Economics of Innovation and New Technology
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/gein20

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Published online: 25 Jul 2013.

To cite this article: Grazia Cecere & Muge Ozman (2014) Technological diversity and inventor networks, Economics of Innovation and New Technology, 23:2, 161-178, DOI: 10.1080/10438599.2013.815473

To link to this article: http://dx.doi.org/10.1080/10438599.2013.815473

Economics of Innovation and New Technology, 2014
Vol. 23, No. 2, 161–178, http://dx.doi.org/10.1080/10438599.2013.815473

Technological diversity and inventor networks

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(*Received 23 January 2013; final version received 10 June 2013*)

This article examines the relationship between the structure of intra-firm inventor networks and the technological diversity of firms. We test this relationship for a panel of 222 firms in the ICT sector for the period 1995–2003, by utilizing data on their granted patents. The results reveal that the relation between the strength of ties between inventors in R&D teams and the firms' technological diversity is curvilinear. In other words, while strong ties between inventors can promote diversity, there is a limit to this positive effect. After this limit, strong ties can inhibit diversity, possibly by limiting the capabilities of network members to process novelty. In addition, we find that the impact of the scale-free metric on technological diversity is negative.

Keywords: ICTs; intra-firm network; technological diversity; innovation; scale-free network

1. Introduction

The history of technological change is full of examples in which a radical innovation is the result of the recombination of previously existing, but disparate knowledge in novel ways (Bassala 1988). Recombination is seen as essential in the innovation process through the lens of an evolutionary view of the industrial system (Schumpeter 1934; Nelson and Winter 1982). In this context, variety in the knowledge base is the most essential part of innovation since it determines the range of possible reconfigurations that knowledge can be put. The positive impact of variety on innovation has been well documented in previous research. As far as variety in an organization is concerned, previous studies focused on firms' strategic – and thus deliberate – initiatives to maintain variety, as in *technological diversification* (Granstrand, Patel, and Pavitt 1997; Cantwell and Santangelo 2006; Hyukjoon, Hyojeong, and Yongtae 2009). On the other hand, the impact of inventors' patterns of collaboration on diversity, while highlighted theoretically, has not been empirically verified. It is important to underline the difference between technological diversification, as a deliberate strategy, and technological diversity, as an emergent property. In this article, technological diversity is taken as an emergent outcome of the structure of interaction patterns between inventors. Therefore, understanding the role of intra-firm networks is important especially in forming and coordinating research teams, in a managerial context.

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The aim of the present article is to explore the ways in which the structure of intra-firm inventor networks shape the technological diversity in firms' R&D output, as measured by their patents. We focus on the ICT sector, which is characterized by a wide and heterogeneous knowledge base and rapid rate of innovation, which makes it one of the most interesting sectors to explore technological diversity in an organizational context. We use a panel data of patents on 222 firms that were observed over a nine-year period, from 1995 until 2003, retrieved from the UK-DTI R&D database. The data-set includes the top ICT international companies by their technical competences measured by R&D intensity and patenting propensity. The article is organized as follows. Section 2 presents the theoretical background. Section 3 details the method and data used in the study. Section 4 analyzes the results, followed by some concluding remarks.

2. Background and hypotheses

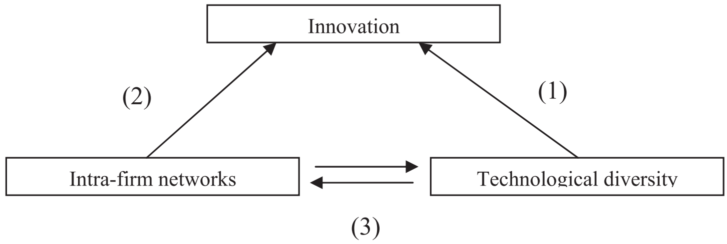
One of the building blocks of innovation is variety. Termed as 'recombinant growth' by Weitzman (1998), it is accepted that the probability of innovation is higher when there is more variety to be recombined. Here, variety is taken as diversity in an innovating organization, which is reflected in the breadth of fields in its R&D output. Miner, Haunschild, and Schwab (2003) term this as 'categorical variety' where firms differ in types and distributions of their categorical entities (technological fields in this case). Variety exists in a localized context where the knowledge base of the firm expands in technologically proximate fields and where firm integrates and combines its internal knowledge and the knowledge close to their boundaries (Antonelli 2006).

In this section, first the role of technological diversity in innovation is explored. Second, the importance of intra-firm inventor networks in innovation activities is presented. The literature is well established concerning these two themes. On the other hand, the impact of intra-firm networks on diversity, which is the subject of this article, is yet to be developed. Figure 1 summarizes the positioning of this article within the existing literature.

In Figure 1, themes (1) and (2) show that both technological diversity and intra-firm networks affect innovation. Theme (3) shows the relation between technological diversity and intra-firm networks and indicates that the causality can be taken in two directions. First, studies in organization theory posit that technological diversification strategies have an impact on the organization structure, mainly through divisionalization within the firm (Argyres 1996; Cantwell and Santangelo 2006). Second, according to social network theories, the structure of networks shapes technological diversity. For example, repeated exchanges between the same inventors or a highly clustered network can result in knowledge convergence, thus reducing technological diversity (Nelson 1989; Milliken, Bartel, and Kurtzberg 2003). In this paper, we emphasize such emergent nature of inventor interactions and how it shapes the research output of firms.

