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Global value chains and domestic innovation

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ABSTRACT

This paper explores how changes in both position and participation in Global Value Chain (GVC) networks affect firm innovation. The analysis combines matched patent-firm data for Japan with measures of GVC network centrality and GVC participation using the OECD Inter-Country Input-Output (ICIO) Tables over the period from 1995 to 2011. We find that Japan's position in 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 accession to the World Trade Organization as an instrumental variable for changes in Japanese centrality. Our analysis shows that increases in Japanese sectors' forward centrality – i.e. as a key supplier - tend to be positively associated with increasing firms' patent applications in these sectors and that firms in key hubs within GVCs, specifically as key suppliers, appear to benefit from knowledge spillovers from downstream markets.

1. Introduction

Today's economies are increasingly interconnected through Global Value Chains (GVCs) and their relative position in this network has changed significantly over the past decades. In particular, most South-East Asian countries have achieved rapid economic growth while becoming increasingly interconnected through value chains, especially after China's accession to the World Trade Organization (WTO). Japan is a noteworthy exception. Although the country remains an important hub in GVCs, it has become less central within the network. Over the same period, China has become more central by increasing the breadth and depth of interconnections with foreign customers and suppliers (Amador and Cabral, 2017; Criscuolo and Timmis, 2018a, 2018b).

Contemporaneous with the large fall in Japan's centrality, is a similar, albeit weaker, declining trend in the centrality of manufacturing industries in many developed countries in Europe and North America (e.g., Criscuolo and Timmis, 2018a). These trends might have important consequences for these countries' innovation and long-run growth, as international trade is an important channel of technology spillovers. Indeed, as pointed out in the seminal work of Coe and Helpman (1995) and many subsequent studies, technological knowledge is embodied in goods traded across borders.

These studies have identified technology spillovers through bilateral international trade (direct ties). Yet, firms, industries or countries may also generate spillovers indirectly to other firms, industries or countries that trade with their direct partners (indirect ties, or network effects). For example, studies on shock propagation through input-output (or buyer-supplier) networks show that better-connected "nodes" in a network display greater complementarities in behaviors and that being a well-connected "node" can have significant effects on performance. This network channel for technology spillovers has been extensively analyzed in the context of research collaborations or for specific industries (Ahuja, 2000; Owen-Smith and Powell, 2004; Soh, 2003; Fleming et al., 2007; König et al., 2019, etc.). We complement this literature by taking into account the network externalities in the context of technology spillovers through global value chains.

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Our paper thus aims at contributing to this growing body of evidence by testing the conjecture that more knowledge is likely to accumulate in more central countries and industries in the GVC network. These well-connected "nodes" – or so-called "central hubs" - have access to a greater variety of foreign products and knowledge (upstream and downstream) compared to peripheral (i.e., less central) countries and industries. Knowledge can flow through traded products, embodied with the skills and technologies used to produce them. Disembodied knowledge flows, however, are also important. For example, exchanges of know-how from downstream users to their suppliers have been found to be particularly important sources for subsequent innovation (see, for example Javorcik et al., 2018 and references therein). "Central hubs" are likely to have access to a greater breadth of knowledge, with greater potential for spillovers.

We explore how changes in centrality of a country-industry in the GVC network affect innovation output of firms in those countries and industries, using Japan as a case. We employ network centrality measures calculated from the OECD Inter-Country Input-Output (ICIO) Tables to identify industries that are central hubs and those that are peripheral in the GVC network. The centrality of different country-industries reflects how directly and indirectly connected they are in the global production network, and is measured using the "*Bonacich-Katz eigenvector*" centrality (following Criscuolo and Timmis, 2018a, 2018b).

Japan is a case in point. Japan's falling centrality coincides with a period of low productivity growth and sluggish innovative activity of Japanese firms (see for example, Bergeaud et al., 2016). The number of patent applications by local firms at the Japan Patent Office (JPO) has been declining since the mid-2000s and many former superstar Japanese innovators have disappeared from the list of top assignees at the United States Patent and Trademark Office. These trends of slowing innovation intensity and declining centrality in production networks may not be independent. In addition, our empirical approach is motivated by our finding that the bulk of the decline of Japanese centrality is due to within-industry changes, rather than structural changes across industries. Accordingly, we go more granular and focus on changes to innovation *within-firms.*

We measure firm-level innovation using patent applications at the JPO, which we combine with industry-level measures of GVC centrality. Inspired by the literature on shock propagation (e.g., Acemoglu et al., 2012) and peer-effects (e.g., Calvó-Armengol et al., 2009), we expect that firms are likely to receive both direct and indirect technology spillovers. Therefore, our hypothesis is that firms in "central" industries are more productive in their innovation activities because they are more strongly connected to foreign sources of knowledge and more likely to subsume the network's peer influences.

Empirically, we consider the effects of two different sources of centrality. Firstly, we focus on the GVC centrality of the firm's headquarter industry (in Japan). Secondly, many patenting firms are multinational conglomerates spread over many different industries and countries and likely to benefit from additional knowledge spillovers from their affiliates abroad. Our second measure focuses on multinationals and reflects the average GVC centrality of a firm's foreign affiliates, using the centrality of their affiliates' countries and industries.

Our centrality metrics also distinguish between key suppliers and key customers, using forward and backward linkages respectively. That is, country-industries with higher forward centrality are key "hub" suppliers in the GVC network and country-industries with higher backward centrality are key "hub" customers.

Our findings show that centrality of a firm's headquarter industry, in particular forward centrality, is linked to more patent applications for firms in those industries over the period 1995–2011. According to our model, Japan's fall in forward centrality, i.e., becoming a less central supplier to GVCs, explains approximately 37 % of the decline in the number of (citation-weighted) patent applications by Japanese firms. For multinationals, the higher centrality of their affiliates' countries and industries is strongly associated with higher firm patenting, and this holds for both backward and forward centrality. Our results thus suggest that network effects are quantitatively substantial and that the position in the GVC network can play a significant role for an individual firm's performance, which is a novel finding to the literature on trade and innovation.

The paper proceeds as follows. The next section reviews the related literature and develops our main hypotheses. Section 3 describes the data and measures of relative position and degree of participation in a GVC network. Section 4 reports descriptives on GVC participation and centrality as well as on firm-level patent applications. Section 5 introduces our empirical framework and section 6 presents the results. The final section discusses our main conclusions.

2. Literature review and conceptual framework

In this section, we briefly summarize how our study contributes to the existing literature and outline the framework that shapes the empirical analysis. Our research question relates to four strands of the literature: (1) importance of external sources of knowledge, (2) the role of network effects on firm performance, (3) multinationals and global knowledge sourcing, and (4) technology spillovers through backward and forward linkages.

2.1. Importance of external (local and foreign) sources of knowledge

Many scholars have emphasized the importance of localized knowledge spillovers for innovation. New ideas easily circulate from one firm to another and knowledge, especially if tacit, is generated through interaction processes within local industrial communities (e.g., Saxenian, 1994; Audretsch and Feldman, 1996; Baptista, 2000). Studies such as Cantwell and Iammarino (2003) and Giuliani and Bell (2005) have highlighted the importance of external linkages for long-term growth. These linkages influence the ability of a cluster to acquire external knowledge and absorb it into its production activities. Thus, firms accumulate knowledge not only from their own activities, but also from those of their partners (Bathelt and Li, 2020). In contrast, clusters that rely solely on localized knowledge can lock firms into obsolete technologies.

Moreover, the literature on multinational enterprises (MNEs) suggests that, due to changes in the production systems accelerated by globalization, MNEs' knowledge advantage is driven by leveraging and integrating ideas and technologies not just across local industrial clusters but also across national borders (Cantwell and Mudambi, 2011; Awate et al., 2015). In turn, MNEs represent an important source of (foreign) knowledge for domestic suppliers, customers, and/or competitors (see also Section 2.3). One of the main external links derives from participation in international trade, which is the subject of this paper. Trade in intermediates underpins several models of international knowledge spillovers, through the diffusion of technology embedded within traded goods. Positive international research and development (R&D) spillovers via bilateral trade are also confirmed in studies such as Coe and Helpman (1995), Coe et al. (2009), Keller and Yeaple (2009). Intermediates embody, and thus provide access to the foreign skills, factors of production and technologies used to produce them (e.g., Keller, 2010; Keller and Yeaple, 2013; Buera and Oberfield, 2020). Therefore, wider access to imported intermediates likely translates into broader access to foreign technologies. This mechanism is not straightforward to test directly, but access to new and better-quality varieties of imported intermediates has been shown to positively impact firm productivity and lead to the creation of new products or upgrading of existing ones (Amiti and Konings, 2007; Goldberg et al., 2010; Bas and Strauss-Kahn, 2015; Halpern et al., 2015).

One key feature of GVC networks is that firms can *indirectly* benefit from (foreign) knowledge spillovers such as domestic suppliers of exporters or as users of intermediates imported by wholesalers or retailers.

Therefore, GVC networks capture the importance of indirect trade linkages. Exchanges between downstream users and their suppliers enhance (disembodied) knowledge flows (Alcácer and Oxley, 2014; Giuliani et al., 2005).[1]

Trade, increasingly organized around GVCs, can lead to improvements in firm innovation and productivity performance through several well-known channels. Access to foreign markets can increase innovation. Firms can learn from exporting to advanced foreign markets (Bustos, 2011; Lileeva and Trefler, 2010; Verhoogen, 2008; Crespi et al., 2008; De Loecker, 2013; Aghion et al., 2019). Increased import competition can not only increase learning from foreign competitors but also spur domestic firms to innovate to stay ahead of them (Amiti and Konings, 2007; Bloom et al., 2013, 2016). Participating in GVCs allows firms to offshore parts of their production activities to overseas suppliers and specialize in activities they are better at, including R&D and innovation (Fritsch and Görg, 2015; Grossman and Rossi-Hansberg, 2008).[2]

The evidence from this literature suggests that broader external linkages, through intermediate goods trade with more country-industries, tends to increase access to foreign technologies. Whilst the international trade literature has shown that connectedness matters, it has largely neglected how position in the GVC network might matter for knowledge diffusion and innovation.

