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Abstract

The importance of geographical proximity for interaction and knowledge sharing has been discussed extensively in economic geography. There is increasing consensus that it is one out of many types of proximities that might be relevant. We argue that proximity may be a crucial driver for agents to connect and exchange knowledge, but too much proximity between these agents on any of the dimensions might harm their innovative performance at the same time. In a study on knowledge networks in the Dutch aviation industry, we test this so-called proximity paradox empirically. We find evidence that the proximity paradox holds to some degree. Our study clearly shows that cognitive, social and geographical proximity are crucial for explaining the knowledge network of the Dutch aviation industry. But while it takes cognitive, social and geographical proximity to exchange knowledge, we found evidence that proximity lowers firms' innovative performance, but only in the cognitive dimension.

Keywords: geographical proximity, knowledge networks, proximity paradox, social network analysis, aviation industry

JEL Codes: R11, R12, O18, O33

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Introduction

In Economic Geography, few issues have been studied more frequently as the question of what role geographical proximity plays for knowledge sharing and innovation. Backed by the argument that the exchange of tacit knowledge requires face-to-face contacts, it has long been emphasized that knowledge sharing is highly sensitive to geographical distance (Audretsch and Feldman, 1996; Gertler, 2003). This view on the role of geographical proximity has recently been challenged theoretically (see e.g., Boschma, 2005; Lagendijk and Oinas, 2005; Broekel and Binder, 2007). This critical view has been initiated by the French school of proximity dynamics (Rallet, 1993; Kirat and Lung, 1999; Rallet and Torre, 2005). Their critical voices particularly emphasize that geographical proximity is just one dimension among a number of other proximity dimensions that can explain interaction between geographically proximate actors.

Boschma (2005) proposed five dimensions of proximity that impact on the likelihood of knowledge exchange between actors and their innovative performance. His claim is that geographical proximity is neither a necessary nor a sufficient condition for inter-organizational learning and innovation. Boschma (2005) also argued that geographical proximity is more likely to become effective rather indirectly through the other types of proximity. Breschi and Lissoni (2003) and Ponds et al. (2007), among others, have confirmed this empirically for social, institutional and cognitive proximity.

Extending these ideas, in a recent paper, Boschma and Frenken (2009) introduced what they describe as the so-called proximity paradox. While proximity may be a crucial driver for agents to connect and exchange knowledge, too much proximity between these agents on any of the dimensions might harm their innovative performance. So, while a high degree of proximity may be considered a prerequisite to make agents connected, proximity between agents does not necessarily increase their innovative performance, and may possibly even harm it. Following Nooteboom's work on optimal cognitive distance (Nooteboom, 2000), Boschma and Frenken (2009) claim it depends on the (optimal) level of proximity whether a connection between agents will lead to higher innovative performance or not.

This issue of the proximity paradox is put central in an empirical study on the knowledge network of the Dutch aviation industry. The Dutch aviation industry is an interesting case, because it lost its flagship, the Fokker Company, in 1996, after which it went through a major restructuring and reorientation process. The question then is how the knowledge network looks like in the post-Fokker period, and what are its main drivers. Among other things, we will test whether a shared past in the Fokker company (as a proxy for social proximity) increased the probability of two aviation firms to connect. This study draws on own data that were collected through semi-structured interviews of 59 profit and non-profit organizations that are active in manufacturing activities and engineering services in the Dutch aviation sector.

Our paper has two objectives. The first objective is to assess empirically the extent to which the different forms of proximity affect the technical knowledge network in the Dutch aviation industry. Employing social network analysis, our study confirms the importance of cognitive, organizational, and social proximity for the structure of the technical knowledge network. We also found geographical proximity to be a driver of network formation, even when controlling for the other proximities. The second objective is to determine which proximities determine the innovative performance of aviation firms, while controlling for the usual suspects. Our study provides empirical evidence for the proximity paradox with respect to the cognitive dimension, not the geographical and social dimension. That is, proximity is required to connect firms, but it does not necessarily yield above average innovative performance of these firms.

The paper is structured as follows. In Section 1, the different dimensions of proximity are discussed. We specify how they influence the likelihood that actors are linked and what that means for their innovative performance. Section 2 provides a short description of the Dutch aviation industry, the data and the variables we constructed. Section 3 will briefly present the methodological tools (QAP and network autocorrelation regression) we employed. Results of the analyses are presented and discussed in Section 5. Section 6 concludes.

1 The proximity paradox

Firms' embeddedness in knowledge networks has increasingly been recognized as an important determinant of their economic and innovative performance (see, e.g., Powell et al., 1996). Given limited resources firms can invest into research and development, their ability to collaborate and make use of external knowledge becomes crucial for their success. It is well known that firms have different absorptive capacities, which matter for their usage of external knowledge (Cohen and Levinthal, 1990). This determines not only their likelihood to engage in knowledge sharing but also the likelihood that obtained knowledge can be successfully used and implemented.

It is widely accepted that, in addition to their absorptive capacity, other factors influence economic actors' decisions to become engaged into knowledge sharing activities. An argument frequently put forward in the literature is that geographical proximity facilitates knowledge transfer (Feldman and Florida, 1994). This view on the role of geography for knowledge exchanges has recently been challenged with the argument that it is not mere co-location that matters for knowledge exchanges, but membership in knowledge networks (Castells, 1996). In this sense "geographical proximity only creates a potential for interaction, without necessarily leading to dense local relations" (Isaksen, 2001, p. 110).

The French school of proximity dynamics (see e.g. Rallet and Torre, 1999; Rallet and Torre, 2005) has played a prominent role in this debate. They claim that geographical proximity is just one among a number of proximity dimensions. In this context, Boschma (2005) claimed that geographical proximity is neither a necessary nor a sufficient condition for knowledge sharing and innovation. He proposed five dimensions of proximity (cognitive, social, organizational, institutional, and geographical) that may impact on the likelihood of knowledge exchange between actors and their innovative performance. We will briefly discuss each of these below (for an extensive treatment, see Boschma, 2005), with the exception of institutional proximity, for which we have no variance in our study.

Cognitive proximity

Cognitive proximity refers to the degree of overlap between two actors concerning their knowledge bases. Actors need to have a sufficient absorptive capacity to identify, interpret and exploit knowledge of other actors (Cohen and Levinthal, 1990). However, if two actors' knowledge bases are too similar, the likelihood of an innovative recombination is lower than when dissimilar knowledge bases are merged. According to Nooteboom (2000), there exists a tradeoff "…. between cognitive distance, for the sake of novelty, and cognitive proximity, for the sake of efficient absorption" (p. 152). The relationship between the cognitive distance between two actors and their innovation performance is therefore to be expected to take an inverted u-shape (Cohendet and Llerena, 1997). In other words, both very proximate and very distant actors are likely to gain little from cooperating in innovation activities. The optimal level of cognitive proximity follows from the need to keep some cognitive distance (to stimulate new ideas through recombination) and to secure some cognitive proximity (to enable effective communication and knowledge transfer). Moreover, high cognitive proximity generally implies that two firms have very similar competences, which means that when they engage in knowledge exchange, they run a serious risk of weakening their competitive advantage with respect to the network partner. It is also for this reason that one expects that excessive cognitive proximity may be harmful to performance (see Nooteboom et al., 2007; Boschma et al., 2009; Boschma and Frenken 2009). Consequently, it is not so much the quantity of contacts and intensity of knowledge exchanges that matters for firms' success, but rather the type of knowledge exchanged, and how that matches the existing knowledge base of the firms. In this respect, cooperation is most fruitful when network partners have technologically related, not similar knowledge bases.

