

$$Cos_{jt} = \sum_{i=1}^{43}\sum_{k=1}^{43} Cosine_{ikt} * (\frac{Reg-Appl_{ijt} * Reg-Appl_{kjt}}{Reg-Appl_{jt}}) \tag{5.2}$$

[4]For a detailed description of this index, please see Breschi et al. (2003)

Each value of Cos_{jt} is strictly positive and the higher the more related the regional knowledge base in a certain region is.

In a final step, according to hypothesis H3, the amount ($ln(App)_{jt}$) and the indicator of the related variety of a region (Cos_{jt}) are combined through multiplication. The new variable QKB_{jt} indicates what we called the quality of the regional knowledge base, because it conjoins both dimensions of knowledge Breschi et al. (2003) have claimed as relevant with respect to the regional effects on cooperative innovation.

$$QKB_{jt} = ln(App)_{jt} * Cos_{jt} \tag{5.3}$$

5.3.4. Control variables

Population density (*Density*)
In order to account for agglomeration effects independently of patent activities we include the number of inhabitants per square kilometer as control variable. These data are taken from statistics of the German Federal Statistic Office. Starting in the early nineties of the last century, a vast quantity of empirical research has accumulated on the issue of agglomeration externalities (Raspe & van Oort 2006). A general statement in this body of literature is that agglomeration areas have an advantage for innovative success and economic growth in comparison the rural areas. This advantage is based on hard factors like a better infrastructure as well as on soft factors like an easier recruitment of external high-qualified employees (Acs 2002). Thus, we expect a positive relationship between the population density and the strength of the regional innovation system.

GDP per capita (*GDP*)
Over fifteen years after unification the former socialist parts of Germany are still lagging behind considerably in their economic potential, although large subsidies are still transferred from the western part of Germany (Roehl 2000). Fritsch & Mallok (2002) show that the way how existing physical capital stock is used differs between both parts of Germany. To account for the existence of two growth regimes (Fritsch 2004*b*) and to test for the presence of a catch-up process in Eastern Germany, we include the GDP per capita (*GDP*). As we will later on use dynamic panel data estimations a time invariant dummy variable would be a inappropriate indicator.

Dummy for dot-com bubble (*Dot − com − bubble*)
The "dot-com bubble" was a speculative bubble covering roughly 1995 − 2001 during which stock markets in Germany as well as in other countries of the Western hemisphere saw their value increase rapidly from growth in the new Internet sector and related fields. The period was marked by the founding (and, in many cases, spectacular failure) of a group of new internet-based companies commonly referred to as dot-coms. The bursting of the dot-com bubble in 2001 marked the beginning of a relatively mild yet rather lengthy early 2000s recession in the developed world. We account for this development on the stock market and at least in the whole economy by including a binary variable which has a value of 1 in the last period (2002 − 2003) and 0 otherwise.

5.3.5. Descriptive statistics

The strength of the regional innovation system indicated by RRI is in fact an indicator of the differences in the strength of the regional innovation system. Therefore, the RRI values fluctuate around 1 and the natural logarithm of this values around 0. The mean of RRI, which is shown in table 5.1, is slightly above 0 while the median is below 0. This implies that there are more extreme high values and relatively few extreme low values. More precisely, the majority of all regions are cooperating less than expected, but there are some regions with an extra-ordinary cooperative behavior.

The regional knowledge base is measured according its size ($ln(Pa)$) and related variety (Cos). There are patent applications in all regions in all time periods, the minimum number of patent applications is 11.33 in the fifth period (burst of the dot-com bubble) in the region of Altmark in Saxony-Anhalt (ROR 31). The most patent (6780) have been filed for in the third period in Stuttgart in Baden-Württemberg (ROR 72). The highest related variety (0.31) was calculated for the region Braunschweig in Lower Saxonia (ROR 22) in the fourth period. The regional knowledge base of Hochrhein-Bodensee (ROR 78) has the lowest related variety value (0.082) in the fifth period. The quality of the regional knowledge base variable (QKB) which is the product of $ln(Pa)$ and Cos shows the highest value (2.397) again in Braunschweig.

Berlin (ROR 30) has the most inhabitants per square kilometer (3889) and the region of Vorpommern in Mecklenburg-Western Pomerania (ROR 8) shows the lowest density value (49,925). The regions Hamburg (ROR 6) and Munich (ROR

Table 5.1.: Descriptive Statistics. Pooled Sample

Variable	Explanation	Obs	Mean	Median	Std. Dev.	Min	Max
ln(RRI)	The natural logarithm of the ratio between real and expected amount of regional cooperations which are measured in number of co-applications. The expected amount of regional cooperations is composed of the cooperation propensity per technological field in general and the patent application behavior of the regional actors.	485	0.01	-0.03	0.50	-2.28	1.61
ln(Pa)	The natural logarithm of the number of regional patent applications indicating the amount of valuable knowledge available within the region.	485	5.864	5.927	1.107	2.428	8.822
Cos	This variable indicates the related variety of knowledge available within a region. It is the sum of all products between the general relatedness between two technologies and the product of their shares of patent applications within a region.	485	0.118	0.109	0.033	0.082	0.31
QKB	This variable called "knowledge base" is the product of cos and ln(Pa)	485	0.699	0.635	0.272	0.37	2.397
Density	The number of inhabitants per square kilometer. (rounded values	485	328	179	492	49	3889
GDP	The Gross domestic product measured in mio. Euro per inhabitant.	485	22.5	22.3	5.4	9.0	44.9
$Dot - com$ *bubble*	Dummy variable for the last period	485	0.2	0	0.401	0	1

93) have the highest GDP per capita over time. The lowest value (8,918) was measured for Eastern Thuringia (ROR 56). There exists a East - West divide as well as, but with exception like Hamburg, a North - South divide in our data. The gap of the East-West divide is getting smaller over time, but is still tremendous in the last period. The third control variable $Dot - com - bubble$ is only included for the sake of completeness.

5.4. Empirical tests

The hypotheses made in section 2 will be tested with the data base introduced in the former section. There, it was already mentioned that it is a panel data set which implies specific requirements to the used estimation models. Innovation development in general is a dynamic process, so we have to take time lags between dependent and independent variables into account. We assume that the actor's decisions are made with the knowledge of features from the last period. Thus, the RRI indicating the regional effects on cooperative innovation activities depends on regional characteristics of period $t-1$. To test for these relationships we are using a dynamic panel-data model based on Arellano & Bover (1995) and Blundell & Bond (1998). This model is based on Arellano & Bond (1991) who developed a Generalized Method of Moments estimator that treats the model as a system of equations, one for each time period. The equations differ only in their instrument/moment condition sets. The predetermined and endogenous variables in first differences are instrumented with suitable lags of their own levels. Blundell & Bond (1998) show that the widely used linear generalized method of moments (GMM) estimator are biased on show poor precision for certain panel data structures. These distortions of the estimators occur for data sets where the autoregressive parameter is moderately large and the number of time series observations is moderately small (Blundell & Bond 1998, p.115). They propose an extended linear GMM estimator that uses lagged differences as instruments for equations in levels, in addition to lagged levels as instruments for equations in first differences according to Arellano & Bover (1995). This estimator show for panel data sets with 100 observations and 4 time periods a dramatic improvement on the performance of the usual first-difference GMM estimator. The data set used in this chapter include 97 observations over five periods. Therefore, we have to test first a test for serial correlation to decide about an appropriate estimator to test our hypotheses. We use a method described by Wooldrige (2002) which performs a Wald test of the null hypothesis of no serial the residuals from the regression of the first-differenced variables should have an autocorrelation of -.5. This null hypothesis for RRI can be rejected with an error probability of 0.008, so we conclude that the variable indicating the strength of a regional innovation system follows a path in its development. Thus, we apply a so called Arellano-Bover/Blundell-Bond linear dynamic panel-data estimation which is a system estimator that uses additional moment conditions based on the work of Blundell & Bond (1998).

The system GMM estimation are presented in table 5.2. To test the validity of the instruments we apply a Sargan test for each estimation which tests for overidentifying restrictions. The hypothesis being tested with the Sargan test is that the instrumental variables are uncorrelated to some set of residuals, and therefore they are acceptable, healthy, instruments. If the null hypothesis is confirmed statistically (that is, not rejected), the instruments pass the test; they are valid by this criterion. This requirement is fulfilled for all five system GMM estimations. A second test we run to show the structure and quality of our models we run Arellano-Bond tests for serial correlation in the first-differenced residuals. The moment conditions of these GMM estimators are valid only if there is no serial correlation in the idiosyncratic errors (Arellano & Bond 1991). Because the first difference of white noise is necessarily autocorrelated, we need only concern ourselves with second and higher autocorrelation. The high p-values for the AR(2) in table 5.2 suggest that there are no problems of AR(2) errors in our estimation models.

Table 5.2.: Estimation results

model	M1	M2	M3	M4	M5	M6
	System GMM	System GMM	System GMM	System GMM	System GMM	OLS
dep. Variable	$ln(RRI)$	$ln(RRI)$	$ln(RRI)$	$ln(RRI)$	$ln(RRI)$	$ln(RRI)$
$ln(RRI)_{t-1}$	0.148**	0.128*	0.140**	0.155**	0.155**	
	(0.021)	(0.054)	(0.043)	(0.029)	(0.033)	
$ln(Pa)_{t-1}$			0.122			
			(0.49)			
Cos_{t-1}				9.012**		
				(0.029)		
Cos^2_{t-1}				-24.85*		
				(0.067)		
QKB_{t-1}					1.319*	-0.067
					(0.053)	(0.914)
QKB^2_{t-1}					-0.521**	-0.022
					(0.037)	(0.918)
$density_t$		-0.001*	-0.001*	-0.001*	-0.001**	-0.003
		(0.068)	(0.070)	(0.057)	(0.025)	(0.114)
GDP_t		0.015	-0.004	-0.007	0.001	0.001
		(0.23)	(0.89)	(0.65)	(0.97)	(0.76)
D_2002		0.046	0.061	0.063	0.062	0.061
		(0.38)	(0.29)	(0.25)	(0.25)	(0.28)
Intercept						0.664
						(0.35)
			p - values			
Sargan test	0.223	0.268	0.311	0.504	0.442	
serial autocorrelation						
AR(1)	0.000	0.000	0.000	0.000	0.000	
AR(2)	0.833	0.921	0.891	0.881	0.810	
Observations	383	383	485	383	383	383
Number of ror	97	97	97	97	97	97

Robust z statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Our primary interest is to elucidate the nature of the statistical relationship between the regional knowledge base according to two dimensions and the interaction structure of the regional innovation system. More precisely, we want to know whether the related variety of the knowledge base affects the strength of the regional interaction system.

An actor who is willing to cooperate has to offer valuable knowable by himself to become an attractive research partner, as we have show in an analysis on firm level basis (Cantner & Meder 2007). Transferring this insight to a regional level, we assume that a large amount of valuable knowledge which is available within a region increases the incentives to cooperate of regional actors. This assumption is contributed by suggestions of the learning economy approach where innovative activities like cooperation in research and development are determined among other things by the cumulative base of knowledge (Lundvall 1992, Sharpe & Martinez-Fernandez 2006). Concerning this approach, an actor recognizes the potential external knowledge base in his surrounding and the more external knowledge is accessible, the more this actor is willing to participate in it. Analyzing this relationship we have to take into account a time lag between the knowledge base available in the region and the engagement within a research cooperation. Therefore, as already mentioned before, the regional effects of cooperation behavior ($ln(RRI)_t$) depends on the knowledge amount $ln(Pa)_{t-1}$, its related variety Cos_{t-1} and its regional knowledge base QKB_{t-1} of the former time period.

In table 5.2 we use system GMM estimator to test for the hypotheses H1, H2a, H2b and H3. The first regression model (M1) shows once more the endogeneity effects that are given for the dependent variable $ln(RRI)_t$. The lagged dependent variable $ln(RRI)_{t-1}$ has significant positive impact on the dependent variable. In the regression model the three control variables are included. The coefficients of *density* show a weak significant negative influence on the dependent variable. These results for all system GMM estimations do not contribute the literature dealing with agglomeration effects like Acs et al. (2002), Sorenson et al. (2006) or Bettencourt et al. (2007). Neither GDP nor the dummy variable for the last period show a significant influence on the strength of the regional innovation system variable. So we find no differences between East and West Germany (GDP) and no structural break for the last period.

The third regression model refers to hypothesis H1. Although the coefficient of the variable indicating the available regional knowledge $ln(Pa)$ has a positive sign, as it has no significant influence on regional effects of cooperative behavior we cannot reject the null hypothesis that there is no relationship between both variables for this data base. So we have to reject hypothesis H1 for our sample. This finding is contrary to results in other empirical studies like Fritsch & Franke (2004) or Asheim & Gertler (2004) and the theoretical statements made by the learning economy approach (e.g. Lundvall 2004, 2006). One possible explanation of this non-significance could be the mention by Jaffe (1986) and Griliches (1990) who suggest that such using count patent data as regional knowledge base is a too rough measure and therefore not appropriate. We try to find a more convenient measure of the regional knowledge base with including information about the related variety of the regional knowledge base.

So the main focus of this chapter is on the hypotheses H2a and H2b. The findings are embodied in the coefficients of Cos_{t-1} in the regression model M4 to test for hypothesis H1a and in the coefficients of Cos^2_{t-1} to test for the inverted-U relationship as assumed in hypothesis H2b. The coefficient of the linear cosine term is significant positive, so we can not reject hypothesis H2a for our sample. This finding contributes suggestions by studies dealing with the learning economy approach (Breschi et al. 2003, Lundvall 2004) as well as empirical studies on firm level (Mowery et al. 1998, Wuyts et al. 2005). In H2b we assume that the relationship between the related variety of the regional knowledge base and the strength of the regional innovation system is not a strict positive one as the negative effects of a too similar knowledge base can dominate the positive effects if the related variety indicator exceeds a certain threshold. To test for this, we include in model M4 a squared term for Cos called Cos^2. The inverted-U relationship which is assumed in hypothesis H2b is given in our data the linear term has to be positive and the squared term has to show a negative coefficient. The results for model M4 presented in table 5.2 show these assumed signs. So we cannot reject hypothesis H2b for our sample. This finding is in a line with existing empirical studies on firm level (Mowery et al. 1998, Wuyts et al. 2005, Cantner & Meder 2007). The alluded threshold from which on the relationship turns out to be negative is for our sample around 0.182. This threshold is exceeded by 8 regions in at least one period. The left graphic in figure 5.1 present this relationship without absolute term so that the values for $ln(RRI)$ are strictly positive but the maximum of the curve is not affected by this.

Finally, we follow in hypothesis H3 the argumentation of Breschi et al. (2003) that the combination of both dimensions of the regional knowledge base. Therefore, the product of $ln(Pa)$ and Cos representing the regional knowledge base (QKB) is introduced into the model in M5. As the linear term is positive and significant and the squared term has a negative significant coefficient, we cannot reject hypothesis H3 on the influence of the structure of the regional knowledge base on the strength of the regional innovation system. The relationship between the regional knowledge base variables (QKB and QKB^2) and $ln(RRI)$ is shown in the right graphic of figure 5.1. So we find evidences for the arguments Breschi et al. (2003) made about the importance of two dimensions of the regional knowledge base on the interaction structure.

Again, we find for the regional knowledge base an inverted-U influence on the strength of the regional innovation system ($ln(RRI)$). For our empirical model QKB has its maximum in 1.27, as it is shown in the right graphic of figure 5.1. As the mean (0.699) as well as the median value (0.635) of QKB are below this value, we can conclude that for the majority of our sample the positive influence of a

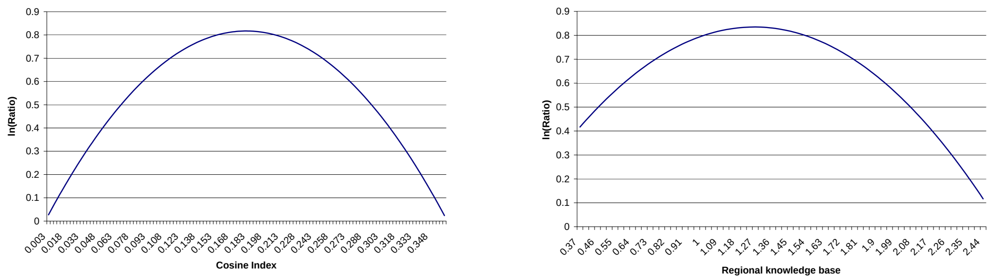


Figure 5.1.: Relationships between the related variety (left side) and the quality of the regional knowledge base (right) and strength of regional innovation system

larger and more related knowledge base on the strength of the regional innovation system is given.

