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## Technological and geographical patterns in the choice of cooperation partner

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## **Technological and geographical patterns in the choice of cooperation partner**

by

**Andreas Meder**

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# Technological and geographical patterns in the choice of cooperation partner

Andreas Meder\*

June 26, 2008

## Abstract

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. This paper is a quantitative study on the impact of technological and geographical proximity on the choice of the cooperation partner. Patents 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 increasing proximity in either of these dimensions has an independent positive impact on the cooperation probability.

*JEL classification:* C30; L14; O32

*Keywords:* cooperation, cognitive proximity, geographical proximity

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# 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). Thus, the mechanisms and processes of knowledge creation are increasingly in the focus of economic literature. As a result, the level of analysis differs between different streams of literature. Authors within the resource-based view of the firm (e.g., Penrose, 1959) concentrate on firm level, whereas authors analyzing various innovation system approaches (e.g., Malerba and Orsenigo, 1997; Edquist, 1997) are interested in differences in the performance of whole systems.

Another stream of literature focuses on the determinants affecting the willingness to engage in a collaborative R&D project. Much has therefore been written on the impact of different dimensions of proximity on learning and knowledge creation. These papers are mainly of a conceptual (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 and Meder, 2007).

This paper contributes to the literature, providing an empirical analysis of the impacts technological and geographical proximity have on cooperative innovation activities and analyzing the interplay of both dimensions. More precisely, this paper asks whether technological and geographical proximity affects the choice of the cooperation partner.

In the following, I want to shed light on the question whether technological 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 four hypotheses that are tested with the methodology introduced in section 3, section 4 presents the empirical tests. Section 5 will conclude.

## 2 Theoretical background

### 2.1 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 in increasing the probability of innovative success of organizations (Oerleman and 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 develop 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). Additionally, R&D cooperation leads to a reduction of uncertainty associated with these projects (Cassiman and Veugelers, 2002). For both studies it is transaction cost theory that provides an analytical basis. Taking up this theory, Kogut (1988) explains why R&D cooperation as a particular mode of transaction is chosen over alternatives like acquisitions or other governance mechanisms.

Second, cooperation might 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 an R&D cooperation or, more precisely, on the probability of success of such a cooperation project (Belderbos et al., 2004). This argumentation goes back to 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 view, Das and Teng (2000) show that the inducement of R&D cooperations is influenced by the mobility, imitability, and substitutability of internal resources.

Third, a further incentive to engage in collaborative R&D projects is to encourage the transfer of knowledge (Ahuja, 2000; Eisenhardt and Schoonhoven, 1996). This incentive is somehow related to the second one as it deals with dynamic learning effects (Ahuja, 2000). The access to an external knowledge base does not only improve the success probability of a particular R&D project but also 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 cannot 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 and 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 and Veugelers, 2002). D'Aspremont and Jacquemin (1988) show that imperfect appropriability increases the incentives to engage in a collaborative R&D project. Nevertheless, Cohen and Levinthal (1990) show that the extent to which these knowledge spillovers can be implemented into firms depends on their internal "absorptive capacities."

The observation that cooperation has considerable potential to contribute to innovation strategies of firms does not mean though 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, but on the other hand it enhances the incentives to free ride on each other's R&D efforts (Kesteloot and Veugelers, 1995) as well as the possibility

for free riding by outsiders of the cooperation (Cassiman and Veugelers, 2002). Such unintended knowledge flows (Teece, 2002) might be a major reason for the estimated failure rate of 60 percent of collaborative agreements in general (Bleeke and 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).