Organizational proximity

Actors may also be close or not in organizational terms. Boschma (2005) defined organizational proximity "… as the extent to which relations are shared in an organizational arrangement, either within or between organizations" (p. 65). It can be seen as a continuous scale going from autonomy to control. It is very low for totally independent actors and very high for actors that are part of the same hierarchical system. According to Boschma (2005), organizational proximity helps to manage knowledge exchange and reduce transactions costs. However, excessive organizational proximity may also hamper interactive learning, as it constrains flexibility.

An alternative way to define organizational proximity is the degree to which organizations have similar routines and incentive mechanisms (Metcalfe, 1994). In innovation studies, researchers tend to make a distinction between profit and non-profit organizations. To put it simply, profit organizations have an interest to keep their knowledge away from competitors, while non-profit organizations like universities have a public mission and, therefore, are more open to exchange knowledge with others. Because of these different routines, a profit and a non-profit organization have a low degree of organizational proximity, which lowers their probability to connect and collaborate. This is in line with the problematic relationship between universities and private firms, which has been documented extensively. According to Broekel and Binder (2007), actors' search biases make it more likely that non-profit organizations will interact with other non-profit organizations. This might also be true for profit-oriented organizations, especially when the firms are not direct competitors.

Social proximity

Social proximity refers to the social embeddedness of actors in terms of friendship, kinship, and experience at the micro-level (Boschma, 2005). This has to be seen as being distinct from institutional proximity, which refers to institutions (like ethnic and religious values) at the macro-level. Of particular interest is the role of trust, which is likely to be positively influenced by social proximity. Trust has frequently been argued to foster knowledge exchange (Maskell and Malmberg, 1999). In particular with respect to secrecy and the dangers of free riding, trust-based relations are often depicted as superior to anonymous or newly established relations. Hence, social proximity should be a strong predictor of the existence of a link between two actors. The existence of "old boys networks", for instance, is likely to influence knowledge sharing activities. The same can be argued for actors with a shared history, like being at the same school, university or company, which generates a sense of belonging to the same community. However, too much social proximity may also be harmful for innovative performance, because of an overload of loyalty and commitment in social relationships (Boschma, 2005).

Geographical proximity

None of the previously introduced proximities require co-location. It can be argued, though, that geography plays a role by facilitating the other types of proximities. Broekel and Binder (2007) have argued that geographical proximity may also directly impact on the likelihood that actors will exchange knowledge. Through various mechanisms, geography influences individuals' motivation and search heuristics and can bias them towards spatially close knowledge sources. Hence, geographical proximity influences the other types of proximity but also increases the likelihood of two actors to engage in knowledge exchange more directly. However, while geographical proximity may offer certain advantages to knowledge sharing activities, there is increasing evidence that a dominance of local linkages may also reduce the innovative performance of a firm (Boschma, 2005; Broekel and Meder, 2008).

In sum, there are good reasons for why these different types of proximities should impact on actors' knowledge networks. Although empirical research is still primarily focused on the role of geographical proximity (see e.g. Jaffe, 1989; Audretsch and Feldman, 1996), there is a growing number of empirical approaches that aim to disentangle the different types of proximity and their effects on firms' behavior (Fleming et al., 2007; Ter Wal, 2009). Breschi and Lissoni (2003) for example, using patent citations show that geographical proximity looses its predictive power for two actors being linked when controlling for social proximity. Ponds et al (2007) find that geographical proximity is of smaller relevance for research collaborations between academic organizations, as opposed to collaborations between academic and non-academic organizations. However, they suggest that geographical proximity is still helpful to overcome institutional barriers between different types of organizations. Cantner and Meder (2007) find that cognitive and social proximity are relevant for cooperation activities. They demonstrate that the technological overlap between two actors (cognitive proximity) positively influences the likelihood of these actors to engage in cooperation. This is also true for having cooperation experience with the same cooperation partner. In this latter respect, past cooperation experiences may have led to a decrease of the social distance between the two partners, which positively impacts on future cooperation. Mowery et al. (1998) found similar results and, moreover, suggested an inverted U-shape relationship between the probability to cooperate and the technological (cognitive) similarity of two actors. However, while most of these studies take into account at least two types of proximity, they hitherto have ignored or overlooked the relevance of the other types.

The proximity paradox

Another critique on existing studies is that in such a proximity framework, it remains unclear whether in the end, the choice of network partner matters for firms' economic performance. In a recent paper, Boschma and Frenken (2009) introduced what they describe as the so-called proximity paradox. While proximity may be a driver for agents to connect and exchange knowledge, too much proximity between these agents on any of the dimensions might not necessarily increase their innovative performance, and may possibly even harm it.

Following Nooteboom's work on optimal cognitive distance (Nooteboom, 2000), Boschma and Frenken (2009) suggest it might depend on the (optimal) level of proximity whether a connection between agents will lead to a higher innovative performance or not. While the cognitive dimension has drawn most attention in the literature, optimal levels of proximity may exist for the other forms of proximity as well (Boschma, 2005). With respect to geographical proximity, it has been suggested that a mixture of local and non-local linkages to be best for firms, and a combination of local buzz and global pipelines to be best for the long-term evolution of clusters. With respect to social proximity, the optimal social distance might consist of a balance between embedded relationships within cliques and strategic 'structural hole' relationships among cliques (Fleming et al. 2007). Uzzi (1996) found evidence of a mixture of low proximity (defined as arm's length ties) and high proximity (depicted as embedded ties) to be best for firms. An optimal level of organizational proximity may be accomplished by loosely coupled networks with weak ties between autonomous agents, which combine advantages of organizational flexibility and coordination (Grabher and Stark 1997). However, the different forms of proximity may also interact in this respect. Excessive proximity in one dimension that is compensated by some degree of distance on another dimension may still enhance the innovative performance of a firm. For instance, a firm may have primarily relationships with other local firms (meaning too much geographical proximity), but when these provide access to a range of different but related knowledge bases, this might still positively affect firm performance.

Our paper aims to add to this literature in two ways. First, we test the influences of four types of proximity (i.e. cognitive, social, organizational, and geographical) on the likelihood of two firms to exchange knowledge in the Dutch aviation industry. Following the literature on knowledge networks (Giuliani and Bell, 2005; Boschma and Ter Wal, 2007; Sammarra and Biggiero, 2008), we focus on the exchange of technological knowledge, which is regarded as most relevant for firms' innovation activities in this sector. Second, we examine whether cognitive, social, organizational and geographical proximity matter for firms' innovation performance, controlling for factors like absorptive capacity. We also test whether there is a curvilinear relationship between the proximity dimensions and innovative performance. Doing so, we determine whether the proximity paradox holds in the Dutch aviation industry.

