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Abstract

This paper explores how changes in both position and participation in Global Value Chain networks affect firm innovation. The analysis combines matched patent-firm data for Japan with measures of GVC network centrality and GVC participation utilizing the OECD Inter-Country Input-Output Tables for the period 1995 to 2011. We find that Japan's position in the GVCs has shifted from being at the core of Asian value chains towards the periphery relative to other countries in the network, i.e. becoming less "central". We use China's WTO accession as an instrumental variable for changes in Japanese centrality. Our analysis shows that increases in forward centrality – as a key supplier - tends to be positively associated with increasing firm patent applications. Firms in key hubs within GVCs, more specifically as key suppliers, appear to benefit from knowledge spillovers from various customers and downstream markets.

Keywords: network centrality, global value chains, patent portfolio, productivity, micro data, Japan

JEL classification: D24, F14, F61, L25, O33, O53

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1. Introduction

Today's economies are increasingly interconnected through Global Value Chains (GVCs) and the position of different economies within them has been changing significantly in the last decades. In particular, East Asian countries have achieved rapid economic growth and become increasingly interconnected through regional value chains - "Factory Asia". While Japan remains an important player in GVCs, she has become increasingly peripheral within the network. Studies such as Amador and Cabral (2017) and Criscuolo and Timmis (2018) that use network measures to reflect position of each country-industry pair in the GVC network, suggest that Japan has moved away from the central core of Factory Asia. Instead, China has joined the central core and through increasing interconnections with foreign customers and suppliers, has been raising her influence in the GVC network.

Changes in position in GVC networks do not only reflect participation within them – as is illustrated by our focus upon Japan. Criscuolo and Timmis (2018), measuring the centrality of cross-country exports and imports network, show that in 1995, a minority of central hubs, such as USA, Germany, and Japan, dominated regional value chains. Although many of them remained key hubs in 2011, Japan is the exception. By 2011, the position of Japan as a key hub within Asian value chains has diminished substantially, with China and India exhibiting strong growth and other economies such as Korea maintaining their position.[2] On the other hand, Criscuolo and Timmis (2018) also show that Japan has been more deeply participating in the GVCs in terms of foreign value added contents in her exports and domestic value added contents in foreign exports. Therefore, while Japan has become increasingly embedded in the GVC network, it has also become more peripheral.

The trends of falling Japanese centrality coincide with a period of stagnating innovative activity of Japanese firms. Patent applications to the Japanese Patent Office (JPO) have been declining since the mid-2000s. Moreover, many Japanese firms have disappeared from the list of top patenters at the United States Patent and Trademark Office (USPTO) since the 2000s. Firms and industries positioned at the center of complex production networks have access to a greater variety of foreign products, compared to those at the periphery. Since these products are embodied with the skills

[2] Criscuolo and Timmis (2018) also find that Japan's aggregate centrality in the GVC network has declined the most amongst high income economies even after removing the effect of size changes.

and technologies used to produce them, central hubs may also have access to a greater breadth of disembodied knowledge, with greater potential for knowledge spillovers. Indeed, agents with a central position within networks – through their broader range of interconnections - have been shown to have greater access to knowledge (see Alatas et al., 2016; Banerjee et al, 2016; Di Maggio et al., 2017). Therefore, whether firms and industries sit at the fringes of global production or are tightly knotted at the center of a complex network, is likely to affect economic outcomes, particularly technological capabilities of firms and industries.

This paper explores how changes in the relative position and degree of participation in the GVCs affect firm patenting activities, focusing on the experience of Japanese firms. In this paper, we utilize network centrality measures to identify those sectors that are highly central hubs and those that are peripheral in the GVC network. The centrality measures we employ reflect the influence of sectors within production networks.[3] Central sectors reflect those that are highly connected (both directly and indirectly) and influential within global production networks, and conversely, peripheral sectors exhibit weak linkages to other sectors and so are less influential. We anticipate that firms in central sectors are likely to be more highly connected to new sources of knowledge and so positively relate to innovation outcomes.

We examine two measures of centrality reflecting different aspects of exposure to GVC networks. The first aspect considers whether firms in more central sectors in the GVC network increasingly innovate, for instance, by receiving more knowledge spillovers from other foreign sectors in the network. However, many firms are not located in a single country or industry and so are likely to benefit from exposure to foreign knowledge from their plants abroad. The second aspect examines whether multinationals that have foreign affiliates in more central sectors also leads to increased innovation.

We leverage instrumental variable estimation out of a concern that changes in centrality may be related to broader industry changes that also impact firm innovation. We use the timing of China's WTO accession as an instrumental variable to predict changes in Japanese industries' centrality. We leverage the findings of Criscuolo and Timmis (2018), who suggest that central hubs in Asian value chains increasingly shifted from Japan to China. We assume Japanese industries that were initially most central,

[3] Acemoglu et al. (2012) show that the network centrality measure reflects the degree of influence of the node (sector in their context) within network.

were disproportionately exposed to China's WTO accession. Our instrumental variable therefore reflects the interaction of China WTO dummy and Japanese initial centrality (in 1995).

This research contributes to a nascent literature that examines the relationship between position within GVC networks and firm-level performance.[4] There is a growing large body of literature describing GVCs and measuring GVC participation on one hand – where GVCs take into account a broader range of direct and indirect trade linkages (e.g. domestic sales to exporters). Despite, research on the link between GVCs and firm-performance remaining scarce, our study relates to several literatures.

First, there is a growing literature that demonstrates that a minority of highly connected firms and sectors are highly influential in determining aggregate outcomes. Research has begun to shift towards addressing the importance of interconnections between firms and sectors in the transmission of micro shocks (e.g., Magerman et al. 2016). Several theoretical models have been advanced that describe the influence that a minority of highly interconnected firms and industries have on aggregate GDP or sales volatility (e.g., Acemoglu et al. 2012). Specifically, these models all advance a particular metric of influence, the "Bonacich-Katz eigenvector centrality", which corresponds to the metric used in this paper. Several empirical papers show that central firms, industries and countries, with a high number of direct and indirect connections (what we call "hubs") play a disproportionate role in determining aggregate performance (e.g., Acemoglu et al. 2012, Magerman et al. 2016).

Second, related to the above studies, several authors investigate downstream and/or upstream shock propagation. While some studies, such as Barrot and Sauvagnat (2016), Boehm, Faaen, and Pandalai-Nayar (2019) and Carvalho et al. (2014), focus on the impact of natural disasters on downstream/upstream firms utilizing firm-to-firm transaction relationship information, Acemoglu et al. (2016) examine downstream/upstream propagation of demand or supply shock through the input-output linkages. Acemoglu et al. (2016) formulate the propagation of shocks through the input-

[4] A large body of literature has pointed out that exporting and/or importing firms are more productive than non-exporting and/or non-importing firms and that the former tend to show a higher growth rate of productivity and/or skill intensity than the latter. Many studies suggest that participating in the GVCs would raise technological capabilities and productivity of firms, not only because exporters/importers can learn from foreign markets but also because they are more likely to be incentivized to upgrade their products (e.g., Verhoogen 2008, Bustos 2011, Lileeva and Trefler 2010). Participating in the GVCs is likely to enable firms to utilize lower-cost and/or higher-quality suppliers in foreign countries and expand sales in international markets, and thereby likely to promote product upgrading. However, the relationship between position within GVC networks and firm-level performance has not been sufficiently explored.

output linkages and show that demand (supply) shocks in the downstream (upstream) industries propagate upstream (downstream) industries via the Leontief inverse matrix derived from the input-output linkages (they call it a network effect). Although the studies listed here do not exclusively focus on the GVCs, their results suggest that various shocks are transmitted through domestic and/or international production networks and that the network effect is quantitatively substantial.

On the other hand, though not focusing on the propagation through the input-output linkages, Aghion et al. (2018) examine the impact of export shock on innovation using the French firms' data. They find that patenting increases more with export demand for initially more productive firms, suggesting that a positive export shock increases market size and therefore innovation incentives particularly for productive firms.[5]

In this paper, we are interested in the effect of knowledge diffusion through the GVC network. Inspired by Acemoglu et al. (2012, 2016) and other related studies, we expect that firms in central sectors in the GVC network would be affected by downstream/upstream industries. In other words, firms closer to the key hubs in the GVC network are expected to receive more knowledge from other industries in the network. In fact, technology diffusion or knowledge spillovers through input-output linkages has been extensively analyzed in previous studies. In many previous studies, the "amount" of knowledge that flows across industries are estimated using the input-output coefficients and knowledge stock in each industry (e.g., Javorcik 2004), assuming that an industry will receive more knowledge spillovers if the industry purchases more from an industry with larger knowledge stock. In contrast to such studies, we assume that sectors that are highly connected (both directly and indirectly) with other sectors in terms of both the number and the thickness of links and that are connected to more central sectors will be affected by and affect other sectors.

The paper proceeds as follows. The next section explains data we use and our measures reflecting the relative position and degree of participation in the GVCs. Section 3 briefly illustrates the summary statistics of the GVC measures and firm-level patent applications. Section 4 introduces our empirical framework and results. The final section provides a discussion of our main conclusions.

[5] There are some studies on the impact of import competition on innovation (e.g., Bloom et al. 2016, Autor et al. 2016, and Yamashita and Yamauchi 2017). Although our study is modestly related to these studies, these studies focus more on the impact of competition while our study focus more on knowledge spillovers through the network.

2. Data

2.1 Patents

The key measures of firm-level innovation are constructed using patent data from the IIP Patent Database. The IIP Patent Database is compiled based on Consolidated Standardized Data, which are made public twice a month by the Japan Patent Office (JPO). As of December 2016, the IIP Patent Database includes information made public from January 1964 until March 2014, which can be downloaded from the Institute of Intellectual Property (IIP) website.[6] The database includes patent application data (application number, application date, technological field (top IPC), number of claims, etc.); patent registration data (registration number, rights expiration date, etc.); applicant data (applicant name, type, country or prefecture, etc.); rights holder data (rights holder name, etc.); citation information (citation/cited patent number, etc.); and inventor data (inventor name and address, etc.). The patent application ID in the IIP Patent Database can be linked to the firm ID in our firm-level data via applicant information such as company name and address as we detail below.

We use the number of patent applications for each firm and for each year as a measure of innovation outcome.[7] In order to take patent quality into account, we use the citation-weighted number of patent applications as our preferred measure. For each applied patent, we count the number of citations utilizing the citation information in the IIP database. As the number of citations tends to be larger for older patents than newer patents[8], we standardize the number of citations for each patent by dividing it by the maximum number of citations for patents in the same IPC class and application year. We use the standardized number of citations as a weight and construct the citation-weighted number of patent applications for each firm and for each year.

[6] https://www.iip.or.jp/e/e_patentdb/

[7] We decided to use the number of patent applications, not the number of granted patents, because it is well known that the examination procedure takes time in the case of the JPO. According to Japan Patent Office (2010), for example, it takes 29.1 months on average for patent applicants to receive the first action from the patent office as of 2009 though the average duration has been becoming shorter in recent years.

[8] We use the number of citations by examiners, because information on citations by inventors are not in a standardized format. Moreover, citations by inventors were not compulsory in Japan until 2002. Therefore, we consider that it is more reliable and consistent to use the information on citations by examiners only as a measure of patent quality. Although Alcácer and Gittelman (2006) admit that the citations by examiners have different characteristics from those by inventors, they conclude that the bias introduced by examiner citations is not necessarily bad. In this paper, we had to rely on examiner citations due to data constraints, but we believe that information on examiner citation should reflect knowledge flows to some extent.

2.2 Firm-level characteristics

We use firm-level panel data for the period 1995-2011 collected annually by the Ministry of Economy, Trade and Industry (METI) for the Basic Survey on Japanese Business Structure and Activities (BSJBSA).[9] The survey is compulsory and covers all firms with at least 50 employees and 30 million yen of paid-in capital in the Japanese manufacturing, mining, and wholesale and retail sectors as well as several other service sectors. Approximately 25,000 – 30,000 firms are surveyed every year, of which approximately 13,000 – 14,000 firms per year are manufacturing firms. The survey contains detailed information on firm-level business activities such as the 3-digit industry in which the firm operates, its number of employees, sales, purchases, exports, and imports. It also contains the number of domestic and overseas affiliates or subsidiaries, and various other financial data such as costs, profits, investment, debt, and assets. The survey also contains information on firm-level R&D expenditures. Using the firm-level panel data, we construct control variables that represent various firm characteristics such as export and/or import status and R&D intensity.

We link the patent statistics compiled from the IIP Patent Database with the firm-level panel data constructed from the BSJBSA using identical company names and locations. In Ikeuchi et al. (2017), they link the Enterprise and Establishment Census conducted by the Ministry of Internal Affairs and Communications and the IIP Patent Database using company names and locations. We follow their methodology to link the BSJBSA and patent databases, additionally utilizing zip codes and telephone numbers. Using the patent-firm-matched data, we analyze the firm-level number of (citation-weighted) patent applications.

