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Participation in the Global Value Chains and Domestic Technology Change: Evidence from Japanese Patent-Firm-Matched Data

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Abstract

Today's economies are increasingly interconnected through Global Value Chains (GVCs) and the importance of different economies in them has been changing significantly in the last decades. This paper explores how changes in the relative position and degree of participation in the GVCs affect firm innovation activities, focusing on the experience of Japanese firms.

The analysis is based on patent-firm-matched data for Japanese firms with information on GVC networks. More specifically, we use firm-level panel data collected by the Japanese government linked with the patent statistics, to measure various patent characteristics for each firm for the period from 1995 to 2011. On the other hand, we reflect position within GVCs using measures of network centrality and GVC participation ratios utilizing the OECD Inter-Country Input-Output Tables.

Based on these measures, we find that Japan's position in the GVCs for many industries has shifted from being the core of Asian value chains towards the periphery relative to other countries in the network. 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) and/or foreign value added embodied in her exports (backward GVC participation). On the other hand, Japanese firms' productivity has stagnated since the early 1990s, and the number of patent applications by Japanese firms has been declining since the mid-2000s.

Our preliminary empirical analysis shows that forward centrality (i.e., having access to a greater breadth of customers) tends to be positively associated with innovation activities (measured as the number of patent applications) particularly in the case of exporters, suggesting that exporters located in the key hubs in GVCs would benefit from knowledge spillovers from various customers and downstream markets. On the other hand, backward GVC participation is strongly negatively correlated with patent applications for importers, but positively associated with TFP growth for importers. These results may suggest that proximity of innovation activities to factory floor may be important to create new knowledge and technology though utilizing imported inputs would promote reallocation of production factors and resources and improve efficiency of production.

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1. Introduction

Today's economies are increasingly interconnected through Global Value Chains (GVCs) and the importance of different economies in them has been changing significantly in the last decades. In particular, East Asian countries have achieved rapid economic growth and gained their presence as "Factory Asia" in the world economy. Japan has been an important player in the GVC, or "Factory Asia," but in fact, her presence has been relatively declining. Studies such as Amador and Cabral (2017) and Criscuolo and Timmis (2017), measuring the relative position of each country-industry pair in the GVC network, suggest that Japan has moved away from the inner core of the global or regional production network. Instead, China has joined the inner core and has been raising her importance in the GVC network.

Figure 1 shows the centrality of cross-country exports and imports network in 1995, while Figure 2 shows the corresponding centrality in 2011, based on the study by Criscuolo and Timmis (2017).[1] The size of the circle in the figures represents the size of centrality, where countries with larger centrality are considered as more influential relative to others in the network. In other words, countries with larger centrality are more important in the network having larger volumes of transactions and larger number of transaction partners. In 1995, a minority of key hubs, such as USA, Germany (DEU), and Japan (JPN), dominate regional value chains (Figure 1). Although many of them remained key hubs in 2011 (Figure 2), Japan is the exception. Japan's centrality decreased significantly from 1995 to 2011, while China's centrality increased in the Asian regional value chains. By 2011, the position of Japan as a key hub within Asian value chains has diminished substantially, with China (CHN) and India (IND) exhibiting strong growth and other economies such as Korea maintaining their position.[2] On the other hand, Criscuolo and Timmis (2017) 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 been becoming less influential in the GVC network relative to other countries, it has been getting more embedded in the GVCs. What does it mean for the Japanese economy? How does it affect activities of Japanese firms?

INSERT Figures 1 & 2

Against the background, this paper explores how changes in the relative position and degree of participation in the GVCs affect firm activities, focusing on the experience of Japanese firms. We are particularly interested in the effects on firms' innovation activities, because we conjecture that

[1] The details on the centrality measure are provided in Section 2.3.2.
[2] Criscuolo and Timmis (2017) also find that Japan's aggregate centrality has declined the most amongst high income economies even after removing the effect of size changes.

knowledge spillovers would depend not only on participation but also on the structure of global production networks, the position within them, and the characteristics of other participants in the network. Firms and industries positioned at the centre of complex production networks have access to a greater variety of foreign inputs, compared to those at the periphery. Since these inputs are embodied with the skills and technologies used to produce them, the central hubs may also have access to a greater breadth of disembodied knowledge, with greater potential for knowledge spillovers. Therefore, whether firms and industries sit at the fringes of global production or are tightly knotted at the centre of a complex network, connecting highly productive foreign firms, is likely to affect economic outcomes, particularly technological capabilities of firms and industries.

In this paper, we utilize the network centrality measure to identify those sectors that are highly central hubs and those that are peripheral. As explained later, 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. Central hubs are likely to affect the diffusion path of new knowledge, with central sectors that are highly connected to these new sources of knowledge likely to benefit more. We also utilize the GVC participation measure to identify sectors that are deeply embedded in the GVCs. Our GVC participation measure is to measure the value of imported inputs in the overall exports of a country (foreign content of exports), and the value of domestic contents in the exports by other countries.

In fact, there is a large body of literature on GVCs on one hand, on the other hand, the relationship between international trade and firm performance has been examined very extensively in previous studies. However, the relationship between GVC embeddedness or positions within the GVC networks and the firm-level performance has not yet been sufficiently analysed. Although the research on this relationship is still scarce, our study relates to several literatures. First, there is a growing literature that demonstrates 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) and 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 (Acemoglu et al. 2012, Carvalho 2014, Magerman et al. 2016, Barrot and Sauvagnat 2016).

[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.

Second, our study also relates to the literature on the impact of import competition on technical change and innovation. For example, Bloom et al. (2016) and Autor et al. (2016) examine the impact of import competition from China on innovation and productivity of domestic firms in the cases of the European firms and the U.S. firms, respectively. The former find a positive effect while the latter find a negative effect. In fact, the effect of market competition on innovation is ambiguous. As shown in Aghion et al. (2005), innovation would be relatively low at very high levels of competition because intensified competition lowers profits and reduces incentives to invest in innovative activity. They argue that firms tend to invest more in R&D at intermediate levels of competition because post-innovation rents may exceed pre-innovation rents. On the other hand, import competition may lower the cost of redeploying factors of production "trapped" in producing old goods to innovation activities, leading to accelerated innovation and productivity growth (Bloom et al. 2013, 2017). Moreover, when firms move production offshore, productivity of factors at home is likely to be improved, which could raise the incentive for investing in innovation and the acquisition of knowledge (Grossman and Rossi-Hansberg 2008). Offshoring, however, may cause R&D and production to occur in locations that are distant from each other. Especially when product innovation requires intense iteration between product and process development and feedback during actual production (in the case of products with low modularity), the distance between designers and factory floor would lower the efficiency of innovation and reduce innovation outcome (Pisano and Shih 2012).[4] Thus, although the relationship between import competition and innovation is ex ante ambiguous, Bloom et al. (2016) find that European firms create more patents, expand investment in information technology, and improve TFP growth rate, in response to greater import competition from China, while Autor et al. (2016) find opposite results for the U.S. firms.

Third, 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. For example, assuming that the production of higher quality exhibits increasing returns to scale due to fixed cost, importers and exporters are more likely to upgrade their quality if their sales increase by international expansion (e.g., Bustos 2011, Lileeva and Trefler 2010). Another explanation is that firms are likely to find lower-cost and/or higher-quality suppliers in foreign countries (Kugler and Verhoogen 2012), and therefore, importers will be incentivized to upgrade their products as a result of reduced cost of producing higher quality. On the other hand, exporters will be also incentivized to upgrade their products because demand for high-quality goods is likely to be higher in foreign countries (Verhoogen 2008). These studies suggest that participating in the GVCs would raise technological capabilities and productivity of firms.

