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Abstract

This study examines how the research collaboration of firms affects the quality of their innovation outcomes using comprehensive patent data for firms in the world from 1991 to 2010. Identifying research collaboration by co-patenting relationships, we find that research collaboration with other firms, particularly with foreign firms, leads to substantial improvement in innovation quality. We also observe an inverted U-shaped effect of the density of a firm's ego network and a positive effect of brokerage in the global network, especially for firms with international collaboration experiences. These results are applicable to the effect on the quality of innovation achieved individually without any collaboration, suggesting that the knowledge of firms diffuses to and is acquired by their collaboration partners. Finally, we find that the collaboration effect is larger in the 2000s than in the 1990s and varies across countries.

Keywords: Research collaboration, Network, Innovation, Co-patenting
JEL classification: F14, F23, L14

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1. Introduction

Because innovation is mostly generated from a combination of different types of knowledge (Schumpeter 1934), knowledge diffusion through networks of individuals, firms, and institutions is an important driver of innovation (Jackson 2010). Accordingly, the effect of networks on innovation has recently been examined extensively in the literature as surveyed in Phelps, Heidl, and Wadhwa (2012). A major type of network for knowledge diffusion is research collaboration (Ahuja 2000, Fleming, King III, and Juda 2007, Fleming, Mingo, and Chen 2007, Forti, Franzoni, and Sobrero 2013, Gonzalez-Brambila, Veloso, and Krackhardt 2013, among many others), while some other types, such as supply chains (Fitjar and Rodríguez-Pose 2013, Todo, Matous, and Inoue 2016) and interpersonal interactions (Brennecke and Rank 2017, Perry-Smith 2006, Sosa 2011), can facilitate knowledge diffusion. Some of the studies above examine research collaboration among firms using patent data or unique firm-level data on research alliances, while others investigate collaboration among academic researchers using data from academic publications or collaboration among project teams or individual workers.

Although numerous studies have used various types of agents and collaborations, the literature has not reached a consensus about the effect of research collaboration networks on innovation in mainly three aspects. First, mixed results have been found concerning the effect of geographically distant ties on innovation. Geographically proximate linkages often observed in practice (D'Este, Guy, and Iammarino 2012, Hoekman, Frenken, and Van Oort 2009, Hong and Su 2013) may facilitate more knowledge diffusion and thus more innovation due to smaller transport costs. However, proximate linkages may also impede innovation due to overlapped and redundant knowledge (Berliant and Fujita 2008, Boschma 2005, Boschma and Frenken 2010) as a result of regional knowledge diffusion (Audretsch and Feldman 1996, Jaffe, Trajtenberg, and Henderson 1993, Murata et al. 2014). Empirically, some studies find a positive effect of proximate linkages on innovation (Whittington, Owen-Smith, and Powell 2009), while others find a larger positive effect of non-local linkages than of local linkages (Fitjar and Rodríguez-Pose 2013, Todo, Matous, and Inoue 2016). The effect of international research collaboration, a particular type of non-local linkage, is also found to be positive (Briggs 2015, Gertler and Levitte 2005), negative (Phelps 2010), or conditional (Qiu, Liu, and Gao 2017). The benefits of international collaboration are not always realized possibly because linguistic, cultural, and institutional barriers hinder knowledge diffusion among collaborators.

Second, characteristics of collaboration networks, particularly network density and brokerage, have been found to have various effects on innovation. For example, when collaboration partners of the focal agent are also connected, the network of the agent, or the agent's egocentric (ego) network, is said to be dense. In a dense network, agents are more likely to trust each other and thus are more willing to share information (Coleman 1988), leading to more innovation. However, because the knowledge of agents in a dense network tends to be redundant, as in the case of local linkages, dense networks are less effective in the diffusion of new knowledge than networks in which agents are connected to diverse partners and bridge a variety of agents in the network (Burt 1992, 2004). The empirical literature has shown mixed results, as some studies find a positive correlation between network density or knowledge redundancy and innovation performance (Ahuja 2000, Forti, Franzoni, and Sobrero 2013, Phelps 2010), while others find a negative correlation (Fleming, Mingo, and Chen 2007, Gonzalez-Brambila, Veloso, and Krackhardt 2013).

Finally, another issue that has mostly been neglected in the literature is whether or not knowledge combined in a research collaboration is in fact acquired by the collaboration partners and effectively utilized in subsequent research conducted individually. Most of the existing studies mentioned above examined how research collaboration affects innovation without distinguishing between outcomes achieved by collaborative and individual research activities. Therefore, although some research collaboration is found to improve the quality of innovation achieved by the collaboration, it is still unclear whether or not the knowledge used in the collaboration diffuses to and is absorbed by collaboration partners. If such knowledge diffusion is not accomplished, the benefits of research collaboration are realized only during the collaboration but end afterwards.

The present study examines these remaining issues in the literature, using a comprehensive firm-level dataset of patent-holding firms in the world for the period 1991–2010. We identify the global research collaboration network among firms by patent co-ownership, following Belderbos et al. (2014) and Briggs (2015). More specifically, we empirically estimate the effect of the research collaboration and characteristics of each firm with the intra- and international collaboration on the quality of innovation measured by the number of citations received by patents of the firm. We find that research collaboration with other firms, particularly with foreign firms, leads to substantial improvement in innovation quality. The relationship between the density of the ego network in the international co-ownership relation and innovation quality is inverted U-shaped, implying that dense linkages promote trust, knowledge diffusion, and innovation to a certain extent. When a firm bridges between a larger variety of firms, its performance is higher, suggesting the important role of diverse linkages in knowledge diffusion. These results are applicable to the effect on the quality of innovation achieved individually without any collaboration, although the size of the effect on innovation without collaboration is smaller than that with collaboration. Hence, we conclude that the knowledge of firms diffuses to and is absorbed by their collaboration partners, at least to some extent. Finally, we find that the collaboration effect is larger in the 2000s than in the 1990s and varies across countries.

We contribute to the literature on the effect of research collaboration on innovation performance in the following four aspects. First, we distinguish between the effect of intra- and international research collaboration, finding a substantially larger effect of the latter. This adds to the evidence in the literature supporting a larger effect of distant ties than of proximate ties. Second, we also highlight possible differences between intra- and international collaboration in the effect of network characteristics. The inverted U-shaped relation between network density and innovation performance can be similarly applied to both firms with only domestic collaborations and those with international collaborations. However, brokerage in the international network can promote more innovation than brokerage in an intra-national network. Third, we estimate the effect of collaboration on the quality of innovation achieved individually without collaboration to confirm knowledge diffusion through collaboration. This examination has not been conducted, to the best of the authors' knowledge. Finally, we carefully investigate cross-country variations in the characteristics of firms' research collaboration and the resulting effect on performance. Based on the examination, we provide practical policy implications in general as well as specific to some countries.

The structure of the paper is as follows. The next section provides testable hypotheses based on theoretical considerations, whereas Section 3 describes the data and variables used in the estimation, including cross-country comparison and network structure. Section 4 explains the estimation equation and methodology, and Section 5 presents the results. Section 6 summarizes and discusses the results and provides policy implications.

2. Conceptual Framework and Hypotheses

2.1. Effect of inter-firm research collaboration

Inter-firm research collaboration generates knowledge networks among firms that can be a major channel of knowledge diffusion (Owen-Smith and Powell 2004). Research collaboration enables firms to exchange new knowledge and information about scientific and engineering technologies from each other and hence improves the quantity and quality of innovation outcomes.

This study particularly focuses on possible differences between intra- and international collaboration. Research collaboration is often performed among agents of geographic proximity (D'Este, Guy, and Iammarino 2012, Hoekman, Frenken, and Van Oort 2009, Hong and Su 2013). However, whether geographically local or non-local linkages promote more innovation is theoretically debatable, as argued in the literature. In local linkages, knowledge can diffuse more quickly due to smaller transport costs (Audretsch and Feldman 1996, Jaffe, Trajtenberg, and Henderson 1993, Murata et al. 2014), and thus, innovation can be facilitated. However, because of active knowledge diffusion, the knowledge of geographically neighboring agents is often overlapped and redundant (Berliant and Fujita 2008, Boschma 2005, Boschma and Frenken 2010). Then, collaboration with neighboring partners may combine only similar knowledge and thus generate innovation of low quality. By contrast, in research collaboration with distant partners, a variety of knowledge is utilized to achieve advanced innovation.

Empirical evidence on this issue is mixed. Some studies, such as Whittington, Owen-Smith, and Powell (2009), find a positive effect of proximate linkages on innovation, while others, such as Todo, Matous, and Inoue (2016) and Fitjar and Rodríguez-Pose (2013), find a positive effect of non-local linkages. Several studies have examined the effect of international research collaboration on innovation, leading to various results. Briggs (2015) and Gertler and Levitte (2005) find a positive effect of international collaboration and foreign researchers, respectively. However, the effect of international collaboration is negative in Phelps (2010) and conditional on absorptive capacity in Qiu, Liu, and Gao (2017). Accordingly, we propose contrasting hypotheses as follows:

Hypothesis 1a: The effect of international research collaboration on a firm's innovation quality is higher than the effect of domestic collaboration.

Hypothesis 1b: The effect of international research collaboration on a firm's innovation quality is lower than the effect of domestic collaboration.

2.2. Effect of characteristics of firms' collaboration network

In addition to whether firms are engaged in research collaboration, the structure of firms' ego network should affect the quality of innovation. We particularly focus on the following three characteristics of the ego network often examined in the literature.

First, when firms are engaged in research collaboration with more firms, they can obtain more knowledge from their partners and hence better improve the quality of their innovation outcomes, as empirically found in Ahuja (2000), Gonzalez-Brambila, Veloso, and Krackhardt (2013), and Owen-Smith and Powell (2004). However, creating and maintaining many collaboration ties may be too costly in terms of physical transportation, social communication, and administration (Phelps, Heidl, and Wadhwa 2012). Accordingly, several studies, such as Guan and Liu (2016) and McFadyen and Cannella (2004), find an inverted U-shaped relationship. Therefore, our hypotheses consider two possibilities regarding the effect of the number of collaboration links.

Hypothesis 2a: A firm's innovation quality is higher when it collaborates with more firms.

Hypothesis 2b: A firm's innovation quality is lower when it collaborates with more firms.

Second, the network density may have two opposing effects. On one hand, when the ego network is dense, that is, when partners of the focal agent are also mutually connected, the agents trust each other and thus are more willing to share knowledge and information (Coleman 1988). Accordingly, in a dense ego-network, more knowledge may diffuse among collaborating agents, possibly resulting in innovation of higher quality. On the other hand, because the knowledge of agents in a dense network tends to be already shared and hence overlapped and redundant, dense networks are less effective in the diffusion of new knowledge than sparse networks. Empirical analysis has shown mixed results. The ego-network density, defined as the ratio of the number of actual ties among partners of the focal agent to all possible ties among the partners, is found to be negatively correlated with innovation performance in Fleming, Mingo, and Chen (2007), Gonzalez-Brambila, Veloso, and Krackhardt (2013), while the opposite relationship is found in Forti, Franzoni, and Sobrero (2013), Phelps (2010), and Todo, Matous, and Inoue (2016). Bordons et al. (2015) find a negative relationship in some scientific fields but an insignificant relationship in others. Rost (2011) and Gilsing et al. (2008) find an inverted U-shaped relationship between network density and innovation. That is, the effect of density is positive when the level of density is low but negative when it is sufficiently high, and thus, the medium level of density is optimal. Thus, we also presume the two possibilities in the following two contrasting hypotheses.