2 Data

2.1 The Dutch aviation industry

The aviation industry is known for being highly agglomerated and clustered in a few locations worldwide, like Seattle and Toulouse (Hickie, 2006). Large multinational firms like Airbus and Boeing dominate this industry. Their headquarters and main facilities function as attractors for other businesses, e.g., specialized suppliers, sub-contractors, and service companies. This caused the emergence of the typical hub-and-spoke type structure in this industry (Gray et al. 1996).

There is no large company in the aviation sector that has its headquarters or a major production facility in the Netherlands. In the past, this was different. Since its establishment in 1919, Fokker B.V. dominated the industry in the Netherlands for almost eighty years. Fokker used to be a crucial player in the aviation related knowledge networks in the Netherlands (van Burg et al., 2008). Its core business was the production of 50-100 seater planes, most famously the F 27, as well as the more recent Fo 50 and Fo 100. At its peak in mid 1991, about 13,000 people worked for Fokker, before employment declined steadily to 7,141 in early 1996 (Ligterink, 2001). In 1996, Fokker had to declare bankruptcy for three core units. This meant the biggest single job cut in the modern history of the Netherlands by putting 5,600 people out of work (Reuters, 1996). While about 950 jobs have been saved through the founding of a new firm, “Fokker Aviation”, which was eventually taken over by Stork B.V., the Dutch aviation industry lost its sole aircraft producer and one of its technological flagships.

More than a decade later, the Dutch aerospace industry consists of about 80 firms, most of which are SMEs (NAG, 2008). These firms contribute to 0.9 percent (275 million Euros) of the EU-25 value added in manufacturing of air- and spacecrafts in 2003 (EUROSTAT, 2002). Total employment is about 5,000 employees. These numbers exclude maintenance and overhaul of aircrafts. Including these, the number of employees increases to 15,000, which generate a turnover of 2.2 billion Euro (NAG, 2008). The industry surely has regained strength by successfully filling niches in the aviation market (Heerkens, 1999). Nevertheless, the Dutch aviation sector can be regarded as marginal in comparison to countries like Germany and France.

A study of the knowledge network in the Dutch aviation sector is interesting for many reasons. First of all, aviation is known to be a highly knowledge intensive industry, in which access to external knowledge might be crucial (Niosi and Zhegu, 2005). Secondly, it is interesting to investigate how this knowledge network is shaped, in the absence of a dominant player. Thirdly, it is intriguing to find out whether the Fokker Company, despite its bankruptcy a long time ago, still affects the nature of this knowledge network. Many of the current entrepreneurs and top-managers in the Dutch aviation industry may have been former employees of Fokker. Given the strong exposure to the very distinct Fokker identity (Kriechel, 2003), their knowledge searching and sharing activities are still likely to be shaped by these experiences and biased towards their former co-workers (see, e.g., Broekel and Binder, 2007). This enables us to construct a social proximity indicator, which might affect the knowledge network in the industry.

2.2 Definition of the industry

Our empirical study is based on own data collection. In late 2008-early 2009, we interviewed 59 organizations that belong to the aviation industry in the Netherlands. Most of these organizations are members of the Netherlands Aerospace Group (NAG), which is the most important trade organization. Their members account for about 95 percent of the total turnover generated by Dutch firms in the aviation industry (NAG, 2008). In 2008, the organization had 83 members. We interviewed only those members that were active in manufacturing and/or engineering, since for these activities, innovation and the exchange of technological knowledge is likely to be of utmost importance.[2] This applies to 40 firms, of which we interviewed 37. The three firms that were not interviewed do not show any eye-catching features. In the course of the interviews, five additional firms were named as being relevant, which were not member of the NAG, but clearly active in the aviation industry. All of these have been interviewed as well. This increased our total population to 45, of which 42 have been interviewed by extensive semi-structured interviews on the spot. Accordingly, our response rate is 93 percent.

The list of the NAG also includes non-profit organizations, which we interviewed in a different way. These organizations, as well as additional non-profit organizations named during the firm interviews as relevant knowledge sources, were asked to indicate the intensity of interaction with the other relevant non-profit organizations. This applied to 17 organizations

[2] We interviewed also 2 firms that were not active in manufacturing or engineering. These firms confirmed the low importance of technological exchange for their firms' competiveness. Moreover, none of the interviewed firms mentioned any maintenance-oriented firm as a relevant knowledge source.

which increased our sample to 59 organizations.[3] The intensity level ranged from 1 to 3, with 1 indicating no interaction, and 2 and 3 medium and very high intensity.

Figure 1 shows the technological knowledge network of the Dutch aviation industry, based on the data of these 59 profit and non-profit organizations. The 59 vertices account for 146 edges and the network has a density of 0.085. This density is half as big as the density observed by Sammarra and Biggiero (2009) for the technological knowledge network in the Italian aerospace cluster of Rome. This cluster consists, however, of only 33 firms. Nevertheless, knowledge network relations are rather sparse in the Netherlands, which is also indicated by the large number of isolates. Non-profit organizations, most noticeably the Technical University of Delft and the successor of the Fokker Company (Stork Aerospace B.V.), represent important contacts for firms and thus, take up prominent positions in the network.

- Figure 1 here -

3 Explaining the technological knowledge network

3.1 Variables

As explained in Section 2, the first part of our analysis aims to assess the impact of the various forms of proximity on the structure of the technological knowledge network of the Dutch aviation industry. More in particular, we estimate the importance of the different types of proximities on the likelihood that two actors are linked. Our dependent variable $LINK_{TEC}$ is dichotomous and indicates whether actor *i* or *j* mentions the other as a relevant source of technological knowledge. We assume that knowledge exchanges are always reciprocal in nature. This implies that if *i* is naming *j* as relevant contact, we also assume that *i* is a relevant contact of *j*. In other words, we assume an undirected network. As independent variables, we have included the 4 dimensions of proximity, as discussed in Section 2, and we have measured these as follows.

[3] While most of the interviewed firms do not show strong connections to the space industry, this is not true for the non-profit organizations. However, our main focus is on firms.

3.1.1 Geographical proximity

To assess the effect of geographical proximity, we calculate the logarithm of the geographical distance in kilometers between two actors, which results in a continuous positive variable.[4] While other studies use travel time (Ejermo and Karlsson, 2006), the spatial scale of the network of Dutch aviation industry is rather small. Few contacts are not located in the direct neighboring countries of the Netherlands (including Great Britain), for why the use of travel distances is unlikely to change the results. The logarithm ensures that outliers in form of trans-continental relations do not disturb the estimations. We also estimate a squared term to control for non-linear effects (GEO^2). In order to reduce multicollinearity problems, we subtract the mean in advance.

3.1.2 Cognitive proximity

We refer to cognitive proximity as the technological similarity of two actors' knowledge bases. We have constructed two measures. For the first measure, we rely on the technology classes that are assigned by the Netherlands Aerospace Agency (NAG). The NAG defines 15 technologies of which 13 are relevant for the firms considered in this study. The technological fields and the according number of organizations are listed in Table 1. In case the interviewed organization is not a member of the NAG, the profile was created on the basis of the organization's webpage. The variable TEC_{NAG} is defined dichotomously, with a value of one if both organizations are active in the same technology, and zero otherwise.