[4] Arkolakis et al. (2017), however, studying the welfare implications of shocks driving increased specialization in innovation and production across countries, reveal that production workers gain even in countries that specialize in innovation.

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 preliminary results. The final section provides a discussion of our main conclusions.

2. Data

2.1 Patents

The key variables on firm-level innovation activities are constructed using patent data. We use two types of patent databases, i.e., IIP Patent Database and PATSTAT (Worldwide Patent Statistical 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.[5] 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 firm ID in our firm-level data via applicant information. We can also match the patent application ID in the IIP database with the patent application ID in the PATSTAT.

We also utilize the PATSTAT, which contains bibliographical and legal status patent data on patent applications and granted patents from more than 40 patent authorities worldwide. The information in the PATSTAT on the patents applied to JPO is originally submitted from JPO, and it is basically same as that in the IIP Patent Database. However, the IIP Patent Database contains only selected information though it is more user friendly. Some information such as patent family and technological field is taken from the PATSTAT. Thus, we use both the IIP Patent Database and the PATSTAT to construct firm-level patent characteristics data.

Moreover, the PATSTAT contains data on patents applied to the European Patent Office (EPO), the US Patent Office (USPTO) and other patent authorities. In particular, the information on patents applied to EPO is standardized and can be compared across applicant firms and/or countries of applicants. We also use the information on patents applied to EPO in order to construct patent

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

characteristics measures for patents applied by Japanese firms to EPO relative to those for patents applied by firms from other countries to EPO. (*We haven't used the relative patent characteristics measures yet.)

2.2 Productivity and firm-level patent 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).[6] 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. 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 (including a breakdown of the destination of sales and exports and the origin of purchases 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, which contain approximately 22,000+ firms per year, we calculate firm-level productivity measures and construct 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 and PATSTAT explained above with the firm-level panel data constructed from the BSJBSA. The BSJBSA and the patent databases are linked using identical company names and locations. In Ikeuchi et al. (2017), they link the Enterprise and Establishment Census and 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 analyse the firm-level number of patent applications and other characteristics of applied patents.

In addition, we should not ignore overseas activities by Japanese firms in the context of GVCs. As we explain below, our GVC embeddedness measures are constructed based on the Inter-Country Input-Output (ICIO) Tables which 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

[6] 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).

Japanese firms drastically have been 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. From the survey, we take the number of affiliates, employment and sales of affiliates by industry and by country for each parent firm.[7]

2.3 Measures of GVC embeddedness

2.3.1 GVC participation

We construct the measures for the degree of participation in the GVCs using the OECD Inter-Country Input-Output (ICIO) Tables, which cover 78 countries/regions and 51 industries for the years from 1995 to 2011.

First, 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 percentage 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." However, the combined measure is also widely used in the literature, because combining the VS and VS1 shares, one can have a comprehensive assessment of the participation of a country in GVCs, both as a user of foreign inputs (upstream links, i.e. backward participation) and supplier of intermediate goods and services used in other countries' exports (downstream links, i.e. forward participation) (De Backer and Miroudot 2013). Following the conventional GVC literature, we construct both the backward GVC participation measure and the forward GVC participation measure.[8] We also use the combined GVC participation measure which is calculated as the simple average of the backward and forward participation measures. The index is expressed as a percentage of gross exports and indicates the share of foreign inputs (backward participation) and domestically produced inputs used in third countries' exports (forward participation).

[7] Currently, we have the affiliate data up to 2009. We will extend the data up to 2011 in the near future.

[8] 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).

2.3.2 GVC centrality

We also use the OECD ICIO Tables to construct measures of network centrality in order to reflect relative position of each country-industry pair within GVCs. Our preferred centrality measure, eigenvector centrality, takes into account both direct and indirect linkages to identify key hubs. The definition and the calculation of the network centrality are described in the following.

The linkages within GVCs reflect ICIO flows of goods and services, but we take into account indirect linkages too. 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 is determined not only based on your own node-strength (number of linkages and the size of each linkage), but also its suppliers node-strength, and your suppliers' suppliers' node-strength, etc.

This class of measure encompasses several variants applied in the sociology literature (such as eigenvector, Katz and Bonacich centrality) or in computer science, such as Google's PageRank search algorithm (Brin and Page, 1998). Formally the eigenvector-type centralities are calculated using the formula given by equations 2.1 and 2.2. The backwards centrality is calculated as the baseline centrality (η) plus the weighted average of upstream (backwards) centralities, where the weights (w_{ji}) are the upstream input linkages (see 2.1). 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. Similarly, forwards centrality is calculated as the baseline centrality (η) plus the weighted average of downstream (forwards) centralities, where the the weights (w_{ij}) are the downstream input linkages (see 2.2). See Criscuolo and Timmis (2017) for more details on the calculations.

$$c^{back}{}_i = \sum_j w_{ji} \cdot \lambda \cdot c_j^{back} + \eta \tag{2.1}$$

$$c^{fwd}{}_i = \sum_j w_{ij} \cdot \lambda \cdot c_j^{fwd} + \eta \tag{2.2}$$

$$c^{back} \; or \; c^{fwd} = \eta(I - \lambda W')^{-1}1 \tag{2.3}$$

where c^{back} or c^{fwd} is a vector of eigenvector centrality measures, 1 is a vector of ones, I is the identity matrix. W is the input-output coefficient matrix. Note this is similar to the Leontief inverse of the input-output matrix = $(I - W)^{-1}$

To facilitate aggregate comparisons, we reflect total centrality as the average of forward and backward centrality. The calculation of backward and forward centrality allows disentangling important distinctions between key and peripheral customers, and key and peripheral suppliers respectively. These mirror the distinction made in GVC participation metrics between forward and backward GVC participation. However, for illustrative purposes it is often useful to have an overall measure of centrality, which we define as the average of backwards and forwards centrality.

$$c^{total}{}_i = {}^1/_2 \cdot \left(c^{fwd}{}_i + c^{back}{}_i\right) \qquad (2.4)$$

However, in this study we employ the Pagerank centrality instead of eigenvector centrality. Pagerank centrality is a variant of eigenvector centrality that has been made famous for underlying the Google search algorithm. A problem with eigenvector is that a high centrality node connected to a large number of others, gives all its neighbours high centrality. Pagerank, divides the centrality contribution by its out-degree centrality, so includes a dampening factor based on the direct connectivity of the node.

$$PageRank = \eta(I - \lambda W D^{-1})^{-1}1 \qquad (2.5)$$

where the dampening factor $D_{ii} = \max(k_i^{out}, 1)$.

We use Pagerank centrality measure defined by equation (2.5) as c^{back} or c^{fwd} in equations (2.1), (2.2), and (2.4), instead of eigenvector centrality measure defined by equation (2.3). We calculate the backward, forward, and total centrality for each country-industry pair for every year from 1995 to 2011 utilizing the OECD ICIO Tables.