Our GVC centrality and participation measures are constructed based on the Inter-Country Input-Output (ICIO) Tables that capture cross-border trade across countries. The ICIO tables focus on the origin and the destination countries of trade flows and do not take account of the ownership of exporting and/or importing firms. Although China shifts towards the hub of Asian value chains in terms of exports/imports flows across countries, a significant part of Chinese exports/imports is conducted by foreign-owned firms located in China. In the case of Japan, even though the growth rate of exports from and imports to “Japan” has been somewhat moderate, many foreign affiliates of Japanese

[9] The compilation of the micro data of the METI survey was conducted as a part of the research project at the Research Institute of Economy, Trade and Industry (RIETI).

firms have been drastically increasing exports from and imports to the country where the affiliates are located. In order to take such global ownership network into account, we use the affiliate-level data underlying the Basic Survey on Overseas Business Activities (BSOBA) collected annually by METI.[10] From the survey, we take the number of affiliates, employment and sales of affiliates by industry and by country for each parent firm.[11]

2.3 Measures of GVC embeddedness

We construct the industry-level measures of GVC embeddedness, using the OECD Inter-Country Input-Output (ICIO) Tables 2015 edition that covers 58 countries and 37 industries for the years from 1995 to 2011. We link the firm-patent-matched dataset with the industry-level GVC measures, using the firm-level industry information.[12]

2.3.1 GVC centrality

We construct measures of network centrality in order to reflect relative position of each country-industry pair within GVCs. Following Criscuolo and Timmis (2018), we use the Bonacich-Katz eigenvector centrality metric, which has recently been implemented by several studies to identify key players in a network.[13] This measure takes both direct and indirect linkages into account. The definition and the calculation of the network centrality are described in the following paragraphs.

The linkages within the GVC network reflect ICIO flows of goods and services. The centrality is determined not only based on direct trade linkages, but also the linkages of your trade partners. Central sectors are those that linked to highly-connected sectors, hence it follows a recursive calculation. It is calculated as some baseline centrality, plus a weighted sum of centralities of downstream or upstream sectors. Thus, centrality of a sector is determined not only based on its own linkages, but also its suppliers' linkages, and its suppliers' suppliers' linkages, etc.

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[10] The compilation of the micro data of the METI survey was conducted as a part of the research project at the Research Institute of Economy, Trade and Industry (RIETI).

[11] We constructed not only these firm-level statistics, but also the country-industry-level aggregated statistics in order to check overall trends of overseas activities by Japanese multinational firms. The country-industry-level statistics are available on the RIETI website.

[12] Unfortunately, the detailed information on products for each firm is not available in the BSJBSA.

[13] This metric has been implemented by macroeconomic studies on shock diffusion (Acemoglu et al. 2012, Carvalho 2014, etc.) and also applied to knowledge diffusion in social networks (Alatas et al. 2016, Carvó-Armengol 2009, Manski 1993, 2000, Bramoullé et al. 2009, etc.).

Formally the eigenvector-type centrality for each sector in a particular country is calculated using the formula given by equations (2.1) and (2.2). The backward centrality is calculated as the baseline centrality (η) plus the weighted sum of centralities of their upstream trade partners, i.e., suppliers, as follows:

$$c^{back}{}_i = \lambda \sum\nolimits_j w_{ji} \cdot c_j^{back} + \eta \qquad (2.1)$$

where *i* or *j* denotes a country-industry pair, λ and η are parameters, and w_{ji} is the share of input *j* in the total intermediates used in *i*, i.e., the upstream input linkages. The parameter λ determines the rate of decay of higher order network linkages, thus supplier linkages have a weight of λ, suppliers of suppliers have a weight of λ^2 and so on. Thus, this is a measure of influence based on being linked to highly connected nodes and also based on the importance of the link. In other words, backward centrality is higher for sectors that are major customers of a central hub in the network. Similarly, forward centrality is calculated as the baseline centrality (η) plus the weighted sum of centralities of downstream trade partners, i.e., customers, as follows:

$$c^{fwd}{}_i = \lambda \sum\nolimits_j w_{ij} \cdot c_j^{fwd} + \eta \qquad (2.2)$$

where w_{ij} is the share of sales from *i* to *j* in the total intermediates supplied by *i*, i.e., the downstream input linkages. Key suppliers that trade with central hubs in the forward network have a larger forward centrality. To facilitate aggregate comparisons, we reflect total centrality as the average of forward and backward centrality (equation 2.3). The calculation of backward and forward centrality allows disentangling important distinctions between key and peripheral customers, and key and peripheral suppliers, respectively. However, for illustrative purposes it is often useful to have an overall measure of centrality, which we define as the average of backward and forward centrality.

$$c^{total}{}_i = {}^1\!/_2 \cdot (c^{fwd}{}_i + c^{back}{}_i) \qquad (2.3)$$

Solving c_i^{back} and c_i^{fwd} in equations (2.1) and (2.2), respectively, we obtain backward and forward Bonacich-Katz eigenvector centrality in the vector and matrix notation:

$$\boldsymbol{c}^{back} = \eta(\boldsymbol{I} - \lambda\boldsymbol{W}')^{-1}\mathbf{1} \tag{2.4}$$

$$\boldsymbol{c}^{fwd} = \eta(\boldsymbol{I} - \lambda\boldsymbol{W})^{-1}\mathbf{1} \tag{2.5}$$

where $\boldsymbol{c}^{back}$ *and* $\boldsymbol{c}^{fwd}$ are the backward and forward centrality vectors, respectively, **1** is a vector of ones, $\boldsymbol{I}$ is the identity matrix. $\boldsymbol{W}$ is the normalized global input-output coefficient matrix.[14]

We decompose the backward and forward centralities into domestic and foreign parts, and define the centrality of domestic backward (forward) linkages and the centrality of foreign backward (forward) linkages. See Criscuolo and Timmis (2018) for more details on the calculations.

2.3.2 GVC participation

We also construct the measures for the degree of participation in the GVCs using the OECD ICIO Tables.

Participation in GVCs generally means to what extent countries/industries/firms are involved in a vertically fragmented production. One way to measure it is to measure vertical specialization (VS) share, i.e., the value of imported inputs in the overall exports of a country. In other words, this measure of GVC participation measures the foreign content of exports.

However, a country also participates in GVCs by being a supplier of inputs used in third countries for further exports. Hummels, Ishii, and Yi (2001) introduce the “VS1” share, which is the share of exported goods and services used by other countries as imported inputs in their production of their exports.

The GVC literature distinguishes VS and VS1, calling the former “backward GVC participation” the latter “forward GVC participation.” The combined measure is also widely used in the literature (De Backer and Miroudot 2013). Following the conventional GVC literature, we construct both the backward GVC participation measure and the forward GVC participation measure. [15] More specifically, our industry-

[14] We specify parameters λ and η from theoretical works of Acemoglu et al. (2012) and Carvalho (2014). We use a value of 0.5 for both λ and η.

[15] As domestically produced inputs can incorporate some of the foreign inputs, there is an overlap and potentially some double counting. For more details on the double counting issue, see Koopman et al. (2014) and Wang et al. (2013).

level backward GVC participation measure is the ratio of imported intermediate goods and services embodied in a domestic industry's exports to the overall exports of a country. Our industry-level forward GVC participation measure is the ratio of domestically produced inputs used in third countries' exports to the overall exports of a country. We also use the total GVC participation measure that is calculated as the simple average of the backward and forward participation measures.

3. GVC Embeddedness and Patenting by Japanese Firms

Figure 1 shows the trend of aggregate GVC centrality and participation over time. While GVC participation has been increasing, the aggregate centrality has been declining. Figures 2 and 3 show the changes in GVC centrality and GVC participation by industry from 1995 to 2011. Figure 2 shows the changes in backward centrality and participation, while Figure 3 shows the changes in forward centrality and participation. For backward and forward participation measures, the contribution of trade with high-income countries is shown separately from the measures calculated from trade with all countries.

Looking at Panel (1) of Figures 2 and 3, both backward and forward centrality declined in many industries. Particularly, industries such as computer and electronics and wholesale and retail trade, show a substantial decline both in terms of backward and forward centralities. The large decline in centrality suggests that these industries have become relatively peripheral in the GVCs by 2011, however, one should bear in mind that these industries were central hubs in 1995.

However, as shown in Panel (2) of Figures 2 and 3, both backward and forward GVC participation measures increased in almost all the industries. In the case of forward GVC participation, while Japan's content of other high-income countries' exports declined in some industries, such as computer & electronics and wholesale & retail trade, Japan's content of exports by all foreign countries increased. In the case of backward GVC participation, although the high-income countries' contents of Japan's exports increased, other countries' contents seem to have increased more. These figures imply that Japan's increased GVC participation was mainly driven by the increases in imported intermediate goods and services from and exports of intermediate goods and services to developing countries. [16] The increased trade with developing countries, that are

[16] For more details on GVC centrality and participation for other countries and industries, see Criscuolo and Timmis (2018). Although developed countries tend to lower centrality in manufacturing sectors while

themselves relatively peripheral in GVC networks, explains at least part of the fall in Japanese centrality noted above.

INSERT Figures 1 & 2 & 3

The number of JPO patent applications was gradually increasing in the late 1990s but has been declining since the mid-2000s (Figure 4). Looking at patent applications by industry (Table 1), firms that apply patents are concentrated in a small number of industries, such as chemicals, machinery and equipment, computer and electronics, electrical machinery and apparatus, and motor vehicles. Table 2 shows the number of firms that applied at least one patent and the share of these firms by industry. Table 2 also indicates that the share of firms with at least one patent application was at the peak in the first half of the 2000s, but it has been declining in many industries since then.[17]

INSERT Figure 4

INSERT Tables 1 & 2

Moreover, the average citation-weighted number of patent applications per firm also shows a declining trend (Figure 5). In particular, the computer & electronics industry shows a drastic decline in the average citation-weighted number of patent applications per firm. If we assume that the number of citations is a proxy for patent quality, Figure 5 implies that patent quality applied by Japanese firms has been declining over time.

We observe a weak positive relationship between changes in the GVC centrality and changes in the average citation-weighted number of patent applications per firm from 1995 to 2011 (Figure 6). Industries that became increasingly peripheral in GVC networks tended to have larger falls in citation-weighted patents. This figure may imply that the

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developing countries tend to raise it, Germany and the United States are still remained as key hubs in industries such as motor vehicles and chemicals. Moreover, the United States was a key hub in many services industries in 1995 and her centrality was even increased by 2011. In Asian countries, particularly in the computer & electronics industry, China' centrality has increased conspicuously while the centrality of some other Asian countries such as Korea and Malaysia also have increased. For changes in centrality for some major industries and countries in Asia, see Appendix Figure A1.

[17] The trend of the share of firms that applied at least one patent for major industry is shown in Appendix Figure A2. Although the share of patenting firms has been declining in most industries since early or mid-2000s, the average number of patent applications per firm seems to be increasing if we focus on the firms with at least one patent application (Appendix Figure A3). These figures may suggest that patent applications tend to be becoming concentrated in a smaller number of firms that are getting more active in patenting.

declining GVC centrality explain at least part of the decline in quality-adjusted patent applications by Japanese firms. In the following sections, we examine the relationship more rigorously by estimating the determinants of firm-level patent applications.

INSERT Figures 5 & 6

4. Empirical Strategy

4.1 Model

As noted earlier, we expect that firms in industries that become more central within GVCs would increase innovation, because the central hubs, either as key customers or suppliers, are likely to have access to a greater variety of foreign inputs embodied with skills and technologies and also a greater breadth of disembodied knowledge. At the same time, the increase in backward and forward GVC participation, i.e., vertical specialization in the GVC, may also affect firms' innovation activities. The increase in backward and forward GVC participation – for instance, through the growth of offshoring – may shift domestic resources towards more innovative activities.

We estimate the following equation to examine the relationship between innovation outcome of Japanese firms and our GVC centrality and participation measures.

$$\begin{aligned} Y_{fit} = {} & \beta_1 DAFF_{fit-3} + \beta_2 FC_{fit-3} + \beta_3 C_{it-3} + \beta_4 VS_{it-3} + \beta_5 Firm\ Controls_{fit-3} \\ & + \delta_f + \tau_t + \varepsilon_{fit} \end{aligned} \tag{4.1}$$

$$Y_{fit} = ln\left(1 + NumPat_{fit}\right) \tag{4.2}$$

The dependent variable, *NumPat*, represents the number of patent applications for firm *f* in industry *i* in year *t*, which is a proxy for the innovation outcome. In order to take patent quality into account, we use the citation-weighted number of patent applications as our preferred measure, reflected as *NumPat*.[18] In fact, a substantial number of firms do not apply any patents, and therefore, a large number of observations with zero patent applications are included in our dataset. In order to reflect these zero-patent observations,

[18] We also estimated the same model using the non-weighted *NumPat* as a dependent variable. The estimation results were more or less consistent but less significant.

we define the dependent variable as equation (4.2). We also restrict our sample to only innovating firms with at least one patent application for the period from 1994 to 2011. In addition, we mainly focus on the manufacturing firms and exclude firms that switch their industry classification at the two digit-level for the period from 1994 to 2011.