2.2. Centrality and firm performance

Most studies that consider knowledge spillovers within industries focus only on direct bilateral business linkages. However, the emerging literature studying the role of network effects on firm performance suggests that knowledge, information, or shocks may diffuse not only through direct linkages but also through indirect linkages within networks.

To study this, economists rely on different network measures to capture the characteristics of each node and show that interconnections between firms and industries are important for the diffusion of shocks (e.g., Acemoglu et al., 2012; Magerman et al., 2016; Boehm et al., 2019; Di Giovanni et al., 2018). These micro-founded macro-models typically find that central firms, industries and countries, with a high number of direct and indirect connections, play a disproportionate role in determining aggregate performance.[3]

In our context of GVC networks, the use of “centrality” to measure the importance of a given node (firm, industry, or country, etc.) in a network has become more and more common. Among the different measures of centrality, eigenvector centrality has become more widely used. The eigenvector centrality we employ is a measure of the influence of a node in a network based on its connection to other influential nodes. Turkina and Van Assche (2018) for example measure the eigenvector centrality of buyer-supplier linkages between industrial clusters across borders and find that vertical connectedness to foreign clusters (i.e., higher centrality in the network) stimulates a cluster’s innovation performance. Although the effects of connectedness vary across cluster types, their study suggests that a cluster’s innovation performance disproportionately gains from strengthening centrality in both horizontal and vertical networks.

These studies suggest that the network structure and the relative position of each actor (firms, sectors or countries) crucially affect the performance of the whole network as well as the performance of each actor. These network effects have been confirmed in the literature on knowledge diffusion through social networks (e.g., Manski, 1993; Bramoullé et al., 2009; Alatas et al., 2016). The “peer effect” model built by Calvó-Armengol et al. (2009) explains that the actions of each agent are positively affected by directly linked peers and that more central actors are more likely to subsume the network peer influences.

These studies also suggest that knowledge is transmitted through production networks and that the resulting global effect is quantitatively substantial – exceeding the direct impacts alone, depending on the position of each node of the network. More specifically, building on this literature, one important question is whether “central” actors (according to the eigenvector centrality metrics) have better access to key knowledge through both their direct and indirect ties in the GVC network, culminating in increased innovation relative to less “central” (or more “peripheral”) actors that may only tap into limited knowledge from the network.

2.3. Multinationals and global knowledge sourcing

Most studies on trade and innovation focus on imports and/or exports of intermediate inputs. However, the participation of firms in GVCs also occurs through the shifting of some parts of their activities to their overseas subsidiaries. This mechanism suggests that MNEs are important players in the organization of GVCs: MNEs typically organize their portfolio of vertical linkages to combine their own knowledge and production capabilities with other tasks that are conducted by domestic or foreign GVC partners (Sturgeon et al., 2008).

Moreover, MNEs, by establishing foreign affiliates, may be able to tap into sources of new and diverse knowledge that are unavailable or more expensive at home (e.g., Almeida and Phene, 2004; Iwasa and Odagiri, 2004; Yamashita and Yamauchi, 2019). That is, MNEs can access foreign knowledge and information through not only their suppliers and customers but also their foreign subsidiaries, i.e., their intra-firm network. In that sense, when setting up subsidiaries it is important for multinationals to choose locations of competence and use them as a source of competitive advantage (e.g., Cantwell and Mudambi, 2005; Belderbos et al., 2016).

However, as emphasized in Bathelt and Li (2020), it is not easy to build cross-border knowledge pipelines that help firms integrate complementary knowledge elements from different locations and make them available to the MNEs’ corporate networks. The establishment of global knowledge pipelines requires a sequence of coordinated mechanisms to acquire knowledge from different sources. In the sequential process, MNEs need to develop contacts with local suppliers and clients to embed themselves in the local business community and obtain firm-specific and relational knowledge. However few studies have data on both firm headquarter and subsidiary locations across borders to measure how intra-MNE networks matter for innovation outcomes.

2.4. Backward and forward linkages

Vertical linkages like buyer-supplier relationships, can be an important channel of technology spillovers. As mentioned in Section 2.1, buyers (i.e., downstream firms) can benefit from the improved performance of their intermediate input suppliers (upstream firms), through provision of more technologically advanced or less expensive inputs. Accordingly, downstream firms can have an incentive to transfer

[1] Global buyers who rely on the competencies of their local suppliers are likely to assist their suppliers if the technology is tacit and requires intense interaction, and local suppliers are likely to upgrade their products by developing new products’ designs, interacting with global buyers, i.e., learning-by-supplying.

[2] However, offshoring may also cause R&D and production to occur in locations that are distant from each other. Increased distance between researchers or designers and factory floor workers risk to lower the efficiency of the innovation process and ultimately reduce innovation outputs (Pisano and Shih, 2012).

[3] Acemoglu et al. (2016) examine propagation of productivity, demand or supply shocks through the input-output linkages. Other studies, such as Barrot and Sauvagnat (2016), Boehm et al. (2019), and Carvalho et al. (2021), focus on the impact of natural disasters on downstream/upstream firms using firm-to-firm transaction information. Donaldson and Hornbeck (2016) and Heiland et al. (2019) show that a shock to one part of transport networks (respectively U.S. railways and world shipping) is amplified through the network affecting other nodes directly and indirectly.

knowledge to suppliers in upstream industries.

The direction of linkages can be important for the magnitude of technology spillovers. While spillovers are possible in both directions, empirical evidence is much stronger for positive spillovers to upstream (supplier) industries from their downstream (buyer) industries, i.e., through forward linkages to foreign knowledge. For example, Javorcik (2004) and her subsequent studies with co-authors, e.g., Javorcik and Spatareanu (2008), Arnold et al. (2011), and Javorcik et al. (2018), find positive productivity spillovers from downstream foreign-owned MNE firms to domestic firms in upstream industries. Alvarez and Lopez (2008) also find that the presence of both foreign-owned MNEs and domestic exporting firms in downstream industries improve productivity of local suppliers. Alcácer and Oxley (2014) and Turkina and Van Assche (2018) find similar results using firm-to-firm buyer-supplier relationships. Giuliani and Bell (2005) suggest that technological gatekeeper firms are key for diffusion of foreign knowledge in local clusters and these firms are characterized by high forward centrality.

2.5. The framework

Based on the results of the literature listed above, our research question can be broken down into two parts. First, we empirically test whether firms that operate in more central industries in a GVC network have a higher innovation performance than those that operate in less central industries. Second, we examine whether MNEs with affiliates in more "central" country-industries are likely to be more innovative.

As explained in Sections 2.1 and 2.2, although many previous studies confirmed the existence of inter-industry knowledge spillovers through direct trade linkages, empirical evidence on knowledge spillovers though GVC *networks* is still scarce. In this paper, we measure the extent of the role of intermediate trade connections between country-industries in the GVC network. To do so, we use the OECD Inter-Country Input-Output Tables and investigate whether knowledge transfers that spread through the GVC network affect the innovation performance of firms, and whether the magnitude of this effect depends on their position in the network. Although inter-country input-output tables have been increasingly used for GVC-related studies, this study is one of the first which focuses on international knowledge spillovers through both the direct and indirect connections to foreign country-industries captured by the network centrality measured using the international input-output tables.[4]

We also use GVC centrality measures to capture the characteristics of the location where MNEs have their affiliates. As suggested by the global knowledge sourcing literature and the cross-border knowledge pipeline literature discussed in Section 2.3, MNEs will receive technology spillovers from countries or industries where their affiliates are located. Therefore, our study considers how firm innovation is affected by changes in centrality not only of the MNE headquarters' country-industry, but also the foreign country-industries where MNEs have their affiliates. That is, we take into account multinationals' heterogeneity in their global networks.

In addition, motivated by the findings listed in Section 2.4, we explicitly consider the direction of centrality in our analysis, distinguishing between forward and backward centrality in the GVC network.

3. Data

3.1. Patents

We proxy innovation at the firm-level using patent data from the Institute of Intellectual Property (IIP) Patent Database. The IIP Patent Database is compiled based on Consolidated Standardized Data, which are made public twice a month by the JPO. As of December 2016, the IIP Patent Database includes public information from January 1964 until March 2014, which can be downloaded from the IIP website.[5] The database includes patent application data (application identification number, application date, main technological field, number of claims, etc.) as well as information on the applicant, the inventor and the list of forward and backward citations to other patents. Moreover, each patent can be linked to a firm using the company name and address as described below.

We use the number of patent applications for each firm in each year as our measure of firm innovation.[6] In order to take the heterogeneity of the quality of patents into account, we weight this count by the number of forward citations received. To consistently measure citations for different cohorts of patents, we follow the literature and standardize the number of citations by the maximum number of citations received in a given year within the same technological field. We consider this weighted measure as our preferred measure of firm innovation.[7]

3.2. 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) with the Basic Survey on Japanese Business Structure and Activities (BSJBSA).[8] The survey is compulsory and covers all firms with at least 50 employees and 30 million yen (that is about $300,000) of paid-in capital in the Japanese manufacturing, mining, wholesale and retail sectors as well as several other service sectors. Approximately 22,000 firms are surveyed every year, of which approximately 10,000 are in the manufacturing sector. Our baseline specification focuses on the manufacturing sector.

The survey contains detailed information on firms such as their 3-digit industry, the number of employees, sales, purchases, exports, and imports. It also contains the number of domestic and overseas affiliates or subsidiaries, and financial data such as costs, profits, investment, debt, and assets. The survey also contains information on R&D

[4] Although various network centrality measures such as betweenness centrality and closedness centrality as well as eigenvector centrality are employed in many previous studies on network effects on innovation, we focus on eigenvector centrality. As shown in Calvó-Armengol et al. (2009), the Bonacich-Katz eigenvector centrality measures the importance of a given node in a network as the importance of both its directly and indirectly connected nodes and captures exactly how each node (actor) subsumes strategic externalities. Itoh and Nakajima (2021), also using the Katz-Bonacich eigenvector centrality, show that more "central" firms in buyer-supplier networks are more likely to undertake foreign direct investment (FDI) in order to be located near their customers/suppliers.

