Configurations of inter-organizational knowledge links: Does spatial embeddedness still matter?

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Abstract

The actor composition of interorganizational ego-networks is largely ignored in research on Territorial Innovation Models. To fill this gap, we explore with which sets of external actors (i.e. configurations) firms maintain interorganizational knowledge links. Subsequently, we analyze the differences in innovative performance between firms engaged in different configurations also taking into account taking their geographical dimensions. Four configurations emerged all of which have positive effects on a firm's innovative performance in comparison to the 'go-at-it-alone' strategy. After controlling for actor composition and tie depth, however, their geographical composition is found to be unrelated to the innovative performance of firms.

JEL Codes: D83, L14, L25, O30

Keywords: Innovation, Configurations, Collaboration, Geographical proximity, Alliance portfolio, Portfolio diversity.

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Introduction

There is a large body of literature arguing that the characteristics of a firm's regional environment explain why some firms are more innovative than others (for an overview see MOULAERT and SEKIA, 2003). Many different concepts, such as clusters, innovative milieus, (regional) systems of innovation, industrial districts, and learning regions, all grouped under the label "Territorial Innovation Models" (TIMs), have been introduced and studied to substantiate this claim both theoretically and empirically. Despite their differences, these concepts have in common that they strongly emphasize the importance of localized interorganizational links for the innovativeness of firms (GORDON and MCCANN, 2000).

In the TIM-literature, however, characteristics of these webs of interorganizational links, like external actor diversity and tie depth, are largely ignored (SACCHETTI, 2009). First and foremost, most studies on (regional) interorganizational links tend to either neglect the type of actor with whom a link is maintained or focus on dyadic relationships between a focal actor and, for example, a single supplier or university, or. This implies that often it is not taken into account that focal actors can be embedded in ego-networks[1], which consist of sets of links with different actors possessing different knowledge sources and different relational characteristics. However, interorganizational network research has shown that the structural and relational characteristics of these links and networks impact on the innovative outcomes of firms (POWELL et al., 1996). Second, many of the empirical studies in this field are not built upon micro-level (i.e. firm level) data but study the clustering of innovative activities at the meso (i.e. the regional) level (BEUGELSDIJK, 2007). As a result, (localized) interorganizational links are often not empirically observed (LEJPRAS and STEPHAN, 2008), but are assumed to exist when firms co-locate (DICKEN and MALMBERG, 2001). However, existing research has shown that this is not necessarily the case (SOHN, 2004) and that the patterns of interaction can widely differ between regions (CANTNER et al., 2010). Third, many of the empirical TIM studies use case studies of (successful) localities and clusters as their research design (STEINER and PLODER, 2008) and therefore focus on interorganizational links *within* one (or a few) regions (SACCHETTI, 2009). This is striking as an emerging body of work conceptually argues (BATHELT et al., 2004; BOSCHMA, 2005) and empirically shows (GIULIANI, 2005; GRAF, 2011; IAMMARINO et al., 2008; MORRISON, 2008; KNOBEN, 2009) that especially ties with organizations outside the home region are sources of new knowledge due to their 'weak tie' or 'global pipeline' nature. Giuliani and Bell (2005), for example, found that some high performing firms are only weakly connected to firms within their cluster but maintain strong links to extra-cluster organizations, thereby acting as a gatekeeper.

Based on the above it can be concluded that the empirical research regarding TIMs would benefit from more micro-level research that *simultaneously* takes the diversity in the types and depth of IOLs as well as their level of localization into account. Therefore, we put forward a framework that emphasizes both geographical variety as well as external actor diversity and tie depth in interorganizational knowledge links (the latter denoted as IOLs). IOLs are defined as 'the links between a firm and external organizations with knowledge exchange or acquisition for its innovative activities as their primary goal'. The main argument developed and tested in this study is that firms are engaged in configurations of IOLs with different types of actors, with different tie depths (defined as the intensity with which firms draw resources from a particular type of actor), with different geographical scopes, resulting in different (innovative) outcomes (GOERZEN and BEAMISH, 2005). Therefore, our research question is: "W*hich configurations of IOLs can be distinguished* *empirically, what role does the level of localization of actors play in these different configurations, and what are the differences in innovative performance of firms engaged in these different configurations*?"

Answering this research question contributes to the scarce micro-level TIM research in four ways by: 1) providing a micro view on actual interorganizational knowledge links instead of only assuming their existence; 2) taking into account that innovating firms are linked to sets of multiple actors and that these links vary on different dimensions (e.g. depth, geographical scale); 3) introducing a configurational approach in the field of regional studies in which a level between dyads and whole networks is analyzed; and in which relational (tie depth) and attribute (type of external actor) variables are combined in one approach; and 4) including both local and non-local IOLs instead of focusing on local IOLs only. This allows us to assess the relative importance of geographical proximity in IOLs compared to the importance of the type of actor with whom the relation is maintained and tie depth. In short, in this research we provide a more realistic and valid picture of (the effects of) one of the main concepts of the TIM-literature than provided by the existing empirical research.

To realize these contributions, we draw from different strands of literature. The reasoning on geographical variety is grounded in the regional and economic geography literature. More specifically, this study departs from one of the main assumptions in the Learning Region literature, namely that the localized interactive model of innovation is highly significant for regional development in general and innovation in particular (MORGAN, 1997; RUTTEN and BOEKEMA, 2007). The thinking on interorganizational ego-networks is mainly developed in organization studies in which often a structural account is applied. In this paper, a structural account (actor diversity) is combined with a relational account (tie depth). Lastly, we draw from an extended version of the resource-based view of the firm (LAVIE, 2006), in which it is argued that firms can derive competitive advantages from resources obtained through interorganizational links.

Empirically we explore which configurations of IOLs exist by applying a latent class cluster analysis to South African firm-level data. For this, we build IOL configurations consisting of direct knowledge links with different types of actors and with different tie depths in terms of the importance of the knowledge and information transferred. Subsequently, we analyze the differences in innovative performance between firms engaged in the different IOL configurations taking into account the variety in their geographical composition as well.

This paper is structured as follows. First, the theoretical relations between IOLs, innovation and geographical proximity will be discussed. Subsequently, the concept of configurations of IOLs will be briefly introduced, followed by a discussion of the data, measurements, and methodology. Next, the results will be presented and interpreted. Finally, the implications of this study will be addressed, limitations will be identified, and directions for future research will be explored.

The Geographical Distribution of Interorganizational Knowledge Links and Innovation

The importance of IOLs for a firm's innovative performance has become more and more profound over time (OWEN-SMITH and POWELL, 2004). The notion that no innovating firm is an island, but needs resources and knowledge resources possessed or controlled by external actors, like clients, suppliers, competitors, stakeholders, central and local public administration actors, and consultants, has been widely accepted. Through these external sources a firm gets access to additional or complementary resources and knowledge that are not available within its own organizational boundaries, which can lead to (innovative) advantages for the firm in question. The main argument behind this reasoning is a resource deficit perspective, in which innovating firms are forced to tap into external knowledge sources to produce innovations (LOVE and ROPER, 2001). In short, by pooling and sharing (complementary) resources, firms can collaboratively perform activities that neither of them could perform alone, and thereby overcoming resource-based constraints on performance (DYER, 1996).

In the literature on TIMs as well as in the IOL-literature, an important influence is attributed to spatial distance between collaborating organizations (BOSCHMA, 2005; KNOBEN and OERLEMANS, 2006). The importance of the localization of IOLs lies in the fact that localization is assumed to facilitate face-to-face interactions (both planned and serendipitous) and trust-building, which foster the exchange of tacit knowledge and resources (TORRE and RALLET, 2005). Tacit knowledge, in turn, is often argued to be one of the main drivers of the innovativeness of firms because only tacit knowledge, as opposed to codified knowledge, is thought to contain truly new and hard to imitate insights (HOWELLS, 2002). The larger the geographical distance between actors, the more difficult it is to transfer tacit knowledge and, therefore, the more difficult it is to transfer resources that are truly conducive to the innovativeness of a firm. Consequently, firms with more localized IOLs would experience higher levels of innovative performance.