As for other explanatory variables, we are most interested in the industry-level GVC network centrality variable, *C*. The variable *C* denotes either the total, backward, or forward centrality measure. We also include the affiliate-size weighted host country-industry centrality measure, *FC*, in order to capture the possibility that multinational firms have access to knowledge through their foreign affiliates. We expect that firms operating foreign countries will receive more technology spillovers from other countries or industries, especially when their affiliates are located in countries or industries with higher network centrality. Therefore, we construct the affiliate-size weighted host country-industry centrality measures to capture knowledge spillovers through foreign affiliates of multinational firms, in the following way:

$$FC_{ft}^{BACK} = \sum_k \sum_j \left({AF_{fkjt}} / {AF_{ft}} \right) C_{kjt}^{BACK} \tag{4.3}$$

$$FC_{ft}^{FOR} = \sum_k \sum_j \left({AF_{fkjt}} / {AF_{ft}} \right) C_{kjt}^{FOR} \tag{4.4}$$

$$FC_{ft}^{TOTAL} = {1}/{2} \cdot (FC_{ft}^{BACK} + FC_{ft}^{FOR}) \tag{4.5}$$

where AF_{fkjt} denotes number of workers employed in the affiliate of the multinational firm *f* in country *k* in industry *j* in year *t*. AF_{ft} denotes number of workers employed in the all foreign affiliates of multinational firm *f* in year *t*. We also construct a dummy variable, *DAFF*, which takes one for firms with at least one affiliate abroad. For firms without affiliates abroad, we define *FC* as zero, but we include *DAFF* in order to capture the difference between multinational and non-multinational firms.

Moreover, to control for the vertical specialization, we include the variable *VS*, which denotes either the total, backward, or forward GVC participation measure.

As for firm-level control variables, we include firm size measured as log number of employees, R&D intensity measured as R&D expenditure divided by sales, export and import intensities measured as exports or imports divided by sales, and trade intensity measured as trade (sum of exports and imports) divided by sales.[19] δ_f and τ_t denote firm-specific fixed effects and year-specific fixed effects, respectively.

We estimate equation (4.1) by using the fixed-effect panel estimation method. For our baseline estimation, we use the three-year lagged explanatory variables and also include firm- and year-specific fixed effects.[20] We also prefer three-year lagged model, because we expect that innovation/patenting decisions are likely to be slow and there is some time lags to make a decision, and this reduces the scope for endogeneity issues. Including firm and year fixed effects also removes any slow-moving firm-specific confounding factors, which may include management capital, and focuses the analysis on within-firm changes.

We also estimate an instrumental variable specification to further mitigate endogeneity concerns. Our instrumental variable uses the timing of China's accession to the WTO, which appears to have resulted in central hub of Factory Asia increasingly shifting from Japan and towards China (Criscuolo and Timmis, 2018). Japanese industries that initially had high centrality experienced a particularly large decline in centrality.[21] Our instrumental variable contains two parts: a dummy variable reflecting the timing of China's WTO accession; and an interaction term reflecting Japanese industries' initial centrality. The China World Trade Organization (WTO) accession dummy variable takes the value one from the year 2002 onwards, and zero for years before 2002. The interaction term reflects the initial year (1995) Japanese industries' centrality.

In the IV estimation, we also use an alternative measure of the affiliate-size weighted centrality. Namely, we construct the variable using the initial-year number of workers employed by foreign affiliates of Japanese multinational firms as a weight, instead of the contemporaneous employment size. We use the number of workers employed by foreign affiliates in year 1995 (the initial year of our dataset) for firms that already had at least one foreign affiliate in 1995. For firms that established the first foreign affiliate after 1995, we take the number of workers employed by foreign affiliates

[19] We estimated the model using an exporter dummy and an importer dummy, instead of export and import intensities. As the results were qualitatively similar, we report the results using the intensity variables in this paper.

[20] We also estimated the model using the one-year lagged or five-year lagged explanatory variables. The results were qualitatively similar to the baseline results.

[21] Appendix Figure A4 shows the trend of GVC centrality for major industries for Japan and China. Centrality is declining continuously for Japan and increasing continuously for China. In particular, centrality of the computer and electronics industry sharply declined for Japan after China's accession to the WTO in contrast to the sharp increase for China.

for the first year when the firm established at least one affiliate abroad. The basic statistics of the variables are summarized in Appendix Table A1.

4.2 Results

Table 3 shows the baseline estimation results. Equations (1) – (3) of Table 3 shows the fixed-effect panel estimation results while equations (4) – (6) of the table shows the results of the IV fixed-effect panel estimation. Equations (1) and (4) show the results when we employ total centrality and participation measures. Similarly, backward centrality and participation measures are used for equations (2) and (5) while forward centrality and participation measures are used for equations (3) and (6). The standard errors are clustered at the two-digit industry level.

Both the OLS and the IV estimation results are broadly consistent. Our instrument strongly predicts changes in centrality of Japanese industries, particularly total or forwards (export) centrality with first-stage F-statistics of 37 and 52 respectively.[22] For backwards (import) centrality the instrument remains reasonably strong, with a first-stage F-statistic of 9.4. The instrument has the expected negative sign – namely that Chinese WTO accession led to larger centrality falls for Japanese industries that were initially central hubs (see Appendix Table A2). The instrument has a reasonably large coefficient – Japanese industries with 1 unit higher centrality, experienced a 0.25 unit fall due to Chinese WTO accession. Recall that over this period, Japanese industries on average experienced around 40% fall in backwards centrality and a 60% fall in forwards centrality (see Figure 1).

Turning to our key variables of interest, (headquarter) centrality and affiliate-weighted centrality, we find that increases in centrality lead to increases in firm innovation. In terms of (headquarter) centrality the positive and significant coefficient of forward centrality in equations (3) and (6) suggests that firms within industries that become more central in the forward linkage network tend to show a higher propensity to innovate. That is to say, connections with foreign customers matter for domestic innovation. For backward (headquarter) centrality (with suppliers) we find no evidence of such a link (see 1 and 3).

In terms of affiliate-weighted centrality we find strong evidence that both backwards and forwards centrality leads to domestic innovation. The estimated

[22] The first-stage results of the IV estimation are shown in Appendix Table A2.

coefficients across all specification (1) to (6) are significantly positive. This suggests that multinational firms with foreign affiliates in countries or industries with higher network centrality are more likely to apply for higher quality patents.

For GVC participation control variable, we find a more mixed picture. The positive and significant coefficient of forward GVC participation (equations (3) and (6)) also suggests that forward linkages are positively associated with patent applications, i.e., innovation. However, backward GVC participation is negatively associated with patent applications (equations (2) and (4)), suggesting that vertical specialization in the backward linkages does not promote innovation, rather likely has a detrimental effect.[23]

As for other explanatory variables, larger firms in terms of the employment size tend to show a higher propensity to innovate. Although the negative coefficient of *RDINT* is somewhat puzzling, it may imply that R&D efficiency has deteriorated for Japanese firms on average. Another puzzling result would be the negative and significant coefficient of the export intensity variable (*EXPINT*). While the positive coefficients of forward centrality and GVC participation suggest a positive correlation between industry-level export orientation and patenting, the firm-level export intensity – at least conditional on the other variables - is negatively associated with patenting. In order to explore this issue in more detail, we next examine an interaction effect of industry-level GVC embeddedness and firm-level trade orientation.

INSERT Table3

Table 4 shows the results including the interaction terms of the GVC centrality/participation and a firm's export/import intensity to examine heterogeneous impact of the GVC centrality/participation across firms. Panel (1) of Table 4 shows the fixed-effect panel estimation results while Panel (2) shows the results of the IV fixed-effect panel estimation.[24] Again, the results in both panels are very similar.

In terms of centrality, we find similar results to Table 3, but that the centrality effects are stronger for those firms that export or import directly. Consistent with the results in

[23] The magnitude of coefficients of the backward and forward GVC participation variables in Table 3 is much larger than that of coefficients of other explanatory variables. As explained in Section 2.3.2, our GVC participation measures are calculated for each industry but the measures are standardized by the country's total exports. That is why the magnitude of the GVC participation measures is small (See Appendix Table A1) and therefore, the magnitude of the estimated coefficients is large.
[24] The first-stage results of the IV estimation are shown in Appendix Table A3.

Table 3, forward centrality tends to be positively associated with patent applications (equations (5) and (6)). Moreover, the positive and significant coefficient of the interaction term of centrality and export/import intensity suggests that more export-intensive firms in industries that become more central through forward linkages tend to apply more patents. Although the stand-alone centrality in the backward linkage network is not strongly associated with patent applications, more import-intensive firms in industries with higher backward centrality also tend to apply for more patents (equation (3) in both panels). The results in both panels in Table 4 suggest that although firm-level trade intensity tends to be negatively associated with the number of patent applications on average, more trade-oriented firms in more central industries tend to apply for more patents. The results imply that more export/import-oriented firms in industries that are the key suppliers/customers in the GVC network, are more likely to innovate probably because they receive more technology or information spillovers from participants in the network and utilize the spillovers.

The results for centrality contrast with those for GVC participation (as in Table 3). As for the forward and backward GVC participation measures, the results in Table 4 also suggest that the former tends to be positively while the latter tends to be negatively associated with patent applications, which is consistent to the results in Table 3. The estimated coefficients of the interaction terms of firm-level export/import intensity and the GVC participation measures are not statistically significant.

The results in Tables 3 and 4 suggest that being involved in the forward linkage network is more important for innovation than being involved in the backward linkage network, particularly for exporters. In other words, having access to a greater breadth of customers would promote innovation activities and lead to larger innovation outcomes. While this appears to be true of firms in those industries more generally, perhaps through indirect export linkages (i.e. domestic sales to exporters), this is particularly true of exporters. Exporters located in the key hubs in GVCs appear to benefit from knowledge spillovers from various customers and downstream markets. In fact, a back-of-the-envelope calculation suggests that fall in the GVC centrality for Japan explains a significant part of the patent slowdown of Japan. During the period from 1995 to 2011, the mean of our dependent variable (citation-weighted number of patent applications in logarithm) declined by 0.225 (the mean value for 2011 was 0.0444 while that for 1995 was 0.2696). On the other hand, the mean of the forward GVC centrality declined by 0.4795 during the same period (the mean value for 2011 was 0.7050 while that for 1995 was 1.1845). Based on the estimated coefficient of the forward GVC centrality in equation (6) in Table 3, the fall in the forward centrality explains approximately 36% (=$0.169 \times 0.4795/0.225$) of the decline in the dependent variable during the period from 1995 to 2011.

On the other hand, backward GVC participation negatively affects patent applications (equations (2) and (5) in Table 3 and equations (3) and (4) in both panels of Table 4). Although one may expect that firms utilizing imported inputs would shift their resources from production to innovation activities and so GVC participation would promote innovation, the result does not seem to support this hypothesis. As Pisano and Shih (2012) argue, proximity of innovation activities to factory floor may be important to create new knowledge and technology, especially for many Japanese firms that are strong in integral-type low-modularity production.[25] Thus, participating and position in GVCs appear to be different.

INSERT Table 4

5. Conclusions

This paper explores how changes in the relative position and degree of participation in the GVCs affects firm innovation activities, focusing on the experience of Japanese firms. The analysis combines patent-firm-matched data with information on GVC networks from the OECD ICIO Tables for the period from 1995 to 2011. We use novel measures of network centrality to measure key hubs and distinguish in our analysis between position and participation within GVCs.

Based on these measures, we find that Japan's position in the GVCs for many industries has shifted from being at the core of Asian value chains towards the periphery relative to other countries in the network – and a substantial part of this is due to China's WTO accession. This is in spite of Japan's increasing participation in GVCs in terms of the domestic value added embodied in foreign exports (forward GVC participation)

[25] We also conducted various robustness checks by using different samples and taking one-year lag for explanatory variables instead of three-year lags. The estimation results for firms including non-manufacturing firms are shown in Appendix Table A4, while the estimation results for manufacturing firms using the one-year lagged explanatory variables instead of the three-year lagged variables are shown in Appendix Table A5. Although the estimated coefficients tend to be less significant for the one-year lagged specification, the results are qualitatively similar to those in Tables 3 and 4.

and/or foreign value added embodied in her exports (backward GVC participation). At the same time, Japanese firms' productivity has stagnated since the 1990s, and the number of patent applications by Japanese firms has been declining since the mid-2000s. We examine if these trends are related.

Our analysis shows that forward centrality (i.e., having access to a greater breadth of customers) tends to be positively associated with firm innovation activities (measured as the number of patent applications) particularly in the case of exporters. This suggests that firms located in the key hubs in GVCs appear to benefit from knowledge spillovers from various customers and downstream markets. On the other hand, more traditional measures of GVC participation do not show a clear picture. Backward GVC participation, i.e., being more vertically specialized in downstream production, tends to have a detrimental impact on innovation, but forward GVC participation, i.e., being more vertically specialized in upstream production tends to have a positive impact on innovation. These results may suggest that knowledge spillovers from the forward linkage network appear to be beneficial for innovation, i.e., knowledge creation, and that becoming a key supplier in the GVC network by specializing in high value-added activities may be important to benefit from knowledge spillovers from downstream foreign customers.

Thus, the results of our study suggest the importance of being a key hub in the GVC network, particularly in terms of customer connections, for knowledge creation. Japanese firms/industries have been increasing vertical specialization and becoming increasingly embedded within GVCs – but embeddedness alone does not seem to clearly translate into improved innovation. More importantly, being more "central" in the GVC network and having access to a greater breadth of customers appears to be more beneficial to developing new technologies. While we focus on China's WTO accession, investigating all the determinants of network centrality is beyond the scope of this paper. Our results suggest that developing new foreign customers and expanding customer base abroad would be important for innovation.