## 2.2 Dimensions of proximity in R&D cooperation

The benefits that cooperation brings about are thus not guaranteed, and whether they can be realized, depends strongly on whether the cooperation partners fit to each other in terms of complementarity of resources, aims, and working routines. In this respects Boschma (2005) suggests five dimensions of proximity affecting the degree of interactive learning within an R&D cooperation. He argues that the degree of interactive learning depends on institutional, organizational, social, cognitive, and geographical proximity between potential cooperation partners. The empirical method introduced later on is applied to the data base containing information about one country. Thus, all actors are involved within the same institutional frame so that this dimension is not of interest here. The organizational proximity is related to the mode of knowledge transfer. Organizational knowledge of how to use a certain type of transfer mode is built up from collaborative experiences gathered in the past. Decarolis and Deeds (1999) show that a stock of organizational knowledge influences the economic firm performance positively. This study focuses solely on cooperative activities which can be allocated somewhere between market and hierarchical interactions, with the activities of all actors showing the same degree of organizational proximity. This leads to the conclusion that the choice of the cooperation partner depends on the remaining technological, social, and geographical dimensions of proximity.

### Technological proximity

Following the learning economy approach (Lundvall, 2004), knowledge is a club good to be developed rather than a public good which is exogenously given. The creation of new knowledge is an uncertain search with an often expected outcome (Nelson and Winter, 1982). Economic actors develop routines which are based on past experiences, as well as on success and failure, in order to reduce this inherent uncertainty. Thus, firms tend to search for new knowledge in the neighborhood of their existing knowledge base. This routine leads to a path-dependent process in the development of knowledge, ultimately explaining the homogeneity of actors' knowledge bases (Antonelli, 2000).

Due to this heterogeneity, the degree of knowledge exchange and the success propensity of an R&D cooperation depend on the technological proximity between the potential cooperation partners. The effective transfer of knowledge requires a common understanding which is based on reciprocal absorptive capacities (Cohen and Levinthal, 1990) to identify and absorb valuable knowledge from a potential cooperation partner. An increasing technological proximity facilitates knowledge exchange, which is one core incentive to engage in a R&D cooperation. Recapitulating, it can be stated that to be able 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. Thus, it is assumed in hypothesis H1 that technological proximity and the cooperation probability are positively related to each other.

H1: A common technological knowledge base is a prerequisite of a cooperative R&D project. The higher the technological proximity the better the understanding of the partners' knowledge base, leading to an increasing cooperation probability.

Beside the exchange of valuable knowledge, cooperation in R&D aims to create new knowledge. Etzkowitz and Leydesdorff (2000) claim that an innovation is often the first combination of already existing knowledge. Taking into account the dependency of innovation probability on the complementarity of the knowledge assets within an R&D cooperation, one can conclude that, from a certain threshold on, the positive effect of a common understanding within an R&D cooperation is dominated by the decreasing probability of a new innovation as a direct result of that cooperation. Based on these arguments, it is assumed in hypothesis H2 that too similar knowledge bases lead to a decrease of the cooperation propensity.

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 and social proximity**

Economic actors willing to innovate rest on a knowledge base that they possess themselves or that must be obtained from partners (Cohen and Levinthal, 1990). Several streams of literature refer to a geographical pattern in the relations of acquisition of external knowledge such as studies on innovative milieus (Camagni, 1991; Capello, 1999), innovation networks based on knowledge spillovers (e.g., Jaffe et al., 1993), or regional innovation systems (e.g., Edquist, 1997). All these papers 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

and Torre, 2004). According to Lundvall (1992), such face-to-face contacts are required for the exchange of tacit knowledge which is, again, a core incentive to engage in R&D cooperation. Antonelli (2000) argues that 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).

However, detractors of this argumentation do not criticize the importance of a co-location per se, but the explanation given. Boschma (2005) argues that, although the exchange of tacit knowledge is essential for interactive learning, this does not need spatial proximity in terms of a 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 trust and understanding within a cooperation rather than a purely geographical co-location. Accordingly, it is suggested in hypothesis 3 that a geographical co-location encourages a collaborative R&D agreement; but whether the requirement of face-to-face contacts or a common social background is the decisive driving force remains open.<sup>1</sup>

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

### **Relatedness of technological and geographical proximity**

The effects of the technological and geographical dimensions of proximity on the willingness to cooperate have so far been discussed separately. Boschma (2005) concludes that geographical proximity has a facilitating function, supporting the presence of other dimensions of proximity, whereas the technological proximity is a must for collaborative R&D projects. Cantner and Meder (2008) conclude that technological and geographical dimensions of proximity are the essential dimensions of proximity in the regional innovation system approach. Based on both argumentations, one can conclude that (i) geographical proximity is a derivative requirement for economic actors to engage in such a project and, thus, (ii) actors with a similar technological knowledge in a nearby location have a higher probability of a common R&D project than actors closely related in only one dimension of proximity.

