Research Policy 45 (2016) 1890–1906

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

The strength of long ties and the weakness of strong ties: Knowledge diffusion through supply chain networks☆

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ARTICLE INFO

Article history:
Received 25 December 2015
Received in revised form 8 May 2016
Accepted 26 June 2016
Available online 9 July 2016

Keywords:
Knowledge diffusion
Supply chains
Networks
Productivity
Innovation

ABSTRACT

Using a large firm-level panel dataset for Japan, this paper examines the effects of the structure of supply chain networks on productivity and innovation capability through knowledge diffusion. We find that ties with distant suppliers improve productivity (as measured by sales per worker) more than ties with neighboring suppliers, which is likely because distant firms' intermediates embody more diversified knowledge than those from neighboring firms. Ties with neighboring clients improve productivity more than ties with distant clients, which is likely because neighboring clients more effectively diffuse disembodied knowledge than distant clients. By contrast, ties with distant suppliers and clients improve innovative capability (as measured by the number of registered patents), whereas ties with neighboring suppliers or clients do not affect innovative capability. In addition, the density of a firm's ego network (as measured by how densely its supply chain partners transact with one another) has a negative effect on productivity and innovative capability, implying knowledge redundancy in dense networks. These results suggest that access to diversified ties is important for improving productivity and innovation capability through knowledge diffusion.

1. Introduction

Growth in the productivity and innovation capability of firms is substantially affected by the diffusion of knowledge, technology, and information from other firms (Bloom et al., 2013; Romer, 1990). An evident channel of such knowledge diffusion is research collaboration (Ahuja, 2000). Another less evident channel is buyer-supplier relations between firms because buyers often provide new knowledge to their suppliers when seeking to procure high-quality products (Dyer and Nobeoka, 2000). In addition, buyers can benefit from their suppliers because the productivity of assemblers is higher when they employ a larger variety of intermediates from different suppliers and utilize the knowledge embodied in their products (Dixit and Stiglitz, 1977). Supply chain ties are often associated with research collaboration for the development of new intermediates (Uesugi, 2015), which promotes knowledge diffusion between suppliers and buyers.

Knowledge diffusion through buyer-supplier relations has been tested extensively in the empirical literature, in which an improvement in the measures of productivity and innovation capability associated with such relations is typically considered to reflect knowledge diffusion. For example, when firms improve their productivity through exporting, it is assumed that exporting has led to new knowledge gains. Knowledge diffusion through international trade has been found by Amiti and Konings (2007), Crespi et al. (2008a), Lööf and Andersson (2010), and Piermartini and Rubínová (2014), among many others. Javorcik (2004) provides evidence of

☆ This research was conducted as part of a project entitled 'Empirical Analysis on Determinants and Impacts of Formation of Firm Networks,' undertaken at the Research Institute of Economy, Trade, and Industry (RIETI). The authors would like to thank RIETI for providing the firm-level data used in the analysis. Financial support from JSPS Kakenhi Grant (No. 25101003 and 26245037 for Todo and Matous, and No. 24530506 and 15K01217 for Inoue) is gratefully acknowledged. Comments from two anonymous referees that substantially clarified the argument of this paper are gratefully acknowledged. The authors would also like to thank Martin Everett, Masahisa Fujita, Akie Iriyama, Johan Koskinen, Toshiyuki Matsuura, Masayuki Morikawa, Garry Robins, Yukiko Saito, Iichiro Uesugi, Ryuhei Wakasugi and seminar participants at the University of Tokyo, RIETI, Waseda University, and the Western Economic Association International Annual Meetings for their helpful comments. The opinions expressed and arguments employed in this paper are the sole responsibility of the authors and do not necessarily reflect those of RIETI, University of Hyogo, the University of Sydney, Waseda University, or any institution with which the authors are affiliated.

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http://dx.doi.org/10.1016/j.respol.2016.06.008

knowledge spillovers from foreign-owned firms to their upstream suppliers.

Other studies pay more explicit attention to supply chain networks as a channel of knowledge diffusion. For example, Crespi et al. (2008b) use firm-level data for the United Kingdom to show that both the number of registered patents and growth in total factor productivity (TFP) are higher when firms report that they gain knowledge from their suppliers. Isaksson et al. (2016) analyze patent data for US firms in the high-tech sectors and find evidence that buyers' innovation has a positive effect on their suppliers' innovation. In the supply chain management literature, Flynn et al. (2010) use firms' subjective measurements and determine that the strength of relations with customers has a positive effect on firm performance but that the strength of relations with suppliers has an insignificant effect. Bozarth et al. (2009) find that the number of suppliers or clients does not affect subjectively measured firm performance. Using a firm-level dataset for Japan similar to that used in this study, Bernard et al. (2014) and Belderbos et al. (2015) examine how firms' productivity is affected by their buyers and suppliers.

However, there are two remaining issues in the literature. First, the existing studies have not focused on how a firm's direct suppliers and clients are connected with other firms. Knowledge diffusion to a particular firm from its supply chain partners may be influenced by whether those partners are connected with one another and/or with whom they are connected. For example, the amount of knowledge that diffuses to a firm from its suppliers may vary depending on whether the suppliers are in the same closed firm group or are connected with different types of firms. However, the previous literature ignores such detailed characteristics of whole supply chain networks in the economy and instead identifies supply chain relations only through firms' engagement in trade (Kimura and Kiyota, 2006; Lööf and Andersson, 2010; Van Biesebroeck, 2005), firms' subjective perceptions (Crespi et al., 2008a; Flynn et al., 2010), input-output tables at the industry level (Javorcik, 2004; Piermartini and Rubínová, 2014), or – at best – firms' direct supply chain partners (Belderbos et al., 2015; Bernard et al., 2014; Isaksson et al., 2016).

The literature on social networks has emphasized the importance of considering the overall structure of networks (Granovetter, 2005). For example, Burt (1992) finds that actors who create bridging links between otherwise disconnected groups of actors – or across structural holes – have superior access to diverse information. This finding is related to the argument of Granovetter (1973) that weak ties to relatively less frequently met partners are instrumental for accessing new information because such links frequently extend beyond the immediate circle of densely interconnected strong ties among similar partners with similar shared information. In other words, network density may prevent active knowledge diffusion due to knowledge overlaps and redundancy among partners.

However, structural holes and weak ties may not always be the key to knowledge diffusion. Other studies have found that dense networks within an organization in which actors are closely connected with one another but are not closely connected with outsiders can promote knowledge diffusion. The positive effect of dense networks most likely emerges in these studies because actors in these networks know one another well and thus trust new knowledge from each other (Ahuja, 2000; Phelps, 2010).

This study adopts methods from social network analysis to examine how the structure of the entire supply chain network affects the knowledge diffusion manifested in innovations and productivity increases using a large firm-level panel dataset for the Japanese manufacturing sector that covers most firms within the country and major buyer-supplier relations. Following the literature, we test for knowledge diffusion by estimating whether the structure of supply chain networks positively affects productivity and innovation capability, as measured by sales per worker and the number of registered patents respectively.

More specifically, we investigate how the density of a firm's ego network – or how frequently its supply chain partners transact with one another – affects its performance, which is the first time this subject has been addressed in the literature on knowledge diffusion through supply chain networks. The effects of ego network density have been studied by Ahuja (2000) and Phelps (2010) in research collaboration networks but not in supply chain networks. Ego network density may have both positive and negative effects on knowledge diffusion, as we argued above. Therefore, the net effect of the network density should be empirically examined.

The second remaining issue in the literature is the role of geographic distance in knowledge diffusion. In their seminal papers, Jaffe and Trajtenberg (1999) and Jaffe et al. (1993) found that geographic distance has negative effects on the degree of knowledge and information diffusion. Knowledge diffusion from neighboring partners may be easier than knowledge diffusion from distant partners because of lower transportation costs (Marshall, 1890). It has been shown that supply chain ties and research collaboration ties are more likely to be created between neighboring firms (Crescenzi et al., 2016; Nakajima et al., 2012). However, geographic proximity may have a negative impact on innovation because neighboring partners are more likely to be similar to the firm and to one another and thus to be characterized by similar knowledge, as argued by Boschma (2005). In other words, more knowledge and intermediate products that are new to the firm are available from the firm's distant partners than from its neighbors. Therefore, the net effect of distance from network partners on firm performance is not particularly clear.

This study incorporates the two issues and examines whether and how knowledge diffuses through supply chain networks using a large firm-level dataset that contains detailed information on the major transaction partners of 800,000 firms in Japan. Our empirical estimation employs a dynamic panel model, assuming that supply chain ties and firm performance interact with one another over time. In this framework, we can incorporate causality between firm performance and characteristics of supply chain networks in both directions and hence can alleviate possible biases in estimations of the effect of networks on performance that are due to reverse causality.

Our findings suggest that the geographic proximity of supply chain partners and the density of supply chain networks tend to reduce the benefits of knowledge diffusion, which is most likely due to knowledge redundancy in such networks. Therefore, this study emphasizes the importance of diverse network partners in knowledge diffusion.

2. Conceptual framework

2.1. Channels of knowledge diffusion through supply chain networks

Supply chain ties can improve firm performance through the diffusion of knowledge in the following three ways. First, clients frequently provide new knowledge and technology for production and market information to their suppliers to improve the quality and reduce the price of the goods they purchase. For example, Dyer and Nobeoka (2000) show that Toyota frequently organizes associations of its suppliers in which it provides valuable technical and managerial assistance to suppliers. Egan and Mody (1992) show that a US shoe importer sent Italian skilled artisans to Taiwanese shoe manufacturers to provide them technical assistance. Through such technical assistance, buyers' knowledge diffuses to suppliers. Second, buyers' production is larger when they utilize a larger variety of inputs from their suppliers, as typically described by the production function developed by Dixit and Stiglitz (1977) that assumes a constant elasticity of substitution among inputs. In other words, suppliers' knowledge is embodied in their products and diffuses – or, following Baldwin and Lopez-Gonzalez (2014), is "lent" – to their clients. Finally, supply chain networks often facilitate research collaboration, as Uesugi (2015) shows. For example, Toyota often conducts research and development activities for parts and components with its suppliers. In some cases, suppliers and clients may not conduct research collaboration explicitly, but they may exchange ideas for productivity improvement and product development. Through research collaboration and knowledge exchanges associated with supply chain ties, suppliers and buyers exchange their knowledge with each other and thus improve their knowledge and technology.