[5] https://www.iip.or.jp/e/patentdb/index.html

[6] We use the number of patent applications, rather than the number of granted patents, because examination can take a long time and procedures are particularly long in the case of the JPO. According to Japan Patent Office (2010), for example, in 2009 it took 29.1 months on average for patent applicants to receive the first action from the patent office. The average duration has been becoming shorter in recent years but continues to remain significant.

[7] 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 is still likely to reflect knowledge flows to a reasonable extent.

[8] 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).

expenditures.

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. We follow the methodology developed in Ikeuchi et al. (2017) which we augment by adding more detailed geographical information (zip codes).

Our GVC centrality and participation measures are constructed from ICIO tables that capture cross-border trade in goods and services 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 of trade has been somewhat moderate, many foreign affiliates of Japanese firms have drastically increased their exports to and imports from the country where their affiliates are located. In order to take such global ownership networks into account, we use the affiliate-level data underlying the Basic Survey on Overseas Business Activities (BSOBA) collected annually by METI[9] which report the number of affiliates, employment and sales by industry and country for each parent firm.

3.3. Measures of GVC embeddedness

We construct industry-level measures of GVC embeddedness, using the OECD ICIO Tables 2015 edition that covers 62 countries and 34 industries for the years from 1995 to 2011. We link the firm-patent-matched dataset with the industry-level GVC measures, using the industry of the firm.[10]

3.3.1. GVC centrality

With these data, we can construct measures of network centrality to reflect the relative position of each country-industry within GVCs. We follow Criscuolo and Timmis (2018a, 2018b) and use the Bonacich-Katz eigenvector centrality metric, which has recently been implemented in several studies to identify key players in a network.[11] This measure takes both direct and indirect linkages into account. The definition and the calculation of network centrality are described below.

The linkages within the GVC network reflect ICIO flows of goods and services. Centrality is determined not only by direct trade linkages, but also those of trade partners – indirect trade linkages. Central sectors are defined as those that are connected to highly connected sectors. To make sure that indirect higher-order connections matter (but have lower weight than direct connections) we rely on recursive calculation. As shown below, centrality is calculated as a baseline level, plus a weighted sum of centralities of downstream or upstream sectors. For example, in the case of a backward network, centrality of a sector is determined based on its own linkages, its suppliers' linkages, and its suppliers' suppliers' linkages, etc.

Formally, the eigenvector-type centrality for each sector in a particular country is calculated using the formula given by eqs. (3.1) and (3.3). 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:

$$c^{back}{}_i = \lambda \sum_j w_{ji} c_j^{back} + \eta \tag{3.1}$$

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 centrality 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.

As noted above, centrality is a recursive calculation that hinges on indirect linkages, not just direct connections. To illustrate this, we can decompose our backward centrality measure given in eq. (3.1) using the recursive relationship below. Here centrality of country-industry i, depends not only on the extent of their direct connections to foreign suppliers (denoted j), but also indirect connections to suppliers of these suppliers' (denoted k):

$$\begin{aligned} c^{back}{}_i &= \lambda \sum_j w_{ji} \left(\lambda \sum_k w_{kj} c_k^{back} + \eta \right) + \eta \\ &= \lambda \eta \sum_j w_{ji} + \lambda^2 \sum_j w_{ji} \sum_k w_{kj} c_k^{back} + \eta \end{aligned} \tag{3.2}$$

where $\eta \sum_j w_{ji}$, reflects the centrality due to *direct* linkages to suppliers. $\lambda^2 \sum_j w_{ji} \sum_k w_{kj} c_k^{back}$ are the higher order sources of centrality components, reflecting *indirect* linkages, to suppliers of suppliers' and so on.

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:

$$c^{fwd}{}_i = \lambda \sum_j w_{ij} c_j^{fwd} + \eta \tag{3.3}$$

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.

Solving c_i^{back} and c_i^{fwd} in Eqs. (3.1) and (3.3), respectively, we obtain backward and forward Bonacich-Katz eigenvector centrality in the vector and matrix notation:

$$\boldsymbol{c}^{back} = \eta (\boldsymbol{I} - \lambda \boldsymbol{W}')^{-1} \mathbf{1} \tag{3.4}$$

$$\boldsymbol{c}^{fwd} = \eta (\boldsymbol{I} - \lambda \boldsymbol{W})^{-1} \mathbf{1} \tag{3.5}$$

where $\boldsymbol{c}^{back}$ *and* $\boldsymbol{c}^{fwd}$ are the backward and forward centrality vectors, respectively, $\mathbf{1}$ is a vector of ones, $\boldsymbol{I}$ is the identity matrix. $\boldsymbol{W}$ is the normalized global input-output coefficient matrix containing the elements w_{ij}.[12]

We decompose backward and forward centrality into their domestic and foreign parts, by partitioning the inverse matrices of eqs. (3.4) and (3.5) into the domestic and foreign components, to define the centrality of domestic backward (forward) linkages and the centrality of foreign backward (forward) linkages. Given our interest in GVCs, we focus on the foreign centrality components in the following analysis. See Criscuolo and Timmis (2018a) for more details on the calculations.

We also examine robustness to decomposing our centrality measure into the component due to direct linkages (equivalent to the so-called degree centrality) and the component due to indirect linkages. The two components are illustrated for backward centrality using eq. (3.2),

[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).

[10] Product information is not available in the BSJBSA.

[11] 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; Calvó-Armengol et al., 2009; Manski, 1993, 2000; Bramoullé et al., 2009, etc.).

[12] 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.

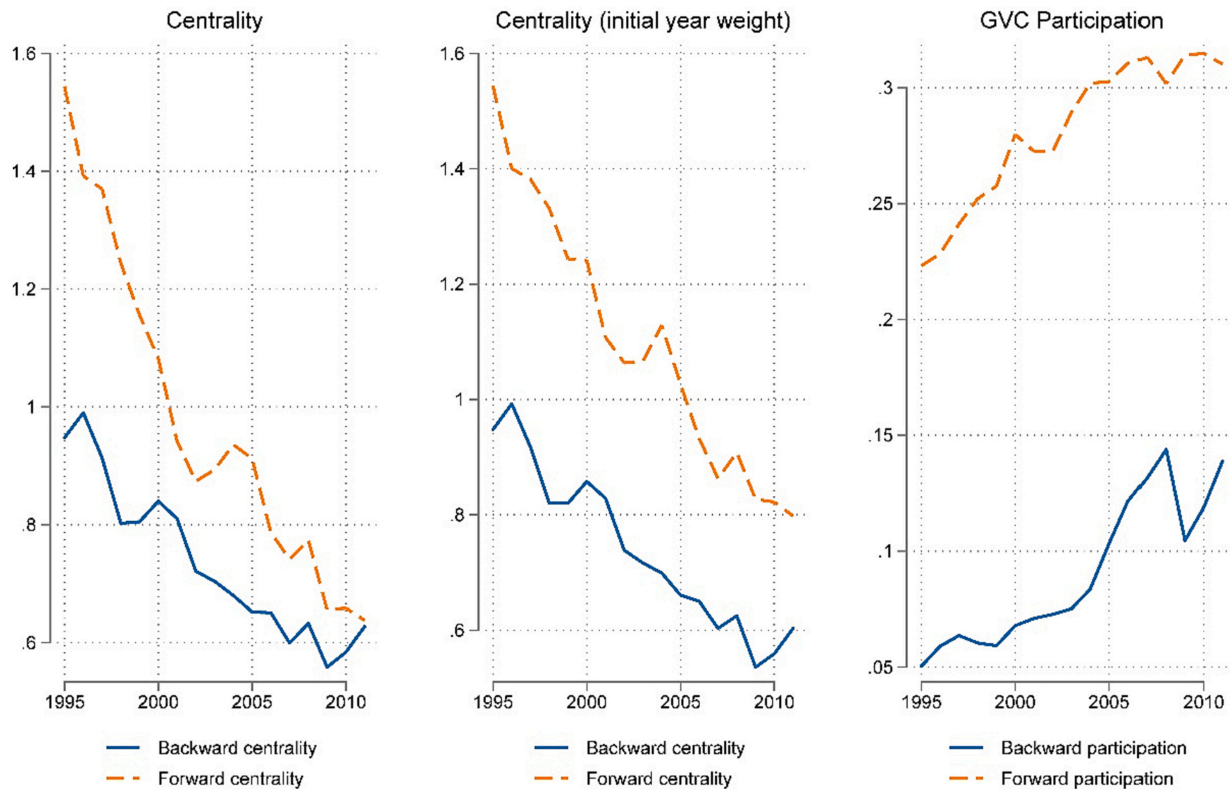

Fig. 1. Japan's GVC centrality and participation overtime: 1995 to 2011
Note: The centrality measures denote the weighted average of the industry-level centrality measures using the industry gross output as weights. The left panel shows the centrality measures using the annual industry gross output as weights, while the mid panel show the centrality measures using the initial year (1995) industry gross output as weights.

with forward centrality calculated similarly.[13]

3.3.2. GVC participation

As control variables we also construct measures of the degree of participation in GVCs using the OECD ICIO Tables. GVC participation reflects the extent to which countries or industries or firms are involved in a vertically fragmented production. One measure of this is the vertical specialization (VS) share, i.e., the value of imported inputs in the overall exports of a country, or in other words, the foreign content of exports.

However, a country also participates in GVCs by being a supplier of inputs used in third countries for their exports. Hummels et al. (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" and the latter "forward GVC participation" (De Backer and Miroudot, 2013). Following convention in the GVC literature, we construct both backward and forward GVC participation measures. More specifically, our industry-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.

4. GVC embeddedness and patenting by Japanese firms

With these measures at hand, we now present some descriptive evidence. Fig. 1 shows the trend of aggregate GVC centrality and GVC participation over time: while Japan has been increasingly participating in GVCs (right panel), its aggregate centrality has been declining (left panel). Importantly, we find that the bulk of the decline in Japan's average centrality is due to within-sector changes, rather than structural changes in activity across sectors. Whether holding industry (gross output) weights at their initial 1995 values or allowing them to vary, we find very similar trends in the weighted average centrality (left and middle panels).[14,15]

Figs. 2 and 3 show respectively the changes in backward and forward GVC centrality and participation across specific manufacturing industries, the focus of our subsequent empirical analysis. For reference we also show the average changes for the 25 OECD member countries as of 1995 (excluding Japan). Fig. 2 shows the changes in backward centrality and participation, and Fig. 3 shows the changes in forward centrality and participation.