- Table 1 here -

The second variable is based on 3-digit NACE codes assigned to each organization. The assignment of the NACE codes has been done as follows. First, if an organization named another organization being a relevant knowledge source, it was asked to provide information about the content of the knowledge exchange, i.e. which technologies this exchange concerned, and to what 3-digit NACE codes this corresponded. Second, we asked each organization to mention the three most important sectors (3-digit NACE codes) from which they recruit their key personnel. Lastly, we searched for information about the organizations on the Internet. This included the

[4] We add 0.001 km to all distances to ensure a positive logarithm.

organizations' own websites as well as the company information webpage: www.mintportal.bvdep.com, which also classifies firms according to the NACE scheme. This last option was particularly relevant for organizations that have not been interviewed, but which were named as relevant knowledge sources. Based on these sources of information, each organization has been characterized by a number of 3-digit NACE codes.

In order to define a similarity indicator for two organizations, we first had to define the similarity between two technologies (NACE codes). In a first step, following Breschi and Lissoni (2003), the similarity between technologies is estimated on the basis of their co-occurrence at the level of the organization. If technology A has frequently been assigned to organizations that are also characterized by technology B, the technologies are perceived being related. In addition to this direct relation, we also consider the indirect relation between two technologies. Accordingly, if technology A is frequently assigned to the same organizations as technology C, and the same is true for technologies B and C, A and B are also comparatively similar. In practice, we estimate the Cosine index, as given in Ejermo (2003):

$$r_{zg} = \frac{\sum_{k=1}^{t} w_{zk} w_{gk}}{\sum_{k=1}^{t} w^2{}_{zk} \sum_{k=1}^{t} w_{gk}^2} \qquad \textbf{(Eq. 1)}$$

with t as the number of technologies and g,k,z as indices of technologies under consideration. In this equation, w_{zk} is the number with which technologies z and k coincide at the organization level. In total, 72 different technologies appear in our data set.

When organizations have multiple technologies, we do not know the technologies' relative importance, i.e. no information is available on the share of turnover or employees attributed to each technology. We therefore estimate similarity in two ways. In the first, we search for the most similar pair of technologies in the firms' technology vectors. More precisely, we compare two organizations' (i,j) vectors of technologies (T_i and T_j). Next, we identify for each technology z (z ε t_i) of organization i, the maximal $r^i{}_{zg}$ within organization j's technologies. The same is done for the technologies of organization j. The $r^i{}_{zg}$ are added up and divided by the sum of the number of technologies assigned to both organization i and j. The latter ensures that the resulting similarity index s_{ij} is not biased positively towards diversified organizations (those with many technologies assigned to). The estimation shows the following.

$$SIM_{ij} = \frac{\sum_{z=1}^{t_i} \max_{g=1,..,t_j} (r_{zg}) + \sum_{g=1}^{t_j} \max_{z=1,...,t_i} (r_{zg})}{t_i + t_j} \qquad \textbf{(Eq. 2)}$$

Because the values of the Cosine index r_{zg} are between 0 and 1, the similarity index ranges from 0 and 1 as well, with 1 indicating perfect technological similarity. In extreme cases, all of organization *i*'s technologies are compared to one technology of organization *j*. The rationale behind this is that lacking information on the relative importance of a technology for an organization we assume that access to just one particular technology makes two organizations similar. This is because their knowledge bases overlap, which enables efficient communication.

In the estimations we also consider a quadratic term of the similarity indicators to check for non-linear effects. Because these variables are likely to cause multicollinearity with the similarity indicators, we subtract the mean of the variable before the squaring.

$$SIM^2 = (SIM - \overline{SIM})^2 \ \textbf{Eq. 3}$$

Hence SIM^2 will be large for small and large values of similarity.

3.1.3 Social proximity

We have constructed a dichotomous variable to account for the (likely) existence of social relations between organizations. The variable (FOK) amounts to one if former employees of Fokker B.V. are members of the top management of both firms and zero otherwise. As pointed out in Section 2.1, having a shared past in Fokker may reflect a community feeling that might still affect the structure of the network, even after its collapse. The importance of Fokker for the Dutch aviation industry has been immense in the past (see van Burg et al., 2008). Hence, "old-boys" networks may still be in place and give exclusive knowledge sharing opportunities. The data for this variable were collected in the interviews by means of the following question: *"Do you or anyone else of the firm's top-management have a personal relation to the former Fokker N.V., i.e. has been a former employee of Fokker N.V.?"*

3.1.4 Organizational proximity

We approximate organizational proximity by differentiating between profit and non-profit organizations (universities, research institutes, associations, and trade organizations). With few exceptions, these non-profit organizations turn out to be highly connected, and are also frequently named by firms as important technological knowledge sources. A dichotomous variable (PUB) is constructed being one when both organizations are universities, research institutes, trade organizations, or associations, and zero when otherwise. In order to keep the number of variables small, we decided to treat all these actors equally although we are aware that they might provide very different functions. A similar variable has been constructed for interactions between profit-oriented organizations, i.e. firms, (PRIVATE).

3.1.5 Control variables

We have included some control variables that might also affect the likelihood of being linked in the technological knowledge network. First, we have taken the logarithm of the absolute size difference of organizations (SIZE), which controls for variations in the cooperation behavior related to the size of organizations (see, e.g. Beise and Stahl, 1999; Graf, 2007). Because the organizations in our sample are heterogeneous, we also control for that fact that some organizations are more focused on the aviation industry than others. More precisely, the variable (AERO) indicates if two organizations are mainly active in the aviation industry. For firms, this implies that the share of their turnover attributed to aviation is above average. In case of other organizations, we define them to be "dedicated" to aviation if their focus is mainly on this sector. To create this dichotomous variable, we primarily rely on information derived from the organizations' websites. Lastly, organizations may also differ with respect to their openness towards external knowledge. Two organizations that perceive external knowledge as being highly relevant, can be expected to have a higher likelihood to be linked than two organizations that rely more on internal knowledge. The variable OPEN therefore is defined to be one if the relative importance of organization i and j attribute to external knowledge is above average. This information is collected by the following question we posted during the interviews: *"Please indicate in terms of percentage the relative importance of: a) knowledge acquired inside the company*; *b) knowledge acquired outside the company (adding up to 100%)"*.

All variables are summarized in Table 2, which also includes some descriptives. Table 3 shows the QAP-correlations among these variables. Most variables turn out to be weakly correlated. Hence, we can include all of them into the network regression. Only the quadratic terms as well as the different versions of the similarity indicators show considerable correlation with their non-squared counterparts. For this reason, these are tested separately.

- Table 2 here –

- Table 3 here –

3.2 Method

In order to test the importance of the types of proximities on the likelihood that two actors are linked, we employ network regression techniques. These techniques allow the use of relational variables. Relational variables describe the "relationship" between two actors, i.e. the extent to which they are distinct, similar, or share certain characteristics. A particular value x_{ij} (i=1…n and j=1…n) indicates the relation between firm i and j with n as the number of observations.