2.2. Density of networks and strength of ties

The effects of supply chain ties may vary depending on the structure of networks and the characteristics of the ties. In particular, the density of networks (how densely actors in a network are connected with one another) and the strength of ties (how closely an actor is connected to another actor) may positively or negatively promote knowledge diffusion. On the one hand, it might be expected that dense networks and strong ties facilitate knowledge diffusion because these network characteristics can foster shared norms and explicit knowledge-sharing institutions (Ahuja, 2000). Using data from leading chemical firms in the United States, Ahuja (2000) finds that when a firm's research collaboration network is dense, the firm generates more patents. Centola (2010) also shows in his social experiment on the Internet that members of an online health forum are more likely to adopt new health behavior from information provided by a member when more members in the forum know one another. Centola (2010) interprets these findings as showing that reinforcement from multiple informants promotes diffusion and adoption of behaviors.

On the other hand, network density and strong ties may weaken the benefits of knowledge diffusion through networks because these characteristics might translate into redundant knowledge (Burt, 1992). When a firm is connected only to partners with which it already shares the same knowledge, the firm cannot learn much from these partners (Berliant and Fujita, 2011). Therefore, the benefits of networks can be maximized when firms are connected with different types of partners so that partners' technology, knowledge, and information access are diversified. The importance of diversified networks in knowledge creation and diffusion has been emphasized in the social network literature. For example, Burt (2004) finds that a measure of the diversity of workers' networks in a firm is positively related to salary and the probability of promotion, arguing that the structural holes that connect different groups facilitate knowledge diffusion. With respect to job seekers, Granovetter (1973) finds that persons that job seekers meet less often are more important information sources, thus emphasizing the strength of weak ties. The importance of network diversity is also confirmed by Beugelsdijk and Smulders (2004), McFadyen and Cannella (2004), and Perry-Smith (2006), who find that strong ties with trustworthy partners or dense networks within the community or organization may not enhance economic performance without links to other communities.

In the case of supply chains in the Japanese automobile industry, Dyer and Nobeoka (2000) argue that *keiretsu*, a dense network in which each major assembler such as Toyota is firmly tied to a group of suppliers, improves the productivity of both assemblers and suppliers. However, Ahmadjian and Lincoln (2001) claim that the benefits of *keiretsu* have recently deteriorated due to the change in its structure.

Thus, whether network density and the strength of ties positively or negatively affects knowledge diffusion may depend on the situation (Phelps et al., 2012). With this in mind, this study focuses on supply chain networks and empirically examines how network density affects supply chain productivity and innovative capability through knowledge diffusion.

2.3. Geographic diversity

The argument in the previous subsection emphasizes the importance of diversity among network partners in knowledge diffusion. The geographic location of network partners is generally acknowledged to generate knowledge diversity. We presume that neighboring firms share more knowledge and information in common with one another than with distant firms. Therefore, we expect that more new knowledge and information diffuse from distant supply chain partners than from neighboring partners. The underlying idea is analogous to the "learning-by-exporting" and "learning-by-importing" hypotheses used to explain how exporters and importers can improve their productivity by learning new knowledge and technology from foreign countries. The former hypothesis was supported by Blalock and Gertler (2004), Kimura and Kiyota (2006), and Van Biesebroeck (2005), whereas other studies, such as Clerides et al. (1998), do not support it. The mixed results may occur because the effects of exporting on productivity are heterogeneous and depend on the characteristics of firms and destination countries, as Lileeva and Trefler (2007) show. The learning-by-importing hypothesis is supported by Amiti and Konings (2007) and Kasahara and Rodrigue (2008). Although not supported by Vogel and Wagner (2010) for Germany, it is still theoretically possible that firms in developed countries can improve productivity by using products of distant firms.

Although knowledge diffusion from distant transaction partners is empirically demonstrated to some extent, creating and maintaining ties with distant partners is more costly than doing so with neighboring partners because of transportation costs. In fact, the low transportation cost of transactions with neighboring suppliers is one of the major factors for industrial agglomeration (Fujita and Thisse, 2013; Marshall, 1890). Jaffe et al. (1993) and Jaffe and Trajtenberg (1999) use data on patent citations and find evidence that geographic distance negatively affects the degree of knowledge diffusion.

Therefore, it is unclear whether ties with neighboring or distant partners are more beneficial to firm performance through knowledge diffusion. Bell and Zaheer (2007) use data from Canadian mutual fund companies and find that proximity can have a positive or insignificant effect on knowledge flows. This paper examines how neighboring and distant supply chain partners affect the productivity and innovative capability of firms differently, distinguishing among partners within the same prefecture and outside of the prefecture.

2.4. Interactions between strong ties and weak ties

Finally, there may be complementarity between strong ties within the community and weak ties with outsiders, as Phelps (2010), Rost (2011), and Tiwana (2008) find. For example, Rost (2011) examines networks among inventors in the German automobile industry and finds that strong ties with regular collaborators promote innovation and that weak ties with unfamiliar researchers leverage the effects of strong ties. This evidence implies that new knowledge obtained from outsiders can disseminate effectively within a community when community members are densely connected, confirming the importance of knowledge diversity in diffusion. This study also tests the complementarity between strong ties within the community and weak ties with outsiders, particularly assuming that network density is associated with the strength of ties and that distant partners are outsiders equipped with new knowledge.

3. Data

3.1. Data sources

The dataset used in this study is mostly based on data collected by Tokyo Shoko Research (TSR), one of the two major corporate research companies in Japan. The TSR data contain corporate information, such as firm location, sales, and the number of employees, in addition to information on up to 24 suppliers of material and intermediates and up to 24 clients of products for each firm. The information on suppliers and clients can be merged with the corporate information data to establish the characteristics of each supplier and client. Although the upper limit of the number of suppliers and clients (24) is clearly too small for many large firms, it nonetheless allows most supply chain networks to be captured by considering supplier-client relations from both directions.

This study utilizes data licensed from TSR to the Research Institute of Economy, Trade and Industry (RIETI) in 2006 and 2012 to construct a panel data set. The number of firms in the TSR data licensed in 2006 and 2012 is 803,531 and 1,109,549, respectively, whereas the number of supplier-client ties in 2006 and 2012 is 3,783,623 and 5,106,081, respectively.

TSR has been collecting information from all firms in Japan recognized by TSR throughout the year to sell the information to other firms. Hence, the time of data collection varies across firms. In the data licensed in 2006 (the 2006 data), information on 67% of firms was collected in 2005, 28% in 2004, and five percent in other years. In the data licensed in 2012 (the 2012 data), information on 12% of firms was collected in 2012, 69% in 2011, and 18% in earlier years. Among the 2006 data, we utilize only data collected in 2004 or 2005 to avoid old information. Among the 2012 data, we utilize only data collected after April 2011 because the Great East Japan earthquake on March 11, 2011 resulted in changes in the suppliers and clients of many firms, including those outside of the directly impacted areas.

Using the TSR data, we identify the suppliers and clients of each firm and their locations and characteristics. Japan is regionally divided into 47 prefectures, which are the basic units of administration and jurisdiction. We count the number of suppliers and clients within and outside of the same prefecture for each firm. It should be noted that because the TSR data are at the firm level, supplier-client relationships at the establishment level cannot be identified. Therefore, the sample in our estimations includes only single-establishment firms to clarify the geographic characteristics of supplier-client relationships, although transaction ties are identified using all firms, including single- and multiple-establishment firms. In other words, we drop multiple-establishment firms from the sample for our analysis, but we utilize the supply chain ties of single-establishment firms with multiple-establishment firms in the analysis.

At this juncture, one problem remains. Consider, for example, that single-establishment firm A in prefecture X has a transaction with a branch of firm B in the same prefecture whose headquarters are in prefecture Y. Our data identify the transaction of firm A with B as that with a firm outside of the prefecture, although it is indeed a tie with a firm within the same prefecture. However, this is acceptable because we distinguish between transactions within the same prefecture and those across prefectures to examine the role of knowledge diversity. The transaction of firm A with a branch in the same prefecture of firm B whose headquarters are in a different prefecture may be regarded as a transaction across prefectures because the branch of firm B may share the knowledge of its headquarters.

The TSR data include data for both manufacturing and non-manufacturing firms. However, because the relation between supply chain networks and firm performance may be different across sectors, this study focuses on firms in the manufacturing sector to highlight the effect of supply chains for parts and components on firm performance. We further restrict the study to firms whose information is available in both 2006 and 2012 data. Thus, the number of firms in our sample for estimations is 36,814.

We merged the TSR data with data for the number of registered patents for each firm taken from the Institute of Intellectual Property Patent Database (Goto and Motohashi, 2007). This database covers all patents registered by the Japan Patent Office from 1963 to 2013. We merge the two datasets using the names and addresses of firms. Addresses in the two datasets cannot be straightforwardly matched using their linguistic characters because the same address may be expressed in different characters due to abbreviations or different mixtures of Japanese, Chinese, and Roman characters. Therefore, we utilize the CSV Address Matching Service of the Center for Spatial Information Science, the University of Tokyo to unify expressions of addresses. Using the unified addresses at the township level, we match addresses between the TSR and the patent data.