2.1. Technological diversity and innovation performance

In management studies, one of the questions that have attracted significant attention is concerned with the effects of diversity on firm performance (Harrison and Klein 2007; Williams and O'Reilly 1998). There is a strand of literature which shows that technological diversity can increase the innovative potential (Fleming 2002; Garcia-Vega 2006; Miller, Fern, and Cardinal 2007; Quintana-Garcia and Benavides-Velasco 2008) through maintaining the availability of a broader set of alternative recombination paths (Weitzman 1998; Fleming 2002; Carnabuci and Bruggeman 2009). Nevertheless, some studies find that the level of



(1) The Impact of diversity on innovation Leten et al., 2007; Harrison and Klein, 2007; Williams and o'Reilly, 1998; Fleming, 2002; Miller et al., 2007; Garcia-Vega, 2006; Quintana-Garcia and Benavides-Velasco, 2008; Carnabuci and Bruggeman, 2009; Van den Bergh, 2008.
(2) The Impact intra-firm networks on innovation Allen and Cohen, 1969; Allen, 1977; Tichy et al., 1979; Hansen, 1999; Tushman and Romanelli, 1985; Nerkar and Paruchiri, 2005; Singh et al., 2010; Tortoriello and Krackhardt, 2010; Cross and Borgatti, 2004; Reagans and McEvily, 2003; Reagans and Zuckerman, 2001; Nahapiet and Ghoshal, 1998.
(3) The relation between diversity and networks
Cowan and Jonard, 2001 ; McFadyen et al., 2004; Nelson, 1989; Argyres, 1996.

Figure 1. Innovation, intra-firm networks and diversity.

diversity is critical. While too little diversity can be beneficial for economies of scale, it creates few opportunities for recombination (van den Bergh 2008). On the other hand, too much diversity increases the costs of coordination and may lead to reduced opportunities for innovation (Leten, Belderbos, and Van Looy 2007). Therefore, technological diversity does not always imply that variety inside the firm is effectively shared, recombined and could be put into new products.

While the importance of diversity on innovation is well documented, few studies investigate the determinants of technological diversity, as an emergent aspect of intra-firm networks (c.f. theme (3) in Figure 1). At the same time, *technological diversification*, which can be seen as a deliberate strategy to create and maintain variety (Granstrand, Patel, and Pavitt 1997), has been studied commonly. Among these deliberate strategies, one can consider external alliances and acquisitions (Cantwell and Santangelo 2006; Nooteboom et al. 2007; Sampson 2007). In addition, a range of human resource practices are shown to generate variety internally, as job rotation (Un 2007) and R&D management between different business units in large organizations (Birkinshaw 2002; Argyres and Silverman 2004). As far as the impact of technological diversification on intra-firm organization is concerned, Argyres (1996) finds that technological diversification reduces divisionalization in companies, because of increased transaction costs of coordinating a diverse range of tasks.

2.2. Intra-firm networks, innovation and technological diversity

Since 1960s, the network approach has been widely adopted in organization studies (Allen and Cohen 1969; Allen 1977; Tichy, Tushman, and Fombrun 1979) to understand how knowledge is created, recombined and disseminated within an organizational context. The characteristics of knowledge (Hansen 1999, 2001) as well as the positions of actors in the network (Tushman and Romanelli 1983; Nerkar and Paruchiri 2005; Singh, Hansen, and Podolny 2010) are found to have an effect on innovative performance of a firm and the literature explores different dimensions of this effect. Some studies emphasize the importance of boundary spanning actors bringing knowledge to a unit from outside (Allen and Cohen 1969; Tortoriello and Krackhardt 2010) and some others investigate how networks relate to patterns of information seeking in organizations (Cross and Borgatti 2004; Singh, Hansen, and Podolny 2010).

Relational embeddedness emphasizes the qualitative aspects of relations among network members. It encompasses the strength of ties among network members which can be measured by the extent to which ties are repeated between them (Reagans and McEvily 2003). This aspect of relations, which is sometimes referred to as 'network closure', emphasizes the role of a dense network structure in facilitating the development of mutual trust, identification with the group and hence fostering common initiatives (Coleman 1988; Reagans and Zuckerman 2001). Strong ties enable thick information exchange and they are considered to be better in deepening the knowledge of network members in specific areas (Rowley, Behrens, and Krackhardt 2000; Uzzi 1997). Moreover, strong ties also have the effect of reducing fears of opportunistic behavior and motivate cooperation among network members. Based on these, they are usually considered to have a positive impact on intellectual capital in an organization (Nahapiet and Ghoshal 1998).

Co-invention patterns between inventors are commonly used to measure knowledge exchanges between them (Balconi, Breschi, and Lissoni 2004; Ejermo and Karlsson 2006). Most of the inventions are made by teams of researchers, complementing their knowledge through collaboration. Inventor teams are usually characterized by mutual interactive learning, transfer of both tacit and explicit knowledge, heuristic and recursive problem solving processes, in which frequent and close interactions are needed. These processes have an important role in fostering creativity in joint research. Because of their positive impact in fostering communication and generation of new ideas, we expect to find a positive association between tie strength and technological diversity in an organization. Despite their positive impact, one of the implications of such repeated/strong ties can also be convergence of members in terms of their knowledge endowments, thus reducing diversity (Cowan and Jonard 2001). Stated differently, repeated exchanges between the same people can have a diminishing returns effect in terms of the added value to knowledge creation (McFadyen and Cannella 2004). For example, in social psychological theories, one of the negative impacts of increased cohesion within a group has been found to be members' reduced abilities to process novelties (Janis 1972; Milliken, Bartel, and Kurtzberg 2003; Nelson 1989). In the case of multitechnology firms, leveraging variety effectively can be hampered through such repeated collaborations, preventing diverse areas of specialization to form synergies with each other. Based on this framework, it can be argued that there is an inverted-u relationship between strength of ties between inventors and technological diversity.