Looking at Panel (1) of Figs. 2 and 3, we see that both backward and forward centrality declined in many Japanese industries. Particularly,

[13] Specifically, we can write Eq. (3.2) as a "degree centrality" and a higher-order centrality term: ${c^{back}}_i = \lambda \sum_j w_{ji} \left(\lambda \sum_k w_{kj} c_k^{back} + \eta \right) + \mu = \lambda\eta$ where ${degree^{back}}_i = \sum_j w_{ji}$, is the degree (or node strength) centrality, reflecting centrality due to direct linkages, weighted by the strength of the linkages. ${indirect^{back}}_i = \sum_j w_{ji} \sum_k w_{kj} c_k^{back}$ are the higher-order sources of centrality, reflecting indirect linkages from k to i (via j). We decompose Eq. (3.3) similarly.

[14] A regression decomposition of Japan's aggregate fall in backward or forward centrality over the period 1995–2011 finds that 70 % of the overall fall in backward centrality or 72 % of the overall fall in forward centrality is driven by within-sector changes, rather than between sectors. Results are available upon request.

[15] While Figure 1 shows all sectors, a similar figure for manufacturing only is available in the Appendix Figure A1.

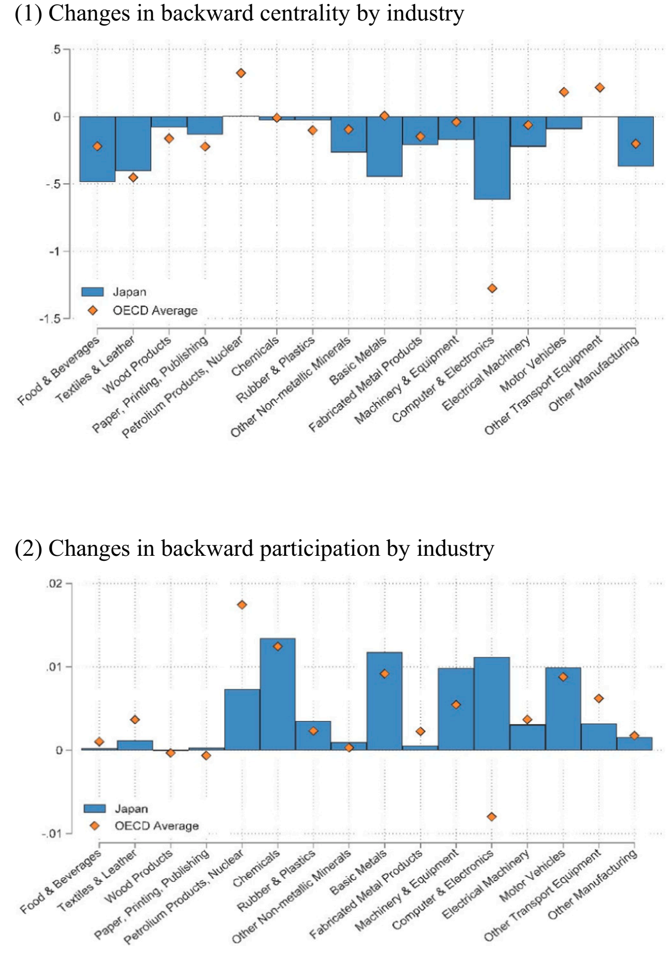

Fig. 2. Changes in backward GVC centrality and participation by industry from 1995 to 2011
(1) Changes in backward centrality by industry
(2) Changes in backward participation by industry
Note: The OECD average denotes the changes in backward centrality/participation for the weighted average of the 25 OECD member countries as of 1995 (excluding Japan) using the country-industry gross output as weights.

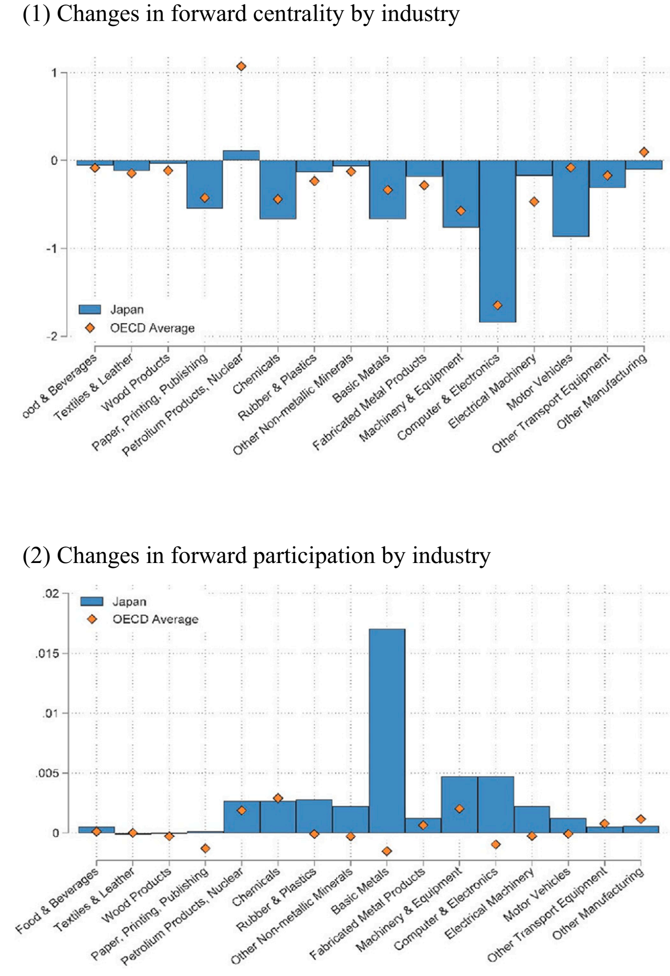

Fig. 3. Changes in Forward GVC Centrality and Participation by Industry from 1995 to 2011
(1) Changes in forward centrality by industry
(2) Changes in forward participation by industry
sNote: The OECD average denotes the changes in forward centrality/participation for the weighted average of the 25 OECD member countries as of 1995 (excluding Japan) using the country-industry gross output as weights.

industries such as computers and electronics, show a substantial decline both in terms of backward and forward centralities.[16] These industries have become much less central in GVCs by 2011, albeit from a high initial level of centrality in 1995. Other OECD countries also experienced falls in centrality in many manufacturing industries, with broadly similar changes as Japan. For instance, OECD countries also experienced falls in computer & electronics centrality at least as large as Japan.[17] Therefore, the decline in Japanese centrality is rather reflective of a broader shift of manufacturing hubs away from high-income economies.[18]

In contrast, as shown in Panel (2) of Figs. 2 and 3, both backward and forward GVC participation increased in almost all industries. A closer look at the data (not reported here) reveals that Japan's increased GVC participation was mainly driven by an increase in both imports and exports of intermediate goods and services with developing countries.[19] The increased trade with developing countries, that are themselves relatively peripheral in GVC networks, explains, at least partly, the fall in Japanese centrality noted above.

[16] The sectoral decline in centrality reflects both the fact that Japan's traditional export destinations such as the U.S. and developed European manufacturing industries have become more peripheral and the fact that Japan has increased transactions with Asian developing countries which were more peripheral in the network. Moreover, the fact that Japan's share of world trade has shrunk, i.e., that the links between Japan's industries and other country-industries have become thinner relative to those among other countries, also contributes to the observed decline in centrality.

[17] Some exceptions are that OECD countries experienced rising centrality in petroleum products, because of several large oil exporters such as the US or Canada, unlike Japan. The OECD also experienced increasing backward centrality in motor vehicle and transport equipment manufacturing, largely related to the development in Central European car manufacturing sectors.

[18] For more details on GVC centrality for other countries and industries, see Criscuolo and Timmis (2018a). Although developed countries tend to lower centrality in manufacturing sectors while developing countries tend to raise it, Germany and the United States remain 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.

[19] The additional information is available upon request.

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

Turning now to innovation measures, the number of JPO patent applications gradually increased in the late 1990s but has been declining since the mid-2000s (Appendix Fig. A3). Looking at patent applications by industry (Table 1), shows that patenting firms 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 for 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 reached its peak in the first half of the 2000s, but has been declining in many industries since.[20]

Moreover, the average citation-weighted number of patent applications per firm also shows a declining trend (Fig. 4). In particular, the computer & electronics industry shows a drastic decline in the average citation-weighted number of patent applications per firm. Since the number of citations is a common proxy for patent quality, Fig. 4 implies that the quality of patents applied for by Japanese firms has been declining over time.

In the following sections, we examine this relationship more rigorously by estimating the determinants of firm-level patent applications.

5. Empirical strategy

5.1. Model

To analyze the relationship between trends in GVC centrality and innovation, we estimate whether firms in industries that become more central within GVCs experience a significant increase in their patent applications. Based on the previous findings reviewed in Section 2, our conjecture is that firms in more central sectors may have access to a greater variety of foreign inputs embodied with skills and technologies, either as key customers or suppliers. At the same time, we want to control for the possible confounding role that the increase in backward and forward GVC participation may have on firms' innovation activities, for instance, through the growth of offshoring which may allow

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	1393	1419	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	1022	813	32.9	41.5	43.6	35.4
Computer, Electronic and optical equipment	1318	1201	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
Non-manufacturing	9452	11134	46.9	49.7	50.5	53.2
Total	20156	20913	15.8	21.8	22.2	17.2

domestic resources to be reallocated towards more innovative activities (e.g. Bloom et al., 2013).