With this type of data at hand, social network analysis employs linear or logit regressions. The difference to standard OLS and logit techniques is that the dependent and independent variables are not vectors but $n*n$ (adjacency) matrices. For the application of the standard regression tools, the matrices are vectorized in the sense that the columns are stringed together to form one vector with n^2 elements, i.e. the first elements are the relations of actor 1 to all others, next are those of actor 2, and so on. In networks without loops, the diagonal of the adjacency matrices is meaningless and is eliminated. It reduces the vector length to n*(n-1). In this paper we treat all relations as undirected, for which the upper and lower half of the adjacency matrices are identical. These redundant elements are cut and the number of elements is $n*(n-1)/2$.

The dependent variable is then regressed with a standard logit model on the independent variables. The logit model is chosen because the dependent variable is 0/1 variable with 1 indicating the existence of a link between two actors and 0 for the absence of a link. Such network data are, however, characterized by frequent row/column/block autocorrelation and therefore standard tools of inference are problematic (Krackhardt 1987). A solution is provided by the Quadratic Assignment Procedure (Hubert 1987, Krackhardt 1987, Krackhardt 1988). The idea is to compare the estimated model statistics to the distribution of such statistics resulting from large numbers of simultaneous row/column permutation of the considered variables (before the vectorization). If, for example, the originally estimated positive coefficient is larger than 95 percent of the coefficients estimated from the permutated samples, it represents a significance level of 0.05. More precise for the QAP, Dekker's "semi-partialling plus" procedure (Dekker et. al. 2003) is used that is implemented in the SNA package of the statistical software R. This method is known to be more robust with respect to multicollinearity (Dekker et al. 2003).

3.3 Results

The regression results for the technological knowledge network of the Dutch aviation industry are summarized in Table 4. The pseudo R^2 reveals that our model performs well in explaining the network structure. More interestingly are the fraction of correctly predicted "1s" and "0s", which amount to 0.578 and 0.936 respectively. Hence, the model seems to be better in explaining the absence of a link than the presence. Nevertheless, both values are considerably larger than zero, indicating a satisfactory model fit. Overall, the findings confirm our theoretical predictions: all types of proximity (organizational, cognitive, social and geographical) are found to impact on the likelihood of being linked to another organization as far as technological knowledge exchange is concerned.

- Table 4 here -

Organizational proximity is highly relevant for the existence of links whereby, in particular, public organizations are highly connected among each other. In fact, the variable PUB is positive and highly significant, indicating the high degree of connectedness of non-profit organizations in the knowledge network. This also explains its very high odd ratio.[5] The negative significant coefficient of PRIVAT is not surprising, as we observe only few links between firms.

With respect to cognitive distance, we find a positive and significant impact of technological similarity expressed by SIM_{NACE}. While the significance level of SIM_{NACE} is just 0.1, the odd ratio is very high. This indicates that organizations tend to link more with technologically similar organizations, a result which confirms findings in other studies (e.g.

[5] We checked for multicollinearity but the odd ratio kept its size when removing correlated variables.

Mowery et al. 1998; Sorenson and Singh, 2007; Canter and Meder, 2007). The squared term (SIM_{NACE}^2) is insignificant, implying that the likelihood of being connected increases monotonically with increasing levels of technological similarity. As Canter and Meder (2007), we therefore cannot confirm an inverted-U relationship between the likelihood to cooperate and cognitive proximity. This is also true for the SIM_{NAG} variable.

Our study shows that social proximity (FOKKER) also influences positively the likelihood of two organizations to exchange knowledge. So, as expected, having a shared past in the former Fokker Company matters. Apparently, long after its bankruptcy in 1996, the Fokker Company still affects the Dutch aviation industry: a shared past in this company seems to help persons, now working for different organizations, to establish and maintain knowledge sharing links.

Geographical distance (DIST) has a strong and negative effect on the likelihood of having a knowledge link between two organizations. Its squared version is insignificant, suggesting a rather linear effect. So, even for controlling for the other forms of proximity, we found a positive effect of geographical proximity. While this finding is as expected, it has frequently been shown that the effect of geographic proximity is often caused by (unobserved) social relationships, i.e. social proximity (see, e.g., Breschi and Lissoni, 2003; Ponds et al., 2007). Since our FOKKER variable may not fully cover the social proximity dimension, it cannot be excluded that our geographical proximity variable may still account for some effect of social proximity.

In sum, we found considerable evidence for the first part of the proximity paradox, namely that proximity (in whatever form) is needed (or helpful) for the establishment of links in the technological knowledge network of the Dutch aviation industry.

4 Explaining innovative performance

4.1 Variables

The second objective of the paper is to determine which proximity dimensions (while controlling for usual suspects) determine the innovative performance of firms in the Dutch aviation industry. The focus is now on firms' attributes, not their relations to other firms. For this analysis, only the 42 firms are considered. As common in innovation studies (see, e.g., Sternberg and Arndt, 2001), we approximate the innovative performance of firms by means of the share of significantly improved products / processes on a firm's turnover (INN).

We have constructed attribute variables approximating firms' network positions, based on all links reported related to technological knowledge, i.e. including knowledge sources outside the aviation industry and outside the Netherlands. The 42 firms reported 158 links to 100 organizations inside and outside the Netherlands. As our first network variable, we described the firm's position in a network by the number of links it has (LINKS). This corresponds to the well-known network measure of degree centrality (Freeman, 1979). We also accounted for the internationalization of a firm's ego network (FOREIGN), measured by the share of links with organizations outside the Netherlands to the total number of links a firm has.

With respect to geographical proximity, we measured the variable DIST as the average distance between a firm and the organizations it is exchanging knowledge with. It will also be tested in its squared and mean subtracted form $DIST^2$, to account for potential non-linear effects.

In order to assess the effect of cognitive proximity, we constructed a variable that determined the similarity of a firm's technological profile to the combined technological profiles of the organizations it is linked to, based on the similarity measure (SIM_{NACE}) described in Section 3.1,. A technological similarity variable (SIM) can be defined as the sum of similarity measures (SIM_{NACE}) of those organizations a firm is directly connected to (geodesic distance equal to one). This sum was divided by the firm's total number of links, in order to reduce the correlation with the latter. SIM thus represents the average technological similarity of a firm to the technological knowledge base of its direct contacts. Again, subtracting the mean and squaring this variable accounts for a possible non-linear effect (SIM^2).

With respect to organizational proximity, we measured the share of contacts with non-profit organizations (ORG) for each firm. Social proximity is accounted for by a dummy variable (FOK), which amounts to 1 if the top management of the firm are former Fokker employees, and zero otherwise. It has to be pointed out that this variable may also capture effects related to the experience of the top management in this particular industry. As mentioned before, Fokker went bankrupt in 1996, and its employees had more than a decade to collect experiences in the aviation industry.

We also constructed a number of control variables. First, we accounted for the absorptive capacity of firms, which might positively impact on their innovative performance (see e.g. Boschma and Ter Wal, 2007). This has been approximated by two variables: the share of R&D employees in total employment (R&D), and the share of employees with at least an university bachelor degree (SKILL). Since our dependent variable is measured as a share of turnover, we have ensured that these independent variables are also independent of firm size. Second, we have included the variable AERO that measures the dedication of a firm to the aviation industry (see Section 3.1). Third, we have included firm's age (AGE) and the number of employees to account for any firm size effects (EMPL).