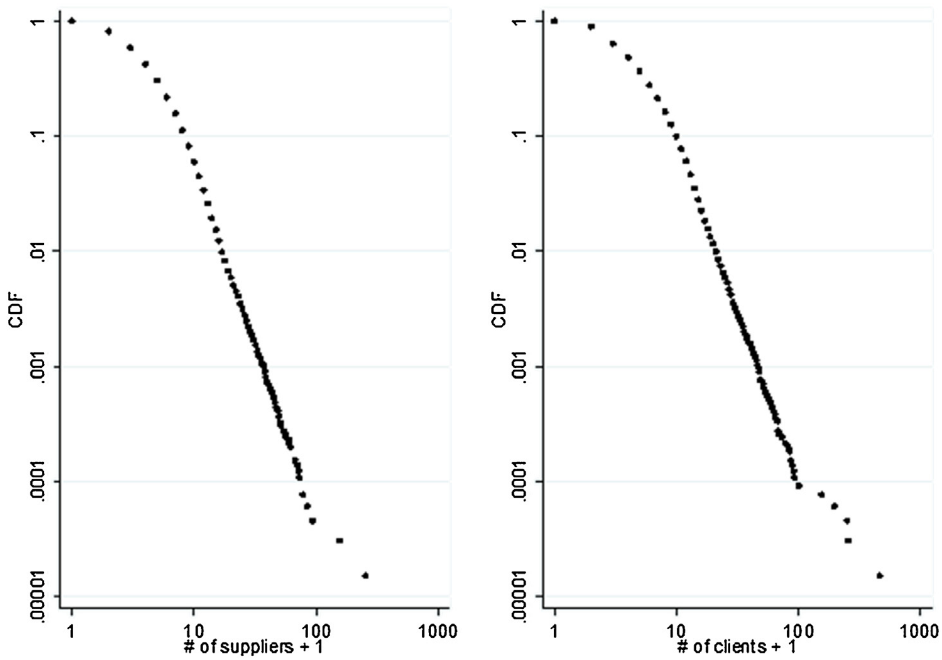
3.2. Key variables for estimation

We examine whether knowledge diffuses through supply chain networks by estimating the effects of variables for the characteristics of networks on measures of productivity and innovative capability. To measure the diversity of knowledge of network partners, we use the number of suppliers and clients, which varies substantially across firms. Fig. 1 shows the cumulative distribution function for the number of suppliers (the left figure) and clients (right) for single-establishment firms in the manufacturing sector in the 2006 data. Both figures show that the median of the number of suppliers and clients is small (two), although it is extremely large for some firms. This power-law nature has been found in previous studies, including Bernard et al. (2014).

We further distinguish between neighboring partners (those within the same prefecture) and distant partners (those outside of the prefecture), assuming that the knowledge of distant partners is more diversified. Although our dataset includes the detailed address of each firm, we do not utilize the distance between supply chain partners to examine the effects of distance to partners but simply distinguish among partners within and outside of the same prefecture to simplify the analysis.[1] This simplification may be justifiable because different prefectures reflect differences in industrial, social, and cultural backgrounds in addition to geographic distance, all of which lead to knowledge diversity. Such border effects are also found in the literature on international knowledge diffusion (Griffith et al., 2011).

Fig. 2 demonstrates the relationship between the numbers of suppliers inside and outside of the same prefecture. There is a weak positive relation between the two variables because the correlation coefficient between the two is 0.20. However, it should be emphasized that many firms are confined to a regionally closed network because they have no suppliers outside of the prefecture. By con-

[1] Belderbos et al. (2015) utilize the full information of the distance by estimating a non-linear model in which the effects of knowledge diffusion decay exponentially with distance.



Mean	Min	10%	Med	90%	Max			Mean	Min	10%	Med	90%	Max
4.0	1	1	3	8	257			4.7	1	1	3	9	462

Fig. 1. Distribution of the Number of Suppliers and Clients. *Notes*: This figure is based on all possible observations in the manufacturing sector in the data licensed in 2006.

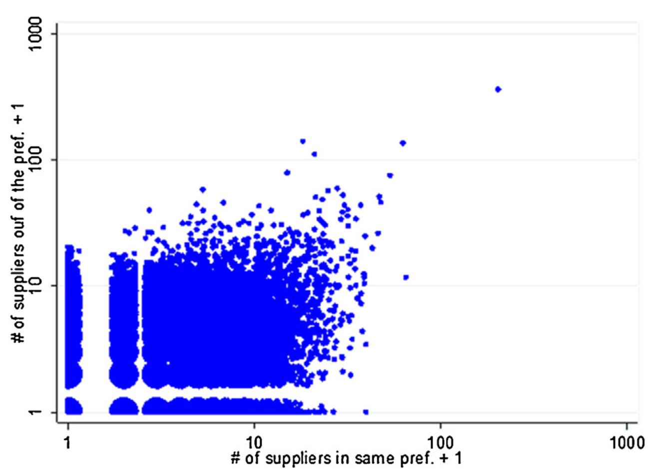


Fig. 2. Suppliers within the Prefecture and outside of the Prefecture.
Notes: This figure is based on all possible observations in the manufacturing sector in the data licensed in 2006.

trast, there are many others whose suppliers are mostly in other provinces.[2]

Firms occasionally change their suppliers and clients, and the number of suppliers and clients can thus change over time. Fig. 3 shows the distribution of the change in the number of suppliers in total (the top figure), in the same prefecture (middle), and outside of the prefecture (bottom). Approximately one-third of firms did not change the number of their suppliers from 2006 to 2012, whereas some increased this number and a smaller number decreased it. As a result, the mean of the change in the total number of suppliers is 0.99. When we focus on the number of clients rather than suppliers, we find similar characteristics.

Another key variable for the network structure is the density of each firm's ego network, which is measured by the ratio of the number of actual ties among each firm's supply chain partners (both suppliers and clients) to the number of all possible ties among them. For example, when a firm has three supply chain partners of which two also transact with one another, the density measure is 1/3 = 0.333. When a firm has only one supply chain partner, we define the density as zero. If the density measure is large, we assume that the diversity of knowledge among supply chain partners is low but that the strength of ties is high. This assumption is tested below in Section 3.3. As shown in Table 1, the mean of the network density is 0.26.

[2] Twelve percent of firms in the sample have no supplier reported in the data. We included them in the subsequent estimations.

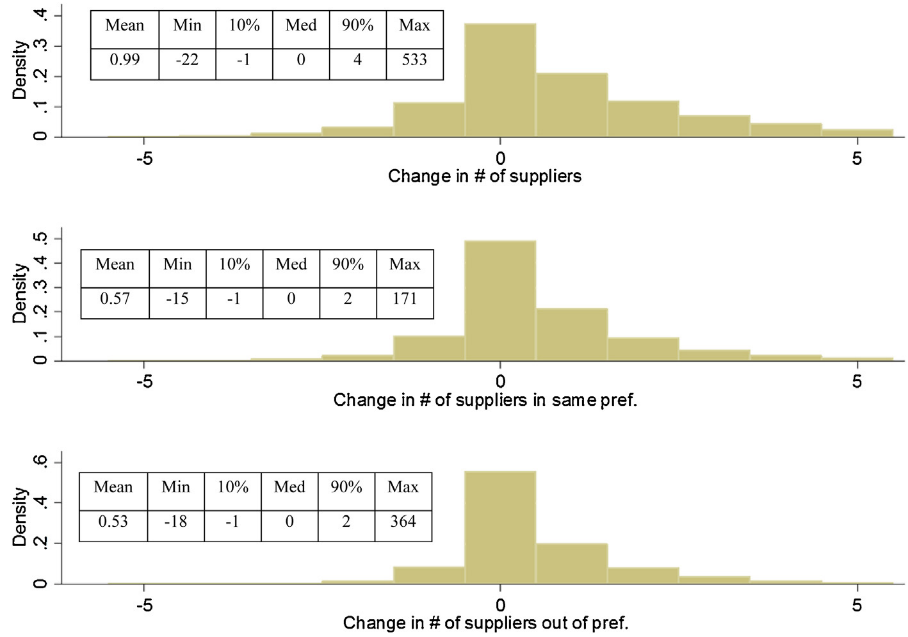


Fig. 3. Changes in the Number of Suppliers from 2006 to 2012.
Note: This figure shows the heat map of technological diversity. Each row shows the measure of the technology classes in a particular prefecture, defined by equation (1) in the text. The technology classes are listed in alphabetical order. The larger number indicates more innovations in the technology class in the prefecture than other prefectures.

Table 1
Summary Statistics.

Variables	Mean	S.D.	Min.	Max.
Number of suppliers in the same prefecture	1.92	2.58	0	204
Added one and logged	0.82	0.68	0	5.32
Number of suppliers outside of the prefecture	1.57	2.72	0	406
Added one and logged	0.69	0.67	0	6.01
Number of clients in the same prefecture	2.34	3.52	0	111
Added one and logged	0.91	0.73	0	4.72
Number of clients outside of the prefecture	2.06	3.44	0	426
Added one and logged	0.81	0.75	0	6.06
Density of ego network	0.26	0.20	0	1
Sales per worker (thousand yen)	24,278	60,871	21	5,155,000
Logged	9.73	0.77	3.06	15.46
Sales (thousand yen)	462,435	4,148,635	64	633,799,000
Logged	11.96	1.31	4.17	20.27
Number of registered patents	0.06	1.18	0	144
Firm age	41	21	0	138

Note: The number of observations is 73,628 (observations for two years for each of 36,814 firms). The density of a firm's ego network is defined as the ratio of the actual number of ties between the firm's supply chain partners to the number of all possible ties between them.

Our productivity measure is sales per worker. Obviously, value added per worker and TFP are better measures of productivity, but because the TSR data do not include value added, the costs of intermediate goods, or the amount of capital stock, we rely on sales per worker. The mean of sales per worker and sales is 24 million yen and 462 million yen, respectively (Table 1). As we have explained above, we focus on firms with only one establishment for which the mean of sales per worker and sales is smaller than the mean for all manufacturing firms (36 million yen and 1458 million yen, respectively).

One material problem with using sales per worker as a productivity measure is that it overvalues productivity for firms that purchase intermediate goods from other firms. Thus, in the context of this study, sales per worker are likely to be higher when firms are connected with more suppliers and thus procure more intermediate goods from suppliers. Regardless of the presence of knowledge diffusion through supply chain networks, a positive correlation between the number of suppliers and our productivity measure may be realized. However, this problem does not arise in this study because we employ a dynamic panel estimation method, as explained in detail below, which essentially estimates the effects of past network characteristics on the change in sales per capita rather than the contemporaneous relation between our network variables and the productivity measure.

Our measure of innovative capability is the number of registered patents. Because the minimum length between the two data periods for the TSR data is five years, we define as the number of registered patents for year t the total number of patents applied for in years from t – 4 to t and registered by 2013.[3] The mean of the number of registered patents is quite small at 0.06, as it is zero for 97.7% of firm-year observations.

[3] The average length of time from application to registration is 11 months in fiscal year 2013 (Japan Patent Office, 2014). Therefore, the patent data up to 2013 used in this study should cover most registered patents that were applied for in 2011 and 2012, the second period of the TSR data.