We therefore estimate the following eq. (5.1) to examine the relationship between Japanese firm patent applications and our GVC centrality and participation measures.

$$Y_{fit} = \beta_1 C_{it-3} + \beta_2 VS_{it-3} + \beta_3 DAFF_{fit-3} + \beta_4 Firm\ Controls_{fit-3} + \delta_f + \tau_t + \varepsilon_{fit} \tag{5.1}$$

The dependent variable, Y_{fit}, represents the log number of patent applications for firm *f* in industry *i* in year *t*, which is a proxy for firms' innovation outcomes. In order to take patent quality into account, we use the citation-weighted number of patent applications as our preferred measure.[21] As a substantial number of firms do not apply for any patents every year, and therefore, a large number of observations with zero patent applications are included in our dataset, following existing literature we consider the logarithm of 1 + x as the functional form for the dependent variable x.[22] We also restrict our sample to innovating firms with at least one patent application between 1994 and 2011. In addition, we mainly focus on manufacturing firms and exclude firms that switch their industry classification at the two digit-level for the period from 1994 to 2011 (these are the same restrictions as in Aghion et al., 2018).

Our variable of interest, C_{it-3}, reflects the (foreign) GVC centrality of the firm's headquarter industry. The variable *C* denotes either the backward or forward (foreign) centrality measure, defined earlier. We expect a positive coefficient for the centrality variable, *C*, if firms in more central sectors in the GVC network benefit from knowledge spillovers and increase their patenting activity.

[20] 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. These observations may suggest that patent applications tend to be concentrated in a smaller number of firms that are getting more active in patenting.

[21] We also estimated the same model using the non-weighted number of patents as a dependent variable. The estimation results were more or less consistent but with lower levels of statistical significance.

[22] Broadly similar results are obtained using a Poisson Pseudo-Maximum Likelihood (PPML) count estimation model, available upon request.

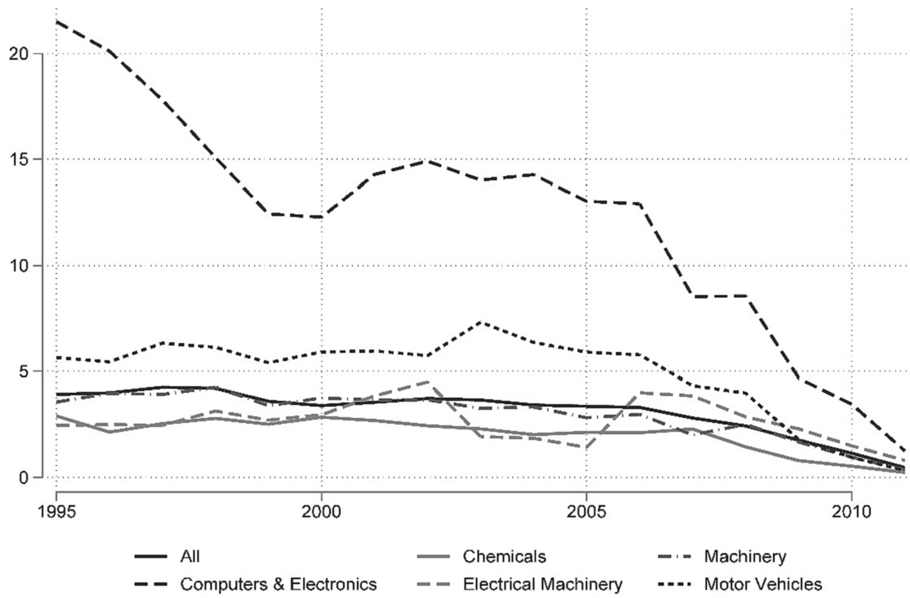

Fig. 4. Average citation-weighted number of patent applications per firm for major industries
Notes: Figures are calculated based on firms with at least one patent application per year. "All" means all sectors including non-manufacturing industries.

Table 3
Baseline estimation results: Manufacturing industries (3-year lagged).

	(1)	(2)	(3)	(4)
	Fixed-effect panel estimation		IV	
	Backward	Forward	Backward	Forward
3-year lagged	(Import)	(Export)	(Import)	(Export)
L3.Centrality (foreign)$_i$	0.0129	0.134***	−0.144	0.173***
	(0.087)	(0.036)	(0.129)	(0.059)
L3.GVC participation$_i$	−12.85***	5.290*	−9.089***	5.997***
	(3.381)	(2.675)	(2.577)	(2.241)
L3.TRADE$_f$	0.0158**	0.00403	0.0164***	0.00414
	(0.006)	(0.009)	(0.005)	(0.008)
L3.ln(Employment)$_f$	0.0704***	0.0666***	0.0733***	0.0674***
	(0.017)	(0.020)	(0.017)	(0.019)
L3.lnRDS$_f$	0.00348***	0.00354***	0.00344***	0.00352***
	(0.001)	(0.001)	(0.001)	(0.001)
L3.DAFF$_f$	−0.0203	−0.0203	−0.0190	−0.0202*
	(0.012)	(0.012)	(0.012)	(0.011)
Number of observations	63,357	63,357	63,008	63,008
Number of firms	6687	6687	6338	6338
R-squared	0.0865	0.0859	0.0851	0.0857
Kleibergen-Paap rk LM statistic			2.726*	5.444**
Kleibergen-Paap rk Wald F statistic			9.366	51.741

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eqs. (1) and (3) denotes the dummy variable for importers while TRADE in eqs. (2) and (4) denotes the dummy variable for exporters. The first-stage results for the IV fixed-effect panel estimations (3) and (4) are shown in Appendix Table A2.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To control for industry-level GVC participation, we include the variable VS_{it-3}, which denotes either the backward or forward participation. Backward GVC participation measures how much an industry uses imported intermediate inputs, and can reflect both the degree of import competition and offshoring. There are many previous empirical studies on the effects on firm productivity or innovation, but the results are mixed. Intensified import competition may either increase or reduce incentives to invest in innovative activity of domestic firms, depending on the degree of competition, with differing impacts of Chinese import competition found across European and U.S. firms (Bloom et al., 2016; Autor et al., 2020).[23] Offshoring may increase innovation by increasing availability of cheaper intermediate inputs, or by allowing firms to focus

[23] For example, Bloom et al. (2016) and Autor et al. (2020) examine the impact of import competition from China on innovation and productivity of domestic firms in the case of European firms and the U.S. firms, respectively. The former find a positive effect while the latter find a negative effect. In the case of Japan, Yamashita and Yamauchi (2020) find a result which is consistent to the findings in Bloom et al. (2016).

Table 4
Estimation results of the extended model: centrality of foreign affiliate country-industries, manufacturing industries (3-year lagged).

	(1)	(2)	(3)	(4)
	Fixed-effect panel estimation		IV	
	Backward	Forward	Backward	Forward
3-year lagged	(Import)	(Export)	(Import)	(Export)
L3.Affiliate-weighted centrality$_f$	0.0696***	0.0797***	0.0707***	0.0796***
	(0.019)	(0.017)	(0.019)	(0.016)
L3.Centrality (foreign)$_i$	0.00942	0.133***	−0.146	0.174***
	(0.087)	(0.037)	(0.128)	(0.061)
L3.GVC participation$_i$	−12.90***	5.412*	−9.182***	6.137***
	(3.349)	(2.673)	(2.610)	(2.247)
L3.TRADE$_f$	0.0155**	0.00383	0.0161***	0.00394
	(0.006)	(0.008)	(0.005)	(0.008)
L3.ln(Employment)$_f$	0.0693***	0.0660***	0.0721***	0.0668***
	(0.018)	(0.020)	(0.017)	(0.019)
L3.lnRDS$_f$	0.00347***	0.00348***	0.00344***	0.00345***
	(0.001)	(0.001)	(0.001)	(0.001)
L3.DAFF$_f$	−0.0758***	−0.0803***	−0.0753***	−0.0801***
	(0.017)	(0.016)	(0.017)	(0.016)
Number of observations	63,357	63,357	63,008	63,008
Number of firms	6687	6687	6338	6338
R-squared	0.0885	0.0887	0.0872	0.0885
Kleibergen-Paap rk LM statistic			2.727*	5.445**
Kleibergen-Paap rk Wald F statistic			9.378	51.769

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eqs. (1) and (3) denotes the dummy variable for importers while TRADE in eqs. (2) and (4) denotes the dummy variable for exporters. The first-stage results for the IV fixed-effect panel estimations (3) and (4) are shown in Appendix Table A3.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

on their core activities, but may reduce innovation if geographical proximity of assemblers and parts suppliers is important for product innovation (Delgado et al., 2014, etc.). Turning to the forward linkages, as reviewed in Section 2, several papers have found a positive link between exporting and innovation (Bustos, 2011; Lileeva and Trefler, 2010; Aghion et al., 2018).

Thus, while the industry-level forward GVC participation is expected to increase domestic firms' innovation incentives, the relationship between industry-level backward GVC participation and firm innovation is ex-ante ambiguous. Therefore, we include these GVC participation variables in the estimation equation to control for the degree of vertical specialization.

As for firm-level control variables, we include firm size, measured as log number of employees, a firm's knowledge stock, measured as log of R&D stock.[24] We include a firm-level trade dummy, which for regressions using backward GVC measures reflects an importer dummy which takes the value one for importing firms, for regressions using forward GVC measures reflects an exporting firm dummy. We also include a dummy variable, $DAFF_{fit-3}$, which switches on for firms with at least one affiliate abroad. δ_f and τ_t denote firm-specific fixed effects and year-specific fixed effects, respectively.

We supplement our first centrality measure above (GVC centrality of the firm's headquarter industry) with a second centrality measure reflecting the average centrality of a firm's foreign affiliates. Many patenting firms are multinational conglomerates spread over many different industries and countries and are likely to benefit from additional knowledge spillovers from their affiliates abroad. We construct an 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 in foreign countries will receive more technology spillovers from countries or industries where their affiliates are located, especially if these countries or industries have higher GVC network centrality. Therefore, we construct an affiliate-size weighted host country-industry centrality measure to capture knowledge spillovers through foreign affiliates of multinational firms. The affiliate-size weighted host country-industry centrality measures are defined in the following way:

$$FC_{ft}^{BACK} = \sum_k \sum_j \left(AF_{fkjt} / AF_{ft} \right) C_{kjt}^{BACK} \tag{5.2}$$

$$FC_{ft}^{FOR} = \sum_k \sum_j \left(AF_{fkjt} / AF_{ft} \right) C_{kjt}^{FOR} \tag{5.3}$$

where AF_{fkjt} denotes number of workers employed in the multinational firm f's affiliate in country k in industry j in year t. AF_{ft} denotes number of workers employed in all foreign affiliates of multinational firm f in year t. For firms without affiliates abroad, we define *FC* as zero.