However, this view on the effects of geographical proximity on innovation has been highly criticized over the last years. Some researchers question whether spatial proximity is a prerequisite for successful collaboration and knowledge exchange, and propose that other relational characteristics are more important (KNOBEN and OERLEMANS, 2006). In this regard, there is evidence that temporary geographical proximity (TORRE, 2008) and high levels of organizational (KNOBEN et al., 2008) or social proximity (BRESCHI and LISSONI, 2009) can negate the need for geographical proximity in IOLs for successful knowledge exchange. Moreover, some scholars have argued that maintaining predominantly local IOLs could lead to a lock-in situation (e.g. ‘group-think’ and knowledge redundancy) in which firms are less open to opportunities and resources outside of their own region (BOSCHMA, 2005; GIULIANI, 2005). Finally, some authors argue that there is no reason to assume that nearby firms will be the most suitable partners or that all required knowledge is available within the own region (ROSENKOPF and ALMEIDA, 2003; BATHELT et al. 2004). These lines of reasoning would lead to the conclusion that sets of IOLs with both local and non-local ties would lead to higher innovative outcomes as compared to geographically local ones, because a higher level of geographical variety prevents spatial lock-in and allows firms to select the most suitable partners accessing valuable knowledge, regardless of whether they are located inside or outside the region in which the firm is located.

It seems possible, however, to combine the insights put forward by the two lines of reasoning presented in the above. In order to do so, the type of innovation is a highly relevant dimension to take into account. Often the type of innovation is depicted on a scale ranging from incremental to radical, on which radical stands for paradigmatic technological change impacting on, and changing large parts of the economy. For two reasons, such an approach is not very applicable when doing firm-level research. First, the generation of truly radical innovations is extremely rare; therefore, using this definition would lead to the absence of observations at one end of the scale. Second, this definition takes an “objective” macro perspective in which external experts have to determine the type of innovation and its economic and social importance, which basically makes it not feasible when conducting large scale firm-level research. In most firm-level research, therefore, the type of innovation is based on whether the products and/or services are: 1) improved versions of products that the firm already produced; 2) products that are new to the firm; or 3) products that are new to the market.

For incremental types of innovation, maintaining predominantly local IOLs could be a worthwhile strategy, because such innovations do not cause severe internal knowledge deficits and less specialized and unique external knowledge is required. Therefore, there is a higher probability that actors in the local environment possess the required knowledge. It is less likely, however, that all knowledge required to generate more radical types of innovation will be available within the own region. More radical types of innovation cause more severe internal knowledge deficits and a need for more specialized, diverse or unique knowledge. In order to gain access to specialized knowledge required for such types of innovation, it can be argued to be most beneficial to maintain a geographically diverse set of IOLs (KNOBEN, 2009). In this perspective, there is some evidence that firms with combinations of local and non-local IOLs experience the highest levels of radical innovative performance (ARNDT and STERNBERG, 2000; GIULIANI and BELL, 2005; GRAF, 2011; STERNBERG and ARNDT, 2001;) because in this way they are able to develop relatively unique propositions in the market. Based on these insights, the following working hypotheses can be posed:

H1: The more geographically localized the set of direct knowledge links a firm maintains, the higher its incremental innovative performance.

H2: The higher the geographical variety of the set of direct knowledge links a firm maintains, the higher its radical innovative performance.

Configurations of Interorganizational Knowledge Links and Innovation

Innovating firms can maintain IOLs with different types of actors in order to gain access to resources that help to generate innovations. Links with lead users/buyers can provide important information for new products or services or on how to further improve them (VON

HIPPEL, 1988), whereas suppliers can be a source of knowledge and information for process innovations leading to product quality improvements and cost reduction. Research labs and universities often are sources of fundamental knowledge, as is shown for the biotechnology sector (ZUCKER et al., 1998). Competitors are knowledge sources for those firms that are in an imitation mode or use such links to monitor their markets (PARK and RUSSO, 1996), whereas consultants can offer important market information or advice on how to improve products, services and processes (TETHER and TAJAR, 2008).

Instead of asking the question what type of ties provide more or better access to such resources or whether having many ties is preferable over having fewer ties, a configurational approach focuses on the question which combinations of types of ties with different types of actors are utilized by firms. The notion of a configuration of IOLs requires, for the purpose of this paper, some elaboration.

A configuration denotes *"any multidimensional constellation of conceptually distinct characteristics that commonly occur together"* (MEYER et al., 1993). In the context of IOLs, configurations refer to, for example, patterns of combinations of relations or ties with different types of actors with different intensities (GEMUENDEN et al., 1996). Our configurational approach builds on the extensive case-study work by Uzzi (1996) but goes beyond the distinction between embedded ties and arm's length ties and focuses on tie depth and the types of actors with whom IOLs are maintained. In other words, the focus is on configurations of ego-networks in which structural (actor diversity) and relational characteristics (tie depth) are taken into account.

The core idea of the configurational approach in an interorganizational context is that different firms maintain different sets of IOLs, both in terms of the type of actors with whom they interact (actor diversity) as in terms of the depth of these links. As a result, different configurations of IOLs are expected to yield different outcomes in terms of the innovative performance of the focal firms (LAVIE, 2007).

In the literature, several theoretical arguments can be found that ground the relationship between actor diversity, tie depth, and innovation. First, if a focal actor relies on interorganizational links with actors of the same type, there are no mechanisms for iterative and diverse learning feedback with respect to an innovation (RUEF, 2002). In this argument actor diversity functions as a sounding board for the innovating focal actor. Second, having interorganizational links with a diverse set of actors implies access to a complementary and diverse set of assets (FAEMS et al., 2005). This diversity in external resources lowers the risk of information redundancy, so (really) new knowledge and information is acquired, which increase innovative performance (DUYSTERS and LOKSHIN, forthcoming). Moreover, diversity in their IOLs allows firms to exploit synergetic effects between different types of actors, effectively resulting in economies of scale and scope, resulting in higher levels of innovative performance (BAUM et al., 2000).

For successful innovation, however, just having links with a wide range of actors is not sufficient; it also requires drawing knowledge from these sources. In other words, a flow of knowledge and information to the focal actor has to occur as well. Given the fact that our concept of IOL or tie depth is defined as the intensity with which firms draw resources from different types of actors we expect firms that draw deeply from external sources to be more innovative. In short, intensively interacting with a more diverse set of actors might encourage the transfer of important and new knowledge and information, which, when productively combined with internally available knowledge resources, could lead to the creation and development of processes and products that would otherwise be difficult to mobilize and develop (GOERZEN and BEAMISH, 2005). Acquiring knowledge through these diverse and deep ties enables firms to develop new or improved products/services that have value-adding features for users.

Based on these arguments, one would expect that the more different types of IOLs a firm maintains (i.e. the more diverse its configuration of IOLs), and the deeper these IOLs the better its access to different types of knowledge, resulting in higher innovative outcomes (LAURSEN and SALTER, 2006). This line of reasoning leads to the following working hypothesis:

H3: The more an innovating firm is embedded in a diverse and deep set of direct interorganizational knowledge ties, the higher its innovative performance.

However, not all types of innovation are equally affected by the depth and diversity of a firm's IOL-configuration. Deep IOLs are often argued and found to be especially valuable for firms that develop more radical types of innovations (LAURSEN and SALTER, 2006; POWELL et al., 1996). For incremental types of innovation shallow ties that perform the aforementioned sounding board function might be sufficient. For more radical types of innovation deeper ties are likely to be required, because the transfer of the (tacit) knowledge required for radical innovations erases existing communication codes which raises the need for frequent and intense interactions (LAURSEN and SALTER, 2006; LUNDVALL, 1992).

Regarding the other dimension of IOL-configurations, highly diverse sets of IOLs can be argued to be most conducive to incremental types of innovation, because the very novel types of knowledge required for radical types of innovation are only possessed by a limited number of actors, such as universities or lead-users (LAURSEN and SALTER, 2006). Empirical research has provided us with several examples of this. Riggs and Von Hippel (1994) showed that a majority of innovations in the scientific instruments industry came from lead users, whereas innovations in the biotechnology sector are mainly triggered by university research (HALL and BAGCHI-SEN, 2007).

Based on the above, it is expected that in the case of radical innovation firm use a few resources intensively (lower diversity combined with higher tie depth). For more incremental innovation, it is expected that a more diverse set of external knowledge sources are important but less intensively used. Therefore, the following working hypothesis is posed:

H4: Higher radical innovative performance is reached by firms embedded in configurations of less diverse but deeper direct interorganizational knowledge links, whereas higher incremental innovative performance is reached by firms embedded in configurations of diverse but shallower direct interorganizational knowledge links.