3. Industry-Level GVC Participation and Patenting by Japanese Firms

Figure 3 shows the changes in GVC centrality and GVC participation by industry from 1995 to 2011. Panel (1) of Figure 3 shows the changes in in-degree centrality and backward participation, while Panel (2) shows the changes in out-degree centrality and forward participation. Looking at the upper panels, both in-degree and out-degree centrality declined in many industries. Particularly, industries such as electrical machinery and apparatus, computer, electronic and optical equipment, construction, and wholesale and retail trade, show a substantial decline both in terms of in-degree and out-degree centralities. The large decline in centrality suggests that these industries become relatively peripheral in the GVCs by 2011, though it also reflects the fact that these industries were key hubs in 1995. On the other hand, however, the lower panels show that both backward and forward GVC participation increased in almost all the industries. In the case of forward GVC participation, Japan's contents of other high-income countries' exports declined in some industries, such as electrical machinery and apparatus, computer, electronic and optical equipment, and wholesale and retail trade, though Japan's contents of exports by all foreign countries increased. In the case of backward GVC participation, although the share of inputs imported from high-income countries increased, the share of inputs from other countries seems to have increased more. These figures imply that Japan's increased participation was mainly driven by the increases in imported intermediate goods and services from and exports of intermediate goods and services to developing countries.

INSERT Figure 3

The sharp decline in centrality and increase in participation might be correlated with the rapid expansion of overseas production by Japanese multinational firms.[9] Figure 4 compares the trends of industry-level foreign centrality and industry-average overseas employment ratio for Japanese firms. Each plot in Panel (1) shows the industry-level total centrality in each year, and the downward-sloping fitted line indicates that the aggregate centrality has been declining over time. On the other hand, each plot in Panel (2) shows the industry average overseas employment ratio in each year. The firm-level overseas employment ratio is calculated as the number of workers employed in foreign affiliates of Japanese firms divided by the total number of workers employed in domestic headquarter firm and foreign affiliates of the firm. The firm-level data are taken from the microdata underlying the BSJBSA and the BSOBA. The fitted line in Panel (2) is upward sloping, suggesting that the overseas employment ratio has been increasing and that Japanese firms have been expanding their overseas activities. These figures imply that the decline in Japanese centrality may be partly driven by the expansion of overseas activities of Japanese firms. Moreover, the increase in backward and forward GVC participation may be partly driven by the increases in intra-firm trade between headquarters of Japanese multinational firms and their foreign affiliates.

INSERT Figure 4

[9] Criscuolo and Timmis (2017) argue that the decline in Japanese centrality does not seem to be mainly driven by the slow growth of the Japanese economy over the same period. They checked the centrality changes having stripped out the effect of size from the centrality metrics. Although some portion of the decline in the centrality was due to the slow growth in traded inputs, the bulk was not explained by size.

As for the number of patent applications to JPO, it was gradually increasing in the latter half of the 1990s but has been declining since the mid-2000s (Figure 5). The share of firms that applied at least one patent seems to be also declining in the 2000s (Figure 6). Looking at patent applications by sector (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. Figure 6 and Table 2 also indicate that the share of firms with at least one patent applications has been declining in these major patenting industries.

However, focusing on the firms with at least one patent application, the average number of patent application per firm seems to be increasing (Figures 7 & 8), which may suggest that patent applications tend to be becoming concentrated in a smaller number of firms that are getting more active in patenting. In addition, looking at the average number of patents with at least one foreign inventor per firm has been increasing in the 2000s, though the number is still very small (the right axis of Figure 7).

INSERT Figure 5, 6, 7, & 8

INSERT Tables 1 & 2

4. Empirical Strategy

4.1 Model

Based on the arguments and results in previous studies related to our study, the relationship between GVC embeddedness and technological change can be either positive or negative. The increase in backward GVC participation may enable firms to have better access to better foreign inputs, which will lower downstream firms' cost of technology upgrading. The increase in forward GVC participation may also enable firms to have technologically advanced customers abroad, which would bring more technology spillovers to the firms and promote their technology upgrading. Backward and forward GVC participation is also expected to have a positive impact on innovation if it lowers the costs of intermediate inputs and makes firms more profitable by increasing sales in foreign countries. Moreover, the increase in backward and forward GVC participation as a result of the expansion of offshoring and optimal location of firm activities would shift domestic resources towards more innovative activities. However, if the increase in backward GVC participation means intensified import competition, it will reduce profits of domestic firms and result in lower levels of innovation.

As for the relative position within the GVC networks, we expect that firms in more central industries would increase innovation, because the central hubs 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. We expect that firms and industries that are tightly knotted at the centre of a network would benefit more from greater knowledge spillovers than peripheral firms and industries, and that they would have more incentive to invest in innovative activities.

We estimate the following equation in order to examine the relationship between innovation outcome of Japanese firms and participation/relative position in the GVCs of Japanese industries.

$$\begin{aligned} Y_{fit} = {} & \beta_1 DNoPat_{fit} + \beta_2 FC_{fit-1} + \beta_3 C_{it-1} + \beta_4 GVC_{it-1} + \beta_5 Firm\ Controls_{fit-1} + \\ & \beta_6 Industry\ Controls_{it-1} + \delta_f + \tau_t + \varepsilon_{fit} \end{aligned} \tag{4.1}$$

$$Y_{fit} = \begin{cases} \ln(1 + NumPat)_{fit} & if\ NumPat_{fit} = 0 \\ \ln(NumPat)_{fit} & if\ NumPat_{fit} > 0 \end{cases} \tag{4.2}$$

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. Taking patent quality into account, we use the citation-weighted number of patent applications for *NumPat*. 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[10], we standardize the number of citations for each patent by dividing it by the maximum number of citations for the patents in the same IPC class and application year. We use the standardized number of citations as a weight and construct the variable *NumPat*.[11] 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 take these zero-patent observations into account, we define the dependent variable differently for observations with zero patent applications and for observations with non-zero patent applications. In the case of observations with zero patent applications, we include a dummy variable, *DNoPat*, as an explanatory variable which takes one if the firm does not apply any patents in that year.

As for other explanatory variables, we are most interested in the GVC embeddedness variables, *C* and *GVC*. The variable *C* denotes the centrality measure while the variable *GVC* denotes the GVC participation measure. We use either total centrality/participation, in-degree (backward) centrality/participation, or out-degree (forward) centrality/participation measure. We also include the affiliate-size weighted 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 centrality measures in the following way:

[10] 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 to use the information on citations by examiners.

[11] We also estimated the same model using the non-weighted *NumPat* as a dependent variable, and the estimation results were very similar to the results based on the weighted *NumPat*.

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

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

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

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, HQ_{ft} denotes number of workers employed in the parent firm in Japan of multinational firm f in year t.

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, an exporter dummy and an importer dummy. We construct an exporter (importer) dummy variable which takes one if the firm exports (imports), zero otherwise. We also construct another dummy variable which takes one if the firm either exports or imports, zero otherwise. δ_f and τ_t denote firm-specific fixed effects and year-specific fixed effect, respectively. We include industry-specific fixed effects. (At this stage, we have not included any other industry-level control variables yet.)

For our preliminary analysis, we estimate equation (4.1) by using the fixed-effect panel estimation method. Although we have to address endogeneity issues, we have not tried the System GMM method or IV estimations yet. For our baseline estimation, we use the three-year lagged explanatory variables, except *DNoPat,* firm-, industry-, and year-specific fixed effects.[12] In addition, we estimate equation (4.1) using firm-level TFP as a dependent variable, instead of the number of patent applications.

4.2 Results

Table 3 and 4 show the estimation results when we use the citation-weighted number of patent applications as a dependent variable. Table 3 shows the results for all the firms in our dataset including non-manufacturing firms while Table 4 shows the results for the manufacturing firms only. Equation (1) in Tables 3 and 4 shows the results when we employ total centrality and total GVC participation measures. Similarly, backward centrality and GVC participation measures are used for equations (2)-(4) and forward centrality and GVC participation measures are used for equations (5)-(6). The standard errors are clustered at the industry level.