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Figure 1. Japan's GVC Centrality and Participation Overtime: 1995 to 2011

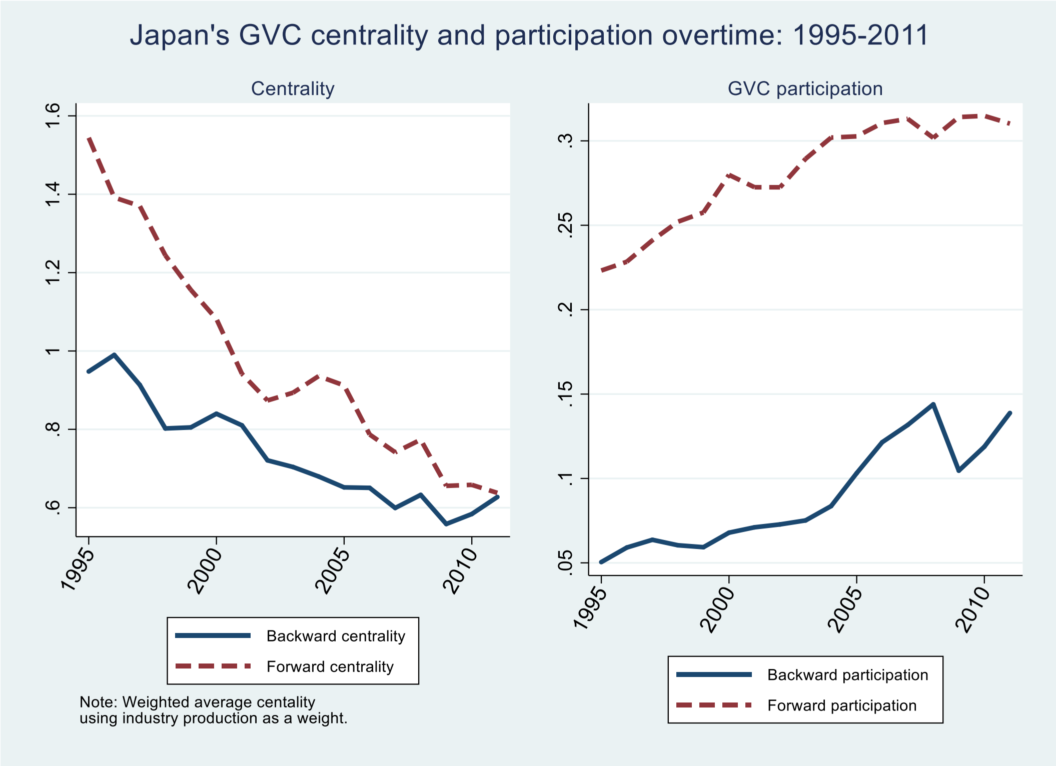
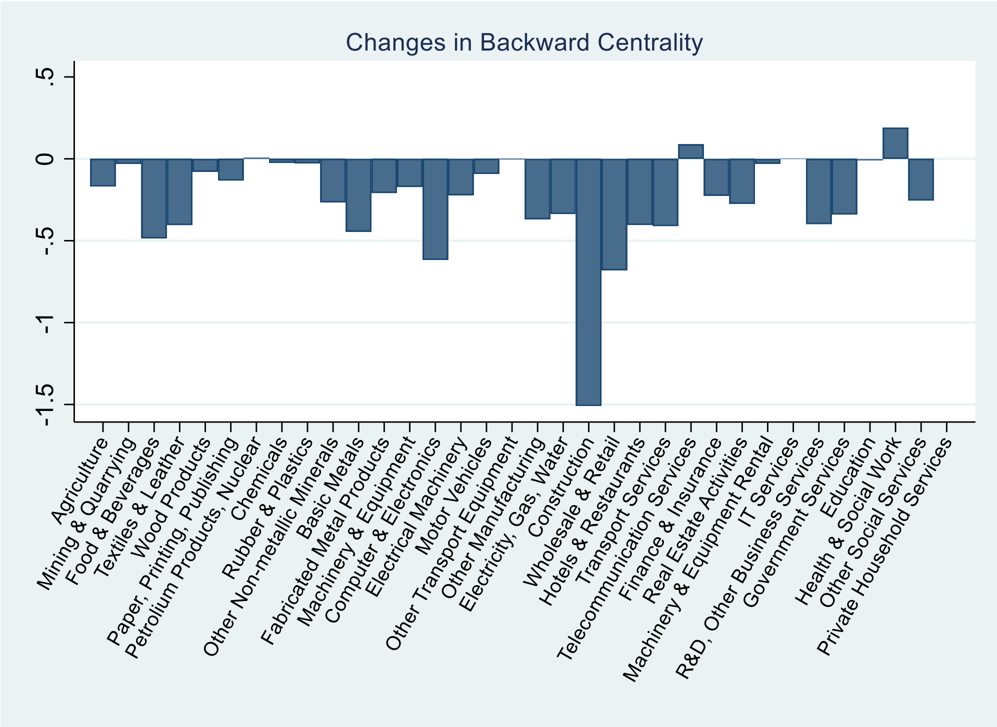


Figure 2. Changes in Backward GVC Centrality and Participation by Industry from 1995 to 2011

(1) Changes in backward centrality by industry



(2) Changes in backward participation by industry

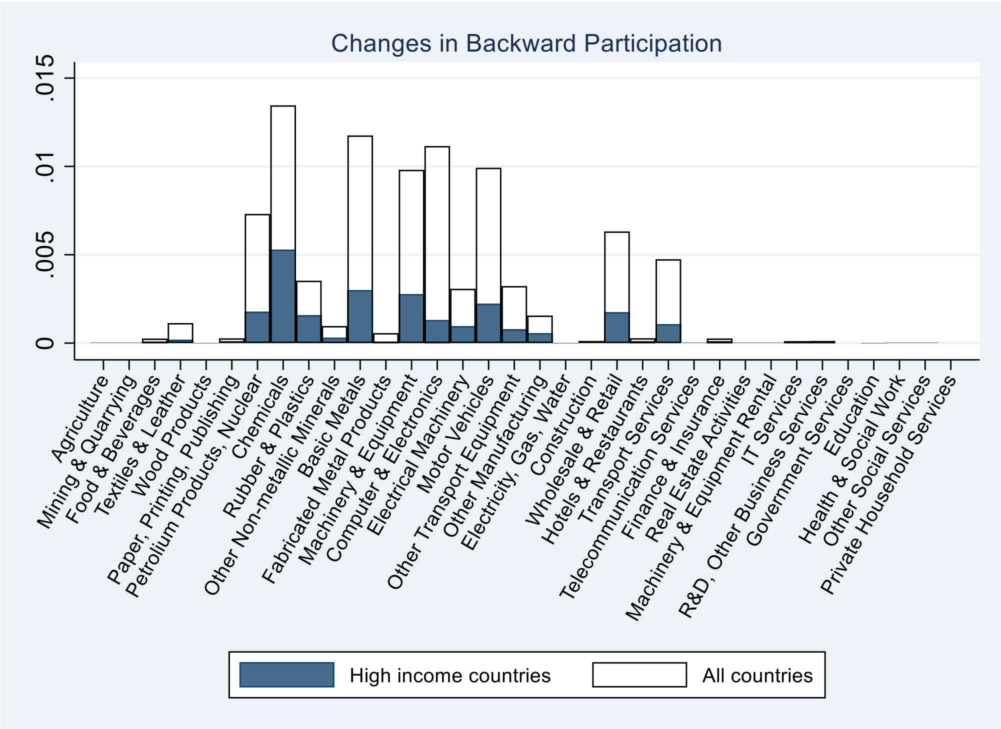
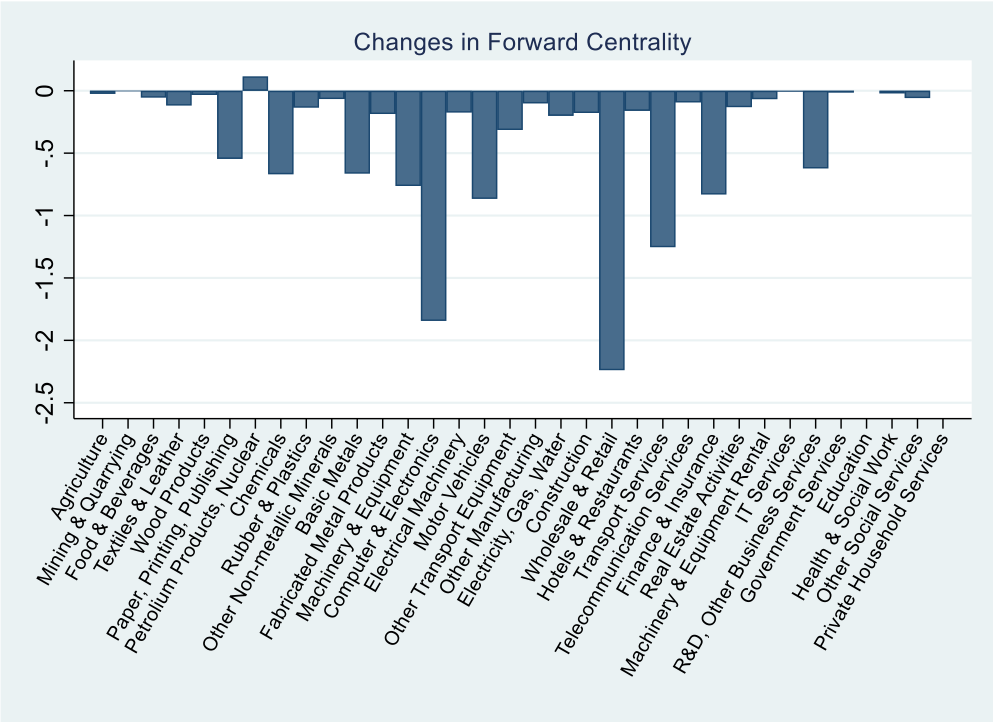


Figure 3. Changes in Forward GVC Centrality and Participation by Industry from 1995 to 2011

(1) Changes in forward centrality by industry



(2) Changes in forward participation by industry

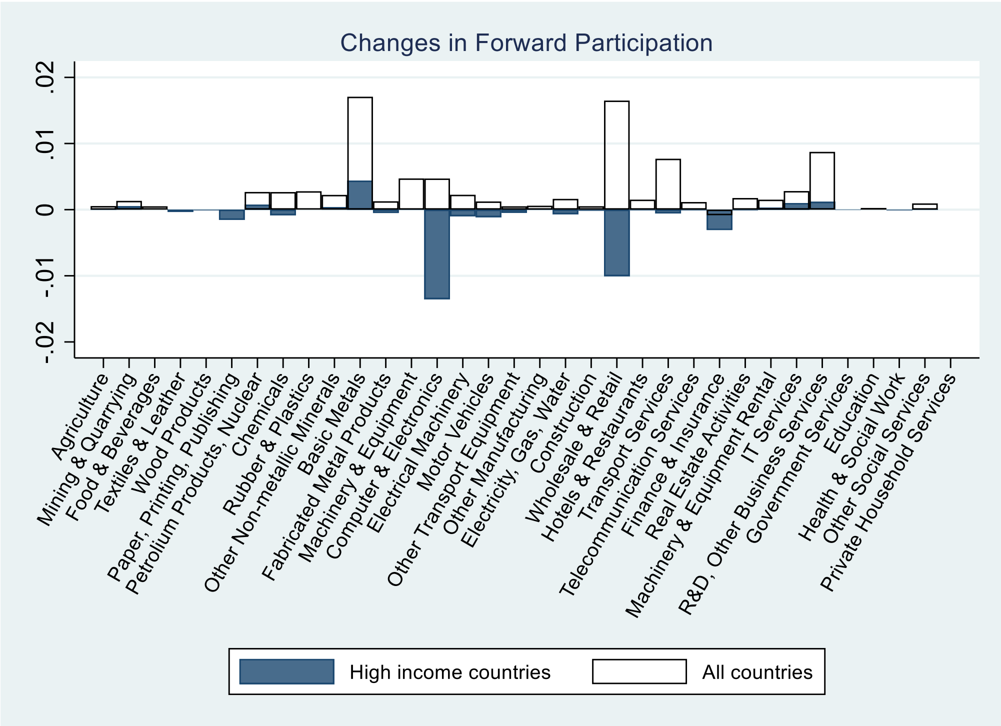


Figure 4. Total Number of Patent Applications to the Japan Patent Office 1995-2011