Below, our hypotheses will be put to the test by identifying the existing configurations of IOLs, exploring to what extent these configurations are geographically localized, and by using both the configuration and its level of localization to explain the innovative performance of firms.

Data and Methodology

The theoretical ideas put forward in the above will be explored using data of the South African Innovation Survey 2001 (SAIS2001). The SAIS2001 questionnaire was based on the European Community Innovation Survey, but adapted to the South African context (OERLEMANS et al., 2006). The population of firms in the survey consisted of all South African firms in manufacturing, services, and wholesale with 10 or more employees that conducted economic activities in the period 1998-2000. This lower limit is used because non-response levels are often very high among very small firms. As a sampling frame the

Reedbase Kompass database (August 2000 version) was used. This database contains 16,931 South African firms with a known number of employees. In SAIS 2001 stratified sampling was used as the sampling technique. The population of South African firms was divided into three different size classes (strata). Taking the number of employees as an indicator of the size of a firm, the following three strata were distinguished: Stratum 1: firms with 11 to 20 employees; Stratum 2: 21-50 employees, and; Stratum 3: more than 50 employees.

The survey was mailed to, in total, 7,339 firms of which 8.4% returned the survey. This is a low figure, but not uncommon for organizational research, which often yields relatively low response rates (BARUCH, 1999). Nevertheless, the fact that a large group of firms did not respond raises the question whether or not the data might suffer from sample bias. Therefore, a telephone non-response analysis among 462 firms was conducted. Questions were asked about specific reasons not to respond and about some firm characteristics, like for example R&D activity. The response to the non-response survey was very high (90%). Amongst others, non-responding firms were asked whether they had technological innovations in the period 1998-2000 and with what frequency they conducted R&D. As the same information was gathered in the written questionnaire as well, a comparison of the response and the non-response group could be made. The results of this comparison can be found in Table 1. As can be derived from this table, the comparison between respondents and non-respondents revealed no statistically significant differences.

Insert Table 1 here

To further substantiate the representativeness of the data, population estimates of our survey have been compared with estimates produced by Statistics South Africa. All estimates based on the SAIS-database were very close to the population estimates. In particular, our population estimate of the yearly growth of employment in the period 2000-2003 is 1.2%. This is exactly the same figure as the estimate provided by Statistics South Africa. These results give us reason to believe that the external validity of our results is high. Based on the non-response analysis and the comparison of population estimates, the response group can be considered as representative of the total population of South African firms, which implies that the data is likely to be unbiased despite the relatively low response rate.

Ultimately, this database contains information on 617 firms. In this research, (the IOL configuration of) a subset of 400 firms will be analyzed. This subset has been created by selecting only firms that reported to conduct innovative activities (not necessarily successful). These firms were not necessarily engaged in IOLs. Only firms with innovative activities were selected because all the theoretical mechanisms discussed earlier use the need to acquire (control over) resources for innovative activities as a main driver of the formation of IOL-configurations. Firms that do not conduct any innovative activities are unlikely to be influenced by these mechanisms and are therefore excluded. The choice to include firms with innovative activities but without IOLs was made as previous research has shown that there is a group of innovators that "go it alone" (BAUM et al., 2000). This implies that there is an "empty" IOL configuration, which will serve as a reference group.

Measurements

To operationalize a firm's innovative performance, we used self-reported measures of innovativeness that were developed for the Community Innovation Survey (CIS). First, managers of firms were asked whether or not their firms had introduced new or improved products or services in the previous two years (1998-2000). A two year period was chosen to avoid a strong bias resulting from measuring accidental innovation. For firms that indicated to have done so, we determined their innovativeness by asking what percentage of the firm's turnover in 2000 was generated by these innovative products and services. The novelty of the innovations was determined by differentiating between three types of innovation sales, that is by turnover generated by products or services that were (1) improved versions of existing ones, were (2) new for the firm, or were (3) new to the market.

To construct IOL-configurations, firms were asked to indicate for seven different types of external actors whether they had any IOLs with that type of actor and what the importance of IOLs with this type of actor was for their innovative activities. The possible answers ranged from (0) of no importance, to (3) very important. On the basis of the responses to this question, the configuration of IOLs can be constructed in which relations with (groups of) buyers, suppliers, competitors, consultants, public research labs, universities, and innovation centers and sectoral institutes as well as the depth (shallow to deep) of these relations can be discerned. See Table 2 for descriptive statistics of these measures. Important to note is that this question refers to linkages maintained in the period 1998-2000, whereas the measures of innovative performance pertain to the year 2000. This lag has been introduced to capture the fact that it takes some time before the resources obtained through alliances find their way into innovative products and/or services. In this way, endogeneity problems in our analyses are reduced and reverse causality problems are dampened as well.

Insert Table 2 here

In order to measure the level of localization of the IOLs of a firm, firms were asked to indicate for each type of actor mentioned above where their most important partner was located. The possible response categories were: 1) in the same town/city; 2) in the same province; 3) in South Africa; or 4) outside the country. With these responses, two indicators were constructed which have been used in different model specifications as will be discussed below. First, the total number of localized IOL partner types has been calculated by computing the number of partner types located within the same province or town/city. Second, the number of localized IOL partner types has been divided by the total number of IOL partner types a firm maintains to calculate the percentage of a firm's IOL partner types that are localized.

Not all regions offer the same potential to form localized IOLs. In regions with a larger pool of organizations, the likelihood of finding a suitable intra-regional knowledge source is higher. In order to control for this effect, we included dummy variables that took the value '1' for firms located in one of the three main economic metropolitan areas of South Africa; Pretoria, Johannesburg, and Cape Town. In 2006, these urban areas made up about 48% of the national GDP.[2] Because of the high concentration of firms in these three regions, the possibilities to control for specific regional characteristics, such as the level of urbanization or specialization, are extremely limited. Therefore, we have opted for this fixed effects approach.

IOLs are not the only mechanism through which firms can obtain knowledge. Labor mobility and new firm formation are other knowledge spillover mechanisms that are often considered to be important in this regard (FELDMAN, 1999). To prevent a potential omitted variable bias, we included measures for both mechanisms in our analyses. For labor mobility, a self reported importance of new personnel (on a scale from 0 to 3) for a firm's innovative activities has been included. To control for new firm formation effects we included a dummy variable that took the value '1' for firms started in the period 1998-2000.

Furthermore, a firm's internal capacity to generate and process knowledge is also likely to impact on its innovative performance because acquired external knowledge has to be processed and combined with internally developed knowledge. Therefore, the R&D intensity of a firm is used as a control by including a measure that captures the expenditures on R&D as a percentage of total turnover. This variable also is included since R&D is an important alternative source of new knowledge and a device to absorb externally acquired knowledge (COHEN and LEVINTHAL, 1990). Therefore, it is likely to influence both the propensity of a firm to form IOLs as well as its innovative performance.

Finally, several other control variables were included in the analyses. First, we control for firm size by including the natural logarithm of the amount of full-time employees that a firm has in the analysis. This variable is included since on average larger firms maintain more IOLs and firm size is likely to influence the innovativeness of a firm as well. Second, we control for sectoral differences by including dummy-variables for service and wholesale firms (manufacturing is the reference category). Sectoral differences need to be controlled for since the average level of innovativeness differs between sectors due to, among others, differences in product life-cycle length. We also estimated all models using two other industry classifications, namely Pavitt dummies and 2-digit NACE dummies. Given the fact that both yielded identical results for the relations under scrutiny, we opted to report only the most parsimonious model. Third, we include dummy variables for multi-site firms (as opposed to single-site firms) and for South-African owned (versus foreign owned) firms.

In Table 3 and 4, descriptive statistics and collinearity diagnostics for all variables discussed in this section can be found. These tables show that, based on both bivariate correlations and variance inflation factors (VIFs), that there are no problems of multicollinearity in the data. Problems with heteroskedasticity, however, were encountered in the data when performing the analyses. Therefore, we utilized a Huber/White robust specification of the standard errors in all analyses.

Insert Table 3 here

Insert Table 4 here

Statistical techniques applied

Two different statistical techniques have been used. First, a latent class cluster analysis has been performed on the IOL-variables to construct the IOL-configurations of focal innovators. We explicitly choose not to incorporate the level of localization of the IOLs in this analysis because doing so would imply that certain configurations have an inherent geographical composition. It seems more likely that different firms can maintain the same IOL-configuration but with different geographical compositions (ISAKSEN and ONSAGER, 2010). Our approach leaves this options open.