3.3. Network structure and knowledge diversity

As explained in the previous section, we presume in the conceptual framework (1) that knowledge of densely interconnected firms is more redundant than the diversity of knowledge acquired by firms in topologically distant parts of the economic networks and (2) that firms located in different regions are more likely to have access to diverse types of knowledge compared with geographically similar firms in the same prefectures. The two presumptions are supported by our data.

First, to examine the former presumption, we check the correlation between supply chain ties and the similarity of knowledge between pairs of firms. The measure of the similarity of knowledge between firms *i* and *j* is defined as the angle of vectors of the number of registered patent for the different technology classes of the two firms. However, if we simply calculate the angles, most of the similarity measures are zeros because most firms do not have many patents; thus, most elements of technological vectors are zeros. Therefore, we incorporate the relatedness between technologies using the weighted angular separation of Breschi et al. (2003). More specifically, let c_i be the vector that represents the number of registered patents for each of the 121 technology classes for firm *i*. In addition, let Ω be the matrix that is constructed from patent citation data and represents the relationship between technology classes. Each element shows the total number of citations between technologies. Both citing and cited relationships are counted equally. Then, the similarity measure calculated by the weighted angle[4] is

$$a_{ij} \equiv \frac{c_i \Omega c'_j}{\sqrt{(c_i \Omega c'_i) * (c_j \Omega c'_j)}}$$

Fig. 4 shows the cumulative probability distributions of the similarity measure for sub-samples of firm pairs with and without supply chain links using a sub-sample of firms with any positive number of patent applications during the period examined. This figure indicates that the knowledge of firm pairs with supply chain ties is more likely to be similar to one another than the knowledge of pairs without a tie. Further, we test whether supply chain ties and knowledge similarity are correlated using a tobit estimation with the sales of both firms, the difference between their sales, and the diversity of their knowledge as controls. Our results show a positive and highly statistically significant relation between the measure of knowledge similarity and the presence of supply chain ties.[5] When two firms are connected with a supply chain tie, their measure of knowledge similarity is larger by twice the size of its standard deviation than otherwise, on average. At this juncture, we are not concerned with causality, but this result implies that when firms are connected through supply chains, their knowledge is more likely to be similar. It is thus further implied that firms that are densely connected with one another share similar knowledge, as we have so far assumed.

Second, to examine the second presumption, we compare a measure of the revealed comparative advantage (RCA) in the innovation of different types of technology across prefectures. Applying the method developed by Balassa (1965) for RCA in the context of international trade, our RCA index for the innovation of technology class *k* in prefecture *p* is defined as

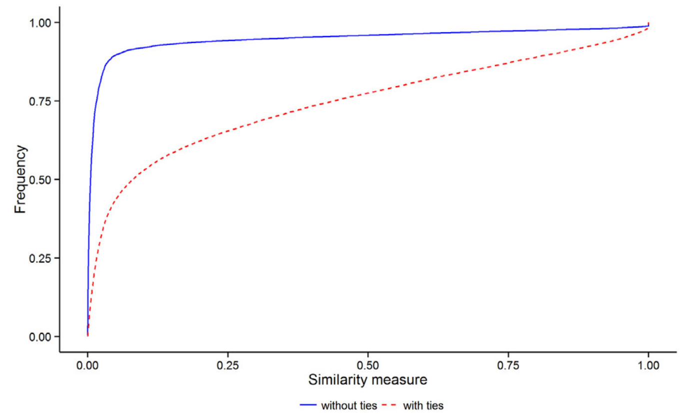


Fig. 4. Knowledge Diversification across Prefectures.
Notes: This figure shows the CDF of the similarity measure for firm pairs without supply chain ties (the solid line) and with ties (the dotted line).

$$RCA_{kp} \equiv \frac{C_{kp}/\sum_k C_{kp}}{\sum_k C_{kp}/\sum_k \sum_p C_{kp}}, \quad (1)$$

where C_{kp} is the number of registered patents in class *k* in prefecture *p*. This measure indicates the share of patents in a particular class in a particular prefecture in all patents in the prefecture, normalized by the share of the prefecture in all patents in Japan. Fig. 5 shows this measure for each of 9 prefectures, Miyagi, Tokyo, Kanagawa, Chiba, Aichi, Osaka, Hyogo, Hiroshima, and Fukuoka, the major economic hubs in Japan, illustrating that the distribution of innovations for each prefecture in terms of technology classes is not necessarily similar to one another.[6] This finding provides evidence for knowledge diversification across prefectures.

4. Empirical strategy

The conceptual framework in Section 2 shows that firms' supply chain networks affect productivity and innovative capability through the diffusion of embodied and disembodied knowledge. However, estimations of the effects of supply chain networks can be biased because of the endogeneity of covariates. For example, higher productivity may lead to larger supply chain networks, generating reverse causality because more productive firms can more easily find and be found by suppliers and clients. We employ the following estimation methods to alleviate possible biases due to endogeneity.

4.1. Effects on productivity

As we have argued, firms' performance results, including productivity and supply chain network performance, are interlinked with one another. In addition, firms' performance results and networks are affected by their own dynamics, as the recent literature on social networks suggests (Snijders and Doreian, 2010, 2012). To investigate the interlinked dynamics of firms' performance results and networks, we employ a dynamic panel simultaneous equation model in which outcome variables are assumed to be functions of their lags and other control variables, as follows:

$$\boldsymbol{Y}_{it} = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{Y}_{1t-1} + \boldsymbol{\delta}\boldsymbol{X}_{it} + \boldsymbol{\varepsilon}_{it}. \quad (2)$$

[4] We experimented with other similarity measures, such as the Horn index (Horn, 1966), the Jaccard index (Jaccard, 1912), and normalized Euclidean distance, and we obtained similar positive correlations between supply chain ties and each of the similarity measures.

[5] We employ a tobit estimation because the similarity measure is zero for many pairs. We find that the coefficient on the dummy variable for supply chain ties is 0.193 and its standard error is 0.00183, whereas the standard deviation of the similarity measure is 0.275. These results can be obtained from the authors upon request.

[6] The results for all prefectures are qualitatively the same; these results are available from the authors upon request.

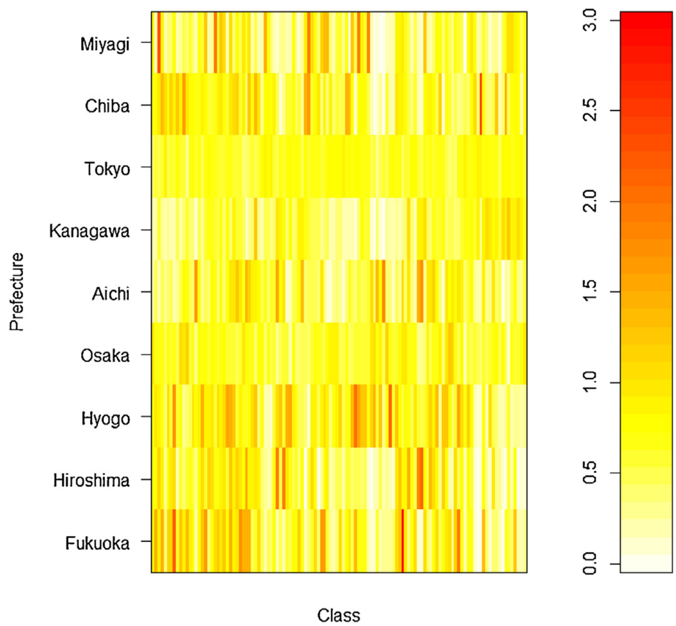


Fig. 5. Knowledge Diversification across Prefectures.
Note: This figure shows the heat map of technological diversity. Each row shows the measure of the technology classes in a particular prefecture, defined by equation (1) in the text. The technology classes are listed in alphabetical order. The larger number indicates more innovations in the technology class in the prefecture than other prefectures.

where $\boldsymbol{Y}_{it}$ is a vector of five variables that represent firm *i*'s supply-chain networks and performance: the number of suppliers or clients in the same prefecture plus one in logs, the number of suppliers or clients outside of the prefecture plus one in logs, the density of firm *i*'s ego network, sales per worker in logs, and sales in logs. Total sales are included in the set of outcome variables to represent firm size. $\boldsymbol{X}_{it}$ is a vector of control variables including firm age, firm age squared, and dummies for industries, prefectures, and years of data collection, while $\boldsymbol{\varepsilon}_{it}$ is the vector of error terms. Industries are defined at the two-digit level of the Japan Standard Industrial Classification. We allow for correlation between error terms. In this framework, $\boldsymbol{\beta}$ can be considered as a Markov matrix. We estimate equation (2) separately for ties with suppliers and clients because the numbers of suppliers and clients are closely correlated with one another; hence, incorporating both suppliers and buyers in one estimation may cause multicollinearity.

Because Eq. (2) can be rewritten as

$$\mathbf{Y}_{it} - \mathbf{Y}_{it-1} = \boldsymbol{\alpha} + (\boldsymbol{\beta} - 1)\mathbf{Y}_{it-1} + \boldsymbol{\delta}\mathbf{X}_{it} + \boldsymbol{\varepsilon}_{it} \tag{3}$$

and $\mathbf{Y}$ is in logs, we can interpret this equation as estimating effects on the growth of network and performance variables. In addition, fixed effects that determine $\mathbf{Y}$ can be eliminated in the estimation.

Given the estimates of $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\delta}$, we simulate the model to examine what would occur if the number of suppliers within or outside of the same prefecture or the network density increased. This computational exercise may lead to deeper insights into the dynamics of firms' performance and interlinked networks than estimation coefficients. In this computational analysis, we assume a hypothetical firm for which industry and prefecture dummies take their mean values and all other variables take their median values.

One shortcoming of this empirical strategy is notable. Although the number of supply chain partners is always a non-negative integer, Eq. (2) implicitly assumes that the log of the number of partners plus one is continuous. However, incorporating this limited dependent variable nature into the simultaneous equation framework requires additional assumptions in the distribution of error terms. Therefore, we assume that the log of the number of suppliers plus one is continuous.