Hypothesis 1: There is a curvilinear relation between the strength of ties between inventors in a firm and the firm's technological diversity.

The impact of tie strength on diversity can be better understood if we take into account the number of *distinct* teams in an organization. Figure 2 shows two networks with the same total number of nodes and ties and the same tie strength between members. The difference between the two networks is concerned with the existence of three components in network 1. On the other hand, network 2 is composed of a single component, in which all nodes are reachable from all other nodes. The notion of component used here refers to a subgroup in the network, whereby all nodes in one component are connected directly or through intermediaries, and there is no other node in the rest of the network in which the nodes of the

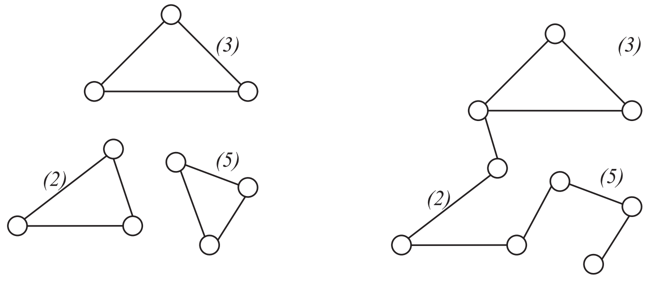


Figure 2. Tie strength and number of components.

component are connected to. Consequently, the lack of ties between such components may limit the diffusion of knowledge between inventors. In this case, technological diversity is expected to be higher when there are a higher number of inventor components in the network.

Hypothesis 2: There is a positive relation between number of inventor components in a firm and its technological diversity.

An interaction effect between number of inventor components and strength of ties within components is likely to exist. In particular, it can be argued that the stronger the intra-component ties, and the higher the number of components, the less will be technological diversity. This is the case when an increasing number of strongly embedded, yet unconnected teams lead to coordination problems, resulting in redundancy – or repetition – of research efforts in different parts of the network. In other words, technological diversity may be hampered when there are too many strongly connected teams, which are not connected to each other.

Hypothesis 3: There is a negative interaction effect between the number of inventor components and tie strength between inventors as far as their impact on diversity is concerned.

2.3. Scale-free networks and diversity

In addition to the network measures explained above, we also investigate the impact of hubs on technological diversity. A scale-free network is characterized by a very high degree of tie asymmetry. In other words, a small number of nodes have very high number of connections, while the majority of the nodes in the network are connected to few others. A network is termed as scale free when the frequency distribution of its degrees follows a power law distribution (Barabasi and Albert 2000; Solla de Price 1965). One of the mechanisms which have been shown to yield a scale-free network is preferential attachment, whereby highly connected nodes are more likely to attract more linkages, as the network grows. In the literature, the impact of a scale-free network structure has been studied under two general frameworks. The first one is related with the resilience of scale-free networks. While scale-free networks exhibit high resilience to random accidents (Cohen et al. 2000), their performance is quite low in terms of vulnerability to targeted attacks. The second framework is concerned with diffusion, mainly carried out within the context of epidemics and knowledge diffusion. It is found that scale-free networks result in faster diffusion in the system (Lin and Li 2010).

While a preferential attachment mechanism results in a scale-free network, it is not a *necessary* condition for the emergence of a power law degree distribution. Li et al. (2005) propose a metric which measures the extent to which a network is scale free. In doing so, they define a spectrum, the opposite ends of which are a scale-rich network and scale-free network. Their conceptualization of scale-free network is based on the extent to which highly connected nodes are connected to other highly connected nodes. On the other hand, a scale-rich network corresponds to one in which nodes are similar to each other in terms of their degrees, lacking significant differences in terms of their connection patterns. In this paper, we utilize this scale-free metric to investigate the impact of scale freeness of an inventor network on technological diversity. In other words, the metric measures the extent to which the degree distribution of a network is asymmetric.

The speed of knowledge diffusion in a network is likely to influence the network's capacity to maintain diversity. Fast knowledge diffusion can result in network members' becoming increasingly similar to each other, thus reducing the network's potential to maintain diversity. Accordingly, we propose that:

Hypothesis 4: There is a negative relation between the scale-free metric of a firm and its technological diversity.

3. Method and data

The foregoing hypotheses are tested by using a sample of firms in the ICT sector. ICT sector is one of the fastest growing sectors of the economy, accompanied by rich opportunities for technical change, as also revealed by the increasing number of patent applications during the recent decade (Corrocher, Malerba, and Montobbio 2007). Several features of this industry make it a suitable framework for this study. In the ICT sector, the main input in production is knowledge. Because knowledge can be inexpensively reproduced (expansible) and it is non-rival (its use by one party does not exclude others from using it), an original design can be reused in meeting different markets, which is a source of economies of scope (Steinmuller 2007). In other words, economies of scope in ICTs stems from the ability to 'address different application needs with the same designs' (Steinmuller 2007, 198). This creates important opportunities in the industry for the existence of a diverse range of knowledge and products. This variety is also one of the factors which shape the heterogeneous industrial architecture, giving rise to small and specialized firms alongside established ones, as well as a large number of universities and research centers (Corrocher, Malerba, and Montobbio 2007).