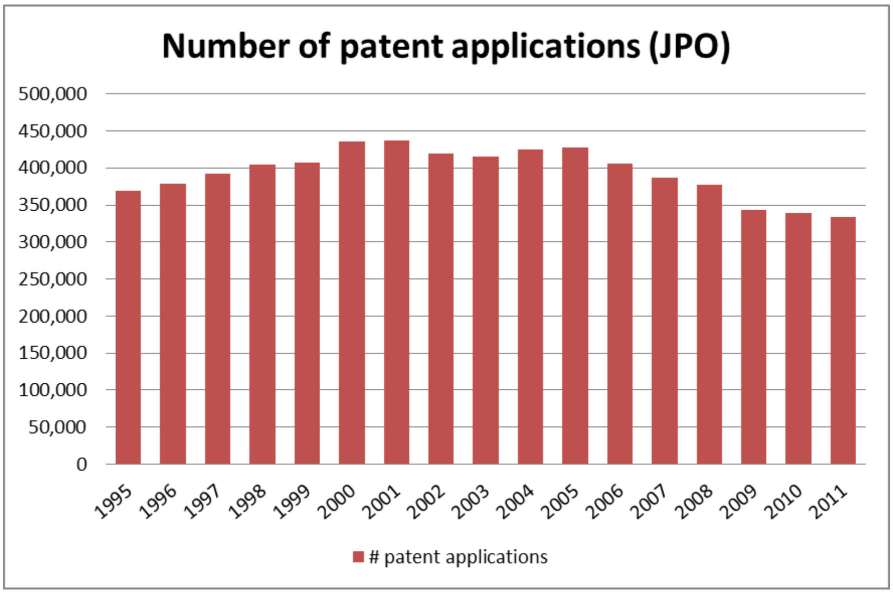
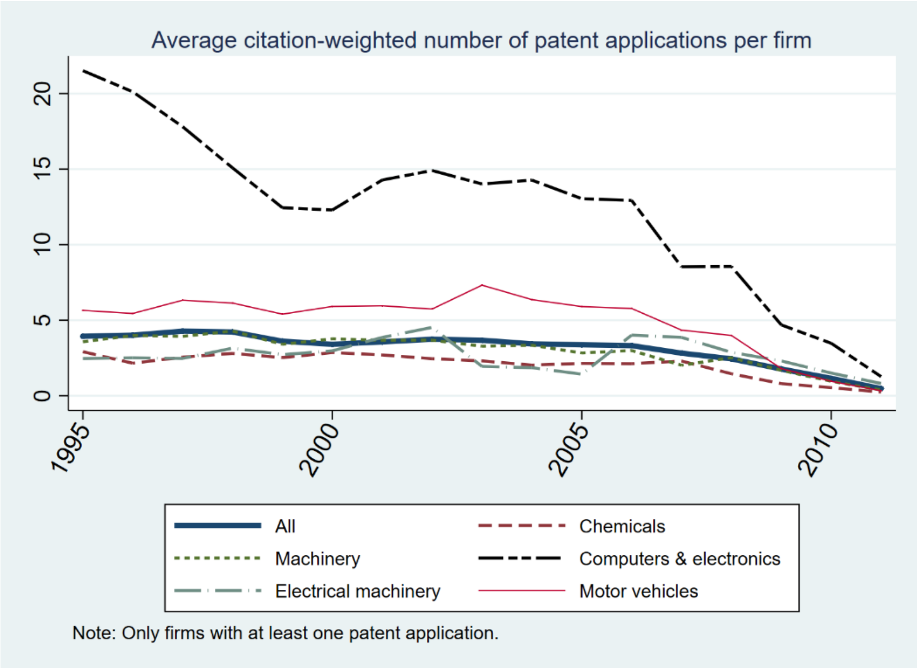


Figure 5. Average Citation-Weighted Number of Patent Applications per Firm for Major Industries



Note: Figures are calculated based on firms with at least one patent application per year.

Figure 6. Changes in Centrality versus Changes in Industry Average Citation-Weighted Number of Patent Applications per Firm (Manufacturing industries only)

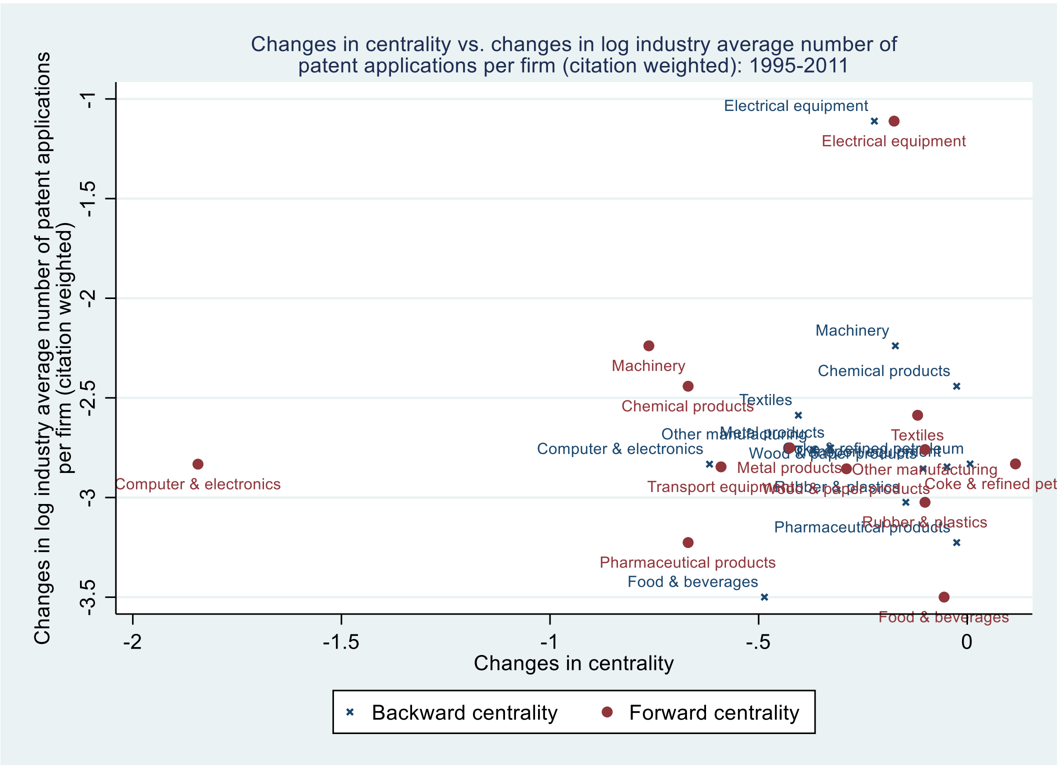


Table 1. Patent Applications by Sector (Patents matched to BSJBSA firms only, duplicates included)

(%)

Firms' Primary Industry	1995	2000	2005	2010
Food products, beverages and tobacco	0.9	0.6	0.5	0.4
Textiles, textile products, leather and footwear	1.5	1.6	0.8	0.2
Wood and products of wood and cork	0.3	0.4	0.3	2.7
Pulp, paper, paper products, printing and publishing	1.6	2.0	2.2	3.3
Coke, refined petroleum products and nuclear fuel	0.1	0.0	0.1	0.1
Chemicals and chemical products	5.9	6.0	4.2	2.9
Rubber and plastics products	2.5	3.6	2.5	2.1
Other non-metallic mineral products	1.5	0.7	0.6	0.4
Basic metals	4.9	4.1	3.0	2.7
Fabricated metal products	2.1	2.8	0.9	0.7
Machinery and equipment, nec	12.9	13.6	9.0	5.3
Computer, Electronic and optical equipment	27.7	22.7	24.0	27.8
Electrical machinery and apparatus, nec	3.3	3.1	2.7	11.5
Motor vehicles, trailers and semi-trailers	9.0	9.6	9.8	7.0
Other transport equipment	0.6	0.8	0.5	0.5
Manufacturing nec; recycling	0.9	1.1	1.9	1.0
Non-Manufacturing	24.2	27.2	37.0	31.5
Total	100.0	100.0	100.0	100.0

Table 2. Number of Firms in the Dataset and the Share of Firms with Patent Applications

	Number of firms		Share of firms with patent applications (%)			
Firms' Primary Industry	1995	2010	1995	2000	2005	2010
Food products, beverages and tobacco	1,393	1,419	11.0	13.8	15.1	10.9
Textiles, textile products, leather and footwear	811	382	10.6	18.2	19.6	18.6
Wood and products of wood and cork	312	233	14.4	18.8	24.2	17.2
Coke, refined petroleum products and nuclear fuel	51	47	19.6	38.0	43.5	29.8
Chemicals and chemical products	829	821	38.0	51.9	55.6	43.7
Rubber and plastics products	712	789	27.4	35.6	34.3	28.6
Other non-metallic mineral products	545	372	19.8	31.1	30.3	27.4
Basic metals	692	706	22.0	29.5	27.5	23.7
Fabricated metal products	895	885	25.4	35.4	32.8	25.3
Machinery and equipment, nec	1,022	813	32.9	41.5	43.6	35.4
Computer, Electronic and optical equipment	1,318	1,201	26.9	36.8	40.4	34.2
Electrical machinery and apparatus, nec	744	645	26.7	35.2	38.6	33.5
Motor vehicles, trailers and semi-trailers	849	868	26.9	37.0	31.7	25.7
Other transport equipment	198	247	22.7	28.4	32.7	21.9
Manufacturing nec; recycling	333	351	32.4	37.6	43.9	35.6
Construction	417	341	17.5	24.8	20.1	16.7
Wholesale and retail trade; repairs	8,565	7,686	6.0	9.4	9.2	6.9
Computer and related activities	246	1,650	5.7	15.1	13.8	10.5
R&D and other business activities	224	1,457	10.3	14.1	15.1	10.4
Total	20,156	20,913	15.8	21.8	22.2	17.2

Table 3. Baseline Estimation Results: Citation-weighted number of patent applications, Manufacturing industries (3-year lagged)

Dependent variable: ln(1+Citation-weighted number of patent applications)

	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed-effect panel estimation			IV fixed-effect panel estimation		
3-year lagged	Total Centrality (Import+Export)	Backward Centrality (Import)	Forward Centrality (Export)	Total Centrality (Import+Export)	Backward Centrality (Import)	Forward Centrality (Export)
L3.Affiliate-weighted centrality$_f$	0.0752***	0.0668***	0.0513***	0.0941***	0.0713***	0.0795***
	(0.016)	(0.011)	(0.011)	(0.017)	(0.019)	(0.016)
L3.Centrality (foreign)$_i$	0.0877	0.0209	0.123***	0.132***	-0.136	0.169***
	(0.086)	(0.081)	(0.034)	(0.048)	(0.114)	(0.058)
L3.GVC participation$_i$	-5.615	-12.29***	5.698**	-4.925	-8.734***	6.563***
	(8.090)	(3.491)	(2.553)	(7.468)	(2.339)	(2.225)
L3.TRADEINT$_f$	-0.0917**			-0.0916**		
	(0.040)			(0.038)		
L3.EXPINT$_f$		-0.274***	-0.274***		-0.271***	-0.268***
		(0.081)	(0.088)		(0.078)	(0.085)
L3.IMPINT$_f$		0.00915	0.00700		0.00545	0.00843
		(0.031)	(0.030)		(0.028)	(0.030)
L3.ln(Employment)$_f$	0.0693***	0.0762***	0.0735***	0.0670***	0.0781***	0.0729***
	(0.019)	(0.017)	(0.020)	(0.019)	(0.017)	(0.018)
L3.RDINT$_f$	-0.181*	-0.180*	-0.172	-0.176*	-0.185*	-0.172*
	(0.098)	(0.100)	(0.099)	(0.092)	(0.097)	(0.094)
L3.DAFF$_f$	-0.0746***	-0.0690***	-0.0551***	-0.0924***	-0.0734***	-0.0784***
	(0.020)	(0.018)	(0.015)	(0.019)	(0.016)	(0.015)
_cons	-0.110	-0.0674	-0.272**			
	(0.200)	(0.134)	(0.112)			
N	63364	63364	63364	63014	63014	63014
r2	.0863	.0882	.0869	.0875	.0888	.0901
Kleibergen-Paap rk LM statistic				3.577*	2.732*	5.496**
Kleibergen-Paap rk Wald F statistic				36.692	9.404	51.811

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADEINT in equations (1) and (4) denotes the ratio of exports plus imports to sales. The first-stage results for the IV fixed-effect panel estimations (4) - (6) are shown in Appendix Table A2.