4.2. Effects on innovation capability

When we focus on the effects of supply chain networks on innovative capability, we cannot employ the approach described above because the measure of innovative capability, the number of registered patents, is zero for 98% of firms. Therefore, we estimate a tobit model in which the dependent variable is the log of the number of registered patents plus one. It is important to take a log form because the effect of the network structure on the number of patents may diminish as the number of patents increases. To alleviate endogeneity biases due to reverse causality from innovative capability to networks, we employ the minimum chi-squared estimator from Newey (1987) using lagged network variables to instrument current network variables. We do not employ the full information maximum likelihood estimation of the tobit model because it does not converge, possibly because of the many dummy variables for industries and prefectures.

5. Results

5.1. Effects on sales per worker and total sales

The results of the estimation of dynamic panel Eq. (2) that focus on ties with suppliers for the manufacturing firms are shown in Table 2 and highlight the following five notable findings. First, the results in columns (4) and (5) highlight differences in the effects on firm performance between suppliers within the same prefecture and those outside of the prefecture. The effect of the number of suppliers within the same prefecture on productivity measured by sales per worker or firm size measured by total sales is not statistically significant at the 5% level. On the contrary, the effect of the number of suppliers outside of the same prefecture on sales per worker and sales is positive and significant at the 1% level. The results imply that ties with neighboring suppliers are less likely to improve productivity through knowledge diffusion, whereas ties with distant suppliers are more likely to do so.

Second, the density of a firm's ego network, defined as the ratio of the number of actual ties among the firm's supply chain partners to the number of all possible ties among them, has a negative and significant effect on both productivity and firm size. The negative effect of the ego-network density implies that the benefits from closely related partners are smaller than those from unrelated partners, possibly because knowledge among dense networks is overlapped to a large extent and not well diversified.

Third, the number of suppliers in the same prefecture negatively affects the number of suppliers outside of the same prefecture, and vice versa. This finding suggests that ties within and beyond the region are substitutes for one another, most likely due to the costs of creating and maintaining supply chain ties.

Fourth, the effect of the ego-network density on the number of suppliers within and outside of the same province is negative and significant. This finding implies that when the suppliers of a firm transact with one another, the firm is likely to lose some of its suppliers over time, possibly to avoid redundant ties.

Finally, we find that the effect of the number of suppliers in the same prefecture in the previous year on the same variable in the current year is positive and significant but less than one. This is also the case for the number of suppliers outside of the prefecture and the ego-network density. This evidence implies that shocks to the network structure, such as the number of suppliers, diminish over time.

Table 2
Ties with Suppliers, Network Density, and Firm Performance.

Dependent variable	(1)	(2)	(3)	(4)	(5)
	# of suppliers in the same prefecture	# of suppliers outside of the same prefecture	Density of networks among direct partners	Sales per worker	Sales
# of suppliers in the same prefecture (t-1)	0.684**	−0.0542**	−0.0366**	−0.00630	0.00256
	(0.00394)	(0.00389)	(0.00112)	(0.00470)	(0.00499)
# of suppliers outside of the same prefecture (t-1)	−0.0792**	0.705**	−0.0105**	0.0310**	0.0263**
	(0.00394)	(0.00389)	(0.00112)	(0.00469)	(0.00499)
Density of ego network (t-1)	−0.169**	−0.177**	0.729**	−0.0270*	−0.0681**
	(0.0113)	(0.0111)	(0.00319)	(0.0134)	(0.0143)
Sales per worker (t-1)	−0.0256**	−0.00582	−0.00218	0.699**	−0.113**
	(0.00393)	(0.00388)	(0.00111)	(0.00468)	(0.00498)
Sales (t-1)	0.128**	0.112**	−0.00414**	0.104**	1.056**
	(0.00260)	(0.00256)	(0.000737)	(0.00310)	(0.00329)
Observations	36,814	36,814	36,814	36,814	36,814
R-squared	0.619	0.637	0.619	0.610	0.850

Notes: Standard errors are in parentheses. * and ** signify statistical significance at the 5 and 1% level, respectively. The number of suppliers of any type is added one and logged. Sales per worker and sales are also logged. The density of a firm's ego network is defined as the ratio of the actual number of ties between the firm's supply chain partners to the number of all possible ties between them. Age, age squared, industry dummies, prefecture dummies, and survey year dummies are included, but the results are not shown for brevity.

Table 3
Ties with Clients, Network Density, and Firm Performance.

Dependent variable	(1)	(2)	(3)	(4)	(5)
	#of clients in the same prefecture	# of clients outside of the same prefecture	Density of networks among direct partners	Sales per worker	Sales
# of clients in the same prefecture (t-1)	0.746**	−0.0503**	−0.0383**	0.00877*	0.00718
	(0.00368)	(0.00366)	(0.000974)	(0.00412)	(0.00437)
# of clients outside of the same prefecture (t-1)	−0.0735**	0.743**	−0.0102**	0.00639	0.0304**
	(0.00383)	(0.00380)	(0.00101)	(0.00428)	(0.00454)
Density of ego network (t-1)	−0.304**	−0.182**	0.723**	−0.0301*	−0.0646**
	(0.0120)	(0.0119)	(0.00318)	(0.0134)	(0.0143)
Sales per worker (t-1)	−0.00697	−0.0179**	−0.000801	0.699**	−0.112**
	(0.00419)	(0.00417)	(0.00111)	(0.00469)	(0.00498)
Sales (t-1)	0.0649**	0.106**	−0.00645**	0.106**	1.054**
	(0.00270)	(0.00269)	(0.000715)	(0.00302)	(0.00321)
Observations	36,814	36,814	36,814	36,814	36,814
R-squared	0.632	0.663	0.623	0.610	0.850

Notes: Standard errors are in parentheses. * and ** signify statistical significance at the 5 and 1% level, respectively. The number of clients of any type is added one and logged. Sales per worker and sales are also logged. The density of a firm's ego network is defined as the ratio of the actual number of ties between the firm's supply chain partners to the number of all possible ties between them. Age, age squared, industry dummies, prefecture dummies, and survey year dummies are included, but the results are not shown for brevity.

Next, we focus on ties with clients rather than suppliers and repeat the same analysis; we show the results in Table 3. The five major findings from the analysis focusing on suppliers apply to the analysis using clients, except for one. The number of neighboring clients in the same prefecture has a positive effect on sales per worker, whereas the number of neighboring suppliers has no significant effect. By contrast, the number of distant clients has a positive effect on total sales, as does the number of distant suppliers. The difference in the effects on productivity between ties with suppliers and clients suggests that knowledge diffusion from suppliers and clients is different in nature, as we argue below in greater detail.

To illustrate how changes in supply chain networks affect firm performance and the structure of networks over time, we simulate Eq. (2) using the results presented in Tables 2 and 3. In the simulation, we first assume that a hypothetical median firm with median characteristics in terms of all independent variables increases the number of suppliers or clients within or outside of the prefecture by 50%. The median value of the number of suppliers or clients within or outside of the prefecture is 1, and we add one to the number of suppliers before taking a log. Therefore, a 50% increase in the variable implies an additional one supplier or client within or outside of the prefecture.

Fig. 6 illustrates the simulation results when the number of neighboring suppliers or clients increases. On the one hand, the left figure indicates that when the number of suppliers within the prefecture increases by a shock, the number of suppliers outside of the prefecture declines due to substitutability between the two types of suppliers. Then, because ties with neighboring suppliers do not contribute to firm performance whereas ties with distant suppliers do (Table 2), sales per worker decline slightly, and sales do not change substantially over time. On the other hand, the right panel of Fig. 6 shows that when the number of neighboring clients increases, sales per worker improve over time due to the positive effect of neighboring clients on productivity.

We now repeat the same simulation assuming an increase in the number of distant suppliers or clients by 50% and show the results in Fig. 7. Unlike the effect of neighboring suppliers, the effect of

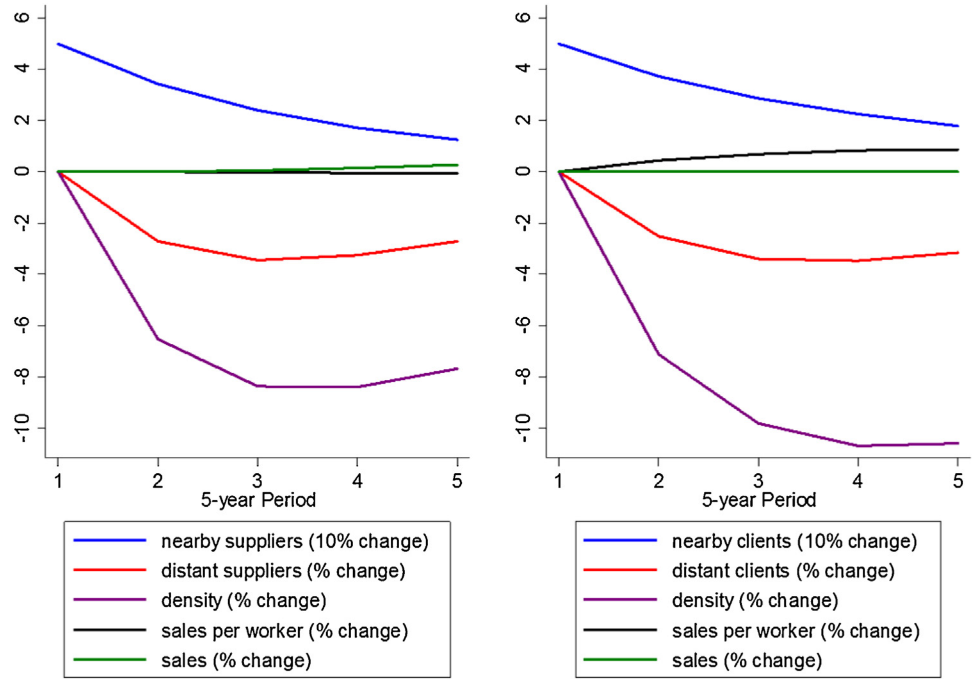


Fig. 6. Long-run Effect of an Increase in the Number of Suppliers (left) and Clients (right) within the Same Prefecture.
Notes: These figures are drawn from simulations of the five variables, the log of the number of nearby suppliers (right) or clients (left) within the same prefecture plus one, the log of the number of distant suppliers (right) or clients (left) outside of the same prefecture plus one, the density of each firm's ego network (measured by the ratio of actual ties among supply chain partners to all possible ties), the log of sales per worker, and the log of sales of the hypothetical median firm. An increase in the log of the number of nearby suppliers or clients within the same prefecture by 50% is assumed. Each line indicates the percentage change (or 10% change, if indicated) in the variable assuming the change in the number of suppliers or clients compared with the variable without the change.