The coexistence of established firms and young firms and the diverse knowledge base of the industry augment the propensity of innovation through recombination (Koumpis and Pavitt 1999) and suggest increased technological diversity at the firm level (Granstrand, Patel, and Pavitt 1997; Mendonca 2006; Patel and Pavitt 1997). Finally, ICTs are considered to be general purpose technologies (Bresnahan and Trajtenberg 1995) which provide a suitable basis upon which a very diverse range of fields can be incorporated (Koumpis and Pavitt 1999).

3.1. Data

The primary goal of this article is to analyze how technological diversity at the firm level relates to the structure of networks formed by inventors. We constructed a unique database which includes all ICT firms classified in the UK-DTI R&D database (BIS – Department for Business Innovation and Skills). We retrieved data on the top worldwide ICT firms during the period 1995–2003. The DTI database collects detailed data on the R&D expenditures of these firms. Therefore, the sample consists of a set of big firms, where the smallest firm has around 500 employees and the largest one has 477,100 employees. The database includes 222 firms, operating in electronics, telecommunications and computer sectors, with high technical competences (jointly considering R&D and patent counts). The data-set includes the patents granted to these firms by the US Patent and Trademark Office (USPTO), which were retrieved using the Worldwide Patent Statistical Database (PATSTAT). In this way, we included a total of 349,070 patents granted to these firms during the period 1995–2003.

Although patents are usually considered to be a good source of measuring innovation output, patent data have some limitations (Griliches 1990; Silverman 1999). There is a part of technical knowledge which might remain unpatented, either because it is not patentable or because a firm may strategically keep it secret. Further analysis of data revealed that firms which are in the range of highest R&D spending are not necessarily the ones with the highest propensity to patent. Therefore, we included only the firms with high patenting propensity.

3.1.1. Dependent variable: technological diversity

By using the information related to the International Patent Classification (IPC) codes,[1] each patent in the data-set was allocated into one of the 30 main technology fields (Schmoch 2008).[2] A technologically diverse firm will have a patent portfolio covering a wider range of technology fields, compared with a specialized firm. The technological diversity of firm i in period t is measured by the Blau Index (1977) which was originally used to measure diversity in population studies

$$\mathrm{Div}_{it} = 1 - \sum_k q_{ik}^2,$$

where Div_{it} is the technological diversity of firm i in period t and q_{ik} is the proportion of technology field k in all the patents granted to the firm in period t.

3.1.2. 3.1.2 Independent variables

Three network measures were computed: tie strength (RT), the number of distinct inventor components (NbC) and the scale-free metric (ScaleFree). The networks are constructed for a two-year period in the following way. A link between two inventors exists if their names have appeared together at least once in a two-year period.

Hypotheses 2 is concerned with the number of disconnected components of inventors. Here, a component is defined as a group where all the members are reachable by the other members of the group, directly or through intermediaries. For each firm and every two years, the number of inventor components is computed (NbC_{it}).[3]

Hypotheses 1 and 3 are concerned with the strength of ties between inventors (RT_{it}). Strength is measured by the extent to which the same inventor names appear in different patent documents. The weight of tie strength is measured as a percentage of total ties. Formally, it is measured in the following way:

$$\mathrm{RT}_{it,t-1} = \frac{\left(\sum_{i=1}^{N}\sum_{j=1}^{N} r_{ij}\right) - T}{\sum_{i=1}^{N}\sum_{j=1}^{N} r_{ij}},$$

where r_{ij} is the total number of times inventors i and j have collaborated in years t and $t-1$ and T is the total number of links in the network during the same period. In this way, the variable is normalized with respect to the total number of pairs in the network, given by T. This normalization is necessary to be able to standardize the measure corresponding to firms with different sizes.

Hypothesis 4 is concerned with the scale-free metric. Li et al. (2005) propose the following metric to measure the extent to which a network is scale free. For firm i, and for each connected inventor j and k

$$\text{ScaleFree}_i = \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} d_j d_k}{\max(\text{ScaleFree}^N)},$$

where d_j and d_k refer to the number of connections of j and k respectively, and N is the total number of inventors in the network. The denominator of the metric gives the maximum possible value of the metric, with the given degree distribution of nodes in the network. In other words, it connotes the maximum possible value of the metric, had the given degree distribution of the network characterized a network in which highest degree nodes were connected to other highest node degrees. Li et al. (2005) show that relatively high values of scale-free metric characterize networks with a hub-like core structure, where hubs play an important role in the overall connectivity of the network.

3.1.3. Control variables

In order to control for alternative determinants of technological diversity, a set of control variables are used.

R&D expenditure. The intensity of research effort is used as a proxy of innovative activities of firms. We include the annual R&D expenditure of each firm in millions of pounds and we instrument the variable considering the one-year lagged R&D expenditure. In this paper, R&D expenses control for the effect of firm size, as all firms in our sample has a high level of R&D expenditure. We expect to have a negative sign of these covariates. Smaller firms can have more willingness to exchange internal information. Larger firms are expected to have more financial means with respect to smaller firms. However, large firms can have operational rigidities, which may hamper the explorative activities as well as the coordination of research teams. We include the deflated stock of R&D expenditure[4] which measures the accumulated R&D efforts over time, stocks influence the profitability and the value of the firms.