Hypothesis 3a: A firm's innovation quality is higher when the density of its egocentric research collaboration network is higher.

Hypothesis 3b: A firm's innovation quality is higher when the density of its egocentric research collaboration network is lower.

Third, Burt (1992, 2004) argues and empirically finds that nodes that are connected with a variety of nodes and that bridge different groups of nodes conduct knowledge between groups and perform better. This argument is closely related to that of Granovetter (1973), that an individual obtains valuable information more easily from weak ties, ties with partners the individual does not frequently meet or does not closely interact with. Burt (1992) develops a measure to represent the level of brokerage for each node in a network. The measure, Burt's constraint measure, which is defined in detail in the next section, is negatively related to the level of brokerage and thus is small when the focal agent is bridging various types of groups in the network. Burt's constraint measure is positively correlated with innovation performance in Ahuja (2000), implying that more clustered networks lead to more innovation. However, the same variable is found to be negatively correlated with innovation performance in Gonzalez-Brambila, Veloso, and Krackhardt (2013), implying that brokerage of a variety of firms leads to higher performance. The relationship between the constraint measure and creativity is inverted U-shaped in Sosa (2011), whereas Rost (2011) and Guan, Yan, and Zhang (2017) find the relationship statistically insignificant. These findings imply that network brokerage may positively or negatively affect innovation performance, depending on the situation, as suggested by Fleming, Mingo, and Chen (2007). Accordingly, our hypotheses related to network brokerage are as follows:

Hypothesis 4a: A firm's innovation quality is higher when Burt's constraint measure is higher.

Hypothesis 4b: A firm's innovation quality is higher when Burt's constraint measure is lower.

2.3. Effect on non-collaborative innovation

When firms collaborate for particular innovation, they can combine different types of knowledge specific to each firm and thus are more likely to achieve innovation of higher quality than when they conduct research activities individually. However, this quality improvement from research collaboration does not necessarily mean that the knowledge base of each firm in the collaboration network expands because the knowledge exchanged in the collaboration may be specific to the innovation and may not be applied to other innovations. Alternatively, although various knowledge is utilized for the collaboration, it is not fully disclosed to collaboration partners and thus cannot be utilized afterwards. In either case, a firm's research collaboration with others may not improve the knowledge capital of the firm or the quality of innovation outcomes achieved by the firm's subsequent individual research activities without collaboration. If this is the case, the benefits of research collaboration do not persist in the long term and are quite limited.

Although this issue is important, existing studies in the literature typically examine the effect of collaboration on innovation performance at the firm level (Ahuja 2000, Belderbos et al. 2014, Gilsing et al. 2008, Owen-Smith and Powell 2004, Phelps 2010, Whittington, Owen-Smith, and Powell 2009), researcher level (Fleming, King III, and Juda 2007, Fleming, Mingo, and Chen 2007, Forti, Franzoni, and Sobrero 2013, Gonzalez-Brambila, Veloso, and Krackhardt 2013, Rost 2011), or patent level (Briggs 2015) and do not distinguish between innovation performance from research activities conducted individually and jointly. Therefore, this study tests the following contrasting hypotheses.

Hypothesis 5a: The quality of innovation achieved only by a firm without research collaboration improves when the firm is engaged in research collaboration if the firm absorbs knowledge from collaboration partners.

Hypothesis 5b: The quality of innovation achieved only by a firm without research collaboration does not improve when the firm is engaged in research collaboration if the firm does not absorb knowledge from collaboration partners.

3. Data

3.1. Data sources

To test the hypotheses in the previous section, our empirical analysis utilizes data for patents of firms in the world, taken from the Orbis dataset compiled by Bureau van Dijk (BvD). Orbis includes various firm attributes, in addition to information on patents granted to each firm that is originally provided by PATSTAT. PATSTAT is the worldwide patent data created by the Organization for Economic Cooperation and Development (OECD) in corporation with the Patent Statistics Task Force consisting of patent offices in the world, such as the World Intellectual Property Organization (WIPO), the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), and the Japan Patent Office (JPO), and distributed by the EPO.[1] PATSTAT contains detailed information, such as the identification number, date of filing, name and address of applicants and inventors, country code, international patent classification, abstract, and identification numbers of patents cited by the focal patent. In the Orbis, because identification numbers of applicant firms are provided in a consistent manner, we can aggregate the patent data at the firm-year level.

In this study, we utilize data for patents that were applied for from 1991 to 2010 and granted by 2014, the final year in our dataset. We exclude patents applied for in the most recent four years because it takes several years for an applied patent to be actually granted. Harhoff and Wagner (2009) report that the average duration from application of a patent to EPO to its grant was 4.36 and 5.10 years in 1991 and 1998, respectively. Therefore, many patents applied for in recent years have not been granted and thus are not included in our data. Because we will eventually aggregate the patent data at the firm level using the firm identification numbers in the Orbis data, we focus on the patents owned by firms with an identification number in Orbis. The total number of such patents in the period from 1991 to 2010 is 26,181,824, and the number of firms that have been granted any patent is 534,569. The number of patents for firms located in each of the top six countries is 8,506,558 for Japan, 6,528,207 for the United States (US), 2,833,394 for Germany, 1,547,916 for South Korea, 1,043,371 for France, and 972,034 for China. These six countries account for approximately 80% of all patents.

Because our dataset includes any firm that has been granted a patent, including small- and medium-sized enterprises (SMEs), most firms in our data do not apply for patents frequently but rather once every few years. Therefore, rather than using annual panel data, we divide the whole 20-year period into four five-year periods, 1991–1995, 1996–2000, 2001–2005, and 2006–2010, and use patent data at the firm-period level in our estimations later.

Our rich dataset allows us to construct a measure of the citations the patents of each firm receive. Because a patent cites another patent when the former is influenced by the latter, the number of forward citations and the number of forward citations per patent are often regarded as an indicator of the quality of innovation (Griliches 1998, Nagaoka, Motohashi, and Goto 2010, Trajtenberg 1990) and are used in the literature on the effect of firm network on innovation (Belderbos et al. 2014, Briggs 2015, Rost 2011). We first count the number of forward citations that the focal patent received from subsequent patents, excluding self-citations (i.e., citations by patents granted to the same firm). Because the number of citations tends to be smaller for more recent patents than for

[1] The data are available at https://www.epo.org/searching-for-patents/business/patstat.html.

earlier ones, we further divide the number of citations by the average number of citations in each year. As a result, the average of the standardized citation index for each year is one. Then, we aggregate the standardized number of citations per patent at the firm-period level to construct a measure of the quality of innovation at the firm level.

Although firm attributes, such as sales and the number of employees, are included in the Orbis dataset, we have access to information on firm attributes only from 2007 to 2014. Because our patent data from 1991 to 2010 do not much overlap with the firm attribute data, we do not use any firm attribute information from Orbis but only use the location and industry classification of each firm. To overcome possible shortcomings from not using standard firm attributes, we will use fixed effects at the firm level and at the country-industry-year level, as we will explain later in detail.

Using the data described above, we create measures of the co-patenting network of firms, i.e., the network in which firms are connected through the co-ownership of patents. Identifying the co-patenting network is possible because each owner firm or institution of a patent is provided an identification number in the Orbis dataset. Following Belderbos et al. (2014), we regard the co-patenting network as an indication of the research collaboration network because collaborating partners are most likely to own a patent together. In practice, firms may not co-own patents generated from their research collaboration because of their strategic decision to avoid possible complications in co-patenting (Hagedoorn 2003). Therefore, some existing studies utilize firm-level data in which research alliances are identified by sources other than co-patenting (Ahuja 2000, Owen-Smith and Powell 2004, Whittington, Owen-Smith, and Powell 2009). However, these studies must focus on a small sample because of the uniqueness of the data. The present study relies on co-patenting links to identify research collaboration in order to cover a number of firms around the world.

The number of patents with more than one owner is 959,363, or 3.7% of the total number of patents, whereas the number of firms that co-own any patent with other firm or institution is 89,175, or 17% of those that own any patent. The total number of links in the co-patenting network is 166,183. The number of patents whose owners are located in more than one country, or internationally co-owned patents, is 248,909, or 0.95% of all patents, whereas the number of firms that co-own any patent with a foreign firm or institution is 20,445, or 3.8% of patent-holding firms.

3.2. *Changes in the global co-patenting network over time by country*

In this subsection, we highlight changes in the global co-patenting network over time and differences across countries so that we can later obtain more adequate interpretation and implication from our estimation results on the relationship between the network structure and innovation. In particular, we focus on the top six countries in terms of the number of patent grants, which represent approximately 80% of all patent grants.

Figure 1 shows changes in the number of patents granted by application year from 1991 to 2010. Japanese firms are granted the largest number of patents throughout the period, whereas the US is granted the second largest number. However, in the last few years of the period examined, the number of patents in both Japan and the US reduced, while China emerged as the third largest country. These dynamics in the number of patents for each country presented here are mostly consistent with what is reported by the five largest intellectual property offices, EPO, JPO, USPTO, the Korean Intellectual Property Office, and the State Intellectual Property Office of the People's Republic of China (IP5 Offices 2012, Figure 3.2). There are slight differences because we focus on patents granted to firms and institutions included in the firm-level Orbis dataset. Notably, the number of patents granted to China reported in IP5 Offices (2012), 312,507, is larger than that in Figure 1.

Figure 2 indicates the changes in the ratio of the average number of citations per patent for a country to the overall average number of citations per patent. Note that the ratio is standardized so that the average of this ratio in each year is one. Thus, Figure 2 illustrates the average quality of innovation in each country relative to other countries. Then, we can see that the US has created innovations of the highest quality, while its relative quality declined from 1991 to 2003. This decline is partly because the relative quality of patents granted to Japan increased during the same period but later decreased. Thus, we conclude that both the quantity and quality of innovation generated by Japanese firms have recently deteriorated. By contrast, Chinese firms have recently increased both the quantity and quality of innovation, although the quality measure is the lowest among the six countries at the time of the year 2010.

Looking at the dynamics in the extent of co-patenting for each country, we illustrate changes in the share of co-owned patents in all patents in Figure 3. The overall co-patenting share at the patent level has been increasing from 3% in 1990 to 4.3% in 2010, indicating that research collaboration has been increasingly performed over time, possibly because of the spreading recognition of the effectiveness of open innovation (Chesbrough 2003). The share has been the highest for France in most years during the period examined, increasing substantially. The recent increase in the share of China is also prominent.

