

**Does Proximity Matter in the Choice of Partners in  
Collaborative R&D Projects? – An Empirical Analysis  
of Granted Projects in Germany**

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# **Does Proximity Matter in the Choice of Partners in Collaborative R&D Projects? – An Empirical Analysis of Granted Projects in Germany**

## **Abstract**

This paper contributes to the discussion on the importance of physical distance in the emergence of cross-region collaborative Research and Development (R&D) interactions. The proximity theory, and its extensions, is used as a theoretical framework. A spatial interaction model for count data was implemented for the empirical analysis of German data from the period from 2005 to 2010. The results show that all tested proximity measurements (geographical, cognitive, social and institutional proximity) have a significant positive influence on collaboration intensity. The proximity paradox, however, cannot be confirmed for geographical, social and institutional proximity, but for cognitive proximity.

Keywords: proximity theory, proximity paradox, gravity models, cross-regional collaborations, spatial interaction

JEL Classification: O18, R00, R11

# **Ist Nähe bei der Wahl von FuE-Kooperationspartnern von Bedeutung? – Eine empirische Analyse geförderter Projekte in Deutschland**

## **Zusammenfassung**

Das Papier leistet einen Beitrag zur Diskussion über die Bedeutung physischer Distanz für die Herausbildung von Zusammenarbeit in der Forschung und Entwicklung (FuE) über Regionsgrenzen hinweg. Den theoretischen Rahmen bilden die Proximity-Theorie und ihre Erweiterungen. Mit Hilfe eines räumlichen Interaktionsmodells für Zählraten werden deutsche Daten des Zeitraums von 2005 bis 2010 empirisch analysiert. Die Ergebnisse zeigen, dass alle getesteten Maße für Nähe (geographische, kognitive, soziale und institutionelle) einen signifikant positiven Einfluss auf die Intensität der Zusammenarbeit haben. Das „Paradox der Nähe“ kann hingegen nur für kognitive Nähe bestätigt werden, nicht aber für geographische, soziale und institutionelle Nähe.

Schlagwörter: Proximity-Theorie, Nähe-Paradox, Gravitationsmodell, regionenüberschreitende Zusammenarbeit, räumliche Interaktion

JEL-Klassifikation: O18, R00, R11

# 1 Introduction

Inter-regional collaborations have been studied extensively over the past years. Scholars have investigated the relationship between collaborations, knowledge diffusion and innovation to analyse the determinants of regional growth (see e.g. ROMER, 1990; JAFFE *et al.*, 1993; AUDRETSCH and FELDMANN, 1996; TORRE and GILLY, 2000; BOSCHMA, 2005; MARROCU *et al.*, 2013 and many others). In theoretical and empirical works, scholars have found that, in addition to other factors, interactive learning is a main driver in generating innovation (JAFFE, 1989; GROSSMAN and HELPMAN, 1990; JAFFE *et al.*, 1993; HELPMAN, 1995). In this context, SCHERNGELL and BARBER (2009) describe collaborations as ‘*conditio sine qua non*’ for innovations, highlighting their importance. Within this context, there is great interest in the literature in the relevance of the ‘location’ under the conditions of globalized markets. Despite the ease of modern communication through the internet, geographical proximity could play a key role in the exchange of knowledge and information. However, some branches of the literature regard geographical proximity as neither a necessary nor a sufficient condition for knowledge interactions. In order to generate a deeper understanding of how actors choose their collaboration partners, BOSCHMA (2005) formulated a concept that highlights the importance of five different proximity measurements. These are geographical, social, cognitive, institutional and organizational proximity. In fact, geographical proximity influences other forms of proximity, such as technological, social, organizational and institutional. Since BOSCHMA’s seminal work, the number of theoretical (KNOBEN and OERLEMANS, 2006; BOSCHMA, 2007; BOSCHMA and FRENKEN, 2010) and empirical contributions (PONDS *et al.*, 2007; AGRAWAL *et al.*, 2008; WETERINGS and BOSCHMA, 2009; BROEKEL and BOSCHMA, 2011; BALLAND *et al.*, 2013; MARROCU *et al.*, 2013 and others) made to evaluate his hypotheses has risen. While several studies examine the importance and significance of the proximity forms at an actor based level, only a little is known about their importance at a regional level and their interdependencies with other regional variables. Furthermore, this phenomenon has not been studied in Germany. Besides scholars, policy makers might also be interested in this field. Intensive proximity collaborations are regarded as a competitive advantage for the respective region.

The empirical approach in this paper is in line with the work of SCHERNGELL and BARBER (2009). The data were aggregated on a regional level to generate insights into the importance

of inter-regional collaboration intensity. For this reason, the dependent variable is the number of inter- and intra-regional collaborations for the possible regional pairs. In order to test the significance of the proximity concept in the context of inter-regional collaborations, two research questions were derived:

- (i) Does the importance of geographical proximity remain high if social, institutional and cognitive proximity are included in the model?
- (ii) Does the proximity paradox hold true?

In order to account for the distribution of the dependent variable and the regional effects in the data, a gravity type spatial interaction model with a Poisson distribution was conducted (see e.g. LESAGE *et al.*, 2007; PONDS *et al.*, 2007; LESAGE and PACE, 2008; FISCHER and SCHERNGELL, 2009; SCHERNGELL and BARBER, 2011; AUTANT-BERNARD, 2012). The results of the specification test indicate the use of a zero-inflated negative binomial model, to account for the over dispersion and the excessive zeros in the sample. The results of the estimation support the importance of geographical, cognitive, social and institutional proximity. In contrast to the theory, the proximity paradox was not confirmed for all forms.

This paper is structured as follows: in the second section, the proximity theory will be described in detail. This is followed by section three, in which the empirical method will be presented. Section four focuses on the data and the chosen variables. The fifth section contains the results, and the paper ends with the conclusion in the sixth section.

## **2 Revisiting the Proximity Theory**

BOSCHMA'S (2005) proximity theory is used as a theoretical foundation. This work has its grounding in the French school of proximity dynamics (TORRE and GILLY, 2000). The theory focuses on the idea that knowledge flows between actors, generates knowledge spillovers, innovation and, finally, regional growth. The question is, which factors affect the choice of collaboration partners and hence the flow of knowledge? The proximity theory centres on the relative position of the actors in a multidimensional framework. These dimensions are geographical, cognitive, social, institutional and organizational proximity. With increasing closeness between the actors in terms of the dimensions, the probability of collaboration will increase. However, within the proximity debate it is argued that this relationship is not linear. If two actors are too close in one dimension, the collaboration intensity may decrease as a result

of lock-in effects. This is the so-called proximity paradox (BOSCHMA and FRENKEN, 2010). Furthermore, the different forms of proximity influence each other and their optimal value (BOSCHMA, 2005).