We extend the model of (5.1) to include the second centrality measure, *FC*, reflecting the average centrality of a firm's foreign affiliates, as noted below:

$$Y_{fit} = \beta_1 C_{it-3} + \beta_2 FC_{fit-3} + \beta_3 VS_{it-3} + \beta_4 DAFF_{fit-3} + \beta_5 Firm\ Controls_{fit-3} + \delta_f + \tau_t + \varepsilon_{fit} \tag{5.4}$$

Beyond the overall potential effects of centrality of the headquarter industry, β_1, if multinationals benefit from additional knowledge spillovers from their affiliates abroad then β_2 in eq. (5.4) is expected to be positive.

As a robustness analysis, we examine whether firms that are directly embedded in GVCs via exporting or importing benefit more from knowledge spillovers through the network.[25]

We estimate eqs. (5.1) and (5.4) using fixed-effects panel estimation.

[24] R&D stock for each firm is calculated using the firm-level R&D expenditure data by the perpetual inventory method. We take R&D deflators and R&D depreciation ratio from the RDIP Database which is available at the NISTEP (National Institute of Science and Technology Policy) website: https://www.nistep.go.jp/research/scisip/data-and-information-infrastructure/rdip-database.

[25] To estimate heterogeneous impacts of the GVC measures for trading and non-trading firms, we supplement equation (5.4) by including the interaction terms of the industry-level GVC variables and a firm's export/import status (*TRADE*): $Y_{fit} = \beta_1 C_{it-3} + \beta_2 FC_{fit-3} + \beta_3 DAFF_{fit-3} + \beta_4 TRADE_{fit-3} \times C_{it-3} + \beta_5 VS_{it-3} + \beta_6 TRADE_{fit-3} \times VS_{it-3} + \beta_7 Firm\ Controls_{fit-3} + \delta_f + \tau_t + \varepsilon_{fit}$

Table 5
Heterogeneity by firms' trade orientation: Manufacturing industries (3-year lagged).

Panel (1) Fixed-effect panel estimation

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

	(1)	(2)	(3)	(4)
	Backward	Backward	Forward	Forward
3-year lagged	(Import)	(Import)	(Export)	(Export)
L3.Affiliate-weighted Centrality$_f$	0.0693***	0.0698***	0.0782***	0.0796***
	(0.018)	(0.020)	(0.016)	(0.017)
L3.Centrality (foreign)$_i$	−0.0256	−0.0268	0.0728*	0.131***
	(0.065)	(0.095)	(0.040)	(0.037)
L3.GVC participation$_i$	−13.10***	−6.210	4.990*	6.307*
	(3.164)	(4.574)	(2.537)	(3.130)
L3.TRADE$_f$*L3.Centrality (foreign)$_i$	0.105		0.117***	
	(0.084)		(0.026)	
L3.TRADE$_f$*L3.GVC participation$_i$		−11.18		−1.535
		(7.006)		(1.257)
L3.TRADE$_f$	−0.0543	0.0863*	−0.111***	0.0202
	(0.057)	(0.041)	(0.033)	(0.019)
L3.ln(Employment)$_f$	0.0688***	0.0667***	0.0651***	0.0658***
	(0.018)	(0.017)	(0.020)	(0.020)
L3.lnRDS$_f$	0.00338***	0.00331***	0.00323***	0.00347***
	(0.001)	(0.001)	(0.001)	(0.001)
L3.DAFF$_f$	−0.0745***	−0.0700***	−0.0755***	−0.0800***
	(0.017)	(0.019)	(0.016)	(0.016)
Number of observations	63,357	63,357	63,357	63,357
R-squared	0.0893	0.0928	0.0923	0.0888

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eqs. (1) and (2) denotes the importer dummy variable, while TRADE in eqs. (3) and (3) denotes the exporter dummy variable.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Panel (2) IV fixed-effect panel estimation

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

	(1)	(2)	(3)	(4)
	Backward	Backward	Forward	Forward
3-year lagged	(Import)	(Import)	(Export)	(Export)
L3.Affiliate-weighted centrality$_f$	0.0653***	0.0709***	0.0725***	0.0795***
	(0.017)	(0.019)	(0.015)	(0.016)
L3.Centrality (foreign)$_i$	−0.427***	−0.202	−0.0817	0.173***
	(0.138)	(0.141)	(0.072)	(0.062)
L3.GVC participation$_i$	−16.30***	−1.533	4.645**	6.959***
	(5.918)	(5.673)	(2.274)	(2.548)
L3.TRADE$_f$*L3.Centrality (foreign)$_i$	1.392**		0.550***	
	(0.596)		(0.123)	
L3.TRADE$_f$*L3.GVC participation$_i$		−12.11*		−1.415
		(6.646)		(1.214)
L3.TRADE$_f$	−0.908**	0.0928**	−0.533***	0.0190
	(0.394)	(0.038)	(0.133)	(0.019)
L3.ln(Employment)$_f$	0.0630***	0.0697***	0.0632***	0.0666***
	(0.018)	(0.016)	(0.020)	(0.018)
L3.lnRDS$_f$	0.00222**	0.00326***	0.00227***	0.00345***
	(0.001)	(0.001)	(0.001)	(0.001)
L3.DAFF$_f$	−0.0580***	−0.0690***	−0.0575***	−0.0798***
	(0.015)	(0.019)	(0.016)	(0.016)
Number of observations	63,008	63,008	63,008	63,008
R-squared	−0.0295	0.0911	0.0434	0.0886
Kleibergen-Paap rk LM statistic	4.606**	2.768*	5.312**	5.439**
Kleibergen-Paap rk Wald F statistic	7.553	9.458	16.951	51.555

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eqs. (1) and (2) denotes the importer dummy variable, while TRADE in eqs. (3) and (4) denotes the exporter dummy variable. The first-stage results for the IV fixed-effect panel estimations are shown in Appendix Table A4.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

For our baseline estimation, we use the three-year lagged value of each explanatory variable and include firm and year fixed effects. We choose to (three-year) lag the explanatory variables, to capture the time lags involved in the innovation process, such as the patenting decision and application process, which are likely to be slow-moving and imply delays before any effects of GVC centrality are realized in innovation outcomes. This also reduces the scope for endogeneity issues. Including firm fixed effects also removes any time invariant unobserved firm-specific confounding factors, which may include management capital, and means the analysis captures *within-firm* changes. Year dummies also control for the role of macro-shocks.

We also consider an instrumental variable specification to further mitigate endogeneity concerns. We instrument our first centrality measure, centrality of the firm's headquarter industry, using the timing of China's WTO accession. China's accession to the WTO appears to correspond with the central hub of "Factory Asia" increasingly shifting from Japan towards China (Criscuolo and Timmis, 2018a). Japanese industries that initially had high centrality experienced a particularly large decline in centrality, coinciding with a conspicuous increase in centrality of Chinese industries.[26] 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 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. We assume that China's WTO accession is highly correlated with the decline in centrality of Japanese industries, particularly in industries where Japan was initially more central in the GVC network.

Our instrument is therefore similar to *Bartik* or shift-share instruments that have been used for the impact of import competition. The China shock has been used as an instrumental variable for the impact of China's WTO accession on US labor markets (Autor et al., 2013, 2020) and import competition in European countries (Bloom et al., 2016). We include time and firm dummies, which pick up any aggregate timing effects of the China shock or initial differences across industries or firms. Our exclusion restriction therefore relies on future changes in patenting at the firm-level being unrelated with initial industry differences in Japanese exposure to China's accession.

To address endogeneity of the location of foreign affiliates, such as potential knowledge-seeking FDI, we construct an instrument for our second centrality measure by holding the MNE's affiliate network fixed as of 1995 (the first year of our data). Specifically, our instrument reflects each firm's average foreign affiliate centrality but holds the affiliate structure and location fixed at 1995. We construct this 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 1995 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 for the first year when the firm established at least one affiliate abroad.[27] Again, similar to shift-share instruments, the exclusion restriction for the second instrument assumes that future changes in firm innovation are unrelated to their initial foreign affiliate networks. The basic statistics of these variables are summarized in Appendix Table A1.

6. Results

In this section, we first present results for how firm innovation relates to the centrality of the headquarter industry (eq. 5.1). Next, we examine how centrality differs across firms. For multinationals we examine how innovation relates to the centrality of a firm's foreign affiliates (eq. 5.4). We then examine the heterogeneous impact of GVC centrality/participation across trading and non-trading firms. Finally, we examine the robustness of our results.

Table 3 shows the estimation results of the baseline eq. (5.1). In Table 3, columns (1) and (2) show the fixed-effect panel estimation results while columns (3) and (4) show the results of the IV fixed-effect panel estimation. Columns (1) and (3) show the results when we employ backward centrality and participation measures. Similarly, forward centrality and participation measures are used for estimates reported in columns (2) and (4). 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 forward centrality of Japanese industries with values of first-stage F-statistics of 52.[28] For backward (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. The instrument has a reasonably large coefficient – Japanese industries with 1 unit higher initial centrality, experienced a 0.36 unit (backward) and 0.25 unit (forward) larger fall due to Chinese WTO accession (see Appendix Table A2). Recall that over this period, Japanese industries on average experienced around 40 % fall in backward centrality and a 60 % fall in forward centrality (see Fig. 1). The fact that our results are robust to using this IV strategy suggests that the positive link between GVC centrality and innovation is not driven by potentially confounding omitted factors, such as a market size, whereby greater access to foreign markets through international trade would lead to more innovation (Aghion et al., 2018).

Turning to our key variable of interest, (headquarter) centrality, we find that increases in centrality are linked to increases in firm innovation as we expected.[29] However, the direction of centrality matters, i.e., it is important to distinguish a central supplier versus a central buyer in GVCs. The positive and significant coefficient of forward centrality reported in columns (2) and (4) suggests that firms within industries that become more central in the network via their forward linkages show a higher propensity to innovate. That is to say, being a central supplier, with greater connectivity with foreign customers matters for domestic innovation. For backward centrality we find no evidence of such a link (see columns 1 and 3).[30] This is consistent with the literature on FDI spillovers, that finds that suppliers of multinationals tend to benefit from knowledge spillovers, but there is far less evidence of FDI spillovers in the opposite direction (Javorcik, 2004; Havranek and Irsova, 2011).