Furthermore, we focus on the dynamics of international co-patenting in Figure 4. We find that the share of patents internationally co-owned in all patents has also been increasing overtime. However, there is a substantial gap in the share between Japan and South Korea, the lowest two countries, and the others. Because the other four countries, France and China in particular, considerably increased the share of international co-patenting in the 2000s, while Japan and South Korea were stagnant, the gap has widened over time. This feature of Japan and South Korea will be confirmed in the visualization of the global network in next subsection.

3.3. *Structure of the global co-patenting network*

To provide an overview of the structure of the global co-patenting network of firms, we visualize the network using a visualization algorithm, ForceAtlas2 (Jacomy et al. 2014), in Gephi, open-source software for network visualization. ForceAtlas2 assumes gravity between linked nodes and repulsion between unlinked nodes. Accordingly, a set of nodes linked with each other are located closely together and form a group. Consequently, nodes linked with many others, or hubs, tend to be located in the center of the network.

Figure 5 shows the visualization in the period 1991–1995 (Panel [A]) and 2006–2010 (Panel [B]) for comparison across periods. The figure uses different colors for firms located in each of the top six countries in terms of the number of patents granted, Japan (red), the US (blue), Germany (green), South Korea (light blue), France (yellow), and China (black), while other firms are colored in gray. In the visualization, we pick up the largest connected component, i.e., the largest sub-network in which firms are directly or indirectly linked with each other. This is because there are many fragmented sub-networks separated from the largest connected component and located far away from the center of the visualized space, and they are less important in the big picture of the network. However, we use all firms in the estimations conducted in later sections. The share of firms in the largest connected component is 48% and 63% in the periods 1991-1995 and 2006-2010, respectively. This share varies across countries. In the period 2006–2010, 91% of Japanese firms are in the largest connected component, while the shares are substantially smaller for other countries: 69% for South Korea and China, 64% for France, 60% for Germany, and 59% for the US.

Figure 5 also illustrates that firms are likely to be linked within each country. In particular, firms in Japan and South Korea form two groups that are remarkably separated from firms in other countries. While firms in the US, Germany, and France are also located closely together, these clusters are located closely with each other. This finding implies that firms in the US, Germany, and France collaborate more across national borders with each other, while firms in Japan and South Korea mostly collaborate with other firms in the same country.

The comparison between panels (A) and (B) further indicates the following. First, the isolation of Japanese and South Korean firms has remained over time. Second, US, German, and French clusters are more closely linked with each other in the period 2006–2010 than in the period 1991–1995, implying that firms in these countries have become more active in international collaboration. Finally, Chinese firms, the black dots, are not clearly visible in the period 1991–1995 but form a cluster located closer to the combination of the US, German, and French clusters than to the Japanese and South Korean clusters in the period 2006–2010.

We further show the distribution of the number of firms linked with the focal firm, or the degree centrality (Newman 2010), in Figure 6. The degree distribution is of great interest because if it follows the power law, i.e., there are a few nodes with an extremely large number of links, or hubs, the network is classified as a scale-free network. It is well known that because in a scale-free network, most nodes are indirectly connected with each other with a small number of steps through hub nodes, diffusion of information can be quick (Barabási, 2016). Many types of networks have been found to be scale free, including firms' transaction networks (Saito, 2015).

Panels (A) and (B) of Figure 6 show the cumulative density function (CDF) of the degree centrality by period and by country, respectively. Panel (A) illustrates the linear relationship between the log of the cumulative density and the log of degree, indicating that the global research collaboration network in any period is scale free. The gradient of the linear relationship is similar, while the size of network (the total number of firms) increases over time. Because a smaller gradient (or a larger gradient in absolute terms) of the log-log relationship indicates larger heterogeneity in the degree centrality among nodes, and a similar gradient over time implies that such heterogeneity is unchanged for the 20 years examined.

In panel (B) of Figure 6, we observe that the gradient is different across countries. The gradient calculated by a linear regression is the largest (or the smallest in absolute terms) for Japan, −0.91, and the smallest for the US, −1.42. This implies that there are more hubs with many links in Japan than in the US and that the median firm in Japan has more links than that in the US. These results suggest that the structure of the research collaboration network differs substantially across countries.

Finally, we examine the assortativity of nodes, i.e., whether nodes are likely to be connected with others with a similar value of degree centrality. Assortativity for a network can be measured by the correlation coefficient of the degrees of all pairs of connected nodes (Newman 2010) and can be positive or negative, depending on the network structure. For example, Bernard, Moxnes, and Saito (2018) find negative assortativity in firms' transaction networks in Japan, indicating that hub firms are more likely to transact with firms with a small degree. In our research collaboration network, the correlation coefficient is 0.45, indicating positive assortativity. In other words, firms collaborating with many others are more likely to collaborate with each other, while firms collaborating with only a few others are likely to collaborate with each other. Figure 7 demonstrates the changes in assortativity over time for each country. Here, we use the average of Spearman's rank correlation between a firm's own degree and the mean of the degree of firms directly connected with the firm to define country-level assortativity. Assortativity is larger for France, the US, and Germany than for Japan and South Korea, whereas it is the smallest for China. The variation in assortativity across countries also suggest that we conduct analysis for each country.

3.4. *Variables for co-patenting networks*

This study considers three measures that represent the characteristics of the ego network of each firm in each period: the degree centrality, the local clustering coefficient, and Burt's constraint measure. When we construct the network measures, we exclude isolates, i.e., firms that do not co-own any patent with others, because the measures cannot be defined for isolates. The co-patenting network is regarded as an undirected graph, i.e., a network in which links have no direction.

The degree centrality in a network is the number of nodes directly linked to the focal node. In the co-patenting network examined in this study, degree centrality represents the number of firms that co-own any patent with the focal firm. The degree centrality is a widely used index that measures the centrality of the focal firm in the network (Ahuja 2000, Whittington, Owen-Smith, and Powell 2009). When we use the degree centrality in the estimation, we take its log because its distribution has a fat tail, as shown in Figure 6.

The local clustering coefficient is an index to measure the density of each firm's ego-network (the sub-network of the focal firm and its patent co-ownership partners). It is defined as the ratio of the number of pairs of firms that are connected with the focal firm and are also connected with each other to the number of all possible pairs of firms that are connected with the focal firm. When a firm is linked with only one firm, we define that its clustering coefficient is zero, following the standard literature (Barabási 2016). Because this definition is rather arbitrary, we will include a dummy variable for firms with only one link. The clustering coefficient ranges from zero to one, and its higher value indicates that a firm's research collaboration partners are also collaborating with each other. This measure has been used in the literature on the effect of network characteristics on innovation (Fleming, Mingo, and Chen 2007, Gonzalez-Brambila, Veloso, and Krackhardt 2013, Phelps 2010, Rost 2011).

The constraint measure of Burt (1992) for node i is defined as follows:

$$C(i) = \sum_{j \in V_i,\ j \neq i} \left(p_{ij} + \sum_{q \in V_i,\ q \neq i,j} p_{iq} p_{qj} \right)^2 , \tag{1}$$

where V_i represents the set of nodes in i's ego network, p_{ij} is the relative link strength between nodes i and j and is assumed to be $1/N_i$ for any $j \in V_i$. N_i represents the degree centrality of i. In other words, we assume the same weight across links. Everett and Borgatti (2018) show that equation (1) can be rewritten as

$$C(i) = \frac{1}{N_i} + \frac{2}{N_i^2} \sum_{j \in V_i,\ j \neq i} \sum_{q \in V_i,\ q \neq i,j} p_{qj} + \frac{1}{N_i^2} \sum_{j \in V_i,\ j \neq i} \left(\sum_{q \in V_i,\ q \neq i,j} p_{qj} \right)^2 \tag{2}$$

Thus, the constraint measure for node i is smaller when node i is connected with more nodes (N_i is larger), i's direct neighbors are not connected with each other (p_{qj} is zero), or i is connected with many more others (p_{qj} is smaller). In other words, this measure is small when the focal node is connected with a variety of nodes directly and indirectly, bridging between different clusters of nodes. When a firm is linked with only one firm, we assume that p_{qj} is zero although there is in fact no firm j and thus that this measure is one. Because this definition is arbitrary, similar to the case of the clustering coefficient when the degree is one, we will include a dummy for firms with one link in the estimations. This measure ranges from zero when a node is connected with an infinite number of nodes to 1.125 when a node is connected with two nodes that are also connected (Everett and Borgatti 2018). Burt's constraint measure is also used in the literature on the effect of networks on innovation (Ahuja 2000, Gonzalez-Brambila, Veloso, and Krackhardt 2013, Guan, Yan, and Zhang 2017, Rost 2011).

3.5. *Descriptive statistics*

In our estimation, we drop firm-period observations in singleton groups, i.e., groups with only one observation, to fully exploit the benefits of using fixed effects at the firm level and at the country-industry-period level (Correia 2015). Note that the results are essentially the same if we do not drop singletons. In addition, when we estimate the effect of the three network measures on innovation performance, we restrict the observations to firms with any co-patenting relationship because these measures can be defined only for these firms. Then, our sample contains 356,397 and 48,910 firm-period observations for the estimation of the effect of research collaboration and the three network measures, respectively.

Table 1 shows the descriptive statistics of the variable used in the estimations for the sample for estimations. Among all firms, the average number of patents granted is 63.8, although its distribution is quite skewed, as its median is only 5 and its maximum is 139,275. The number of citations is also skewed: its mean is 63.9, whereas its median is 2.41. The number of citations per patent, which can be considered as an indicator of innovation quality at the firm level, is 1.3, on average. The dummy for firms with any co-patenting relationship with other firms or institutions is 0.2, on average. The dummy for firms with any co-patenting relationship with foreign firms or institutions is 0.05, on average, indicating that international research collaboration is quite rare. The dummy for firms in the largest connected component of the co-patent network, the largest sub-network of firms linked directly and indirectly with each other, is 0.13, on average. Therefore, the share of firms in the largest connected component among firms in the sample firms in the co-patenting network is approximately 65% (=0.13/0.20). The lower rows of Table 1 show that firms with a co-patenting relationship are more likely to be granted more patents and receive more citations in total and citations per patent. Thus, it is inferred that firms that engage in research collaboration with other firms innovate more in terms of both quantity and quality. We will test this inference by econometric analysis later.

In addition to the summary statistics of the three network measures in Table 1, we present histograms of the distributions for firms in the sample for estimations in Figure 8. The distribution of the degree is shown by logarithmic scale in panel (A) of Figure 8. We confirm a power-law distribution, as found for all firms in our data before singletons and firms with no link are dropped in Figure 6. The median and mean of the number of partners are 2 and 5.36, respectively, indicating that most firms have only a few co-patenting partners. Panels (B) and (C) of Figure 8 illustrate the distribution of the clustering coefficient and Burt's constraint measure, respectively. In these figures, we exclude firms with only one partner, which represent 43% of all firms in the estimation sample, because the clustering coefficient and Burt's constraint measure of those firms are arbitrarily defined as zero and one, respectively. Neither distribution is standard bell-shaped. The clustering coefficient is zero for 32% of firms, whereas it is one for 17%, of which 78% have two partners. Firms with a clustering coefficient between 0.5 and one are scarce. Burt's constraint is 0.5 for 20% of firms, among which all have two partners. Firms with Burt's constraint measure between 0.6 and one are scarce.