### *Geographical Proximity*

Over time, many scholars have dealt with the influences of geographical distance on economic interactions (see e.g. THÜNEN, 1826; MARSHALL, 1890; WEBER, 1909; HOTELLING, 1929; CHRISTALLER, 1933; PALANDER, 1935 and LÖSCH, 1948). Friedrich LIST (1841), for example, was one of the first scholars to focus on individual aspects of economic agents and the way they are incorporated in institutional and geographical systems, especially in ‘face-to-face’ interactions (i.e. human and physical capital). As a starting point in the ongoing debate, one could use KRUGMAN (1991), AUDRETSCH and FELDMAN (1996) as well as JAFFE *et al.* (1993). They claim that in increasing geographical proximity between the economic actors, the amount of positive externalities in the form of knowledge spillovers also increases. The reason for this is that with an increased physical distance it is harder to transfer tacit knowledge between them. A major reason for this is that ‘face-to-face’ collaborations help to transfer this knowledge. In addition, HOWELLS (2002) states that this also concerns codified knowledge because of the need for tacit knowledge in the interpretation. Nevertheless, this argument can be disputed if ‘face-to-face-interactions’ are ‘cyberized’ by modern technologies (WHEELER *et al.* 2000). BOSCHMA (2005), in contrast, uses a more detailed view of the different forms of proximity and their interactions. To this end, he defines geographical distance as ‘the spatial or physical distance between economic actors, both in its absolute and relative meaning’ (BOSCHMA, 2005, p. 69). He claims that geographical, together with technological proximity is sufficient to generate interactive learning. Other proximity forms, however, could serve as substitutes for geographical proximity (e.g. organizational or social proximity). On the other hand, excessive proximity can cause spatial lock-in effects, known as proximity paradox. This can occur in very specialized regions and is the result of the potential inward orientation of the actors (BOSCHMA and FRENKEN, 2010). Recent technologies and trends in other regions could be missed, depending on the other forms of proximity. In order to overcome this problem, BATHELT *et al.* (2004) propose building additional inter-regional connections. Nevertheless, BOSCHMA (2005) concludes that geographical proximity ‘is neither a necessary nor a sufficient condition’ (BOSCHMA, 2005, p. 71). Interactive learning,

however, is still indirectly influenced by geographical proximity, because it can facilitate the other forms of proximity (BROEKEL and BOSCHMA, 2011).

### *Cognitive Proximity*

BOSCHMA (2005) follows SIMON (1955) as well as NELSON and WINTER (1982) in claiming that economic agents act under uncertainty. In order to reduce this insecurity in face of the future, agents conduct routinized behaviour and research close to their knowledge base. This creates a path dependence and limits potential collaboration partners because there must be an overlap in their knowledge base if costs are to be reduced and innovation generated. This hypothesis is supported by the argument that because knowledge is implicit, access alone does not generate learning. If learning is to be generated, absorptive capacity is required. This enables the economic actor to identify, interpret and exploit new knowledge (COHEN and LEVINTHAL, 1990). In addition to the degree of shared knowledge, it is essential that new knowledge also enters the collaboration. Therefore, too much cognitive proximity between actors reduces the efficiency of the collaboration (NOOTEBOOM, 2000). A second reason is the potential lock-in effect of a substantial overlap in the partners' knowledge bases. Existing routines and technologies could become inefficient with respect to the rest of the market and are difficult for the partners to unlearn. Cognitive proximity in combination with geographical proximity, however, is regarded as sufficient for interactive learning (BOSCHMA, 2005).

### *Organizational Proximity*

Organizational proximity is defined as 'the rate of autonomy and the degree of control that can be exerted in organizational arrangements' (BOSCHMA, 2005, p. 65). Only minimal control can be exerted on the spot market; thus the partners cannot influence each other. Maximum control can be found in a hierarchical firm or network. The benefit of a strong organizational boundary is the reduction in opportunism and uncertainty. This is particularly so where ownership rights can be managed in a hierarchical cooperation. Furthermore, the transfer of tacit knowledge will be simplified by strong organizational boundaries (HANSEN, 1999). The negative effect of too much organizational proximity lies in the hold-up problem. A very powerful partner can demand inefficient cooperation specific investments. Besides this, the asymmetrical distribution of power can cause a block in novel information and, finally, in innovation (BOSCHMA, 2005). This is why GRABHER and STARK (1997) claim that the optimal value for organizational proximity can be accomplished by loosely coupled networks,



whereas the advantages of autonomous agents and organizational flexibility are combined with weak ties. This makes it clear that network structures in particular play a decisive role at both the national and the international level (BLUM, 2003) and may generate small-world phenomena (WATTS and STROGATZ, 1998).

### *Social Proximity*

UZZI (1996) argues that all economic interactions are embedded in a social context; thus micro-level trust, based for example on former experience, kinship or friendship, may also exert an influence on the probability of collaboration. MASKELL and MALMBERG (1999) claim that if there is a high level of trust, the exchange of implicit knowledge will be facilitated. Furthermore, with high social proximity, opportunistic behaviour will be reduced in comparison with a market based exchange (BOSCHMA, 2005). If the social proximity between two partners or in a collaboration network is too great, negative effects will occur. New and innovative actors cannot enter such a collaboration because the partners cling to an inefficient connection (BOSCHMA, 2005). UZZI (1996) claims that a mix of embedded ties and arm`s length ties are necessary to generate the optimal level of collaboration probability.

### *Institutional Proximity*

Institutions can be divided into explicit (laws, enforceable rules) and implicit (habits, routines) institutions (NORTH, 1990). Institutional proximity describes which habits, routines, rules and laws two actors have in common (BOSCHMA, 2005). With rising similarities in their institutions, transaction costs will decrease because of an increasing level of trust. Too much institutional proximity, however, can be a source of inefficient cooperation. As HALL and SOSKICE (2001) and ACEMOGLU and ROBINSON (2012) point out, there are possible interdependencies in the institutional framework. If an innovative entrepreneur wants to change some established routines in a network, a high resilience may interfere with this endeavour because of the interconnection of the institutions (FREEMAN and PEREZ, 1988).

### *The Proximity Paradox*

As described above, a rise in proximity forms does not necessarily increase the likelihood of cooperation between two actors. The threat of different lock-in effects may even decrease the potential for such collaboration. BOSCHMA and FRENKEN (2010) follow NOOTEBOOM (2000) as well as BOSCHMA (2005) in arguing that there is an optimal value not only for cognitive

proximity but also for other forms. The concept becomes more complex if one considers the possible interdependencies between the proximity forms. The optimal level for every form is then influenced by the levels of all the other forms.

### 3 The Spatial Interaction Estimation model

In order to examine the number of inter-regional collaborations, a spatial interaction model is applied. By changing the level of analysis, the model can account for the notion that knowledge also flows at the level of regions or organizations (JAFPE *et al.*, 1998). This approach is in line with LESAGE *et al.*, (2007), SCHERNGELL and BARBER (2009), FISCHER and SCHERNGELL (2009) as well as with SCHERNGELL and BARBER (2011), even though other authors have used a knowledge production function at the regional level to explain the knowledge flows (see e.g. JAFPE *et al.*, 1993; MAGGIONI *et al.*, 2007; BROEKEL and BOSCHMA, 2011). In contrast to most of these studies, patent data instead of collaboration data are used. The reason for this is that collaboration data include more information because patents reflect only successful collaborations. By using collaboration data, unsuccessful partnerships are also included.