Other organizational variables. Organizational variables can also affect the technological diversity of firms, and for this reason, different organizational time-unvarying regressors are added into the estimation. We include dummy variables indicating the company headquarters which take into account the difference among the different continents; namely Europe (EU), USA (US), Japan (JAPAN) and other countries (OTHER). The reference variable in the regression is the dummy variable OTHER. These set of variables may account for different corporate strategies. Particularly, the well-known 'American' corporate model followed by US firms is characterized by the capability to accumulate and take advantage of internal stocks of existing knowledge which is the result of effective central coordination and hierarchical implementation. For those firms, diversity allows to firm to widen the scope of knowledge applications, enabling recombination process (Antonelli, Kraft, and Quatrato 2010).

For each firm, we collected information on the age of the firms and on the industrial classification code. We include in the regression the variable age – AGE (we add the variable in square to control the overdispersion – AGESQ). We expect that older firms have higher capabilities to manage diversity in internal knowledge as they have more experience on the

Table 1. Detailed data on firms by segment.

	Variable	Firms	Examples
Professional, scientific and technical services	NAICS 541	30	3COM, Nvidia, Redback Network and Telstra
Computer and electronic product manufacturing	NAICS 334	91	Dell, Apple, Cisco, L3 communications, Nokia and LG Electronics
Office machinery manufacturing and printing and related support activities	NAICS 33	23	Dainippon Screen MFG, Avid Technology and Xerox
Producing and distributing information and cultural products; transmission and processing of data or communications	NAICS 511-8	27	I2 Technologies, Adobe System and Oracle
Professional, scientific and technical services	Other_NAICS	51	Minolta, IBM and Macronix International

NAICS, North American Industry Classification System.

Table 2. Definitions of dependent and independent variables.

Variable	Description
Dependent	
Diversity – Div_{it}	Measured by a single Blau Index for the pool of patents taken by the firm in a specific year
Independent variables	
Number of components ($\log \mathrm{NbC}_{it}$)	Log of the number of components based on the networks constructed every two years
Tie strength (RT_{it})	The weight of strength of ties in the network measured the repeated link between inventors. Networks are constructed by taking into account patents of two-year periods
$\mathrm{ScaleFree}_{it}$	Measures the extent to which intra-firm networks are scale free
AGE_i	Based on the establishment year of the firm
Country of origin	Based on the country of origin of the firm
RD_{it-1}	Natural log of the R&D investment in time $t-1$ in £m
Stock $\mathrm{R\&D}_{it}$	The deflated stock of R&D variable in time t in £m
NAICS 541, NAICS 334, NAICS 33, NAICS 511-8 and Other_NAICS	Industrial segment of the firm

NAICS, North American Industry Classification System.

other hand, thus we expect a negative sign for the coefficient of the variable AGE. In addition, to control for industry differences we included a set of dummy variables based on the firms' three-digit NAICS code as it might be possible that firms behave differently according to their industry segment. Table 1 presents some information on the firms presented in our sample, it shows that computer and electronic product manufacturing (91 firms) are the largest group of firms and the smallest group is represented by the group of firms belonging to Office Machinery Manufacturing and Printing and Related Support Activities sector (23 firms). Additionally, all regressions include year dummies to capture the exogenous change in the competition environment of the firms.

Table 2 summarizes the dependent variable and the independent variables. Table 3 presents some descriptive statistics.

Table 3. Descriptive statistics.

Variable	Obs.	Mean	Std. dev.	Min	Max
Div_{it}	1282	0.6049672	0.2276466	0	0.9095884
RT_{it}	1282	0.2661976	0.1521364	0	0.875
RTsq_{it}	1282	0.0939886	0.0987533	0	0.765625
RT_{it} (mean)	1282	0.2726541	0.1037576	0.0139096	0.5865568
RTsq_{it} (mean)	1282	0.0995222	0.0648916	0.0004548	0.3673618
Log NbC_{it}	1282	2.925677	1.444602	0	6.380123
Log NbC_{it} (mean)	1282	0.8299967	0.6125036	0	3.721418
ScaleFree_{it}	1282	0.3087539	0.3107587	0.0019558	1
ScaleFree_{it} (mean)	1282	0.3093068	0.2389089	0.0136782	0.9903253
Stock $\text{R\&D}_{it-1}$	1282	5.876066	1.683882	1.1619	9.973317
Stock $\text{R\&D}_{it-1}$ (mean)	1282	5.878582	1.475371	2.656824	9.097918
AGE	1282	52.8869	36.35393	8	163
AGESQ	1282	4117.601	5338.75	64	26569
USA	1282	0.5904836	0.4919365	0	1
EU	1282	0.1123245	0.3158885	0	1
JAPAN	1282	0.2535101	0.4351902	0	1
NAICS541	1282	0.1170047	0.3215513	0	1
NAICS334	1282	0.4134165	0.4926384	0	1
NAICS33	1282	0.1115445	0.314928	0	1
NAICS511-8	1282	0.1107644	0.3139627	0	1

NAICS, North American Industry Classification System.