Table 2 indicates the correlation coefficients between the three network measures. Here, as mentioned before, we exclude firms with only one link in common with Panels (B) and (C) of Figure 8. As implied by equation (2), Burt's constraint measure includes the inverse of the degree centrality by definition. Accordingly, the correlation coefficient between the two measures is −0.758 and quite high. We also find a negative correlation between the degree and the clustering coefficient, as often found in the literature (Barabási 2016). In addition, the correlation coefficient between Burt's constraint measure and the clustering coefficient is 0.588, a reasonably high value, because the former is related to the latter, as shown by the second term of equation (2).

Table 3 shows international comparison in the number of firm-period observations, the number of patents per firm, and the three measures of the global co-patenting network at the firm-period level. This table conspicuously shows that Japanese firms are different from firms in other countries. The number of firm-period observations for Japan is small, compared with its large number of patents granted. Accordingly, the number of patents per firm is substantially larger for Japan than for other countries. The average of the logarithm of the degree centrality and the clustering coefficient is the largest for Japan. By contrast, Burt's constraint measure, which is smaller when the focal firm bridges different groups of firms, is the smallest for Japan. The evidence reveals that in Japan, a limited number of large firms are densely connected with many other domestic firms.

4. Estimation Method

4.1. Estimation equation

To test the hypotheses provided in Section 2, we estimate the following equation that determines the quality of innovation:

$$\ln CITATION_{ickt} = \beta_1 \ln PATENT_{ickt} + \beta_2 NETWORK_{ickt} + \lambda_i + \mu_{ckt} + \varepsilon_{ickt} . \quad (3)$$

The dependent variable, $\ln CITATION_{ickt}$, is the log of the standardized number of citations that patents owned by firm *i* in country *c* in industry *k* during time period *t*. Alternatively, when we test hypothesis 5 in Section 2, i.e., whether knowledge obtained through research collaboration is effectively utilized in the focal firm's individual research activities without any collaboration, the dependent variable is the standardized number of citations that patents owned only by the firm receive, excluding citations that co-owned patents receive. $\ln PATENT_{ickt}$ is the log of the number of patents applied for and owned by the firm during the time period *t*. We include $\ln PATENT_{ickt}$ as an independent variable to control for the quantity of innovation and firm size. Because equation (1) can be rewritten as

$$\ln\left(CITATION_{ickt} / PATENT_{ickt}\right) = (\beta_1 - 1)\ln PATENT_{ickt} + \beta_2 NETWORK_{ickt} + \lambda_i + \mu_{ckt} + \varepsilon_{ickt} , \quad (4)$$

our specification essentially estimates how the number of citations per patent, a measure of innovation quality at the firm level, is determined, controlling for the size effect. We take a natural logarithm of *CITATION* and *PATENT* because these values are quite skewed and fat-tailed (Section 3.5). Because *CITATION* is zero when no patent of a firm is cited, we add one before taking its log, following the convention.

$NETWORK_{ickt}$ represents two sets of variables for characteristics of research collaboration at the firm level. First, using the sample of firms including those with no collaborator, we utilize three dummy variables for overall co-patenting, international co-patenting and the largest connected component of the co-patenting network. In this case, we test hypothesis 1 in Section 2, examining the effect of research collaboration and international research collaboration in particular on the quality of innovation. Second, using the sample of firms with at least one collaborator, we utilize the three measures of the firm's characteristics in the global co-patenting network, i.e., the logarithm of degree centrality, clustering coefficient, and constraint. Here, we test hypotheses 2–4 and examine the effect of more detailed characteristics of firms in the global co-patenting network on the quality of innovation. Because the three measures are correlated with each other, we will incorporate each of them in separate estimations. In addition, to examine possible non-linearity of the effect of the network measures found in the literature (Guan and Liu 2016, Guan, Yan, and Zhang 2017, McFadyen and Cannella 2004, Rost 2011, Sosa 2011), we incorporate the squared term of each measure in alternative specifications and compare the results with those from linear specifications. We further check the validity of the quadratic form by experimenting with first-, third-, and fourth-order equations. As explained in Section 3.4, the definition of the clustering coefficient and Burt's constraint measure is arbitrary for firms with only one link. Therefore, we include the dummy variable for firms with only one link whenever either of the two measures is used.

As we mentioned earlier, we cannot control for firm attributes, such as sales, number of employees, and research expenditures, due to lack of data in the long term, and hence, we incorporate fixed effects at the firm level to control for time-invariant firm attributes. In addition, we include fixed effects at the country-industry-period level to control for any common shock in an industry in a country during a time period. The number of firms and country-industry-period groups is 139,997 and 2,137, respectively, when the co-patenting dummies are used, whereas it is 19,225 and 986, respectively, when the three network measures are used.

4.2. Estimation method

We estimate equation (1) by ordinary least squares (OLS) estimations. Standard errors are clustered at the firm level, at the country-period level, and at the industry-period level to account for possible correlation between the error terms. The number of country-period and industry-period groups is 261 and 82, respectively.

There are two concerns about this estimation methodology. First, the dependent variable is zero when the firm's patents do not receive any citation. In our benchmark estimations where the key independent variables are the two dummies for research collaboration, the log of the standardized number of citations plus one is zero for 114,229 among 356,397 observations. When we focus on the sub-sample of co-patenting firms, it is zero for 5,112 among 48,910 observations. Under these circumstances, we usually use Tobit estimations (Tobin 1958) or the extended Tobit estimations that incorporate fixed effects (Honore 1992). However, because we utilize fixed effects at two levels, one with 139,997 groups and the other with 2,137, it is infeasible to achieve convergence using Tobit estimations with this large number of fixed effects. When we drop these fixed effects at two levels, we find that the results from Tobit and fixed-effect Tobit estimations are mostly consistent with the OLS results but not robust across specifications. Therefore, we will rely on OLS estimations. It should be noted that when the dependent variable has many zeros, OLS estimations tend to underestimate the true effect of the independent variables. Therefore, the OLS estimates can be viewed as a lower bound of the true effect.

Second, the dependent variable, *CITATION*, and an independent variable, *PATENT*, are simultaneously determined; hence, estimation results may be biased due to endogeneity. Although the bias may be minimized because we control for fixed effects at two levels so that the remaining disturbance is less likely to correlate with *PATENT*, one may still be concerned about endogeneity bias. Therefore, as an alternative specification, we replaced $\ln PATENT_{ickt}$ with that in the previous period to alleviate the possible endogeneity bias. However, because the results are quite similar to those from equation (1), we focus on the results from equation (1), not using lagged *PATENT*.

5. Results

5.1. *Effect of research collaboration*

Table 4 shows the benchmark results from the estimation of equation (1) using various independent variables. Column (1) shows the effect of the dummies for co-patenting in general and international co-patenting in particular. Because the two dummies are not exclusively defined, the coefficient of the co-patenting dummy indicates the effect of co-patenting with firms in the same country, whereas the sum of the coefficients of the two dummies represents the effect of co-patenting with foreign firms. The results show that the effect of the two dummies is positive and highly significant. The size of the coefficients indicates that co-patenting with domestic and foreign firms improves the quality of innovation by 13% and 36% (= 0.133 + 0.226), respectively. Therefore, our findings imply that research collaboration can lead to substantial improvement in innovation quality most likely because a variety of knowledge is combined in collaboration. Moreover, the effect of international collaboration is considerably larger than the effect of domestic collaboration, confirming hypothesis 1a in Section 2, most likely because foreign collaborators are equipped with knowledge that is not available domestically. In addition, we incorporate a dummy variable that is one for firms in the largest connected component and zero otherwise and find a positive and significant effect of the dummy, as shown in column (2) of Table 4. This is because firms in the largest connected component are indirectly linked with more firms and thus can access more knowledge than firms in separate smaller components.

5.2. *Effect of network measures*

We further estimate the effect of each of the three measures of network characteristics, provided that the firm is engaged in any collaboration, i.e., using the sub-sample of co-patenting firms. The results in columns (3), (4), and (6) of Table 4 show that the effect of the log of the degree centrality (the number of collaboration partners) on innovation quality is positive and highly significant, and the effect of the clustering coefficient (a measure of network density) and Burt's constraint measure (an inverse measure of brokerage) is negative and highly significant, supporting hypotheses 2a, 3b, and 4b. The size of the effect of the degree centrality and Burt's constraint measure is large. When a firm with only one collaboration partner adds one more collaborator or increases the degree by 69% of its standard deviation, it can improve innovation quality by 10%. A decrease in

Burt's constraint measure of one standard deviation leads to an increase in innovation quality by 18%. By contrast, the clustering coefficient has a smaller effect because a one-standard-deviation decrease improves innovation quality by only 3%.

We further check possible non-linearity of the relationship between the three measures and innovation quality using second-, third-, and fourth-order equations. Almost all the coefficients in the higher-order specifications are highly significant. Figure 9 illustrates the non-linear relationship between each of the three and innovation quality estimated by the linear and higher-order equations. Panel (A) of Figure 9 indicates that the effect of the degree centrality is always positive, regardless of the specifications. The U-shaped relationship for the degree between one and two in the cases of the third- and fourth-order equations can be ignored because the degree must be an integer. However, the results from the higher-order specifications are slightly different from the result from the linear specification in that the marginal effect is smaller for smaller degrees, suggesting that the marginal effect is increasing with the degree centrality. Panel (C) also shows that the effect of Burt's constraint is negative, regardless of specifications employed, although the negative effect is likely to be smaller in absolute terms when the measure is close to one. Because the results for the degree centrality and Burt's constraint measure from the linear specification are not substantially different from those from higher-order specifications, we will stick with the linear specification for simple presentation.

However, Panel (B) of Figure 9 indicates that the effect of the clustering coefficient is most likely to be inverted U-shaped when it is between zero and 0.5. Because the clustering coefficient rarely takes a value greater than 0.5 and less than one (Panel [B] of Figure 8), we can ignore substantial differences across specifications in the range between 0.5 and one. Although the coefficient of the first-order term in the quadratic specification is only weakly statistically significant (column [5] of Table 4), all other coefficients in all specifications are highly significant. To further check the inverted U-shaped relation between the clustering coefficient and innovation quality, we create dummy variables to indicate the quartile of the clustering coefficient for each firm and incorporate the dummies into the estimation. Setting the first quartile as the base case, we find that the coefficients of the second, third, and fourth quartiles are 0.23, 0.083, and −0.046, respectively and are highly significant. Therefore, we conclude that the relation between the clustering coefficient and innovation quality is inverted U-shaped, rather than simply negative, supporting both hypotheses 3a and 3b conditional on the current value. Accordingly, we will show results from linear and quadratic specifications for the clustering coefficient in later estimations.