#### *Spatial Interaction Modelling*

The major objective is to explain which separation effects account for the differences in the number of cross-regional collaborations in Germany. For this reason a squared  $n$ -by- $n$  matrix  $C$  will be introduced, which includes our observed cross-region R&D collaborations. These regions can be labelled from  $i, j = 1, \dots, n$ . One element of this matrix ( $c_{ij}$ ) embodies the number of collaborations between region  $i$  and  $j$ . The form of the model is therefore

$$C_{ij} = V_{ij} + \varepsilon_{ij} \quad i, j = 1, \dots, n \quad (1)$$

where  $\varepsilon_{ij}$  is a random term and its expected outcome is zero ( $E(\varepsilon_{ij}|c_{ij}) = 0$ ). The systematic part of the model is  $V_{ij}$  and thus this is the expected value of our cross-regional R&D collaborations, because  $E(C_{ij}|c_{ij}) = V_{ij}$ .

In order to model this relationship, a spatial interaction model of the gravity type is applied (see LESAGE *et al.*, 2007, SCHERNGELL and BARBER, 2009). A standard spatial interaction classification can be described by three functions: the origin function ( $A_i$ ), the destination

function ( $B_i$ ) and a spatial separation function ( $S_{ij}$ ) (SEN and SMITH, 1995). These functions describe the variations in the observations. The destination and origin function are weight matrices for the regions under analysis. A connection to the gravitation theory by Isaac Newton can be found in these weights (ROY and THILL, 2004). The separation function is modelled by explicit functions of numerical variables that are likely to explain the differences between the numbers of cross-regional collaborations (LESAGE *et al.*, 2007). Thus, the model is expressed as

$$V_{ij} = A_i B_j S_{ij} \quad i, j = 1, \dots, n \quad (2)$$

As in the literature,  $A_i = A(a_i, \delta_1) = a_i^{\delta_1}$  and  $B_i = B(b_i, \delta_2) = b_i^{\delta_2}$ ;  $a_i$  and  $b_j$  will be represented by appropriate origin and destination variables and will embody mass terms of the regions under analysis. The most important part of the model for the purposes of the analysis is the separation function  $S_{ij}$ . The variables that enter the separation function are geographical, technological, social and institutional proximity. In addition, a border region dummy and a neighbouring dummy are included.

$$S_{ij} = S(g, \beta) = \exp \left[ \sum_{z=1}^Z \beta_z g_{ij}^{(z)} \right] \quad i, j = 1, \dots, n \quad (3)$$

$g_{ij}^{(z)}$  describes the different measurements of separation ( $Z$ ). If all equations are incorporated into equation (1), the result is as follows

$$c_{ij} = a_i^{\delta_1} b_j^{\delta_2} \exp \left[ \sum_{z=1}^Z \beta_z g_{ij}^{(z)} \right] + \varepsilon_{ij} \quad (4)$$

During the estimation,  $\delta_1$ ,  $\delta_2$  and  $\beta_z$  will be calculated.  $\delta_1$ ,  $\delta_2$  represent the elasticities and  $\beta_z$  the semi-elasticities of cross-regional R&D collaborations  $c_{ij}$ .

### *The Estimation Model*

A Poisson model specification is applied to calculate equation (4) because of the count distribution of the data. Standard OLS estimators are requiring for normally distributed residuals with an expected value of zero. The current data does not fulfil these assumptions (see section 4). As usual, a Poisson model specification is used as a starting point; to extend this model an over-dispersion test and a test for the existence of excessive zeros are applied. It appears that

the data demand the use of the zero-inflated negative binomial model (see section 5), which can be calculated with a probability function as follows<sup>1</sup>

$$f(c_{ij}|x_i) = \varpi_i d_i + (1 - \varpi_i) \frac{e^{-\lambda_i} \lambda_i^{c_i}}{c_{ij}!} \quad (5)$$

In this framework a binary variable ( $q_i$ ) is introduced; this equals one if the observed outcome is zero. For any value larger than zero,  $q_i = 0$  holds true. The variable  $\varpi$  denotes the probability that  $q_i = 1$ . For this model, the probability of a zero outcome is  $P(c_{ij} = 0|x_i) = \varpi + (1 - \varpi) \exp \lambda_i$  and this is strictly greater than for a standard Poisson model as a result of the two regimes of the data generating process. Finally, it can be concluded that the zeros in this model arise from two regimes ( $q_i = 1$  with probability  $\varpi$  or  $q_i = 0$  with probability  $1 - \varpi$ ) (WINKELMANN and BOES, 2009). The same can be argued for the theory of collaborations. A company may not cooperate because there is no collaboration partner, so it is not possible for the collaboration seeking actor to find a partner ( $q_i = 1$ ). The second regime, which means that the number of collaborations is greater than one, implies that the relative position of the proximity values influences the choice of partner ( $q_i = 0$ ). Therefore, these two arguments can be separated by a zero-inflated negative binomial model.

## 4 Applying the Spatial Interaction Model for Count Data

### 4.1 The Data: Granted R&D Projects in Germany

The dataset contains 4,344 collaboration projects that have been (co-)funded by the German Federal Ministry of Education and Research and covers the period from 2005 to 2010. The dataset provides an identifier that indicates which single projects form part of a collaboration project. The dataset also provides further variables, such as regional codes, industry codes and the type of organization. As a first step, the project matrix is aggregated to the regional level. In so doing, information on the number of cross-region collaborations is obtained. The analysis is carried out for the 405 German NUTS 3-regions (districts and district-free cities). This yields to the matrix ( $C_{ij}$ ) with the dimensions  $n \times n$ , whereas one region runs from  $i$  to  $n$  with  $n = 405$ . In this way, it is possible to develop a collaboration matrix at the regional level. This matrix is symmetrical since it is assumed that knowledge flows are bilateral. In the

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<sup>1</sup> For more information see WINKELMANN and BOES (2009).

next step, the matrix  $C$  is transformed to an upper triangular matrix. In contrast to SCHERNGELL and BARBER (2009), all the entries below the main diagonal have been dropped. This means that one collaboration with three partners from three different regions is recognized as three links. In the case of a project with two partners from one region, one link is counted. The use of a symmetrical matrix would produce biased results because the observation  $c_{ij} \geq c_{i+1,j+1}$  is equal to  $c_{i+1,j+1} \geq c_{ij}$ . In other words, the observation  $c_{i+1,j+1} \geq c_{ij}$  does not provide additional information.

There is a rich body of literature that uses patent data to investigate cross-region collaborations. However, the application of patent data has some drawbacks in that not all innovations are reflected in patent applications (e.g. ARUNDEL and KABLA, 1998). The advantage of granted cross-regional R&D projects over patent data is that the former include successful as well as unsuccessful cooperative projects. This is why this study captures a wider variety of collaborations.

