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Inventor networks, knowledge dynamics and new products: A longitudinal study on North-American medical device firms

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Abstract

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This study examines the relation between intra-organizational network structure and new product development. Extant literature has either looked at the effects of intra-firm network structure upon individual performance or focused mainly on organizational learning. This article aims to explore the relation between intra-firm social network structure, observed via inventor collaboration networks, and firm innovation, observed by new product development. I propose that network clustering (i.e. the presence of cliques) and path length (i.e. the average distance between inventors) will have independent consequences for the levels of knowledge diversity and diffusion within an organization. Knowledge variety and dispersion, in turn, improve the rate of new product development. I find partial support for my propositions in a longitudinal analysis on ten North- American medical devices firms between 1990 and 2000.

Keywords: network structure, technological innovation

INTRODUCTION

This article asks how the intra-organizational network structure affects firm innovative performance. On the one hand, there is an abundant literature on the effects of intra-firm networks and employee performance, creativity, and innovativeness (Brass et al., 2004). On the other hand, there is vast stream of literature on the importance of inter-organizational networks for firm-level learning and innovation (Borgatti & Foster, 2003). Extant research linking intra-firm social networks to organizational learning has provided unclear or opposing results. The aim of this article is to relate intra-organizational networks to firm innovativeness by identifying the mediating mechanisms.

First, there might be a divergence in results of organizational network structure at the individual and network level. Within a research and development setting, numerous studies have shown that the social network position and structure of scientists affects their creative performance (e.g. Ibarra, 1993, Obstfeld, 2005, Paruchuri, 2010). However, it remains unclear if results observed at the individual as unit of analysis can be forthrightly applied to the complete firm as level of analysis. Individual-level analysis has provided results that are incompatible at the network-level. For instance, Fleming et al. (2007) show that degree centrality increases, but cohesion decreases inventor creativity. The implication for individual scientists is to gain more connections with unconnected alters to improve their innovativeness. But at the network level it is not feasible to increase density without increasing clustering. This may cause a divergence of findings at the individual micro- and the network macro-level.

Second, current research on network structure and organizational learning has provided inconsistent results. To start, these simulation studies have contradictory regarding the performance effects of average path length within the intra-organizational networks. Short average paths between actors stimulates the diffusion of knowledge within the system, but is also linked to quick convergence of the inventor's knowledge (Lazer & Friedman, 2007).

Fang et al., (2010) found that high short path length improves the network's overall performance while the knowledge diversity is reduced, but this finding is not confirmed by Cowan and Jonard (2004). Second, the consequences of clusters are less well understood. Fang et al. (2010) argues that isolated subgroups are beneficial since they maintain heterogeneity in the network, but do not obtain empirical support. This argument is supported by Cowan and Jonard (2004), though Lazer and Friedman (2007) show the exact opposite effect of clustering.

To resolve these discrepancies in current research, this study asks the following question: *how does the inventor social network structure affect firm innovative performance?* Existing limitations can be resolved by identifying the mediating mechanisms between network structure and firm innovation. This paper proposes that the relation between informal organizational structure and firm innovative performance is mediated by knowledge diffusion and knowledge diversity. Since network structure guides the flow of information within an organization, particular structures in the collaboration network among inventors will result in higher levels of knowledge sharing. Simultaneously, the structure of interactions among scientific staff also affects the organizational knowledge heterogeneity. I argue that an inventor network with high clustering and short path lengths improves the information diffusion and diversity. This knowledge heterogeneity combined with accessibility then improves the innovative performance of the complete intra-firm network.

These propositions are tested on a sample of ten major American medical device firms between 1990 and 2000. This study fails to fully support the hypothesized relationship, but has promising findings regarding the mediated links. Regarding the direct relationship between network structure and new product development, path length and network isolates reduce innovativeness, but clustering has no significant effect. In accordance with the expectations, clustering increases knowledge diversity in the firm, but shorter path lengths actually reduces knowledge diffusion. Both diversity and diffusion increase innovativeness, but have a strong negative interaction effect.

This article makes two significant contributions towards social network theory. First, this study shows how network clustering and path length have distinct effects upon information diffusion and diversity. The contradictory findings in past literature argued that both path length and local clusters would affect knowledge flows and variety. However, this study shows that path length is the major determinant for knowledge dissemination whereas clustering assists in both sustaining knowledge diversity and diffusion.

A second contribution towards social network theory is related to the unit and level of analysis. Only a limited number of past studies have investigated the effects of network structure on the performance of whole networks (Phelps et al., 2012). Since organizations aim to maximize total firm innovativeness instead of the creativity of its individual employees, this is a more relevant level of analysis. Here it is shown that full network structure matters for the performance of the network, regardless of its effect upon the individual employee.

THEORY AND HYPOTHESES

Intra-organizational network structure

The importance of social networks for creativity and innovation in organizations has been shown in many occasions (Phelps et al., 2012). The inter-personal relations are important mechanisms for knowledge flows between teams, departments, and business units (Burt, 2004; Ibarra, 1993). Unplanned and unforeseen knowledge spillovers between individuals of different project teams cause the diffusion of novel technologies and practices (Cross & Parker, 2004; Wenger, 1998). The information exchange also tends to be of higher quality than formal communication mechanisms (Uzzi, 1996; 1997). Social networks can therefore be considered as an alternative organizational structure linking individual employees, teams, and departments in manners diverging from the formal organizational structure.