[12] 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.

Looking at the stand-alone centrality variable, the coefficient tends to be negative and significant in Table 3 while it is not statistically significant for all the cases in Table 4 except equation (7). Equation (7) indicates that forward (out-degree) centrality is positively associated with patent applications in the case of the manufacturing sector. Equation (5) in both Table 3 and 4 also shows that forward centrality is positively associated with patent applications particularly for exporters, suggesting that having access to a greater breadth of customers would promote innovation activities and lead to larger innovation outcomes. Exporters located in the key hubs in GVCs would benefit from knowledge spillovers from various customers and downstream markets.

As for the GVC participation measure, the coefficient of both the stand-alone and interaction terms tend to be negative and significant except equation (6) in Table 3. Particularly, backward GVC participation is strongly negatively correlated with patent applications for importers (equation 3 in both Tables 3 and 4). Although we expected that firms utilizing imported inputs would shift their resources from production to innovation activities and 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 which are considered to be strong in integral-type low-modularity production.

INSERT Tables 3 & 4

However, the results using firm TFP as a dependent variable shown in Tables 5 and 6 look quite different from those in Tables 3 and 4. Looking at equation (3) in both Tables 5 and 6, the interaction term of importer dummy and backward GVC participation has a positive and significant coefficient. It suggests that firms utilizing imported inputs tend to show higher TFP growth. The result may imply that utilizing imported inputs would promote reallocation of production factors and resources and improve efficiency of production. However, GVC participation would not be necessarily beneficial for technical changes in terms of patenting, i.e., knowledge creation. The results in Tables 3 and 4 may imply that forward centrality, i.e., being the key hub in the network having access to a greater breadth of customers would be more important for knowledge creation.

INSERT Tables 5 & 6

Next steps:

-Address endogeneity issue, IV or GMM

-Patent quality measures

-Determinants of GVC centrality and GVC participation (causality goes from innovation to centrality?)

5. Conclusions

TO BE COMPLETED.

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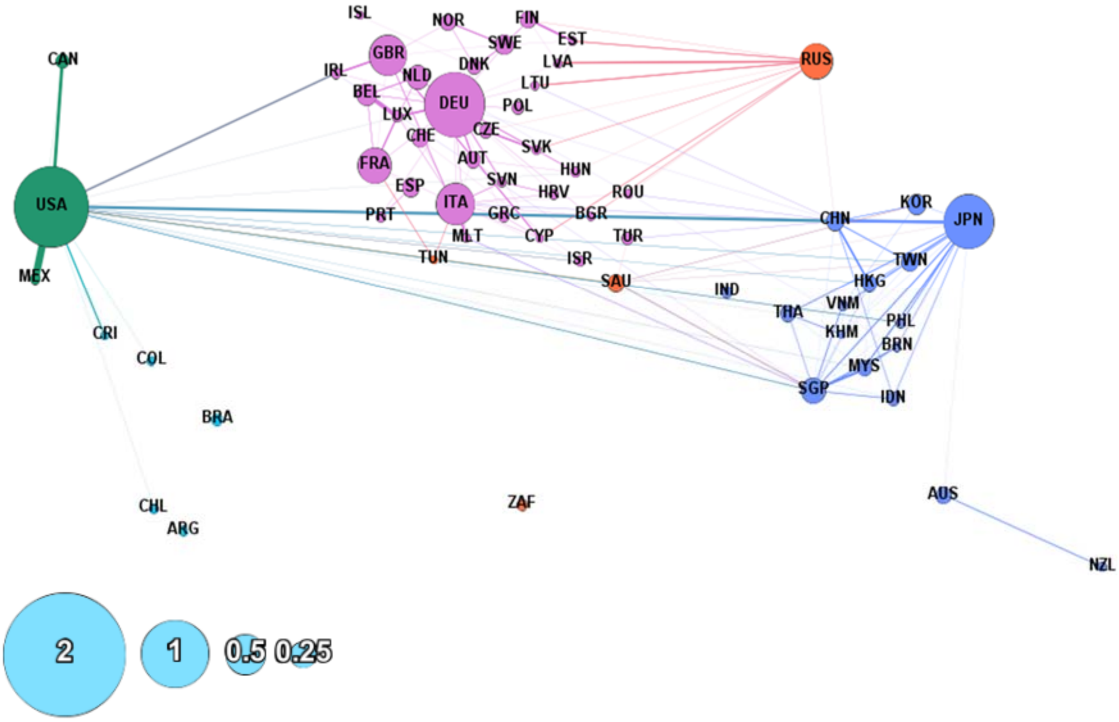
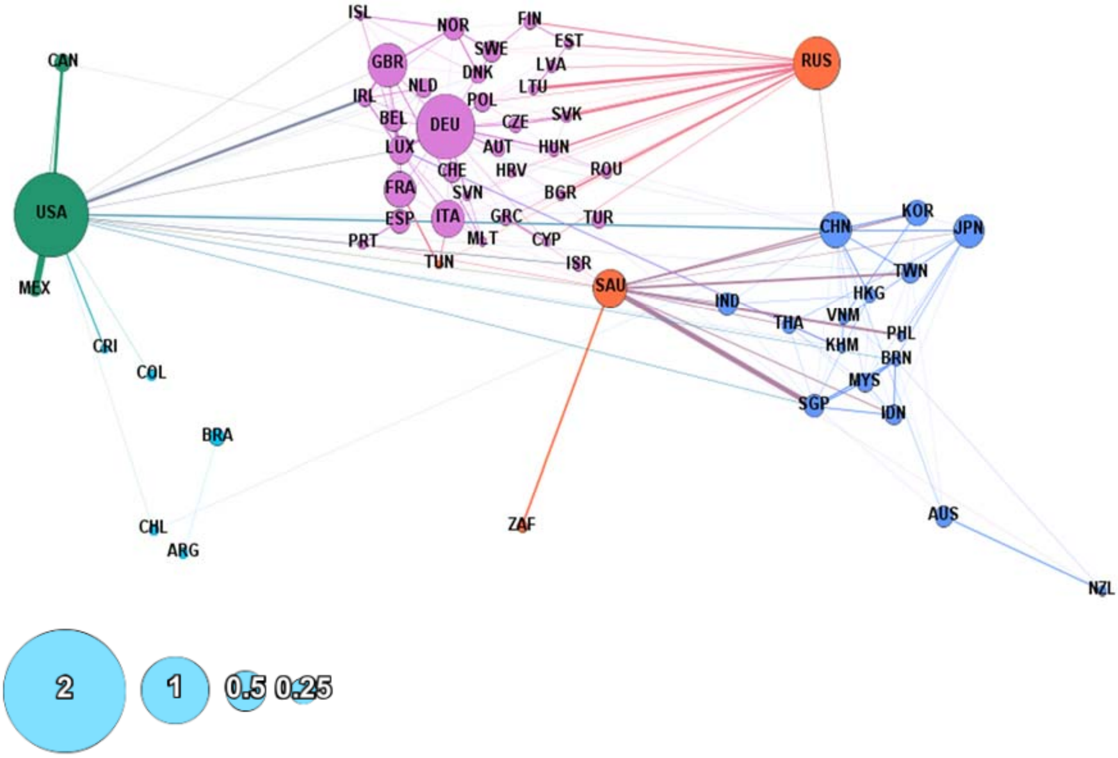
Figure 1. Aggregate Central and Peripheral Economies – (Foreign Centrality) 1995