On average, the number of connections is 0.55 with a standard deviation of 5.125. In total, 45,202 linkages (interregional and intraregional) are observed. If one considers the observations (pairs of regions) that reflect at least one collaboration (10,953 out of 82,215), the average number of collaborations is 4.127 with a standard deviation of 13.504.

*Fig. 1. Distribution of the cross-regional R&D collaborations*

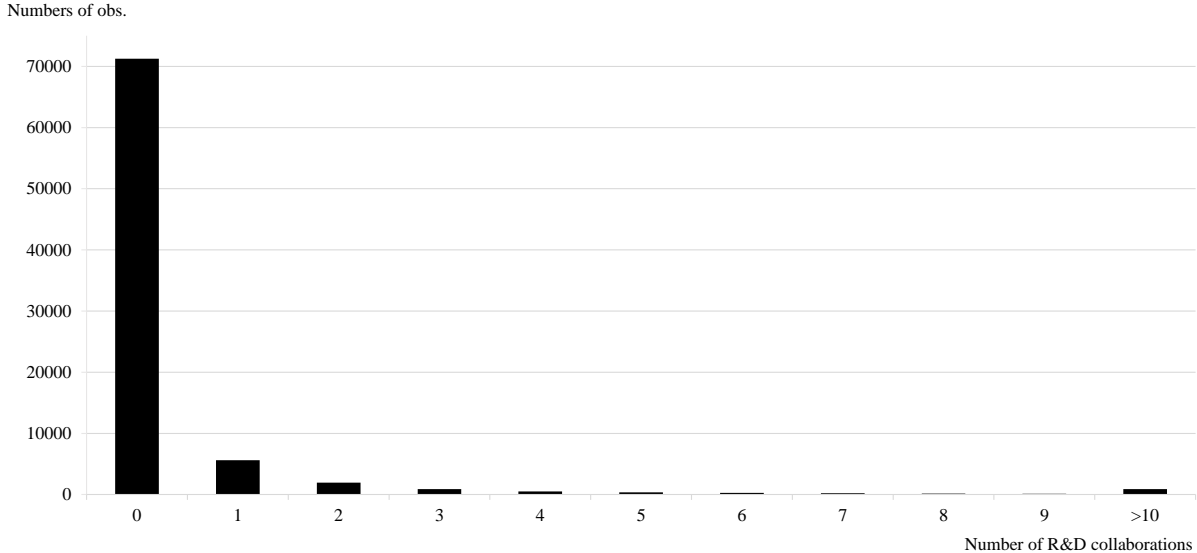


Figure 1 indicates that almost 86.68 percent of possible pairings have no connection and that 1,007 pairings reveal more than nine collaborations. The highest number of collaborations can be observed within Berlin, with a total number of 882.

## 4.2 Independent Variables

### *Geographical Proximity*

Most scholars (e.g. PAIER and SCHERNGELL 2011; BALLAND *et al.*, 2013) use the Euclidean distance between the capitals of two regions to capture the physical distance between two actors. Other than this measurement, some scholars (e.g. EJERMO and KARLSSON, 2006) use the time it takes to travel between two points. Both measurements were used in this study, but as there was no significant difference in the parameters, the Euclidean distance is preferred. As an additional non-linear influence on the collaboration intensity and in order to examine the proximity paradox, a quadratic term is included, as in BROEKEL and BOSCHMA (2011) and MARROCU *et al.* (2013).<sup>2</sup>

### *Cognitive Proximity*

According to SCHERNGELL and BARBER (2009), the cognitive proximity is measured as  $1 - r$ , where  $r$  equals the Pearson correlation coefficient between the vectors  $t(i)$  and  $t(j)$ . The vector  $t(i)$  represents the relative share of an industry in region  $i$ , measured by the number of granted projects  $c_{ij}$  in sector  $r$  as a proportion of the total number of granted projects in region  $i$ . This can be expressed in an equation as

$$t(i) = \frac{x_{ri}}{\sum_r x_{ri}} \quad (6)$$

The vector  $t(j)$  is calculated in the same way. The data are derived from the Foerderkatalog database. The co-domain of this coefficient lies between 0 and 2. If the application patterns of two regions are exact opposites, the coefficient will be 2 (1-(-1)). If the industrial line-up is not correlated at all, the coefficient will be 1. If the industrial orientation in two regions is the same, the variable will be 0. Reasons for keeping to this notation are the path dependencies and the additional costs that result if regions wish to change their industrial alignment.

### *Social Proximity*

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<sup>2</sup> As for every quadratic proximity value, we subtracted the mean before we squared it to avoid multicollinearity.

In order to grasp micro-level trust, two measures from the network literature are used. Generally, scholars distinguish between two basic concepts: clique members and brokers, whereas both positions enrich knowledge diffusion. Clique members can be identified by the concept of closeness centrality, whereas brokers can be identified by the concept of betweenness centrality (FREEMAN, 1979). In order to calculate closeness centrality ( $W_c$ ), the geodesic proximity (or distance  $\mathbf{d}$ ) will be measured from one region  $\mathbf{r}_i$  to another region  $\mathbf{r}_k$ . A high value for closeness centrality means that only a few edges have to be overcome to connect both regions.

$$W_c(l_k)^{-1} = \sum_{i=1}^n d(r_i, r_k) \text{ with } i \neq k \quad (7)$$

Brokers' positions can be identified by measuring the betweenness centrality. Betweenness centrality stands for the amount of control a region  $k$  could exert over the knowledge flow between region  $i$  and  $j$ . A high degree of control means a high value of betweenness centrality (FREEMAN, 1979). The mathematical formulation is

$$W_b(r_k) = \sum_{i < j}^n \sum_j \frac{o_{ij}(r_k)}{o_{ij}} \text{ with } i \neq j \neq k \quad (8)$$

where  $\mathbf{o}_{ij}$  represents the number of geodesic connections between  $\mathbf{r}_i$  and  $\mathbf{r}_j$ . Together with  $\mathbf{o}_{ij}(\mathbf{r}_k)$ , the number of geodesic links between  $\mathbf{r}_i$  and  $\mathbf{r}_j$ , given that the path includes  $\mathbf{r}_k$ , are counted.<sup>3</sup> We calculate social proximity as the difference in the centrality measures between each pair of regions.<sup>4</sup>

### *Organizational Proximity*

Owing to a lack of data, no measurement can be included to account for the organizational proximity in the analysis. Besides, there are no data available for the ownership structure of the actors, nor is the type of organization an approximation (as in BROEKEL and BOSCHMA, 2011). This is because a university or research institute was required to obtain funds for an uncertain part of projects.

### *Institutional Proximity*

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<sup>3</sup> The calculations had been made using the UCINET software.

<sup>4</sup> Because of interpretation difficulties, a quadratic term for social proximity was not included.