5.5. Concluding remarks

This chapter contains an analytical and empirical exploration of the RIS approach. The main objective is to explore the effects of the regional knowledge base and its characteristics on the strength of the regional innovation system. Following the literature on system approaches, the increase of interactions as relations connecting the entities of a system is the principal goal of a regional innovation system. Based on the analysis of regional development in Germany, the following conclusion can be drawn with respect to the theoretical assumptions we state in three hypotheses:

1. For regional cooperative activities in terms of regional co-application, we find evidences for positive but not significant influence of the amount of knowledge present with the region.

2. Contrary, the related variety of the knowledge base indicated by a method based on the Cosine index concept does affect the strength of the regional innovation system significantly.

3. The combination of both indicators representing the overall regional knowledge base has an inverted-U influence on the strength of the regional innovation system.

As we are mainly interested in explaining the strength of the regional innovation system with the regional knowledge base available within the region, we combine theoretical and empirical results mainly of firm level analysis with the RIS approach. As knowledge is a factor affecting the competitiveness of firms and regions, we have to take into account the nature of knowledge and its development over time more seriously. With this German wide analysis we are going an unusual way of RIS analysis. As recent literature emphasizes the importance of institutions and regional specifities, factors which we have totally neglected in this study, it makes an objective analysis of more than a few regions quite difficult. So mainly empirical studies are concentrating on comparing a couple of preselected regions in order to cover regional institutions and specificizes (e.g. Sternberg 2000, Doloreux & Parto 2005, Asheim & Gertler 2004, Sharpe & Martinez-Fernandez 2006). We attempt to find evidence on a more abstract and general level. Of course, doing so we can not include many information that might explain the interaction within the regional innovation system in certain regions, as do results stemming from case studies.

Nevertheless, we have find general results from an economic point of view if the regional innovation systems approaches will be considered seriously. Beside the methodological improvements the general view is one main advantage of this chapter, at least in our opinion.

6. The dark and bright side of R&D cooperation

6.1. Introduction

Recently, cooperativeness has gained a wide attention in the literature.[1] By seeing cooperation as being mutually beneficial for the involved partners, it is widely claimed and empirically confirmed that cooperation play a significant role for firms' performance. In particular, their cooperation are crucial for research and development (R&D) activities (e.g. Oerleman & Meeus 2000, Hagedoorn 2002). While there are also studies pointing towards potential negative effects of cooperation resulting from, e.g., leakage of knowledge (Granovetter 1985), in general, cooperation are being viewed positively for firms' R&D success.

In the literature on regional innovativeness, cooperativeness takes a central position in the popular concepts 'innovative milieu' and 'regional innovation system' which are argued to characterize regions that are outstandingly innovative. These concepts emphasize that regional collective learning processes which can be realized via cooperation, can promote firms' innovative abilities (see, e.g., Allen 1983, Ronde & Hussler 2005).

Hence, in light of this it can be hypothesized that "*regional differences in cooperation behavior are to a considerable extent responsible for differences with regard to innovation activity, particularly the efficiency of R&D*" (Fritsch 2004*a*, p. 831). However, while there is qualitative evidence for a positive impact of cooperativeness on regions' innovativeness the quantitative empirical evidence for this is rather thin. For example, Broekel & Brenner (2007), contributing one of the few quantitative studies, finds no support for this hypotheses.

The present study adds to the literature by providing a quantitative empirical

[1] This chapter is based on Broekel & Meder (2008).

analysis of intra-regional and inter-regional cooperativeness' effects on regions' innovation performances. More precisely, an empirical investigation is conducted for the case of the Electrics / Electronics industry and 270 German labor market regions in the years 1999-2003. Moreover, in the study some of the challenges inherent to the empirical endeavor are discussed. These challenges result from the tight-knit of regions' endowment with factors relevant in firms' R&D activities and the level of intra- and inter-regional cooperativeness. With respect to this empirical problem, it is argued that a nonparametric frontier approach is particularly an helpful technique in the investigation of cooperativeness' impact on regional innovation performance.

The obtained results suggest that the relationship between intra-regional and inter-regional cooperativeness with regions' innovation performances are characterized by the existence of a 'bright' and a 'dark side'. It is shown that below a turning point both types of cooperativeness foster innovativeness while when this point is exceeded they yield negative effects. Moreover, we find that to a certain extent intra- and inter-regional cooperativeness are characterized by a complementary relationship. This gives some quantitative evidence for the existence of regional lock-in situations.

The chapter is organized as follows. Section 6.2 gives an overview of the literature on cooperativeness and its relation to firms' and regions' innovativeness. In Section 6.3 the empirical challenges as well as the methodology to overcome them are described. This is followed by a presentation of the employed data on intra- and inter-regional cooperativeness, regional factor endowment, and regional innovativeness in Section 6.4. The results of the empirical analyses are presented and discussed in Section 6.5. Section 6.6 concludes.

6.2. Theory

6.2.1. Cooperativeness and its effects on R&D activities

Interorganizational cooperation in the field of research and development (R&D) has been recognized as important in supplementing firms' internal innovative activities (Hagedoorn 2002) and to increase the probability of their innovative success (Oerleman & Meeus 2000). There is a clear conclusion in recent literature that firms improve their innovative capabilities by developing collaborative

R&D projects (Faems et al. 2005).

The ways how these cooperation affect the effectiveness and efficiency of the development of new products and processes are manifold. First, cooperation between firms or between firms and non-profit actors can reduce R&D costs for the involved actors (Hagedoorn 2002). For example, the achieved sharing of risk can reduce the uncertainty firms associate with these projects (Cassiman & Veugelers 2002). This incentive to reduce costs by cooperating is mainly claimed in studies that are based on the transaction-cost theory. In this manner, e.g. Kogut (1988) explains why this particular mode of transaction is frequently chosen over alternatives like acquisitions or other governance mechanism.

Second, cooperation can be driven by the motive to get access to complementary knowledge and assets which are required for successful R&D projects (Teece 1986, Faems et al. 2005). Getting access to complementary knowledge concentrates on the direct results of a R&D cooperation or, more precisely, on the probability of success of this cooperation project (Belderbos et al. 2004). This argumentation is contributed by the concept of the resource-based view of the firm in which a firm is seen as a bundle of strategic resources that are hard to imitate (Wernerfelt 1984, Barney 1991). Within this concept, Das & Teng (2000) show that the inducement of R&D cooperation is influenced by the mobility, imitability, and substitutability of internal resources. Moreover, the cooperation structure is selected on the basis of whether resources are property based or knowledge based.

The third incentive to engage in collaborative R&D projects is to encourage the transfer of knowledge (Ahuja 2000, Eisenhardt & Schoonhoven 1996). This motive is somehow related to the second one but it is stronger concentrated on long-term learning effects (Ahuja 2000). The access to an external knowledge base does not only improve the success probability of a single R&D project, it can also improves the efficiency of internal R&D efforts.

Several studies have documented additionally that economic actors can not fully appropriate the benefits of their innovations. Knowledge tends to spill-over and "flows" between actors. Empirical evidence for the importance of these flows for firms' innovativeness at the firm level has been found by, e.g. Jaffe (1986), Cassiman & Veugelers (2002). Collaborative R&D projects are one channel to internalize these knowledge flows (Cassiman & Veugelers 2002). In line with this

D'Aspremont & Jacquemin (1988) show that imperfect appropriability increases the incentives to engage in a collaborative R&D project. However, Cohen & Levinthal (1990) point out that the extent to which firms R&D activities can profit from these knowledge spill-overs depends on their internal "absorptive capacities". Later empirical studies highlight that technological proximity between actors takes effect on their ability to internalize knowledge spill-overs as well (Mowery et al. 1998, Sorenson et al. 2005). Hereby, the cooperation probability is larger in case of that firms are technological neighbors (Wuyts et al. 2005, Cantner & Meder 2007).

The observation that cooperation has a considerable potential to contribute to innovation strategies of firms does not imply that such voluntary agreements are always successful though (Faems et al. 2005). On the one hand, imperfect appropriability of knowledge increases the benefits from collaborative R&D projects as described above. On the other hand, it enlarges however the incentives to free ride on the cooperation partners' R&D efforts (Kesteloot & Veugelers 1995). In addition, it enhances the possibility for free-riding by outsiders of the cooperation (Cassiman & Veugelers 2002). This can cause the estimated failure rate of collaborative agreements of about 60 percent (Bleeke & Ernst 1993). Other reasons for failure can be *'learning races between the partners[...], diverging opinions on intended benefits [...] and a lack of flexibility and adaptability"* (Faems et al. 2005, p.240).

Hence, the benefits that cooperation brings about are not guaranteed and whether they are realized depends strongly on whether the cooperation partners fit to each other in terms of complementarity of resources, aims, and working routines. Or in other words, it can be doubted whether the resource allocation resulting from actors' cooperation activities are always superior, in terms of innovation performance, to the case the case that no cooperation are established. In particular, (regional) biases in the actors' search for cooperation partners can result in the establishment of inferior solutions (Broekel & Binder 2007). Furthermore, the situation of a (regional) lock-in resulting in a lack of fresh ideas (Grabher 1993), or certain policy activities that allocate factors according to, e.g lobbying activities, can prevent actors from choosing their cooperation partners such that innovativeness is maximized.

Despite this potential existence of a 'dark side' of cooperativeness for innovation activities, there is a large body of studies provide evidence that collaborative R&D has a positive impact on the innovative performance of firms (Deeds & Hill 1996, Baum et al. 2000, Oerleman & Meeus 2000, Boschma & ter Wal 2005).

6.2.2. Cooperation & R&D processes in a regional context

In the literature on regional innovativeness it is argued that firms' innovation performances depend upon others on their embeddedness into their geographical surroundings. This implies that inter-regional differences in the levels of actors' regional embeddedness can explain some variance in regional innovativeness.[2]

This embeddedness of firms into a regional context is in particular the focus of concepts such as the 'innovative milieu' (Camagni 1991) and 'regional innovation system' Cooke (1992, 2001). These concepts promoted the view that (some) regions can be seen as systems of innovative actors. These systems consist of a set of actors or entities (e.g., firms, universities) that interact in the creation, use, and diffusion of innovative solutions (Carlsson et al. 2002). In contrast to concepts of technological innovation systems, these territorial systems' boundaries are defined in a spatial dimension (Malerba 2005).

Different levels of firms' regional embeddedness show as differences in their interactivity with other regional actors. In these concepts it is argued that variations in the regional levels of interactivity cause innovativeness to differ between regions. In other words, it is claimed that firms' (and by this regions') innovativeness can be fostered by, e.g. "*regular and strong internal interaction*" (Kostiainen 2002, p. 80), or "*through synergetic and collective learning processes*" (Camagni 1991, p. 3) that take place among actors located within the same region. It has been pointed out before, one important way how actors can interact is to cooperate.

The pronounced role of intra-regional interactivity is argued to result from that geographic proximity in general, and regional proximity in particular, "*promote information transfer and spill-overs that lower the costs and reduce the risks associated with innovation*" (Feldman & Florida 1994, p. 214). With respect to cooperation, regional proximity tends to increase the chances that actors will engage in a cooperative activities. Involved costs can additionally be lower and

[2]Regional innovativeness is to be understood as the aggregated innovativeness of the actors located within a region.

the rate of success is likely to be higher compared to cooperations between more distant partners.

Beside theoretical contributions qualitative evidence is also provided that if specific patterns of cooperative behavior are shared by a number of regional actors, their region is likely to be successful with respect to innovativeness and economic performance (see, e.g., Storper & Venables 2003). However, the theoretical conceptions as well as the qualitative evidence are difficult to be generalized because of a number of problems.

A cooperation attitude that is (too) strongly focused on regional actors can lead to a lock-in situations as for the Ruhr-Area described in (Grabher 1993). In such situations geographically concentrated clusters can become insular, inward looking systems. Such can occur not only in resource-based, mono-industry areas like the Ruhr-Area, but also in case of inflexible modern industrial districts such as the offshore engineering (Isaksen 2004). Certainly, such a pattern is likely to go along with a comparatively low innovation performance.

Furthermore, Broekel & Binder (2007) emphasize that R&D employees' search for knowledge is likely to be biased towards regional knowledge sources. This can even be the case if the resulting cooperation solutions delivers inferior results. This 'regional bias' can be caused, among others, by frequent (unintended) confrontation with other regional actors. In addition, a strong dedication towards regional networks may give rise to such patterns. Over time this leads to higher familiarity with these actors that makes them, independently of their actual value for the project, more likely to be chosen as cooperation partners. Hence, a strong orientation towards regional actors that goes along with low inter-regional cooperativeness can result in a lack of fresh ideas from outside the region. Eventually, this reduces a region's innovation performance, despite a comparatively high level of intra-regional cooperativeness.

While the above mentioned concepts mainly highlight the 'bright side' of cooperativeness for regional innovation performance, there are good theoretical reasons that suggest the existence of a 'dark side' as well. This has however found little attention in the literature so far.

Most likely the 'bright' as well as the 'dark side' play a role for regional innovativeness. On the one hand there is the danger of a becoming (regionally) locked-in. On the other hand, if the advantages of geographic proximity are relevant, not to cooperate intra-regionally reduces firms' innovation performance compared to firms' that engage in cooperations with proximate actors. Thus, it needs intra- as well as inter-regional cooperations for firms' to be successful in their innovative activities (Owen-Smith & Powell 2004). Bathelt et al. (2002) even suggests in this context that both types of cooperation are mutually reinforcing.

In addition, to the possibility of a dark side to cooperativeness, the proclaimed advantages of geographic proximity are not as clear cut as they are often argued to be. There exist some studies that find spill-overs to be localized (see, e.g., Griliches 1992). However, for example, Jaffe et al. (1993) do not find that proximity to public research institutions promotes collaboration between firms and public research, nor does it increases the levels of received knowledge spill-overs. Hence, it is still largely unclear whether geographic proximity fosters cooperativeness.

From an empirical point of view additional problems exits. Bathelt et al. (2002) argue that learning processes themselves are not observable and that the pure agglomeration of innovative successful firms *"...seems to be assumed to signify localized learning."* (p.14). There are also few studies that include explicit regional cooperativeness measures which is likely to be caused by the limited data availability approximating cooperative behavior. One of the few studies that takes a broader quantitative approach is the study by Fritsch (2004*a*). Using firm-level data for eleven European regions he finds though "*no support for the suggestion that cooperation or a relatively pronounced cooperative attitude in a region is conducive to innovation activity*" (Fritsch 2004*a*, p. 844).

While there is little quantitative evidence supporting the theoretical arguments for a positive impact of cooperativeness on regional innovativeness, the supportive qualitative findings account for a limited number of regions. In addition they seem to be selected rather arbitrarily. *"The concept of innovation as a partly territorial phenomenon is, to a great extent, based on the successes of some specialized industrial agglomerations or regionally concentrated networks"* (Doloreux & Parto 2005, p.135).

Summarizing, while there are theoretical reasons as well as qualitative evidence for why inter-regional differences in intra- and inter-regional cooperativeness take effect on regions' innovation performance, the "*[t]he empirical picture of the regional dimension of R&D activity and cooperation behavior is still largely unclear*" (Fritsch 2004*a*, p. 831).

The present chapter contributes to the literature in a number of ways. First, it is tested simultaneously whether intra- as well as inter-regional cooperation agreements influence the innovative behavior of firms on a regional level. Second, evaluated the existence of positive as well as negative effects of either type of cooperativeness for innovativeness. Third, a quantitative approach is chosen using data on 270 German labor market regions and the Electric & Electronics industry.