Latent class analysis is a statistical method for finding subtypes of related cases (latent classes) from multivariate numeric or categorical data on the basis of a maximum likelihood (ML) estimation (MAGIDSON and VERMUNT, 2004). This method provides a more reliable estimation of configurations than standard cluster analysis because no assumptions about the distribution of the clustering variables are made. Whereas normal cluster analysis assumes normally distributed continuous variables, latent class cluster analysis can also deal with nominal and ordinal variables. Moreover, standard cluster analysis does not provide an objective measure to determine the number of clusters that fit the data best. In latent class cluster analysis, a Maximum Likelihood-algorithm classifies cases into clusters based upon membership probabilities estimated from a parametric model (MAGIDSON and VERMUNT, 2004). Therefore, latent class cluster analysis is highly suitable for the construction of taxonomies of multidimensional concepts, such as configurations of IOLs.

In the second part of the analysis, firm membership of a particular configuration of IOLs as well as the level of localization of the IOLs of that firm have been used in regression analyses which try to explain the innovative performance of the firm. For all three measures of innovative performance, by definition the score lies between 0 and 100. The most appropriate method to analyze such left and right censored data is a Tobit analysis (GREENE, 2000). Moreover, the data for the measures of innovative performance is also highly skewed to the left. As a result, it is very likely that the assumption of a normal distribution of the residuals that is made in a Tobit analysis is violated. In order to deal with this problem we have log-transformed the dependent variable (PAPALIA and DI IORIO, 2001).

To explicitly show the impact of incorporating actor diversity and tie depth, first models are estimated with geographical variety in IOLs but without actor diversity. Subsequently, the IOL-configurations are added to show how it changes the results. Before turning to the results of these regressions, however, the outcomes of the latent class cluster analysis will be discussed.

Results of the Latent Class Cluster Analysis

The results of the latent class cluster analysis reveal that a solution with five clusters fits the data best, as this solution yields the lowest BIC. The clusters incorporate 28% (117), 22% (92), 12% (51), 4% (16), and 33% (137) of all firms respectively. In order to gain insight into the configurations of IOLs represented by these five clusters, a graph has been constructed with the tie importance of IOLs on the vertical axis and the type of actor on the horizontal axis. Subsequently, all five configurations are depicted in this framework (see Figure 1).

Insert Figure 1 here

The first configuration incorporates firms that have knowledge links with moderate levels of tie depth with buyers, suppliers, and competitors, and virtually no links with other actors (relatively low actor diversity). Since this configuration represents firms that are only engaged in IOLs (vertically or horizontally) in their own value chain, this configuration is labeled as the "shallow production chain networkers". The second configuration consists of firms that have links with almost all types of actors (high actor diversity) with moderate levels of tie depth. This configuration can therefore be categorized as the "diverse and shallow networkers". The third configuration consists of firms that only maintain shallow ties with consultants and competitors (low actor diversity). This configuration is labeled as the "shallow market followers". The fourth configuration is made up of firms that have deep IOLs with all types of actors. Even though the depth of the IOLs differs somewhat between different types of actors, the links in this configuration are significantly deeper than in any of the other configurations. Therefore, this configuration can be labeled as the "diverse and deep networkers". Finally, the fifth configuration consists of firms that are not engaged in any IOLs. This configuration contains firms that "go it alone" and are, therefore, labeled as the "unembedded innovators".

Insert Table 5 here

Table 5 depicts descriptive statistics for each of the configurations. These reveal that there is a pronounced difference in innovative performance between the "unembedded innovators" and each of the other configurations. The differences between the other IOL-configurations are, however, less pronounced and are dwarfed by their standard deviations. Regarding the level of localization, the “shallow production chain networkers” and the “diverse and shallow networkers” maintain on average more localized IOLs. Again, however, the difference is dwarfed by the large variation in localization within each configuration. When looking at the types of firms that maintain the different IOL-configurations no clear pattern with respect to size or sector emerges. What can be said is that “diverse and deep networkers” and the “diverse and shallow networkers” are on average slightly larger as compared to firms with other IOL-configurations. “Shallow market followers” are often foreign-owned, whereas “diverse and deep networkers” are more often domestic firms. Finally, “shallow production chain networkers” are often located outside the main South African urban areas and also exhibit relatively high levels of internal R&D. Despite these patterns, no IOL-configuration is dominated by a single type of firm in terms of sector, size, or (foreign) ownership. Moreover, all these differences are univariate. In the subsequent sections, the relation between the different configurations and innovative performance will be assessed more systematically.

IOL configurations and innovative performance

To get a grasp of the impact of explicitly modeling IOL-configurations of actor diversity and tie depth, we first estimated several models without these configurations but with variables indicating levels of (localized) IOLs of a firm. As described earlier, three dependent variables that reflect a firm's level of innovative performance at three different levels of newness are used. For each of these three dependent variables, two different model specifications are estimated. The first specification only includes the number of localized IOL partner types of a firm. This specification is highly similar to studies that focus on a single spatial unit and only take intra-regional IOLs into account. The second specification includes both the number of IOL partner types a firm maintains as well as the percentage of these IOL partner types that is localized. This specification allows the idea that not all IOLs are necessarily localized and thereby utilizes a more elaborate conceptualization of a firm's level of spatial embeddedness, but still not taking IOL configurations into account. The results of these estimations are reported in Table 6.

Insert Table 6 here

The results reported in Table 6 show that the level of localization of IOL partner types matters. Specification one yields positive and significant results for the number of localized IOL partner types except in the case of the generation of products that are new to the firm, whereas specification two yields positive and highly significant coefficients for the percentage of localized IOL partner types that a firm maintains for all types of innovative performance. These findings are in line with those of earlier studies with similar designs (ARNDT and STERNBERG, 2000; LEJPRAS and STEPHAN, 2008; STERNBERG and ARNDT, 2001). Also similar to earlier studies, specification two provides a much better model fit as compared to specification one, indicating that it is important to take both localized and non-localized IOL partner types into account.

After showing that the findings of earlier TIM studies can be “replicated”, we add the IOL-configurations to the models. The level of localization of a firm's IOL-configuration (linear and squared) has been included to address the geographical composition of a firm's IOL-configuration. The results of the analyses are reported in Table 7. All models are highly statistically significant and the percentages of variance[3] explained lie between 19% and 41%, which is quite high for cross-sectional, micro-level research.

Insert Table 6 here

The results clearly show that the IOL configuration in which a firm is involved is heavily related to its innovative performance. For all types of innovative performance it holds that firms that are involved in IOLs are better of compared to firms that "go it alone". However, the magnitude of the relation with innovative performance differs considerably between the IOL-configurations. With regard to the generation of sales by improved products (incremental innovations), the “shallow production-chain networkers” and the “shallow and diverse networkers” configurations have a significantly larger relation than the other two configurations. The more radical the types of innovative performance become, the smaller the differences between the configurations.

Interestingly, even though its impact is positive on all types of innovative performance, being a “diverse and deep networker” is relatively weakly related to a firm's innovative performance. Apparently, this configuration with relatively high levels of actor diversity and tie depth does not yield any benefits that cannot be obtained through shallow networking or simply using the knowledge links to buyers, suppliers and competitors. A possible explanation for this finding lies in the fact that the relation between innovativeness and deep ties is moderated by the density of relations between the focal firm’s partners (ROWLEY et al., 2000). The underlying argument is that strong ties and ego-network density are substitutes because both lead to higher trust levels and the establishment of behavioral norms (COLEMAN, 1988). As a result, the impact on performance is highest when an ego-network is based on deep ties or on density, but not on both. As our data does not capture the density of ties between the focal firm’s partners, this unobserved moderation effect might explain the relatively modest impact of this particular configuration on a firm’s innovative performance.

There is no indication that more diverse types of IOL configurations have a positive impact on a firm's innovative performance as compared to less diverse configurations. Even though the two configurations with relatively high levels of actor diversity have a positive relation with a firm's innovative outcomes, the less diverse configurations, and the “shallow production-chain networker” in particular, yield similar or even higher coefficients. So even though being involved in configurations of knowledge links is clearly positively related to a firm's innovative performance, working hypothesis 3 is rejected.