3.2. Method

The model is estimated using the ordinary least squares (OLS) command. The Hausman test was significant, showing that there is correlation between the explanatory variables and the unobserved effects. However, Mundlak (1978) pointed out that there is no justification for treating the individual effects as being uncorrelated with the other regressors. It is important to take into account this correlation, since it may lead to inconsistency in estimators due to omitted variables (Hausman and Taylor 1981). To control for unobserved individual effects, while also including explanatory variables, we introduced a second specification, which is the Mundlak–Chamberlain (Mundlak 1978; Chamberlain 1984) random effects model. Mundlak's method (1978) is commonly used in the estimations of unbalanced panels. This model assumes that the correlation between the unobservable firm characteristics and the exogenous variables acts only through their time averages, which permits controlling for unobserved heterogeneity. Mundlak's method requires calculating the within individual mean of explanatory variables. To control for the possible correlation between observed heterogeneity and explanatory variables, we estimate Chamberlain–Mundlak model. In order to test the above-mentioned hypothesis, the regressions are specified as follows:

$$\text{Div}_{it} = \beta_0 + \beta_1\text{RT}_{it} + \beta_2\text{RTsq}_{it} + \beta_3 c_i + \beta_4 m_i + \delta_i + \varepsilon_{it}, \qquad \text{(Model a)}$$

$$\text{Div}_{it} = \beta_0 + \beta_1\text{RT}_{it} + \beta_2\text{RT}_{it}{}^{*}\text{NbC}_{it} + \beta_3 c_i + \beta_4 m_i + \delta_i + \varepsilon_{it}, \qquad \text{(Model b)}$$

$$\text{Div}_{it} = \beta_0 + \beta_1\text{ScaleFree}_{it} + \beta_2 c_i + \beta_4 m_i + \delta_i + \varepsilon_{it}, \qquad \text{(Model c)}$$

with Div_{it} being the technological diversity index, where i and t indicate, respectively, the firms and the time period, and ε_{it} represents the error which is assumed to satisfy the usual regression model conditions. NbC_{it} and RT_{it} refer, respectively, to the number of components and tie strength. The variable ScaleFree_{it} measures the extent to which intra-firm network is characterized by scale-free structure. δ_i denotes the random effect for ith firm and it considers the firm-specific heterogeneity. Additionally, the Mundlak–Chamberlain specifications introduce the mean of time-varying variables. In addition, m_i represents the average value of the all time-varying variable of firm i (the variable RD_{it-i} namely the firm i's R&D expenditure in year $t-1$). And, C_i includes the set of firm's time-unvarying variables (age of the firms, the geographical location of the headquarter and so forth).

4. Results

Tables 4 and 5 present the results of the estimations with cluster–robust estimators at firm level. Table 4 includes models with tie repetition and number of clusters. Table 5 includes the results with scale-free metric as the independent variable. We estimate three set of models with different specifications in order to test the robustness of our results. In particular, the specifications (2–3), (5–6) and (8–9) include the mean of time-varying variable (using the Mundlak–Chamberlain method) in order to capture the unobserved effects associated with the explanatory variables.[5] By definition it is assumed that these are associated with the ability of firms to diversify their knowledge. The coefficients remain significant when we control for unobserved individual-specific effects.

The specifications 4–6 confirm our expectation of a curvilinear relation between tie strength and technological diversity. While strong ties can foster generation of new ideas and thus have a positive impact on diversity, they can also have a negative impact. Intuitively, this negative effect can be the result of knowledge convergence among inventors, in terms of their common knowledge endowments, limiting their potential for generating variety in research output. In social network theories, the negative impact of increasingly cohesive ties on processing novelty has been documented before (Nelson 1989). While our regression results permit to offer such an intuitive result, case studies at the firm or team level could be very useful in verifying this interpretation.

The regressions 1–3 show that there is a significant positive relation between number of components and diversity, which confirms Hypothesis 2. The number of inventor components in the network is reflected in the firms' research output as a higher diversity in the technology fields encompassed. However, this result should be interpreted with caution and together with the interaction effect between tie strength and number of components.

The significant and negative interaction effect between tie strength and the number of components in models 1–3 reveals that, there exist a critical number of components above which the impact of tie strength on diversity becomes negative. Before this critical level, increasing the number of components may still increase diversity, albeit at decreasing rates depending on tie strength. In other words, as number of unconnected inventor components increases, greater tie strength within components will start reducing diversity at one point. Coordinating the research activities of diverse teams can bring forth redundancy in research activities, if different inventor teams work on similar technological fields, yet when the coordination is poor between them. In addition, as the links between the members of existing teams get stronger, the inter-team relations might weaken, further contributing to the problem of coordination.

Building strongly connected teams can be accompanied by establishing linkages *between* these teams (in other words, reducing number of isolated components) if firms want to promote diversity. This can be realized through assigning inventors to bridging positions between different teams. At the same time, if organizational constraints necessitate the existence of a high number of isolated teams, then avoiding the teams to be too much embedded in their current networks can promote diversity. This can be realized, for example, by forming inventor teams in once and for all projects, or implementing programs like job rotations.

Table 4. OLS panel regression: dependent variable technological diversity and independent variables RT and NbC.