Before the methodology is introduced it will be discussed that the endeavor of empirically identifying an influence of cooperativeness on regions' innovation performance in a quantitative setting is a challenging task..

6.3. Method

6.3.1. An empirical challenge

The difficulty in quantitatively analyzing the effect of cooperativeness on regional innovativeness arises from that there are two strongly inter-woven effects that can cause innovativeness to vary between regions.

First, because of the fact that innovation are outcome of economic efforts (see, e.g., Nelson & Winter 1982) a 'endowment effect' on innovativeness exists. This refers to the idea that the probability of innovative success will increase with the 'magnitude' of efforts invested into the corresponding R&D activities. Hereby, these efforts show as R&D staff, offices, laboratory equipment, venture capital, etc. As these efforts cove a wide range of different things, they are referred as *input factors* in the following. In the context of innovation processes the exact definition of these input factors is rather difficult and will be discussed at the end of this chapter. At this point, the input factors are defined as:

> *all elements that are necessary for the innovation process to be conducted, except those elements that regard the organizational structure of these processes.*

Second, the mere existence of input factors is not a sufficient condition for them being actually utilized in R&D processes. Input factors are scattered and held by various actors that are part of different organizations in diverse geographic locations. This scattering of the input factors is likely to increase with growing division of labor and specialization. Hence, R&D processes are largely about searching for, accessing of, and absorbing these input factors (resources) (see, e.g., Nelson & Winter 1982). Or put differently, the input factors can be organized in different ways for them to become utilized in R&D activities. The organizational structure of the input factors determines the performance of R&D employees to create innovative solutions to technological problems. Hence, we may refer to them as:

> *the organization of input factors which determines the efforts that need to be made in order to utilize input factors in R&D activities. Most importantly, this regards the set-up of formal and informal institutions, actors' attitudes towards sharing resources, the actors' know-who, and know-where, etc.*

This is to say that regions' differ not only with respect to their input factor endowment, but also with respect to the organization of these factors. The effect of the inter-regional variance in this organization of input factors is denoted as *organizational effect* in the following. In light of the previous discussion, it is clear that cooperativeness is part of this effect.

In order to get an empirical grip on cooperativeness' influence on innovativeness both effects have to be separated in a regional context. That is, when the parts of the organizational effect, e.g. cooperativeness, are to be analyzed it has to be controlled for the endowment effect. This is however problematic because both effects in combination not only influence firms' R&D activities, they are also strongly inter-woven with each other. On the one hand, the existence of input factors can depend on organizational aspects. For example, certain organizational set ups may raise the attractiveness of a region. Eventually, other firms or organizations will (re-) located their facilities to these regions and increase the resource endowment in the region. As argued before, because of the endowment effect, this tends to raise the number of innovations generated in this region.

On the other hand, the organizational set up in general, and cooperativeness in particular, depend also on the input factors available in a region. This is highlighted by, e.g. Isaksen (2001) who argues that "*[i]n many areas a regional innovation system does not exist due to lack of relevant actors (i.e. organization* *'thinness')*" (p. 109). As regional innovation systems are characterized by strong interactions among the regional actors (Kostiainen 2002), this illustrates nicely that in order to interact (cooperate) it needs at least other actors that are attractive for interaction (cooperation). However, the input factor endowment does not alone determine the organizational set-up because "*geographical proximity only creates a potential for interaction, without necessarily leading to dense local relations*" (Isaksen 2001, p. 110). Hence, besides the input factor endowment there are factors that influence regions' organization of input factors.[3]

Furthermore, lacking regional input factors firms are forced to expand their geographic search for cooperation partners to more distant locations (see, e.g., Mayer-Krahmer 1985). This suggests that to some extent firms' inter-regional cooperativeness depends upon the existing resource endowment in the region they are located.

This inter-woveness represents a serious empirical challenge. In quantitative empirical assessments variables that are thought to approximate the input factor endowment effect, in fact, explain also parts of the organizational effect. For example, a university (e.g. approximated by its graduates) does not only represent the potential benefit that closely located firms gain from its resources, e.g. by hiring graduates, renting laboratories, or out-sourcing parts of their R&D activities. In addition, a university can change the structure of regional networks, for example by functioning as gatekeeper (Cantner & Graf 2006) and by serving as cooperation partner itself. Hence, it can also have strong effects on the cooperativeness level in the region. Too a considerable extent, this can result from the attitude of its employees, i.e. its effect is independent of it's endowment with resources.

In order to disentangle this in an ordinary regression framework, interaction terms, non-linearities, etc. have to be (explicitly) modeled. Furthermore, multicollinearity will certainly be a problem. We therefore refrain from apply a regression approach and instead propose an alternative, but elegant, empirical approach which consists of two parts.

First, we define cooperative measures independent of the firms' technological

[3]In this chapter we concentrate only on regional actors' cooperativeness as one of the many factors that can have an influence in this respect. However, other factors, such as institutional settings, the existence of externalities, certainly play a role as well.

opportunities to cooperate intra- and inter-regionally. Or in other words, the used cooperativeness measures reflect the degrees to which regional firms' intra- and inter-regional cooperativeness depart from what could be expected given their region's specific technological profile. This will be explained in detail in section 6.4.3.

Second, for the estimation of the regional innovation performance as well as for the effect of cooperativeness we make use of a performance approach. It will be shown that it nicely solves the problem of dealing with the inter-woveness of endowment and organizational effect.

6.3.2. Nonparametric frontier analysis

Following Broekel (2008) we employ the non-convex order-m frontier approach introduced by Cazals et al. (2002) in order to estimate the regions' innovation performances. In addition, the *conditional* order-m analysis developed by Daraio & Simar (2005 a,b) and extended to a multivariate scenario in Daraio & Simar (2007) is used for estimating the influence of the cooperativeness measures on innovation performance.[4]

In comparison to traditional regression analyses the chosen approach has a number of methodological advantages for analyzing R&D systems that result from its character as nonparametric frontier analysis.[5] However, here, it is of greater importance that the method allows to disentangle the inter-woveness of endowment and organizational effect. In particular, as it allows to compare the organizational effect inter-regionally without the need to explicitly model it's inter-woveness with the endowment.

The idea behind the proposed performance approach is that a region's innovation performance is evaluated with respect to the performance of other regions. Hereby, the regions' input factors - innovativeness relations are compared on the basis of the principle of *weak dominance*: if a region shows a lower level in the

[4]For an extensive treatment of the methodology see Daraio & Simar (2007). Detailed discussions about the applicability as well as the advantages of nonparametric performance analyses in the context of (regional) innovation research can be found in Bonaccorsi & Daraio (2007) as well as in Broekel (2008).

[5]Most importantly, there is no need to specify ex-ante a functional relationship between the input factor and innovativeness space, and multiple input factors and innovativeness measures scenarios can easily be handled. Further, no universal production function is assumed. The production frontiers are non-convex and can differ between regions.

input factor vector and higher level in the innovativeness vector (if multiple innovativeness measures are used) a higher performance is assigned to it.[6] In case of that according to this comparison, a region is not weakly dominated by another it serves as benchmarking region, i.e. becomes part of the performance frontier and is declared well-performing. Regions that are weakly dominated by such *best-practice* regions are declared less-performing. In this chapter, their degree of less-performance is estimated as the vertical distance between a less-performing region and the *best-practice* region found on the frontier that has at maximum the same level of input factor endowment.[7] Because of the comparison the obtained performances are 'relative' (relative to the group of reference regions) performance measures.

A performance frontier estimated on this basis is likely to be shaped by outliers and noise in the data. Cazals et al. (2002) suggest therefore to compare a region not to the complete population of regions, but rather to a randomly drawn sub-sample. Thus, only a sub-sample of the observations are enveloped and extreme values are likely to lie outside the frontier (Cazals et al. 2002). The sub-sample's size has to be specified by the researcher and is denoted by m, giving the name to the procedure.[8] Based on this frontier the evaluation of the region's innovation performance as well as the estimation of the performance score is done as described above.

However, what do performance measures estimated like this mean in the context of regional innovativeness? Given that the level of regional innovativeness is determined by the endowment and organizational effect we argue that the obtained performance measures reflect inter-regional differences in the latter. Since in this procedure regions with *similar* input factor endowment but different levels of innovativeness are compared, the effect of different input factor endowments are excluded from the results, the obtained performance measure represents differences in the organizational effect. Hence, the simple idea of comparing regions with similar input factor endowment solves elegantly the interrelatedness problem. However, we do not obtain measures for the actual magnitude of the

[6]Following (Bonaccorsi & Daraio 2007) we add 0.001 to the input factors as well as innovativeness values. This avoids distortion in the estimation but does not influence the results.

[7]Following Broekel & Brenner (2007) an output-oriented type of analysis is applied. For an introduction into performance analyses see also Daraio & Simar (2007).

[8]We follow Bonaccorsi et al. (2005) in setting the level of robustness to below ten percent, i.e. ten percent of the units are outside the frontier. Given 258 valid observations this is true for $m = 70$.

organizational effect on firms' R&D activities. Instead, a measure is estimated that accounts for the *difference* in the organizational effect between regions. This means that we do not obtain information about the extent of cooperativeness influences' on regional innovativeness: The obtained measures reflects how its variance causes regional innovativeness to differ between regions.

In order to analyze the impact of variables (denoted as 'external factors' in the following) on this kind of performance measure, Daraio & Simar (2005 a) suggest the estimation of two different measures. The first, the *unconditional* performance measure, is calculated as described above: regions are evaluated with respect to a randomly drawn sub-sample of other regions which are characterized by equal or lower levels of input factor endowment.

The second measure, the *conditional* performance measure, is estimated similarly to the unconditional one, in this case the sub-sample of regions used for the comparison is not drawn randomly. Instead, it is drawn conditional on the values (density) of a number of external factors.[9] The conditional drawing is done in a way that the sample of regions by which a region's performance is evaluated is positively biased towards those regions with similar values in the external factors. In other words, the likelihood that a region is part of another region's comparison group, depends among others negatively on the difference between the values of the regions' external factors.

Further, the ratios between the conditional and unconditional performance measures Q_z are set into relation with the regions' values in the external factors. From this relation inference can be made on the effects of the external factors on the regional innovation performance. In a setting with two external factors, i.e. two external factors are analyzed at the same time, Daraio & Simar (2007) suggest to estimate three-dimensional regression plots showing the non-parametrically estimated surfaces of Q_z in dependence of the two external factors. In addition, non-parametric regressions are conducted showing the relation ship between each of the external factor on Q_z for each of the other external factors' first three quartiles.

From the shape of the surfaces and curves the following inference can be made.

[9] For the estimation of the probability we use the truncated gaussian kernel as well as the bandwidth selection method for multivariate cases given in Daraio & Simar (2007).

An increasing regression surface (curve) indicates a positive influence, while a decreasing curve (surface) hints at a negative impact.[10] In this chapter, intra-regional cooperativeness and inter-regional cooperativeness are defined as two external factors that effects on the innovation performance is to be analyzed.

For example, the case of a positive effect of intra-regional cooperativeness on regions' innovation performance shows as that regions characterized by lower levels of intra-regional cooperativeness are dominated in terms of innovativeness by regions with similar input factor endowment but comparably higher levels of intra-regional cooperativeness.

In this chapter the performances analyses are conducted separately for each year. However, the subsequent analyses of the influence of the two cooperativeness types are conducted on the basis of the pooled yearly performance measures. Hence, in the plots, and the estimated regressions, each region is represented as many times as years are considered.[11] The motivation for this is that by using the pooled ratios the impact of short term change (statistical noise) is reduced. Moreover, the robustness of the nonparametric regressions used to illustrate potential trends in the data increases.

From a methodological point of view such an endeavor is appropriate if the underlying mechanisms determining a region's innovation performance do not change significantly in the considered time period. The theories on intra- and inter-regional cooperativeness provide little reason for their levels to change systematically on a short term basis, see Section 6.2.1. Contrasting the theories, the two cooperativeness indices show however considerable variance between the years. In deed, from year to year they are weakly correlated, the correlation coefficients are in all cases smaller than 0.25.[12]. This indicates the presence of short term noise in their empirical estimation. In this chapter the interest is however on the general influence of the two types of cooperativeness on regional innovation performance. Hence, the influence of this "noise" needs to be minimized which justifies this procedure.

[10]See for an extensive presentation of this method Daraio & Simar (2007).

[11]In this chapter this corresponds to four times because the performances are estimated for the years 1999-2002, see Section 6.4.

[12]Pearson's rank correlation coefficient is used.

6.3.3. The definition of the regional resource endowment

While this approach seems to be very conclusive it assumes that the regions' input factor endowment can be defined properly and (in an empirical assessment) correctly measured. The very nature of R&D processes makes the exact identification of a region's input factor endowment impossible though (see Broekel & Brenner 2005). For example, there may be regions in which the local university is an active intermediate in R&D processes. In other regions it can play a rather passive role. Should the university then be considered as a general input factor and be taken into account when evaluating regions' innovation performance?

The outcome of the performance analyses are however largely dependent on the definition of the considered input factor set. In this case do the obtained performance scores not only represent differences in the 'organizational effect'. In addition, they reflect the effects of omitted but relevant input factors.

Being aware of this dilemma, Broekel & Brenner (2005) argue that it is impossible to set up an 'optimal' or 'correct' performance analysis that would fit every region's particular situation. Instead they suggest to estimate different performance analyses using varying input factor sets and compare the obtained scores. "*... [D]ifferent approaches measure different things, and measuring innovation performance in different ways provides us with additional information about the causes of the different performances*" (Broekel & Brenner 2005, p. 12). We follow their approach and estimate two types of regional innovation performance measures.

In the first one the R&D employees of a single industry are defined as input factor endowment. In this setting the emphasize is on the endowment effect of firms internal resources invested into R&D activities (see Section 6.4 for the exact definition). It is denoted as *firm-oriented* analysis in the following.[13]

In the second analysis this input factor set is expanded by a number of firm external (regional) input factors which are frequently considered to be relevant in empirical regional innovativeness research. The setting takes up the idea of seeing regions' as systems of interactive actors. By taking additional regional characteristics into account, the evaluation of cooperativeness effects on the innovation performances accounts not only for firms' R&D efforts, but also for,

[13]Lacking firm-level data we are restricted to the use of regional data to model this situation.

e.g. the availability of skilled labor, cooperation partners (universities, science institutions), and financial capital. This analysis is denoted as *region-oriented* as it corresponds to a regional innovation system view.

For both settings the effects of the two cooperativeness measures are estimated as described before. By comparing the results of the two analyses two goals are achieved. First, the two analyses function as robustness checks whether the obtained results are driven by varying definitions of the considered input factor set. Second, this allows us to get additional insights on the impact of firm external input factors on the relation of cooperativeness and regions' innovation performances.

6.4. The employed data

6.4.1. Data on patent applications and R&D

The 270 German labor market regions are chosen as units of analysis, because they seem to fit best to the theoretical arguments of a regional dimension of innovation processes (see, e.g., Broekel & Brenner 2007).[14] As it is common in innovation research innovativeness is approximated by patent applications. The data on patent applications for the years 1999-2005 are published by the *Deutsches Patent- und Markenamt (German Patent Office)* in Greif & Schmiedl (2002) and Greif et al. (2006) (called *Patentatlas* in the following). The applications by public research institutes, e.g., universities and research societies (e.g. Max Planck Society) as well as the patent applications by private inventors are not included. The latter is because the corresponding R&D employment data covers only industrial R&D. Hence, only the patent applications of industrial R&D should be considered.

Data on R&D employees is obtained from the German labor market statistic. Following Bade (1987) the R&D personnel is defined as the sum of the occupational groups: agrarian engineers (032), engineers (60), physicists, chemists, mathematicians (61) and other natural scientists (883).