Because the data are from a legally equal area, implicit institutions like norms and values are used to model the proximity between the regions in respect of a macro-level trust (see e.g. BLUM and DUDLEY 2001; FALCK *et al.*, 2012 and BECKER and WOESSMANN, 2009). In order to do so, the same approach is applied as for the cognitive variable. The dataset contains information on the share of ‘Protestants’, ‘Catholics’ and ‘Others’ for every region. Therefore, the Pearson correlation coefficient between the religious orientations of the regions was calculated and subtracted from 1. The higher the resulting value, the higher the institutional distance.

### *Control Variables*

According to the model structure, weightings for the origin and destination variables are required. These are, namely, the number of employees and the number of establishments in the pairs of regions under analysis. These variables, in addition to others, can be used as mass terms in a gravity model. However, a potential endogeneity problem may arise, which is a common specification issue in gravity models (DE GRANGE *et al.*, 2009; DE VRIES *et al.*, 2000). In addition to these weights, a neighbouring dummy, which is equal to one if the two regions are neighbors, and a border region dummy are included. This dummy is equal to one if one of the two regions is on the German border.

## **5 Results**

### *Overview*

In this section, the results of the Poisson, negative binomial and the zero-inflated model are discussed. The dependent variable is the number of cross-regional collaborations. The explanatory variables can be divided into two groups. The first group includes the proximity variables, the neighboring dummy and the border region dummy. These can be interpreted as semi-elasticities. The second group contains the separation variables. These include the respective number of employees and establishments in the regions under analysis and can be interpreted as elasticities.

Table 1 presents the results for our three model specifications. The significant dispersion parameter of 2.96 with a p-value of 0.000 indicates the rejection of a Poisson model. Unobserved heterogeneity would lead to overdispersion and cause biased estimations. As a result of



the significant Vuong statistic, the model has to be enhanced with a zero-inflated part (WINKELMANN and BOES, 2009). The values for the Akaike and Bayesian information criteria as well as the log likelihood also identify the zero-inflated negative binomial model as the model with the best fit. When looking at table 1 it is clear that there are various significant parameters, except for the squared term of institutional proximity and the border region dummy. The squared institutional term is also not significant in the inflated part. Furthermore, the number of establishments in the second region does not explain the variation in the dependent variable.

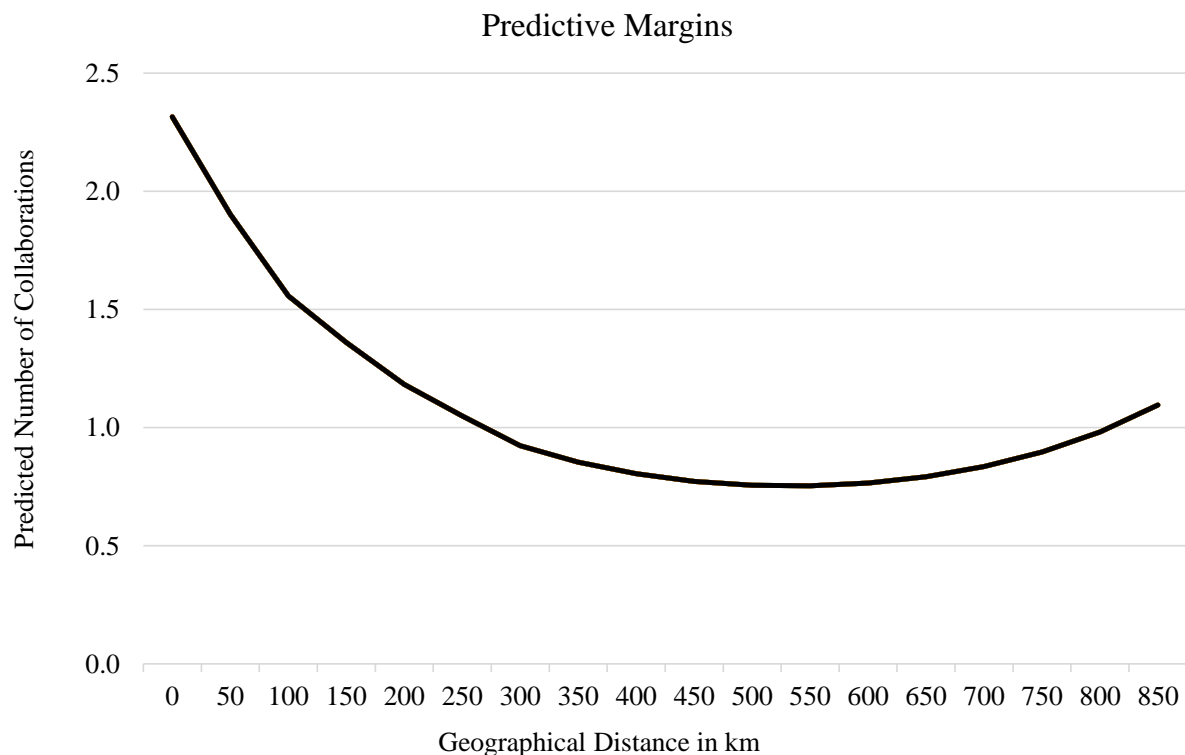
Table 1. Estimation results of the Poisson spatial interaction models

Number of collaborations	Poisson	Negative Binomial	Zero-inflated neg. Binomial
Distance in km	-0.0017*** (-44.75)	-0.0022*** (-27.46)	-0.0017*** (-19.37)
Distance (sq.)	4.46e-06*** (22.24)	4.51e-06*** (10.43)	3.53e-06*** (7.30)
cognitive distance	-1.8445*** (-35.71)	-1.9401*** (-14.72)	-1.4919*** (-11.11)
cognitive distance (sq.)	-0.1401*** (-21.33)	-1.5116*** (-7.80)	-1.3175*** (-6.69)
Institutional distance	-0.1182*** (-15.37)	-0.1142*** (-7.28)	-0.1333*** (-7.77)
Institutional distance (sq.)	-0.1763*** (-11.81)	0.0025 (0.08)	0.02575 (0.82)
Betweenness	0.4721*** (90.45)	1.0228*** (48.16)	0.9142*** (46.09)
Closeness	-0.1194*** (-84.17)	-0.1480*** (-42.67)	-0.1881*** (-50.15)
Neighboring dummy	0.3956*** (15.83)	0.8828*** (11.68)	0.6214*** (7.69)
Border region dummy	-0.0134 (-1.11)	-0.0568** (-2.25)	-0.0453* (-1.79)
Labour force region a	1.4770*** (104.57)	2.5124*** (52.91)	1.5960*** (29.49)
Labour force region b	0.9668*** (70.45)	2.0996*** (44.16)	1.1552*** (22.28)
Number of establishments a	-0.5026*** (-32.37)	-1.4889*** (-31.59)	-1.0525*** (-19.62)
Number of establishments b	0.0093 (0.57)	-1.1171*** (-23.04)	-0.6398*** (-12.18)
Constant	-24.0312*** (-255.09)	-30.2922*** (-93.59)	-16.01884*** (-42.19)
<b>Inflate</b>			
Geographical distance			0.0013*** (6.98)
Geographical distance (sq.)			-3.32e-06*** (-3.43)
cognitive distance			0.8136*** (6.10)
Institutional distance (sq.)			-0.0203 (-0.58)
Betweenness			-8.6500*** (-20.77)
Closeness			0.1950*** (15.88)
Neighboring dummy			-0.5264*** (-3.66)
Labour force region a			-1.1447*** (-10.80)
Labour force region b			-0.7309*** (-6.55)
Number of establishments a			0.2534*** (2.59)
Number of establishments b			-0.09276 (-0.84)
Constant			21.0655*** (26.21)
Dispersion parameter		2.9373***	
Vuong statistic			1.577***
Log-likelihood	-69673.995	-42434.128	-40356.05
AIC	139378	84900.26	80768.11
BIC	139517.7	85049.33	81028.99

