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The coevolution of innovative ties and technological proximity - Towards a Dynamic Approach of Innovation Networks

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Abstract

In innovation research it is widely acknowledged that different dimensions of proximity influence the success of research collaborations and consequently the choice of cooperation partners (Boschma, 2005). However, the interrelations between these dimensions are still hardly explored. Furthermore, the research on the influence of these proximity dimensions on network evolution in the framework of a dynamical analysis is still at an early stage. Seminal studies merely focus on the investigation of static network structures (Giuliani, 2007; Morrison and Rabellotti, 2009; Giuliani and Bell, 2005). Moreover, the relation between certain proximity dimensions and the network configuration is by no means unidirectional (ter Wal and Boschma, 2011). In fact, individual characteristic, such as technological capabilities, and thus the proximity to others coevolve over time with the network (ter Wal and Boschma, 2011). In this paper we make a start in analyzing this interplay between the common evolutions of these factors. We focus on the examination of innovator networks (Cantner and Graf, 2006) and ask the following research question: In how far does the knowledge transfer in research collaboration account for the persistency or non-persistency in cooperation patterns? As we assume other dimensions to be rather static (institutional and organizational proximity), we especially focus on the evolution of technological proximity (induced by knowledge transfer) as an explanatory variable for the formation and break-up of innovative ties. We introduce a new method to measure knowledge transfer and construct networks respectively dyads on the basis of joint patent applications registered at the European Patent Office.

Jelcodes:O31,O33

THE COEVOLUTION OF INNOVATIVE TIES AND TECHNOLOGICAL PROXIMITY

Towards a Dynamic Approach of Innovation Networks

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Abstract

In innovation research it is widely acknowledged that different dimensions of proximity influence the success of research collaborations and consequently the choice of cooperation partners (Boschma, 2005). Mainly, the relevance of geographical, social and cognitive proximity between partners in term of innovation has been a crucial pillar to several concepts explaining the disparity in economic performance of regions. The main argument of previous work is that proximity serves as a vehicle for knowledge flows among the partners. However, the interrelations between these dimensions are still hardly explored. Furthermore, the inclusion of these proximity dimensions into the explanation of the dynamics of networks is still in an early stage. Seminal studies merely focus on the investigation of static network structures (Giuliani, 2007; Morrison and Rabellotti, 2009; Giuliani and Bell, 2005). Studies adapting a dynamic approach to investigate the formation and evolution of innovation networks are still rather scarce. Moreover, the relation between certain proximity dimensions and the network configuration is by no means unidirectional (ter Wal and Boschma, 2011). In fact, individual characteristic, such as technological capabilities, and thus the proximity to others coevolve over time with the network (Guliani, 2007, ter Wal and Boschma, 2011).

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Hence, the investigation of the interplay between the evolution of firm characteristics, proximity and networks is still a young and promising research field. In this paper we make a start in analyzing this interplay between the common evolutions of these factors. We focus on the examination of innovator networks (Cantner and Graf, 2006) and ask the following research question: In how far does the knowledge transfer in research collaboration account for the persistency or non-persistency in partner choice? As we assume other dimensions to be rather static (institutional and organizational proximity), we especially focus on the evolution of technological proximity (induced by knowledge transfer) as an explanatory variable for the formation and break-up of innovative ties. Moreover, we expect that actors break up ties when they become too close in technological space. We introduce a new method to measure knowledge transfer and construct networks respectively dyads on the basis of joint patent applications registered at the European Patent Office. Our findings suggest that firms are rather prone to switch their cooperation partner than to repeat the collaboration with a certain partner. Moreover, we find that firms prefer to cooperate with partners that are different in popularity (degree centrality) but similar in organizational nature (status). Preceding knowledge transfer seems to represent an incentive rather than a barrier for repeated collaboration.

JEL: O31, O33

1. Introduction

The growing complexity and shortening of cycles inherent in the innovation process have changed the industrial and technological environment in which firms operate. The associated increase in uncertainty and costs accompanying R&D projects has shaped a landscape that favors collaborations (Hagedoorn, 2002). Especially in high tech industries where knowledge creation and accumulation is a crucial input factor and competition has developed as learning race, joint research has experienced a continuous growth since the 1980s (Mowery et al, 1996; Powell, 1998).

According to the knowledge based view of the firm, a firm's knowledge base, understood as a unique and difficult to imitate resource, constitutes a key competitive advantage (Grant and Baden-Fuller, 1995). Since the accumulation of internal technological capabilities is a highly path-dependent process, the exploitation of existent knowledge components within firm boundaries is limited and leads mostly to incremental improvements and suboptimal solutions (March, 1991; Yang et al., 2010). To broaden the knowledge base and to explore new possibilities for recombination and radical innovations, firms are reliant on external sources of knowledge (March, 1991; Yang et al.; 2010). It is shown that successful innovators extended their search for the solution of complex problems to external sources in their environment (Freeman, 1991). Consequently, the generation of knowledge and innovation result progressively from an evolutionary and collective learning process among various actors which interact formally or in an informal way (Asheim and Gertler, 2005).

Often cited in this context are concepts on clusters, regional innovation systems and regional networks that elaborate the importance of geographical distance for these linkages (e.g. Porter, 1998; Cooke; 2001, Asheim and Gertler; 2005). Especially in the early stages of technology development, when knowledge is specific and complex, continuous communication and face-to-face contacts are indispensable for the efficient transmission of knowledge (Breschi & Lissoni, 2001; Audretsch and Feldman, 1996). The ease and costs of the linkages and knowledge exchange are related to the geographical distance of the correspondent actors. Moreover, spatial proximity allows for the development of trustful relationships and decreases the social distance among related actors (Boschma, 2005). Hence, a firm's integration into the regional innovation network providing access to external knowledge sources is a crucial determinant of a firm's learning process and resulting innovative capabilities (Koschatzky and Sternberg, 2000).