The descriptives of the variables are shown in Table 5. Since we have 42 observations in our sample, not all explanatory variables can be considered at the same time. We check their correlation structure first and exclude redundant variables. Table 6 shows the correlation among the independent and dependent variables. The correlation shows that R&D is highly correlated with firms' innovativeness ($r=0.58^{***}$). Not surprisingly is also the high correlation between R&D and the share of employees with at least a university bachelor degree ($r=0.61^{***}$). Old firms also have higher levels of employment ($r=0.51^{**}$). Even when excluding some redundant variables, the number of variables is still too high to be included into one model. For this reason, we define a base-line model, with which we test the influence of the other variables.

- Table 5 here –

- Table 6 here –

4.2 Method

In order to determine which proximity dimensions (while controlling for usual suspects) determine the innovative performance of firms in the Dutch aviation industry, we focus on firms' attributes. For the analysis of attribute data, standard regression tools can be used. A central assumption is however that firms exchange knowledge through networks, and for their innovative performance it matters with whom they are connected. In other words, firms' attributes are not independent observations, as they depend on the characteristics (attributes) of the linked actors. This violates the assumption of independence in OLS regressions. This is even more problematic when network measures are used as independent variables. In such settings, standard tools of inference are not valid.

The use of so-called network autocorrelation models allows circumventing this problem (see, e.g., Anselin, 1988; Leenders, 2002). Here the regression model is specified by

$$y = W1 * y + \beta * X + e, e = W2 * e + nu \quad \textbf{Eq. 4}$$

with y as the response, and X the covariance matrix. The error term *nu* has the usual characteristics. W1 and W2 are defined as

$$W1 = \sum_{i=1}^{p} rho1_i * W1_i \textbf{ and } W2 = \sum_{i=1}^{q} rho2_i * W2_i \quad \textbf{Eq. 5}$$

with $W1_i$ and $W2_i$ as the elements of one or two network adjacency matrices. In this sense *W1* and *W2* describe the relationships between the actors, i.e. the technological knowledge network. *Rho1* can be regarded as an autoregression parameter (AR) that parameterizes the autoregression of each *y* value on its neighbors in the network *W1*. In the context of this paper, this accounts for the potential of knowledge spillovers between the actors and *W1*. *Rho2* captures the moving average (MA) and parameterizes the autocorrelation of each disturbance in *y* on its neighbors in network *W2.* It accounts for an incorrect or mis-specified unit of analysis (Anselin and Bera, 1998). In addition, *Rho2* may also take into account effects when certain events or shocks diffuse through he entire network. In our setting *Rho2* is of minor importance as the unit of analysis are firms (which are well defined) and relevant knowledge is very unlikely to diffuse beyond geodesic distances of 1. Because of the limited number of observations and the fact that *Rho1* and *Rho2* represent additional parameters that reduce the available degrees of freedom, we decided to exclude *Rho2*. The models are therefore estimated considering only the autoregession parameter *Rho1* (*W1*), which corresponds to the technological knowledge network. We nevertheless checked the autocorrelation of the residuals. It turned out that the observed network autocorrelation in the residuals is generally low (Geary's C 0.7 =[0.7,1.35] and Moran's I < 0.22 at low geodesic distances).

The model is estimated by a maximum likelihood procedure using the *lnam* function implemented in the SNA package of the statistical software R. Our dependent variable is however a proportion (share of turnover) for which a standard linear regression approach is not valid. We therefore use a *logit* transformation on the dependent variable:

$$\hat{y} = \log(\frac{y}{1-y}) \textbf{ Eq. 6}$$

For zero values, we follow Petrie and Sabin (2000) and set these to 1/(2**n)*, with *n* being the number of observations. The coefficients have to be interpreted as odd ratios.

4.3 Results

In order to test the impact of the different types of proximity on firms' innovation performance, we use a linear knowledge production function model. First, we define a base-line model to explain the innovativeness of the 42 firms on the basis of the control variables R&D, EMPL, AERO, AGE and SKILL. The results are shown in the first column of Table 7.[6]

- Table 7 here -

Only the share of turnover attributed to aviation (AERO) turns out to be negative and significant: aviation oriented firms seem to be less successful in innovation. Another finding is that R&D is insignificant. This changes, however, when we exclude the insignificant control variables and include measures that take into account a firm's knowledge network (Model 1).[7] As expected, R&D becomes positively significant and remains so in all subsequent models, while AERO loses its significance level. We find that the number of links a firm has (LINKS) to be negatively related to innovative performance. We have to point out, though, that its significance level is low, and LINKS loses its significance in subsequent model specifications. An explanation might be that it is not sufficient to be connected to many persons, but that it matters rather to whom one is connected. The share of international linkages does not affect the innovative performance of Dutch aviation firms. Relations with international partners are not more or less important than relations with national partners.

Model 2 shows however that the average geographical distance to knowledge network partners (DIST) has a negative and significant impact on innovative performance. Including this variable also eliminates the significance of the number of linkages. Consequently, local linkages seem to be more beneficial to Dutch aviation firms. $DIST^2$ is not significant, suggesting a

[6] The results are based on the estimations when controlling for autocorrelation with respect to the technological knowledge network.

[7] Note that the following models are estimated on 34 cases, which have a positive number of knowledge links, so excluding the firms that did not indicate any knowledge links.

monotone relationship. Combined with the result in Section 3.3, it seems that firms not only prefer local partners, but these also bring more economic benefits to the firms. In other words, the proximity paradox does not seem to hold in purely geographical terms: geographical proximity is both a driver of knowledge network formation and a stimulus for innovative performance of firms through their geographically close partners. However, as Boschma (2005) mentioned, the effect of geographical proximity may just grasp the relevance of the other types of proximity. This is explored in the subsequent models.

In Models 4 and 5, we included the organizational proximity variable (ORG). Our analysis clearly shows that the share of knowledge linkages a firm has with non-profit organizations does not matter for innovative performance. In other words, while organizational proximity was a driver behind the formation of knowledge network relationships (see Section 3.3), it does not positively affect the innovative performance of firms. The same holds for its squared version (ORG^2). This result tends to provide some evidence for the proximity paradox.

In Model 6, the geographical distance measure is confronted with the social proximity variable FOKKER. Both variables are significant. Having a positive effect, a firm's embeddedness in the "old-boys" network related to the former Fokker Company tends to increase its innovative performance. This result was also confirmed in some of the interviews. Consequently, the proximity paradox does not seem to hold in the case of social proximity: a shared past in the Fokker company did not only increase the likelihood to establish a knowledge link, but it also enhanced the effectiveness of knowledge exchange.