	Model a R&D (1)	Model a M. C. R&D (2)	Model a M. C. Stock R&D (3)	Model b R&D (4)	Model b M. C. R&D (5)	Model b M. C. Stock R&D (6)
RT_{it}	0.300***	0.284***	0.288***	0.504***	0.394***	0.407***
	(0.077)	(0.082)	(0.083)	(0.121)	(0.122)	(0.124)
Log NbC_{it}	0.115***	0.101***	0.107***			
	(0.013)	(0.016)	(0.107)			
RD_{it-1}	0.011	0.030**		0.055***	0.046***	
	(0.009)	(0.012)		(0.007)	(0.012)	
RT_{it}*log NbC_{it}	−0.130***	−0.128***	−0.133***			
	(0.030)	(0.031)	(0.032)			
RD_{it} (mean)		0.271	0.275		1.284***	1.273***
		(0.169)	(0.171)		(0.290)	(0.290)
Stock $R\&D_{it-1}$			0.015			0.022
			(0.011)			(0.014)
$RTsq_{it}$				−0.652***	−0.522***	−0.554***
				(0.162)	(0.159)	(0.162)
RD_{it-1} (mean)		−0.053***			−0.015	
		(0.018)			(0.015)	
RT_{it}*log NbC_{it} (mean)		−0.073	−0.072			
		(0.058)	(0.058)			
Log NbC_{it} (mean)		0.044*	0.036			
		(0.022)	(0.022)			
Stock $R\&D_{it-1}$ (mean)			−0.034*			0.004
			(0.019)			(0.018)
$RTsq_{it}$ (mean)					−1.773***	−1.745***
					(0.431)	(0.430)
AGE		0.002*	0.002*		0.002*	0.002*
		(0.001)	(0.001)		(0.001)	(0.001)
AGESQ		−0.000*	−0.000*		−0.000*	−0.000
		(0.000)	(0.000)		(0.000)	(0.000)
USA		−0.051	−0.051		−0.078*	−0.084**
		(0.039)	(0.038)		(0.040)	(0.041)
EU		0.038	0.030		−0.001	−0.014
		(0.048)	(0.047)		(0.054)	(0.054)
JAPAN		0.037	0.038		0.048	0.041
		(0.045)	(0.044)		(0.046)	(0.046)
NAICS541		−0.069**	−0.071**		−0.099***	−0.097***
		(0.032)	(0.032)		(0.036)	(0.035)
NAICS334		−0.002	−0.003		0.004	0.004
		(0.023)	(0.023)		(0.026)	(0.025)
NAICS33		0.066***	0.065***		0.068**	0.065**
		(0.022)	(0.022)		(0.029)	(0.029)
NAICS511-8		−0.138***	−0.147***		−0.176***	−0.182***
		(0.040)	(0.039)		(0.039)	(0.038)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.252***	0.297***	0.288***	0.229***	0.184***	0.195***
	(0.042)	(0.080)	(0.079)	(0.042)	(0.065)	(0.065)
N	1282	1282	1289	1282	1282	1289

M.C. stands for Mundlak–Chamberlain effect method robust standard errors in parentheses; NAICS, North American Industry Classification System.

*$p < .10$.

**$p < .05$.

***$p < .01$.

Table 5. OLS panel regression: dependent variable technological diversity and independent variable ScaleFree.

	Model c R&D (7)	Model c M. C. R&D (8)	Model c M. C. (9)
RD_{it-1}	0.051***	0.045***	
	(0.007)	(0.011)	
Stock $R\&D_{it-1}$			0.021
			(0.014)
Scale $Free_{it}$	−0.128***	−0.092***	−0.094***
	(0.024)	(0.025)	(0.025)
RD_{it-1} (mean)		−0.024	
		(0.015)	
Stock $R\&D_{it-1}$ (mean)			−0.004
			(0.018)
Scale $Free_{it}$ (mean)		−0.217***	−0.216***
		(0.052)	(0.052)
AGE		0.002*	0.002*
		(0.001)	(0.001)
AGESQ		−0.000*	−0.000
		(0.000)	(0.000)
USA		−0.053	−0.058
		(0.039)	(0.039)
EU		0.030	0.018
		(0.053)	(0.052)
JAPAN		0.062	0.056
		(0.045)	(0.045)
NAICS541		−0.094***	−0.093***
		(0.035)	(0.034)
NAICS334		−0.004	−0.004
		(0.025)	(0.024)
NAICS33		0.067**	0.064**
		(0.027)	(0.027)
NAICS511-8		−0.170***	−0.177***
		(0.038)	(0.038)
Year dummies	Yes	Yes	Yes
_cons	0.372***	0.553***	0.563***
	(0.041)	(0.066)	(0.065)
N	1282	1282	1289

NAICS, North American Industry Classification System.

Models 7–9 in Table 5 reveal that the scale freeness parameter has a negative and significant effect on diversity. This result confirms Hypothesis 4. High values of the scale-free metric point to a network where highly connected inventors are increasingly in collaboration with other highly connected inventors, and there is a strong asymmetry of degrees in the network. When this is the case, fast knowledge diffusion can be accompanied by reduced diversity. Contrarily, diversity is more likely to be supported in networks with a more homogeneous distribution of node degrees, as revealed by lower values of the scale-free parameter.

Interestingly, the sign of RD_{it-1} coefficient is positive and significant. This variable measures the innovative efforts and also the firm size. Firms that invest more in R&D increase their technology diversity which implies that innovative efforts need financial supports. It also shows that larger firms have more opportunities to manage the diversity of knowledge within their boundaries. At the same time, the stock of R&D does not affect the diversity.

To remove the possible bias due to the unobserved heterogeneity, a set of control variables are included in the specifications with the Mundlak–Chamberlain. In particular, we include a full set of three-digit industry NAICS code to take into account industry differences, the age of the firm and the country of origin. The set of NAICS code measures of sector characteristics such as industry concentrations. The results show that technology diversity is particularly important for the ICT manufacturing sectors NAICS33 in respect to other as the coefficient is positive and significant at $p < .01$. As, these firms have been crucial into the innovative development of the overall ICT sector. On the other hand, the variable indicating the Professional, Scientific and Technical Services (NAICS541) has negative and significant sign. This sector has been less technologically diversified as compared with others, this is possibly associated with the fact that the innovation in this subsector is more oriented toward services rather than products and thus patents do not adequately reflect innovation. The country of origin does not influence technology diversity significantly. The age of the firms positively affect the intensity of technological diversity showing that firms' experiences are important to improve the innovative activities of the firm.