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

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<sup>1</sup>Later on, geographical and social proximity are summed up under the term geographical proximity.



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 and Deeds (1999) show that a stock of organizational knowledge influences the economic firm performance positively.

### 3 Methodology and data base

The hypotheses are tested on a specific source of information about inventions, namely 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 and Trademark Office (DPMA) as well as data from the European Patent Office (EPO). Since this study relies on patent applications, the activities leading to these applications are of an inventive type and not of an innovative one, which would also require an economizing of the new idea. As this study examines the initializing conditions of cooperative agreements in the field of R&D, this concentration on inventive activities meets the conceptual requirements.

#### 3.1 Study design

The theoretical discussion in the last section applied a dynamic perspective, where the willingness to engage in a specific R&D agreement depends on factors which have been developed in the past. Therefore, the data base is separated into two parts. First, as shown in figure 1, the cooperative activities are identified in patent data of the year 2003. Second, information about patent applications between 1998 and 2002 are used to indicate the independent variables which are claimed to have affected the cooperative activities in 2003.

This study's focus is on an individual level which means that the incentives and conditions for engaging in interactive learning processes are examined by analyzing the impact of different actors' characteristics on the cooperative activities. An actor in this respect is identified as a patent applicant. This implies that all kinds of actors who are filing for patents are included into the analysis.

According to figure 1, the formation of research cooperations the year 2003 are in the focus of this study. In this year, 1,333 German actors filed for at least one patent together with a cooperation partner. Foreign actors are dropped as the information used in the independent variables is based on German data; the inclusion of foreign actors would distort the information and this

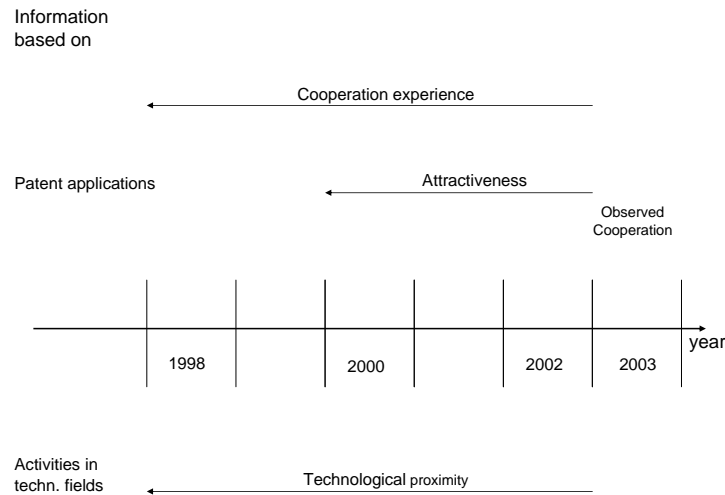


Figure 1: Research concept

would tend to result in an overestimation of German actors activities.

As only those actors that filed for a patent together with a cooperation partner are included into the analysis, the main question here is not whether an actor was willing to cooperate or not, but why a certain partner was chosen. Overall, these 1,333 actors filed for 1,089 collaborative patents in 2003. In order to answer the question why these 1,089 collaborative pairs were realized and all other combinations of potential cooperation were not, the data set includes all possible pairs of German actors who were willing to cooperate in the year 2003. So the data set ends up with 887,778 observations (possible pairs of cooperation), with 1,089 observed cooperations.

### 3.2 Composition of the variables

#### Dependent variable (*Coop*)

A cooperation in terms of the resource-based view of the firm is a unique constellation of valuable knowledge assets (Conner, 1991). Therefore, the unit under consideration are pairs of actors; more precisely this means that the influence of several combinations of actor's characteristics on the propensity of an observed cooperation between these actors is analyzed.