According to these perceptions, analyses of regional networks as vehicles for knowledge flows are flourishing. Though, many of the early studies focus on the investigation of static network structures (Giuliani, 2007; Morrison and Rabellotti, 2009; Giuliani and Bell, 2005). Studies on the formation and evolution of innovation networks are rather scarce. First promising studies in this direction found three mechanisms that drive the evolution of networks (Balland et al., 2012): endogenous structural mechanisms (Barabasi and Albert, 1999, Davis, 1970), dynamics related to proximity between actors (Boschma et al., 2011; Boschma and Frenken, 2010) and individual characteristics of actors (Balland et al.,2012). Apart from a few exceptions (e.g. ibid.), these factors have not been considered simultaneously in one empirical framework. Furthermore, the relation between these factors and the network configuration is by no means unidirectional (ter Wal and Boschma, 2011). In fact, individual characteristic, such as technological capabilities, and thus the proximity to others coevolve over time with the network (Guliani, 2007, ter Wal and Boschma, 2011). The interplay between the evolutions of firm characteristics, proximity and networks is yet hardly explored.

In this paper we make a start in analyzing this interplay between the common evolutions of these factors. We focus on the examination of innovator networks defined as networks built up by partners which cooperatively engage in the creation of new ideas and then economize on the result (Cantner and Graf, 2006) and ask the following research question: In how far do various dimensions of knowledge transfer in research collaboration account for the persistency or non-persistency in partner choice? More specific, we argue that changes in the knowledge stock of firms caused by knowledge transfer in R&D-cooperation leads to a dynamic evolution of cognitive proximity among them what in turn influences their connections.

2. Knowledge exchange and the evolution of innovation linkages

Our research question refers to persistent and transient patterns in innovation cooperation and focusses on the determinants of partner choice over time. To lay down the analytical basis of our analysis we pursue in three steps. We first address the knowledge related motives for innovation cooperation and then turn, in a second step, to the conditions for the involved dynamics. The relation of these dynamics to network dimensions is considered in the third step.

Knowledge exchange and innovation cooperation

There exist several motives to engage in collaborative innovation projects. Besides the sharing of risks and R&D costs, a main motif to enter collaboration is to gain access to technology and knowledge related resources of a partner, whether in form of a certain technical infrastructure or more importantly in form of technological capabilities and complementary skills (Hagedoorn, 2002). This argument draws on the knowledge based view of the firm. According to this approach, a firm's knowledge base, understood as a unique and difficult to imitate resource, constitutes a key competitive advantage (Grant and Baden-Fuller, 1995). Since the accumulation of internal technological capabilities is a highly path-dependent process, the exploitation of existent knowledge components within firm boundaries is limited and leads mostly to incremental improvements and suboptimal solutions (March, 1991; Yang et al., 2010). To broaden the knowledge base and to explore new possibilities for recombination and radical innovations, firms are reliant on external sources of knowledge (March, 1991; Yang et al.; 2010). It is shown that successful innovators extended their search for the solution of complex problems to external sources in their environment (Freeman, 1991). Consequently, the generation of knowledge and innovation result progressively from an evolutionary and collective learning process among various actors which interact formally or in an informal way (Asheim and Gertler, 2005).

In this context, to understand how actors select cooperation partners is of utmost importance. Quite generally, actors tend to primarily choose cooperation partners that possess capabilities that allow expecting a high potential of knowledge flows (Cantner and Graf, 2006; Boschma et al., 2011).

The knowledge transfer itself, however, is rather bound to the fulfillment of certain prerequisites than to a guaranteed outcome of cooperation. In this sense and quite generally, the potential for knowledge spillovers between two partners depends on their similarity or better proximity in terms of dimensions easing the transfer of knowledge. As Boschma (2005) argues, various dimensions of proximity influence the common understanding and learning between actors and eventually the innovative performance of research collaborations. Among the dimensions of technological (cognitive), social, geographical, organizational and institutional proximity, in analyzing the evolution of cooperative linkages we focus on technological and social proximity since they are affected by and change due to cooperation.

With respect to the technological dimension, actors tend to engage in cooperation with partners that are proximate in cognitive sense. For partner choice, the cognitive endowments, i.e. the knowledge stocks, of potential partners are evaluated relatively to the own technological endowment. The criteria for this evaluation are as follows: First, the own knowledge base needs to overlap to some degree with the one of a potential partnering firms to warrant the understanding of the information exchanged, since the ability to absorb external knowledge (absorptive capacity) is to a large extent a function of the relatedness of the knowledge bases of collaboration partners (Cohen and Levinthal, 1990, Cantner and Meder, 2007, Boschma, 2005). The lack of absorptive capacities results rather in the sharing of knowledge than in exchanging it, as the partners are not able to integrate the external knowledge into their own knowledge stock. Secondly, the cognitive distance towards the potential partnering firm should not be too close. Otherwise the combinatorial possibilities for the exploration of novelties diminish (Nooteboom, 2005). Consequently, knowledge can be exchanged between partner firms, if they exhibit a certain degree of overlap but are also complementary to have the potential for creating novelty. In addition to that, as cooperations base on mutual agreement, partners need to have reciprocal incentive to engage in this cooperation. They will only do so if they expect to receive an amount of new knowledge "equivalent" to the knowledge they contribute to the collaboration (Cantner und Meder, 2007, Giuliani, 2007).