Notes: Z-values in parentheses. The dependent variable (n\_coll) is the number of cross-regional collaborations between region  $i$  and  $j$ . The number of observations is 82,215. The null hypothesis of the over-dispersion test can be rejected at a 0.1% level. The significant value of the Vuong statistics indicates the use of the zero-inflated model specification. The mean VIF is 3.88 and the maximum is 8.72, therefore it can be assumed that no multicollinearity is present. \* 10% significance level, \*\* 5% significance level, \*\*\* 1% significance level

### *Interpretation of Proximity Measurements*

With a significant parameter between -0.0017 and -0.0022, the influence of the geographical distance is present in the data. The average marginal effect for the zero-inflated model is 0.0020, which means that an increase in the Euclidean distance by 100 km decreases the collaboration frequency by on average 22.14%.<sup>5</sup> As BOSCHMA and FRENKEN (2010) propose, the relationship of the influence of the geographical proximity value on the collaboration intensity is non-linear. They state, too, that many local connections will decrease the collaboration intensity. Hence, an actor should establish a mixture of local and non-local links.



*Fig. 2. The average marginal effects for distance in km*

In contrast, figure 2 indicates a sharp decrease in collaboration intensity up to a distance of 500 km and an increase for more distant regions.<sup>6</sup> Potential explanations for the local minimum are the dataset and the distribution of important technology clusters in German. The stark influence of physical distance at very close quarters is because 10.27% of all collaborations are intra-regional. This high share can be ascribed to the structure of the German econ-

<sup>5</sup> The value has to be calculated as  $\exp(\Delta x * \beta) - 1$ . The average marginal effects we used can be found in the appendix.

<sup>6</sup> Owing to the mean centering, about 300km have been subtracted from every observation.

omy, where many small and medium sized enterprises collaborate and conduct research. A rising importance in higher values is the result of the collaboration between clusters which are located in or near metropolitan regions.<sup>7</sup> The combination of local and non-local links is what BOSCHMA and FRENKEN (2010) proposed; the empirical results are, however, different from this proposed inverted U shape. Owing to these results, the proximity paradox for geographical distance cannot be confirmed in this analysis. Focusing on the effects of an increasing distance, the results from the inflated part of the model can be interpreted as evidence that the likelihood of two regions being part of the excessive zero regime rises as the distance between them increases. The excessive share of regions with no collaborations explains this result. The findings for the physical distance reflect those of other studies. A significant influence of geographical proximity has been found by AGRAWAL *et al.* (2008); PONDS *et al.* (2007) and BALLAND (2012), for example. The significant parameters of cognitive distance indicate that the knowledge base plays a key role in the choice of a collaboration partner. This is in line with BOSCHMA's (2005) claim that technological proximity is a necessary condition for collaboration. Because NOOTEBOOM (2000) asserts that close actors cannot share new knowledge, Boschma and FRENKEN (2010) suggest that there is an optimal level of cognitive proximity for the innovativeness of a collaborative relationship. In addition to the negative effects of the linear and quadratic term, this optimal value can be seen in figure 2. This inverted U shape indicates that intensive collaborations can be observed not only in regions with exactly the same industry structure but also that the prospective combination of new and different knowledge also favours collaboration. This claim is supported by the high proportion of within-regional collaborations (10.27%). Excluding these, figure 5 is obtained, which clearly supports this interpretation. Thus the proximity paradox can be confirmed for the cognitive distance and the findings for the linear and quadratic term are in line with those of BROEKEL and BOSCHMA (2011), and the findings for the linear term reflect those of MARROCU *et al.* (2011) and CANTNER and MEDER (2007). As in the case of physical distance, a higher cognitive proximity raises the likelihood of being in the inflated part of the model. This supports BROEKEL and BOSCHMA's (2011) claim that proximity in at least one dimension is necessary to generate collaborations. The indicator for institutional proximity is highly significant with a parameter of -1.33 and an average marginal effect of -0.1417. As can be seen in figure 6, the

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<sup>7</sup> A main collaborating region was Berlin, which cooperated intensively with Munich, Aachen, Stuttgart and Karlsruhe. All these regions are situated more than 500 km away from Berlin.

marginal effects are regressive in the tradition of gravity models. The hypothesis that non-explicit institutional norms and values influence cooperation behaviour positively can be proved in this study. Regions with similar religious orientation are more likely to share more links. These findings are in line with those of BALLAND (2012). However, the quadratic term is not significant. Therefore the proximity paradox for the institutional form cannot be confirmed in the data. In order to capture social proximity, measurements derived from network theory are applied. As was made clear in the theoretical section of this paper, network theory relies on two basic concepts: the position within a clique and the broker's position. The results reveal that pairs of regions showing similar values for betweenness centrality (representing broker positions) are positively correlated with the number of cross-region collaborations. A significant negative correlation is observed for the difference regarding closeness centrality. Clearly, regions representing a strong clique position develop linkages to relatively less connected regions – perhaps in order to avoid problems caused by lock-in effects.

#### *Other Regional Influences*

Intuitive results are obtained for the control variables. If two regions are neighbors, the expected collaboration count is higher. This supports the influence of the physical distance and may also support the influence of institutional distances. If one region is on the German border, the collaboration frequency decreases. Looking at the regional weights, it is observed that the number of establishments has a negative influence and the labour force a positive influence. This could be an indicator that large rather than small companies engage in more collaborations. These interpretations are restricted, however, as a result of potential endogeneity in the dependent variable.