As the main question of this study is whether some constellations of potential cooperation were realized while others were not, the dependent variable for the analyses below has a binary nature,

with a value of 1 if this pair of actors filed for a patent in 2003 and 0 otherwise. The problems of a sufficient estimation model for this unbalanced data set toward the potential, but not observed, cooperation ("0s") is discussed below.

**Technological proximity ( $TProx$ )**

The reciprocal learning activities depend on "absorptive capacities" (Cohen and Levinthal, 1990) of both cooperation partners. In a former study (Cantner and 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 the measure of technological proximity, I refer to information about 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 shown in figure 1, the technological endowment  $T$  of an actor  $A$  is indicated by the number of his or her patent applications for the years 1998 to 2002. It is possible that a patent was filed for a 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 partners divided by the sum of all activities of both partners.

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

This value increases with the technological proximity between actors  $A$  and  $B$  and has a maximum value of 1. This would imply that the pair of actors had an identical knowledge base or, more precisely, both applied for the same number of patents in the same technological fields so the absorptive capacities were at a maximum for both actors. In case both actors of a pair that did not engage in 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 an actor filing for many patents and an actor filing for very few patents researching in the same technological fields would have a lower technological

proximity value, because the understanding would be unbalanced in favor of the larger firm which could fully absorb the technological knowledge of the smaller one but not vice versa.

### **Geographical proximity ( $GProx$ )**

In the theoretical section of this paper, it is assumed that geographical proximity facilitates the exchange of tacit knowledge between the partners of an R&D project. To account for the distance in space and to test for the assumptions of hypothesis 3, the geographical proximity ( $GProx$ ) is calculated by  $GProx_{A,B} = \frac{1}{Dist_{A,B}}^2$ . Here,  $Dist_{A,B}$  is the distance between the locations of actor A and B, measured in kilometers according to the postal code marked on the patent application. This method has at least two shortcomings. First, actors are located according to the applicant's address listed on the patent document. However, it is widely known that especially larger firms file for patents by giving the headquarters address which does not have to be identical to the location of the R&D process. On the other hand, inventors' addresses, which are also given in the application, are not always the same, and for a co-application it is impossible to identify the firm an inventor belongs to. Hence, the applicants' addresses are used in this study for allocating the actors involved. Second, there is a problem regarding the quality of the distance in kilometers to express "easiness" in terms of exchanging tacit knowledge. Gallaud and Torre (2004) differentiate between real and functional distance. The latter means the real time which is required to initiate a face-to-face contact, while the former 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 and Torre, 2004, p.5), this information is not available for this data set and, therefore, the observed distance between actors will be used here.

### **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; accordingly thereby, the availability of valuable knowledge is assumed. To account for the valuable knowledge which is offered by actors of a certain pair in the data set, variable  $Atr$  is included. As shown in figure 1, it contains the number of patent applications of the three years 2000-2002.

The attractiveness of  $B$  being a cooperation partner for  $A$  ( $Atr_A^B$ ) depends on activities of  $B$  (sum of  $P^B$ ) related to the amount of activities of  $A$  (sum of  $P^A$ ). This corresponds to the results

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<sup>2</sup>In the case both actors were located in the same area,  $GProx$  has a value of 0.

of Sadrieh and Verbon (2002) who claim that 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. Equation 2 shows both steps of computing the reciprocal attractiveness indicator:

$$Atr_A^B = \frac{\sum_{i=1}^n P^A + \sum_{i=1}^n P^B + 1}{\sum_{i=1}^n P^A + 1} \quad (2)$$

$$Atr_{A,B} = \ln(Atr_A^B * Atr_B^A).$$

### **Former cooperation experiences (*Ocoex* and *Bcoex*)**

The managerial experiences of both actors of a pair is indicated by two dummy variables (*Ocoex* and *Bcoex*). According to figure 1, both variables are composed of information about the cooperation activities of the actors in the five years between 1998 and 2003. In case that only one of a pair of actors has experiences of how to manage a cooperation the variable *Ocoex* had a value of 1 and 0 otherwise. The goes same for *Bcoex* if both actors of a pair had such experiences.