Besides this technological dimension, social proximity (which is not unrelated to spatial and institutional proximity) influences the ease of knowledge flows and the potential to cooperate. Social proximity accounts for familiarity and trust between cooperation partners which in turn ease the transfer of tacit knowledge and reduce the occurrence of opportunistic behavior. Geographical proximity may further that, as Jaffe et al. (1993) find for firms being located proximate in space to cooperate more often than others . In this context, Breschi and Lissoni (2003) argue that spatial proximity enables the establishment of trustful relationships or social ties between actors at the micro-level which are conducive to the success of the collaboration project. Another mechanism for social proximity to develop is the mobility of inventors which often maintain social relations to their former place of work (ter Wal and Boschma, 2009) but also through positive experience gained in previous collaboration. Social proximity among the cooperation partners in turn can substitute low levels of cognitive proximity, since trust and positive experiences foster the transfer of knowledge and lead to a diminishing of cognitive distance (Boschma, 2005).

Evolution of innovation cooperation

Given these characterizations of technological and social proximity, for a certain decision situation, appropriate levels or degrees of technological and social proximity are required in order to establish cooperative links between two potential partners. When cooperation has been settled on this basis, the ongoing exchange of knowledge and the working together rather necessarily feed back on the proximities between collaborators. The working together, whenever pursued successfully, will increase social proximity; the exchange of knowledge tends to increase cognitive proximity. Seen in this way, cooperation in innovation does not only affect the likelihood of innovative success, it also affects the basic conditions, i.e. proximities, for further cooperation in the future. Hence, we may ask, given the cooperation affected development of the two core proximity dimensions, in how far can they explain the observed pattern of persistent cooperation on the one hand and pattern of transient cooperation on the other?

With social and technological proximity between two partners tending to increase during cooperation and knowledge exchange, several assumptions on the dynamic pattern of persistent and transient cooperative behavior can be derived. Here we expect differences between the effects of social and of cognitive proximity development.

As to social proximity, given that trust establishes through experience gained in prior successful cooperation and in turn facilitates knowledge exchange, actors are inclined to engage repeatedly in cooperation with the same partner(s). Hence, the process of successfully cooperating with each other tends strengthening the trust relationship and works on repeated cooperation. Therefore this trust dimension could explain the persistency in cooperation observed for alliances of firms quite frequently (e.g. Gulati, 1995).

Contrariwise, since during cooperation knowledge is exchanged between partners, repeated cooperation leads to the assimilation of their knowledge bases and higher technological proximity. Although this leads to a better understanding of the partners, the increased proximity reduces the potentials for cooperative innovation success. With declining cooperation potentials the time horizon for repeated cooperation among the same partners is finite; at some time a breaking off of the cooperation is to be expected and, hence, cooperation is transient. Indeed, by examining the regional network of innovators in Jena, Cantner and Graf (2006) find no persistency in cooperation patterns between inventor pairs. In relation to that, they find that the configuration of technological proximity among the actors changes over time. Hence, the very process of knowledge exchange depletes the cooperation potential between two partners which eventually renders cooperation obsolete.

Innovation cooperation and network dynamics

The suggested bi-directional relationship between proximity and innovation cooperation is corroborated by studies on the network level. Ter Wal and Boschma (2011) emphasize that the relation between the proximity dimensions and the network configuration is by no means to be seen as uni-directional. Relating that to our level of analysis, individual characteristics, such as technological capabilities, and thus the proximity to others coevolve over time with the underlying knowledge, innovation or industrial network (Guliani, 2007, ter Wal and Boschma, 2011). In other work it has been demonstrated, that proximity configurations change over time and during the life cycle of an industry (Balland et al. 2012, Broekel, 2012).

Despite these contributions, the study of the evolution of networks is still in its infancy and empirical evidence for this bi-directional relationship is still pending.

In particular, the underlying mechanisms that drive the dynamics in individual characteristics and thus in proximity dimensions have not been incorporated in the analysis of network evolution so far. In this respect, the primary contribution of this paper is to provide evidence for the simultaneous evolution of the firms' endowment, proximity and network configuration.

In order to do so, we analyze the changes in pairwise firm-cooperations (or dyads) in relation to changes in firms' knowledge endowment. The basic idea is that firms enter a research collaboration (create a link) and the associated assimilation of knowledge endowments (through learning and knowledge transfer) causes the two partners to increase their technological proximity eventually ending in a breakup of the tie. Therefore, a special focus of our analysis is on the breaking up of ties and not only on the formation of new ties. In this respect, we on the one hand look at the pairs that are persistent cooperators and also at pairs that are transient or sporadic in their cooperation behavior. In offering a new approach for measuring knowledge transfer in firm cooperation, we explain that knowledge transfer drives the dynamics in technological proximity among actors and thus causes changes in the configuration of the whole network of research cooperation.

3. Methodology

As network ties establish and break up due to the decisions of actors to collaborate, we aim to analyze the formation of pairwise research linkages or dyads. As our main explanatory variable of interest is the prior knowledge transfer in the bilateral collaboration context, we apply a binary choice model (random effects logistic regression) in which the dependent variable is an observed link (realized cooperation) or a potential link (unrealized) between two actors. Primarily, we aim to explain linkages that are non-observed in current period, but were observed in prior periods. Or in other words, our focus lies on links that are not reestablished. In order to do so we regress the existing or non-existing links against knowledge transfer in prior collaboration and further historical variables. Additionally the literature on networks has shown that the position of a firm in the overall network (e.g. Rivera et al., 2010) also has a crucial influence on the tie formation. Therefore we incorporate descriptive network statistics into our regression framework to control for these additional effects. As our analysis will be based on patent data, the nodes of the networks are represented by applicants and the linkages are represented by co-applications.

3.1 Data

Our analysis will be based on relational information found in patent applications. For the analysis of the dynamics of networks, patents provide more adequate information since they allow the observation of networks over long periods of time compared to the collection of primary data. This also allows us to create a panel database on cooperation behavior.