5. Conclusion

The aim of the present article is to explore the ways in which the structure of intra-firm inventor networks influences technological diversity, as revealed by the patents granted to a sample of firms in the ICT sector. The article investigates the impact of tie strength, number of components and the scale-free metric of inventor networks on technological diversity of firms. The results of the panel data analysis can be summarized as follows. First, the analysis reveals a curvilinear relationship between strength of the ties between inventors and technological diversity. On one hand, strength of ties (as measured by the extent to which the same inventors repeatedly publish patents together) can promote diversity through facilitating communication between people, promoting creativity and novel recombinations. On the other hand, being excessively embedded in networks can render inventors similar to each other, reducing opportunities for learning, as well as processing of novelty. This can lead to reduced technological diversity.

Second, such a possible negative impact of strong ties depends on the number of unconnected inventor components in the network. While the number of distinct inventor groups promotes technological diversity, their precise effect depends on tie strength within existing components. As number of components increase, the stronger the bonds between the members of existing components get, the less will be diversity. Some managerial implications of this result are as follows. Increasingly cohesive inventor teams, which are characterized by strong ties between members, should be accompanied by a network strategy in which the teams are connected to each other. This can be done through bridging inventors, as an example, or promoting job rotation programs to reduce tie strength at the group level. Third, the results reveal that increasing tie asymmetry, measured by the extent to which inventors with high connections collaborate with each other, reduces technological diversity. This result is obtained through utilizing the scale-free metric as an explanatory variable.

To what extent are the results obtained in this paper valid for other industries and contexts? The data that are used in this article cover the ICT industry, which has peculiarities concerning the nature of knowledge and organizations. Consequently, while it is difficult to draw robust conclusions that might be applicable in other contexts, the article offers a few insights especially for knowledge intensive industries in which collaboration in research is a critical aspect of innovation. We focus on two peculiarities of the knowledge base of ICTs, which are important in drawing implications for other industries. One of the important peculiarities of the knowledge base of ICT industry is rich economies of scope, in which knowledge in one context can be reused in other contexts. Such economies of scope are a source of diversity in organizations (Teece 1980) and also in the industry. This is an important peculiarity which strengthens the ultimate negative impact of many teams with strong ties in an organization. More precisely, although the nature of knowledge base potentially fosters diversity because the same knowledge can be used in different domains, this positive impact can be easily hampered through the existence of isolated inventor components which are strongly connected within. Thereby, the potential of the knowledge base to maintain variety might not be leveraged. Consequently, it can be argued that in other organizational contexts apart from ICTs, in which economies of scope is an important aspect of knowledge base, similar results are expected to be obtained. In addition, the impact of scale-free characteristics is also specific to the nature of the knowledge base. ICTs draw upon a complex and tacit knowledge base as far as innovative activities are concerned. Faster knowledge diffusion within an organization can be more difficult, yet more destructive as far as diversity is concerned, reducing the opportunities through which diverse domains can be created and maintained by inventors, and rendering knowledge bases increasingly similar. These aspects of the knowledge base, which are economies of scope, complexity and tacitness, are important in determining the extent to which the current results can be valid in other contexts.

Limitations of this study are as follows. First, the model assumes a fixed knowledge space by taking into account a fixed number of IPC fields in the patents. In other words, the model does not take into account growth in the knowledge base of the ICT sector. Nevertheless, we do not expect this to be a serious problem, since the study covers a relatively short time frame. Exclusion of different managerial practices as a control variable is also one of the weaknesses of the current article. However, one of the difficulties is that they are difficult to measure in a way suitable for regression analysis.

Last but not least, we should keep in mind the problems associated with drawing robust conclusions from the statistical analysis of large data-sets, especially in organization level studies. A quotation from Hamel (1991) is seen useful at this point:

> Because patterns of causality are extremely complex in most real-world administrative systems, traditional deductive-analytic methodologies force the researcher to declutter the phenomenon by: (1) substituting crude proxies for difficult-to-measure determinants or outcomes; (2) assuming away some of the multidimensionality in causal relationships; and/or (3) narrowing the scope of research. In doing so, much of the potential value of the research is lost. The problem is not that the resulting theories are under-tested (i.e. they fail a test of rigor), but that they are under-developed (i.e. they are so partial in coverage that they illuminate only a fragment of the path between choice, action and outcome).

In this sense, we strongly support the use of detailed case studies to understand in a better way how some causal relations that maybe revealed by statistical analysis work in reality. As far as the subject matter of this article is concerned, avenues for future research include carrying out such case studies at the organization level to complement our findings regarding the relation between inventor network structures and technological diversity.

Notes

1. Each patent document includes the relevant technology codes related with the subject matter of the patent, which is given by the eight-digit International Patent Classification (IPC) code. A patent document is assigned a main code, as well as secondary ones. IPC classes represent an interesting source of information as they show the technology field in which the patent belongs to. In our study, the main and secondary IPC codes of patents are used to derive measures of technological diversity.

2. The mapping between IPC codes and 30 technology fields is based on the study by Fraunhofer Gessellschaft-ISI (Karlsrube), Institut National de la Propriété Industrielle (INPI-Paris) and Observatoire des Sciences et des Techniques (OST, Paris).
3. The software Igraph (Csárdi and Nepusz 2006) was used to calculate the number of clusters for each of the firm in each year in the sample.
4. The R&D stock is deflated with the method proposed by Hall (1993).
5. The specifications 3, 6 and 9 include the stock of R&D.

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