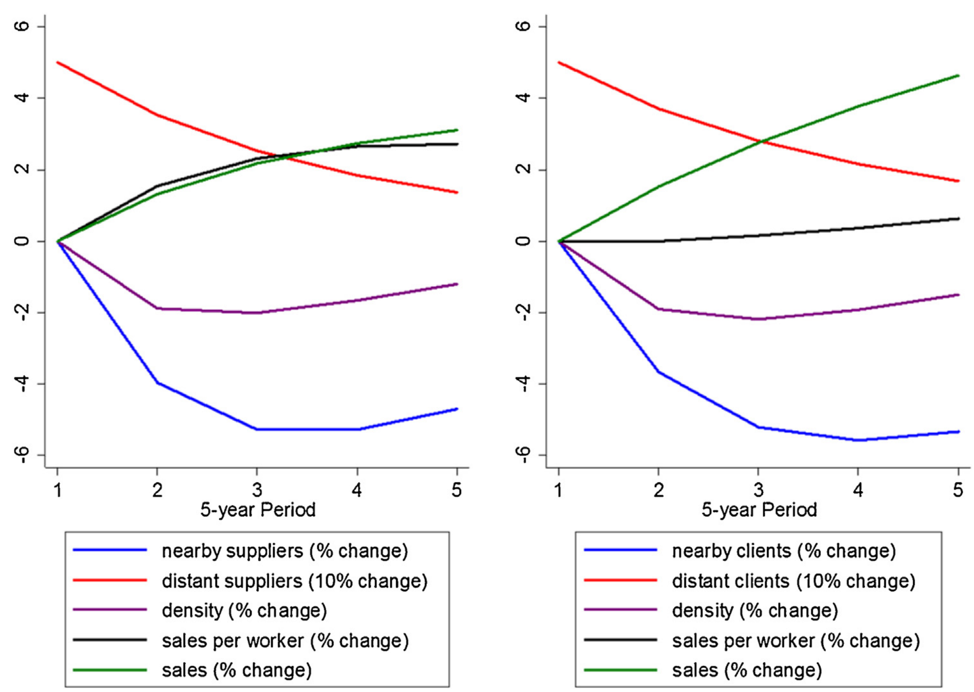


Fig. 7. Long-run Effect of an Increase in the Number of Suppliers (left) and Clients (right) outside of the Prefecture.
Notes: These figures are drawn from simulations of the five variables, the log of the number of nearby suppliers (right) or clients (left) within the same prefecture plus one, the log of the number of distant suppliers (right) or clients (left) outside of the prefecture plus one, the density of each firm's ego network (measured by the ratio of actual ties among supply chain partners to all possible ties), the log of sales per worker, and the log of sales of the hypothetical median firm. An increase in the log of the number of distant suppliers or clients outside of the prefecture by 50% is assumed. Each line indicates the percentage change (or 10% change, if indicated) in the variable assuming the change in the number of suppliers or clients compared with the variable without the change.

distant suppliers on sales per worker and total sales is positive and significant. As a result, in the left figure of Fig. 7, both sales per worker and total sales improve substantially over time due to the expansion of ties with distant suppliers. The effect of the number of distant clients on total sales is also positive and significant, whereas its effect on sales per capita is insignificant. Therefore, in the right figure of Fig. 7, in which ties with distant clients expand, total sales improve to a great extent, whereas sales per worker improve only slightly in association with the increase in firm size.

We conduct the same simulation for an increase in the density of the hypothetical median firm's ego network. Fig. 8 shows that denser ego networks clearly lead to less productivity, smaller firm size, and smaller networks.

We further incorporate the interaction term between the density of the ego network and the number of distant suppliers or clients as a control variable to test the complementarity between strong ties and ties with outsiders, as discussed above in Section 2. The results in column (4) of Tables 4 and 5 shows that the coefficient on the interaction term between the density measure and the number of distant partners is positive and significant which implies that the negative effects of network density can be alleviated when firms are connected with distant partners and are hence exposed to diversified knowledge. Judging from the values of the coefficients of density and the interaction term, the net effect of network density is positive if the log of the number of distant suppliers or clients plus one is approximately greater than one or the number of suppliers or clients is approximately greater than two.

To check the robustness of these results, we run two-stage least squares (2SLS) estimations of the log of sales per worker or the log of total sales on the current number of neighboring and distant suppliers or clients and other controls and use the lagged number of suppliers or clients as instruments. The results shown in Table 6 are virtually identical to the benchmark results in columns (4) and (5) of Tables 4 and 5.

We also check the possible differences across industries by dividing the sample into two, the first for machinery and equipment industries, including the general machinery, electrical machinery, electronics, transportation equipment, and precision equipment industries, and the second for other industries. Because supply chain networks in the machinery and equipment industries in Japan are often characterized as *keiretsu*, in which suppliers and clients are closely connected with one another (Aoki, 1989), the effects of supply chain networks in these industries may be different from those in other industries. However, the main results from the two sub-samples, which are not shown here in the interests of brevity but are available upon request, are similar to the benchmark results for the entire sample.

5.2. Effects on the number of registered patents

The estimation results of the effects of suppliers and clients on registered patents from the two-step Tobit estimation of Newey (1987) are shown in columns (1)–(2) and (3)–(4) of Table 7, respectively. Columns (1) and (3) indicate that the effect of the number of distant suppliers and clients on innovative capability is positive and significant, whereas the effect of neighboring suppliers and clients is either insignificant or negative but weakly significant. The result implies that ties with distant partners are more important to innovative activities than to productivity improvement in production activities, possibly because the former requires more diversified knowledge than the latter.

When the interaction term between the ego-network density and the number of distant suppliers is incorporated (columns [2] and [4] of Table 7), the coefficient on the interaction term is positive, whereas the coefficient on the density is negative and significant at the 10% level. Although the significance level of the result is quite low, it is nonetheless similar to the result regarding the effect on sales per worker. We interpret this evidence as weakly indicating that dense networks are harmful to knowledge diffusion for innovation, although the negative effect can be alleviated by ties with distant suppliers.

5.3. Discussion

A notable finding from the results delineated above is that sales per worker, a measure of productivity, increases as the number of distant suppliers increases, whereas neighboring suppliers do not affect productivity. This contrasting effect of neighboring and distant suppliers may be explained by the positive effect of input varieties on productivity argued by Dixit and Stiglitz (1977). Because parts, components, and materials from distant suppliers may be more diversified than those from neighboring suppliers, ties with distant suppliers enhance productivity more than ties with neighboring suppliers.

However, the results focusing on clients are completely different: productivity is positively affected by neighboring clients but not by distant clients. Ties with clients enhance productivity when clients provide new information or knowledge to their suppliers. In Japan, this knowledge transfer from clients to suppliers is frequently channeled through explicit knowledge sharing institutions, as Dyer and Nobeoka (2000) illustrate in the case of Toyota. In addition, suppliers and clients are often engaged in research collaboration to develop parts and components that meet the demand of suppliers and are of high quality. Our result implies that such knowledge transfer is easier when suppliers and clients are geographically closer to one another.

The stark contrast between suppliers and their clients indicates that distance plays different roles in knowledge diffusion between suppliers and their clients. Because knowledge from suppliers is embodied in their intermediate products, clients can benefit from having distant suppliers simply by using their products because such products are likely to be different from those of neighboring suppliers. However, because the transfer of disembodied knowledge from clients to suppliers through technical assistance and research collaboration requires direct communication between them (for example, in the provision of technical support by suppliers), suppliers can learn more from neighboring suppliers than they can from distant suppliers. This result is consistent with previous findings in psychology that face-to-face communication builds trust (Burt and Knez, 1995; Das and Teng, 1998; Hill et al., 2009; Vangen and Huxham, 2003; Wilson et al., 2006). When the level of trust among firms is high, they are more likely to understand knowledge disseminated from a member firm and to have faith in the accuracy of the knowledge.

The results regarding the effect on the number of registered patents, a measure of innovative capability, are different from those on productivity because we find a positive effect for distant suppliers and clients but no significantly positive effect for neighboring suppliers or clients. Because knowledge for innovation is more likely to be disembodied and to require face-to-face communication for its diffusion, the result, which is different from the positive effects of neighboring clients on productivity through disembodied knowledge diffusion, is surprising at first glance. However, this result can be convincingly understood because it implies that the diversity of knowledge associated with distant partners is more important to knowledge for innovation than to knowledge for production. Section 3.3 and Fig. 4 shows that knowledge for innovation is indeed diversified across prefectures, supporting this interpretation.