Conducting industry specific analyses requires definitions of industries that, in the context here, cover the input factor as well as the innovativeness measure side. In other words, the industries' R&D employees need to reflect those firms to

[14] We use the up-to-date definition of labor market regions in contrast to the older definition used in Greif & Schmiedl (2002) and Greif et al. (2006).

which the patent applications of the *Patentatlas* correspond. This is an important issue because in the *Patentatlas* the patent applications are classified according to 31 technological fields (TF). In contrast, the industry specific R&D employment is organized according to the German Industry Classification ('Deutsche Wirtschaftskzweig Klassifikation') which is the German equivalent to the international NACE classification. Thus, the technological fields classification in the *Patentatlas* as well as the German Industry Classification need to be matched.

We rely the concordance between these two classifications developed by Broekel (2007). The concordance defines five 'sectors' for which it is possible to assign a number of the *Patentaltas'* technological fields to a number of industries defined by the German Industry Classification (see for further details Broekel 2007).

In this chapter we concentrate on one industry, the Electrics & Electronics (ELEC). Its definition, i.e. the considered technological fields and NACE industries, are presented in table D.3. For this industry patenting represents an important property rights protection mechanism (Arundel & Kabla 1998). This ensures that the innovativeness measure captures most, or at least a significant share of, innovations in this industry.

In Broekel (2007) five technological fields are assigned to ELEC. This implies that the R&D employees apply for five technologically different types of patents. However, in this chapter the patent applications of the five technological fields are summed which results in a single innovativeness measure. This is motivated by the existence of a great number of zeros in most of these fields. While this is as such not a problem in the analyses, it reduces the number of potential reference regions, i.e. the number of regions a region can be compared with, see Section 6.3. Eventually this reduces the variance in the performance measures making the detection of an influence of cooperativeness statistically more difficult. Thus, the summing increases the analyses' explanatory power. This is however achieved at the costs of not taking into account the technological diversity on the innovativeness side.

According to Broekel (2007), ELEC's R&D employees are organized into three different two-digit (NACE) industries, DL31, DL32, DL30. In the case of DL30 147 out of 270 regions are characterized by zero values in 1999. Similar as in for the innovativeness measure this reduces the number of available reference regions, see above. We therefore add this industries R&D employees to that industry with which it is correlated the highest. In this case this is DL32 ($r = 0.72^{***}$).[15] This leaves 258 observations which show at least one positive value in one of the two R&D employment measures, DL31 and DL32_DL30 (sum of DL32 and DL30). The twelve observations with zero values in these two variables are excluded from the analyses as performance analyses with zero values in all input factors are improper.

As has already been mentioned above, in the firm-oriented analysis apart from firms' R&D employees no further regional input factors are considered. Therefore, the first analysis is conducted with a single innovativeness measure, the sum of patent applications of ELEC, and the two input factors DL31 and DL32_DL30. In addition, to this the region-oriented analysis takes additional regional input factors into account.

6.4.2. Regional Factor Endowment

For the choice of the additional regional input factors we follow the idea of the 'technological infrastructure' by Feldman & Florida (1994) which:

> "*consists of sources of knowledge: networks of firms that provide expertise and technical knowledge; concentrations or research and development (R&D) ... ; and business services*" (Feldman & Florida 1994, p.210-211).

Hence, in the *region-oriented* analysis additional input factors included that are firm external. Nevertheless, these input factors are likely to influence regions' innovativeness. We define a 'German regional technological infrastructure' to be consisting of input factors with purely intra-regional effects and factors with inter-regional effects. The first set of factors influencing firms' innovation activities need to be located in the same region in order to become effective. In contrast, the effects of inter-regional factors are to a lesser extent regionally bounded. In their case, firms might benefit from the presence of these factors in neighboring region.[16] In addition to firms' R&D employees that are already considered as input factors, eight firm-external input factors are included in the region-oriented

[15] Pearson's correlation coefficient is used.

[16] All variables are only briefly presented due to space limitations. A more detailed description and literature references of most of the employed variables can be found in Broekel & Brenner (2005).

analysis. They are summarized and their data sources are given in table D.4.

In order to account for urban agglomeration advantages the population density is employed (POP_DEN). The financial situation of the region as well at its economic activity is approximated by the gross domestic product (GDP) per capita.

Furthermore, the literature highlights the importance of business services (see, e.g., Feldman 1994) so that the variable SERVICE has been added. This represents the share of employees in industry KA74 (according to WZ03) on a region's total employment. In a common fashion we compute the influence of SERVICE by using the 'production structure specialization index' (PS) (see Feldman & Audretsch 1999). This index is however non-symmetric, i.e. in case of below average specialization the index takes values between zero and one, and in case of above average specialization its values range between one and infinity. This makes it "basically not comparable on both sides of unity" (Laursen 1998, p.3). Therefore, the index (PS) is made symmetric as proposed by Laursen (1998) in a different context by calculating $\frac{PS-1}{PS+1}+1$ (see for more details Broekel 2008). This index ranges from 0 to +2. One is added to it in order to keep some similarity to the traditional PS. Unity represents that there is no difference between a region's degree of specialization and the national average.

The potential impact of the share of employees with high qualifications (EMP_HIGH) is also considered because it is an often used measure for the quality of local human capital (Weibert 1999).

An industry specific variable (ELEC_PS) accounts for the specialization of a region with respect to ELEC. In a common fashion it is approximated by the PS of the employees of ELEC which is made symmetric as described above. It enters the analysis as variable ELEC_PS. In order to account for effects stemming from the absolute regional employment of ELEC (see Brenner 2004), we include it as EMPL_ELEC. Accounting for the effects of the presence of large firms in ELEC, the average firm size (SIZE) is considered as well.

These six input factors are argued to affect only firms located in the same region. In contrast, the regional input factors presented below are argued to be regionally less bounded. For example, this applies to university graduates that do not stay in the region where they obtained their degree (Mohr 2002) and hence other regions benefit from the educational efforts conducted in universities' host regions. However, in the statistics they are assigned only to these host regions. Following Broekel (2008) we use a distribution procedure to assign adequate shares of such inter-regionally 'mobile' resources to the regions in which they are potentially effective. The parameters of the hyperbolic function that 'distributes' the quantities across the regions are fitted by a maximum likelihood calculation, using geographic coordinates and population counts for 8.196 German five digit postal code areas as well as empirical findings from the literature on the mobility of graduates (see Legler et al. 2001, Mohr 2002).[17].

To control for size effects regarding a region's industry endowment, the distributed graduate counts enter the analysis as ratios of the region's total employment. For technological innovations in particular, graduates of engineering and natural science faculties of technical colleges and universities are of special interest. They enter the analysis in form of the variables GRAD_ENG and GRAD_NAT.

Similar to universities, public research institutes are important actors in innovation processes. Beise & Stahl (1999) show that a significant part of their influence operates inter-regionally. Furthermore, we argue that their effects on firms' innovativeness decreases with a growing distance. In order to approximate the influence of these institutes, the structural factor SCIENCE is constructed. It is defined as the sum of the number of employees working at different public research institutes in a region. Included are the 'big four' institutions in Germany: the *Helmholtz Association of German Research Centers*, the *Max Planck Society*, the *Fraunhofer Gesellschaft* and the *Leibnitz Association*.[18]

In line with the findings of Beise & Stahl (1999), we assume that the influence of the public research institutes decreases with growing geographic distance. Hence, they are distributed hyperbolically in an identical manner as the univer-

[17]Because the mobility data is available separately for the graduates of technical colleges and universities, we had to weight them with their shares in the total numbers and sum them for the analysis of each subject. Furthermore, note that the α values which determine the slope of the hyperbolic functions, are estimated by using the combined data for 1999/2000 because no year specific data on the mobility parameters are available. See Broekel (2008) for a more detailed description of this procedure.

[18]We only consider institutes that are active in technical, engineering, or natural science fields. For the Leibnitz-Association no data is available for 2001 and 2003. In this case data on the previous years are used. In case of the Helmholtz Association, data was only available for 2000 and 2003. Hence, the employment numbers in 1999, 2001 are approximated by that of 2000, and the year 2002 is approximated by 2003.

sities' graduates. The employees of these institutes are distributed via the same procedure as the graduates.[19] Table D.2 summarizes the distribution parameters. SCIENCE is also computed as a ratio of total employment to control for regions' industrial endowment.

It is one of the advantages of the nonparametric performance analysis to easily handle multiple input and output scenarios. In detail this means that the variables approximating the regional factor endowment are simply entered as additional input factors. However, in order to avoid including variables which are statistically redundant, i.e. highly correlated, we check the input factors with respect to their correlation structure. In case that two or more variables are correlated with $r = 0.8$ or above, the variables with less theoretical relevance are excluded.[20]

Applying this rule, seven variables enter the analysis as input factors: the two R&D employee variables (DL32_DL30 and DL31); average firm size (SIZE), gross domestic product (GDP), the share of highly qualified employees (EMP_HIGH), spatially distributed graduates of engineering faculties (GRAD_ENG), and the regions' specialization in business services (SERVICE). With respected to the excluded variables GDP is kept in favor of POP_DEN; DL31 for EMPL_ELEC; GRAD_ENG for GRAD_NAT and SCIENCE; SIZE for ELEC_PS. Tables D.6 and D.7 in the Appendix show the corresponding correlation coefficients and table D.5 summarizes the selection.

6.4.3. Two cooperativeness measures

This subsection gives a brief introduction into the construction of the the intra-regional and inter-regional cooperativeness measures that are characterized by the absence of technological effects .

The initial point is the notion that, according to two different literature streams in the field of innovation systems, the cooperative behavior of firms is affected by

[19] The relevant parameters for the distribution procedure are calculated on the basis of the findings of Beise & Stahl (1999).

[20] The threshold of $r = 0.8$ seems to be well fitting in this context because the number of variables is moderately but sufficiently reduced. In addition, more than eighty percent of an excluded variable's variance is still 'explained' by one variable included in the analysis. Robustness checks have been conducted showing that the results are not sensitive with respect to the inclusion of variables that are correlated with 0.8 or above with already considered variables.

technological as well as regional influences independently. Assuming that only these two have a relevant impact on cooperative behavior of firms[21], we have to control for technological effects when analyzing regional effects of cooperation behavior.

In this context we need information on the technological and regional distribution, as well as on the number of actors involved, for each innovation. This information is obtained from German patent data published in the German "Patentblatt". Hence, the cooperativeness measures correspond to the innovativeness measures in that they represent the same IPC classes assigned to this industry by Broekel (2007).[22]

The methodology includes three steps[23]. First, the cooperation propensity of each technology is calculated by the dividing the total number of cooperation by the total number of innovations within this technology. Cooperation in this respect is defined as an innovation which has been developed by more than one independent economic actor. This initial step accounts for sectoral pattern of innovative activities. The rate of innovation and the cooperation behavior differ among technologies due to *"... some invariant features of learning and knowledge accumulation"* (Malerba & Orsenigo 1997, p.83).

In a second step, the innovations are assigned to the regions of their inventors (inventor principle). This reflects the structure of regions' technological endowment. Next, an expected cooperation value is estimated. This is the number of cooperation that can be expected within a region according to its technological endowment in a certain technology. This expectation is calculated by the multiplication of the number of innovations in technology i (technological endowment) and the cooperation propensity of i which has been calculated in step one.

In the final step, for each region the number of expected cooperation is divided by the number of observed cooperation. The idea is that in the case of both, expected and observed, cooperation numbers being equal, this indicates that the regional actors' cooperation behavior is influenced by technological patterns alone. The core assumption of this calculation is the presence of technological pattern of

[21]Boschma (2005) provides a very good review on existing concepts of proximity.

[22]Note however, that the cooperativeness measures are constructed from patent data while the innovativeness measures are obtained from patent applications.

[23]This is a brief description of the *RRI* value concept that was introduced in chapter 4.

innovation activities as well as of cooperative behavior. The observable amount of cooperation within a region is related to these technological patterns and the residual of this relation is interpreted as "regional effects of cooperative behavior".

Employing German patent data Cantner & Meder (2008*c*) show that this measure differs significantly between German region which implies that regional effects of cooperation behavior exist and that they are not caused by technological pattern alone. Using this measure yields two advantages. First, it is independent of the data base. In this chapter patent data is used, but this method can be applied to any other data base on innovation activities which includes information about technology, spatial distribution and cooperation. Second, by construction, this indicator is independent of regions' size.

Regions in which no cooperation are observed, and given their technological profile, no cooperation can be expected, are treated the same as regions with no observed cooperation but for which positive levels of cooperativeness are expected. Empirically, both regions are indicated by zero values. We are expecting an influence of cooperativeness on regional innovation performance and, thus, regions lacking cooperativeness are expected to show lower performance levels independently of the reason for this lack.

Again the index is made symmetric by $\frac{I-1}{I+1}+1$. This allows an easier interpretation as well as more meaningful graphical representation. Hence, a value of one implies a level of cooperativeness that corresponds to what can be expected given the technological structure of the region. Lower values indicated cooperativeness below the expected level and values above one the opposite.

The intra-regional or inter-regional cooperativeness is constructed by that in case of the first cooperations are indicated by co-applications of independent actors where the listed inventors being located within the same region. In case of inter-regional cooperativeness, cooperations are indicated by the inventors being located in different German regions. The latter implies that in this chapter inter-regional cooperativeness refers to national cooperations only. International cooperation are not considered.

Because the cooperativeness measures are based on patent data as well we also consider a time lag of one year with the input factors. Hence, the cooperativeness measures and the innovativeness measures are constructed on the same years' data.

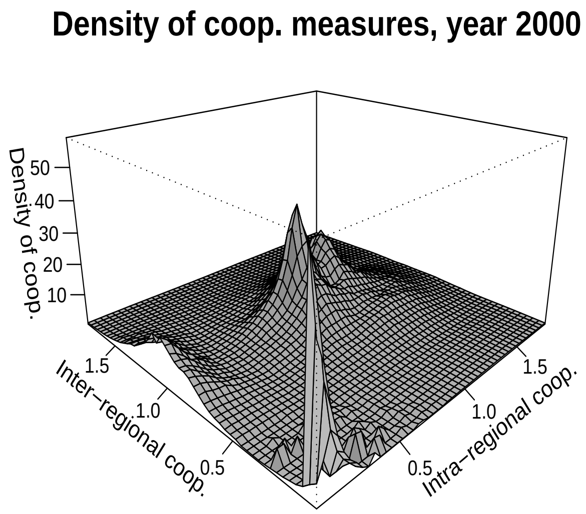


Figure 6.1.: Density plot of coop. measures

Surprisingly, intra- and inter-regional cooperativeness measures are only weakly correlated. Hence, there seems to be a difference in actors' cooperative attitude with respect other actors' geographic location. Furthermore, this is an indicator for differences in the strength of regional interaction structures.

Moreover, they also show weak correlations with the innovativeness measures. For the pooled data of 1999-2002, the correlation between the two cooperativeness measures and the numbers of patent applications in ELEC (PAT) is just $r = 0.29^{***}$ for $CoopIntra_{t-1}$ and $r = 0.08^{***}$ in the case of $CoopInter_{t-1}$. The correlation between the two measures is only $r = 0.01^{***}$. This is illustrated also in Fig. 6.1 and 6.2 showing the density of the two cooperativeness measures as well as the corresponding contour plot.[24] In addition, both measures' histograms are included in the Appendix, see top left graphs in Fig. D.1 and D.2.

The plots illustrate that the masses of observations are characterized by values around one in both cooperativeness measures. However, there is also a significant mass with zero values in both measures. In addition, a considerable number of

[24]For the estimating the density we used the truncated Gaussian kernel proposed by Daraio & Simar (2007).