* p<0.10, ** p<0.05, *** p<0.01

Table 4. Heterogeneity by Firms' Trade Orientation: Citation-weighted number of patent applications, Manufacturing industries (3-year lagged)

Panel (1) Fixed-effect panel estimation

Dependent variable: ln(1+Citation-weighted number of patent applications)

3-year lagged	(1) Total Centrality (Import+Export)	(2) Total Centrality (Import+Export)	(3) Backward Centrality (Import)	(4) Backward Centrality (Import)	(5) Forward Centrality (Export)	(6) Forward Centrality (Export)
L3.Affiliate-weighted Centrality$_f$	0.0749***	0.0752***	0.0666***	0.0668***	0.0499***	0.0514***
	(0.016)	(0.016)	(0.011)	(0.011)	(0.011)	(0.011)
L3.Centrality (foreign)$_i$	0.0721	0.0826	0.0130	0.0214	0.114**	0.128***
	(0.083)	(0.090)	(0.078)	(0.085)	(0.038)	(0.036)
L3.GVC participation$_i$	-8.825	-5.091	-13.32***	-12.35***	3.024	4.786*
	(7.439)	(7.803)	(3.050)	(3.402)	(2.292)	(2.270)
L3.TRADEINT$_f$*L3.Centrality (foreign)$_i$	0.374***		0.420**		0.646***	
	(0.046)		(0.157)		(0.123)	
L3.TRADEINT$_f$*L3.GVC participation$_i$		-1.761		0.400		5.615
		(4.038)		(4.898)		(3.850)
L3.TRADEINT$_f$	-0.394***	-0.0730				
	(0.067)	(0.047)				
L3.EXPINT$_f$			-0.282***	-0.274***	-0.938***	-0.352**
			(0.076)	(0.080)	(0.169)	(0.120)
L3.IMPINT$_f$			-0.263**	0.00630	0.00850	0.00511
			(0.114)	(0.037)	(0.029)	(0.030)
L3.ln(Employment)$_f$	0.0685***	0.0692***	0.0762***	0.0763***	0.0724***	0.0735***
	(0.019)	(0.019)	(0.017)	(0.017)	(0.020)	(0.020)
L3.RDINT$_f$	-0.166*	-0.181*	-0.177	-0.181*	-0.143	-0.170
	(0.093)	(0.098)	(0.100)	(0.100)	(0.086)	(0.098)
L3.DAFF$_f$	-0.0726***	-0.0746***	-0.0682***	-0.0690***	-0.0524***	-0.0552***
	(0.020)	(0.020)	(0.018)	(0.018)	(0.014)	(0.015)
_cons	-0.0725	-0.108	-0.0573	-0.0677	-0.235*	-0.270**
	(0.193)	(0.201)	(0.132)	(0.135)	(0.111)	(0.113)
N	63363	63363	63363	63363	63363	63363
r2	.0905	.087	.0915	.0903	.0953	.0892

Notes: Standard errors clustered at industry level in parentheses. Firm fixed effects and year fixed effects are included.

TRADEINT in equations (1) and (2) denotes the ratio of exports plus imports to sales. TRADEINT in equations (3) and (4) denotes the ratio of imports to sales, while TRADEINT in equations (5) and (6) denotes the ratio of exports to sales.
* p<0.10, ** p<0.05, *** p<0.01

Panel (2) IV fixed-effect panel estimation

Dependent variable: ln(1+Citation-weighted number of patent applications)

3-year lagged	(1) Total Centrality (Import+Export)	(2) Total Centrality (Import+Export)	(3) Backward Centrality (Import)	(4) Backward Centrality (Import)	(5) Forward Centrality (Export)	(6) Forward Centrality (Export)
L3.Affiliate-weighted centrality$_f$	0.0816***	0.0942***	0.0690***	0.0714***	0.0736***	0.0797***
	(0.015)	(0.017)	(0.019)	(0.019)	(0.012)	(0.016)
L3.Centrality (foreign)$_i$	0.0230	0.129***	-0.128	-0.141	0.122*	0.172***
	(0.106)	(0.049)	(0.092)	(0.117)	(0.074)	(0.058)
L3.GVC participation$_i$	-22.84**	-4.516	-12.31***	-8.381***	-1.038	5.458***
	(11.355)	(7.274)	(3.455)	(2.610)	(3.143)	(1.865)
L3.TRADEINT$_f$*L3.Centrality (foreign)$_i$	2.250**		1.515*		2.047***	
	(0.917)		(0.798)		(0.640)	
L3.TRADEINT$_f$*L3.GVC participation$_i$		-1.296		-2.258		6.570
		(3.580)		(4.633)		(4.058)
L3.TRADEINT$_f$	-1.928***	-0.0778*				
	(0.592)	(0.045)				
L3.EXPINT$_f$			-0.321***	-0.269***	-2.407***	-0.360***
			(0.088)	(0.078)	(0.428)	(0.115)
L3.IMPINT$_f$			-0.966**	0.0215	0.0158	0.00615
			(0.492)	(0.032)	(0.034)	(0.029)
L3.ln(Employment)$_f$	0.0629***	0.0670***	0.0782***	0.0780***	0.0696***	0.0728***
	(0.020)	(0.019)	(0.018)	(0.017)	(0.019)	(0.018)
L3.RDINT$_f$	-0.103	-0.176*	-0.190*	-0.184*	-0.0944	-0.169*
	(0.083)	(0.092)	(0.105)	(0.097)	(0.075)	(0.093)
L3.DAFF$_f$	-0.0712***	-0.0924***	-0.0698***	-0.0734***	-0.0682***	-0.0785***
	(0.017)	(0.019)	(0.015)	(0.017)	(0.013)	(0.015)
N	60396	63014	60396	63014	60396	63014
r2	0.0046	0.0876	.0818	.0887	.0672	.0903
Kleibergen-Paap rk LM statistic	2.256	3.562*	3.925**	2.764*	2.417	5.426**
Kleibergen-Paap rk Wald F statistic	7.299	36.252	6.891	9.423	25.536	51.125

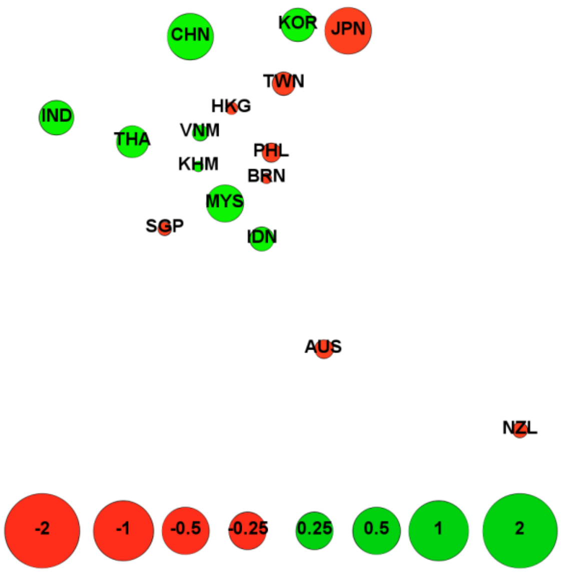
Notes: Standard errors clustered at industry level in parentheses. Firm fixed effects and year fixed effects are included.

TRADEINT in equations (1) and (2) denotes the ratio of exports plus imports to sales. TRADEINT in equations (3) and (4) denotes the ratio of imports to sales, while TRADEINT in equations (5) and (6) denotes the ratio of exports to sales. The first-stage results for the IV fixed-effect panel estimations are shown in Appendix Table A3.
* p<0.10, ** p<0.05, *** p<0.01

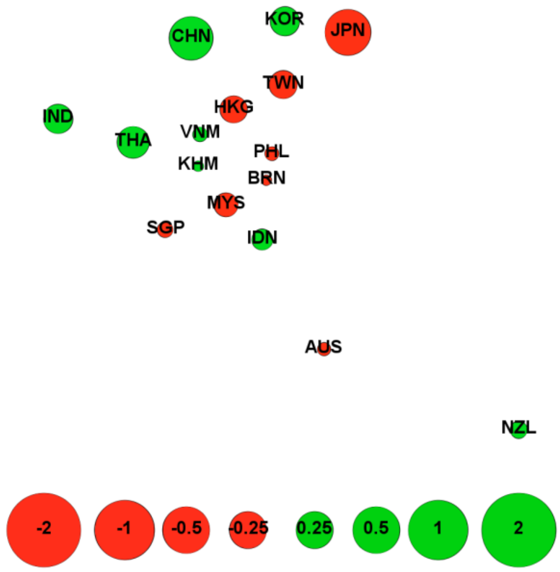
Appendix A: Appendix Figures and Tables

Appendix Figure A1. Changes in Centrality 1995-2011 for Key Manufacturing Industries

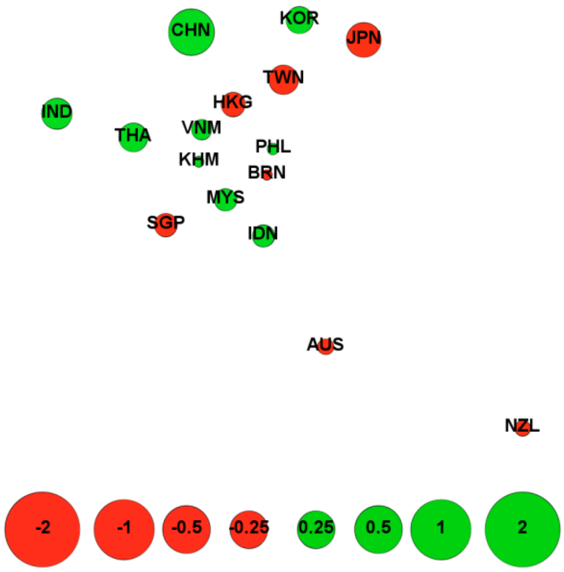
a) Motor Vehicles



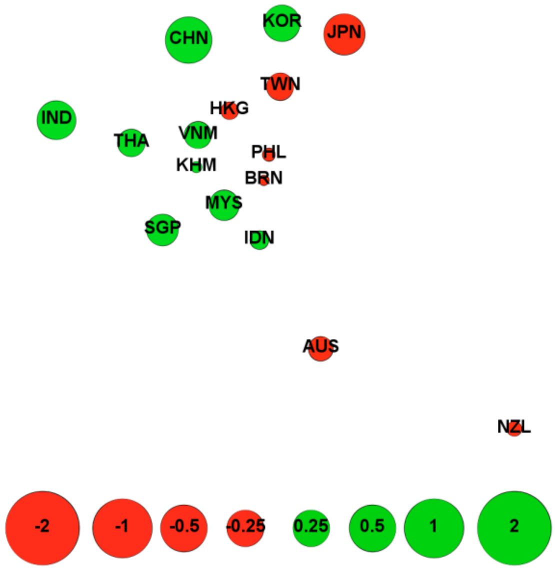
b) Machinery and equipment



c) Electrical Machinery

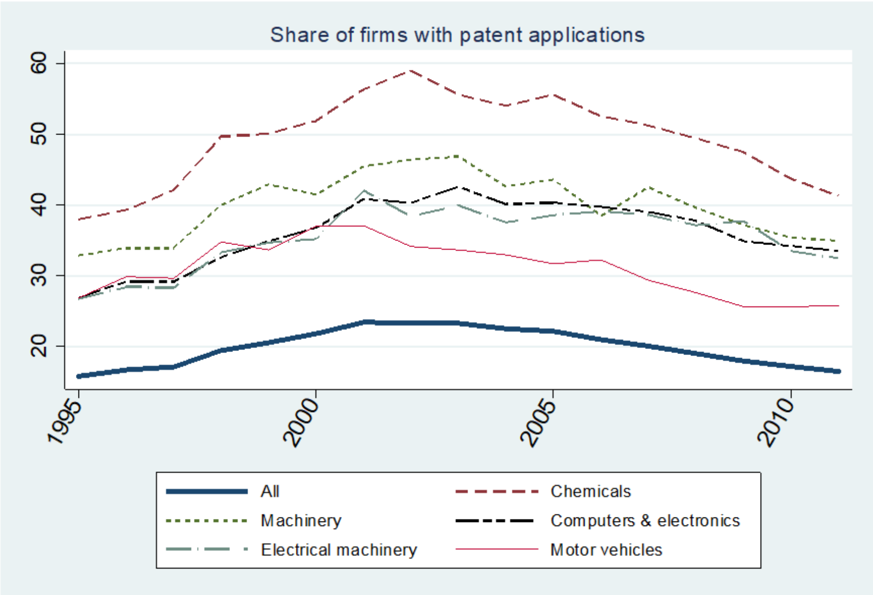


d) Chemicals and chemical products

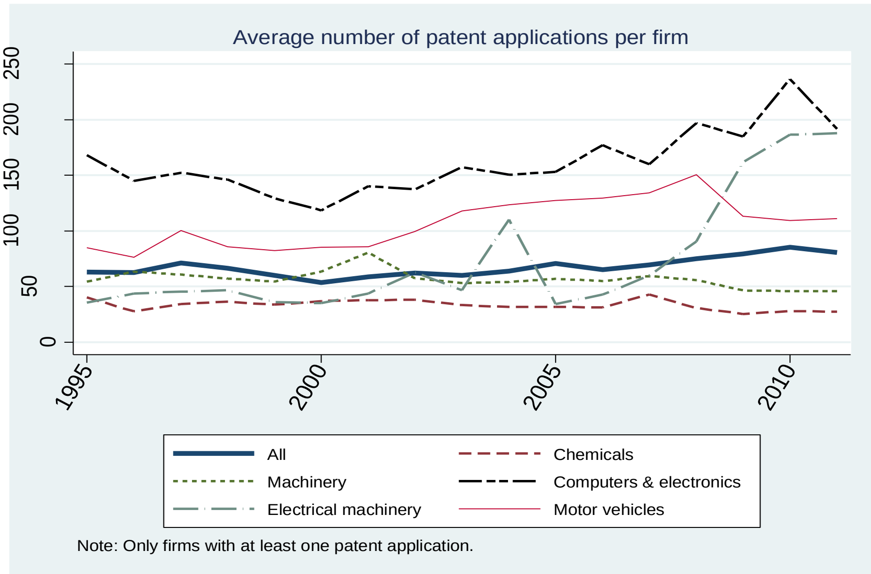


Notes: Economies are placed according to their location. Size of the nodes reflects the magnitude of the change (in levels) of total foreign centrality (forward and backward) over the period 1995-2011. As reflected in the key, these changes are graphed using a log scale for readability. Green coloured nodes reflect increasing centrality and red denotes falling centrality. Motor vehicles manufacturing reflects ISIC rev.3, 34. Machinery and equipment manufacturing reflects ISIC rev.3, 29. Electrical machinery manufacturing reflects ISIC rev. 3, 31. Chemical and chemical products manufacturing reflects ISIC rev.3, 24.