Source: Criscuolo and Timmis (2017)

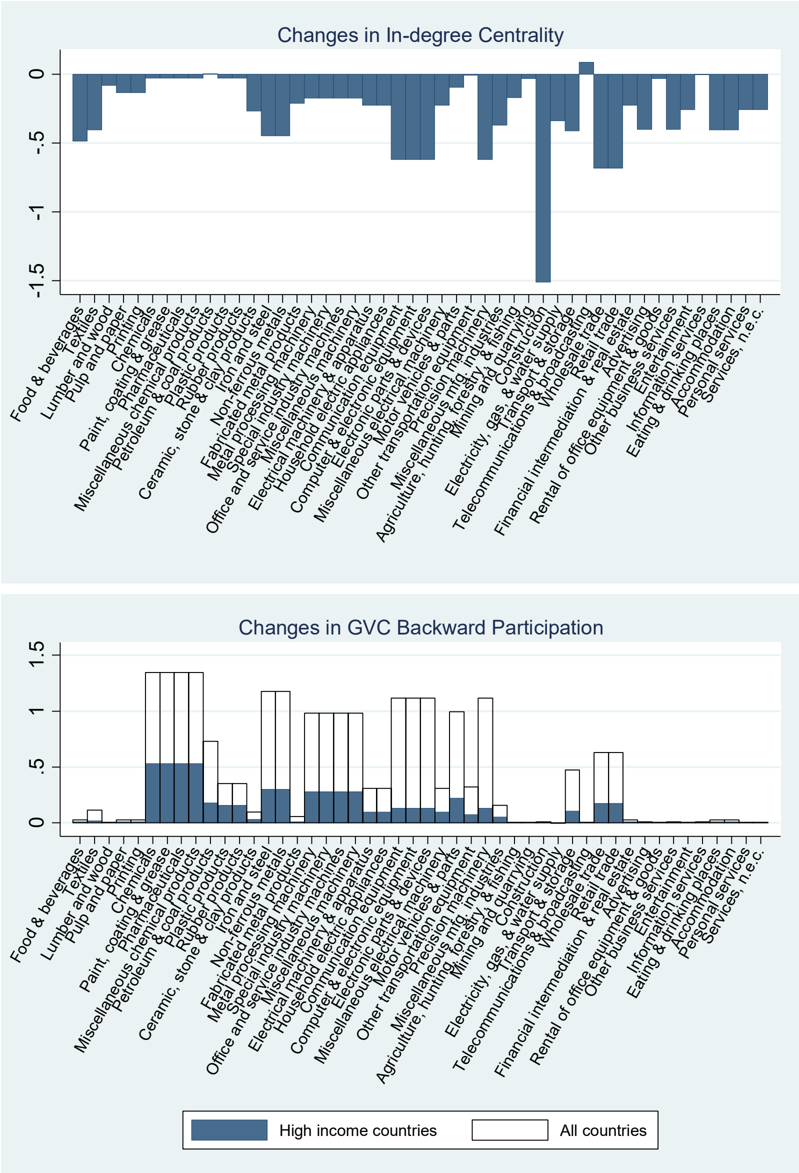
Figure 2. Aggregate Central and Peripheral Economies – (Foreign Centrality) 2011



Source: Criscuolo and Timmis (2017)

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

(1) In-degree Centrality & Backward Participation



(2) Out-degree Centrality & Forward Participation

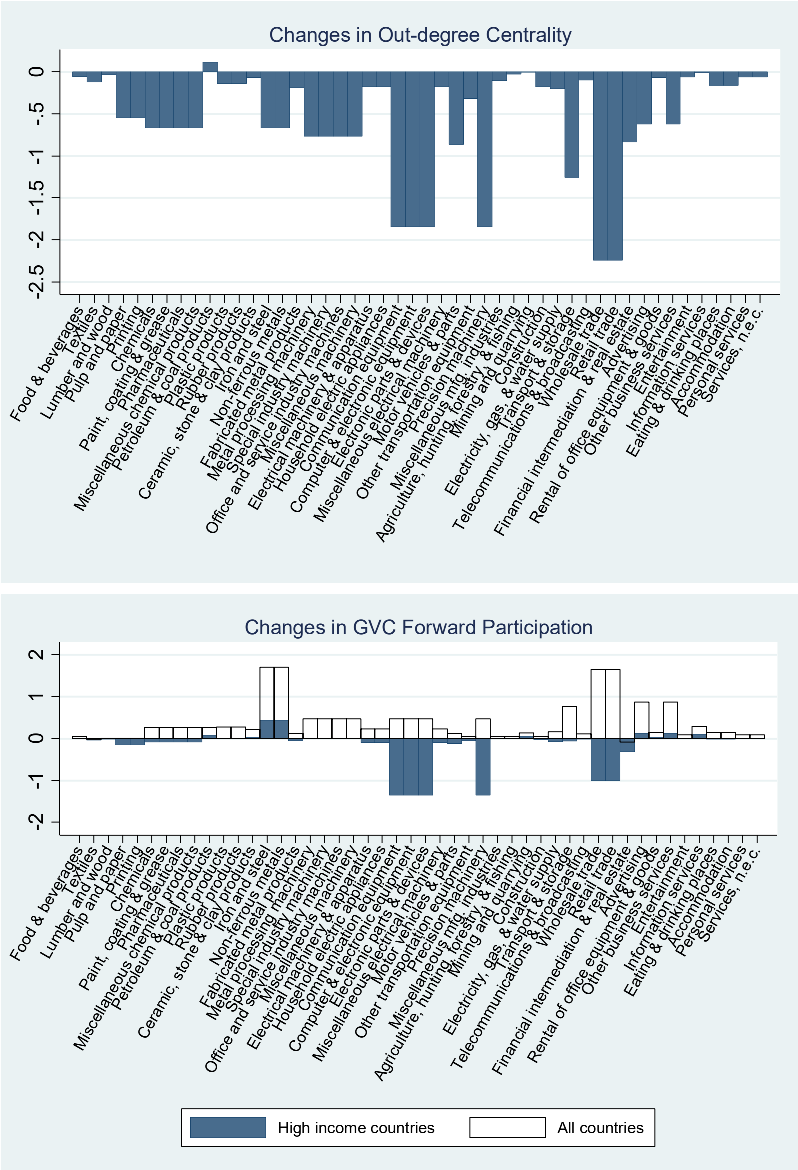
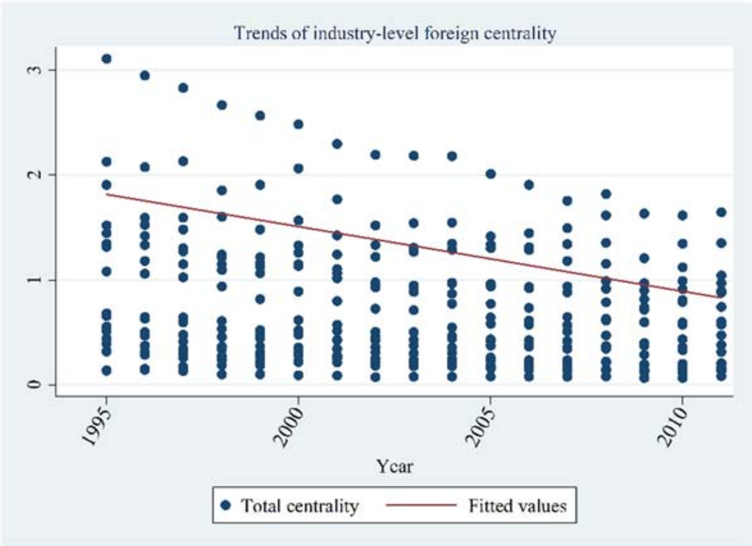