When using patent data, we define cooperation as co-applications meaning that more than one applicant occurs on the patent document. This implies that an intensive cooperative research process preceded the final patented invention (Singh, 2005). In this context, cooperations identified by patents comprise by nature innovative success.

Apart from that, we are also aware of shortcomings that come along with the use of patent data for analyzing networks. The revealed picture will not completely reflect the real underlying network structures, since we only observe cooperations that have led to a patentable invention. However, when analyzed with consideration of the possible shortcomings, patents provide a powerful tool for the examination of cooperation networks, as there exists empirical evidence that cooperative linkages found on patents reveal a comprehensive picture of ties between inventors (Fleming et al. 2003, 2004).

We gather information on patent applications from the OECD REGPAT database[2] that contains patent applications filed to the EPO from 1977 to 2008. These patent applications are linked to geographical administrative units according to the addresses of applicants and inventors.

Our analysis is furthermore restricted to the investigation of Biotechnology patents that were filed by German applicants, as actors in this sector exhibit a high propensity to patent and also to cooperate (Griliches, 1990, ter Wal 2009). This procedure reduces the bias introduced by different patenting behavior across different industries.

3.2 Sample

According to Cantner and Meder (2007) we model the creation of a link between actors as the preceding choice of a cooperation partner from a pool of potential partners. We aim to explain the linkages that were established between 1983 and 2010 by historical variables collected for the 5 preceding years of the realized cooperation. Hence, the historical variables are created within a 5 years moving window between 1978 and 2009. Since the explanation of general cooperative behavior, i.e. the propensity to cooperate, is not the focus of our analysis[3], we included only firms that cooperated at least twice in the focal time period (N=91). This allows us to track multiple cooperations per firm. For each year we construct a pool of possible partners (actors that were active in focal year and/or entered in years before) and assign a one for each realized cooperation and a zero otherwise. The size of the pool of potential partners is increasing from year to year or is at least equal from prior year to the following year. It amounts 2,369 potential partners in maximum. This implies that the observations are not symmetric, i.e. we focus on firms, but we allow the potential partner in the pool to be of any type (university, etc.). Or in other words, each collaboration includes per definition at least one firm. In sum, our sample consists of 321,683 possibilities to form dyads, of which 293 actually occurred.

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[2] For a comprehensive description of the OECD REGPAT database see Maraut et al. 2008.

[3] Nevertheless we include the general decision to cooperate into a two stage model (Heckit) to correct for sample selection bias.

3.3 Variables

As a tie in an undirected network is only established based on the agreement of two actors, we need to take into account the relative characteristics (the fit) of both actors when establishing the explanatory variables.

Dependent Variable

The dependent variable represents the cooperation among two actors in the current year and is of binary nature, taking the value one if there is cooperation between partners and zero, if there is none. Since we are interested in explaining repeated collaboration respectively the dissolution of cooperation, non-existing links, that were existent before (or technically speaking the variable changed from 1 to zero), are detected by the control variable experience (see below).

Independent Variables

Knowledge transfer

A bulk of studies has bothered with measuring knowledge and knowledge transfer in several contexts. Besides raw measures such as the R&D intensity (e.g. Nakamura et al., 1996, Montgomery and Hariharan, 1991), patents have established as an alternative measure of technological capabilities (Mowery et al., 1996). The qualification of patent data as a proxy for firms' knowledge stock derives from the disaggregate information it provides. The international patent classification (IPC) offers a standardized and very fine technological classification system that allows for locating firms in technological space. Jaffe (1986) was one of the first to use patent data as a proxy for firm's technological competences. He constructed the knowledge portfolios as a vector of patent classes in which firms patented and computed the distances between technology vectors of firms to obtain a measure of proximity among them. Following studies also applied patent classes to display a firm's technology portfolio, technological distances among firms or potential knowledge spillover pools in the firm's environment. (Cantner and Meder, 2007, Cantner and Graf, 2006, Boschma and Frenken, 2010; Benner and Walfogel, 2008).

In addition, citations of previous documents (patents and publications) on the patent became a favored instrument of scientific authors to detect knowledge spillovers (e.g. Griliches, 1990, Jaffe et al., 1993, Hall et al. 2001, Nomaler &Verspagen, 2008, Nelson, 2009, Schmoch, 1993, Mowery et al., 1996, Singh, 2005). A common critical remark is that patent citations do not imply real knowledge flows since a large amount of citations is added rather by the patent examiner than by the inventor/ applicant himself.

Our empirical approach to measure knowledge transfer is new in that we compare the knowledge stocks of firms over time and define changes in the knowledge stock of firms as knowledge exchange if they can be attributed to prior cooperative activities. Therefore, we define the vector of technological classes that a firm has patented in as its cumulated knowledge stock. The occurrence of a new[4] patent class in the firm's patent portfolio after the collaboration indicates that knowledge was transferred. To attribute the changes in the portfolio to the cooperation, the newly added class must be consistent with the class on the prior co-patent or be a part of the knowledge base of the collaboration partner. Figure 1 illustrates a knowledge transfer between two hypothetical firms.

Firm A

Patent \ Classes	1	2	3	4	5	6	7	8
1	1	0	1	0	1	0	0	0
2	1	0	0	0	1	0	0	0
3	0	0	1	1	0	0	0	0
4	0	0	0	1	1	1	0	0
5	1	0	1	0	0	1	0	0
6	0	0	0	0	0	1	0	0

Firm B

Patent \ Classes	1	2	3	4	5	6	7	8
1	0	0	0	0	0	1	1	1
2	0	0	0	1	0	0	1	1
3	0	0	0	0	0	1	1	0
4	0	0	0	1	1	1	0	0
5	0	0	0	0	1	1	1	1
6	0	0	0	1	1	0	0	1

Figure 1: Hypothetical example of knowledge transfer between two firms

Both tables show the knowledge base of two firms that collaborate with each other once (Patent 4). The rows display the patents of firm A respectively B in chronological order (patent 1 has earliest application date, patent 6 the latest one). The columns indicate the patent classes in which the patents are hold. In the interest of simplicity, we assume that there exist overall only 8 technology classes, in which firms can patent in.