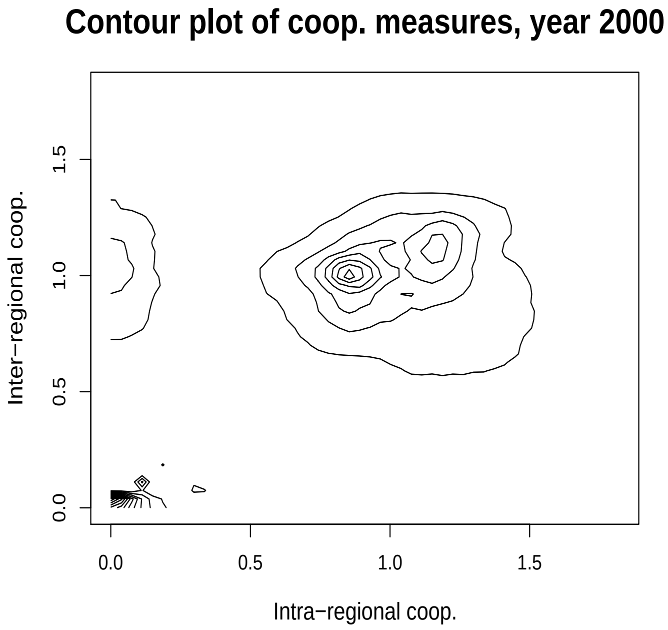


Figure 6.2.: Contour plot of coop. measures

observations shows close to zero or zero values in $CoopIntra_{t-1}$ and values of one or close to one, in $CoopInter_{t-1}$. Not surprisingly the latter ones are regions with comparatively low R&D employment in ELEC. Lacking regional alternatives, firms located in such regions need to cross regional boundaries in order to find cooperation partners.

It strikes furthermore that both measures show almost no correlation to the variables approximating the regions' input factor endowment, see table D.7 in the Appendix. Given the rather strong correlations between the input factors, this may indicates the following. As described above the cooperativeness measures are estimated such that it is controlled for the technological opportunities to interact existing in regions. Hence, controlling for the technological effects on cooperation behavior seems to account to a considerable extent for the non-technological regional characteristics. Or put differently, the cooperativeness measures are already taking parts of the endowment effect into account. Summarizing, the performance approach in combination with the specific cooperativeness measures seem to be sufficient for disentangling the endowment and organizational effect.

6.5. Results

6.5.1. Robustness and reliability

Before the results are presented and discussed in detail it is worthwhile to analyze their robustness and reliability. At this point, the employed performance analysis does not allow to estimate the significance of the relationship between cooperativeness and innovation performance, i.e. confidence intervals can not be calculated for Q_z. Hence, it is necessary to take a look at the numbers of observations backing the estimated relationships between the two cooperativeness measures and the regional innovation performance. The histograms for the two cooperativeness measures seem to be a natural choice in this manner. They can be found in the Appendix in the top left corner of Fig. D.1 and D.2. However, in order to get a more comprehensive picture, histograms for different sub-samples of the data have also been estimated. These sub-samples will also be used in the analysis of the relationship between cooperativeness and innovation performance, see below.

The sub-samples are defined the following: for each cooperativeness measure three sub-samples are drawn from the (over the years) pooled observations which consist of those observations that fall into the 1^{st}, 2^{nd}, and 3^{rd} quartile of the other cooperativeness measure. The idea behind it is to reduce the three-variate relationship between cooperativeness measures and performance measures to a bivariate one. This is achieved by analyzing separately those observations with 'similar' values, i.e. those that fall into a certain interval, in one cooperativeness measure. Here, 'similar' means that they fall into one of the quartiles of the other cooperativeness measure. Within this sub-sample, the remaining two dimensions can then be analyzed without the third dimension interfering (because it is held 'constant'). Hence, in addition to the cooperativeness measures' histograms, the histograms for each of the six sub-samples are shown as well, see Fig. D.1 and D.2. Please note again that the frequencies are based on the pooled observations of the four considered years.

What do these graphs tell us? With respect to CoopIntra, we find that the number of regions with zero values in this variable is in particular dominating in the sub-sample of CoopInter's first quartile. Nevertheless, about 44 percent of the observations are characterized by CoopIntra having positive values. In the case of CoopInter's third quartile, the share of positive observations increases to about 64 percent. Apart from the case of CoopIntra being zero, in particular the CoopIntra's interval of 0.5 and 1.5 seems to be backed by sufficiently large numbers of observations. In the case of CoopInter and CoopIntra's quartiles, similar patterns can be observed. However, here the share of observations with zero values in CoopInter that are located in the first quartile of CoopIntra is just about 31 percent. For the third quartile of CoopIntra it even decreases to 17 percent. Again, there are few observations with values of CoopInter lying in the intervals $]0, 0.5]$ and $]1.5, 2]$.

Summarizing, the histograms suggest to restrict results' interpretation to the ones which are based on the observations that are characterized by values between 0.5 and 1.5 in both Cooperativeness measures. In addition, we find the relationships between the cooperativeness measures and performance scores to be fairly robust with respect to small changes in the data.[25]

6.5.2. General results

The first impression of the results is that they confirm the main findings in the literature that cooperation play a role for R&D activities for the case of the Electrics & electronics industry. This is clearly shown in that the surfaces, representing the influence of the two types of cooperativeness on regions' innovation performances depart clearly from a flat horizontal plane, see in Fig. 6.3 (firm-oriented analysis) and 6.4 (region-oriented analysis).

Interestingly in both, firm-oriented and region-oriented, analyses the surfaces take the form of a bump, i.e. with increasing levels of cooperativeness the surfaces turn upwards. However, when exceeding a certain turning point their slope becomes negative.

In general do the results correspond nicely to the theoretical arguments presented before as we find evidence for a positive impact of cooperativeness, i.e. the 'bright' side of cooperativeness. However, by benefiting from the use nonparametric techniques we find also that high levels of cooperativeness are not per se a guarantor for outstanding innovativeness. To the contrary, when a certain

[25] Several robustness checks have been conducted showing the stability of the results. For example, it has been checked whether regions for which no influence of cooperativeness on the innovation performance is found (regions with identical unconditional and conditional performance scores) cause the observed patterns. This was done by conducting the regressions again and excluding these regions. However, the resulting relationship between cooperativeness and innovation performance did not change significantly.

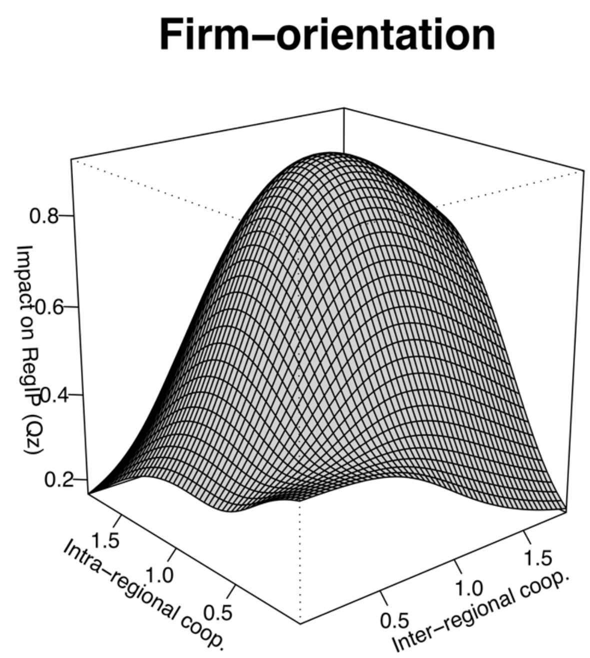


Figure 6.3.: Surface of Qz, Analysis 1

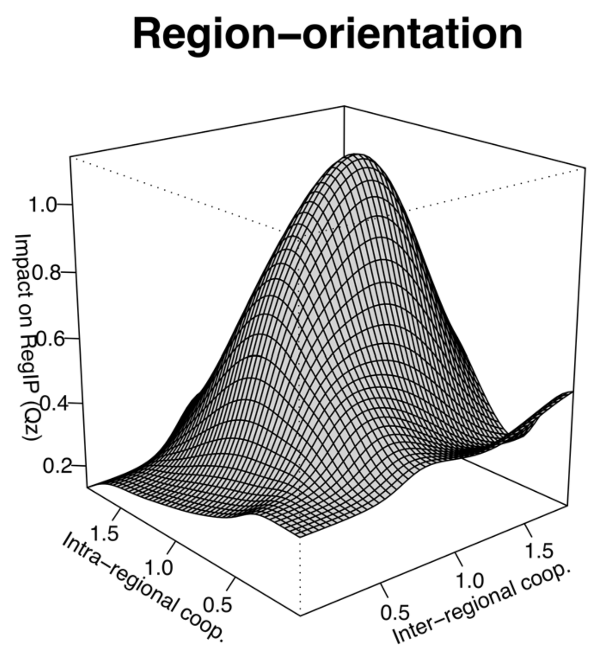


Figure 6.4.: Surface of Qz, Analysis 2

level of cooperativeness is exceeded the negative aspects of cooperation seem to outweigh the positive effects. Hence, the results are in line with the 'dark' side theory according to which too intensive engagements in cooperation can reduce the innovation performance.

	Min.	**Max.**	**Mean**	**Median**	**TP firm orient.***	**TP regional orient.***
$CoopIntra_{t-1}$	0.001	1.81	0.78	0.90	1.33	1.25
$CoopInter_{t-1}$	0.001	1.82	0.87	0.96	1.18	1.03
* According to the maximum value of surfaces of Q_z in Fig. 6.3 and 6.4.						

Table 6.1.: Descriptives of cooperativeness' impact

The turning point of cooperativeness' impact is interesting in itself. In case of $CoopIntra_{t-1}$ it is considerably larger than one, while in case of $CoopInter_{t-1}$ it is just somewhat larger than one, see table 6.1. As has been argued in Section 6.4.3 the cooperativeness measures indicate whether a region's actors cooperate more intensively with other, regional or non-regional, actors than what can be expected given the region's technological profile. Or put differently, it signals that the degree to which regional actors exploit their technological cooperation potential. With respect to the difference in the levels of intra- and inter-regional cooperativeness at the turning point it can be inferred that within a certain range the intra-regional cooperation potential can be exploited to a higher degree than the inter-regional cooperation potential without firms suffering from negative effects. In this case the advances of geographic proximity work in favor of intra-regional cooperation as they compensate some of the negative effects resulting from too much intra-regional cooperativeness. This leads to higher values for the turning point in case of $CoopIntra_{t-1}$.

A more detailed view at the results can be achieved by depicting the influence of each cooperativeness measure for the previously introduced sub-samples. Following Daraio & Simar (2007), hereby nonparametric smoothed regressions are estimated between Q_z and a cooperativeness measure for those observations which fall into the first three quartiles of the other cooperativeness measure. The resulting two-dimensional figures are represented as Fig. 6.5, 6.6, 6.7, and 6.8.[26] The dashed regression curve indicates the relationship of the considered coopera-

[26]Note that in the two-dimensional plots the turning points may depart from the one in the three-dimensional surface plot. However, the two-dimensional plots represent only helping illustrations.

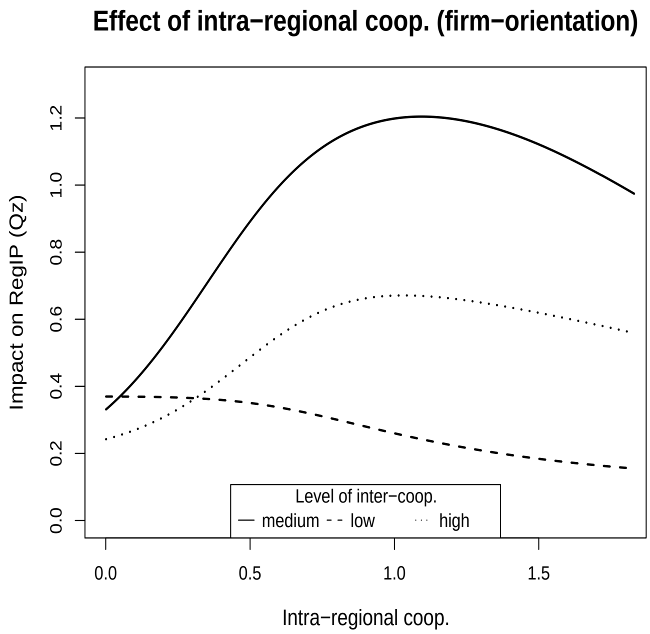


Figure 6.5.: Effect of intra-regional coop. for inter-regional coop. quartiles, Analysis 1

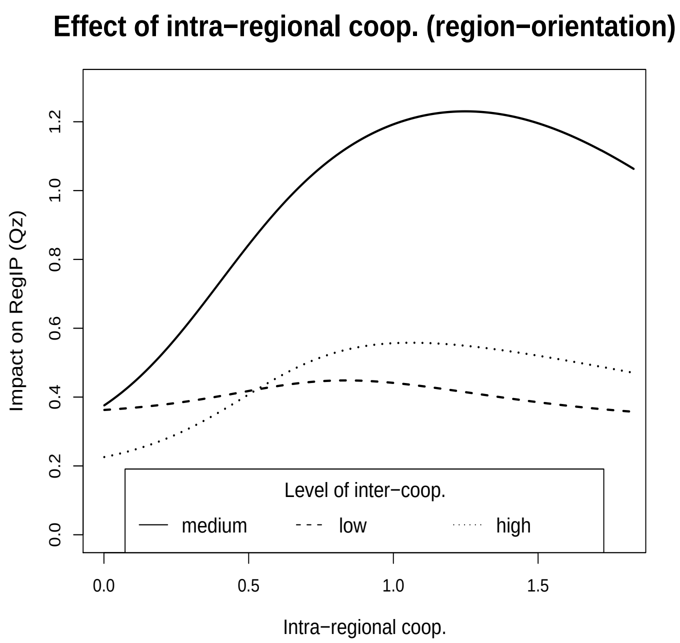


Figure 6.6.: Effect of intra-regional coop. for inter-regional coop. quartiles, Analysis 2

tiveness measure for the other's first quartile, the solid line for the second quartile (median) and the dotted line for the third quartile.

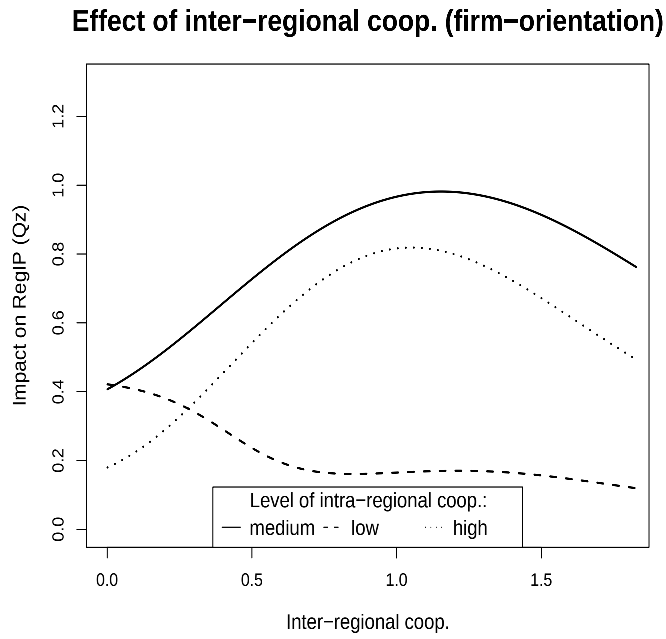


Figure 6.7.: Effect of inter-regional coop. for intra-regional coop. quartiles, Analysis 1

In the four figures the regression curves for the median and the third quartile show similar patterns. The regression curves for the first quartile, however, highlight a relationship that is difficult to be noticed when looking at the surfaces only. With the exception of the case of intra-regional cooperativeness and regional orientation (Fig. 6.6) which will be discussed later, the regression curves show a monotonic decreasing trend. This indicates that a sole orientation on intra- or inter-regional cooperation lowers the innovation performance. Or in other words, to a certain extent and below the turning point, intra- and inter-regional cooperativeness are complements which only in combination foster innovativeness.