Figure 4. Industry-Level Centrality and Industry-Average Overseas Employment Ratio

(1) Trends of industry-level foreign centrality (total centrality)



(2) Trends of industry-average overseas employment ratio

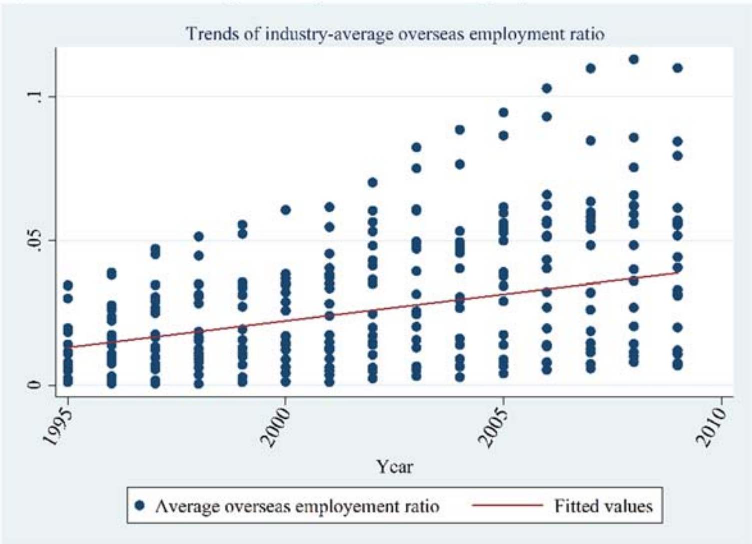


Figure 5. Number of Patent Applications to the Japan Patent Office 1995-2011

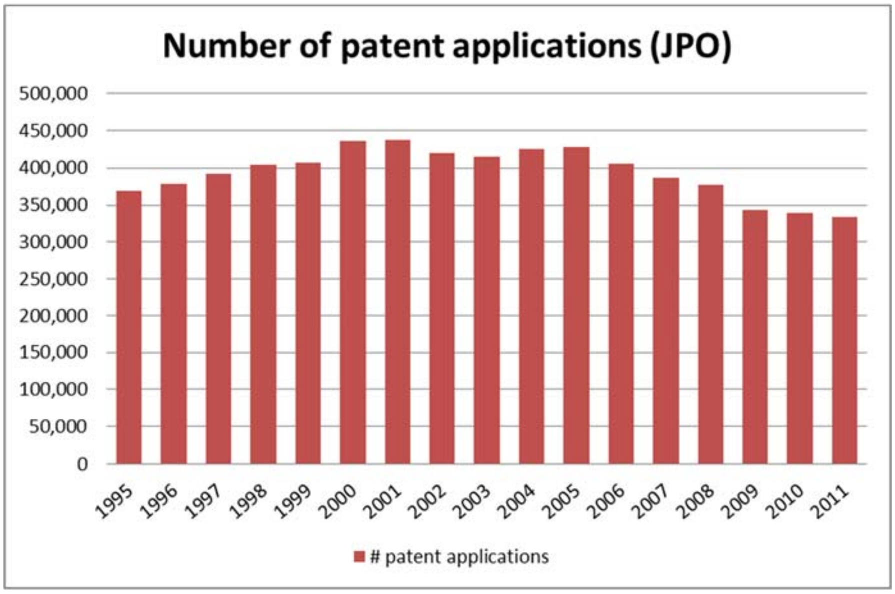


Figure 6. Share of Firms with at Least One Patent Applications (%)

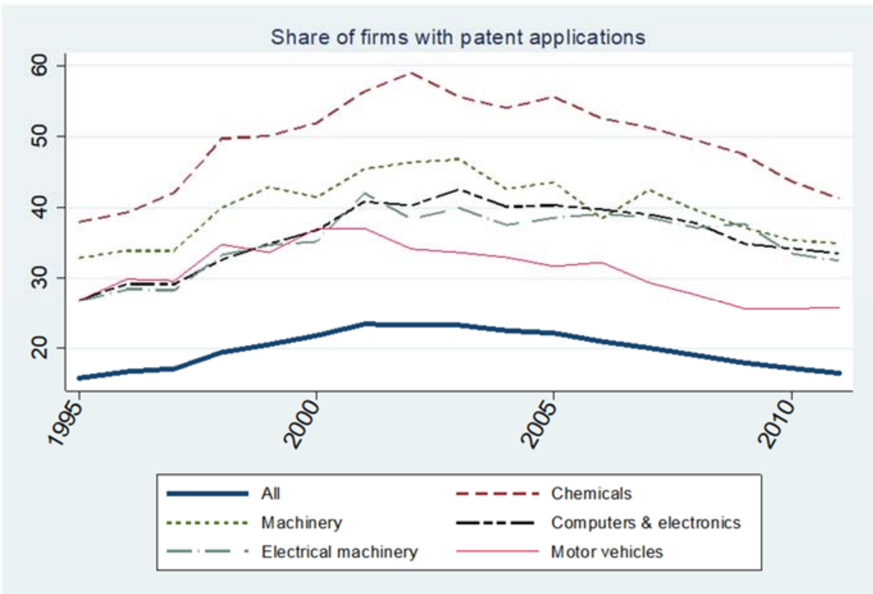
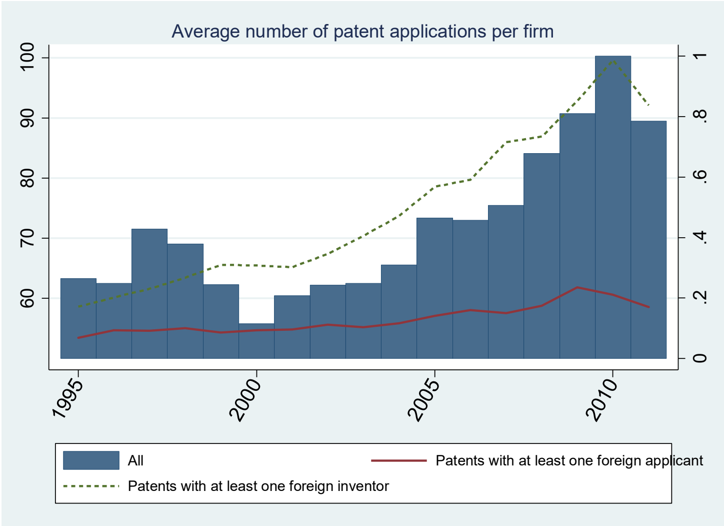
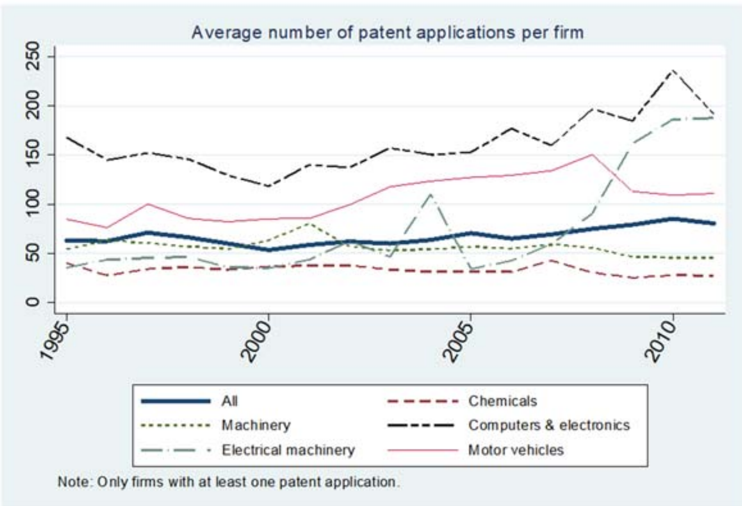