Giving that, the table reads as follows: Firm A's first patent (patent 1) covers the classes 1, 3 and 5. Patent 2 covers the classes 2 and 4 and so forth. The red marked patent in both tables (Patent 4 for firm A and B) indicates the joint patent of firm A and B, meaning that both firms are listed as applicants at the same patent. In the case of firm A, the technological class number 6 was added to its portfolio. Since subsequent patent applications by firm A cover still class 6, we assume that knowledge flew from B to A. The same holds for firm B. After the collaboration, class 5 accrued persistently to firm B's portfolio. In this regard, the choice

[4] New in this context means, that the patent class may not occur in the pre-cooperation portfolio before the application of the co-patent.

of an appropriate aggregation level of the technology classes is crucial for receiving reliable results.

Analytically, we calculate the accumulated variety of the knowledge base as the cumulative sum of technology classes that a firm patented in (Stirling, 1998). A change in the firm's variety (breadth of the knowledge base) that follows a previous collaboration is defined as knowledge transfer.

Controls

Table 1 provides an overview over all explanatory variables included in the model. As mentioned above all explanatories are constructed as relational indicators, i.e. as an interaction between the individual characteristics or variables that are specific to the common history of both collaboration partners. Variables concerning individual characteristics (I.) comprise the innovativeness as measured by patent counts and the general cooperation activity as measured by the number of shared patents in prior years and the year of observation. Furthermore we control for the composition of the cooperation, that is to say whether the focal actors exhibit the same organizational status (interfirm collaboration) or not. As cooperation related variables, we include the number of partners involved in the cooperation, the cooperation intensity within one year, the relative knowledge endowment (overlap, difference in breadth of portfolio, potential benefit) and the shared common cooperation experience as a proxy for social proximity. The variable experience allows us to distinguish the sources of zeros in dependent variable. If the experience variable takes on the value zero, then the focal collaboration has never been existent. If the dependent variable is zero und the experience variable takes on a value larger than zero, then the tie has been dissolved. Moreover, Guliani (2007) argues, due to reciprocal incentives, it is more likely that central actors connect to central actors since the potential for knowledge spillovers is higher on both sides. Therefore we use a relative measure of centrality of actors as measured by the absolute difference of the degree centrality between two partners. Moreover, we include the number of indirect links the partners had before to control for transitivity.

Estimation Strategy

In detail, we estimate the following model:

$$\begin{aligned} COOP_{i,j,t} = {} & \beta_0 + \beta_1 CCP1_{i\times j,t} + \beta_2 CCP5_{i\times j,t} + \beta_3 CSP1_{i\times j,t} + \beta_4 CSP5_{i\times j,t} + \beta_5 D\_DC_{i,j,t} \\ & + \beta_6 COOP_{i,j,t-n} + \beta_7 D\_KBBreadth_{i,j,t} + \beta_8 STATUS_{i,j,t} + \beta_9 OVERLAP_{i,j,t-1} \\ & + \beta_{10} KT_{i,j,t-n} + \varepsilon_{i,j,t} \end{aligned}$$

In this case, one runs all i, j combinations with at least one of them being 1, the rest 0. In case of $CCP1_{i\times j,t}$,$CCP5_{i\times j,t}$ (single patents), $CSP1_{i\times j,t}$,$CSP5_{i\times j,t}$(cooperative patents) and $D\_DC_{i,j,t}$ (degree centrality), $D\_KBBreadth_{i,j,t}$ (breadth of knowledge base), the explanatory variables address always a comparison (difference - D.) or combination ($\times$) of i and j. Previous cooperation between i and j is accounted for by $COOP_{i,j,t-n}$ and preceding knowledge transfer is represented by $KT_{i,j,t-n}$.

Table 1: Explanatory variables

Variable name	Description	Type
I. Individual characteristics		
a. Same status	Are the partners of same type? (firms, universities, etc.)	Binary (1=yes, 0=no)
b. Cooperation activity		
i. Interaction Cooperation activity in focal year (number of co-patents)	Product of number of co-patents of both partners in current year	Count
ii. Interaction Cooperation activity in 5 previous years (number of co-patents)	Product of number of co-patents of both partners in previous 5 years	Count
c. Innovativeness		
i. Interaction patenting activity in year of observation (number of single patents)	Product of number of single patents of both partners in current year	Count
ii. Interaction Patenting activity in 5 previous years (number of single patents)	Product of number of single-patents of both partners in previous 5 years	Count
II. Cooperation related variables		
a. Team size	Number of partners in collaboration	Count
b. Cooperation intensity in year of observation	How often did focal partners collaborate within one year?	Count / Binary (1=yes, 0 =no)
c. New/Repeated cooperation		Categorical (n= new, r= repeated, non= no cooperation)
d. Knowledge Portfolio		
i. Technological proximity (Overlap)	Number of technology classes shared by both actors	Count
ii. Knowledge Transfer	Gain of a new IPC class?	Binary (1=yes, 0=no)
iii. Breadth of Knowledge Bases	Number of IPC in Knowledge Portfolio	Count
iv. Potential Benefit	Difference between breadth of knowledge base and overlap	Count
e. Social proximity (common experience)		Count
i. previous collaboration with same partner within 5 prior years (short term)	How often did partners collaborate in previous 5 years?	Count
ii. previous collaboration with same partner more than 5 years prior to cooperation (long term)	How often did partners collaborate before?	Count
f. Geographical proximity	Geographical distance between locations of actors	Count
III. Network structure		
a. Indirect connections in prior period	Number of indirect linkages	Count
b. Reciprocal centrality (popularity)	Difference in degree centrality of both actors	Count

4. Preliminary Results

4.1. First descriptives

Actor types

We focus on the linkages established by firms that at least cooperated twice in the focal period. We identified 91 firms that correspond to this definition. As potential partners we consider 2,369 actors (firms, universities, research institutions, persons and other institutions) that applied for at least one Biotechnology patent between 1978 and 2010.