The economic rationale behind this finding is that firms need to access specific resources from within as well as from outside the region. One might think of these as 'necessary cooperation'. These can be cooperation with close costumers or suppliers that cannot be substituted and hence have to exists irrespectively of their geographic location. If these necessary cooperation cannot be established the innovation performance cannot be raised. In fact, the performance even decreases when taking additional cooperation efforts of the cooperativeness type which is not underdeveloped. Because this is the case for both types of cooperativeness

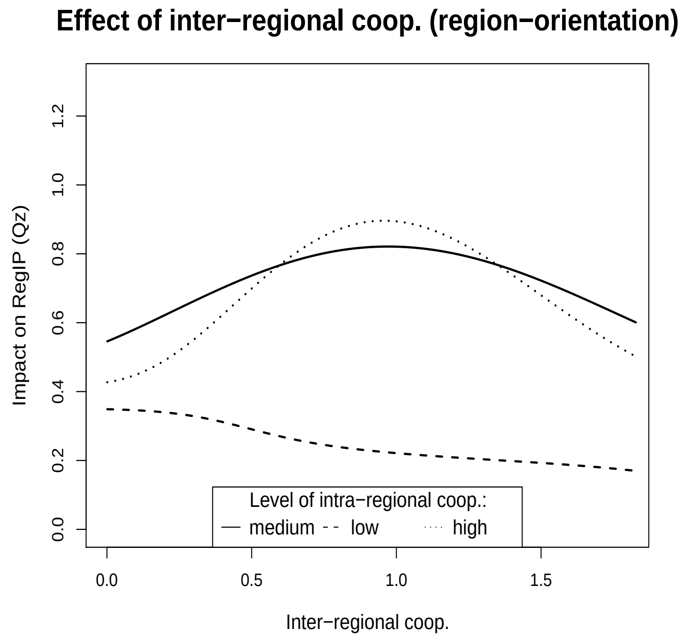


Figure 6.8.: Effect of inter-regional coop. for intra-regional coop. quartiles, Analysis 2

this suggests that the necessary cooperation partners are located within as well as outside a firm's home region. This situation can also be interpreted as 'lock-in' (lacking inter-regional cooperation) or 'lock-out' (lacking intra-regional cooperation) phenomena. Here, actors lack the ability to cooperate inter-regionally and intra-regionally respectively.

Lock-in effects, as described already above, can lead to a loss of regional competitive advantages because of regional actors' inability of regional actors to replace decrepit resources, to rebuild obsolete structures and to renew economically "important regional" institutions (Maskell & Malmberg 1999). Opposite to this we found hints for an other phenomena we call *"regional lock-out"*. It is defined as a situation in which firms in a region show a comparable level of inter-regional cooperation, but very low intra-regional cooperation activities. This results in below average innovative performance.

With respect to the magnitude of the effects, the height of the bump suggest further that intra-regional cooperativeness yields higher benefits. The benefits of geographic proximity between the cooperating actors can again be put forward for causing this finding. With respect to the magnitude of the negative effects there seems to be not much of a difference for the two types of cooperativeness.

Summarizing, do these results cast some doubts on that cooperativeness has just a 'bright side'. To the contrary, the evidence points towards 'dark side' effects that are relevant in the case of too strong intra- and inter-regional cooperativeness as well as when the focus is only put on one of the two. Hence, while confirming the general consensus in the literature that cooperativeness has an impact on regional innovation performance and that this influence is often positive, there seem to be significant negative effects in place as well. In this the study contributes to the demanding of Dahl & Pedersen (2002) that "*[t]he downside of information trading, for example the loss of information to competitors, which could potentially weaken a firm's performance, has to date, not received sufficient attention*" (p. 1685).

It has been noted above that in case of intra-regional cooperativeness the regression curve for the first quartile of inter-regional cooperativeness in the region-oriented analysis shows a behavior that departs from the other cases. This will be subject to the next subsection in which the impact of the definition of the resource endowment on the results is discussed in detail.

6.5.3. The impact of the resource endowment

In Section 6.3.3 it has been argued that there is no 'correct' definition of what resources should be considered in the definition of regions' input factor endowment. When comparing the results of the firm-oriented and region-oriented analyses, the first thing to notice is that the obtained non-parametrically estimated surfaces do not change strongly when considering the firm external input factors, see Fig. 6.3 and 6.4. This suggests that in general the definition of the regions' input factor set does not seem to have a dominating effect on the results.

However, when taking a closer look at the four Figures 6.5, 6.6, 6.7, and 6.8, two things become apparent. First, in Fig. 6.6 the second, and to a smaller extent the third, quartile regressions show a stronger increasing slope on the left side of the bump than their counterparts in Fig. 6.5. Second, in contrast to the situation in Fig. 6.5, the regression for intra-regional cooperativeness and the first quartile of inter-regional cooperativeness does not decrease as strongly as in Fig 6.6.

The latter indicates that for the first quartile of inter-regional cooperativeness the ratios between conditional and unconditional performances do not change as the level of intra-regional cooperativeness increases. Hence, increasing the level of intra-regional cooperativeness does not seem to have an effect in the particular situation of low inter-regional cooperativeness and a region-oriented analysis. In contrast, in the same situation, but a firm-oriented approach it shows as a negative impact. Or put differently, the consideration of the regional input factor endowment levels out the negative effect of increasing intra-regional but constant low inter-regional cooperation that can be observed in the firm-oriented analysis. This means that the structure of these regions' input factor endowment explains a large extent of the negative effects resulting from low levels of inter-regional cooperation and high intra-regional cooperativeness.

Methodically this implies that when controlling for the firm external input factor endowment the negative effects caused by a too strong inward orientation of the regional actors are taken into account. Hence, extensive intra-regional orientation accompanied by low inter-regional cooperation seems to be compensatively by a decent regional input factor endowment. This yields however weaker positive effects on the innovation performance than an increase in the cooperativeness with actors located outside the region would bring about.

Similar is not the case for strong inter-regional cooperativeness accompanied by low intra-regional cooperativeness. If this would have been the case, the same change would have been observed in the regression curves of inter-regional cooperativeness for the first quartile of intra-regional cooperativeness in Fig. 6.8 when comparing it to Fig. 6.7.

The compensative effects of decent input factor endowments additionally can explain why the effect of intra-regional cooperativeness show as a stronger increase in the regression curve on the left side of the bump (larger magnitude) in case of the region-oriented analysis, see Fig. 6.6 and Fig. 6.5. Because when considering the regional input factor endowment, at the same time it is controlled for the negative effects of strong intra-regional cooperativeness in the case of the existence of non-supportive input factor endowments. Following the previous argumentation these effects are particularly relevant in the case of low inter-regional cooperativeness. In Fig. 6.6 this shows in form of the larger slopes of the increasing regression curves for the first and second quartile of inter-regional cooperativeness than it is the case in the corresponding curves in Fig. 6.5.

So what is the economic rationale behind this finding? Broekel & Brenner (2007) point out that R&D employees' search for knowledge (the most important resource in R&D processes) can be biased towards regional knowledge sources even if this results in inferior solutions. For example, daily confrontation with the regions' resource profile can be a cause for this. Within a certain time period actors become more familiar with the regional input factors which then leads to that these come to mind more easily in the search processes. Taken to an extreme this can correspond to a lock-in situation described by Camagni (1991).

In this particular case actors are strongly oriented towards their region (low inter-regional accompanied by low intra-regional cooperativeness). Lacking fresh ideas from outside the region their innovation performance decreases, even in the case that intra-regional cooperativeness is increased. However, the degree to which innovation performance decreases depends on the existing regional input factor endowment. For example, if there are world class science institutes located in a region, this will likely reduce the chance that a cooperation ends up in an unsatisfactory result. The negative effects of regional lock-ins may thus be softened by investments in the technological infrastructure.

6.6. Conclusion

There are few topics in the literature on regional innovativeness that have gained as much attention as cooperativeness. Concepts like the 'innovative milieu' and 'regional innovation system' are to a large extent based on the idea that actors that cooperate in R&D projects are able to achieve higher innovativeness. Transferred to a regional level this implies that regions in which actors engage more frequently and more intensively in cooperative actions will in terms of innovativeness outperform other regions in which cooperative behavior is less prominent.

On a firm-level there are numerous studies that show empirically that cooperativeness indeed has an effect on firms' innovation activities (e.g. Oerleman & Meeus 2000). On the regional level there is however mainly qualitative evidence.

This chapter contributes to the literature by providing a quantitative empirical analysis of the effects of intra-regional and inter-regional cooperativeness on the regional innovation performance of the Electric / Electronics industry and the

German labor market regions.

In addition, the relevance of the effects of regions' endowment with factor relevant in R&D processes and the effect of the organization of these resources for regional innovativeness is discussed. From this it is derived that in order to investigate the effect of cooperativeness, both effects have to be separated, theoretically as well as empirically.

In the empirical analysis of this chapter, this is accomplished by using cooperativeness measures that are characterized by the absence of technological effects. In addition, a specific nonparametric performance analysis is employed for investigating the effects of intra- and inter-regional cooperativeness on the regions' innovation performance.

In general, we confirm the findings from firm-level research that cooperativeness has an impact on firms' innovation performance for the case of the Electrics & electronics industry on the regional level. In particular, we find that below a turning point this effect shows as a positive influence on innovation performance. When the turning point is exceeded the impact of higher cooperativeness diminishes and eventually turns negative. The turning point is characterized by higher cooperativeness than the level that can be expected given regions' technological profiles.

In addition, we find evidence that intra- and interregional cooperativeness are complements. Moreover, the results show that when regions lack interactions with other regions, the negative effects of strong intra-regional cooperativeness seem to depend on the region's endowment with factors relevant in R&D processes. Hence, decent factor endowment can, at least to some extent, compensate the negative effects of regional lock-ins.

7. Conclusion

This thesis comprises five empirical studies which all share the common goal to improve our understanding of systemic innovations. While these studies differ in manifold terms such as firm level vs. systemic level analysis, they uniformly provide evidence that the regional component plays a decisive role in the field of economics of innovation.
With this general notion in mind, the thesis initially (chapter 2) intended to shed more light on the relationship between different types of interaction and the impact of the regional knowledge base on these interactions. While this study is a case study of three regions, the following four chapter avoid the concentration on specific regions by dealing with all regional systems embedded in one national innovation system in order to strengthen the explanatory power of the empirical results. Thus, the data set of the next chapters was based on German-wide data, mainly on patent data. The usage of patent data was critically discussed and it was shown that information gathered from patent data – this is at the readers discretion – are a sufficient indicator of inventive, cooperative and innovative activities.

To what extent can the amount of intra-regional cooperation be explained by the ability to get access to external knowledge as one incentive to cooperate?

The first self-contained chapter examines the relationship between different types of regional interaction and how these different types are affected by the regional knowledge base. According to the resource-based view of the firm, the incentives to engage in R&D cooperation increase as the regional knowledge base grows (accumulates etc...) (Lockett 2001). Thus, it was assumed that the amount of regional interaction is positively related to the amount and homogeneity of the regional knowledge base. However, these positive relationships can be found solely for the more formal oriented patent co-applications. As this type of interaction fits with the suggestions of the resource-based view of the firm, it is further on used as an indicator of individual as well as regional R&D cooperations.

Do technological and geographical patterns play a role in the choice of the R&D cooperation partner?

When examining the importance of technological and geographical proximity for the choice of the cooperation partner we found evidence that both dimensions have a positive and self-contained impact. Although this result is contrary to the notions of Boschma (2005), it contributes to the conclusion of chapter 1 that there exist at least two types of innovation systems, technological and regional, at the same point in time.

Is it possible to disentangle the effects of different dimensions of proximity on cooperative innovation activities?

One main finding of chapter 3 is the co-impact of different dimensions of proximity in the choice of the cooperation partner which implies the co-existing of different types of innovation systems. Thus, in chapter 4 a methodology is introduced how to disentangle regional and technological effects on cooperative innovation activities. We find an indicator called relative regional impact of cooperative innovation activities (RRI) by extracting technological effects on cooperative innovation activities. This indicator combines the influences of geographical and social dimension of proximity on the one hand and, on the other hand, it is a indicator relative to the average regional effects.

Is the strength of the regional innovation system influenced by characteristics of the regional knowledge base?

In chapter 5 this RRI is related to the characteristics of the regional knowledge base that have been identified as relevant for cooperation behavior in Breschi et al. (2003). Doing so this chapter is, somehow, a refinement of chapter 2. The number of cooperations is replaced by the RRI values and the regional knowledge base is analyzed according to its related variety instead of homogeneity. The latter assumes that all technologies are independent of each other, whereas the former explicitly analyzes the relationships among all technologies. The results of 5 contribute to the absorptive capacity concept introduced by Cohen & Levinthal (1990) by showing that the intensity of the regional interaction structure depends positively on the related variety of the regional knowledge base.

Does the strength of the regional innovation system matter for the efficiency of regional innovative activities?

The results of chapter 6 contribute to the ongoing discussion in recent literature about the impact of regional resources on the innovative performance. The presented empirical study on regional level shows that the relative regional effects on cooperative behavior, indicated by the RRI-value, has a positive impact on firms' innovative performance. As the indicator introduced in chapter 4 can be interpreted as the strength of the regional interaction system, one can conclude that the regional innovative performance depends on the degree of systemic innovations in that region. More precisely, this result gives evidence in favor of the common assumption of all innovation systems concepts that collaborations in the field of R&D tend to be more successful than R&D projects in isolation.

After presenting the results of all five papers separately, the next step is to regard these single results to the broader topic of this thesis, the relevance of technological and geographical patterns for the innovative performance. From the author's viewpoint, the following findings are helpful for a better understanding of the conditions determining collective and interactive learning:

1. Technological proximity is a prerequisite for collective learning.
   Based on the empirical findings, we conclude that economic actors willing to cooperate are seeking after potential cooperation partner in their technological neighborhood. Following the resource-based view concept, this is due to the incentive to cooperate for acquiring external knowledge. As stated in the introduction, the concept of technological innovation systems encloses the concept of social proximity by emphasizing individual behavioral differences among sectors and technologies. Thus, the notion about the importance of technological proximity for the described seeking mechanisms accompanies the notion about the importance of social proximity. This might be due to an eased implication of control mechanisms during the cooperation process.

2. Geographical proximity facilitates cooperation agreements.
   A nearby location in terms of the spatial dimension of proximity increases the cooperation probability. It can be shown that this is rather a self-contained influence than only a facilitating tool. This result is, somehow,

essential for those authors dealing with the regional innovation system approach. By showing that regional resource apart from technological pattern influence the cooperative behavior and, thus, the innovative performance of regions, this thesis gives evidence in favor to the common assumption of the regional innovation system approach and corroborate its existence.

3. Regional cooperative activities differ.
   The regional innovation system approach emphasizes the importance of regional resources on the innovative and cooperative behavior of firms. We can contribute to this approach by showing that the cooperative behavior without any technological influences differ among German regions. As all our empirical studies deal with German-wide data, international effects are excluded. The residual effects after the extraction of technological effects on cooperative behavior are interpreted as regional pattern of cooperative behavior.
   Furthermore, it can be shown that these differences in the relative regional effects on cooperative behavior follow a certain path in their development and are influenced by the related variety of the regional knowledge base. Regarding political implications, it can be concluded that a low number of regional cooperations is not an indicator for problems in those regions. The low number of cooperations can either be driven by a low number of innovations in general or solely by the technological pattern. The latter implies that the *RRI* value is not necessarily below 1. This is the case in a region where the actors are mainly engaged in technologies with a general tendency of a single development of innovations. Here, the expected number of cooperations would be low for that region, so that the ratio between observed and expected number of cooperations does not have to be below 1. This scenario does not necessarily require political interventions, whereas a low number of innovations denotes rather problems in innovative capabilities than in cooperative behavior.

4. Cooperations are not uniformly positive.
   The results of chapter 6 refute the purely positive effects of cooperation on regional innovation performance. The empirical evidence provided here highlights the 'dark' side of cooperation. In particular, it is crucial to analyze carefully whether actors in a region lack intra- or inter-regional

cooperation before initiating support for either of them because false incentives for cooperative behavior may induce cooperation overload situations. However, support for the type of cooperation that is already comparatively well-developed in a region can entail regional lock-in and lock-out situations which can yield even lower innovation performance.