The benchmark results suggest that when firms collaborate with more firms, they can absorb a larger amount of knowledge and thus improve innovation quality. Moreover, when firms are connected directly and indirectly with more firms, i.e., firms are bridging different groups of firms, they can learn a variety of knowledge and thus achieve innovation of higher quality. When the density of a firm's ego network is currently small or its collaboration partners are less connected, increasing the density has a positive effect on innovation quality possibly because a dense network can nurture trust and thus promote knowledge sharing within the network. However, when the density is already sufficiently high, increasing it more deteriorates innovation because the knowledge of collaboration partners tends to be overlapped and redundant.

5.3. *Effect on innovation without collaboration*

Next, we examine whether a firm's research collaboration with others can improve not only the quality of innovation resulting from the collaboration but also the quality of innovation resulting from the firm's research activities individually conducted without any collaboration. For this purpose, we employ as the dependent variable the standardized number of citations received by patents that the firm owns without any co-owner. Columns (1) and (2) of Table 5 indicate that the dummies for co-patenting in general, international co-patenting, and co-patenting in the largest connected component significantly and positively affect the innovation quality of individual research. These effects are slightly smaller in size than the effects on the total number of citations (columns [1] and [2] of Table 4). For example, the effect of domestic and international research collaboration on the performance of individual research is 0.118 and 0.336, respectively, while their effect on the performance of overall research is 0.133 and 0.359, respectively. Thus, the results suggest that the knowledge of collaborating firms is partly, not fully, absorbed by their partners and utilized in other research, supporting hypothesis 5a.

Columns (3)–(6) of Table 5 show the coefficients of the three network measures. The effect of the log of the degree on the quality of innovation without collaboration is positive and highly significant (column [3] of Table 5), although it is smaller than the effect on overall innovation quality (column [3] of Table 4). Similarly, the effect of Burt's constraint measure is significant (column [6] of Table 5) but smaller in absolute terms than the measure in Table 4, although the coefficient of the clustering coefficient in the linear specification is similar in column (4) of Tables 4 and 5. The finding that the effect of two of the three measures on individual research performance is smaller than that on overall research performance confirms our previous conclusion that part of the knowledge used in collaboration can be absorbed by collaboration partners.

5.4. *Comparison between firms with only domestic collaborators and those with foreign collaborators*

In column (1) of Table 4, we find that international research collaboration is more effective than domestic collaboration. To examine differences between the two modes of collaboration further, we incorporate interaction terms between the three measures of network characteristics and the dummy variable for any international patent co-ownership link. The coefficient of each network measure alone can be interpreted as the effect of characteristics of firms with only domestic collaborators, whereas the sum of the coefficients of each network measure and the dummy signifies the effect of firms with foreign collaborators.

The results estimated from this specification are shown in Table 6. In column (1) of Table 6, we find that the interaction term between the degree centrality and the dummy for any international link is positive and significant. This finding suggests a larger effect of the number of collaborators on innovation quality for firms with foreign collaborators than for firms with only domestic collaborators, consistent with the previous finding. In column (3), the effects of the interaction term with the clustering coefficient or with its square are not statistically significant at the 5% level. This result indicates that the inverted U-shaped relationship between network density and innovation performance can be applied to both firms with only domestic links and those with international links. In other words, trust among firms is nurtured in a dense domestic network, as it is nurtured in a dense international network. The effect of Burt's constraint measure is larger in absolute terms when firms collaborate with foreign firms than when they collaborate with only domestic firms (column [4] of Table 6). This finding indicates that bridging firms in the global research network can facilitate innovation more than bridging only domestic firms, suggesting the importance of combining a variety of knowledge across countries for high-quality innovation.

5.5. *Heterogeneity across time*

In addition, we examine how the effect of research collaboration and network characteristics changes over time. Because our data contain four five-year periods, we divide them into two, one in the 1990s and the other in the 2000s, and incorporate the interaction term between each network measure and the dummy variable for the 2000s. Thus, the effect in the 1990s is represented by the coefficient of a variable, whereas the effect in the 2000s is the sum of the coefficients of the variable and the interaction term with the 2000s dummy.

The results presented in Table 7 show that the effect of most network variables is larger in absolute terms in the 2000s than in the 1990s. For example, column (1) indicates that domestic and international co-patenting improves the innovation quality by only 5% and 13%, respectively, in the 1990s but by 19% and 26%, respectively, in the 2000s. The coefficient of the log of the degree centrality is 0.09 in the 1990s and increases to 0.16 in the 2000s. Using the quadratic specification, the effect of the clustering coefficient is mostly negative in the 1990s but becomes inverted U-shaped in the 2000s. The effect of Burt's constraint is insignificant in the 1990s, while it is negative and highly significant in the 2000s. All of these findings suggest that the effect of research collaboration and network characteristics has increased over time.

5.6. *Heterogeneity across countries*

Section 3.2 shows heterogeneity in the characteristics of research collaboration across countries. We further examine heterogeneity in the effect of network characteristics across countries by applying the same estimation method to the subset of firms in each of the top six countries. In these estimations, we keep singleton firms, although they have been dropped so far to maximize benefits of using fixed effects. This is because, if we drop singletons in country-specific specifications, the number of observations for France and China amounts to only several hundreds and is too small.

The first two rows of Table 8 show the effect of the two dummies for overall and international co-patenting, corresponding to column (1) of Table 4. For all countries, the effect of domestic and international collaboration is positive and highly significant. The effect is particularly large for China possibly because China is still a latecomer in the global research field in the 1900s and 2000s considered in this study and thus can benefit substantially from learning from other countries. The effect of international collaboration is also large for South Korea, France, and Germany. For South Korea, this is because of the benefit of backwardness as in the case of China. For France and Germany, the two most innovative countries in Europe, this is possibly because of benefits from collaboration within the European Union, where international collaboration is officially subsidized.

The lower rows of Table 8 indicate the coefficients of the degree centrality in logs, clustering coefficient, and constraint measure from regressions using each of the three separately, corresponding to columns (3)–(6) of Table 4. For the clustering coefficient, we show the results from the quadratic specification as well. The results show that the effect of the degree is the largest for China, followed by Germany, South Korea, France, and Japan, and the smallest for the US. The effect of the clustering coefficient and Burt's constraint measure is larger for Germany, France, and South Korea than for other countries. The results indicate an important role of both network density and brokerage in innovation in the three countries, suggesting that they benefit substantially from the global research collaboration network. By contrast, all the results shown in Table 8 imply a smaller role of the global network in Japan and the US.

6. Discussion and Conclusion

This study examines how the research collaboration of firms affects the quality of their innovation outcomes using comprehensive patent data for firms in the world from 1991 to 2010. We identify research collaboration by co-patenting relationships. The results above can be summarized as follows.

Most importantly, research collaboration substantially improves the quality of innovation of firms by combining a variety of knowledge in the collaboration. Further, the knowledge of collaborators is partly absorbed by other firms and effectively utilized in subsequent individual research of other firms. Notably, because existing studies have not distinguished between the collaboration effect on the performance of innovation achieved by collaborative and individual research, whether the knowledge of firms used in collaboration is indeed acquired by their partners was unclear. However, our results reveal that research collaboration is an effective channel of knowledge diffusion among firms.

Moreover, we find that three measures of firms' research network greatly affect the outcome of research collaboration. First, when firms collaborate with more firms, i.e., when their degree centrality is larger, they are exposed to a larger amount of knowledge and thus achieve higher innovation quality. According to our higher-order specifications, the positive effect is particularly large when firms are already collaborating with two or more firms. This finding is consistent with the findings of Ahuja (2000), Gonzalez-Brambila, Veloso, and Krackhardt (2013), and Owen-Smith and Powell (2004), although some studies, such as Guan and Liu (2016) and McFadyen and Cannella (2004), find an inverted U-shaped relationship because of the costs of creating and maintaining many linkages. We find an increasingly positive relationship possibly because the benefits of collaboration increase as firms experience more research collaboration and thus absorb others' knowledge more easily. In other words, the marginal cost of creating and maintaining collaboration ties is likely to be diminishing, rather than increasing, as found in Guan and Liu (2016) and others.

Second, when the density of a firm's ego network is low, or when many of the firm's collaborators do not collaborate with each other, the innovation quality improves as the density increases. This is because dense networks promote trust and knowledge diffusion, as suggested by Coleman (1988). However, when the density is already high, increasing density deteriorates innovation possibly because of the redundancy of knowledge in a dense network, as suggested by Burt (1992). Our finding suggests that there is an optimal level of density and is consistent with Rost (2011) and Gilsing et al. (2008).

Third, by expanding the role of brokerage, i.e., connecting with more firms indirectly and bridging a variety of firms, firms can achieve a higher quality of innovation. This finding of a positive effect of brokerage on innovation performance is consistent with that of Gonzalez-Brambila, Veloso, and Krackhardt (2013), while many other studies find either negative, U-shaped, or insignificant effects. Combined with the results on density, our results confirm the conjecture of Fleming, Mingo, and Chen (2007) that both Coleman (1988) and Burt

(1992) are right; i.e., dense and strong linkages promote knowledge diffusion in some cases, while linkages to a variety of nodes promote it in others.

In addition, we find that international research collaboration is substantially 2.7 times more effective than domestic research collaboration. We further distinguish between firms with only domestic collaborators and those with foreign collaborators and examine the effect of the network measures for each type of firms. Then, we find that the positive effect of the number of collaborators and brokerage of firms is larger for firms with foreign collaborators than for those with only domestic collaborators. These findings suggest that because the knowledge of firms around the world varies more than the knowledge of firms in the same country, linking with a variety of foreign firms directly and indirectly is a more effective means to high-quality innovation than linking with domestic firms. By contrast, the density of the ego network of firms with only domestic collaborators has the same effect on innovation quality as that of firms with foreign collaborators. This evidence highlights that the role of trust among domestic firms is as important to knowledge diffusion and innovation as the role of trust among firms in different countries. This contrasts with the results from the degree and Burt's constraint that indicate a minor role of domestic collaboration.

Finally, we investigate changes in the effect of research collaboration over time and find that the effect has intensified in more recent years. This is consistent with Chesbrough (2003), the seminal work in the open-innovation literature, who argues that open innovation is more important after the late 1990s than before due to the growing mobility of knowledge workers and the availability of venture capital. Rising technological complications in the high-technology sectors may also have increased the need to combine a variety of knowledge in innovation.

The results suggest a number of policy implications. Generally, our findings emphasize the importance of international research collaboration for better innovation performance. However, firms are often connected within each country, as shown in Figure 5. Particularly, Japanese and South Korean firms are considerably less connected to foreign firms (Figures 4 and 5) than are firms in other countries. As the effect of international collaboration is substantially large in South Korea (Table 8), an obvious policy prescription to South Korea is to promote international collaboration. In the case of Japan, the effect of international collaboration is the lowest among the top six countries (Table 8); therefore, policies should also alleviate barriers to knowledge diffusion through international collaboration, e.g., linguistic, cultural, and institutional barriers, when promoting international collaboration. Because the innovation quantity and quality have recently deteriorated in Japan (Figures 1 and 2), increasing international collaboration and its effectiveness is an urgent policy agenda. By contrast, Chinese firms have actively collaborated with foreign firms (Figure 4), improving the quantity and quality of innovation (Figures 1 and 2), because the effect of international collaboration on Chinese firms is extremely large (Table 8). European firms are also actively collaborating with foreign firms (Figure 4) and generate a large effect of international collaboration on innovation (Table 8). Japan and South Korea should follow the trajectories of China and Europe.