### **Public research agreements (*Pr*)**

On the one hand, such an actor is more likely to possess a very broad knowledge base which is due to the high probability of several research intensive departments. This tends to result in a low technological proximity between two public research actors. On the other hand, there exist empirical studies in several streams of economic literature, arguing that the community of publicly financed researchers is not so much bounded in space as communities of researcher working for private companies (e.g., David, 1990). Furthermore, public research institutions are claimed to play a special role in the innovation development process (Balconi et al., 2004). In this context, Jaffe (1989), in a early work, shows 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 and Schwirten (1999) mention, in the context of analyzing regional development, that 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 is identified as a public research actor.

### 3.3 Descriptive statistics

Table 1 provides descriptive statistics for the variables. In order to get a first impression of the relationships between the independent variables and the probability of an observed cooperation, the descriptive statistics are given separately for the potential ( $Coop = 0$ ) and observed cooperation ( $Coop = 1$ ).

First, the technological proximity ( $TProx$ ) for the pairs of potential cooperation shows a mean value of 0.011, whereas the  $TProx$  for the observed cooperation has a value of 0.350. This obvious difference between observed cooperation and potential cooperation tends to support 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 observed cooperation (0.019) is higher than the value for potential cooperation (0.005). More precisely, this means that the partners in observed cooperation had, on average, to cope with a geographical distance of 52 kilometers, whereas the partners in potential cooperation had have to cope with a mean distance of 185 kilometers. This finding supports hypothesis 3 in that the geographical proximity facilitates the exchange of tacit knowledge and, therefore, fosters the cooperation probability. Surprisingly and contrary to this, the median value is the same for both groups. This is due to a higher variance of the observed cooperation values.

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

### 3.4 Limitations of the methodology and data base

An interpretation of the results should be approached with care because of the problems that may arise using patent data. These data are suited to characterize the technological knowledge base

Table 1: Descriptive statistics according to cooperative or non-cooperative pairs

<i>Coop</i>	stats	<i>TProx</i>	<i>GProx</i>	<i>Atr</i>	<i>Ocoex</i>	<i>Bcoex</i>	<i>Pr</i>
0	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
	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 <i>Coop</i> = 0: 886689							
1	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
	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 <i>Coop</i> = 1: 1089							

within a firm which might attract other firms for seeking cooperation. However, two obvious qualifications should be made 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 and Ketchen (1999) have claimed for competitively relevant resources. They are supposed to be rare, as well as valuable and specific in their nature. For this reason, patent data at least indicate the technological competitive advantages of a firm. Second, other incentives exist influencing the choice of the cooperation partner likewise exist. Unfortunately, variables for firm structure as size, age, or industry firms are acting in, cannot be included into the model yet.

Beside this theoretical justification of using patent data, Griliches (1990) has shown that patents are a sufficient indicator for the innovative output of firms.<sup>3</sup> As an innovation is a knowledge driven phenomena I assume that without the necessary knowledge base a firm cannot file for a patent.

## 4 Empirical tests

### 4.1 Regression models

The variable of interest in this study, *Coop*, is binary, requiring logistic regression models for testing our hypotheses. In logistic regression, a single outcome variable,  $Y_i$  ( $i = 1, \dots, n$ ), is coded 1 (here for observed cooperation) with probability  $\pi_i$ , and 0 (here for potential cooperative pairs) with probability  $1 - \pi_i$ . Then  $\pi_i$  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 is mathematically

<sup>3</sup>For a deeper analysis of patents as innovative output see, e.g., Trajtenberg (1990) who has introduced a weighted scheme to overcome the shortcomings of counting measures.