This thesis examines the impacts of technological and geographical patterns in the field of R&D in order to contribute to the ongoing discussion about the importance of innovation systems in general and in particular of regional innovation systems for the innovative performance of single actors and whole systems. The applied methodology mainly uses national data dividing Germany into a number of regions. In the field of RIS this is an uncommon approach as most of the existing studies use case study designs. The more general perspective used in this chapter losses to a certain degree information about specifities of regions, but this methodology enables us to find universally valid results about the mechanisms of systemic innovations. This is a requirement for the innovation system approach as this view aspires towards a higher acceptance in the literature of economics.

The methodology applied in this thesis in terms of using a more general perspective and disentangling the effects of different types of proximity can be used for manifold further research projects. So far we only concentrated on more formal cooperations. It would be very interesting to see whether the provided results hold true for more informal interactions like scientist' mobility linkages. Furthermore, an analysis of the relationship between regional network structure and the RRI-values might lead to highly interesting results in terms of whether both are complementary in their explanatory power or more substitutable. We started with a dynamic perspective of the development of regional interactions. A more detailed analyzes of the importance of experiences in the past for current cooperative behavior on individual as well as on regional level is a third possible project building on the results of this thesis.

A. Appendix to chapter 2

Table A.1.: Description of 43 NACE oriented technological fields

Fi.No.	Description	Fi.No.	Description
F1	Food, beverages	F23	Machine-tools
F2	Tobacco products	F24	Special purpose machinery
F3	Textiles	F25	Weapons and ammunition
F4	Wearing apparel	F26	Domestic appliances
F5	Leather articles	F27	Office machinery and computers
F6	Wood products	F28	Electric motors, generators, transformers
F7	Paper	F29	Electric distribution, control, wire, cable
F8	Petroleum products, nuclear fuel	F30	Accumulators, battery
F9	Basic chemical	F31	Lightening equipment
F10	Pesticides, agro-chemical products	F32	Other electrical equipment
F11	Paints, varnishes	F33	Electronic components
F12	Pharmaceutical	F34	Signal transmission, telecommunications
F13	Soaps, detergents, toilet preparations	F35	Television and radio receivers, audiovisual electronics
F14	Other chemicals	F36	Medical equipment
F15	Man-made fibres	F37	Measuring instruments
F16	Rubber and plastics products	F38	Industrial process control equipment
F17	Non-metallic mineral products	F39	Optical instruments
F18	Basic metals	F40	Watches, clocks
F19	Fabricated metal products	F41	Motor vehicles
F20	Energy machinery	F42	Other transport equipment
F21	Non-specific purpose machinery	F43	Furniture, consumer goods
F22	Agricultural and forestry machinery		

B. Appendix to chapter 4

Figure B.1.: RRIs for Germany in 1999

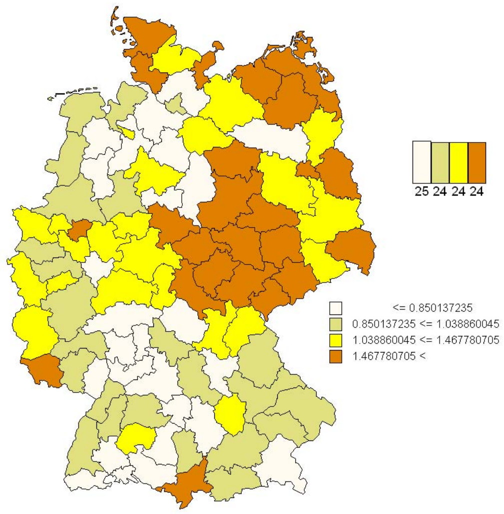


Figure B.2.: RRIs for Germany in 2000

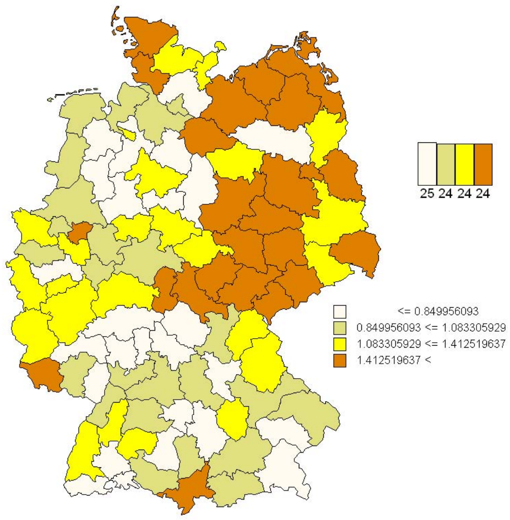


Figure B.3.: RRIs for Germany in 2001

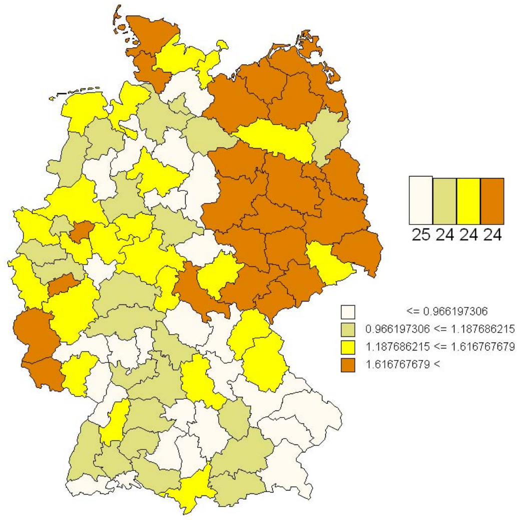
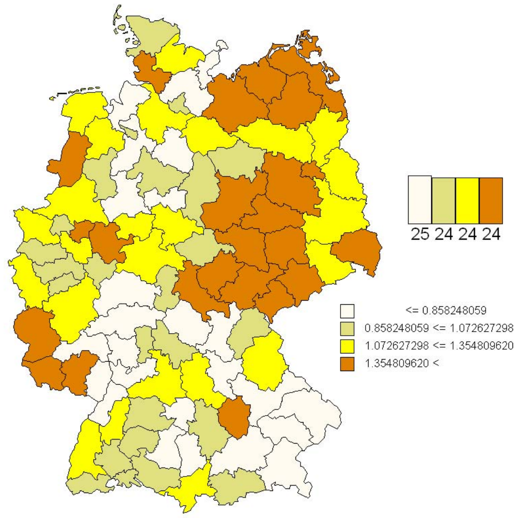


Figure B.4.: RRIs for Germany in 2002



C. Appendix to chapter 5

Table C.1.: Relatedness of field numbers (FiNo) for 1999 based on Cosine index

FiNo	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	1	0.046	0.111	0.031	0.016	0.028	0.068	0.08	0.203	0.152	0.057	0.269	0.1	0.093
2		1	0.061	0.033	0.018	0.021	0.064	0.026	0.026	0.005	0.014	0.007	0.017	0.046
3			1	0.161	0.051	0.111	0.213	0.13	0.442	0.169	0.204	0.225	0.215	0.229
4				1	0.104	0.055	0.068	0.043	0.086	0.024	0.058	0.027	0.032	0.078
5					1	0.026	0.023	0.02	0.039	0.014	0.066	0.015	0.011	0.022
6						1	0.088	0.043	0.089	0.021	0.144	0.025	0.022	0.08
7							1	0.088	0.208	0.055	0.129	0.076	0.082	0.133
8								1	0.303	0.095	0.092	0.147	0.086	0.208
9									1	0.331	0.325	0.396	0.289	0.424
10										1	0.18	0.555	0.26	0.132
11											1	0.096	0.091	0.173
12												1	0.278	0.164
13													1	0.126
14														1
15														
16														
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Table C.2.: Relatedness of field numbers (FiNo) for 1999 based on Cosine index

FiNo	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1	0.106	0.071	0.042	0.038	0.024	0.019	0.097	0.059	0.046	0.153	0.011	0.079	0.018	0.018	0.009
2	0.034	0.11	0.025	0.034	0.027	0.06	0.054	0.049	0.029	0.158	0.022	0.023	0.016	0.033	0.018
3	0.377	0.141	0.257	0.092	0.059	0.034	0.108	0.079	0.071	0.277	0.032	0.055	0.028	0.027	0.015
4	0.085	0.1	0.105	0.056	0.173	0.029	0.06	0.036	0.047	0.137	0.051	0.049	0.027	0.029	0.021
5	0.033	0.097	0.043	0.034	0.03	0.01	0.05	0.036	0.014	0.04	0.009	0.024	0.014	0.009	0.01
6	0.073	0.11	0.342	0.088	0.157	0.055	0.139	0.042	0.157	0.11	0.024	0.054	0.019	0.026	0.017
7	0.14	0.118	0.144	0.066	0.08	0.031	0.082	0.043	0.067	0.287	0.025	0.041	0.158	0.03	0.021
8	0.158	0.076	0.068	0.065	0.069	0.046	0.156	0.062	0.057	0.136	0.101	0.047	0.125	0.058	0.046
9	0.555	0.175	0.209	0.117	0.071	0.034	0.226	0.099	0.051	0.193	0.025	0.063	0.052	0.024	0.017
10	0.153	0.036	0.052	0.023	0.018	0.005	0.053	0.057	0.012	0.043	0.005	0.018	0.012	0.004	0.002
11	0.194	0.049	0.206	0.045	0.053	0.01	0.054	0.113	0.023	0.089	0.015	0.021	0.015	0.008	0.004
12	0.163	0.039	0.05	0.028	0.016	0.008	0.062	0.046	0.015	0.059	0.013	0.021	0.027	0.008	0.006
13	0.159	0.039	0.047	0.034	0.019	0.012	0.051	0.034	0.02	0.128	0.008	0.034	0.012	0.009	0.003
14	0.236	0.109	0.163	0.094	0.084	0.035	0.131	0.05	0.061	0.183	0.161	0.038	0.04	0.028	0.025
15	1	0.121	0.193	0.074	0.044	0.04	0.122	0.072	0.049	0.225	0.018	0.05	0.03	0.021	0.01
16		1	0.172	0.17	0.136	0.094	0.136	0.055	0.095	0.201	0.037	0.121	0.061	0.051	0.135
17			1	0.194	0.219	0.046	0.147	0.077	0.11	0.154	0.049	0.088	0.036	0.035	0.03
18				1	0.15	0.068	0.172	0.057	0.144	0.194	0.04	0.072	0.037	0.057	0.086
19					1	0.138	0.128	0.058	0.21	0.106	0.056	0.114	0.063	0.111	0.081
20						1	0.112	0.068	0.134	0.101	0.05	0.082	0.041	0.239	0.059
21							1	0.092	0.135	0.217	0.043	0.183	0.049	0.082	0.035
22								1	0.06	0.125	0.022	0.043	0.029	0.04	0.019
23									1	0.184	0.033	0.05	0.044	0.063	0.047
24										1	0.054	0.079	0.075	0.09	0.031
25											1	0.022	0.057	0.039	0.028
26												1	0.063	0.069	0.079
27													1	0.091	0.093
28														1	0.123
29															1
30															
31															
32															
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Table C.3.: Relatedness of field numbers (FiNo) for 1999 based on Cosine index

FiNo	30	31	32	33	34	35	36	37	38	39	40	41	42	43
1	0.029	0.014	0.014	0.026	0.008	0.008	0.07	0.052	0.023	0.026	0.008	0.022	0.014	0.023
2	0.01	0.024	0.024	0.022	0.012	0.008	0.036	0.029	0.032	0.021	0.009	0.113	0.03	0.04
3	0.07	0.028	0.032	0.049	0.021	0.012	0.065	0.046	0.029	0.047	0.008	0.039	0.029	0.04
4	0.022	0.037	0.033	0.028	0.033	0.022	0.135	0.031	0.037	0.068	0.031	0.05	0.075	0.265
5	0.007	0.017	0.011	0.01	0.009	0.011	0.131	0.018	0.043	0.022	0.021	0.01	0.014	0.226
6	0.025	0.034	0.028	0.031	0.015	0.008	0.04	0.047	0.033	0.034	0.011	0.043	0.035	0.06
7	0.054	0.034	0.045	0.054	0.061	0.052	0.04	0.061	0.051	0.112	0.051	0.03	0.023	0.058
8	0.076	0.053	0.183	0.091	0.1	0.068	0.112	0.314	0.138	0.089	0.063	0.112	0.049	0.039
9	0.163	0.037	0.041	0.084	0.026	0.017	0.107	0.082	0.04	0.08	0.012	0.047	0.032	0.033
10	0.04	0.009	0.009	0.018	0.004	0.005	0.092	0.045	0.009	0.022	0.004	0.008	0.006	0.012
11	0.053	0.017	0.012	0.027	0.006	0.006	0.077	0.02	0.009	0.029	0.007	0.009	0.012	0.067
12	0.048	0.012	0.022	0.032	0.011	0.014	0.137	0.141	0.029	0.041	0.013	0.014	0.009	0.013
13	0.039	0.009	0.008	0.025	0.005	0.004	0.049	0.025	0.01	0.023	0.002	0.013	0.008	0.01
14	0.078	0.042	0.034	0.112	0.038	0.038	0.078	0.066	0.041	0.104	0.015	0.056	0.039	0.028
15	0.087	0.023	0.034	0.047	0.012	0.009	0.067	0.035	0.021	0.048	0.006	0.028	0.021	0.049
16	0.047	0.076	0.066	0.056	0.065	0.027	0.094	0.085	0.085	0.104	0.031	0.13	0.08	0.1
17	0.061	0.063	0.049	0.088	0.035	0.017	0.053	0.047	0.036	0.071	0.015	0.051	0.056	0.056
18	0.039	0.059	0.058	0.107	0.05	0.025	0.052	0.068	0.054	0.08	0.019	0.073	0.069	0.049
19	0.046	0.091	0.102	0.065	0.068	0.031	0.064	0.072	0.106	0.079	0.049	0.193	0.118	0.133
20	0.024	0.077	0.081	0.077	0.048	0.023	0.056	0.102	0.111	0.054	0.026	0.422	0.169	0.067
21	0.05	0.053	0.069	0.071	0.041	0.02	0.094	0.11	0.091	0.051	0.021	0.182	0.114	0.062
22	0.022	0.031	0.04	0.028	0.02	0.013	0.045	0.064	0.048	0.032	0.021	0.125	0.04	0.031
23	0.024	0.033	0.047	0.077	0.059	0.026	0.061	0.092	0.103	0.076	0.028	0.106	0.05	0.035
24	0.053	0.029	0.046	0.14	0.039	0.035	0.098	0.112	0.079	0.085	0.017	0.072	0.057	0.06
25	0.021	0.044	0.08	0.039	0.053	0.041	0.029	0.132	0.07	0.05	0.04	0.133	0.056	0.045
26	0.02	0.132	0.087	0.06	0.063	0.026	0.059	0.081	0.113	0.053	0.065	0.113	0.051	0.12
27	0.049	0.053	0.232	0.136	0.375	0.328	0.103	0.19	0.276	0.209	0.262	0.108	0.05	0.078
28	0.032	0.079	0.219	0.14	0.125	0.066	0.049	0.115	0.154	0.052	0.05	0.247	0.099	0.045
29	0.044	0.132	0.128	0.121	0.264	0.08	0.027	0.098	0.121	0.063	0.091	0.13	0.039	0.035
30	1	0.034	0.069	0.051	0.123	0.05	0.031	0.11	0.066	0.042	0.037	0.057	0.03	0.013
31		1	0.189	0.096	0.08	0.056	0.073	0.095	0.088	0.212	0.046	0.197	0.074	0.074
32			1	0.135	0.275	0.196	0.08	0.277	0.277	0.115	0.154	0.237	0.106	0.048
33				1	0.201	0.103	0.074	0.187	0.157	0.111	0.064	0.095	0.042	0.027
34					1	0.429	0.06	0.184	0.35	0.151	0.273	0.123	0.046	0.047
35						1	0.118	0.154	0.177	0.207	0.16	0.067	0.029	0.036
36							1	0.232	0.105	0.156	0.085	0.054	0.045	0.127
37								1	0.363	0.192	0.149	0.244	0.094	0.046
38									1	0.123	0.169	0.279	0.09	0.052
39										1	0.105	0.094	0.054	0.065
40											1	0.081	0.028	0.091
41												1	0.232	0.091
42													1	0.067
43														1

D. Appendix to chapter 6

D.1. Smoothing & Bandwidths

With respect to the employed nonparametric regression technique that helps to interpret the scatter-plots, we follow Daraio & Simar (2007) in using a simple Nadaraya-Watson (Nadaraya 1964, Watson 1964) estimator with a Gaussian kernel. A crucial aspect in nonparametric regression is the choice of the degree of smoothing, i.e. the choice of the appropriate bandwidths (see, e.g., Bowman & Azzalini 1997). In the context of the employed analysis Daraio & Simar (2007) suggest to use a least-squares cross-validation (CV) automatic procedure.
However, it seems that that the CV-obtained bandwidth is in this context too small, hence it seems that this method 'undersmoothes' the relationship. Therefore, the bandwidths are chosen using the *Improved Akaike Information Criterion* (AICC) developed by Hurvich et al. (1998).