Another important issue is that although a certain level of density maximizes innovation quality, the density of most firms in practice is either close to zero or one (panel [B] of Figure 8). Similarly, although a smaller value of Burt's constraint measure is better for higher quality, its average is 0.64 and relatively high (Table 1). Therefore, policies should facilitate the creation of a network for research collaboration that is denser but not too dense and expand the direct and indirect linkages to foreign partners.

One caveat of this study should be noted. Although we show the large effect of international collaboration, our analysis does not explicitly consider the costs of creating and maintaining linkages. Therefore, it is still unclear how we can reduce the costs and thus promote international linkages and whether collaborating with foreign firms results in a net positive benefit. We leave this important research agenda to future research.

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Figure 1: Changes in the Number of Patents Granted

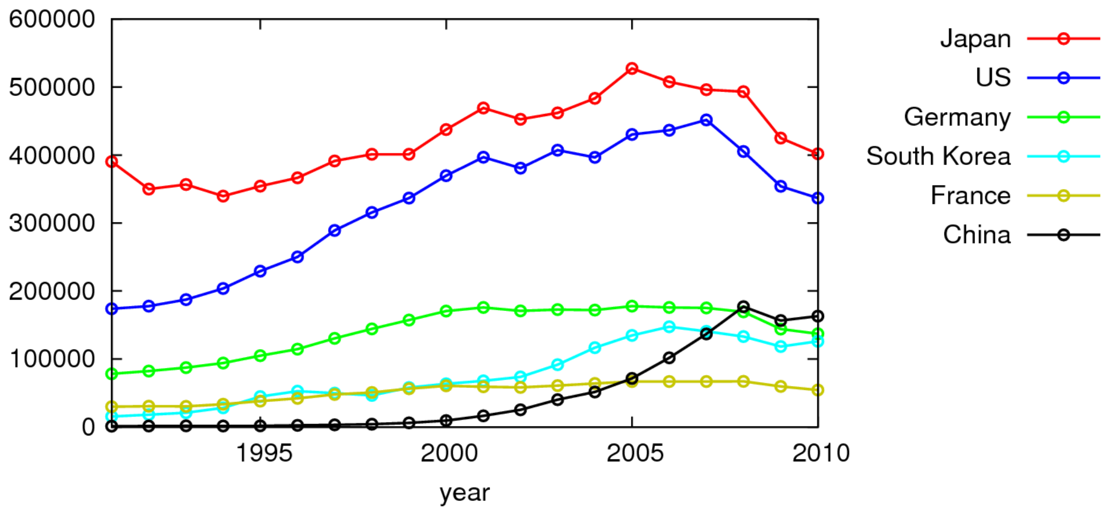


Figure 2: Changes in the Standardized Number of Citations per Patent

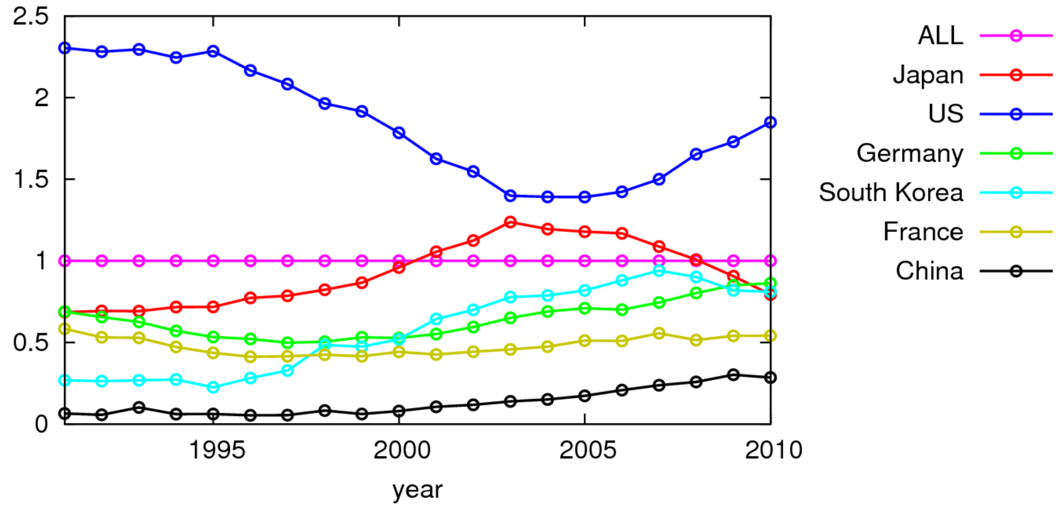


Figure 3: Changes in the Share of Co-owned Patents among All Patents

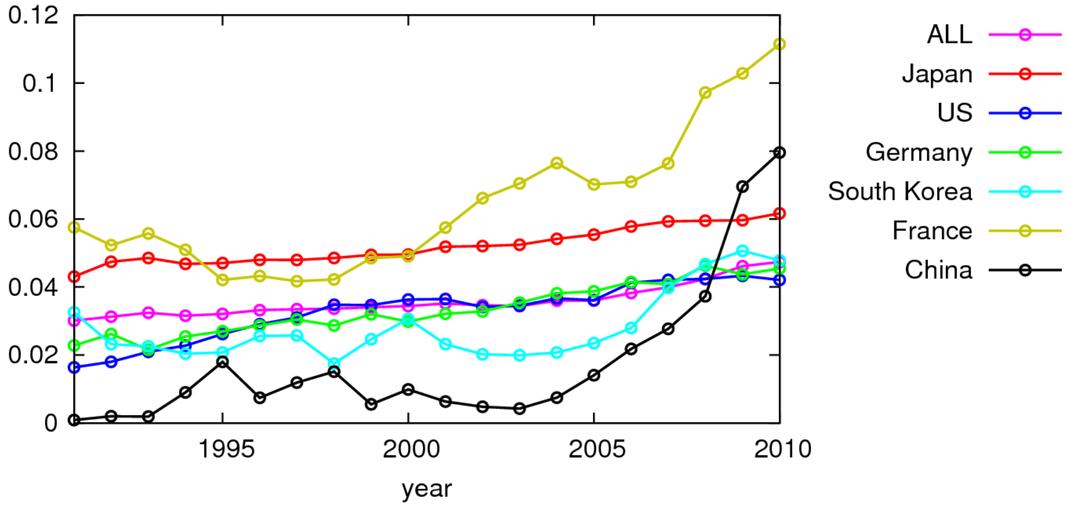


Figure 4: Changes in the Share of Internationally Co-owned Patents among All Patents

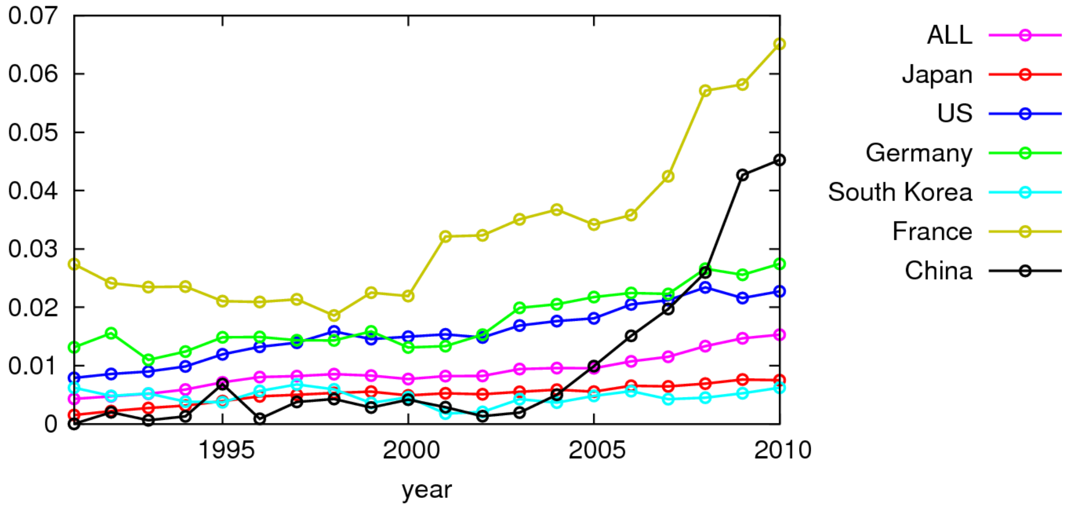
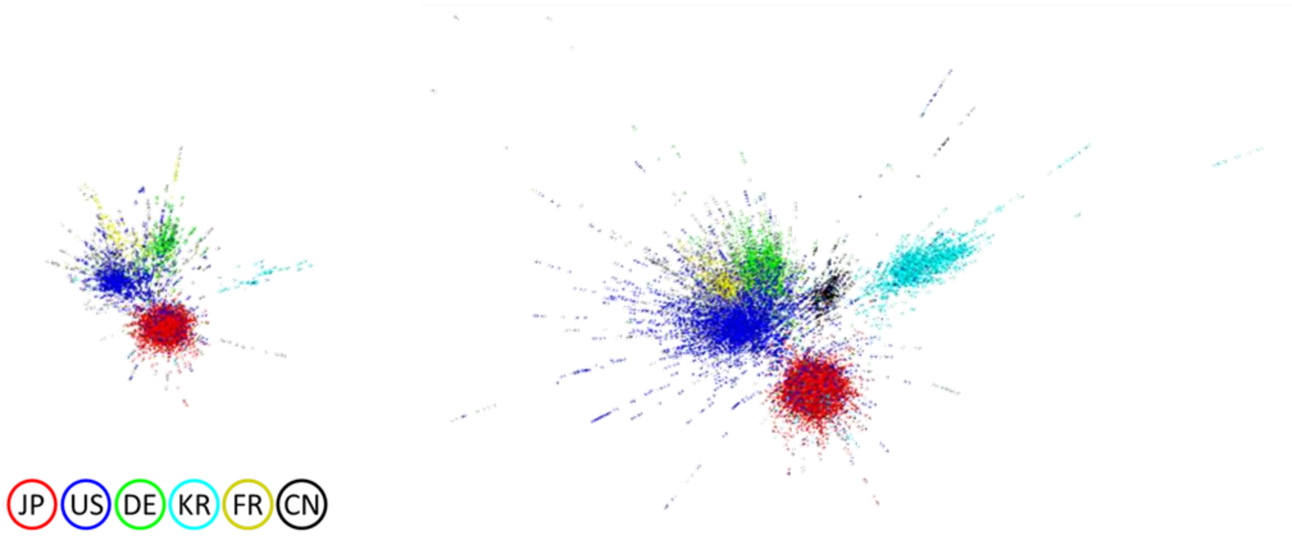