In Models 7 and 8, we assess the economic effect of cognitive proximity through the ego networks of firms. In addition to the negative effect of geographical distance and the positive influence of social proximity, the technological similarity indicator shows a negative and significant effect. In other words, as expected, the more the technological profile of the partners in a firm's ego network overlap with the technological profile of the firm, the more cognitive proximity between the firm and its partners, and the lower the innovative performance of the firm. In Model 8, the squared term turns insignificant indicating a rather linear effect. This does not meet our expectations of an inverted u-shape relationship. A possible explanation for this might be found in the construction of the cognitive proximity indicator. We consider only a subsample of all existing industries' NACE codes (and technologies), namely those that are linked to the aviation industry. The subsample is therefore likely to be biased towards aviation related industries. In other words, the subsample is more related to aviation than the average of the entire spectrum of industries and technologies. Our analysis' negative coefficient may hence reflect the decreasing slope of the inverted u-shape while the increasing part is not captured by our measure. This deserves more attention in future research.

In sum, our analysis demonstrates that geographical, social and cognitive proximity matter for the innovative performance of firms in the Dutch aviation industry. The first two impact on innovative performance positively, while the latter has a negative effect. All three have also been shown to positively influence network formation. In other words, the proximity paradox seems to hold for the cognitive dimension, and to a lesser extent for organizational proximity.

5 Conclusion

In this paper, we tested the so-called proximity paradox, as proposed by Boschma and Frenken (2009). This is about the fact that proximity is required to connect to knowledge networks, but proximity does not necessarily yield superior innovative performance. We have collected data on 59 profit and non-profit organizations that are active in the Dutch aviation industry, and employed QAP and network autocorrelation regression models to test this paradox. In our analyses, we distinguished between four forms or proximity (cognitive, geographical, social and organizational) that might impact on network formation and the innovative performance of firms.

Our analyses provided strong evidence for the first part of the proximity paradox, which concerns the forms of proximity as drivers of knowledge network formation. We found indeed that cognitive, organizational, geographical and social proximity between organizations increased their likelihood to connect and exchange knowledge. Most interestingly, we also found geographical proximity to be a driver of network formation, even when controlling for the other proximities. The study provided, however, mixed evidence for the second part of the proximity paradox, which concerns the effects of proximity on the innovative performance of firms while controlling for the usual suspects. It did seem to hold for the cognitive dimension and to some extent to the organizational dimension of proximity. However, the proximity paradox did not hold for the geographical dimension: geographical proximity is both a driver of knowledge network formation and a catalyst for innovative performance through local network partners. The same is true for social proximity: it helps to establish and maintain knowledge network linkages, but it also enables a more effective utilization of this network fostering innovative performance.

Our analyses also showed that there is an interesting relationship between cognitive and geographical proximity. In the light of the first part, the results show that firms chose their knowledge partner because of geographical closeness as well as technological similarity. The second analysis rather suggests that networking with local knowledge partners as well as with technologically distant actors is beneficial for firms' innovation performance. Put differently, being linked to geographically close partners that have divergent knowledge bases is likely to increase firms' innovation performance. This result calls for further research.

Further research is also needed concerning the effect of geographical proximity. We cannot exclude in our analysis that geographical proximity might still capture some other effects, like social proximity (see, Breschi and Lissoni, 2003), as the latter was quite broadly defined in our study With the data at hand, we cannot disentangle any further these two effects. This certainly needs to be explored in future work. Finally, we are in need of more dynamic analyses, accounting for knowledge network formation over time, and examine how that is not only affected by the various proximities, but also how proximities change over time due to the evolution of networks (Balland, 2009; Boschma and Frenken, 2009; Ter Wal, 2009).

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7 Tables and figures

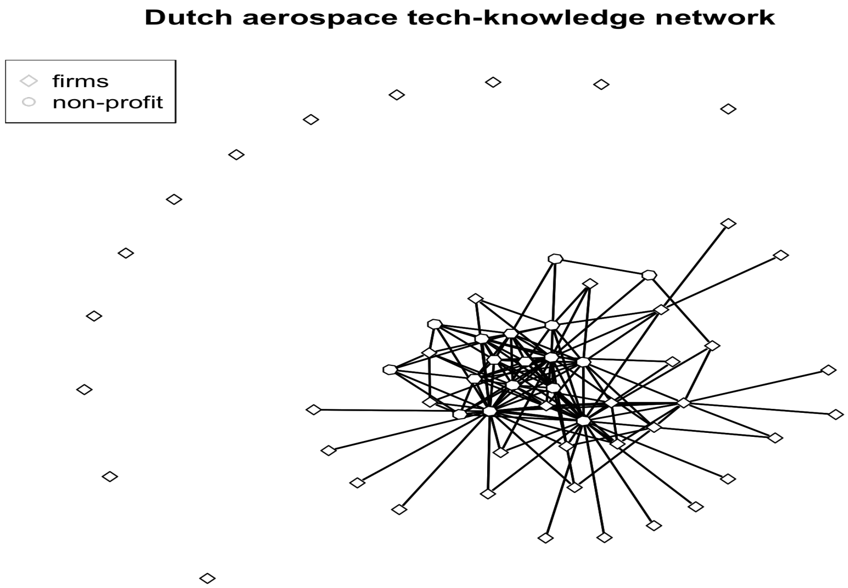

Figure 1: Dutch aviation knowledge network

Technological field according to NAG	*Number of firms*
Airframe subsystems & components	17
Interiors	10
Propulsion & engine components	15
Auxiliary systems	5
Avionics, simulation & control	12
Education & training	13
General services	3
Engineering & R&D	31
Space subsystems & components	15
Maintenance & overhaul	11
Spare parts	10
Special materials.	10
Consultancy	5

Table 1: NAG technological fields

Relational variables	*Type*	*Share of zero values*	*Mean*
Size difference (SIZE)	Continuous	0%	4.3
Non-firm links (PUB)	Dichotomous	92%	0.078
Firm links (PRIVATE)	Dichotomous	51%	0.49
Geographic distance (DIST)	Continuous	0%	4
Technological similarity NAG (TEC_{NAG})	Dichotomous	55%	0.45
Technological similarity NACE code (SIM_{NACE})	Continuous	0%	0.75
Related variety effect $(SIM_{NACE})^2$	Continuous	0%	0.012
Shared Fokker history (FOK)	Dichotomous	93%	0.069
Dedicated towards aerospace (AERO)	Dichotomous	77%	0.23
Importance of external knowledge (OPEN)	Dichotomous	78%	0.22

Table 2: Relational variables

	SIZE	PUB	PRIVATE	DIST	$DIST^2$	SIM_{NAG}	SIM_{NACE}	SIM_{NACE}^2	FOK.	AERO
PUB	0.11^{**}									
PRIVATE	-0.18^{***}	-0.30^{***}								
DIST	0.06	-0.12^{**}	0.08^{*}							
$DIST^2$	-0.03	-0.00	0.05	-0.66^{***}						
SIM_{NAG}	0.09^{*}	0.01	0.16^{**}	0.05	0.00					
SIM_{NACE}	-0.09^{*}	0.14^{*}	0.20^{***}	-0.01	-0.00	0.24^{***}				
SIM_{NACE}^2	-0.12^{*}	0.21^{**}	-0.28^{***}	-0.08	-0.00	-0.09^{*}	-0.48^{***}			
FOK.	-0.01	-0.08^{*}	0.27^{***}	-0.01	0.02	0.14^{**}	0.12^{**}	-0.10^{*}		
AERO	-0.03	-0.16^{**}	0.21^{***}	-0.03	-0.02	0	0.15^{**}	-0.12^{**}	0.27^{***}	
OPEN	0.14^{**}	-0.16^{**}	-0.11^{*}	0.07	0.01	0.12	-0.09^{*}	0.04	0.05	-0.01