Focusing on the GVC participation control variables, we find a more nuanced picture. The positive and significant coefficient of forward GVC participation (columns 2 and 4) also suggests that forward linkages are positively associated with patent applications, i.e., innovation. However, backward GVC participation is negatively associated with patent applications (columns 1 and 3), suggesting that vertical specialization in the backward linkages does not promote innovation, but may rather have a detrimental effect.[31]

As for other explanatory variables, larger firms in terms of the employment size tend to show a higher propensity to innovate and firms

[26] Appendix Figure A2 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.

[27] For non-multinational firms this second centrality term is zero. Note we also include a multinational dummy as a control in the regressions to capture changes in multinational status.

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

[29] Although we employ linear regressions of a log-transformed dependent variable as explained above, we also tried PPML estimation, taking the existence of zero-patent or zero-citation observations into account. The centrality variables tend to have a positive coefficient also in the PPML results, though the point estimates are less precisely estimated. They are not statistically significant.

[30] Backward centrality reflects being a central customer, through connections with suppliers.

[31] 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 3.3.2, 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.

with a larger R&D stock tend to be more innovative, as one would expect. Although status change from non-importer to importer is positively associated with more patent applications, the coefficient of exporter dummy variable is not statistically significant. 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 status – conditional on the other variables – is not positively associated with patenting. In order to explore this issue in more detail, later in this section we examine the interaction effect of industry-level GVC embeddedness and firm-level trade.

Table 4 shows the estimation results of the extended model that includes the average centrality of foreign affiliate country-industries (eq. 5.4). Columns (1) and (2) of Table 4 show the fixed-effect panel estimation results while columns (3) and (4) of the table show the results of the IV fixed-effect panel estimation.[32] Again, the results in both panels are very similar.

We find strong evidence that both backward and forward affiliate-weighted centrality are linked to domestic innovation. The estimated coefficients across all specifications reported in columns (1) to (4) are significantly positive. This suggests that MNEs with foreign affiliates in countries or industries with higher network centrality are more likely to apply for higher quality patents. In terms of (headquarter) centrality, we find similar results to Table 3, namely forward (headquarter) centrality matters for firm innovation (columns 2 and 4). Affiliate centrality is significant, conditional on headquarter centrality, suggesting that multinationals have an additional channel to leverage knowledge spillovers due to GVC centrality – via their foreign affiliates.

Estimates of other control variables are similar to those presented in Table 3.

In Table 5 we add the interaction terms of GVC centrality and participation and the firm's export/import status to examine the heterogeneous role of GVC centrality/participation across firm types. Panel (1) of Table 5 shows the fixed-effect panel estimation results while Panel (2) shows the results of the IV fixed-effect panel estimation. We find that the role of centrality is stronger for firms that export or import directly. Consistent with the results in Table 3, forward centrality tends to be positively associated with the number of patent applications (column (3) in Panel (1) and column (4) in both panels). Moreover, the positive and significant coefficient of the interaction term of centrality and export dummy suggests that exporters in industries that become more central through forward linkages tend to apply for more patents (column (3) in both panels). The results in both panels of Table 5 suggest that trading firms in more central industries are significantly more likely to innovate. In contrast to centrality, however, we do not find any significant firm heterogeneity relating to GVC participation. The coefficients on affiliate-weighted centrality and other control variables are similar to Table 4.

The results in Tables 3 to 5 suggest that being central in GVC networks through forward linkages is more important for innovation than backward linkages, and this is magnified for exporting firms. In other words, having access to a greater breadth of customers may promote innovation activities and lead to better innovation outcomes. While this appears to be true for all firms in these industries, e.g., via indirect export linkages (i.e., domestic sales to exporters), this is particularly true for exporters. Exporters located in key GVC hubs appear to benefit relatively more from knowledge spillovers from various customers in downstream markets. In fact, a back-of-the-envelope calculation suggests that the fall in GVC centrality for Japan explains a significant part of the patent slowdown of Japan. Between 1995 and 2011, the citation-weighted number of patent applications (our dependent variable) declined on average by 22.5 %.[33] On the other hand, the average forward GVC centrality declined by 48.0 % during the same period.[34] Based on the estimated coefficient of the forward GVC centrality in column (4) in Table 3, the fall in the forward centrality explains approximately 37 % ($=0.173 \times 0.480/0.225$) of the decline in citation weighted patent applications between 1995 and 2011.

On the other hand, backward GVC participation is negatively related to patent applications (columns (1) and (3) in Tables 3 and 4 and columns (1) and (2) in both panels of Table 5). There is a growing literature on the relationship between offshoring and innovation at home and there is no consensus on the sign of any link between them. As shown in Branstetter et al. (2021) and Fort et al. (2020), spatial proximity of production and innovation within a firm is likely to increase patenting. On the other hand, studies such as Delgado et al. (2014) and Delgado (2020) suggest that innovation and production co-location in regional clusters matters for subsequent innovation.[35]

Although our current paper does not focus on the relationship between vertical specialization in production and R&D activities at home, co-location of innovation and production within a firm/industry/region would be another important issue to further scrutiny in future studies. In fact, according to Ito et al. (2021), the total R&D expenditure of Japanese manufacturing multinational firms' overseas affiliates increased 3.3 times from 1995 to 2011 while MNEs' R&D expenditure at home increased only 1.5 times for the same period. Although the offshore R&D share was still very low and Japanese manufacturing multinationals' R&D activities are highly concentrated in parent firms, increasing GVC participation may be associated with relative reduction of R&D activities close to production bases at home. Moreover, increases in offshore R&D and offshore production by Japanese multinationals may have been reducing spatial proximity of innovation and production within industrial clusters at home. Although investigating the co-location of innovation and production in the context of GVCs is beyond the scope of this paper, it would be a promising avenue for future research.

Finally, we examine robustness of our main results. Firstly, our (headquarter) centrality measure reflects both direct and indirect linkages. We decompose centrality into a direct linkage component (degree centrality) and the indirect higher order linkages (see, eq. (3.2)), and re-estimate eq. (5.1) using these two components. Clearly these are often highly correlated, with country-industries with greater direct trade connections also having greater indirect connectivity. Unfortunately, because of this collinearity we are not able to jointly include both the direct and higher-order terms in the same regression, for instance, as a horse-race between these two components. However, Appendix Table A5 shows broadly similar results when using only the direct or indirect components, suggesting that indirect connections also matter for innovation.

In addition, we include alternative measures of GVC networks, to compare the role of centrality to alternative metrics of network position. In particular, we repeat the baseline estimation of eq. (5.1), but include measures of GVC upstreamness following Fally (2012). We showed above that for Japan most of the changes in centrality are due to within-industry changes, rather than across-sector changes in comparative advantage or specialization. However, to control for the role of comparative advantage we include a measure of each sector's (value-added) revealed comparative advantage following Koopman et al. (2014). Finally, we also include sector output as a measure of size, which is often highly correlated with centrality measures. In Appendix Table A6 we find broadly similar results, of a strong relationship between forward GVC centrality and firm innovation, even conditional on these

[32] The first-stage results of the IV estimation are shown in Appendix Table A3.

[33] The mean log value for 2011 was 0.0444 while that for 1995 was 0.2696

[34] The mean value for 2011 was 0.7050 while that for 1995 was 1.1845

[35] Although one may expect that firms using imported inputs would shift their resources from production to innovation activities and so GVC participation would promote innovation (e.g., Arkolakis et al., 2018), 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.

alternative measures of network position.[36]

Nevertheless, we should note that due to data constraints, firm-level functional specialization is not fully controlled for, though we do include a measure of firm-level R&D stock. In Appendix Table A6, only industry-level upstreamness and RCA controls are included. Although in this paper we assume that firms in more central industries receive more technology spillovers, changes in centrality due to adding/dropping/switching customers and suppliers may induce or be induced by changes in firms' functional specialization (e.g., firms specialize in knowledge-intensive activities).[37] We have not explored such an alternative mechanism through which network centrality affects innovation performance in this paper, but we would leave it as a direction for future research.

Finally, we repeat our baseline estimation (eq. 5.1) but examine robustness to dropping the computer & electronics industry (the sector with the largest changes in centrality) or using one-year lagged variables instead of three-year lagged variables. The results mirror the baseline and are presented in Appendix Tables A7 and A8, respectively.

7. Conclusions

This paper explores how changes in the relative position and degree of participation in GVCs affect 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. In our analysis, we use novel measures of network centrality to measure key hubs and distinguish between position and participation within GVCs.

Based on these measures, we find that for many industries Japan's position in GVCs has shifted from being at the central core of Factory Asia towards the periphery relative to other countries in the network – and a substantial part of this is due to China's WTO accession. This loss in centrality is evident in spite of Japan's increasing participation in GVCs in terms of domestic value added embodied in foreign exports (forward GVC participation) and/or foreign value added embodied in exports (backward GVC participation). At the same time, the number of patent applications by Japanese firms has been declining steadily since the mid-2000s. In light of the extensive literature showing that international trade is an important means for knowledge diffusion, we investigate whether these trends in innovation outcome, GVC centrality and participation are related.

Our analysis shows that forward centrality (i.e., having access to a greater breadth of customers directly and indirectly) tends to be positively associated with firm innovation activities (measured as the number of patent applications) and is particularly strong for exporting firms. This suggests that firms located in key GVC hubs appear to benefit significantly more from knowledge spillovers from customers in downstream markets. This result closely complements the literature on FDI spillovers (e.g., Javorcik, 2004). The analysis based on more traditional measures of GVC participation, might not capture the importance of the full network but it nevertheless provides a complementary picture. While backward GVC participation, i.e., being more vertically specialized in downstream production, tends to have a negative link with innovation, forward GVC participation, i.e., being more vertically specialized in upstream production tends to be positively linked with innovation.