The relation with the different IOL configurations becomes weaker as the type of innovations becomes more radical, whereas an alternative source of new knowledge, internal R&D, becomes more important. So conducting your own research remains vital in order to generate products that are new to the market (STERNBERG and ARNDT, 2001). Moreover, there is no real indication in the results that less diverse IOL-configurations with relatively high levels of tie depth are more beneficial for more radical types of innovation. Therefore, working hypothesis 4 is rejected as well.

With regard to the role of geography in IOL configurations it is found that maintaining a local IOL-configuration does not influence a firm’s innovative performance beyond the effect resulting from being a member of that IOL configuration. The only exception is the “diverse and deep networker” and the generation of sales with products that are new to the market. For this particular case, maintaining predominantly local ties has a negative relation with innovative performance. This result stands in sharp contrast to what is generally advocated in the TIM literature, where it is argued that maintaining deep localized knowledge links is beneficial to (more radical) innovation. In line with theoretical ideas that criticize this view (BOSCHMA, 2005) and recent empirical evidence from the social network literature (MOLINA-MORALES and MARTÍNEZ-FERNÁNDEZ, 2009), our findings point in an opposite direction and show that high levels of spatial embeddedness have negative implications.

The variety in the localization of IOLs, reflected in the combination of the normal and squared effect of the localization variable, has no significant relation with a firm's innovative performance. These results indicate that there is no single geographical IOL-composition that goes together with superior innovative performance for the focal firm. Even for the most radical type of innovative outcome, which is often argued to require highly tacit knowledge and therefore face-to-face contacts and localized IOLs, maintaining local IOLs does not yield higher levels of innovative performance.

All in all, the impact of the geographical distribution of the IOL configuration of a firm is negligible or even negative compared to the effect of the configuration itself. Consequently, working hypothesis 1 and 2 are rejected after including the IOL-configuration of innovating firms. This lack of results regarding the spatial dimension of the IOL-configurations might seem puzzling, because several earlier studies with similar designs have found significant positive effects. In this regard, it is important to note that the IOL configurations differ in their level of localization. The "shallow production-chain networker" is, on average, the most localized configuration, followed by the "diverse and shallow networker". The "shallow market followers" and the "diverse and deep networker" are the least localized IOL configurations. This ordering seems logical because many, especially small, firms operate primarily on local markets, and therefore primarily have local buyers, suppliers, and competitors. The same does not necessarily hold for knowledge institutes such as universities en public research labs. Such organizations are often more geographically dispersed making it less likely that a firm can tap into them as a local knowledge source. In other words, the geographical distribution of their IOL-configuration represents the prevalence of potential partners at different geographical distances. As a result, the fact that we explicitly take the diversity of actors within an IOL configuration into account also captures part of the variety in their spatial distribution.

The differences between the results reported in Table 6 and Table 7 imply that it is highly important to take actor diversity in IOL-configurations into account. In short, our results show that, when controlling for combinations of actor diversity and tie depth, the differences in spatial distribution are no longer related to a firm's innovative performance. As such, it seems likely that the results of the earlier studies are biased due to unobserved actor diversity and the systematic relation of this diversity with the spatial distribution of actors. This applies equally to studies that focus on single (successful) spatial units and IOLs therein as to studies that analyze the impact of both local and non-local IOLs but do not control for the type of actors with whom these IOLs are maintained.

Discussion

This research set out to provide a classification of configurations of IOLs, their geographical composition, and explore the relation between these configurations and the innovative performance of firms. Our findings indicate that, when excluding IOL configurations based on actor diversity and tie depth, geographical proximity in IOLs matters. Having more local partner types is associated with higher levels of innovative performance. When incorporating the diversity of types of actors with whom IOLs are maintained and the tie depth of these links, the results change drastically. First, it is shown that IOL-configurations are highly related to a firm’s innovativeness. Therefore, a “going-at-it-alone” strategy is not very beneficial to firms striving to be innovative, which shows the empirical validity of the extended version of the resource-based view of the firm (LAVIE, 2006) for the study of innovation. Second, we show that is not geographical proximity as such, but rather diversity in the types of actors with whom a firm maintains direct IOLs and variation in tie depth that impact on its innovative performance. These configurations capture part of the geographical composition of a firm's IOLs, because regions offer different opportunity structures in terms of available partner types. We have empirically shown that after controlling for this effect, the level of geographical proximity of a firm's IOL configurations has a negligible or even negative relation with innovative performance.

These findings echo the results of earlier research into the importance of geographical proximity in other contexts, such as knowledge spillovers. Breschi and Lissoni (2009), for example, find that the importance of geographical proximity in patent citations is largely driven by the social relations between, and the mobility of, researchers. Both in their research as well as in our results, the importance of geography is driven by the fact that the relevant actors are not randomly distributed in geographical space. The selection of partners therefore leads to an endogenous geographical distribution which, if the underlying cause is not explicitly taken into account, leads to the erroneous conclusion that geographical distance itself matters for the outcome variable under scrutiny.

Our findings have strong implications for the theoretical lines of reasoning underlying Territorial Innovation Models (TIM). First, the sole focus of TIM-studies on spatially proximate IOLs leads to biased results. Some IOL configurations, notable the "innovation follower" and the "shallow production-chain networker" are on average more geographically concentrated than others. When only studying intra-regional IOLs, such configurations are likely to be over-sampled and their impact overestimated. Therefore, the TIM-literature should pay more attention to the role of inter-regional IOLs rather than focusing on intra-regional IOLs only (BATHELT et al., 2004).

Second, it is important to take into account the different types of actors that firms maintain relations with. The fact that firms are located within the same area does not necessarily imply that they interact. Given the fact that our results clearly show that the sets of IOLs in which a firm is embedded have a substantial influence on the innovative performance of the firm it seems logical to try to incorporate these notions in future TIM-studies.

In general, we argue that TIM-studies can be enhanced both in terms of internal validity as in terms of explanatory power by shifting the level of analysis from the region to the firm and its IOL-configuration. Doing so implies focusing less on the territorial part of the TIM-concept and more on the types of actors that are present in a territory and how (deep) these actors are linked to each other. In other words, the composition of actors in a region and the linkages between firms inside and outside that region deserves more attention in the TIM-literature at the expense of the focus on the region as such. Making this shift still allows for a study of regional differences, yet also makes it possible to take the diversity in IOLs of firms into account which this research has shown is of large importance for the innovative performance of firms.

Limitations and directions for future research

Besides the contributions of this research, several limitations apply. First, the operationalization of IOLs does not allow us to identify individual IOLs, but only the aggregated existence of IOLs with certain types of actors. Moreover, at this aggregated level, we only have information regarding the tie depth of IOLs with these actors, which is only one of the relevant dimensions of interorganizational relationships distinguished when studying innovation in the literature. This approach, which is adopted from the European Community Innovation Survey and has been used in earlier research by others as well (LAURSEN and SALTER, 2006), was applied because the data collection problems become exceedingly large when firms are asked about characteristics of more than one IOL. In order to be able to collect large scale data and, thereby, derive more externally valid results, we chose the research approach discussed in the above. Nevertheless, replication with more detailed ego-network data seems a fruitful next step in this kind of research. One could, for example, take other relational characteristics into account like organizational trust and reciprocity.

Second, the existence of nation specific aspects to the innovation process and institutions leads to the conclusion that there are limitations to the extent in which county-specific findings can be generalized to other contexts (LUNDVALL, 1992). In the specific case of South Africa, previous research (BLANKLEY and KAHN, 2005) showed that the South African system of innovation is in an imitation-mode. This state of affairs is described as South Africa being a technology colony: product and processes are improved using imported and imitated, most often foreign, technological knowledge, with large parts of the revenues flowing to companies outside South Africa. In this imitation mode, firms are less likely to collaborate with organizations that develop new knowledge such as universities and public research institutes. This tendency might be reflected in the data by the relatively low proportion of firms that reports links with universities or other research institutes. As a result, it is unclear whether the findings presented in this study will hold in highly developed and industrialized regions and economies. Nevertheless, the fact that we were able to "replicate" the findings of earlier Western research and are thereby explicitly able to show the effects of controlling for actor diversity in a firm's IOLs allows us to make a strong and robust argument in favor of controlling for actor diversity is this type of research.

Notes

1: In our study an ego-centric network is a network consisting of a focal organization and its partners (direct ties). It should be noted that, even though this is the most prevalent definition of an ego-centric network, the partners of the partners (indirect ties) are sometimes included in ego-centric network studies as well.