As a result, social networks are better determinants of learning and knowledge flow than formal procedures initiated by the management. This is the reason why a significant amount of research takes place in research and development departments (e.g. Guzzo & Dickinson, 1996; Nerkar & Paruchuri, 2005; Obstfeld, 2005; Fleming et al., 2007): the relation between knowledge sharing and innovation is most likely to occur here. Nevertheless, results regarding the effects of the whole network structure upon the overall firm innovative performance remain ambiguous (Cowan & Jonard, 2004; Fang et al., 2010).

A potential reason for this literature gap is the lack of a uniform theory regarding network structure and individual performance. In fact, the current literature is dominated by two major debates: closure vs. brokerage and weak vs. strong ties. First, there has been an extensive discussion about the benefits of brokerage and closure. Closure improves collaboration and knowledge-sharing (Coleman, 1988). It creates mutual understanding and similarity in values and beliefs, which facilitates efficient information exchange. Closure also increases trust and reciprocity that lead to sharing valuable resources and mutual favors while averting opportunistic behavior. Brokerage, on the contrary, implies that a person connects otherwise unconnected parts of the network (Burt, 1992). Since less connected parts of a social network are more likely to have different ideas, brokers can tap into more diverse knowledge to identify new opportunities.

Second, there has been an intensive dialogue regarding the role of tie strength: both strong and weak ties seem to offer distinct sets of benefits. Granovetter's (1973) study has revealed how weak ties are more likely to provide novel information. Weak ties tend to be person that are part of different social groups or communities of practice and they may therefore tap into different knowledge sources. Inventors will thus benefit from having a lot of weak ties that provide them with diverse and unfamiliar knowledge. An opposing perspective argues that strong ties are necessary for efficient collaboration and knowledge transfer (Gupta & Govindarajan, 2000). The strong ties create familiarity and trust which supports an environment of sharing and mutual understanding. In this case inventors are more effective in realizing new ideas by collaborating with strong ties.

Small-world networks

I argue that the theoretical debates above can be reconciled by considering the complete intra-organizational network and its effect upon firm innovativeness. First, if individual-level network structure influences the performance of R&D projects, then organizational-level network structure is likely to have an effect on firm R&D performance. Second, whereas individuals face a direct trade-off between closure and brokerage or strong and weak ties, these counterparts can co-exist at the whole network-level. In fact, in small-world networks (a pretty common network structure) they actually do co-exist (Watts & Strogatz, 1998). Therefore I argue that firm innovative performance increases when intra-organizational inventor networks show the characteristics of small-world networks.

The structure of inventor social networks within organizations will vary in several important dimensions. First, it varies on the overall degree of connectivity (Lazer & Friedman, 2007; Mu et al., 2010). Second, the degree of clustering indicates how density differs over sub-groups of the network (Provan & Sebastian, 1998). Finally, average path length among all actors indicates the average social distance in steps between any two employees. Small-world networks are network that, independent of their density, display high levels of both clustering and short paths (Watts & Strogatz, 1998).

The benefits of small-world networks will stem from both high clustering and short paths under a limited degree of density. First, the intermediate level of density balances the benefits of information sharing and burdens of information overload. In networks with very low to non-connectivity among its members, information transfer and knowledge sharing will hardly occur (Lazer & Friedman, 2007). At the other extreme, in a fully connected network, inventors lose much time, effort and resources in establishing and maintaining social ties (Zhou et al., 2009). Besides, individuals with many acquaintances can face an information overload (O'Reilly, 1980). Inventor networks with intermediate levels of connectivity optimize the trade-off between disadvantages of high isolation and high interaction frequency (Rowley, 1997; Zhou et al., 2009).

Second, small-world networks contain both closure and structural holes. At the individual level, evidence has shown that both brokerage and closure contribute to the innovativeness of individuals (Burt, 1992; Walker et al., 1997). Cohesion leads to a shared understanding and trust required for effective information sharing (Reagans & McEvily, 2003), but will lead to homogeneity over time. Bridging structural holes, on the other hand, gives access to new knowledge and improves creativity (Obstfeld, 2005). Small-world networks are characterized by high levels of clustering, inducing closure, but simultaneously by random connections, allowing for brokerage. It is most likely the combination of these two that improves network performance.

Thirdly, small-world networks have both weak ties and strong ties. Strong ties, characterized by frequent communication and rich knowledge sharing, contribute strongly to the effectiveness of an individual (Coleman, 1988; Krackhardt, 1992). However, since they are less likely to provide new information, innovation may also be spurred by weak ties that tap into different information sources and provide new knowledge to the inventor (Granovetter, 1973; 1983). As a result, individuals can increase their performance by balancing their strong and weak ties over time. The characteristics of small-world networks display such balancing behavior: high clustering exhibits the strong ties among a group of inventors and short average path length can only exist if some inventors have ties to scientists in different clusters in the network.

In short, small-world networks optimize the tradeoffs present in density, cohesion and tie strength. Therefore I argue that a combination of low average path length and high clustering improve firm innovation:

H1: Intra-organizational inventor networks characterized by a combination of short path length and high clustering are positively related to the organization's innovative performance.

The role of clustering

Here it is argued that the effect of small-world inventor networks upon firm innovative performance is mediated by knowledge diversity and knowledge diffusion. High levels of clustering improve the diversity of information and expertise present in the organization, whereas short path length improves the diffusion of new knowledge.

Social networks have a tendency to become more homogeneous over time (March, 1991). Frequent interaction starts a socialization process in which norms, values and beliefs converge. Such homogeneity can greatly improve the efficiency of cooperation (Hara, 2009; Wenger, 1998). Simultaneously, it may increase the level of trust and reciprocity among actors, since all actions of each actor become observable to all other actors (Adler & Kwon, 2002; Coleman, 1988; Uzzi, 1997). But in the end, stable social networks with strong connections among actors create knowledge homogeneity with sever effects for firm innovativeness (Fox, 2000; Nonaka, 1994).