Appendix Figure A2. Share of Firms with at Least One Patent Applications (%)

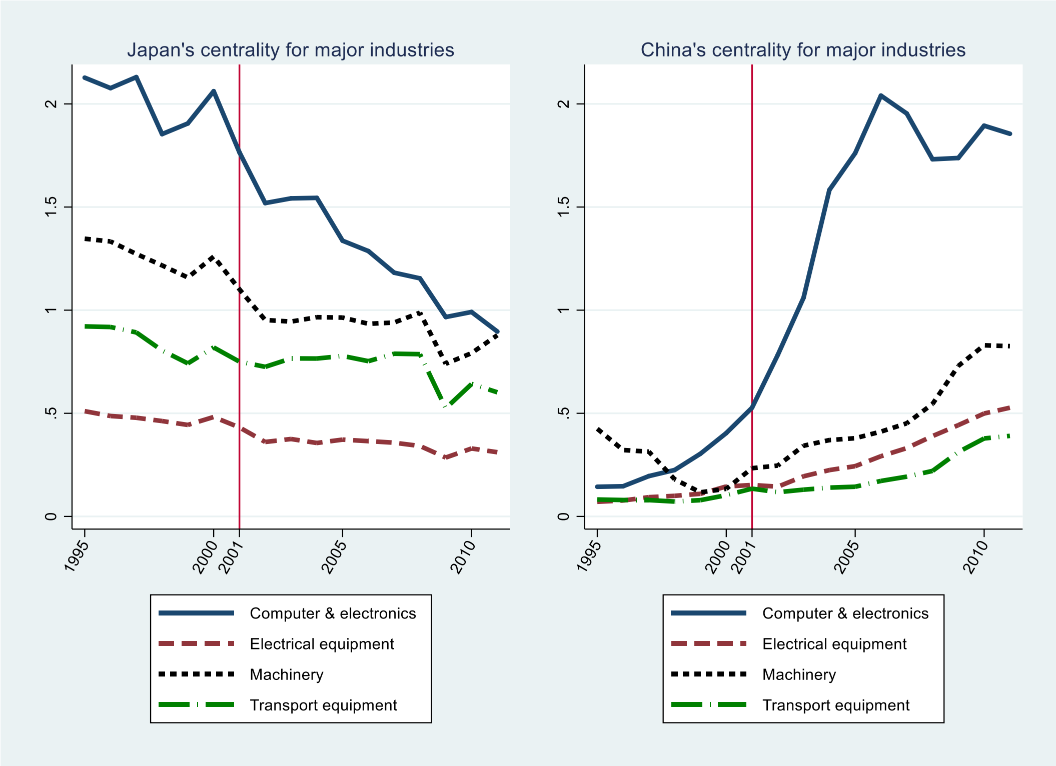


Appendix Figure A3. Average Number of Patent Applications per Firm in Major industries



Note: Figures are calculated based on firms with at least one patent application per year.

Appendix Figure A4. The Trend of GVC Centrality for Major Industries: The comparison for Japan and China



Appendix Table A1. Basic Statistics (Manufacturing industries)

Variables	Obs	Mean	Std. Dev.	Min	Max
Variables for baseline model					
ln(1+weighted NumPat)	109,749	0.2452	0.6367	0	6.4697
Affiliate-weighted centrality (Total)	75,373	0.1160	0.4497	0	4.3807
Affiliate-weighted centrality (Backward)	75,373	0.1221	0.4976	0	5.4944
Affiliate-weighted centrality (Forward)	75,373	0.1100	0.4755	0	6.3044
Centrality (Foreign, Total)	109,749	0.7431	0.3831	0.1129	2.1300
Centrality (Foreign, Backward)	109,749	0.6184	0.2797	0.1507	1.7003
Centrality (Foreign, Forward)	109,749	0.8678	0.5825	0.0681	2.8482
GVC participation (Total)	109,749	0.0081	0.0073	0.0005	0.0390
GVC participation (Backward)	109,749	0.0062	0.0061	0.0001	0.0307
GVC participation (Forward)	109,749	0.0101	0.0090	0.0008	0.0478
ln(Employment)	109,749	5.4183	1.0705	3.9120	11.3002
RDINT	86,330	0.0164	0.0400	0	4.1975
TRADEINT	95,656	0.0946	0.2072	0	2
EXPINT	95,657	0.0499	0.1259	0	1
IMPINT	95,656	0.0447	0.1362	0	1
DAFF	76,486	0.1445	0.3516	0	1
TRADEINT*Centrality (Foreign, Total)	95,656	0.0733	0.1857	0	3.7075
IMPINT*Centrality (Foreign, Backward)	95,656	0.0275	0.0946	0	1.7003
EXPINT*Centrality (Foreign, Forward)	95,657	0.0480	0.1393	0	2.3318
TRADEINT*GVC participation (Total)	95,656	0.0010	0.0033	0	0.0757
IMPINT*GVC participation (Backward)	95,656	0.0004	0.0016	0	0.0307
EXPINT*GVC participation (Forward)	95,657	0.0007	0.0023	0	0.0473
Instrumental variables					
China_WTO*Initial_Centrality (Foreign, Total)	109,749	0.5774	0.5948	0	2.127429
China_WTO*Initial_Centrality (Foreign, Backward)	109,749	0.4541	0.4305	0	1.406614
China_WTO*Initial_Centrality (Foreign, Forward)	109,749	0.7008	0.8283	0	2.848244
Initial_TRADEINT*China_WTO*Initial_Centrality (Foreign, Total)	90,677	0.0428	0.1620	0	2.693103
Initial_IMPINT*China_WTO*Initial_Centrality (Foreign, Backward)	90,677	0.0170	0.0813	0	1.406614
Initial_EXPINT*China_WTO*Initial_Centrality (Foreign, Forward)	90,677	0.0355	0.1489	0	2.69312

Appendix Table A2. First stage regression results for equations (4)-(6) in Table 3

Dependent Variable	(4) Total Centrality (Import+Export)	(5) Backward Centrality (Import)	(6) Forward Centrality (Export)
IV: China_WTO*Initial_Centrality (foreign)$_i$	-0.2578 ***	-0.3562 ***	-0.2443 ***
	(0.043)	(0.116)	(0.034)
Affiliate-weighted centrality$_f$	0.0008	0.0054 **	0.0030
	(0.002)	(0.002)	(0.002)
GVC participation$_i$	10.1031	30.6013 *	6.4498
	(11.178)	(8.420)	(12.536)
TRADEINT$_f$	-0.0200 *		
	(0.012)		
EXPINT$_f$		0.0248	-0.1045 ***
		(0.020)	(0.036)
IMPINT$_f$		-0.0263 *	-0.0170
		(0.016)	(0.021)
ln(Employment)$_f$	0.0182 *	0.0260 *	0.0006
	(0.010)	(0.016)	(0.006)
RDINT$_f$	-0.0349	-0.0396	-0.0200
	(0.029)	(0.028)	(0.039)
DAFF$_f$	0.0048	0.0013	-0.0007
	(0.004)	(0.003)	(0.004)
Sanderson-Windmeijer multivariate F test of excluded instruments:	36.69 ***	9.40 ***	51.81 ***

Notes: Standard errors clustered at industry level in parentheses. Firm fixed effects and year fixed effects are included.

TRADEINT denotes the ratio of exports plus imports to sales.
* p<0.10, ** p<0.05, *** p<0.01

Appendix Table A3. First stage regression results for equations in Panel (2) of Table 4

Dependent Variable	(1) Total Centrality (Import+Export)	(1) TRADEINT$_f$* Total Centrality (Import+Export)	(2) Total Centrality (Import+Export)	(3) Backward Centrality (Import)	(3) TRADEINT$_f$* Backward Centrality (Import)	(4) Backward Centrality (Import)	(5) Forward Centrality (Export)	(5) TRADEINT$_f$* Forward Centrality (Export)	(6) Forward Centrality (Export)
IV1	-0.2525 ***	0.0018	-0.2536 ***	-0.3520 ***	0.0127 **	-0.3499 ***	-0.2380 ***	0.0047	-0.2423 ***
	(0.042)	(0.011)	(0.042)	(0.115)	(0.006)	(0.114)	(0.035)	(0.004)	(0.034)
IV2	-0.0405 **	-0.1037 ***		-0.0412	-0.0874 ***		-0.1038 **	-0.1478 ***	
	(0.017)	(0.028)		(0.029)	(0.024)		(0.050)	(0.021)	
Affliate-weighted Centrality$_f$	0.0001	0.0060	0.0013	0.0057 **	0.0020	0.0059 **	0.0010	0.0022	0.0027
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
GVC Participation$_i$	10.2749	8.9724 ***	12.6519	30.7618 ***	2.7163 ***	31.5865 ***	6.6743	4.4205 ***	8.8859
	(11.227)	(2.105)	(11.453)	(8.423)	(0.648)	(8.465)	(12.581)	(0.578)	(13.093)
TRADEINT$_f$*GVC Participation$_i$			-8.5936 ***			-9.7259 ***			-14.7977 **
			(2.896)			(2.000)			(6.310)
TRADEINT$_f$	-0.0158	0.8252 ***	0.0718 ***						
	(0.010)	(0.139)	(0.018)						
EXPINT$_f$				0.0248	0.0265	0.0320	-0.0879 ***	1.0644 ***	0.1025 **
				(0.020)	(0.026)	(0.020)	(0.034)	(0.209)	(0.051)
IMPINT$_f$				-0.0263	0.6467 ***	0.0434 ***	-0.0117	0.0035	-0.0117
				(0.017)	(0.083)	(0.011)	(0.019)	(0.010)	(0.019)
ln(Employment)$_f$	0.0172 *	0.0013	0.0176 *	0.0250	-0.0007	0.0251	-0.0009	0.0011	0.0008
	(0.010)	(0.002)	(0.010)	(0.015)	(0.002)	(0.015)	(0.006)	(0.001)	(0.006)
RDINT$_f$	-0.0342	-0.0322 *	-0.0338	-0.0378	-0.0068	-0.0371	-0.0160	-0.0333 **	-0.0254
	(0.030)	(0.017)	(0.028)	(0.027)	(0.004)	(0.026)	(0.038)	(0.017)	(0.041)
DAFF$_f$	0.0060	-0.0089 *	0.0048	0.0013	-0.0025	0.0014	0.0021	-0.0038	-0.0004
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.004)	(0.005)	(0.003)	(0.004)
Sanderson-Windmeijer multivariate F test of excluded instruments:	73.24 ***	80.54 ***	36.25 ***	19.69 ***	25.48 ***	9.42 ***	88.10 ***	67.09 ***	51.13 ***

IV1: China_WTO*Initial_Centrality (Foreign)i

IV2: Initial_TRADEINT*China_WTO*Initial_Centrality (Foreign)i

Appendix Table A4. Fixed-Effect Panel Estimation Results: Citation-weighted number of patent applications, All industries except wholesale and retail trade (3-year lagged)

Panel (1) Fixed-effect panel estimation

Dependent variable: ln(1+Citation-weighted number of patent applications)

3-year lagged	(1) Total Centrality (Import+Export)	(2) Total Centrality (Import+Export)	(3) Total Centrality (Import+Export)	(4) Backward Centrality (Import)	(5) Backward Centrality (Import)	(6) Backward Centrality (Import)	(7) Forward Centrality (Export)	(8) Forward Centrality (Export)	(9) Forward Centrality (Export)
L3.Affiliate-weighted centrality$_f$	0.0618***	0.0622***	0.0618***	0.0580***	0.0582***	0.0579***	0.0419***	0.0412***	0.0419***
	(0.015)	(0.015)	(0.015)	(0.011)	(0.011)	(0.011)	(0.010)	(0.009)	(0.010)
L3.Centrality (foreign)$_i$	0.0533	0.0364	0.0448	0.0471	0.0392	0.0482	0.119***	0.109***	0.120***
	(0.080)	(0.078)	(0.085)	(0.069)	(0.067)	(0.072)	(0.030)	(0.032)	(0.031)
L3.GVC participation$_i$	-9.571	-12.62*	-8.530	-12.47***	-13.32***	-12.61***	3.762	1.836	3.630
	(7.933)	(7.333)	(7.339)	(3.385)	(3.100)	(3.345)	(2.640)	(2.482)	(2.404)
L3.TRADEINT$_f$*L3.Centrality (foreign)$_i$		0.386***			0.406***			0.678***	
		(0.057)			(0.138)			(0.131)	
L3.TRADEINT$_f$*L3.GVC participation$_i$			-3.581			1.058			0.998
			(5.162)			(4.373)			(5.754)
L3.TRADEINT$_f$	-0.0836**	-0.378***	-0.0478						
	(0.030)	(0.060)	(0.046)						
L3.EXPINT$_f$				-0.254***	-0.259***	-0.254***	-0.251***	-0.926***	-0.266*
				(0.065)	(0.062)	(0.064)	(0.071)	(0.145)	(0.141)
L3.IMPINT$_f$				0.00353	-0.240**	-0.00212	0.00265	0.00716	0.00232
				(0.024)	(0.093)	(0.026)	(0.023)	(0.023)	(0.022)
L3.ln(Employment)$_f$	0.0711***	0.0692***	0.0711***	0.0724***	0.0733***	0.0742***	0.0734***	0.0717***	0.0734***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)
L3.RDINT$_f$	-0.149*	-0.137*	-0.149*	-0.159*	-0.144*	-0.148*	-0.140*	-0.120	-0.140*
	(0.081)	(0.075)	(0.081)	(0.084)	(0.079)	(0.080)	(0.081)	(0.072)	(0.081)
L3.DAFF$_f$	-0.0646***	-0.0627***	-0.0644***	-0.0614***	-0.0606***	-0.0614***	-0.0494***	-0.0465***	-0.0494***
	(0.018)	(0.018)	(0.018)	(0.016)	(0.016)	(0.016)	(0.014)	(0.013)	(0.014)
_cons	-0.0798	-0.0360	-0.0774	-0.102	-0.0892	-0.103	-0.266**	-0.230**	-0.266**
	(0.176)	(0.174)	(0.177)	(0.115)	(0.116)	(0.116)	(0.105)	(0.102)	(0.104)
N	84097	84097	84097	84097	84097	84097	84097	84097	84097
r2	.0778	.081	.0779	.0807	.0817	.0807	.0788	.0845	.0789

Notes: Standard errors clustered at industry level in parentheses. Firm fixed effects and year fixed effects are included.