As we want to explain the cooperative behavior of firms explained by dynamics in proximity among them, we give a first overview over general cooperation patterns among the firms in our sample. In this context five different types of firms can be identified. Table 2 gives an overview over the definition of the different actor types.

First, there exist applicants that only filed for single patents, i.e. they have a dichotomized degree of zero (calculated over the whole period from 1978 to 2010).

Our sample contains 894 of these individualists. Furthermore we identified 91 cooperative firms, which can be distinguished by their intensity of cooperation and their persistency in choosing the cooperation partners. Our sample includes 27 pure hop-on-hop-off-cooperators, which always cooperate with new partners and never repeat a cooperation.

Table 2: Identified actor types

Actor type	Label	Definition
1	Hop-on-hop-off-cooperators	Dichotomized degree>=1, difference between dichotomized degree and valued degree = 0
2	Persistent cooperators	Dichotomized degree =1, difference between dichotomized degree and valued degree >0
3	Mixed type	Dichotomized degree>1,difference between dichotomized degree and valued degree>0
4	One shot cooperators	Dichotomized degree=1, Valued degree =1
5	Individualists	Dichotomized degree =0

On the opposite we identify 24 persistent cooperators, which once chosen a partner, stick to it during the whole period. Furthermore we find 40 mixed types, which cooperate with new and also already known partners. Finally we identified 106 one-shot cooperators, which only cooperated once during the whole period. Figure 2 gives an overview over the frequency of firms by category. These first findings provide evidence that firms pursuit different strategies of partner choice. In opposite to the results of previous studies (e.g. Gulati, 1995), we find that the majority of firms changes the partner immediately after they cooperated once (hop-on-hop-off-cooperators). As we want to observe sequences of cooperation, we excluded firms from the sample that cooperated only once (one-shot) or which never cooperated (individualists). Among the remaining firms, the majority is assigned to the mix type, followed by hop-on-hopp-off cooperators and persistent cooperators.

Figure 3 gives an overview over the number of different partners firms cooperated with during the whole period from 1978 to 2010. One can see that most firms cooperate in sum but also on average (Median equals 2) with two different partners, whereas only few actors cooperate with a larger number of different actors. In maximum the number of different partners for one actor amounts 17. In other words, one firm cooperated with 17 different actors. This implies that, at least for the firms in our sample, the repeated collaboration with only one partner is not a dominant strategy.