Clustering in social networks can help to create or maintain knowledge diversity via communities of practice that elude the pressures for homogenization (Boland & Tenkasi, 1995). Communities of practice are groups of people sharing a similar professional interest who strengthen their knowledge and know-how about this topic via continuous social interactions (Wenger et al., 2002). Communities of practice first and foremost develop around types of work and professions. Because of that, communities of practice do not per se align with the formal organizational structure (Hara, 2009). Communities of practice may be spread over several business units and members of inter-disciplinary project teams may belong to different communities.

The similarity in work in communities of practice results in increased inter-personal learning between members of the same community of practice (Fox, 2000; Hara, 2009). Interactions within communities of practice result in sharing information, insight and advice (Huber, 1991). The shared background and experiences facilitate the transfer of tacit knowledge via socialization processes. Members of such a community therefore share a common knowledge base related to their field of expertise. Organizations have the ability to stimulate this learning by increasing opportunities for communication (Orr, 1996), but in general communities are difficult to manage and tend to develop autonomously.

Despite the informal nature of communities of practice, groups are internally strongly connected and tend to have boundaries (Wenger, 2000). Social connections among these employees are created during formal events or informal occasions, where participation is often based on their shared expertise and functional similarity. Members of the same community are therefore strongly connected to each other. The development of epistemic knowledge within clusters also functions as a boundary mechanism, determining who will become part of the community (Brown & Duguid, 1991; Knorr-Cetina, 1999). Individuals lacking similarity in background or expertise can neither benefit from nor contribute to the community.

The consequences of communities of practice are increased inter-personal learning and innovation, but also potential deviation and resistance (Wenger, 1998; 2000). Inventors have the ability to apply new information received via their community in the tasks for their project teams, but communication in communities may also lead to accidental discovery and inventions. Working, learning, and innovation are all embedded in the same system of formal organizational structure and informal communities. This particular professional culture is shared by all members via a socialization process for new members and sustained via collective enforcement of values and belief. As such, clusters tend to become silent powers present within the organization (Brown & Duguid, 1991). Like profession, these communities may even alter, modify or ignore managerial directives (Cox, 2005). As such, a cluster within the network may resist the pressures to converge over time and instead develop its specialized knowledge base semi-independently (Boland & Tenkasi, 1995).

In conclusion, an informal organizational structure with high levels of clustering results in a reduction of heterogeneity within a cluster but an increased diversity between clusters.

H2a: Intra-organizational inventor networks characterized by high clustering are positively related to organizational knowledge diversity.

The role of path length

The role of short average path length in inventor networks is related to the rate of knowledge diffusion. As said before, the informal organizational structure stimulates the dispersion of information both actively and passively. Actively inventors use their peers to solve particular problems and challenges they face (Singh et al., 2010). This advice-seeking from colleagues results in focused learning and expansion of expertise. Passively, the social network acts as a mechanism for uncoordinated and unplanned diffusion of information. Social talk among colleagues is a well-known source for knowledge transfer and can strongly improve the efficiency and effectiveness of employees (Knorr-Cetina, 1999; Orr, 1996).

Novel information normally enters the inventor network via one particular person and is passed on from actor to actor. Short average path length has three distinct benefits: likelihood, speed, and reliability of diffusion.

First, the likelihood that information will eventually be passed from one inventor to any another specific inventor in the network increases when the path length is reduced (Bell et al., 1999; Borgatti, 1995). Communication is important because knowledge about new technologies or novel applications may enter the inventor network places in a different location than where it could be used. For example, if the R&D staff of one unit involved in an alliance learn about a new technology that would be useful for another laboratory, then it is important that knowledge and expertise are shared efficiently for the overall levels of invention and discovery in the organization. However, not all individuals, but only a fraction of the inventors in a social network will pass on information they receive from their acquaintances. The probability that information will be passed from one actor to another reduces therefore exponentially with the number of nodes between them. So a short average path length in the informal organizational structure makes it most likely that useful information will reach the relevant inventors.

Second, the speed by which information is transferred from its source to the position where it is most useful is influenced by the path length (Borgatti, 2005). Information is passed through social networks with delays: infrequent communication between inventors slows down the dispersion of knowledge. So even when knowledge is successfully transferred from its source to the inventor applying it in new recombination, the time it takes increases with the number of nodes it has to pass before reaching its destination (Singh, 2005). Particularly in environments where speed is crucial like innovation, because of first-mover advantages or exclusivity rights, short average path lengths can improve the performance of organizations.

Third, the reliability of information transfer is affected by the path length. Each time information between individuals is transferred, it is likely to be slightly altered by distortions, omissions, and additions (Freeman, 1977). The precision and richness of technological knowledge will have a positive effect upon the inventor's ability to use it for new products, processes or technologies. A lower the number of steps between the initial owner and the eventual user of this knowledge is therefore important. Short average path length makes it thus more likely that knowledge received by inventors is in an unbiased form.

H2b: Intra-organizational inventor networks characterized by short average path length are positively related to organizational knowledge diffusion.

The combination of clustering and path length

The effect of small-world organizations upon firm performance is the combined effect of knowledge diversity and diffusion within the organization. Despite their potential independent effects on finding novel applications and solutions, the complementary nature of knowledge diversity and diffusion is the main source of benefits provided by small-world networks.