expressed as follows:

$$\pi_i = \frac{1}{1 + e^{-\beta_0 - \beta_1 * X_{1i}}}. \quad (3)$$

King and 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 and Zeng, 2001, p.144). They suggest that this information should come from census data for example. The data set of this paper contains information about the whole of Germany, so that it can be assumed that the fraction of 1's for the data base is very similar to the true value, even if it is calculated for only one period. To correct for rare events data this first method is easy to apply for each logistic regression model. The second method, suggested by King and Zeng (2001), is to weight the data to compensate for differences in the sample. This estimator based on the notions of Manski and Lerman (1977) does not maximize the usual log-likelihood function but the weighted log-likelihood. Scott and Wild (1986) show that this second method is less efficient for smaller samples. Although the used data base is sufficiently large, the *WC – Logit* estimator is not applied in this paper.

## 4.2 Empirical Results

Before testing our hypotheses, the impact of the included control variables on the cooperation probability, *Coop*, is tested in the PC-Logit regression model M1. The coefficient for the balanced attractiveness indicator, *Atr*, presented in table 2, is positive and significant. Thus, the result for our data base is in a line with empirical studies analyzing the impact of valuable assets offered by actors who are willing to cooperate on the probability that another actor is accepting this offer, as those by Sadrieh and Verbon (2002) or Cantner and Meder (2007).

To account for the organizational skills in terms of how to manage a cooperative agreement the variables *Ocoex* and *Bcoex* are included into the regression model. The coefficient of *Ocoex* is negative and significant which means that pairs of actors where one actor had experiences in cooperation (at least one co-application for 2003) have a lower cooperation probability than pairs where neither actor had such experiences. This finding is, however, contrary to empirical findings like those of Decarolis and Deeds (1999). By contrast, the coefficient for the second variable of



the organizational skills, *Bcoex*, is positive and significant. Thus, pairs where both actors had cooperation experiences in terms of co-applications in the past were more likely to file for a patent together than pairs without such experiences. Both results together could be interpreted in a way that actors who are willing to cooperate in R&D are continuously seeking partner for new R&D projects. At this stage of analysis, one cannot say whether these new projects are initiated with the same partner or not.

Finally, *Pr* is included into the regression models in order to account for specific characteristics of cooperation between public research actors. As presented in table 2, the coefficient for *Pr* is not significant. The sign of the coefficient cannot be interpreted. Thus, one can conclude that pairs of actors identified as public research actors have no higher probability to engage in a common R&D project than other pairs of actors.

Table 2: Estimation models of H1 and H2

Depend. var.	M1	M2	M3
	PC-Logit <i>Coop</i>	PC-Logit <i>Coop</i>	PC-Logit <i>Coop</i>
<i>Tprox</i>		1.401*** (0.100)	1.553*** (0.091)
<i>Tprox</i> <sup>2</sup>			-0.028*** (0.002)
<i>Atr</i>	0.043** (0.019)	0.047** (0.019)	0.046** (0.019)
<i>Ocoex</i>	-0.488*** (0.074)	-0.524*** (0.075)	-0.528*** (0.075)
<i>Bcoex</i>	1.118*** (0.076)	0.685*** (0.086)	0.654*** (0.085)
<i>Pr</i>	-0.200 (1.00)	-0.199 (1.00)	-0.203 (1.00)
(Intercept)	-6.742*** (0.047)	-6.755*** (0.048)	-6.755*** (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 into the PC-Logit regression model M2. As shown in table 2, the coefficient of *Tprox* is positive and significant. Hence, hypothesis H1 on the positive relationship between technological proximity and cooperation probability cannot be rejected for our data base. Actors with a closely related technological knowledge base are more likely to initiate a common R&D project. This finding is in a line with the statements of the absorptive capacity concept (Cohen and Levinthal, 1990) and with the conclusions of the resource-based view of the firm approach (Wernerfelt, 1984; Barney, 1991). Furthermore, this finding is consistent with results of comparable empirical studies on firm level, e.g., Mowery et al. (1998), Wuyts et al. (2005), or Cantner and Meder (2007).