TRADEINT in equations (1) – (3) denotes the ratio of exports plus imports to sales. TRADEINT in equations (5) – (6) denotes the ratio of imports to sales, while TRADEINT in equations (8) – (9) denotes the ratio of exports to sales.

* p<0.10, ** p<0.05, *** p<0.01

Panel (2) IV fixed-effect panel estimation

Dependent variable: ln(1+Citation-weighted number of patent applications)

3-year lagged	(1) Total Centrality (Import+Export)	(2) Total Centrality (Import+Export)	(3) Total Centrality (Import+Export)	(4) Backward Centrality (Import)	(5) Backward Centrality (Import)	(6) Backward Centrality (Import)	(7) Forward Centrality (Export)	(8) Forward Centrality (Export)	(9) Forward Centrality (Export)
L3.Affiliate-weighted centrality$_f$	0.0798***	0.0715***	0.0799***	0.0659***	0.0650***	0.0659***	0.0641***	0.0607***	0.0642***
	(0.015)	(0.012)	(0.015)	(0.016)	(0.016)	(0.016)	(0.014)	(0.011)	(0.014)
L3.Centrality (foreign)$_i$	0.131***	0.00438	0.127**	-0.0520	-0.0620	-0.0525	0.185***	0.142*	0.187***
	(0.050)	(0.082)	(0.053)	(0.116)	(0.101)	(0.118)	(0.053)	(0.076)	(0.054)
L3.GVC participation$_i$	-8.334	-24.83***	-7.507	-9.941**	-12.98***	-9.884**	4.850**	-0.577	4.516**
	(7.720)	(9.512)	(7.135)	(3.951)	(4.252)	(4.068)	(2.379)	(2.798)	(2.052)
L3.TRADEINT$_f$*L3.Centrality (foreign)$_i$		2.204***			1.506**			2.125***	
		(0.712)			(0.589)			(0.587)	
L3.TRADEINT$_f$*L3.GVC participation$_i$			-2.712			-0.394			2.472
			(4.613)			(4.081)			(5.601)
L3.TRADEINT$_f$	-0.0811***	-1.774***	-0.0539						
	(0.030)	(0.448)	(0.044)						
L3.EXPINT$_f$				-0.253***	-0.291***	-0.253***	-0.243***	-2.385***	-0.279**
				(0.063)	(0.071)	(0.062)	(0.070)	(0.381)	(0.136)
L3.IMPINT$_f$				0.00228	-0.893***	0.00438	0.00562	0.0223	0.00480
				(0.023)	(0.339)	(0.024)	(0.023)	(0.027)	(0.023)
L3.ln(Employment)$_f$	0.0695***	0.0593***	0.0694***	0.0749***	0.0724***	0.0749***	0.0733***	0.0685***	0.0733***
	(0.017)	(0.018)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
L3.RDINT$_f$	-0.144*	-0.0936	-0.144*	-0.148*	-0.151*	-0.148*	-0.139*	-0.0909	-0.138*
	(0.077)	(0.063)	(0.077)	(0.079)	(0.077)	(0.079)	(0.079)	(0.058)	(0.079)
L3.DAFF$_f$	-0.0813***	-0.0606***	-0.0811***	-0.0687***	-0.0636***	-0.0687***	-0.0682***	-0.0574***	-0.0684***
	(0.017)	(0.016)	(0.017)	(0.015)	(0.014)	(0.015)	(0.015)	(0.013)	(0.015)
N	83524	80043	83524	83524	80043	83524	83524	80043	83524
r2	.0781	.00993	.0782	.0803	.0733	.0803	.0793	.0593	.0793
Kleibergen-Paap rk LM statistic	4.827**	3.050*	4.823**	3.883**	4.580*	3.968**	5.483**	3.066*	5.473**
Kleibergen-Paap rk Wald F statistic	52.285	12.504	52.577	12.141	8.879	12.406	40.649	29.732	40.658

Notes: Standard errors clustered at industry level in parentheses. Firm fixed effects and year fixed effects are included.

TRADEINT in equations (1) – (3) denotes the ratio of exports plus imports to sales. TRADEINT in equations (5) – (6) denotes the ratio of imports to sales, while TRADEINT in equations (8) – (9) denotes the ratio of exports to sales.

* p<0.10, ** p<0.05, *** p<0.01

Appendix Table A5. Robustness checks: Citation-weighted number of patent applications, Manufacturing industries (1-year lagged)

Panel (1) Fixed-effect panel estimation

Dependent variable: ln(1+Citation-weighted number of patent applications)

1-year lagged	(1) Total Centrality (Import+Export)	(2) Total Centrality (Import+Export)	(3) Total Centrality (Import+Export)	(4) Backward Centrality (Import)	(5) Backward Centrality (Import)	(6) Backward Centrality (Import)	(7) Forward Centrality (Export)	(8) Forward Centrality (Export)	(9) Forward Centrality (Export)
L.Affiliate-weighted centrality$_f$	0.0338*	0.0337*	0.0337*	0.0487***	0.0487***	0.0484***	0.00620	0.00556	0.00633
	(0.016)	(0.016)	(0.016)	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)
L.Centrality (foreign)$_i$	0.0419	0.0318	0.0537	-0.0128	-0.0180	-0.00401	0.0503*	0.0456	0.0556*
	(0.033)	(0.038)	(0.033)	(0.045)	(0.046)	(0.046)	(0.025)	(0.028)	(0.026)
L.GVC participation$_i$	2.965	0.871	1.843	-2.650	-3.220	-3.582	7.392***	5.818***	6.540***
	(4.798)	(4.781)	(4.602)	(4.116)	(3.826)	(3.847)	(1.260)	(1.169)	(1.060)
L.TRADEINT$_f$*L.Centrality (foreign)$_i$		0.243***			0.237**			0.367**	
		(0.045)			(0.079)			(0.135)	
L.TRADEINT$_f$*L.GVC participation$_i$			3.844*			6.367*			5.443*
			(1.906)			(3.399)			(2.637)
L.TRADEINT$_f$	0.00962	-0.177***	-0.0314						
	(0.025)	(0.042)	(0.025)						
L.EXPINT$_f$				0.0385	0.0363	0.0346	0.0343	-0.320**	-0.0406
				(0.062)	(0.061)	(0.061)	(0.065)	(0.146)	(0.090)
L.IMPINT$_f$				-0.00232	-0.149***	-0.0491**	-0.00444	-0.00281	-0.00611
				(0.026)	(0.047)	(0.021)	(0.026)	(0.025)	(0.025)
L.ln(Employment)$_f$	0.0904***	0.0900***	0.0907***	0.0922***	0.0921***	0.0926***	0.0927***	0.0923***	0.0928***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)
L.RDINT$_f$	0.0710	0.0785	0.0709	0.0650	0.0654	0.0644	0.0746	0.0896	0.0758
	(0.082)	(0.082)	(0.083)	(0.084)	(0.084)	(0.085)	(0.079)	(0.077)	(0.079)
L.DAFF$_f$	-0.0346**	-0.0334**	-0.0348**	-0.0457***	-0.0452***	-0.0457***	-0.0134	-0.0122	-0.0136
	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)
_cons	-0.285**	-0.260*	-0.291**	-0.216*	-0.210*	-0.222*	-0.357***	-0.337***	-0.358***
	(0.128)	(0.128)	(0.127)	(0.111)	(0.111)	(0.110)	(0.103)	(0.101)	(0.104)
N	71481	71481	71481	71481	71481	71481	71481	71481	71481
r2	.0531	.0548	.0533	.0539	.0544	.0541	.0538	.056	.0539

Notes: Standard errors clustered at industry level in parentheses. Firm fixed effects and year fixed effects are included.

TRADEINT in equations (1) – (3) denotes the ratio of exports plus imports to sales. TRADEINT in equations (4) – (6) denotes the ratio of imports to sales, while TRADEINT in equations (7) – (9) denotes the ratio of exports to sales.

* p<0.10, ** p<0.05, *** p<0.01

Panel (2) IV fixed-effect panel estimation

Dependent variable: ln(1+Citation-weighted number of patent applications)

1-year lagged	(1) Total Centrality (Import+Export)	(2) Total Centrality (Import+Export)	(3) Total Centrality (Import+Export)	(4) Backward Centrality (Import)	(5) Backward Centrality (Import)	(6) Backward Centrality (Import)	(7) Forward Centrality (Export)	(8) Forward Centrality (Export)	(9) Forward Centrality (Export)
L.Affiliate-weighted Centrality$_f$	0.0580***	0.0577***	0.0579***	0.0499***	0.0512***	0.0497***	0.0427***	0.0435***	0.0428***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.011)	(0.010)	(0.007)	(0.008)	(0.007)
L.Centrality (foreign)$_i$	0.0113	-0.0281	0.0191	-0.154***	-0.170***	-0.146**	0.0481	0.0280	0.0515
	(0.049)	(0.066)	(0.047)	(0.057)	(0.064)	(0.058)	(0.046)	(0.054)	(0.046)
L.GVC participation$_i$	1.546	-2.501	0.451	0.167	0.252	-0.472	6.455***	4.434***	5.610***
	(3.975)	(5.715)	(3.833)	(2.786)	(3.303)	(2.721)	(1.003)	(1.702)	(0.858)
L.TRADEINT$_f$*L.Centrality (foreign)$_i$		0.591			0.408			0.624*	
		(0.374)			(0.401)			(0.322)	
L.TRADEINT$_f$*L.GVC participation$_i$			3.597**			4.042			5.228*
			(1.626)			(3.275)			(2.789)
L.TRADEINT$_f$	0.0226	-0.448*	-0.0160						
	(0.024)	(0.264)	(0.023)						
L.EXPINT$_f$				0.0901	0.0780	0.0876	0.0852	-0.535**	0.0132
				(0.058)	(0.063)	(0.058)	(0.062)	(0.257)	(0.082)
L.IMPINT$_f$				-0.0119	-0.272	-0.0417**	-0.0101	-0.0123	-0.0118
				(0.024)	(0.248)	(0.017)	(0.025)	(0.023)	(0.024)
L.ln(Employment)$_f$	0.0916***	0.0910***	0.0919***	0.0955***	0.0955***	0.0957***	0.0934***	0.0928***	0.0935***
	(0.018)	(0.019)	(0.018)	(0.018)	(0.020)	(0.018)	(0.018)	(0.019)	(0.018)
L.RDINT$_f$	0.125	0.126	0.125	0.116	0.102	0.115	0.127	0.136	0.128
	(0.081)	(0.092)	(0.082)	(0.083)	(0.093)	(0.084)	(0.079)	(0.086)	(0.079)
L.DAFF$_f$	-0.0382***	-0.0367***	-0.0384***	-0.0311***	-0.0319***	-0.0312***	-0.0247**	-0.0243**	-0.0249**
	(0.008)	(0.009)	(0.008)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
N	70182	67302	70182	70182	67302	70182	70182	67302	70182
r2	.0419	.0372	.0421	.0414	.0404	.0416	.0425	.0412	.0426
Kleibergen-Paap rk LM statistic	3.286*	2.306	3.286*	2.674	3.559*	2.707*	5.226**	2.366	5.177**
Kleibergen-Paap rk Wald F statistic	35.116	7.607	34.672	8.781	5.278	8.782	52.574	22.566	52.078

Notes: Standard errors clustered at industry level in parentheses. Firm fixed effects and year fixed effects are included.

TRADEINT in equations (1) – (3) denotes the ratio of exports plus imports to sales. TRADEINT in equations (4) – (6) denotes the ratio of imports to sales, while TRADEINT in equations (7) – (9) denotes the ratio of exports to sales.

* p<0.10, ** p<0.05, *** p<0.01