I argue that the relation between clustering and R&D performance is mediated by sustained heterogeneity within the organization. Knowledge heterogeneity is beneficial for two reasons: recombinant opportunities and learning capabilities. Innovation is the outcome of a successful search process in which inventors identify new combinations of existing technological components and processes (Fleming, 2001; Hargadon & Sutton, 1997). To fruitfully identify and realize opportunities for innovation, the complex process of recombination requires extensive knowledge and experience with the technological components involved.

First, knowledge heterogeneity has an immediate positive effect upon the number of combinations a firm can identify and realize since knowledge diversity reflects the sum of know-how of technological components by inventors. Firms with a homogenous knowledge base tend to perform local search with inventors identifying incremental improvements upon existing technologies (Fleming & Sorenson, 2004). When limited expertise is present in the organization, inventors tend to exhaust all opportunities. This results in a cycle of exploitative innovation where firms enter a loop of increased specialization while returns on combinations decrease. Firms with a heterogeneous knowledge base, on the other hand, can combine technologies that have not or hardly been combined before (Fleming, 2001). The formal and informal organizational structure of firms can stimulate such distant recombinant search that results in more novel or radical innovations with potentially larger returns.

Second, knowledge diversity is directly linked to the firm's ability to learn novel, related knowledge outside the organization (Cockburn & Henderson, 1998; Cohen & Levinthal, 1990). The firm's absorptive capacity is directly affected by the firm's current experience and know-how since it is easier to learn and use related technological knowledge than totally unrelated technologies. Firms with low knowledge heterogeneity are therefore constrained in their abilities to benefit from externally accessible knowledge, while organizations with a larger diversity in inventor expertise can benefit more from knowledge resources available in the external environment.

Once knowledge has been developed or acquired at a particular location in the organization, it can increase the innovativeness of this particular project group or laboratory (Ahuja, 2000; Shan et al., 1994). However, the benefits could be augmented if knowledge is diffused throughout other parts of the organization so more R&D units can use it in their recombinant search processes. Short paths in small-world networks improve the level of diffusion in the organization. Diffusion on itself fosters innovation when novel valuable information and know-how is dispersed.

In conclusion, I propose here a strong interaction effect between knowledge diversity and knowledge diffusion. First, knowledge diversity increases the organization's capability to identify, value and learn new internal and external knowledge (Cohen & Levinthal, 1990). Second, knowledge diffusion increases the availability of the newly gotten knowledge within the organization. Third, the novel knowledge can be turned into more practical applications when there are more opportunities for recombination, e.g. when internal knowledge is more diverse.

H2c: The combination of high knowledge diversity and high knowledge diffusion within an organization is positively related to the organization's innovative performance.

METHODOLOGY

Setting

The setting of this study is the North-American medical devices industry. The medical devices industry is a fast-growing and rapidly developing industry with $300 billion annual worldwide sales (Frent, 2011). The industry is currently dominated by nine major corporations, accounting for 40% of the market, after being subject to consolidation for over two decades. Whereas the larger firms focus on incremental innovations, smaller start-ups often bring radical innovations into the industry (Chatterji, 2009).

This industry was chosen for two reasons. First, innovation is a key success factor for firm survival and financial performance in the medical devices industry (Chatterji, 2009; De Vet & Scott, 1992). This is important since the study assumes that organizations are concerned about increasing innovation. Second, the innovative processes, activities, and outcomes of medical devices industry are highly observable. The medical devices industry heavily protects technological inventions via patenting (De Vet & Scott, 1992): in the last couple of years, these firms have applied for thousands of patents each year. Besides, the medical devices industry is a highly regulated business. Actors active in this industry have to meet many requirements regarding product transparency, including formal approval of products by the FDA. This is relevant since some of the measures are patent-based and FDA records leave us with detailed descriptions of firm innovative performance.

Data collection and sample selection

The data for the empirical analysis stem from four resources: WRDS Compustat, the NBER Patent project, the Harvard Patent Network Dataverse, and FDA pre-market approval files. WRDS Compustat is mainly used as data source for various control variables. The second dataset is the U.S. Patent Citations Data File provided by the NBER (Hall et al., 2001). Data collection is limited to the ten patent classes that the concordance in this dataset classifies as Surgery, Prosthesis, Optics, or Dentistry. The use of these patents is limited to the bibliographic fields patent number, classification, and backward citations. The patent number is used to identify the disambiguated patent authors in the Patent Network Dataverse (Lai et al., 2011), my third data source. Fourthly, I collected information about new product development via the pre-market approval (PMA) data from the Food and Drug Administration (FDA). The 180-day premarket approval procedure is required for all novel or improved safety critical medical products. The datasets have been merged and aggregated to the corporate level via the dynamic corporate tree present in the NBER Patent File.

The select sample consists of the ten firms that were most active in the medical device industry between 1986 and 1990 based on a ranking composed of industry sales, patenting activity, and new product development records. The selected corporations are Abbott

Laboratories, C.R. Bard, Baxter International, Becton Dickinson, Cordis Corp, General Electric, Johnson & Johnson, Eli Lilly & Co, Medtronic, and Pfizer. The sample over the period 1990-2000 consists of 95 firm-year observations. It is fairly balanced, with only two firms dropping out of the sample: Eli Lilly & Co after 1993(leaves industry) and Cordis after 1995 (acquired by Johnson & Johsnon).