## **6 Conclusion**

The impact of collaborations on innovation activity is part of an intensely analysed field of research. This paper contributes to empirical research conducted on the proximity theory by BOSCHMA (2005). The results of former studies have been ambiguous if not contradictory. Therefore, the aim was to study the importance of different forms of proximity and the proximity paradox proposed by BOSCHMA and FRENKEN (2010). In so doing, a gravity type spatial interaction model was used to capture the relationship between inter- and intraregional collaboration frequencies, the proximity variables, as well as regional weight variables. The

dataset used contains granted collaborative R&D projects from 2005 to 2010 in Germany. To the authors' knowledge, this is the first study examining the proximity theory using German data. After a theoretical description of the most important coherences of the proximity theory and the empirical theory had been provided, the dataset was described. This was followed by the presentation of the model and the results. The results indicate that inter- and intraregional collaboration frequency is positively influenced if two regions are relatively spatially closer together, their industrial structure is relatively similar, both work as brokers and their religious values are closer. Broadly speaking, there is a positive influence of geographical, cognitive, social and institutional proximity on collaboration intensity. The significance of other regional factors such as the number of establishments and the labor force can be confirmed. More specifically and relating to the proximity variables, we find that the proximity paradox cannot be confirmed for the institutional context, which shows a traditional gravity-type impact. The two other explanatory factors are more complex: the proximity paradox can be recognised in the cognitive distance. The geographical distance can be seen as a new type, where nearby collaborations play a key role, but in which clusters with a high attraction generate collaborations over long distances. Restrictive factors for analysing the proximity theory with the chosen model could be the exclusion of organizational proximity and a potential endogeneity bias resulting from the chosen mass terms. In addition, the cooperative behaviour was analysed at the regional level owing to a lack of firm level data. For these reasons, further research is necessary to examine the proximity theory. Ongoing research in this field can improve the understanding of cooperation and innovation on a regional scale. These lessons are especially important for policy makers, who could use them to adjust the regulatory framework to improve the efficiency of the use of funds.

## Appendices

*Table 2. The average marginal effects for the zero-inflated negative binomial model*

	dy/dx	Std. Err.	z	P> z
Distance in km	-0.0019752	0.0001	-13.69	0.000
Distance in km (sq.)	3.79E-06	5.62E-07	6.75	0.000
cognitive distance	-1.660296	0.1673	-9.93	0.000
cognitive distance (sq.)	-1.414664	0.22	-6.43	0.000
Institutional distance	-0.1417127	0.0194	-7.3	0.000
Institutional distance (sq.)	0.0276544	0.0337	0.82	0.412
Betweenness	1.602133	0.0760	21.08	0.000
Closeness	-0.2159758	0.0132	-16.31	0.000
Neighboring dummy	0.7049576	0.0956	7.38	0.000
Border region dummy	-0.0486221	0.0274	-1.77	0.076
Labor force region a	1.795886	0.1259	14.26	0.000
Labor force region b	1.292911	0.1009	12.81	0.000
Number of establishments a	-1.148248	0.0975	-11.77	0.000
Number of establishments b	-0.6803027	0.0763	-8.91	0.000

*Fig. 3. The average marginal effects for cognitive proximity*

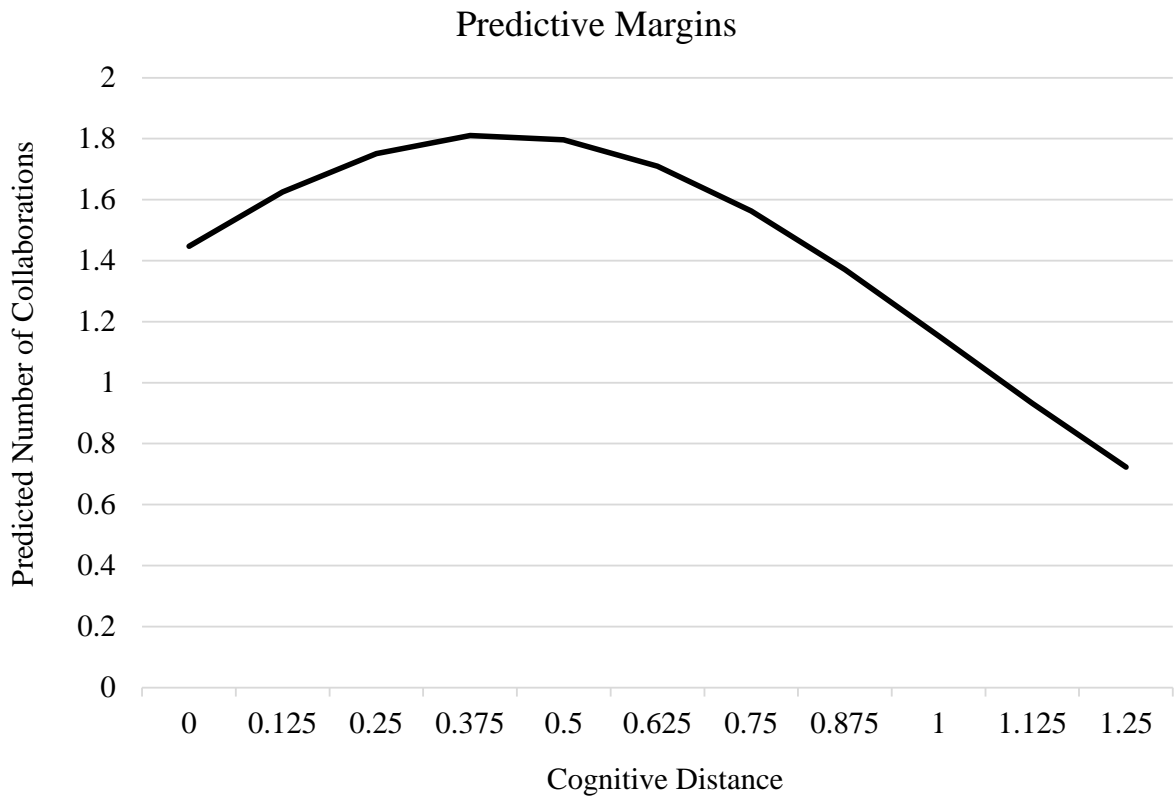


Fig. 4. The average marginal effects for cognitive proximity – linear variables only