Figure 5: Global Co-patenting Network

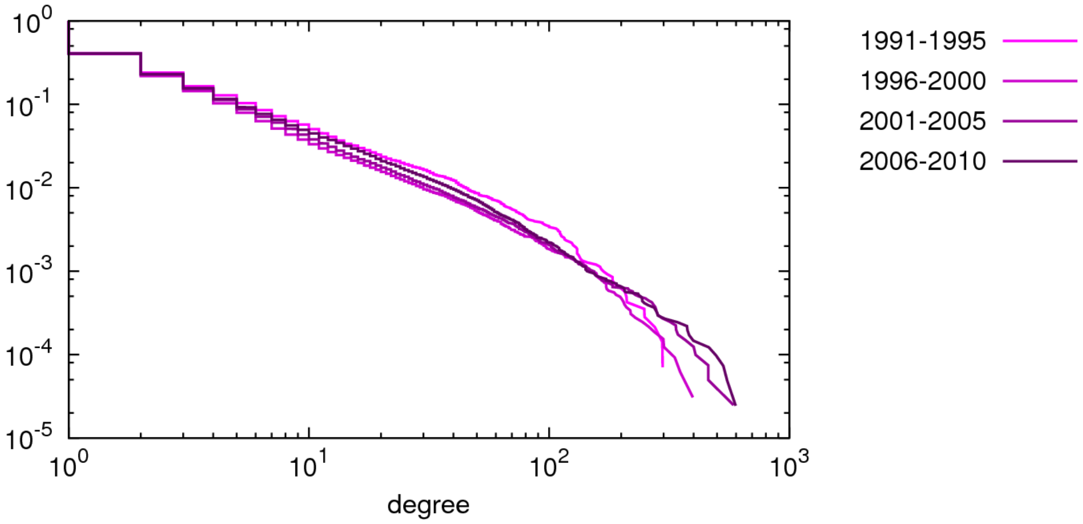
(A) 1991–1995 (B) 2006–2010



Note: Each dot represents a firm, and its color indicates the country of the firm shown by the legend. More precisely, firms in Japan (JP), the US (US), Germany (DE), South Korea (KR), France (FR), and China (CN) are represented by red, blue, green, light blue, yellow, and black, respectively.

Figure 6: Degree Distribution

(A) by Period



(B) by country

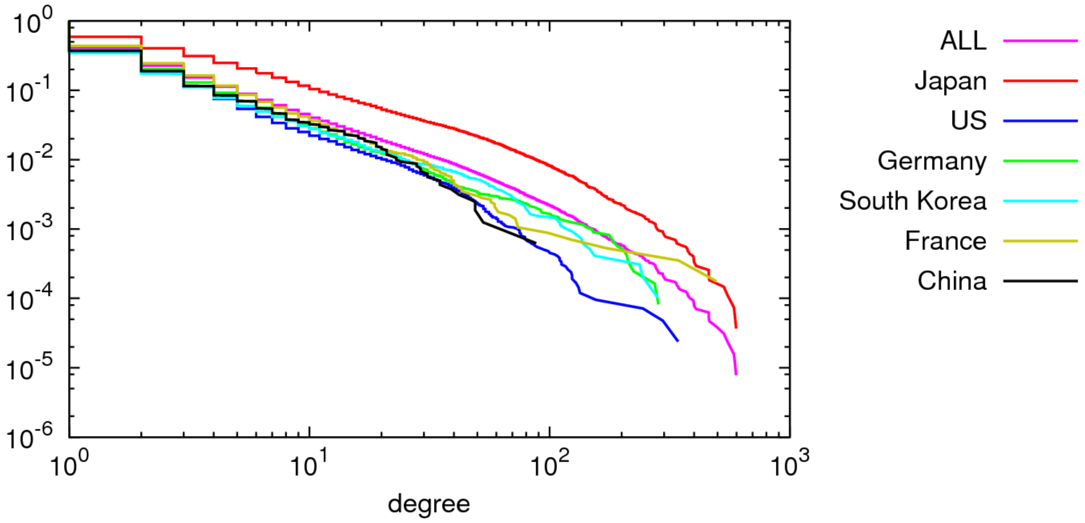


Figure 7: Changes in Spearman's Rank Correlation Coefficients between Firms' Own Degree and the Mean of their Neighbors' Degree

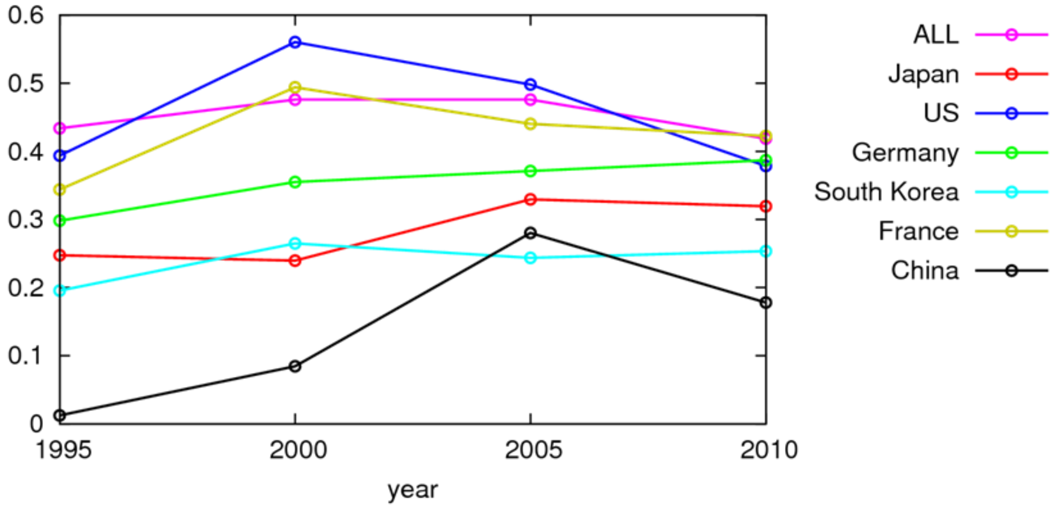
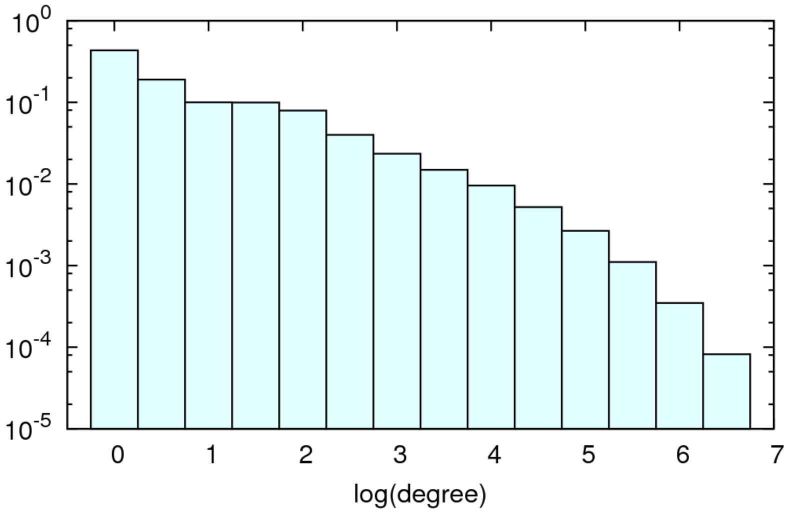
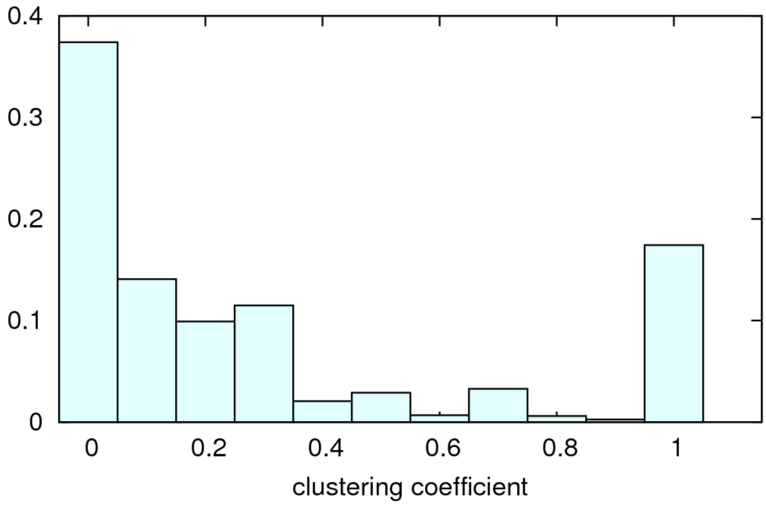


Figure 8: Distribution of Network Measures

(A) Degree centrality (log scale)



(B) Clustering coefficient (Firms with two or more links)



(C) Burt's constraint measure (Firms with two or more links)

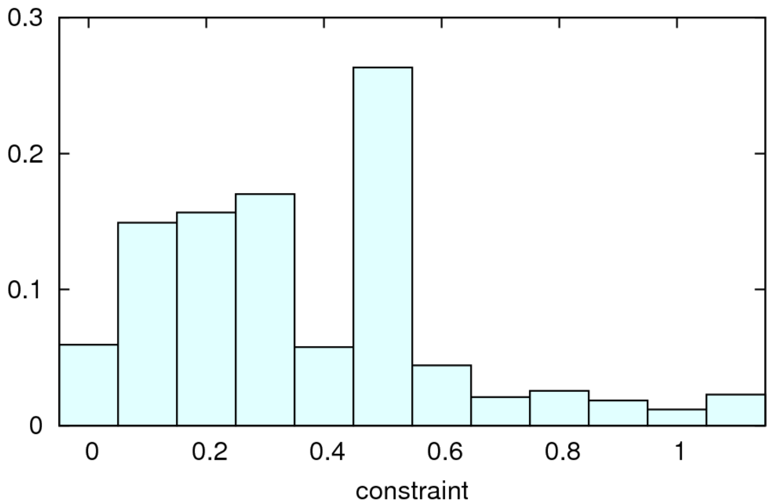
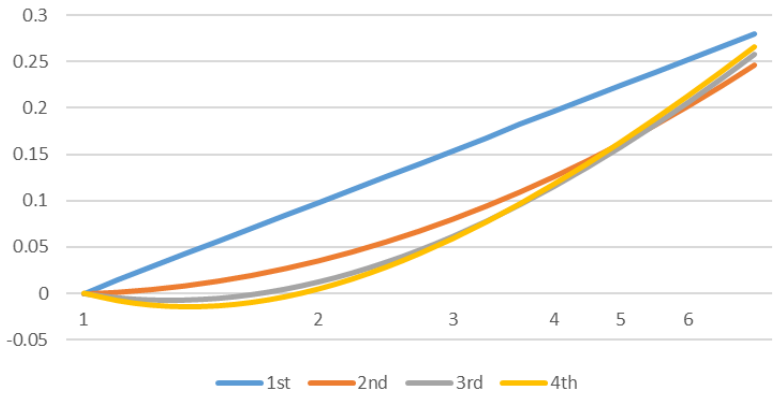