Figure 7. Average Number of Patent Applications per Firm



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

Figure 8. Average Number of Patent Applications per Firm for Major Sectors



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

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 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. Estimation results: Number of patent applications, All industries

Dependent variable: Number of patent applications (citation-weighted) in logarithm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
3-year lagged	Total	Backward	Backward	Backward	Forward	Forward	Forward
L3.Affliated-weighted Centrality	-0.0701	-0.101**		-0.0910**	-0.0656		-0.0757
	(0.049)	(0.040)		(0.039)	(0.049)		(0.049)
L3.Centrality	-0.161***	-0.161***		-0.111*	-0.0648**		-0.0580*
	(0.044)	(0.054)		(0.059)	(0.025)		(0.032)
L3.GVC Paricipation	-8.945**		-8.043**	-9.041**		3.469**	0.0546
	(3.304)		(2.964)	(3.378)		(1.541)	(1.317)
L3.TRADE*L3.Centrality		0.0393			0.0416**		
		(0.037)			(0.018)		
L3.TRADE*L3.GVC Participation			-8.963**			-0.0660	
			(3.401)			(0.213)	
L3.TRADE	0.0190**						
	(0.009)						
L3.EXPORTER		0.00410	0.00522	0.00487	-0.0652***	0.00471	0.00325
		(0.009)	(0.009)	(0.009)	(0.021)	(0.014)	(0.009)
L3.IMPORTER		-0.0268	0.0747***	0.0110	0.00953	0.00878	0.00935
		(0.032)	(0.026)	(0.008)	(0.008)	(0.008)	(0.008)
L3.ln(Employment)	0.0431***	0.0439***	0.0462***	0.0469***	0.0382**	0.0414***	0.0396**
	(0.016)	(0.015)	(0.013)	(0.015)	(0.015)	(0.014)	(0.015)
L3.RDINT	-0.154	-0.146	-0.135	-0.148	-0.140	-0.143	-0.146
	(0.145)	(0.142)	(0.137)	(0.142)	(0.139)	(0.141)	(0.143)
DNoPat	1.451***	1.450***	1.451***	1.450***	1.451***	1.447***	1.449***
	(0.036)	(0.036)	(0.035)	(0.036)	(0.036)	(0.036)	(0.036)
_cons	-1.557***	-1.527***	-1.607***	-1.545***	-1.609***	-1.614***	-1.615***
	(0.086)	(0.108)	(0.075)	(0.112)	(0.076)	(0.078)	(0.076)
N	220478	220478	220546	220478	220478	220546	220478
r2	.401	.401	.402	.401	.401	.4	.4

Standard errors clustered at industry level in parentheses. Industry fixed effects and year fixed effects are included.

TRADE in equation (1) denotes a dummy variable which takes one if the firm exports or imports. TRADE in equations (2)-(4) denotes a dummy variable which takes one if the firm imports, while TRADE in equations (5)-(7) denotes a dummy variable which takes one if the firm exports.

Table 4. Estimation results: Number of patent applications, Manufacturing industries

Dependent variable: Number of patent applications (citation-weighted) in logarithm

3-year lagged	(1) Total	(2) Backward	(3) Backward	(4) Backward	(5) Forward	(6) Forward	(7) Forward
L3.Affliated-weighted Centrality	-0.0617	-0.0931**		-0.0812*	-0.0538		-0.0643
	(0.073)	(0.042)		(0.040)	(0.072)		(0.072)
L3.Centrality	0.00418	-0.107		-0.0286	0.0316		0.0802*
	(0.061)	(0.069)		(0.052)	(0.040)		(0.042)
L3.GVC Paricipation	-7.330		-5.203	-8.434**		-0.832	1.016
	(4.946)		(3.656)	(3.392)		(2.361)	(1.833)
L3.TRADE*L3.Centrality		0.0541			0.108***		
		(0.085)			(0.021)		
L.TRADE*L.GVC Participation			-9.682**			-0.693	
			(3.985)			(0.612)	
L3.TRADE	0.0231*						
	(0.013)						
L3.EXPORTER		-0.00345	-0.00153	-0.00286	-0.119***	0.00470	-0.00379
		(0.013)	(0.014)	(0.013)	(0.030)	(0.020)	(0.013)
L3.IMPORTER		-0.0216	0.0959**	0.0194	0.0202*	0.0179	0.0193
		(0.058)	(0.036)	(0.012)	(0.012)	(0.012)	(0.012)
L3.ln(Employment)	0.0553***	0.0562***	0.0577***	0.0609***	0.0514**	0.0533**	0.0537***
	(0.018)	(0.018)	(0.017)	(0.017)	(0.019)	(0.020)	(0.019)
L3.RDINT	-0.241	-0.240	-0.226	-0.241	-0.224	-0.239	-0.231
	(0.168)	(0.169)	(0.161)	(0.167)	(0.164)	(0.168)	(0.166)
DNoPat	1.424***	1.424***	1.428***	1.426***	1.427***	1.423***	1.425***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
_cons	-1.604***	-1.535***	-1.624***	-1.593***	-1.521***	-1.607***	-1.562***
	(0.126)	(0.132)	(0.109)	(0.124)	(0.115)	(0.120)	(0.115)
N	111707	111707	111739	111707	111707	111739	111707
r2	.381	.381	.383	.382	.383	.381	.381

Standard errors clustered at industry level in parentheses. Industry fixed effects and year fixed effects are included.

TRADE in equation (1) denotes a dummy variable which takes one if the firm exports or imports. TRADE in equations (2)-(4) denotes a dummy variable which takes one if the firm imports, while TRADE in equations (5)-(7) denotes a dummy variable which takes one if the firm exports.

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

Table 5. Estimation results: TFP, All industries

Dependent variable: ln(TFP)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
3-year lagged	Total	Backward	Backward	Backward	Forward	Forward	Forward
L3.Affliated-weighted Centrality	0.0267	0.0337		0.0265	0.0238		0.0289
	(0.021)	(0.025)		(0.019)	(0.021)		(0.022)
L3.Centrality	0.102*	0.110		0.0716	0.0524		0.0261
	(0.055)	(0.068)		(0.086)	(0.036)		(0.035)
L3.GVC Paricipation	2.774		7.486	6.680		-4.997*	-3.386**
	(4.314)		(4.447)	(5.766)		(2.532)	(1.658)
L3.TRADE*Centrality		-0.0309***			-0.0170***		
		(0.006)			(0.004)		
L3.TRADE*L3.GVC Participation			2.112***			0.0576	
			(0.719)			(0.190)	
L3.TRADE	0.0100**						
	(0.004)						
L3.EXPORTER		0.000957	0.000668	0.000394	0.0293***	-0.0000760	0.00139
		(0.004)	(0.004)	(0.004)	(0.010)	(0.005)	(0.004)
L3.IMPORTER		0.0438***	-0.000327	0.0141***	0.0149***	0.0149***	0.0146***
		(0.008)	(0.008)	(0.004)	(0.005)	(0.005)	(0.005)
L3.ln(Employment)	-0.0199**	-0.0222***	-0.0248***	-0.0246***	-0.0176**	-0.0176**	-0.0168*
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
L3.RDINT	0.0252	0.0212	0.0198	0.0245	0.0186	0.0164	0.0182
	(0.043)	(0.043)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
_cons	0.125*	0.104	0.210***	0.146	0.158***	0.186***	0.157***
	(0.062)	(0.092)	(0.051)	(0.110)	(0.051)	(0.044)	(0.051)
N	209058	209058	209124	209058	209058	209124	209058
r2	.0206	.0196	.0206	.0215	.0203	.0201	.0207

Standard errors clustered at industry level in parentheses. Industry fixed effects and year fixed effects are included.