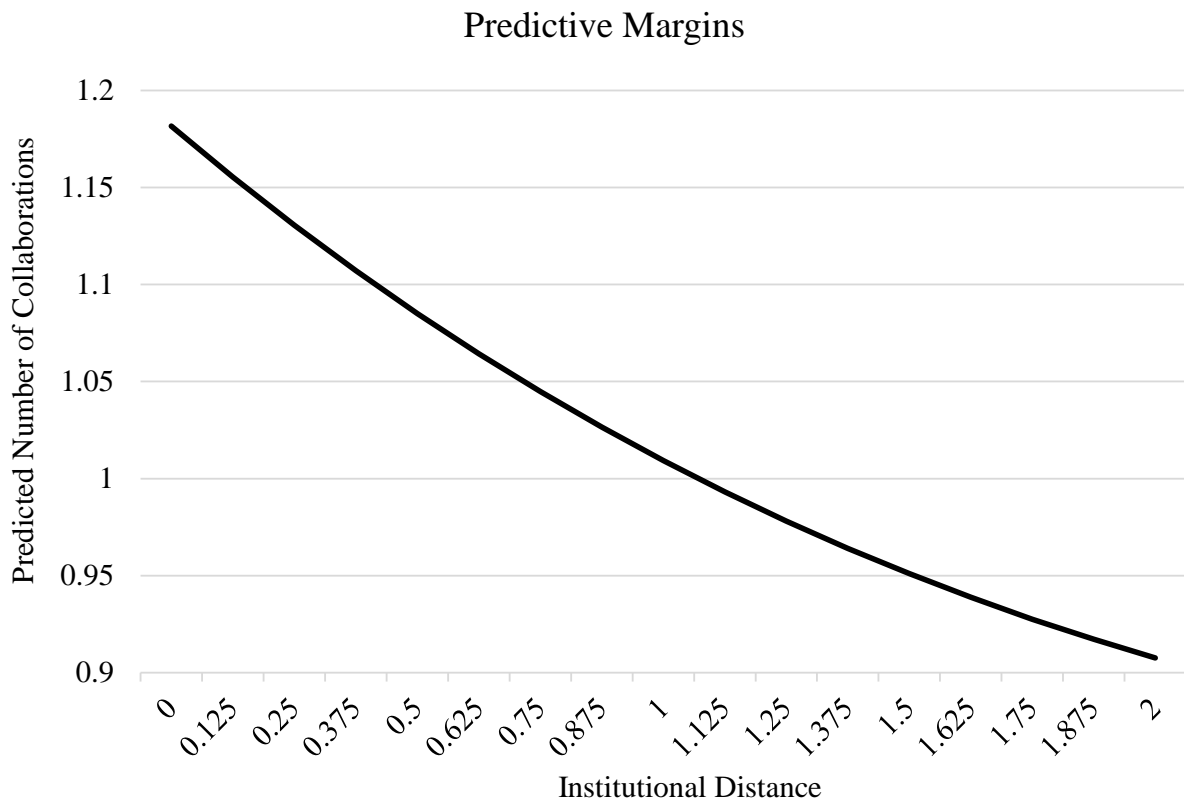




Fig. 5. The average marginal effects for cognitive proximity – excluded within regional collaborations

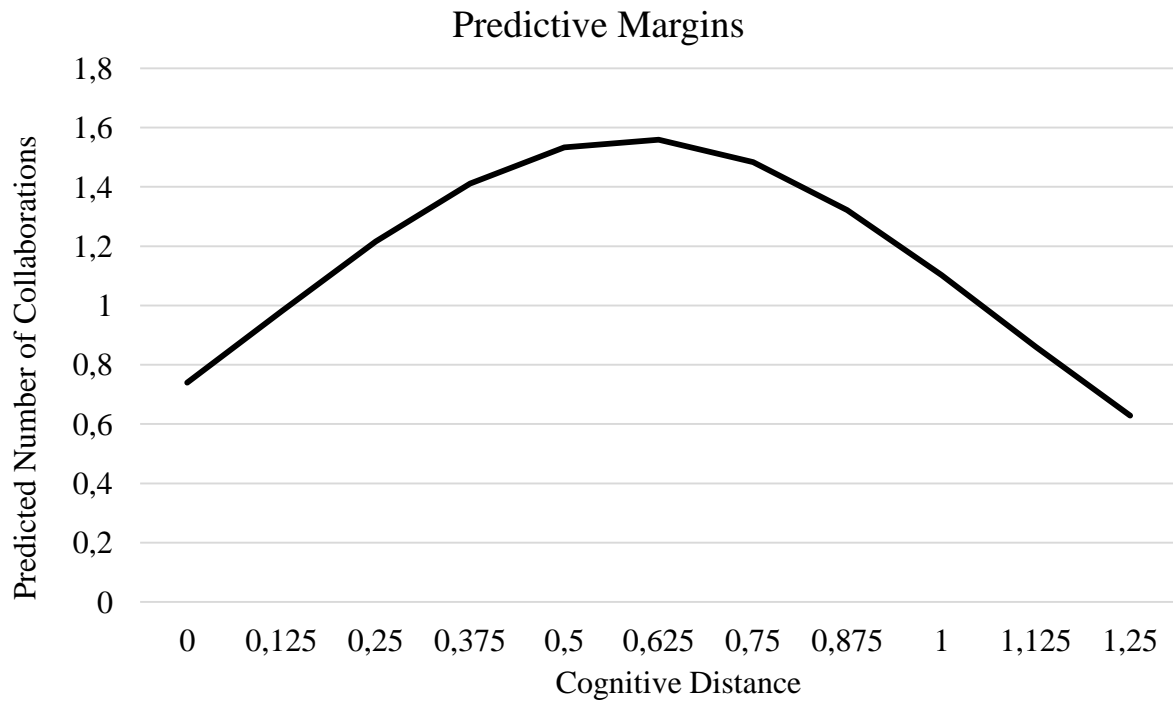
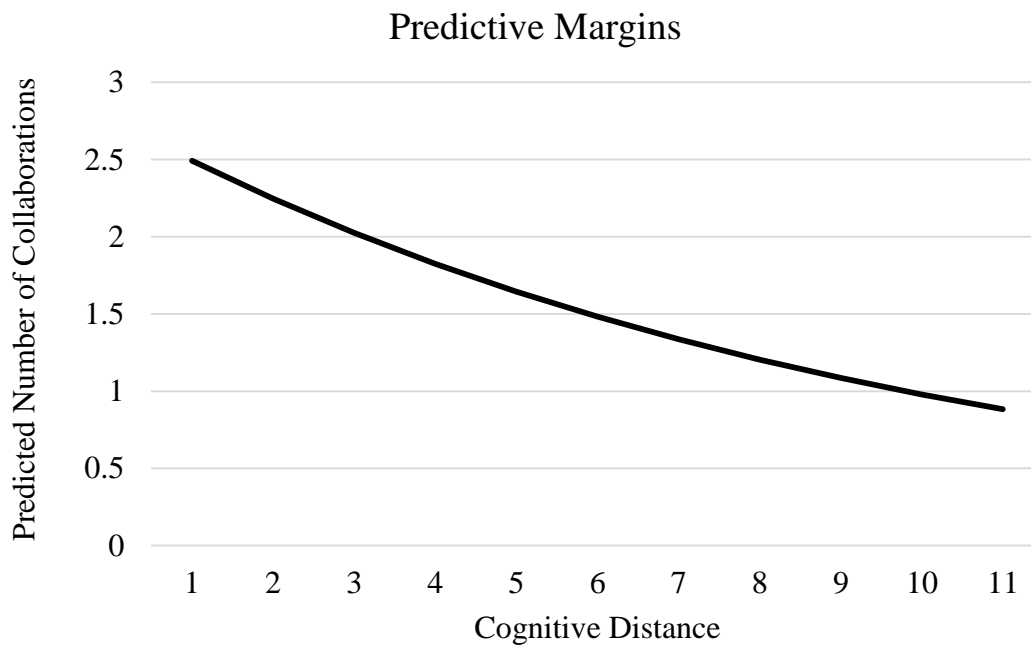


Fig. 6. The average marginal effects for institutional proximity



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