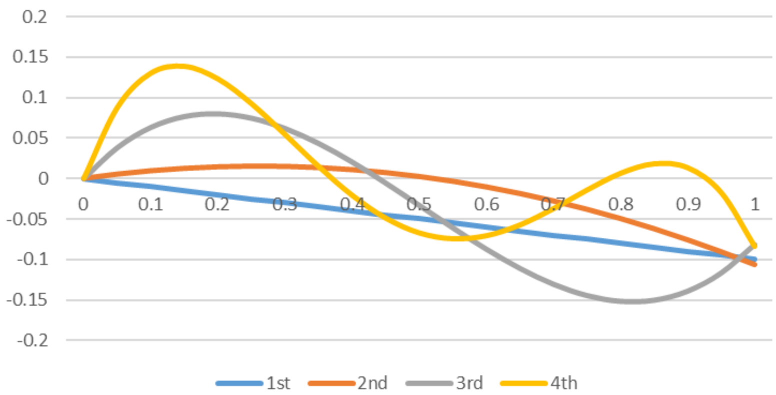
Figure 9: Predicted Relation between Network Measures and Innovation Quality

$$(\ln CITATION = \hat{\beta}_1 x + \hat{\beta}_2 x^2 + \hat{\beta}_3 x^3 + \hat{\beta}_4 x^4)$$

(A) Degree centrality (log scale)



(B) Clustering coefficient



(C) Burt's constraint measure

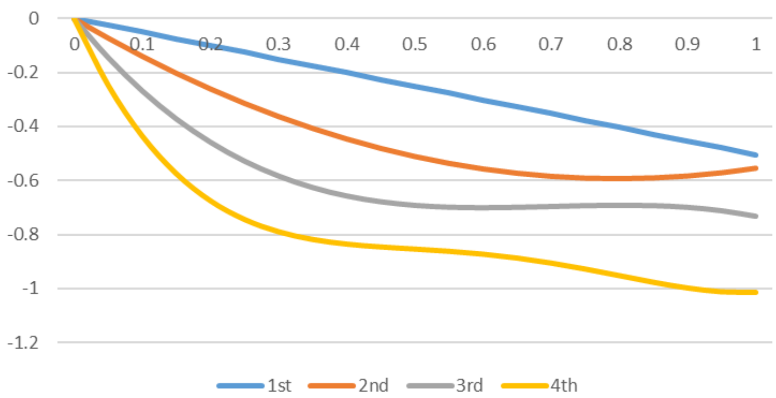


Table 1: Descriptive Statistics at the Firm-Period Level

Variables	*N*	Mean	Std. Dev.	Min.	Median	Max.
All firms granted any patent						
# patents granted	356,397	63.82	1,016.31	1	5	139,275
-- (log)	356,397	1.81	1.57	0	1.61	11.84
# citations	356,397	63.92	1,215.30	0	2.41	207,851
-- (log)	356,397	1.57	1.64	0	1.23	12.24
# citations per patent	356,397	1.32	3.81	0	0.37	475.11
Dummy for co-patenting	356,397	0.20	0.40	0	0	1
Dummy for international co-patenting	356,397	0.05	0.22	0	0	1
Dummy for largest connected component	356,397	0.13	0.34	0	0	1
Firms with co-patenting relationship						
# patents granted	48,910	371.33	2,718.77	1	24	139,275
-- (log)	48,910	3.36	2.05	0	3.18	11.84
# citations	48,910	375.41	3,257.68	0	17.08	207,851
-- (log)	48,910	3.09	2.12	0	2.89	12.24
# citations per patent	48,910	1.21	2.59	0	0.65	259.09
Degree centrality	48,910	5.36	16.81	1	2	599
-- (log)	48,910	0.85	1.01	0	0.69	6.40
Clustering coefficient	48,910	0.17	0.31	0	0	1
Burt’s constraint measure	48,910	0.64	0.36	0.0039	0.61	1.125

Note: Each period consists of five years.

Table 2: Correlation Coefficients between Network Measures

Firms with two or more links ($N = 27{,}700$)

	Degree (log)	Clustering coefficient	Burt's constraint
Degree centrality (log)	1.0000		
Clustering coefficient	−0.2646	1.0000	
Burt's constraint	−0.7576	0.5878	1.0000

Table 3: International Comparison of Descriptive Statistics at the Firm-Period Level

	No. of firm-period observations	No. of patents per firm	Degree centrality (log)	Cluster coefficient	Burt constraint
US	29,069	149.7	0.45	0.18	0.84
Japan	22,392	363.3	0.97	0.20	0.60
Germany	9,939	193.9	0.45	0.12	0.80
South Korea	7,446	175.5	0.44	0.14	0.81
France	2,897	205.5	0.50	0.19	0.79
China	1,099	333.9	0.40	0.14	0.82

Table 4: Effect of Co-patenting Network on Innovation

Dependent variable: log of the standardized number of citations

	(1)	(2)	(3)	(4)	(5)	(6)
Dummy for co-patenting	0.133***	0.0552***				
	(0.0129)	(0.0114)				
Dummy for international co-patenting	0.226***	0.214***				
	(0.0246)	(0.0242)				
Dummy for largest connected component		0.150***				
		(0.0187)				
Degree centrality (log)			0.140***			
			(0.0119)			
Clustering coefficient				−0.100***	0.115*	
				(0.0244)	(0.0603)	
Clustering coefficient^2					−0.221***	
					(0.0591)	
Constraint						−0.504***
						(0.0500)
Dummy for degree of 1				−0.0746***	−0.0654***	0.211***
				(0.0141)	(0.0136)	(0.0288)
log of the number of patents	0.669***	0.667***	0.837***	0.868***	0.866***	0.850***
	(0.0174)	(0.0173)	(0.0144)	(0.0132)	(0.0134)	(0.0133)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry-period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	356,397	356,397	48,910	48,910	48,910	48,910
Adjusted R^2	0.765	0.766	0.885	0.884	0.884	0.885

Notes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 5: Effect of Co-patenting Network on Innovation without Collaboration

Dependent variable: log of the standardized number of citations received by patents that the firm owns without any co-owner

	(1)	(2)	(3)	(4)	(5)	(6)
Dummy for co-patenting	0.118***	0.0435***				
	(0.0117)	(0.0126)				
Dummy for international co-patenting	0.218***	0.207***				
	(0.0233)	(0.0227)				
Dummy for largest connected component		0.139***				
		(0.0178)				
Degree centrality (log)			0.0946***			
			(0.0123)			
Clustering coefficient				−0.101***	−0.0524	
				(0.0239)	(0.0696)	
Clustering coefficient^2					−0.0516	
					(0.0706)	
Constraint						−0.392***
						(0.0545)
Dummy for degree of 1				−0.0593***	−0.0571***	0.182***
				(0.0149)	(0.0152)	(0.0320)
log of the number of patents	0.667***	0.665***	0.873***	0.889***	0.889***	0.879***
	(0.0170)	(0.0170)	(0.0116)	(0.0117)	(0.0116)	(0.0114)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry-period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	338,392	338,392	37,308	37,308	37,308	37,308
Adjusted R^2	0.765	0.766	0.899	0.899	0.899	0.899

Notes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 6: Comparison between Firms with Only Domestic Collaboration and Those with Foreign Collaboration

Dependent variable: log of the standardized number of citations

	(1)	(2)	(3)	(4)
Degree centrality (log)	0.101***			
	(0.0126)			
Degree centrality (log) * dummy for any international link	0.0967***			
	(0.0174)			
Clustering coefficient		−0.0614**	0.161***	
		(0.0254)	(0.0574)	
Clustering coefficient^2			−0.227***	
			(0.0588)	
Clustering coefficient * dummy for any international link		−0.0978**	−0.205*	
		(0.0376)	(0.109)	
Clustering coefficient^2 * dummy for any international link			0.105	
			(0.122)	
Constraint				−0.403***
				(0.0454)
Constraint * dummy for any international link				−0.216***
				(0.0450)
Firm fixed effects	Yes	Yes	Yes	Yes
Country-industry-period fixed effects	Yes	Yes	Yes	Yes
Observations	48,910	48,910	48,910	48,910
Adjusted R2	0.885	0.885	0.885	0.885

Notes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Table 7: Heterogeneity across Time

Dependent variable: log of the standardized number of citations

	(1)	(2)	(3)	(4)	(5)
Dummy for co-patenting	0.0491**				
	(0.0225)				
-- * dummy for 2000s	0.139***				
	(0.0261)				
Dummy for international co-patenting	0.125***				
	(0.0283)				
-- * dummy for 2000s	0.137***				
	(0.0406)				
Degree centrality (log)		0.0904***			
		(0.0174)			
Degree centrality (log) * dummy for 2000s		0.0722***			
		(0.0140)			
Clustering coefficient			−0.108***	−0.317**	
			(0.0321)	(0.122)	
Clustering coefficient^2				0.236*	
				(0.127)	
Clustering coefficient * dummy for 2000s			0.0124	0.700***	
			(0.0294)	(0.135)	
Clustering coefficient^2 * dummy for 2000s				−0.738***	
				(0.146)	
Constraint					−0.0660
					(0.0466)
Constraint * dummy for 2000s					−0.228***
					(0.0463)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Country-industry-period fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	356,397	48,910	48,910	48,910	48,910
Adjusted R2	0.766	0.885	0.884	0.884	0.885

Notes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. The log of the number of patents is included as independent variables, but the results are not presented for brevity.

Table 8: Heterogeneity across Countries

Dependent variable: log of the standardized number of citations

	(1)	(2)	(3)	(4)	(5)	(6)
	US	Japan	Germany	South Korea	France	China
Dummy for co-patenting	0.104***	0.114***	0.130***	0.100***	0.0881***	0.711***
	(0.0173)	(0.0139)	(0.0145)	(0.0171)	(0.0299)	(0.0672)
Dummy for international co-patenting	0.169***	0.155***	0.229***	0.307***	0.253***	0.627***
	(0.0275)	(0.0320)	(0.0396)	(0.0825)	(0.0553)	(0.139)
Number of observations	188,400	45,016	67,794	38,465	18,648	51,019
Degree centrality	0.105***	0.139***	0.234***	0.183***	0.175***	0.321***
	(0.0211)	(0.0153)	(0.0256)	(0.0363)	(0.0448)	(0.103)
Clustering coefficient	−0.0781*	−0.0285	−0.129*	−0.153***	−0.227**	0.0444
	(0.0396)	(0.0295)	(0.0738)	(0.0538)	(0.111)	(0.346)
Clustering coefficient	0.111	0.143*	0.360*	0.704***	−0.326	−1.248
	(0.165)	(0.0817)	(0.183)	(0.220)	(0.378)	(1.102)
Clustering coefficient^2	−0.191	−0.180**	−0.508***	−0.875***	0.101	1.308
	(0.158)	(0.0824)	(0.180)	(0.223)	(0.365)	(1.231)
Constraint	−0.378***	−0.417***	−0.877***	−0.718***	−0.659***	0.0754
	(0.0685)	(0.0551)	(0.155)	(0.119)	(0.168)	(0.625)
Number of observations	29,069	22,392	9,939	7,446	2,897	1,099
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. The log of the number of patents is included as independent variables, but the results are not presented for brevity.