Table 3: QAP-correlation relational variables

	Estimate	*Exp(b)*	*Pr(<=b)*	*Pr(>=b)*
(intercept)	-4.578***	0.010	0.001	0.999
PUB	2.717***	15.138	1.000	0.000
PRIVAT	-1.789***	0.167	0.000	1.000
DIST	-0.233***	0.792	0.009	0.991
($DIST^2$)	(-0.029)	(0.971)	(0.153)	(0.847)
SIM_{NAG}	-0.068	0.934	0.418	0.582
SIM_{NACE}	2.641*	14.022	0.945	0.055
(SIM_{NACE}^2)	(1.852)	(1.852)	(0.863)	(0.137)
FOKKER	0.852**	2.344	0.940	0.060
SIZE	0.117	1.123	0.894	0.106
AERO	0.889**	2.433	0.977	0.023
OPEN	0.907**	2.478	0.983	0.017
Chi-Squared test of fit improvement:	1657.960 on 10 degrees of freedom,	p-value 0		
Pseudo-R^2 Measures:				
	(Dn-Dr)/(Dn-Dr+dfn):	0.492		
	(Dn-Dr)/Dn:	0.699		
Total Fraction Correct:	0.917			
Fraction Predicted 1s Correct:	0.523			
Fraction Predicted 0s Correct:	0.937			

Numbers in parentheses are based on models not reported estimations. Because the other variables' coefficients did not change significantly they are not listed.

Table 4: QAP-logit network regression technological knowledge

	INN	EMPL	R&D	AERO	AGE	OPEN
nbr.val	42	42	42	42	42	42
nbr.null	14	0	7	0	0	9
Min	0	5	0	0.025	2	0
Max	90	1500	4	100	153	100
median	9	51.5	0.09	75	21.5	30
Mean	21.96	121.67	0.33	62.38	33.14	31.19
std.dev	27.54	241.82	0.66	37.37	32.25	25.23
	LINKS	SIM	SIM^2	FOK	ORG	FOREIGN
nbr.val	42	42	42	42	42	42
nbr.null	8	0	0	26	15	25
Min	0	0.51	0.00	0	0	0
Max	15	1	1	1	0.99	0.99
median	2	0.82	0.01	0	0.45	0
Mean	3.60	0.80	0.20	0.38	0.42	0.19
std.dev	3.89	0.13	0.39	0.49	0.38	0.28
	SKILL	CENT	DIST	$DIST^2$		
nbr.val	42	42	42	42		
nbr.null	8	12	0	0		
Min	0	0	0.01	0.00		
Max	100	22	6.94	17.59		
median	9.5	2	2.69	1.63		
Mean	21.02	4.52	2.751	3.14		
std.dev	28.61	5.45	1.79	3.73		

Table 5: Descriptives

	INN	*EMPL*	*R&D*	*AERO*	*AGE*	*FOREIGN*	*LINKS*	*SIM*
EMPL	-0.22*							
R&D	0.58***	-0.18*						
AERO	0.33**	-0.01	0.15					
AGE	-0.04	0.51**	-0.20*	0.23*				
FOREIGN	0.04	-0.02	0.10	0.37**	0.25*			
LINKS	0.06	0.48**	0.11	0.15	0.22*	0.16		
SIM	-0.02	-0.04	-0.18	-0.29*	-0.21*	-0.27*	0.12	
SIM^2	-0.04	-0.07	-0.20*	-0.16	-0.14	-0.28*	0.06	0.55***
FOK	0.14	0.23*	-0.07	0.42**	0.24*	0.25*	0.28*	-0.02
SKILL	0.55***	-0.14	0.61***	0.29*	-0.31**	0.03	0.15	0.02
OPEN	-0.06	0.10	0.07	0.04	0.18	0.22*	0.26*	0.09
CENT	-0.07	0.68***	-0.10	0.08	0.22*	0.03	0.83***	0.15
DIST	-0.16	0.14	-0.01	0.08	0.20*	0.73***	0.46**	-0.11
$DIST^2$	0.27*	-0.28	0.03	0.19	-0.29*	-0.28*	-0.40**	0.26*
ORG	0.09	-0.06	0.02	-0.33**	-0.11	-0.51**	-0.21*	0.47**
ORG^2	0.04	-0.02	0.00	-0.12	-0.03	-0.20	-0.10	0.30*

	SIM^2	FOK	SKILL	OPEN	CENT	DIST	$DIST^2$	ORG
FOK	-0.07							
SKILL	-0.05	0.36**						
OPEN	0.00	0.17	-0.19					
CENT	0.02	0.30*	0.04	0.16				
DIST	-0.18	0.10	-0.12	0.28*	0.28*			
DIST2	0.29*	-0.21*	0.12	-0.19	-0.31*	-0.50**		
ORG	0.44**	-0.13	0.09	-0.07	-0.27*	-0.52***	0.37*	0.37*
ORG^2	0.29*	-0.02	0.02	-0.01	-0.11	-0.34*	0.23	0.72**

Table 6: Correlation matrix

	Base-line	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D	0.765	1.108**	1.135**	1.231***	1.294***	1.215***	1.223***	1.275***	1.329***
SKILL	0.005								
AERO	-0.021***	-0.009							
AGE	-0.015								
EMPL	-0.001								
Rho1	0.033	-0.036	0.039	-0.002	0.007	0.002	0.005	0.038	0.039
LINKS		-0.229*	0.082						
FOREIGN		-0.859							
DIST			-0.501***	-0.459***	-0.380**	-0.388***	-0.528***	-0.269*	-0.222**
$DIST^2$				-0.002					
ORG					-0.921				
ORG^2						-2.814			
FOKKER							1.207*	1.351**	1.389**
SIM								-2.035*	-2.765*
SIM^2									-7.390
Obs.	42	34	34	34	34	34	34	34	34
Adj. R^2	0.141	0.083	0.216	0.221	0.198	0.216	0.319	0.281	0.252
Model log likelihood	-65.4 (35 d.o.f.)	-74.25 (28 d.o.f.)	-65.57 (29 d.o.f.)	-65.8 (29 d.o.f)	64.8 (29 d.o.f)	-65.07 (29 d.o.f.)	-63.71 (29 d.o.f.)	-61.93 (28 d.o.f.)	61.77 (27 d.o.f)
K	6.595	2.513	2.793	3.011	3.134	1.488	1.279	1.533	4.143
BP test	3.453	3.247	1.195	2.154	0.192	0.233	1.458	1.281	2.413
Moran I res. 1st. deg.	-0.25	0.02	-0.01	-0.02	-0.09	-0.04	0.02	0.07	-0.033
Geary C res. 1st deg.	1.23	1.12	1.19	1.22	1.21	1.29	1.16	1.12	1.14

Table 7: Network autocorrelation regression: determinants of innovation performance