2: Source: Statistics South Africa.

3: We report the McKelvey & Zavoina's Pseudo R-square because this measure closely represents the R-square yielded by an OLS in terms of interpretation.

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References

ARNDT O. and STERNBERG R. (2000) Do Manufacturing Firms Profit from Intraregional Innovation Linkages? An Empirical Based Answer, *European Planning Studies* **8**, 465-85.

BARUCH Y. (1999) Response Rate in Academic Studies: A Comparative Analysis, *Human Relations* **52**, 421-38.

BATHELT H., MALMBERG A. and MASKELL P. (2004) Clusters and Knowledge: Local Buzz, Global Pipelines and the Process of Knowledge Creation, *Progress in Human Geography* **28**, 31-56.

BAUM J. A. C., CALABRESE T. and SILVERMAN B. S. (2000) Don't Go It Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology, *Strategic Management Journal* **21**, 267-94.

BEUGELSDIJK S. (2007) The Regional Environment and a Firm's Innovative Performance: A Plea for a Multilevel Interactionist Approach, *Economic Geography* **83**, 181-99.

BLANKLEY W. and KAHN M. (2005) The History of Research and Experimental Development Measurement in South Africa and Some Current Perspectives, *South African Journal of Science* **101**, 151-6.

BOSCHMA R. A. (2005) Proximity and Innovation: A Critical Assessment, *Regional Studies* **39**, 61-74.

BRESCHI S. and LISSONI F. (2009) Mobility of Skilled Workers and Co-Invention Networks: An Anatomy of Localized Knowledge Flows, *Journal of Economic Geography* **9**, 439-68.

CANTNER U., MEDER A., and TER WAL A.L.J. (2010) Innovator Networks and Regional Knowledge Base. *Technovation* **30**, 496-507.

COHEN W. M. and LEVINTHAL D. A. (1990) Absorptive Capacity: A New Perspective on Learning and Innovation, *Administrative Science Quarterly* **35**, 128-52.

COLEMAN J. S. (1988) Social Capital in the Creation of Human Capital, *American Journal of Sociology* **94**, 94-120.

DICKEN P. and MALMBERG A. (2001) Firms in Territories: A Relational Perspective, *Economic Geography* **77**, 345-63.

DUYSTERS G. and LOKSHIN B. (forthcoming) Determinants of Alliance Portfolio Complexity and Its Effect on Innovative Performance of Companies, *Journal of Product Innovation Management*.

DYER J. H. (1996) Specialized Supplier Networks as a Source of Competitive Advantage: Evidence from the Auto Industry, *Strategic Management Journal* **17**, 271-91.

FAEMS D., VAN LOOY B. and DEBACKERE K. (2005) Interorganizational Collaboration and Innovation: Toward a Portfolio Approach, *Journal of Product Innovation Management* **22**, 238-50.

FELDMAN M. P. (1999) The New Economics of Innovation Spillovers and Agglomeration: A Review of Empirical Studies, *Economics of Innovation and New Technology* **8**, 5-26.

GEMUENDEN H. G., RITTER T. and HEYDEBRECK P. (1996) Network Configuration and Innovation Success: An Empirical Analysis in German High-Tech Industries, *International Journal of Research in Marketing* **13**, 449-62.

GOERZEN A. and BEAMISH P. W. (2005) The Effect of Alliance Network Diversity on Multinational Enterprise Performance, *Strategic Management Journal* **26**, 333-54.

GORDON I. R. and MCCANN P. (2000) Industrial Clusters: Complexes, Agglomerations or Social Networks?, *Urban Studies* **37**, 513-32.

GRAF H. 2011. Gatekeepers in Regional Networks of Innovators. *Cambridge Journal of Economics* **35**, 173-198.

GREENE W. H. (2000) *Econometric Analysis* Prentice-Hall, Upper Saddle River.

GIULIANI E. and BELL M. (2005) The Micro-Determinants of Meso-Level Learning and Innovation: Evidence from a Chilean Wine Cluster. *Research Policy* **34**, 47-68.

GIULIANI E. (2005) Cluster Absorptive Capacity - Why Do Some Clusters Forge Ahead and Others Lag Behind?, *European Urban and Regional Studies* **12**, 269-88.

HALL L. A. and BAGCHI-SEN S. (2007) An Analysis of Firm-Level Innovation Strategies in the US Biotechnology Industry, *Technovation* **27**, 4-14.

HOWELLS J. R. L. (2002) Tacit Knowledge, Innovation and Economic Geography, *Urban Studies* **39**, 871-84.

IAMMARINO S., PADILLA-PEREZ R., and VON TUNZELMANN N. (2008) Technological Capabilities and Global-Local Interactions: The Electronics Industry in Two Mexican Regions. *World Development* **36**, 1980-2003.

ISAKSEN A. and ONSAGER K. Regions, Networks and Innovative Performance: The Case of Knowledge-Intensive Industries in Norway. *European Urban and Regional Studies* **17**, 227-243.

KNOBEN J. (2009) Localized Inter-Organizational Linkages, Agglomeration Effects, and the Innovative Performance of Firms, *Annals of Regional Science* **43**, 757-79.

KNOBEN J. and OERLEMANS L. A. G. (2006) Proximity and Inter-Organizational Collaboration: A Literature Review, *International Journal of Management Reviews* **8**, 71-89.

KNOBEN J., OERLEMANS L. A. G. and RUTTEN R. P. J. H. (2008) The Effects of Spatial Mobility on the Performance of Firms, *Economic Geography* **84**, 157-83.

LAURSEN K. and SALTER A. (2006) Open for Innovation: The Role of Openness in Explaining Innovative Performance among U.K. Manufacturing Firms, *Strategic Management Journal* **27**, 131-50.

LAVIE D. (2006) The Competitive Advantage of Interconnected Firms: An Extension of the Resource-Based View, *Academy of Management Review* **31**, 638-58.

LAVIE D. (2007) Alliance Portfolios and Firm Performance: A Study of Value Creation and Appropriation in the US Software Industry, *Strategic Management Journal* **28**, 1187-212.

LEJPRAS A. and STEPHAN A. (2008) Locational Conditions, Cooperation, and Innovativeness: Evidence from Research and Company Spin-Offs, *CESIS Electronic working paper series* **136**.

LOVE J. H. and ROPER S. (2001) Location and Network Effects on Innovation Success: Evidence for UK, German and Irish Manufacturing Plants, *Research Policy* **30**, 643-61.

LUNDVALL B.-A. (1992) *National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning*. Pinter Publishers, London.

MAGIDSON J. and VERMUNT J. K. (2004) Latent Class Models, in KAPLAN D. (Ed) *The Sage Handbook of Quantitative Methodology for the Social Sciences*, pp. 175-98. Sage Publications, Thousand Oakes.

MEYER A. D., TSUI A. S. and HININGS C. R. (1993) Configurational Approaches to Organizational Analysis, *Academy of Management Journal* **36**, 1175-95.

MOLINA-MORALES F. X. and MARTÍNEZ-FERNÁNDEZ M. T. (2009) Too Much Love in the Neighborhood Can Hurt: How an Excess of Intensity and Trust in Relationships May Produce Negative Effects on Firms, *Strategic Management Journal* **30**, 1013-23.

MORGAN K. (1997) The Learning Region: Institutions, Innovation and Regional Renewal, *Regional Studies* **31**, 491-503.

MORRISON A. (2008) Gatekeepers of Knowledge within Industrial Districts: Who They Are, How They Interact, *Regional Studies* **42**, 817-35.

MOULAERT F. and SEKIA F. (2003) Territorial Innovation Models: A Critical Review, *Regional Studies* **37**, 289-302.

OERLEMANS L. A. G., BUYS A. and PRETORIUS M. W. (2006) Research Design for the South African Innovation Survey 2001, in BLANKLEY W., SCERRI M., MOLOTJA N. and SALOOJEE I. (Eds) *Measuring Innovation in OECD and Non-OECD Countries*. Human Sciences Research Council Press, Cape Town.

OWEN-SMITH J. and POWELL W. W. (2004) Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community, *Organization Science* **15**, 5-21.

PAPALIA R. B. and DI IORIO F. (2001) Alternative Error Term Specification in the Log-Tobit Model, in BORRA S., ROCCI R., SCHADER M. and VICHI M. (Eds) *Advances in Classification and Data Analysis*, pp. 185-92. Springer-Verlag, Heidelberg.