TRADE in equation (1) denotes a dummy variable which takes one if the firm exports or imports. TRADE in equations (2)-(4) denotes a dummy variable which takes one if the firm imports, while TRADE in equations (5)-(7) denotes a dummy variable which takes one if the firm exports.

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

Table 6. Estimation results: TFP, Manufacturing industries

Dependent variable: ln(TFP)

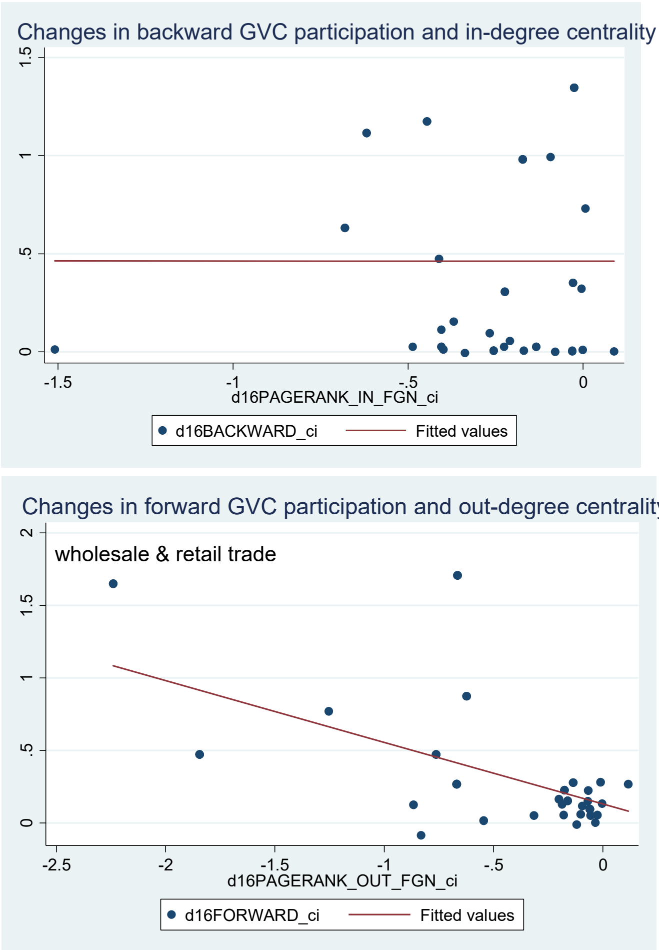
3-year lagged	(1) Total	(2) Backward	(3) Backward	(4) Backward	(5) Forward	(6) Forward	(7) Forward
L3.Affliated-weighted Centrality	0.0110	0.0241		0.0115	0.0144		0.0124
	(0.015)	(0.018)		(0.012)	(0.017)		(0.015)
L3.Centrality	-0.207***	-0.0683		-0.140*	-0.161***		-0.152***
	(0.062)	(0.083)		(0.071)	(0.045)		(0.039)
L3.GVC Paricipation	5.096		5.658	9.123*		6.499	2.558
	(4.674)		(4.710)	(4.785)		(4.452)	(3.519)
L3.TRADE*Centrality		-0.0128			-0.00142		
		(0.012)			(0.005)		
L3.TRADE*L3.GVC Participation			1.444**			0.259	
			(0.686)			(0.396)	
L3.TRADE	0.00981***						
	(0.002)						
L3.EXPORTER		-0.00134	-0.00297	-0.00178	-0.00137	-0.00583	-0.00302
		(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)
L3.IMPORTER		0.0259**	0.00407	0.0154***	0.0128***	0.0155***	0.0128***
		(0.010)	(0.006)	(0.003)	(0.002)	(0.002)	(0.003)
L3.ln(Employment)	-0.0164*	-0.0134	-0.0219**	-0.0184*	-0.0191*	-0.0179*	-0.0194**
	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
L3.RDINT	0.0204	0.0301	0.0379	0.0314	0.0207	0.0385	0.0224
	(0.060)	(0.060)	(0.060)	(0.059)	(0.060)	(0.063)	(0.060)
_cons	0.270***	0.224***	0.225***	0.316***	0.206***	0.188***	0.204***
	(0.051)	(0.079)	(0.054)	(0.068)	(0.054)	(0.057)	(0.055)
N	107099	107099	107131	107099	107099	107131	107099
r2	.0662	.0542	.0567	.0605	.0667	.0561	.0672

Standard errors clustered at industry level in parentheses. Industry fixed effects and year fixed effects are included.

TRADE in equation (1) denotes a dummy variable which takes one if the firm exports or imports. TRADE in equations (2)-(4) denotes a dummy variable which takes one if the firm imports, while TRADE in equations (5)-(7) denotes a dummy variable which takes one if the firm exports.

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

Appendix Figure 1: Correlation between changes in centrality and changes in GVC participation (1995-2011)



Appendix Table 1. Average Number of Patent Applications per Firm and the Average Share of Granted Patents per Firm

	Average number of patent applications per firm				Average share of granted patents per firm (%)			
Firms' Primary Industry	1995	2000	2005	2010	1995	2000	2005	2010
Food products, beverages and tobacco	13	8	9	8	42.8	47.3	55.3	54.9
Textiles, textile products, leather and footwear	36	40	32	10	30.7	26.3	38.1	50.6
Wood and products of wood and cork	14	19	16	16	57.2	43.6	54.3	59.6
Coke, refined petroleum products and nuclear fuel	32	6	16	18	40.4	40.7	63.9	68.7
Chemicals and chemical products	40	37	32	28	35.0	36.3	51.6	60.1
Rubber and plastics products	27	37	33	32	39.6	31.5	48.4	56.6
Other non-metallic mineral products	30	12	16	15	34.8	33.5	48.6	55.1
Basic metals	70	56	59	58	30.2	37.0	52.1	60.5
Fabricated metal products	20	24	11	11	45.3	43.6	60.0	69.1
Machinery and equipment, nec	54	64	57	46	35.5	29.7	44.4	58.8
Computer, Electronic and optical equipment	168	119	153	237	39.0	32.3	44.1	45.3
Electrical machinery and apparatus, nec	35	35	35	187	32.1	27.3	45.9	45.4
Motor vehicles, trailers and semi-trailers	85	86	128	109	39.9	43.2	45.9	58.4
Other transport equipment	30	40	27	34	52.8	46.2	53.7	62.5
Manufacturing nec; recycling	17	27	48	28	39.1	42.0	38.1	61.0
Construction	76	22	13	13	24.9	46.9	55.3	65.0
Wholesale and retail trade; repairs	77	62	102	90	37.2	29.7	39.2	49.4
Computer and related activities	338	48	121	153	35.4	35.5	46.5	60.7
R&D and other business activities	38	33	139	118	23.9	46.4	39.7	61.5
Total	63	54	71	86	37.1	33.9	44.1	51.7

Note: Figures are calculated only for firms with at least one patent application.