Inventor networks within the organization are observed via co-authored medical patents. After inventors collaborate on a particular research project, they often remain in touch for a long period afterwards to exchange information and share experiences (Singh, 2005). I assume social ties among the co-authors are established during the period of collaboration and will remain on average for five years of time (similar to Fleming & Frenken, 2007). An example of such a network is shown in Graph 1 below

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INSERT GRAPH 1 AROUND HERE

Measurement

Dependent variable. The *number of new products* is measured as the number of successful FDA premarket approvals for firm *i* in year *t*. Only premarket approval for entirely new or substantially technologically improved medical devices are included.

Mediating variables. *Knowledge diversity* is measured via a Blau's index of the patent classes the firm patented in during the past three years. The USPTO groups patents in over 100,000 classes and subclasses, based on similarity in technology and field of application. Therefore each class represents similar knowledge. With the Blau's index, I create a measure for the diversity of the firm's medical knowledge based on the patent classes as well as the number of medical patents in each class. The formula for knowledge diversity is:

$$KnowledgeDiversity_{i,t} = 1 - \sum_c^C \frac{p_c}{p} \quad (1)$$

with C: number of subclasses present in the medical patents of firm i
p: total number of medical patents applied for by firm i
p_c: total number of medical patents in patent subclass c applied for by firm i

Knowledge diffusion is measured as the percentage of new citations in the past three years that will be recited by different inventors in the same organization during the next three year. Patent citations are known to display knowledge flows between organizations (Mowery et al., 1996) and also indicate knowledge diffusion within organizations (Rosenkopf & Nerkar, 2001). To ensure knowledge is really novel to the firm, only new patent citations of the organization in the past three years are included. The time lapse covers the period between initial absorption and eventual exploitation. The formula for diffusion is as follows:

$$KnowledgeDiffusion_{i,t} = \frac{\sum Recitations_{\ t+1,t+3}}{\sum NewCites_{t-2,t0}} \quad (2)$$

with *NewCites*: the number of newly cited patents during [t_{-2}; t_0]
Recitations: the number of these new citations recited during [t_{+1}; t_{+3}]

Independent variables. *Path length* is measured by dividing the actual path length over the random path length (Watts & Strogatz, 1998). To compute path length, the farness of each actor to all other actors (the number of steps needed to reach any other actor in the network) is averaged over the complete intra-organizational network (similar to Uzzi and Spiro, 2005). The random path length indicates what the expected path length would be for any random network with the same size and density and is calculated as the natural logarithm of the network size divided by the natural log of the average actor degree centrality. The formula for reach then becomes:

$$Path\ length = \frac{Actual\ path\ length}{Random\ path\ length} = \frac{\left(\sum_{i=1}^{n}\sum_{j\neq i}^{n} d_{ij}\right)/n}{\ln(n)/\ln(k)} \quad (3)$$

with n: number of nodes in the network
k: average degree centrality
d_{ij}: number of steps between node i and j ($i \neq j$)

Clustering is computed as the actual degree of clustering divided by the random clustering level (Watts & Strogatz, 1998). The degree of clustering per inventor is calculated as the number of observed triples (e.g. connected alters) divided by the potential triples. Inventor network clustering is the average clustering degrees of all actors. This measure is scaled by the level of clustering that would be expected in random networks, calculated as the number of connections divided by the number of actors in a network (Watts & Strogatz, 1998). So the formula for clustering is:

$$Clustering = \frac{Actual\ clustering}{Random\ clustering} = \frac{\left(\sum_{i=1}^{n}\left[\sum_{l}\ \sum_{m} d_{ilm}/(.5l(l-1))\right]\right)/n}{k/n} \qquad (4)$$

with *l*: alters of node *i*
m: alters of node *i* (not *l*)

Small-worldliness of inventor networks is measured by dividing clustering over path length (Uzzi & Spiro, 2005).

Control variables. A number of firm- and network-specific control variables will be included to control for alternative explanations. At the firm level, firm size is included via *Medical device sales* (log of annual sales in $000). Firm performance is included via *Return on Assets*, and firm origin via the *Foreign dummy* for non-American organizations. *Diversification* is measured via a Herfindahl index based on the sales in four-digit SIC market segments.

To correct for the firm's formal innovation strategy and resources, three additional variables are included. First, the *R&D intensity* (annual R&D expenditures as percentage of annual sales) will affect firm innovativeness. Second, slack, proxied via the organization's *Current Ratio*, is known to influence creativity (Nohria & Gulati, 1996). Finally, the *medical device patent stock* (the number of medical device patents applied for in the past five years).

Finally, control variables are added for intra-firm inventor network characteristics since they might be related to clustering and path length. First, I add *network size* via the number of inventors present in the network. Second, I add both *network density* (the number of observed connections divided by all possible connections) and the *number of isolates* (the number of unconnected inventors) as controls.

Estimation techniques

Two estimation techniques have been used to test the hypotheses empirically. First, firm innovativeness measured via the number of new products is a non-negative count variable with a high number of zeros (about 20% of the cases). Therefore I use a zero-inflated negative binomial model. Normal negative binomial models are preferred for non-negative over-dispersed counts because of their robustness, but was inappropriate for this dataset with many zeros (Vuong-test z = 5.09, p<.000). Similarly, overdispersion of the data made zer-inflated negative binomial preferred over a zero-inflated Poisson model (likelihood-ratio test X^2=146.44, p<0.000). The inflated model here included the firm and time fixed effects.

Second, a logit generalized linear model (logit GLM) is used for tests including the mediating variables, since these are ratios limited between 0 and 1. This generalized linear model, based on a binomial probability mass function with the predicted variable following a logit distribution, is preferred when the dependent variable is such a ratio (Papke & Wooldridge, 1996).