PARK S. H. and RUSSO M. V. (1996) When Competition Eclipses Cooperation: An Event History Analysis of Joint Venture Failure, *Management Science* **42**, 875-89.

POWELL W. W., KOGUT K. and SMITH-DOERR L. (1996) Inter-Organizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology, *Administrative Science Quarterly* **41**, 116-45.

RIGGS W. and VON HIPPEL E. (1994) The Impact of Scientific and Commercial Value of the Sources of Scientific Instruments Innovation, *Research Policy* **23**, 459-69.

ROSENKOPF L. and ALMEIDA P. (2003) Overcoming Local Search through Alliances and Mobility, *Management Science* **49**, 751-66.

ROWLEY T., BEHRENS D. and KRACKHARDT D. (2000) Redundant Governance Structures: An Analysis of Structural and Relational Embeddedness in the Steel and Semiconductor Industries, *Strategic Management Journal* **21**, 369-86.

RUEF M. (2002) Strong Ties, Weak Ties and Islands: Structural and Cultural Predictors of Organizational Innovation, *Industrial and Corporate Change* **11**, 427-49.

RUTTEN R. P. J. H. and BOEKEMA F. W. M. (2007) A Future for the Learning Region, in RUTTEN R. P. J. H. and BOEKEMA F. W. M. (Eds) *The Learning Region: Foundations, State of the Art, Future*, pp. 275-92. Edward Elgar, Cheltenham.

SACCHETTI S. (2009) Why, Where and with Whom Do You Link? The Nature and Motivation of Linkages within and Outside an Italian Local System, *Regional Studies* **43**, 197-209.

SOHN J. (2004) Do Birds of a Feather Flock Together?: Economic Linkage and Geographic Proximity, *The Annals of Regional Science* **38**, 47-73.

STEINER M. and PLODER M. (2008) Structure and Strategy within Heterogeneity: Multiple Dimensions of Regional Networking, *Regional Studies* **42**, 793-815.

STERNBERG R. and ARNDT O. (2001) The Firm or the Region: What Determines the Innovation Behavior of European Firms?, *Economic Geography* **77**, 364-82.

TETHER B. S. and TAJAR A. (2008) Beyond Industry-University Links: Sourcing Knowledge for Innovation from Consultants, Private Research Organisations and the Public Science-Base, *Research Policy* **37**, 1079-95.

TORRE A. (2008) On the Role Played by Temporary Geographical Proximity in Knowledge Transmission, *Regional Studies* **42**, 869-89.

TORRE A. and RALLET A. (2005) Proximity and Localization, *Regional Studies* **39**, 47-59.

UZZI B. (1996) The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect, *American Sociological Review* **61**, 674-98.

VON HIPPEL E. (1988) *The Sources of Innovation*. Oxford University Press, New York.

ZUCKER L., DARBY M. R. and BREWER M. (1998) Intellectual Capital and the Birth of the U.S. Biotechnology Enterprises, *American Economic Review* **88**, 290-306.

Table 1. Non-response analysis

Variable	Respondents	Non-respondents	Difference	Significance
Continuity of R&D activities				
More or less continuously R&D	37%	40%	3%	
Occasionally R&D	29%	29%	0	0.46[a]
No R&D	34%	31%	-3%	
Firms with technological innovations	54%	58%	4%	0.17[b]

a: Mann-Whitney U-test
b: Phi-test

Table 2. Descriptive statistics of the IOL-variables[a]

		Mean (variable range 0-3)	St.dev.	Bivariate correlations* 1	2	3	4	5	6	7
1	Buyers	1,03	1,04	-						
2	Suppliers	1,26	1,05	0,31**	-					
3	Competitors	1,39	0,99	0,17**	0,19**	-				
4	Consultants	0,81	0,98	0,18**	0,14*	0,07	-			
5	Public Research Labs	0,46	0,82	0,14*	0,11	0,06	0,33**	-		
6	Universities	0,49	0,84	0,22**	0,22**	0,29**	0,27**	0,48**	-	
7	Innovation Centers and Sector institutes	0,55	0,87	0,32**	0,15*	0,24**	0,32**	0,39**	0,42**	-

a: Based on those observations that reported at least one IOL (N=276)
**: p<0.01
*: p<0.05

Table 3. Descriptive statistics

Variable	Mean	Min	Max	St.dev.	VIF
% sales from improved products	14.42	0	100	19.07	-
% sales from products new to the firm	7.36	0	100	13.04	-
% sales from products new to the market	8.96	0	100	19.81	-
CF1 – Shallow production-chain networkers	0.28	0	1	0.45	1.57
CF2 – Diverse & shallow networkers	0.22	0	1	0.41	1.88
CF3 – Shallow market followers	0.13	0	1	0.33	1.36
CF4 – Diverse & deep networkers	0.04	0	1	0.20	1.35
Number of localized IOL partner types	1.23	0	7	4.67	1.18[a]
Number of IOL partner types	4.26	0	7	2.71	1.07[a]
% of IOL partner types localized	2.40	0	100	10.16	1.10
Pretoria urban area	0.08	0	1	0.27	1.11
Johannesburg urban area	0.30	0	1	0.46	1.13
Cape Town urban area	0.04	0	1	0.20	1.05
New personnel	0.59	0	3	0.91	1.54
Start-up firm	0.16	0	1	0.37	1.08
R&D intensity	4.67	0.00	81.63	9.01	1.15
Size	4.79	11	26000	1.64	1.27
Service firm	0.18	0	1	0.39	1.15
Wholesale firm	0.15	0	1	0.36	1.15
Multi-site firm	0.32	0	1	0.47	1.09
South-African firm	0.83	0	1	0.38	1.08

CF = Configuration
a: Based on the model specification as reported in table 5. All other VIFs refer to the specification of the model as reported in table 6.

Table 4. Collinearity diagnostics

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	CF1 – Shallow production-chain networkers	-														
2	CF2 – Diverse & shallow networkers	-0.33	-													
3	CF3 – Shallow market followers	-0.24	-0.20	-												
4	CF4 – Diverse & deep networkers	-0.13	-0.11	-0.08	-											
5	% of IOL partner types localized	0.12	0.06	-0.04	-0.01	-										
6	Pretoria urban area	-0.04	0.07	0.03	0.03	-0.01	-									
7	Johannesburg urban area	0.04	-0.07	0.07	-0.02	0.09	-0.19	-								
8	Cape Town urban area	-0.04	0.08	-0.08	0.02	-0.02	-0.06	-0.13	-							
9	New personnel	0.05	0.36	-0.02	0.29	0.12	-0.01	0.01	0.02	-						
10	Start-up firm	-0.13	0.03	0.02	0.08	0.15	-0.08	0.02	0.01	0.03	-					
11	R&D intensity	0.07	0.00	0.01	-0.01	-0.03	0.13	-0.03	-0.01	0.04	-0.01	-				
12	Size	-0.04	0.23	0.01	0.11	0.10	0.07	0.00	0.03	0.26	0.05	-0.25	-			
13	Service firm	-0.04	-0.07	0.17	-0.06	0.10	0.05	0.17	0.00	0.00	0.00	0.09	-0.04	-		
14	Wholesale firm	-0.06	-0.12	-0.07	0.09	-0.06	-0.02	0.08	0.06	-0.08	0.00	-0.12	-0.12	-0.20	-	
15	Multi-site firm	-0.08	0.13	0.01	0.05	0.11	0.03	0.04	-0.03	0.08	0.13	-0.02	0.17	0.03	0.01	-
16	South-African firm	0.08	-0.02	-0.19	0.06	-0.01	0.04	0.01	-0.04	0.07	0.00	0.08	-0.02	-0.01	-0.03	-0.11