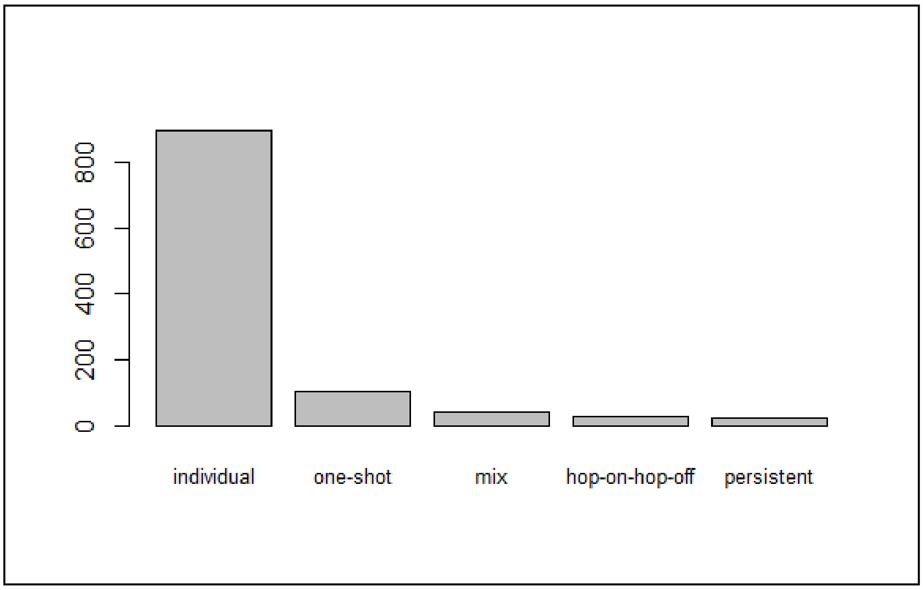

Figure 2: Patterns of Cooperative Behavior of focal firms

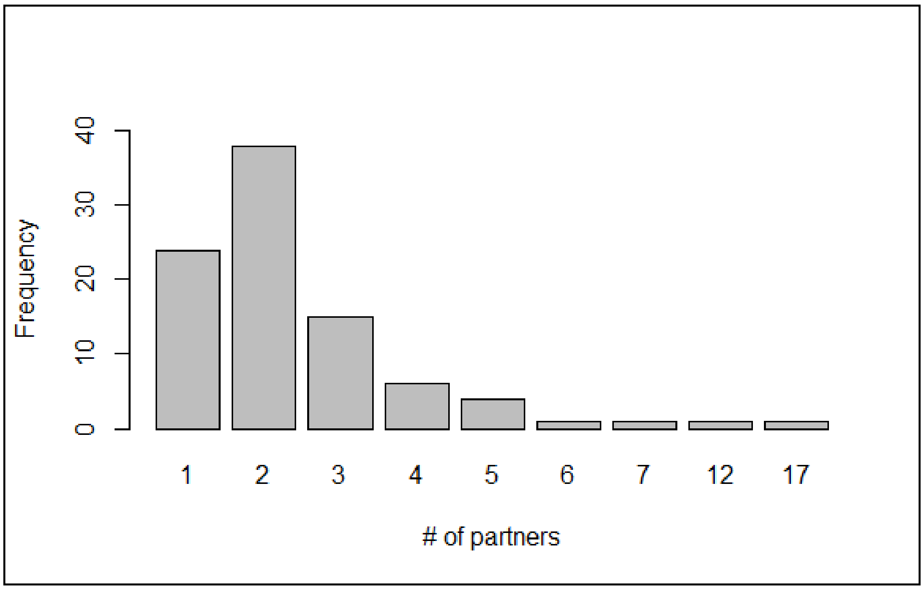

Figure 3: Distribution of collaboration partners

Table 3: Main descriptives

Main descriptives							
# Patenting actors	2,369						
# Cooperating actors	918						
# Cooperating firms	197						
# Firms with at least two links (focal firms)	91						
	Firm	University	RI	Person	Other		
# Patenting actors by type	1089	69	111	1087	13		
# Cooperative Actors by type	197	47	47	625	2		
	Hop-on-Hop-off	Mix-type	One-shot	Persistent			
# Actors by cooperative behavior	314	152	399	53			
# Firms by cooperative behavior	27	40	106	24			
	Min	Max	Median				
# Collaboration partners of focal firms	1	17	2				
# Possible links	321.683						
# Realized links	293						
# Repeated links	60						
# Non-recurring link	138						
Number of repetitions	0	1	2	3	4	5	6
Distribution of linkages across times of repetition (without duplicates)	138	41	11	3	3	1	1

Persistency of links

Table 3 provides an overview over the first descriptive results. We find that of 293 realized links, 138 (70 %) were realized just once (non-recurring), whereas 60 links were repeated at least once. The majority of recurred links was repeated once (41) and the maximum of repetition of links equal 6. At a first glance, these findings suggest, in contrast to prior findings, that firms are rather prone to change partners regularly than to repeat collaboration with the same partner.

Knowledge Transfer and repetition of links

Table 4 shows the distribution of realized (repeated) cooperations when knowledge was transferred in prior collaborations or not. The percentages represent the shares of the rows. In general, more than half of the links (51 %) out of 193 dyads, that were active in previous periods, were dissolved afterwards. Furthermore, in 62 % of the cases (193 dyads), knowledge has been transferred to the other partner previously. In 47 % (of 120 cases) the cooperation broke up after knowledge has been exchanged. In contrast, in 42 % of the cases, linkages have been repeated even though knowledge was not transferred in the past.

Table 4: Knowledge Transfer and repetition of links

Cooperation (yes/no)	Kowledge Transfer (yes/no)		Sum
	0	1	
0	42	56	98
	58 %	47 %	51 %
1	31	64	95
	42 %	53 %	49 %
Sum	73	120	193
	38 %	62 %	100 %

4.2. Estimation results

Table A-1 in the Appendix shows the correlations between the explanatory and the dependent variable. We find that both, the relative innovativeness and the relative cooperation experience are slightly positive and significant correlated with cooperation. Moreover partners tend to choose partners that are similarly popular (as measured by degree centrality). In contrast, firms seem to prefer organizational diversity, as they are prone to choose partners that have a different organizational form. Furthermore, firms decide for partners, that exhibit a certain similarity in knowledge endowment (overlap) and which they know already from prior collaboration (experience). Also a preceding knowledge exchange seems to foster cooperation propensity between certain partners. To gain a more detailed understanding of the forces that determine the partner choice, we ran a random effects logistic regression on our panel data.

Table 5 provides the outcome of our preliminary estimation of the 3 base models, including our main variable of interest (KT_before) and the important control variables. While we find no significant effects for the relative innovativeness of partners in the last five years before the cooperation, the difference in the breadth and the overlap of knowledge bases, we found evidence for the importance of the relative innovativeness of partners in the whole past, a common history and of our main variable of interest – knowledge transfer in the cooperation before the recent one - for cooperative ties. In more detail, we find a strong positive relation (2.05) between the shared cooperation experience and the (repeated) cooperation. This implies, the more often they collaborated in the past, the more likely becomes a new link between them. This finding seems to contradict our assumption on the change of cooperation partners and support findings from prior literature, that social proximity is decisive for the partner choice.

Table 5: Estimation results of logistic regression for panel data

Method	Random-effects logistic regression		
Depvar	koop_intens_binary		
Reportet coefficients	odds ratios		
	Model 1	Model 2	Model 3
Interact_shared_pat_pair	1.000027**	1.000019	
	(2.16)	(1.58)	
Interact_sum_shared_5years_pair	0.9997242		0.9997919
	(-1.44)		(-1.19)
Interact_single_pat_pair	1.0000000*	1.000000**	
	(1.78)	(2.14)	
Interact_sum_single_5years_pair	1.000019		1.000022
	(1.17)		(1.40)
Diff_central	0.4802365***	0. 4788226***	0. 481696***
	(-21.39)	(-23.52)	(-21.41)
experience	2.051459***	2.018065***	2.031069***
	(5.32)	(5.21)	(5.28)
Diff_breadth	1.00013	1.00016	1.000084
	(0.78)	(1.10)	(0.51)
Status_Same	0.5141001***	0.5279835***	0. 512007***
	(-4.32)	(-4.25)	(-4.35)
overlap	0.9992847	0. 9994616	1.00078
	(-0.45)	(-0.35)	(0.63)
Kt_before	61.19451***	59.29346***	58.6444***
	(12.27)	(12.22)	(12.20)
No. of Obs.	309407	309407	309407
No. of Groups	140772	140772	140772
lnsig2u	0.0128768	0.0134299	0.0133599
sigma_u	1.006459	1.006738	1.006702
rho	0 . 2354173	0.2355168	0.2355042
Wald chi2(9)	1197.11	1198.48	1196.69
Prob > chi2	0.0000	0.0000	0.0000