Another important finding from our results is that the density of a firm's ego network, which represents the extent to which a firm's supply chain partners are connected with one another, has a negative effect on all key variables, namely, sales per worker, total sales, the number of registered patents, and ties with suppliers and clients. Section 3.3 and Fig. 3 shows a positive correlation

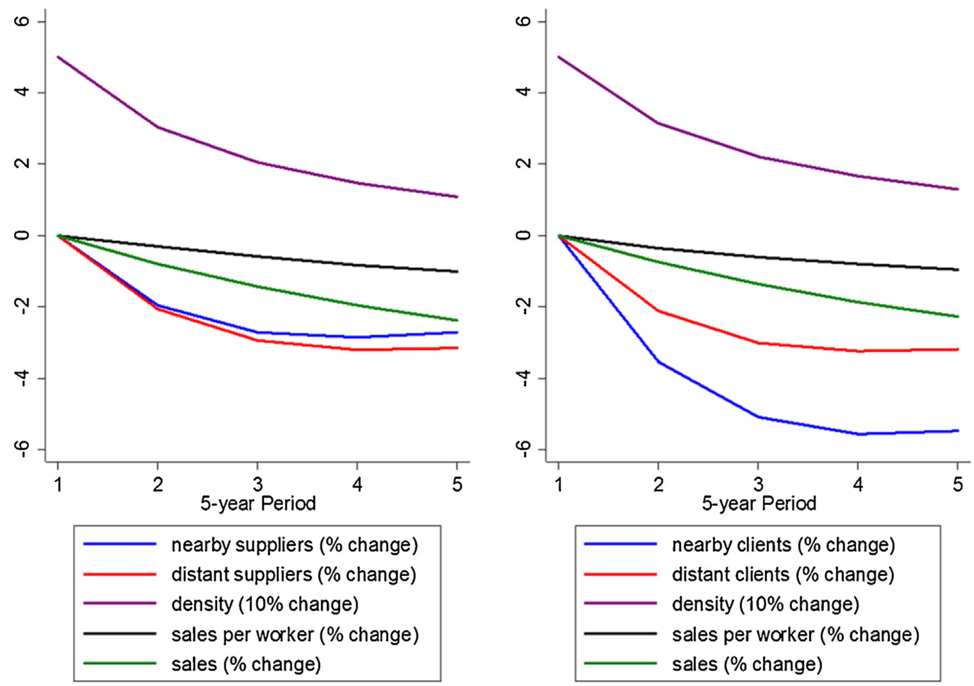


Fig. 8. Long-run Effect of an Increase in the Density of Ego Network.
Notes: These figures are drawn from simulations of the five variables, the log of the number of nearby suppliers (right) or clients (left) within the same prefecture plus one, the log of the number of distant suppliers (right) or clients (left) outside of the same prefecture plus one, the density of each firm's ego network (measured by the ratio of actual ties among supply chain partners to all possible ties), the log of sales per worker, and the log of sales, of the hypothetical median firm. An increase in the density of the firm's ego network by 50% is assumed. Each line indicates the percentage change (or 10% change, if indicated) in the variable assuming the change in the number of suppliers or clients compared with the variable without the change.

Table 4
Interaction between Ties with Suppliers and Network Density.

Dependent variable	(1)	(2)	(3)	(4)	(5)
	# of suppliers in the same prefecture	# of suppliers outside of the same prefecture	Density of networks among direct partners	Sales per worker	Sales
# of suppliers in the same prefecture (t-1)	0.684**	−0.0538**	−0.0365**	−0.00574	0.00240
	(0.00395)	(0.00390)	(0.00112)	(0.00471)	(0.00500)
# of suppliers outside of the same prefecture (t-1)	−0.0774**	0.695**	−0.0114**	0.0202**	0.0295**
	(0.00578)	(0.00571)	(0.00164)	(0.00689)	(0.00732)
Density of ego network (t-1)	−0.165**	−0.198**	0.727**	−0.0506**	−0.0610**
	(0.0146)	(0.0144)	(0.00413)	(0.0174)	(0.0185)
# of suppliers outside of the same prefecture * Density of ego network (t-1)	−0.00748	0.0411*	0.00378	0.0464*	−0.0139
	(0.0182)	(0.0179)	(0.00515)	(0.0217)	(0.0230)
Sales per worker (t-1)	−0.0256**	−0.00584	−0.00218	0.699**	−0.113**
	(0.00393)	(0.00388)	(0.00111)	(0.00468)	(0.00498)
Sales (t-1)	0.128**	0.112**	−0.00415**	0.104**	1.056**
	(0.00260)	(0.00256)	(0.000737)	(0.00310)	(0.00329)
Observations	36,814	36,814	36,814	36,814	36,814
R-squared	0.619	0.637	0.619	0.610	0.850

Notes: Standard errors are in parentheses. * and ** signify statistical significance at the 5 and 1% level, respectively. The number of suppliers of any type is added one and logged. Sales per worker and sales are also logged. The density of a firm's ego network is defined as the ratio of the actual number of ties between the firm's supply chain partners to the number of all possible ties between them. Age, age squared, industry dummies, prefecture dummies, and survey year dummies are included, but the results are not shown for brevity.

between supply chain ties and knowledge similarity. Therefore, the negative effect of the density of networks on productivity and innovation capability, although weak for the latter, implies that firms in dense networks already share the same knowledge and cannot learn substantially from one another, as a consequence. However, this negative effect of density can be alleviated when the firm is connected with distant firms because distant partners can bring new knowledge that is unavailable in dense networks.

The results described above contradict those of some previous studies. For example, Bernard et al. (2014) and Belderbos et al. (2015) used the TSR data for 2006 and found a negative effect of distance to supply chain partners on productivity. This contradiction is most likely because the two studies did not focus on

Table 5
Interaction between Ties with Clients and Network Density.

Dependent variable	(1)	(2)	(3)	(4)	(5)
	# of clients in the same prefecture	# of clients outside of the same prefecture	Density of networks among direct partners	Sales per worker	Sales
# of clients in the same prefecture (t-1)	0.746**	−0.0499**	−0.0385**	0.00928*	0.00718
	(0.00369)	(0.00366)	(0.000974)	(0.00412)	(0.00438)
# of clients outside of the same prefecture (t-1)	−0.0843**	0.731**	−0.00329*	−0.0104	0.0302**
	(0.00574)	(0.00570)	(0.00152)	(0.00642)	(0.00682)
Density of ego network (t-1)	−0.330**	−0.212**	0.740**	−0.0715**	−0.0650**
	(0.0160)	(0.0159)	(0.00423)	(0.0179)	(0.0190)
# of clients outside of the same prefecture	0.0449*	0.0499**	−0.0289**	0.0700**	0.000529
* Density of ego network (t-1)	(0.0179)	(0.0178)	(0.00472)	(0.0200)	(0.0212)
Sales per worker (t-1)	−0.00718	−0.0181**	−0.000666	0.699**	−0.112**
	(0.00420)	(0.00417)	(0.00111)	(0.00469)	(0.00498)
Sales (t-1)	0.0650**	0.106**	−0.00649**	0.106**	1.054**
	(0.00270)	(0.00269)	(0.000715)	(0.00302)	(0.00321)
Observations	36,814	36,814	36,814	36,814	36,814
R-squared	0.632	0.663	0.624	0.610	0.850

Notes: Standard errors are in parentheses. * and ** signify statistical significance at the 5 and 1% level, respectively. The number of clients of any type is added one and logged. Sales per worker and sales are also logged. The density of a firm's ego network is defined as the ratio of the actual number of ties between the firm's supply chain partners to the number of all possible ties between them. Age, age squared, industry dummies, prefecture dummies, and survey year dummies are included, but the results are not shown for brevity.

Table 6
Ties with Supply Chain Partners and Firm Performance: Results from IV Estimations.

Dependent variable	(1)	(2)	(3)	(4)
	Sales per worker	Sales	Sales per worker	Sales
# of suppliers in the same prefecture (t)	−0.00538	0.00147		
	(0.00714)	(0.00757)		
# of suppliers outside of the same prefecture (t)	0.0254*	0.0421**		
	(0.0108)	(0.0115)		
# of clients in the same prefecture (t)			0.0124*	0.00838
			(0.00586)	(0.00620)
# of clients outside of the same prefecture (t)			−0.0160	0.0422**
			(0.00951)	(0.0101)
Density of ego network (t)	−0.0741*	−0.0687*	−0.107**	−0.0712*
	(0.0292)	(0.0310)	(0.0286)	(0.0303)
# of suppliers outside of the same prefecture (t)	0.0734*	−0.0247		
* density of ego network (t)	(0.0355)	(0.0377)		
# of clients outside of the same prefecture (t)			0.106**	−0.00632
* density of ego network (t)			(0.0310)	(0.0329)
Sales per worker (t-1)	0.698**	−0.113**	0.699**	−0.111**
	(0.00469)	(0.00497)	(0.00470)	(0.00497)
Sales (t-1)	0.0994**	1.051**	0.104**	1.048**
	(0.00381)	(0.00404)	(0.00340)	(0.00360)
Observations	36,814	36,814	36,814	36,814
R-squared	0.611	0.851	0.611	0.852

Notes: Standard errors are in parentheses. * and ** signify statistical significance at the 5 and 1% level, respectively. The number of suppliers or clients of any type is added one and logged. Sales per worker and sales are logged. The density of a firm's ego network is defined as the ratio of the actual number of ties between the firm's supply chain partners to the number of all possible ties between them. Age, age squared, industry dummies, prefecture dummies, and survey year dummies are included, but the results are not shown for brevity.

single-establishment firms as we do. In fact, when we included multi-establishment firms in our analysis, we found a positive and negative effect for the number of suppliers within and outside of the same prefecture, respectively, on sales per worker. As discussed above in Section 3.1, distance to supply chain partners cannot be identified clearly when these partners have multiple establishments because the TSR data for supply chain partners are at the firm rather than the establishment level. Therefore, our focus on single-establishment firms is justified. In addition, Bernard et al. (2014) and Belderbos et al. (2015) did not distinguish between ties with suppliers and clients or incorporate network density, as we do in this study.

The negative role of network density in knowledge diffusion found in this study contrasts with the findings of Ahuja (2000) and Centola (2010), who found a positive role for network density. However, our finding is consistent with many other studies in the previous literature that have found the "strength of weak ties" (Granovetter, 1973), or the importance of ties with outsiders in information diffusion. Burt (1992, 2004) also argues that structural holes – actors who connect groups with complementary resources or information – can promote their performance. Using data from university laboratories, Perry-Smith (2006) found that the number of strong ties for each member of a laboratory, as measured by the subjective closeness, duration, and frequency of his/her relation-

Table 7
Ties with Suppliers and Clients and Innovation.
Dependent variable: log of the number of patents plus one.