CF = Configuration

Figure 1. Configurations of IOLs

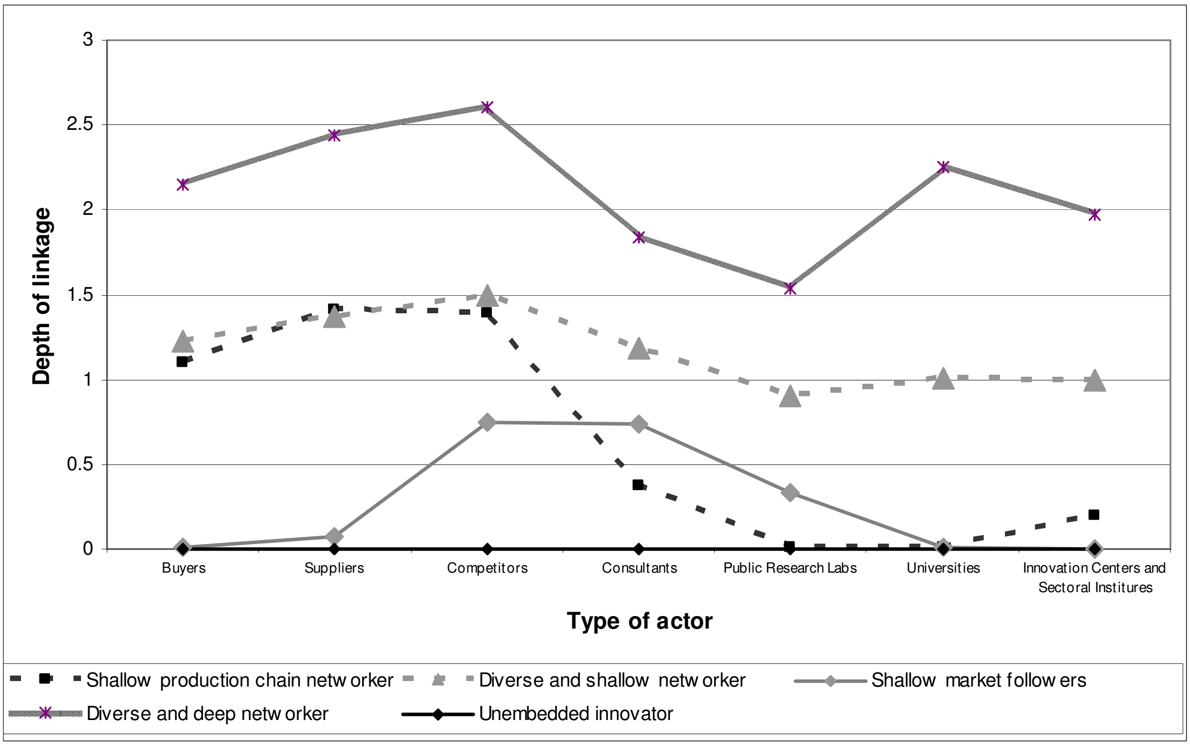

Table 5. Composition and characteristics of the IOL-configurations

	CF0 - Unembedded innovators		CF1 – Shallow production-chain networkers		CF2 – Diverse & shallow networkers		CF3 – Shallow market followers		CF4 – Diverse & deep networkers	
	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
% sales from improved products	3.56	11.08	19.43	19.47	22.88	20.89	14.73	15.69	24.31	26.54
% sales from products new to the firm	1.94	9.04	9.58	14.45	10.61	12.37	8.45	9.62	16.56	24.68
% sales from products new to the market	3.52	13.21	11.76	20.55	9.83	19.95	13.82	26.74	15.44	26.03
% of IOL partner types localized	0.00	0.00	4.41	14.78	3.59	11.25	1.39	7.28	2.08	5.82
Pretoria urban area	0.06	0.24	0.06	0.24	0.12	0.32	0.10	0.30	0.13	0.34
Johannesburg urban area	0.29	0.45	0.33	0.47	0.23	0.42	0.38	0.49	0.25	0.45
Cape Town urban area	0.04	0.21	0.03	0.16	0.07	0.26	0.00	0.00	0.06	0.25
New personnel	0.00	0.00	0.66	0.90	1.21	0.96	0.54	0.95	1.87	0.89
Start-up firm	0.19	0.39	0.09	0.29	0.19	0.39	0.18	0.39	0.31	0.48
R&D intensity	3.73	9.00	5.70	10.20	4.69	7.63	5.01	9.16	4.12	6.44
Size	4.29	1.40	4.67	1.66	5.51	1.71	4.85	1.54	5.67	1.72
Service firm	0.19	0.39	0.16	0.37	0.13	0.34	0.36	0.48	0.06	0.25
Wholesale firm	0.24	0.43	0.12	0.32	0.07	0.26	0.08	0.27	0.31	0.48
Multi-site firm	0.27	0.45	0.27	0.44	0.44	0.50	0.34	0.48	0.44	0.51
South-African firm	0.85	0.36	0.88	0.33	0.81	0.39	0.64	0.49	0.94	0.25

Table 6. Model results with geographical heterogeneity

	Ln % of sales from					
	Improved products		Products new to firm		Products new to market	
	Specification 1	Specification 2	Specification 1	Specification 2	Specification 1	Specification 2
Constant	0.98**	-0.69	-0.47	-1.71***	0.93***	-3.35***
Number of localized IOL partner types	0.38**	-	0.37	-	1.06***	-
Number of IOL partner types	-	0.20***	-	0.15***	-	0.22***
% of IOL partner types localized	-	0.04***	-	0.04***	-	0.07***
Pretoria urban area	0.91**	0.90***	0.11	0.12	1.66**	1.82***
Johannesburg urban area	0.37	0.20	-0.20	-0.32	0.05	-0.01
Cape Town urban area	0.36	0.74	0.73	1.01*	-0.96	-0.31
New personnel	0.85***	0.48***	0.73***	0.47***	0.20	-0.13
Start-up firm	-0.43	-0.01	0.06	0.31	0.78	1.21**
R&D intensity	0.02	0.02*	0.01	0.01	0.05**	0.06***
Size (ln)	0.03	0.01	0.07	0.06	-0.04	-0.06
Service firm	-0.36	-0.13	-0.11	0.02	-0.27	-0.16
Wholesale firm	-1.39***	-0.79**	-1.20***	-0.78*	-0.38	0.17
Multi-site firm	-0.08	-0.06	0.44	0.48*	0.38	0.41
South-African firm	-0.53*	-0.60**	-0.30	-0.35	-0.40	-0.40
Significance	0.000	0.000	0.000	0.000	0.001	0.000
McKelvey & Zavoina's Pseudo R-square	17.7%	37.1%	10.9%	18.3%	8.0%	14.2%
Sigma	2.17	1.84	2.41	2.26	3.38	3.17
N	400	400	400	400	400	400

Significance levels based on a Huber/White robust specification of the standard errors.

***: p<0.01
**: p<0.05
*: p<0.10

Table 7. Model results with IOL configurations and geographical heterogeneity

	Ln % of sales from		
	Improved products	Products new to firm	Products new to market
Constant	-0.65	-2.36***	-3.20***
CF1 – Shallow production-chain networkers	0.54***	0.40***	0.33***
CF2 – Diverse & shallow networkers	0.55***	0.45***	0.31***
CF3 – Shallow market followers	0.35***	0.34***	0.24***
CF4 – Diverse & deep networkers	0.27***	0.25***	0.23***
% of IOL partner types localized	-0.30	-0.63	0.32
CF1 * % of IOL partner types localized	0.31	0.65	-0.27
CF2 * % of IOL partner types localized	0.12	0.59	-0.33
CF3 * % of IOL partner types localized	0.05	0.46	-0.36
CF4 * % of IOL partner types localized	0.09	0.86	-0.78**
% of IOL partner types localized squared	0.02	0.02	-0.01
CF1 * % of IOL partner types localized squared	-0.02	-0.02	0.01
CF2 * % of IOL partner types localized squared	-0.02	-0.02	0.02
CF3 * % of IOL partner types localized squared	-0.02	-0.01	0.02
CF4 * % of IOL partner types localized squared	-0.02	-0.03	0.15
Pretoria urban area	0.74*	-0.06	1.64**
Johannesburg urban area	0.25	-0.34	0.09
Cape Town urban area	0.36	0.75	-1.23
New personnel	0.16	0.05	-0.46**
Start-up firm	-0.06	0.31	1.02**
R&D intensity	0.01	0.02	0.04**
Size	-0.08	-0.03	-0.19
Service firm	-0.15	-0.03	-0.30
Wholesale firm	-0.85***	-0.75**	-0.08
Multi-site firm	-0.20	0.26	0.21
South-African firm	-0.26	0.15	0.04
Significance	0.000	0.000	0.000
McKelvey & Zavoina's Pseudo R-square	40.8%	26.9%	18.7%
Sigma	1.74	2.07	3.02
N	400	400	400

CF = Configuration
Significance levels based on a Huber/White robust specification of the standard errors.

***: p<0.01
**: p<0.05
*: p<0.10