Robust z statistics in parentheses

*significant at 10%, **significant at 5%, ***significant at 1%

Also, we find a significant effect of the equality in status (0.51) and evidence for a negative impact of the equality in popularity (0.48) of the partners on collaboration. In other words, firms are prone to rather collaborate with other firms than with other types of organizations. Quite surprisingly, we find that an increase in the difference in the degree centrality, as a proxy for mutual popularity, increases the chance of cooperation. In other words, firms rather tend to collaborate with partners that exhibit a different amount of collaborative linkages or enjoy a different degree of popularity.

Regarding our research question, we find that successful knowledge transfer in the prevalent cooperation enlarges the probability to cooperate again in the following period very extremely – about 60 times.

5. Conclusion and further research

The aim of the current paper is to explain different cooperative behavior by underlying mechanisms of knowledge transfer. In the literature there is still ambiguity on whether networks are rather static (i.e. actors cooperate always with the same partners) or whether network structures are volatile (i.e. actors change partners regularly). Our findings suggest that firms are rather prone to switch their cooperation partner than to repeat the collaboration with a certain partner. Moreover, we find that firms prefer to cooperate with partners that are rather dissimilar in popularity (degree centrality) but similar in organizational nature (status). In contrast, the breadth and the overlap of the knowledge portfolio seem to have no effect on the (repeated) link formation. Furthermore, knowledge transfer seems to lead to follow up cooperation which may at this stage not fit to the theory of decreasing potentials for innovation with an increasing overlap of the knowledge bases (Nooteboom 2008?).

At this stage, our methodology faces some limitations. First, the observed linkages heavily depend on the patenting practices among actors (for instance cross patenting or cases in which central institution may administrate the patenting process and will therefore be the only applicant). This problem can be addressed by involving multi-applicant inventorship as a proxy for inter-institutional relationships (Ter Wal and Boschma, 2009). This means, that one inventor occurs on the patents of different applicants. In most of the cases, these incidences rather stem from strategic patenting than from inventor mobility (Ter Wal and Boschma, 2009). This allows us to obtain a more comprehensive picture of cooperative linkages between applicants. Moreover, matching patent data with further information on cooperations that are not restricted to outcomes (for instance the PROFI data base, which provides information on publicly funded cooperations in Germany5) will also help to reduce the shortcomings.

Related to the first step of analyzing the formation of pairwise research alliances, the next step is to broaden the perspective and to expand our analysis to the overall network of linkages. The change in technological proximity may have two effects on the overall network structure: On the one hand, the successful knowledge transfer will lead to a cut off of the linkage with current cooperation partner. On the other hand, actors will connect to the

[5] Even though this database imposes the restriction of containing only subsidized collaboration.

neighbors of their current partner, since the technological distance to the neighbors decreased and therefore they got more similar through the knowledge transfer. This idea is to a certain degree related to the idea of closure (Balland et al., 2012) which leads to a increased propensity to cluster. Also broadened knowledge bases of actors will influence their network position as actors with stronger knowledge bases get more prominent respectively central due to the larger pool of problem solutions they offer (Giuliani, 2007).

In a further analysis we therefore aim to incorporate the variable of knowledge transfer into a broader statistical framework to explain the evolution of the overall network. Newly developed statistical models, especially stochastic actor-oriented models, allow for examining the relationship between individual partner choice and network dynamics (Snijders et al. 2010, Ripley et al., 2011, Balland et al., 2012)

Appendix

Table A-1: Correlation between explanatory variables and dependent variables

	koop_intens_binary	Interact_shared_pat_pair	Interact_sum_shared_5years_pair	Interact_single_pat_pair	Interact_sum_single_5years_pair	Diff_central	experience	Diff_breadth	Status_Same	overlap	kt_before
koop_intens_binary	1,0000	-	-	-	-	-	-	-	-	-	-
Interact_shared_pat_pair	0,0348*	1,0000	-	-	-	-	-	-	-	-	-
Interact_sum_shared_5years_pair	0,0075*	0,1320*	1,0000	-	-	-	-	-	-	-	-
Interact_single_pat_pair	0,0121*	0,1814*	0,0387*	1,0000	-	-	-	-	-	-	-
Interact_sum_single_5years_pair	0,0103*	0,0720*	0,1918*	0,1760*	1,0000	-	-	-	-	-	-
Diff_central	-0,0569*	-0,0202*	0,0682*	0,0119*	0,2315*	1,0000	-	-	-	-	-
experience	0,2479*	0,0440*	0,0220*	0,0077*	0,0106*	-0,0294*	1,0000	-	-	-	-
Diff_breadth	-0,0024	-0,0150*	0,3197*	0,0024	0,7175*	0,1663*	0,0024	1,0000	-	-	-
Status_Same	-0,0123*	0,0191*	0,0078*	0,0355*	0,0260*	0,0159*	-0,0058*	-0,0587*	1,0000	-	-
overlap	0,0299*	0,2788*	0,1479*	0,5228*	0,2677*	0,0007	0,0573*	0,0842*	0,1010*	1,0000	-
kt_before	0,2593*	0,0540*	0,0271*	0,0119*	0,0186*	-0,0307*	0,6621*	0,0032	-0,0065*	0,0770*	1,0000

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