Each regression uses robust standard errors since there is a strong correlation among several explanatory variables and the sample is rather limited. All independent variables in each regression have been lagged by one year to improve internal validity.

RESULTS

The descriptive statistics of the sample are included in Table 1 and an overview of the number of new products per firm is shown in Graph 2 below. A medical device firm in the sample develops on average twelve new devices per year, but there is a larger variation: as the graph shows Becton Dickinson does not develop any new devices during the 90s whereas Abbot Laboratories has asked for approval for over 400 new devices. Clustering and path length differ substantially from what would have been expected if these networks were completely random, confirming the idea that each network shows some small-worldliness (Uzzi & Spiro, 2005). High correlations among explanatory variables may be problematic, in particular for network clustering and path length. Therefore robust standard errors, controlling for the covariance of the independent variables, are used.

INSERT TABLE 1 AND GRAPH 1 AROUND HERE

The regressions results are included in Table 2 and 3 below. Table 2 uses zero-inflated negative binomial regression to estimate the number of new products a firm produces in each particular year. This two-step maximum likelihood procedure first estimates the probability of the outcome equalling zero in the inflated model, before performing a negative binomial regression. The inflated model includes firm and time fixed effects to correct for unobserved heterogeneity. The individual firm dummy (base value is Abbott; dummies not included in table) are often highly significant, particularly for firms with many zero observations like Becton Dickinson. Similarly, the year dummies (base value 1990) become more significant and negative over time, indicated the general increase in the number of innovations over time. In the main model, some control variables have strong effects upon the firm's innovativeness. First, profitability has a positive impact on the number of new products. As expected, firm R&D intensity has strong positive effects. Surprisingly, firm size, slack and technological resources have no consistent significant effects.

Model 2 to 4 provide an empirical test for hypothesis 1: the expected benefits of small-worldliness (high clustering and short paths) for the number of new products. Model 2 shows that network size has no significant effect, but that density has positive effect while the number of isolated notes has a negative effect. This proves the importance of connectivity in a social system for the realization of new products (Guler & Nerkar, 2012). Model 3 and 4 fail to find evidence in support of hypotheses 1: while average path length among scientists reduce innovativeness, clustering and small-worldliness have no significant effect.

Model 6 and 7 provide confusing outcomes regarding the role of knowledge diffusion. Individually, they seem to have no significant outcomes. The interaction term, however, is strongly significant. Calculating the net effects of changes on diversity and diffusion at their mean levels, it turns out that increases in either one have a marginally negative effect. The negative interaction effect just cancels out the positive effect upon the number of new products. A potential reason for this effect is multicollinearity, but qualitatively similar results are obtained with alternative regressions methods (negative binomial, zero-inflated Poisson) or different sets of control variables. Overall, we can conclude that there is no unilateral support for hypothesis 2c, but that diversity and diffusion independently influence new product development.

INSERT TABLE 2 AND 3 AROUND HERE

Table 3 shows the effects for network structure upon knowledge diversity and diffusion. Diversity is positively influenced by firm size (measured via industry sales), profitability, and patent stock. Slack (measured via the current ratio) and diversification have a negative effect upon diversity. Diffusion is positively related to firm slack and diversification, but is negatively affected by firm size. In accordance with earlier studies regarding density (Lazer & Friedman, 2007), network density is positively related to knowledge dispersion, but has no effect upon knowledge diversity.

Model 3 finds just significant support for hypothesis 2a. Whereas path length has no effect upon knowledge diversity, clustering has a positive influence (p=.005). This confirms the idea that clusters in the network represent unique communities of practice with distinct professional knowledge. The findings in model 6 result in a rejection of hypothesis 2b: the coefficient for path length is significant, but in the opposite direction. The results here indicate that knowledge diffusion is supported by strong clusters that are hardly connected.

In summary, whereas the analysis fails to find a direct relationship between small-world network characteristics (i.e. H1 not supported), it reveals strong evidence that clustering and reach effect knowledge diversity and diffusion, respectively. These two factors independently affect the rate of new product development in medical device firms. A direct link between network characteristics and new product development is only found for path length, which has a significant negative effect.

DISCUSSION AND CONCLUSION

The first aim of this study was to gain more insight in the relations between macro-level characteristics of intra-firm networks and firm innovative outcomes. The importance of innovation for organizational survival and prosperity has been emphasized for a long time and result in a rich extant literature on social networks. However, this stream of literature has been dominated by two opposing hypothesis: closure vs. brokerage and strong vs. weak ties. Second, it remained unknown if results regarding the network position of individuals (degree centrality, cohesion, closeness) could be translated directly to innovative performance of the collective of inventors based on their overall network structure (density, clustering, path length). Finally, the limited empirical results provided opposing outcomes for organizational learning. It has retrieved opposing findings regarding network density and clustering for overall learning in the intra-organizational network of employees.

The first theoretical contribution of this paper is that the brokerage vs. closure and weak vs. strong tie debates at the individual level can be resolved by considering the network-level performance. Inventor networks that display both closure and brokerage, and both strong and weak ties are more likely to innovate effectively. Short paths, present via many close ties combined with a few distant ties, increases intra-organizational knowledge diffusion in the inventor network, similar to the knowledge benefits of weak ties and bridging structural holes (Burt, 1992). High network clustering sustains knowledge heterogeneity within the inventor network, equivalent to closure and communities of practice which are efficient in internal information processing but withstanding the tendencies for similarity (Coleman, 1988).