D.2. Tables & Figures

Distance	$< 50km$	$50 < 200km$	Share 1999	Share 2000
GRAD_ENG (university)	48.8%	29.8%	41.6%	40.7%
GRAD_ENG (tc)	42.3%	35.5%	58.4%	59.3%
GRAD_NAT (university)	61.2%	14.9.9%	89.7%	89.8%
GRAD_NAT* (tc)	45.4%	36.0%	10.3%	10.2%
* No data available, the shares of all technical graduates taken together are used. # Data based on Legler et al. (2001) but adjusted for inner Germany mobility				

Table D.1.: Graduates Mobility

	Empirical values		Estimation		
Spill-over source	$< 50km$	$200km <$#	$< 50km$	$200km <$	α
GRAD_ENG	45,1%	33,1%	44.70%	34.35%	1.4851
GRAD_NAT	60.0%	17.0%	56.34%	29.29%	1.6358
SCIENCE #	36.0%	34.0%	34.82%	37.36 %	1.3197
Estimation based on sum of 1999 and 2000 data.					
# Numbers are approximated from data in Beise & Stahl (1999).					

Table D.2.: Range of spill-overs of R&D institutes, hyperbolic distribution

Technological fields *	NACE industries**
TF27, TF28, TF29, TF30, TF31	DL31, DL32, DL30
* As defined in Greif & Schmiedl (2002)	
** According to the GIC DESTATIS (2002)	

Table D.3.: Definition of the Electrics & Electronics industry according to Broekel (2007)

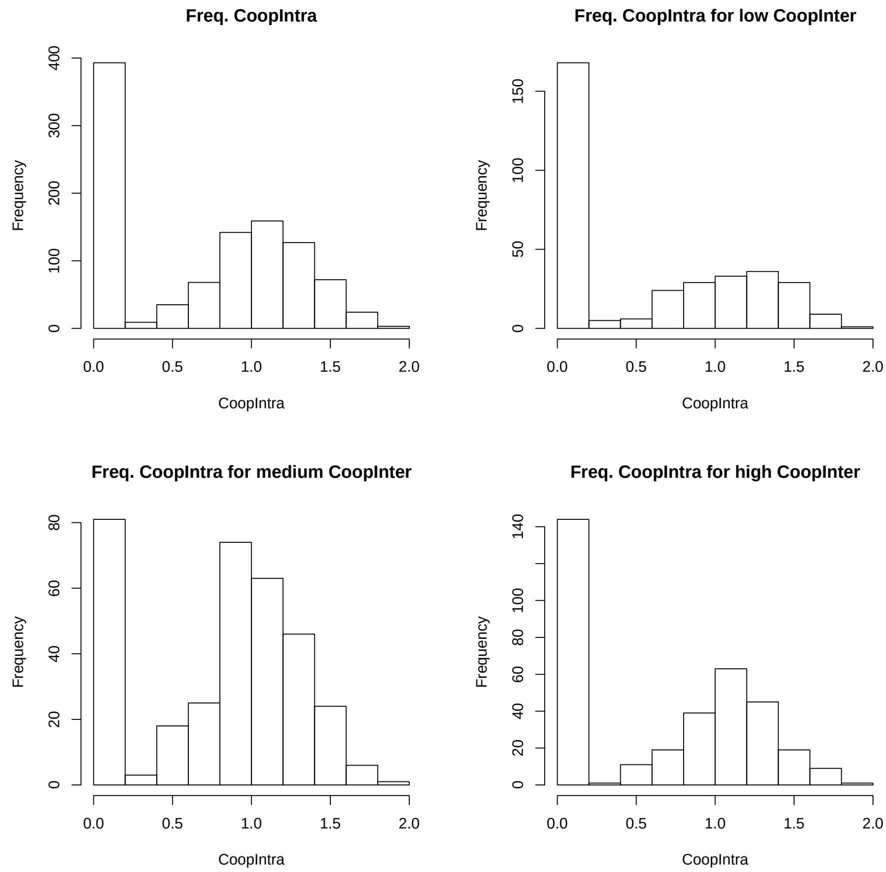

Figure D.1.: Histograms of CoopIntra

Variable	**Description**
PAT	Sum of patent applications of TF27, TF28, TF29 ,TF30, TF31 in Greif & Schmiedl (2002), Greif et al. (2006)
DL_31	R&D employees of DL31
DL_32_30	Sum of R&D employees of industries DL32, DL30
POP_DEN	Inhabitants per *kilometer*^{2} land area
GDP	Gross domestic product per inhabitant
SERVICE	Production structure specialization index of WZ03' category 74: 'other business activities' (business services) industry
EMP_HIGH	Share of employees with high qualification
ELEC_PS	Production structure specialization index (PS) of RD_ELEC)
EMPL_ELEC	Absolute regional employment of ELEC
GRAD_ENG	Distributed engineering graduates per employee
GRAD_NAT	Distributed natural and science graduates per employee
SCIENCE	Distributed researchers at public research institutions per employee
All shares refer to total employment	

Table D.4.: Variables, estimation base, and sources

Variable	**Firm-level orientation**	**Regional orientation**
Innovativeness measures		
PAT_t	×	×
Input factors		
$DL32\_30_{t-1}$	×	×
$DL31_{t-1}$	×	×
$SIZE_{t-1}$		×
$EMPL\_ELEC_{t-1}$		−
EMP_HIGH_{t-1}		×
GDP_{t-1}		×
$ELEC\_PS_{t-1}$		−
POP_DEN_{t-1}		−
$SERVICE_{t-1}$		×
$GRAD\_ENG_{t-1}$		×
$GRAD\_NAT_{t-1}$		−
$SCIENCE_{t-1}$		−
× Indicates inclusion, − exclusion because of correlation.		

Table D.5.: Variables and their employment

	DL32_ DL30	DL31	EMPL_ELEC	ELEC_ PS	POP_ DEN	DistriNAT	DistriENG
DL32_DL30	1***	0.48***	0.75***	0.62***	0.5***	−0.05*	−0.12***
DL31	0.48***	1***	0.83***	0.73***	0.44***	−0.1***	−0.16***
EMPL_ELEC	0.75***	0.83***	1***	0.84***	0.59***	−0.12***	−0.2***
ELEC_PS	0.62***	0.73***	0.84***	1***	0.23***	0.02	0.01
POP_DEN	0.5***	0.44***	0.59***	0.23***	1***	−0.21***	−0.32***
DistriNAT	−0.05*	−0.1***	−0.12***	0.02	−0.21***	1***	0.8***
DistriENG	−0.12***	−0.16***	−0.2***	0.01	−0.32***	0.8***	1***
DistriScience	−0.17***	−0.22***	−0.29***	−0.06**	−0.4***	0.75***	0.81***
GDP	0.45***	0.45***	0.58***	0.25***	0.81***	−0.08***	−0.16***
EMP_High	0.38***	0.33***	0.43***	0.08***	0.77***	−0.21***	−0.31***
Service	0.11***	0.02	0.09***	0.02	0.29***	−0.12***	−0.13***
Firm size	0.53***	0.65***	0.78***	0.85***	0.26***	−0.02	−0.05*
$CoopIntra_{t-1}$	0.22***	0.17***	0.23***	0.14***	0.2***	0.06**	0.02
$CoopInter_{t-1}$	0.07***	0.06**	0.1***	0.05*	0.17***	−0.02	−0.06**

Table D.6.: Pearson's correlation coefficients I

	DistriScience	GDP	EMP_High	Service	SIZE	$Coop$ $Intra_{t-1}$	$Coop$ $Inter_{t-1}$
DL32_DL30	−0.17***	0.45***	0.38***	0.11***	0.53***	0.22***	0.07***
DL31	−0.22***	0.45***	0.33***	0.02	0.65***	0.17***	0.06**
EMPL_ELEC	−0.29***	0.58***	0.43***	0.09***	0.78***	0.23***	0.1***
ELEC_PS	−0.06**	0.25***	0.08***	0.02	0.85***	0.14***	0.05*
POP_DEN	−0.4***	0.81***	0.77***	0.29***	0.26***	0.2***	0.17***
DistriNAT	0.75***	−0.08***	−0.21***	−0.12***	−0.02	0.06**	−0.02
DistriENG	0.81***	−0.16***	−0.31***	−0.13***	−0.05*	0.02	−0.06**
DistriScience	1***	−0.2***	−0.34***	−0.12***	−0.13***	−0.03	−0.09***
GDP	−0.2***	1***	0.68***	0.22***	0.32***	0.2***	0.11***
EMP_High	−0.34***	0.68***	1***	0.19***	0.08***	0.11***	0.16***
Service	−0.12***	0.22***	0.19***	1***	0.05*	0.06**	0.03
Firm size	−0.13***	0.32***	0.08***	0.05*	1***	0.12***	0.02
$CoopIntra_{t-1}$	−0.03	0.2***	0.11***	0.06**	0.12***	1***	0.08***
$CoopInter_{t-1}$	−0.09***	0.11***	0.16***	0.03	0.02	0.08***	1***

Table D.7.: Pearson's correlation coefficients II

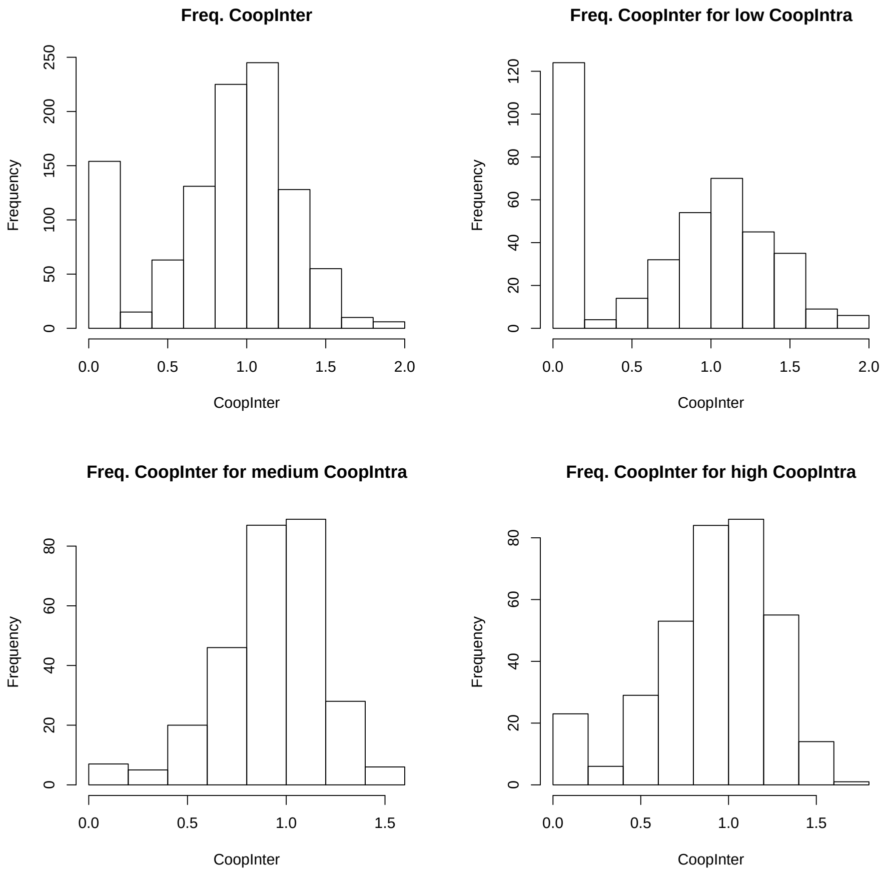

Figure D.2.: Histograms of CoopInter

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E. Curriculum vitae

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03/2005–03/2007	Wissenschaftlicher Mitarbeiter am LS für Mikroökonomik, von Prof. Dr. Uwe Cantner an der Friedrich-Schiller Universität

Veröffentlichungen

Aufsätze in referierten Zeitschriften

in 2007

- "Technological proximity and the choice of cooperation partner", Journal of Economic Interaction and Coordination, 2007, Vol. 2, p. 45-65 [together with Uwe Cantner].

Beiträge zu Sammelwerken

in 2008

- Cantner, U., Graf, H. & Meder, A. (2008), "Urbane Innovationssysteme als kollektive Innovationsprozesse", in: A. Ebner & K. Heine, eds, *"Innovation zwischen Markt und Staat"*, Nomos.

Working Papers

in 2008

- "The bright and dark side of cooperativeness for regional innovativeness", Jena Economic Research Paper, FSU Jena, forthcoming [together with Tom Brökel, work in progress]
- "The role of social capital and networks in fostering firms innovative capacity. evidence from the Jena region", Jena Economic Research Paper, FSU Jena, forthcoming [together with Elisa Conti, work in progress]
- "Technological and geographical patterns in the choice of cooperation partner" , Jena Economic Research Paper, FSU Jena, 2008-54.
- "The Bright and Dark Side of Cooperation for Regional Innovation Performance" , Jena Economic Research Paper, FSU Jena, 2008-53 [together with Tom Broekel].
- "Innovators and the Diversity of Innovation Systems" , Jena Economic Research Paper, FSU Jena, 2008-43 [together with Uwe Cantner].
- "Innovator networks and regional knowledge base" , Jena Economic Research Paper, FSU Jena, 2008-42 [together with Uwe Cantner and Anne ter Wal].
- "Regional and technological effects of cooperation behavior" , Jena Economic Research Paper, FSU Jena, 2008-14 [together with Uwe Cantner].

in 2007

- "Prior knowledge and entrepreneurial innovative success", Jena Economic Research Paper, FSU Jena, 52/2007 [together with Uwe Cantner and Maximilian Goethner].

in 2006

- "Determinants influencing the choice of a cooperation partner", Jenaer Schriften zur Wirtschaftswissenschaft, FSU Jena, 20/2006 [together with Uwe Cantner].
- "Die Wirkung von Forschungskooperationen auf den Unternehmenserfolg - eine Fallstudie zum Landkreis Saalfeld Rudolstadt", Jenaer Schriften zur Wirtschaftswissenschaft, FSU Jena, 24/2006 [together with Uwe Cantner].

F. Eidesstaatliche Erklärung

Erklärung gemäß Par.4 Abs.1 Pkt.3 (PromO)

Hiermit erkläre ich,

1. dass mir die geltende Promotionsordnung bekannt ist;
2. dass ich die Dissertation selbst angefertigt und alle von mir benutzten Hilfsmittel und Quellen in meiner Arbeit angegeben habe;
3. dass ich bei der Auswahl und Ausfertigung des Materials sowie bei der Herstellung des Manuskriptes keine fremde Hilfe in Anspruch genommmen habe;
4. dass ich nicht die Hilfe eines Promotionsberaters in Anspruch genommen habe und dass Dritte weder unmittelbar noch mittelbar geltwerte Leistungen von mir für Arbeiten erhalten haben, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen;
5. dass ich die Dissertation noch nicht als Prüfungsarbeit für eine staatliche oder andere wissenschaftliche Prüfung eingereicht habe;
6. dass ich die nicht gleiche, eine im wesentlichen Teilen ähnliche oder eine andere Abhandlung bei einer anderen Hochschule bzw. anderen Fakultät als Disseration eingereicht habe.

Jena, den 15. Juli 2008