Hypothesis H2 assumes that this positive impact of the technological proximity on the cooperation probability diminishes when the knowledge bases of two actors are too close to each other. To test for this inverted-U relationship, the squared  $Tprox$  values, called  $Tprox^2$ , are included in regression model M3. As displayed in table 2, the coefficient for  $Tprox^2$  is negative and significant. Although this sign actually contributes to H2, we have to reject this hypothesis as the peak of the inverted-U (at  $Tprox = 3.736$ ) is outside the range of the  $Tprox$  values of our data base. The Ramsey Regression Equation Specification Error Test (RESET) based on Ramsey (1969) shows no misspecification of the regression model. This finding is contrary to the results of comparable empirical studies, e.g., Wuyts et al. (2005). This difference might be due to the definition of the technological space. The 43 technological fields we use to indicate the technological proximity between two actors apparently describe the relatedness of the knowledge bases rather than their homogeneity (Nesta and Saviotti, 2005).

Having tested for the impact of the technological proximity, hypothesis H3 about the impact of geographical proximity on cooperation probability is tested on the given data base. Thus,  $Gprox$  is included into the regression model M4 as shown in table 3. The coefficient for  $Gprox$  is significant and positive. Thus, hypothesis H3 cannot be rejected for our data base. Actors who are located nearby are more likely to engage in a R&D cooperation than actors located far away from each other. This result is in a line with findings of empirical studies such as Jaffe (1989) or Audretsch and Feldman (1996). Furthermore, it contributes to the ongoing discussion about the relevance of spatially oriented innovation systems. As discussed before, a shortcoming of this finding is that effects of geographical proximity are often overlapping with effects of social proximity (Boschma, 2005). The positive impact of  $Gprox$  on the cooperation probability can be explained either by easier face-to-face contacts (Morone and Taylor, 2004) or by a common social background of both actors (Sorenson et al., 2006).

After testing the individual influence of technological and geographical proximity on the cooperation probability, the regression models in table 4 are tested on the interrelatedness between both dimensions of proximity. First,  $Tprox$  and  $Gprox$  are included into the PC-Logit regression model M5. Both variables show a positive and significant coefficient. The significance levels as well as the signs for the coefficients of  $Tprox$  and  $Gprox$  remain the same when the squared technological proximity term  $Tprox^2$  is included into model M6. Thus, one can conclude that both dimensions of proximity enhance the cooperation probability independently. This finding is contrary to the

Table 3: Estimation models of H3

Depend. var.	M1	M4
	PC-Logit <i>Coop</i>	PC-Logit <i>Coop</i>
<i>GProx</i>		3.438*** (0.24)
<i>Atr</i>	0.043** (0.019)	0.044** (0.019)
<i>Ocoex</i>	-0.488*** (0.074)	-0.489*** (0.074)
<i>Bcoex</i>	1.118*** (0.076)	1.111*** (0.076)
<i>Pr</i>	-0.200 (1.00)	-0.453 (1.02)
(Intercept)	-6.742*** (0.047)	-6.768*** (0.047)
Observations	887778	887778
Robust standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

conceptual conclusion of Boschma (2005) who argues that geographical proximity is a facilitating element rather than a fundamental condition of an R&D cooperation. This discrepancy can be explained by the restricted definition of geographical proximity Boschma (2005) uses. He analyzes, on a conceptual level, the effects of geographical aspects in the absence of social or other influences, which is not the case in our empirical study.

To test hypothesis H4, an interaction term,  $Tprox * GProx$ , is included linearly ( $Tprox * GProx$ ) and squared ( $Tprox^2 * GProx$ ) into the regression model M7. The coefficients for both terms, as presented in table 4, are not significant. In model M8 the effects of both dimensions of proximity are tested together with both interaction terms. Here again, the linear interaction term ( $Tprox * GProx$ ) shows no significant impact on cooperation probability, but the interaction term between the squared technological proximity and geographical proximity ( $Tprox^2 * GProx$ ) shows a negative significant impact. Nevertheless, mainly based on the results of model M7, hypothesis H4 has to be rejected for our data base. The actors with a similar knowledge base who are located nearby are not more likely to engage in an R&D project together than actors with a similar knowledge base or actors who are located nearby in general.