	(1)	(2)	(3)	(4)
# of suppliers in the same prefecture (t-1)	0.120	0.146+		
	(0.0781)	(0.0791)		
# of suppliers outside of the same prefecture (t-1)	0.214**	0.0734		
	(0.0724)	(0.114)		
# of clients in the same prefecture (t-1)			−0.118+	−0.104
			(0.0658)	(0.0661)
# of clients outside of the same prefecture (t-1)			0.295**	0.228*
			(0.0616)	(0.0995)
Density of ego network (t-1)	−0.116	−0.747+	−0.225	−0.721+
	(0.245)	(0.424)	(0.250)	(0.436)
# of suppliers outside of the same prefecture (t-1) * density of ego network (t-1)		0.666+		
		(0.398)		
# of clients outside of the same prefecture (t-1) * density of ego network (t-1)				0.338
				(0.344)
Sales (t-1)	0.233**	0.227**	0.264**	0.269**
	(0.0608)	(0.0612)	(0.0578)	(0.0581)
# of workers (t-1)	0.195*	0.201*	0.214**	0.211**
	(0.0789)	(0.0794)	(0.0787)	(0.0794)
# of patents (t-1)	1.667**	1.673**	1.650**	1.648**
	(0.0751)	(0.0754)	(0.0741)	(0.0741)
Observations	36,839	36,839	36,839	36,839

Notes: Standard errors are in parentheses. +, *, and ** signify statistical significance at the 10, 5, and 1% level, respectively. The number of clients of any type is added one and logged. Sales per worker and sales are also logged. The density of a firm's ego network is defined as the ratio of the actual number of ties between the firm's supply chain partners to the number of all possible ties between them. Age, age squared, industry dummies, prefecture dummies, and survey year dummies are included, but the results are not shown for brevity.

ship, has a negative effect on the creativity of laboratories, whereas the number of weak ties has a positive effect. Furthermore, our finding that the negative effect of network density can be alleviated by ties with distant firms is consistent with Phelps (2010), Rost (2011), and Tiwana (2008), who found complementarity between strong ties within the community and weak ties with outsiders.

In summary, our results emphasize the importance of the diversity of networks in knowledge diffusion. Therefore, we suggest that to maximize the benefits of knowledge diffusion through supply chain networks, firms should be connected with outsiders, including distant firms and firms unrelated to current suppliers and clients.

However, these results should be viewed with caution for the following two reasons. First, the results do not necessarily mean that having any additional supply chain partners outside of the prefecture stimulates productivity and innovative capability because firms typically choose high-productivity partners carefully. Our results may suggest that distant partners promote knowledge diffusion when they are carefully – not randomly – chosen.

Second, geographic diversification of supply chain partners is costly; we find that a larger number of ties with distant supply chain partners is associated with a smaller number of ties with neighboring partners. This substitution between neighboring and distant partners is most likely due to the costs of maintaining supply-chain ties, which are also found in Phelps et al. (2012), among others. Therefore, the net benefit of the geographic diversification of supply chain partners – or its benefits from knowledge diffusion less its creation and maintenance costs – remains unclear.

Nonetheless, the need for cautious interpretation does not alter our main conclusion. Distant firms enjoy more diversified knowledge than neighboring firms. This diversified knowledge can improve partner firms' productivity and innovative capabilities, although it may be costly to find such valuable partners outside of the prefecture.

5.4. *Robustness checks*

To check the robustness of our empirical results, we experimented with several alternative specifications. First, to examine the effects of geography on knowledge diffusion, we distinguished between suppliers/clients within and outside of the same prefecture. This is because the current prefecture borders are mostly based on historical regional borders and thus reflect differences in culture and identity. However, it is possible that geographical distance affects knowledge diffusion more than prefecture borders do. Therefore, we incorporated the number of suppliers/clients within or outside of a 50 km radius to test which geographic measure is more important. To calculate the distance between two firms, we converted their addresses to geographic coordinates using the CSV address matching service of the Center for Spatial Information Science of the University of Tokyo.

Second, it is possible that firms in industrial regions, such as Tokyo and Osaka, play a more important role in knowledge diffusion than firms in rural regions do. For example, as Fig. 4 illustrates, the technical expertise accessible in the Tokyo metropolis is not limited to any particular technological category, as opposed to smaller prefectures that tend to host more specialized industries. Therefore, the positive effects of distant firms may reflect the effects of firms in major industrial prefectures on firms in remote prefectures. To check the effect of firms in industrial centers, we incorporate the number of suppliers/clients in the four most populated prefectures, Tokyo, Kanagawa, Aichi, and Osaka, in the benchmark regressions.

Third, positive effects of distant firms may pick up positive effects of distant firms related through capital ownership because distant partners are more likely to be affiliated than neighboring partners are. If this is the case, the positive correlation between firm performance and ties with distant firms may come from knowledge diffusion within the firm group. Thus, we incorporate the number of affiliated suppliers/clients, which are defined in the TSR data, in the estimations.

The results from these alternative specifications in Table 8 indicates that the benchmark results hold and that the effect of the additional variables is either insignificant or significantly negative. In columns (4) and (8) of Panel B, the effect of affiliated partners is negative, confirming our previous conclusion that overly strong ties are harmful to firm performance.

Table 8
Robustness Checks.

Panel (A): Effects on sales per worker from seemingly unrelated regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# of suppliers				# of clients			
In the same prefecture	−0.00138	−0.00641	−0.00551	−0.00639	−0.00392	0.00915*	0.0142**	0.00881*
	(0.0106)	(0.00474)	(0.00523)	(0.00470)	(0.00960)	(0.00417)	(0.00450)	(0.00413)
Outside of the same prefecture	0.0319**	0.0296**	0.0326**	0.0307**	0.00402	0.0103	0.0196**	0.00640
	(0.00503)	(0.00856)	(0.00677)	(0.00469)	(0.00457)	(0.00806)	(0.00614)	(0.00428)
Within 50 km	−0.00539				0.0139			
	(0.0104)				(0.00952)			
Beyond 50 km		0.00165				−0.00478		
		(0.00883)				(0.00823)		
In industrial prefectures			−0.00254				−0.0204**	
			(0.00740)				(0.00678)	
Related through capital ownership				0.0660				0.00600
				(0.0424)				(0.0350)

Panel (B): Effects on the number of patents from IV-tobit estimations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# of suppliers				# of clients			
In the same prefecture	−0.0153	0.128	0.139+	0.126	0.0124	−0.126+	−0.179**	−0.127+
	(0.159)	(0.0786)	(0.0819)	(0.0780)	(0.134)	(0.0662)	(0.0687)	(0.0661)
Outside of the same prefecture	0.184*	0.370*	0.260*	0.218**	0.318**	−0.150	0.113	0.283**
	(0.0766)	(0.162)	(0.102)	(0.0722)	(0.0642)	(0.173)	(0.0911)	(0.0619)
Within 50 km	0.152				−0.147			
	(0.158)				(0.132)			
Beyond 50 km		−0.188				0.489**		
		(0.167)				(0.177)		
In industrial prefectures			−0.0755				0.276**	
			(0.113)				(0.105)	
Related through capital ownership				−1.254**				−0.629*
				(0.423)				(0.303)

Notes: Standard errors are in parentheses. +, *, and ** signify statistical significance at the 10, 5, and 1% level, respectively. The number of clients of any type is added one and logged. The other independent variables used in the benchmark regression are also included, but the results are not shown for brevity.

One exception is column (6) of Panel B of Table 8, which shows a positive effect of clients outside of the 50 km radius and an insignificant effect of clients outside of the prefecture. This implies that geographic distance is more important than prefecture borders in some types of knowledge diffusion. However, our conclusion that distant firms contribute to the diffusion of knowledge for innovation more than neighboring firms do remains unchanged.

The other exception is column (7) of Panel B, which shows a positive effect of clients in industrial centers and an insignificant effect of distant clients. This result implies that the positive effect of distant clients on innovative capacity in the benchmark result indicates that knowledge from clients in industrial centers promotes innovation. This is probably because firms in remote regions may be connected to assemblers in industrial regions but not to buyers in other remote regions. However, in the other three specifications (columns 3 and 7 in Panel A and column 3 in Panel B), partners in industrial centers are found to have no positive effect on firm performance, whereas distant partners have an effect. Therefore, our conclusion that the diversity of partner firms promotes firm performance through knowledge diffusion should still be valid, although we must note that in some cases, access to advanced knowledge in industrial centers may be more important than access to diversified knowledge.

Finally, the correlation between the number of transaction partners and sales may reflect higher prices due to the monopoly power of firms with many clients. As Rauch (1999) finds, differentiated products are more likely to be traded locally than homogeneous products are. Therefore, we added the share of each firm's sales in the total sales at the 3-digit industry and prefecture level as a control variable. However, the effect of the market share on sales and sales per worker is insignificant, whereas the other results are virtually the same. The results are not shown for brevity but are available upon request.

6. Conclusion

This paper examines the effects of the structure of supply chain networks on productivity and innovation capability through knowledge diffusion using firm-level panel data for Japan. The dataset is large, including 800,000 to one million firms per period and four to five million buyer-supplier ties, although we ultimately focus on a sub-sample of single-establishment manufacturing firms. This study is the first to examine the effect of the structure of the entire supply chain network in a large economy – and notably the density of each firm's ego network – on knowledge diffusion. We find that ties with distant suppliers improve productivity, measured by sales per worker, which is most likely because intermediates from distant firms embody diversified knowledge. Ties with neighboring clients also improve productivity, which is most likely because the diffusion of disembodied knowledge from neighboring clients is more effective than from distant clients. By contrast, ties with distant suppliers and clients improve innovative capability, as measured by the number of registered patents, more than ties with neighboring suppliers and clients, which emphasizes the particular importance of the diversity of knowledge to innovation. In addition, the density of a firm's ego network, which is measured by how densely its supply chain partners transact with one another, is found to have a negative effect on productivity and innovative capability, implying knowledge overlaps and redundancy in densely connected firms. Overall, our results emphasize the importance of diversified partners in knowledge diffusion through supply chain networks, although the net benefit from diversified networks should be evaluated with caution because of the higher costs of creating ties with diversified partners than with geographic or relational neighbors.

This paper provides unique policy implications. Many existing studies have emphasized knowledge spillovers within geographical regions (Marshall, 1890; Rosenthal and Strange, 2004) and thus have emphasized the importance of policies to promote industrial clusters for regional development by, for example, promoting research collaboration within the region. On the contrary, this paper suggests the promotion of supply chain ties with outsiders, which can be achieved by organizing trade fairs in the region and subsidizing firms' participation in trade fairs outside of the region.

Some shortcomings and suggestions for future work are notable. First, when examining the effects of geographic distance to supply chain partners, we distinguish only among partners within and outside of the same prefecture to simplify the estimation. Nonlinear estimation methods, as used in Belderbos et al. (2015), may lead to more accurate estimates of the effect of geography. Second, we utilize sales per worker as a measure of productivity due to data limitations. Although our use of a dynamic panel simultaneous equation model can alleviate the problem arising from this approach, as we argued in Section 3.2, using labor productivity or TFP is clearly preferable. This problem might be overcome by merging the TSR data with other data in which value added and the amount of capital are available.

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