The second theoretic contribution are the mediating mechanisms between network structure and technological innovation: diffusion and diversity. Past studies on network structure and organizational learning may have obtained opposing results because they concentrated mainly on knowledge diffusion (e.g. Lazer & Friedman, 2007; Fang et al., 2010). However, if innovation is the outcome of knowledge recombination, diffusion should be accompanied by sufficient diversity. Network structures favoring diffusion (i.e. high density) may weed out diversity quickly. On the contrary, structures sustaining heterogeneity may involve little communication and reduce innovation. The effect of intra-organizational network structure for firm innovation should therefore also be related to knowledge heterogeneity and knowledge dissemination.

An empirical analysis of this model in the medical devices industry has provided inconclusive though promising results: inventor collaboration network structure influences knowledge diversity and flows within the organization, but only path length has a direct (negative) effect upon innovativeness.

These outcomes have theoretical and managerial implications. At the individual level, the existing disputes on the benefits of particular social network structures are partially brought together. Whereas extensive past research has attempted to identify when closure and strong ties or brokerage and weak ties contribute to individual creativity, this study aims to show that both simultaneously stimulate innovation but potentially at different locations in the network. Nevertheless, the overall system performs better when its internal structure has each of these elements.

From a practical perspective, this study has shown the importance of the firm's informal organizational structure for its innovative capabilities. This informal structure complements the formal structure in coordinating and sourcing R&D activities. Nevertheless, organizational management seems to be predominantly concerned about the formal structure and hardly incorporate the consequences for the informal structure when evaluating decision alternatives.

Limitations and future research directions

This study is subject to several limitations that should be taken into account when interpreting the results. First, the setting is particular in several ways: high levels of innovation, high R&D intensity, and a dispersed knowledge base (De Vet & Scott, 1992). Despite these particularities, the main findings of the study are likely to apply in most organizations: an informal structure providing inventors the ability to collaborate and communicate effectively will enhance innovation in all situations. Yet, the importance of intra-firm collaboration for innovation, or the significance of innovation in general, will vary per industry.

A second limitation to this study are potentially imprecise measures. Current network measures are based on readily available measures, but may need to be adapted for inventor collaboration networks: these networks tend to show more unconnected clusters (which the path length measures cannot deal with) and higher levels of cohesion because of co-patenting with multiple inventors (which the clustering measures do not correct for). Future research should deal better with these issues.

A more important limitation is potential endogeneity via organizational structure. The informal organizational structure is shaped via current and past collaboration, which in itself may be influenced by the formal organizational structure. The formal structure may indirectly influence the social structure via shaping team-work, via the way R&D units are structured, and via the physical structure within and between laboratories. The social network structure is no longer fully exogenous as a consequence and instrumental variables are needed to rule out alternative explanations.

Another limitation of this study is related to the type of innovations. Innovations differ in their novelty towards the firm (exploration vs. exploitation) and towards the industry (incremental vs. radical). The structure of the inventor network might affect the types of innovations that an organization develops. The FDA data permit to distinguish between radical and incremental innovations and further research can build upon this data.

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TABLE 1

Descriptive Statistics and Correlation Table[a,b]

Variable	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. New products	12.53	14.97	0	65	1														
2. Knowledge diffusion	0.33	0.12	0.09	0.55	0.35	1													
3. Knowledge diversity	0.97	0.02	0.91	0.99	0.24	0.40	1												
4. Small-worldliness	2.04	2.35	0.49	15.22	-0.08	0.08	-0.27	1											
5. Clustering	60.36	38.41	15.96	152.47	0.06	0.33	0.58	-0.07	1										
6. Path length	45.35	34.58	3.31	146.23	0.22	0.38	0.58	-0.40	0.82	1									
7. Network size	241.96	192.30	56	916	0.22	0.39	0.59	-0.27	0.92	0.96	1								
8. Nr of isolates	21.75	15.83	3	65	0.01	0.33	0.49	0.05	0.91	0.62	0.77	1							
9. Network density	0.02	0.01	0.01	0.06	0.13	-0.30	-0.55	-0.09	-0.80	-0.61	-0.69	-0.75	1						
10. Medical device sales	7.98	0.96	4.96	9.20	-0.06	-0.18	0.26	-0.72	0.26	0.48	0.36	0.05	-0.06	1					
11. Diversification	0.27	0.33	0	0.90	-0.25	-0.27	-0.17	-0.15	0.26	0.20	0.20	0.15	0.01	0.48	1				
12. Return on assets	0.10	0.06	-0.04	0.23	0.62	0.39	0.38	-0.19	0.22	0.25	0.29	0.22	0.01	-0.04	-0.30	1			
13. R&D intensity	0.08	0.03	0.02	0.15	0.49	0.43	0.50	-0.01	0.22	0.21	0.25	0.22	-0.15	0.04	-0.45	0.62	1		
14. Current ratio	1.51	0.70	0	3.04	0.26	0.60	0.49	0.29	0.40	0.23	0.35	0.45	-0.48	-0.46	-0.56	0.42	0.40	1	
15. Med device patent stock	217	202.888	30	1041	0.23	0.36	0.51	-0.18	0.90	0.89	0.97	0.81	-0.67	0.26	0.18	0.30	0.26	0.38	1

[a] $N = 95$

[b] All values greater than |0.21| are significant at $p < .05$

TABLE 2

Zero-inflated negative binomial regression for New Products[a,b,c]