## 5 Discussion and conclusion

Cooperation in the field of R&D has been widely discussed in several streams of economic literature. One stream focuses on the effects of such agreements on performance on the individual (e.g., Combs

Table 4: Estimation models of H4

Depend. var.	M5	M6	M7	M8
	PC-Logit <i>Coop</i>	PC-Logit <i>Coop</i>	PC-Logit <i>Coop</i>	PC-Logit <i>Coop</i>
<i>Tprox</i>	1.367*** (0.10)	1.520*** (0.095)		1.530*** (0.095)
<i>Tprox</i> <sup>2</sup>		-0.028*** (0.002)		-0.027*** (0.002)
<i>Gprox</i>	2.958*** (0.32)	2.948*** (0.32)		3.011*** (0.31)
<i>Tprox</i> * <i>GProx</i>			-2.439 (3.89)	0.148 (0.50)
<i>Tprox</i> <sup>2</sup> * <i>GProx</i>			0.904 (0.91)	-0.120*** (0.038)
<i>Atr</i>	0.0477** (0.019)	0.0471** (0.019)	0.0465** (0.019)	0.0469** (0.019)
<i>Ocoex</i>	-0.523*** (0.075)	-0.527*** (0.075)	-0.488*** (0.074)	-0.528*** (0.075)
<i>Bcoex</i>	0.682*** (0.087)	0.651*** (0.086)	1.074*** (0.077)	0.649*** (0.085)
<i>Pr</i>	-0.419 (1.02)	-0.429 (1.02)	-0.191 (1.00)	-0.446 (1.02)
(Intercept)	-6.774*** (0.048)	-6.774*** (0.048)	-6.746*** (0.047)	-6.775*** (0.048)
Observations	887778	887778	887779	887780

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

and Ketchen, 1999; Oerleman and Meeus, 2000; Belderbos et al., 2004) as well as on the systemic level (e.g., Raspe and van Oort, 2006; Asheim and Coenen, 2005). Another stream of literature focuses on the determinants influencing the willingness to engage in such cooperation projects. This paper addresses the second focus by asking how economic actors that have already made their decision to cooperate search for an appropriate cooperation partner.

In this paper, 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. Our findings contribute to the ongoing discussion about the conditions for interactive learning. The main findings of this paper are as follows:

- Technological proximity between two economic actors enhances the probability that they initiate a collaborative R&D project together.
- A negative effect of knowledge bases that are too closely related, as suggested by Nooteboom (2000) and other studies, cannot be shown for this data base. This might be due to the measurement of technological proximity. Here, in contrast to Wuyts et al. (2005), for example, the relatedness of the knowledge bases is calculated rather than their homogeneity.
- Actors located nearby in a geographical dimension are more likely to initiate an R&D project together than actors located far away from 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, it has to be concluded that there is an effect of geographical proximity which is independent of technological proximity.

In economic literature, there has been a long discussion, which is still ongoing, about the usage of patent data for empirical studies. Griliches (1990) shows that patents are a sufficient indicator for innovative success. Beyond using patents as indicator for 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 paper patent data are used (i) to identify collaborative R&D agreements, to allocate actors in (ii) the technological or (iii) the geographical space. As discussed above, this methodology has some serious shortcomings such as the problem of using the applicants' postal code for geographical allocation, but patents are a core resource for firms (Combs and Ketchen, 1999) nevertheless. Furthermore, the availability of objective measurements are strong advantages of this methodology.

The findings of this paper contribute to the learning economy approach in the sense that it is shown that firm A is more likely to engage in collaborative R&D projects with partners possessing valuable knowledge which can be understood by firm A due to a common knowledge base. Furthermore, firm A seeks partners located nearby, hinting at the requirement of face-to-face contacts for the exchange of tacit knowledge according to Polanyi (1966). After examining the determinants influencing the choice of the cooperation partner, a detailed analysis of how these determinants affect the success of collaborative projects will be necessary.

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