	(1) New prod.	(2) New prod.	(3) New prod.	(4) New prod.	(5) New prod.	(6) New prod.	(7) New prod.
Main model							
Small-worldliness				0.058			
Clustering			0.004	-0.000			
Path length			-0.068***	-0.075***			
Network size		0.004	0.023***	0.026***			
Nr of isolates		-0.019*	-0.027**	-0.021			
Network density		28.227**	55.169**	56.792**			
Diffusion x diversity							-128.672**
Knowledge diffusion						-0.043	124.742**
Knowledge diversity						1.528	40.874**
Medical device sales	-0.133	-0.318**	-0.236*	-0.093	-0.133	-0.147	-0.178
Diversification	-0.279	0.075	-0.184	-0.340	-0.279	-0.271	-0.450
Return on assets	7.321***	4.223*	2.253	3.047	7.321***	7.392***	7.298***
R&D intensity	13.115***	16.243***	16.538***	14.594***	13.115***	13.022**	10.902**
Current ratio	0.113	0.193	0.184	0.185	0.113	0.099	-0.085
Med device patent stock	-0.000	-0.001	-0.009***	-0.010***	-0.000	-0.000	0.001
Constant	1.421	1.845	0.513	-0.653	1.421	0.091	-37.548**
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inflated model							
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-56.925***	-61.784***	-60.648***	-70.911***	-56.925***	-56.908***	-57.265***
Ln Alpha	-0.999***	-1.181***	-1.307***	-1.323***	-0.999***	-1.000***	-1.043***
Alpha	0.368***	0.307***	0.271***	0.266***	0.368***	0.368***	0.352***

[a] N = 95 (75 non-zero observations)

[b] Firm-fixed effects have been added for 10 firms and time-fixed effects have been added for 11 years

[c] *** p<0.01, ** p<0.05, * p<0.1 based on robust standard errors

TABLE 3

Logit GLM regression for Knowledge Diversity and Diffusion[a,b,c]

	(1) **Diversity**	(2) Diversity	(3) Diversity	(4) **Diffusion**	(5) Diffusion	(6) Diffusion
Clustering			0.022***			0.024***
Path length			-0.001			0.058***
Network size		-0.001	-0.002		0.006***	-0.011***
Nr of isolates		-0.001	-0.010**		0.010*	0.010
Network density		7.184	25.367***		23.561***	17.415
Medical device sales	0.300**	0.393**	0.243*	-0.744***	-0.735***	-0.739***
Diversification	-0.097	-0.140	-0.293**	0.639**	0.603**	0.866***
Return on assets	1.179**	0.977*	0.813	-0.799	-1.203	0.270
R&D intensity	0.535	-0.314	0.353	2.906	0.942	3.547
Current ratio	-0.419***	-0.457***	-0.457***	0.609***	0.623***	0.598***
Med device patent stock	0.001***	0.002**	0.001	-0.001	-0.006***	-0.002
Constant	1.265	0.456	0.592	3.810**	2.737*	2.092
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

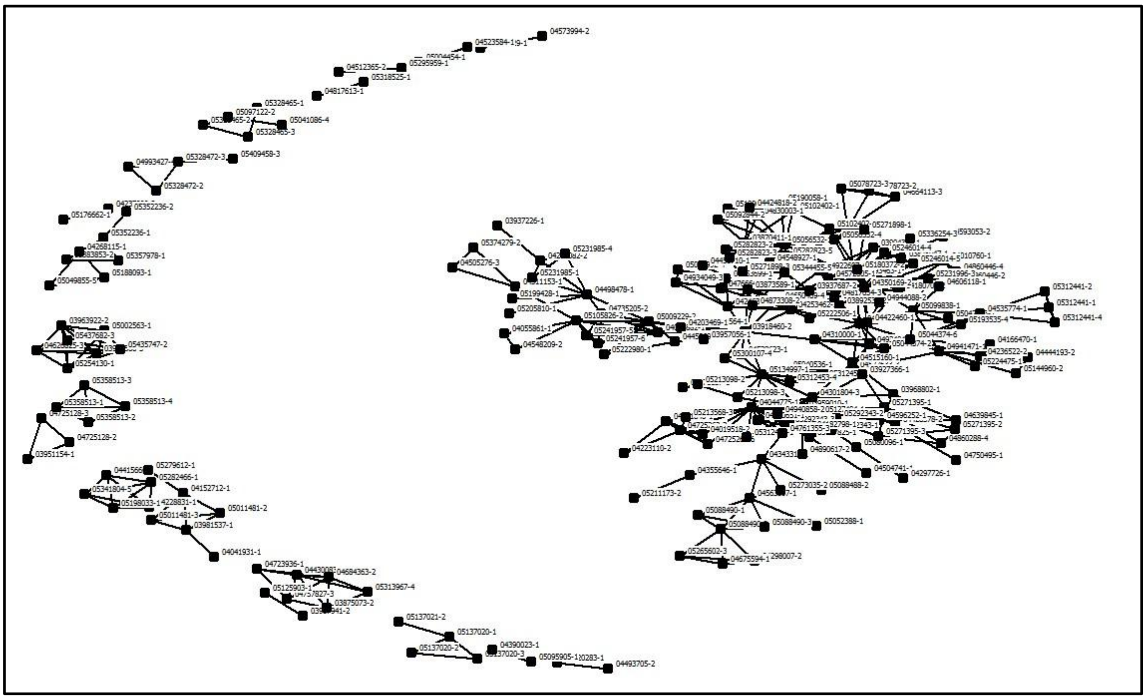
[a] $N = 93$

[b] Firm-fixed effects have been added for 10 firms and time-fixed effects have been added for 11 years

[c] *** $p<0.01$, ** $p<0.05$, * $p<0.1$ based upon robust standard errors

GRAPH 1

Visualization of the inventor collaboration network in Medtronics in 1992



GRAPH 2

New products by company by year