Some anecdotal evidence also supports our empirical findings. For example, while both suppliers and customers are important sources of technological information and knowledge for innovating firms (e.g., NISTEP, 2009), the RIETI Inventor Survey reports that clients/users tend to be much more important sources of knowledge than suppliers for patent inventors to get inspired for research and conduct research (Nagaoka and Tsukada, 2007). There are also cases where information from downstream customers played a crucial role in new technology development in upstream firms. For example, in the 1980s, Japanese chemical firms started developing electronic materials (materials for semiconductor and liquid crystal display) such as silicon wafer, photoresist, and polarizer protective film, in response to requests from Japanese electric machinery and electronics manufacturers, i.e., their downstream customers (Hirano, 2016). These examples suggest that information spillovers from downstream customers may be more relevant for invention of new knowledge and technologies than spillovers from upstream suppliers.

Taken together, these results seem to suggest that knowledge spillovers from the network via forward linkages 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, our study confirms the importance of being a central 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 more innovation. Rather, being more "central" in the GVC network and having access to a greater breadth of customers appears to be particularly beneficial to developing new technologies.

Although we focus on the case of Japan in this paper, our findings can speak to other developed economies. For example, trends in patenting activity of German and US firms are not dissimilar to those of Japan (see OECD STI Scoreboard). We show that the falls in manufacturing centrality that Japanese industries experienced is also broadly mirrored by the rest of the OECD, as manufacturing hubs pivoted away from developed countries and increasingly towards emerging markets.

Our results have several important policy implications.

First, the decline in the manufacturing sector's centrality is a somewhat natural phenomenon in developed countries reflecting deindustrialization and a shift to services. However, our findings suggest that continued efforts to expand the breadth of foreign customers and strengthen connections with them are required, if countries do not want to experience a deterioration of innovation capabilities particularly where manufacturing innovation is highly complementary to service innovation.

Second, our results suggest that, increasing trade openness or expanding free trade agreement networks, particularly incorporating central countries, would be an effective policy to support firms to connect with a larger number of foreign customers, and thus result in a higher country-industry centrality of the GVC network. For example, European countries have not lowered their country-level centrality, as shown in Criscuolo and Timmis (2018a), likely as a result of the fact that they have strengthened intra-regional linkages within the European Union. The European experience may indicate the importance of trade openness to maintain centrality in GVC networks. Policy changes in this direction might be particularly important for the Latin American region where efforts to build a "single" market have not yet been successful.

Third, export supporting services such as providing information on foreign markets, legal rules, and potential transaction partners, etc., may be an effective policy support for firms and may ultimately increase cross-border knowledge sharing. Although export subsidies may not be always effective, recent studies such as Munch and Schaur (2018), Broocks and Van Biesebroeck (2017), and Van Biesebroeck et al. (2015) find a positive effect of export promotion policies, at least for some type of firms.

The analysis in this paper can, indeed, be furthered in several

[36] We also estimated the equation excluding the GVC participation variables, but it did not change the results for other variables. Moreover, whether including the industry size variable (log gross output) or not did not change the results.

[37] We are grateful to an anonymous referee for pointing out this issue.

directions. Firstly, while we focus on China's WTO accession, future research could investigate other determinants of centrality. Secondly, future research could look beyond Japan to the case of other countries and regional GVCs beyond "Factory Asia". Thirdly, while we focus on patents, future research, conditional on data availability, could look at other proxies of innovation outcomes by firms, such as trademarks, or measures of innovation in services. Fourthly, although data are scant, data on domestic firm-to-firm linkages would allow measuring the impacts of relative position and centrality of firms within domestic supply chain networks and also capture how domestic suppliers of exporters may benefit from knowledge spillovers through GVCs. Finally, novel data on firm-level importer-exporter trade linkages could allow measuring GVC participation and centrality at the firm-level and examining impacts on firm innovation, productivity and wages – which could be the ultimate frontier in this field.

CRediT authorship contribution statement

Keiko Ito: Supervision, Conceptualization, Methodology, Data curation, Software, Formal analysis, Visualization, Writing- Original draft preparation, Funding Acquisition.

Kenta Ikeuchi: Data curation, Software, Validation.

Chiara Criscuolo: Supervision, Conceptualization, Methodology, Writing- Reviewing and Editing.

Jonathan Timmis: Conceptualization, Methodology, Data curation, Software, Writing- Reviewing and Editing.

Antonin Bergeaud: Data curation, Writing- Reviewing and Editing.

Declaration

The opinions expressed and arguments employed herein are solely those of the authors and do not necessarily reflect the official views of the OECD and its member countries, the World Bank Group and its member countries, RIETI, Banque de France, or Chiba University.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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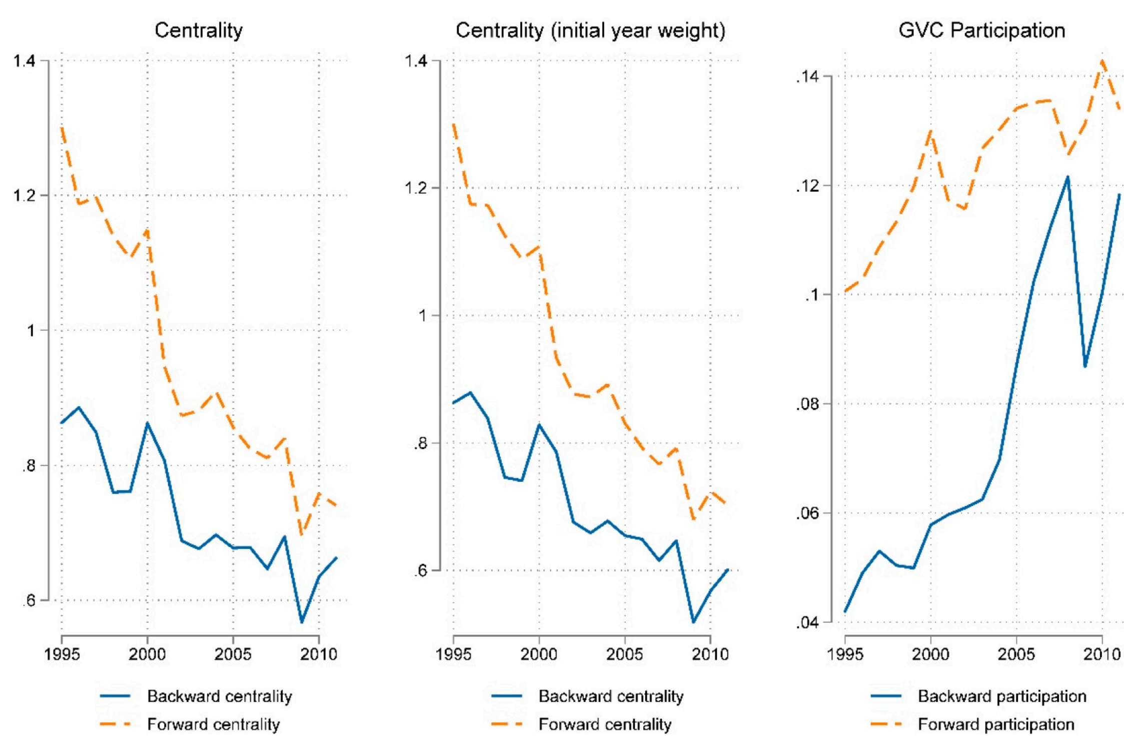
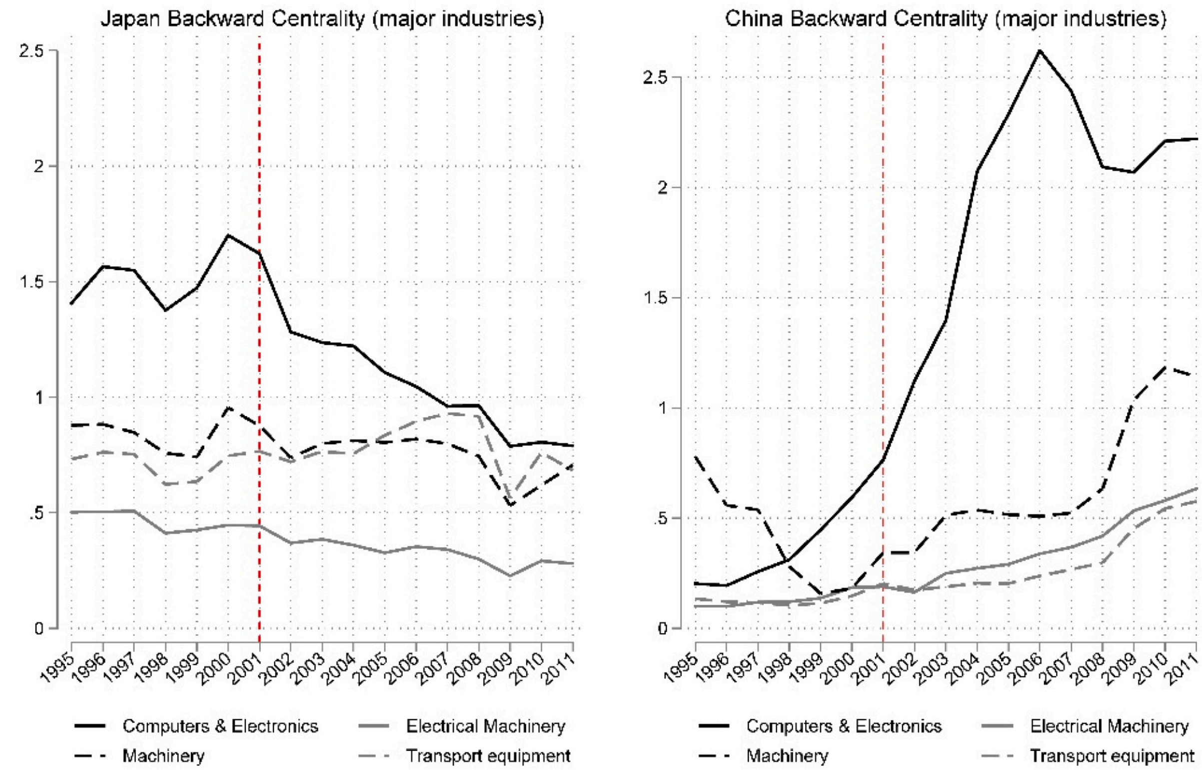
Appendix A

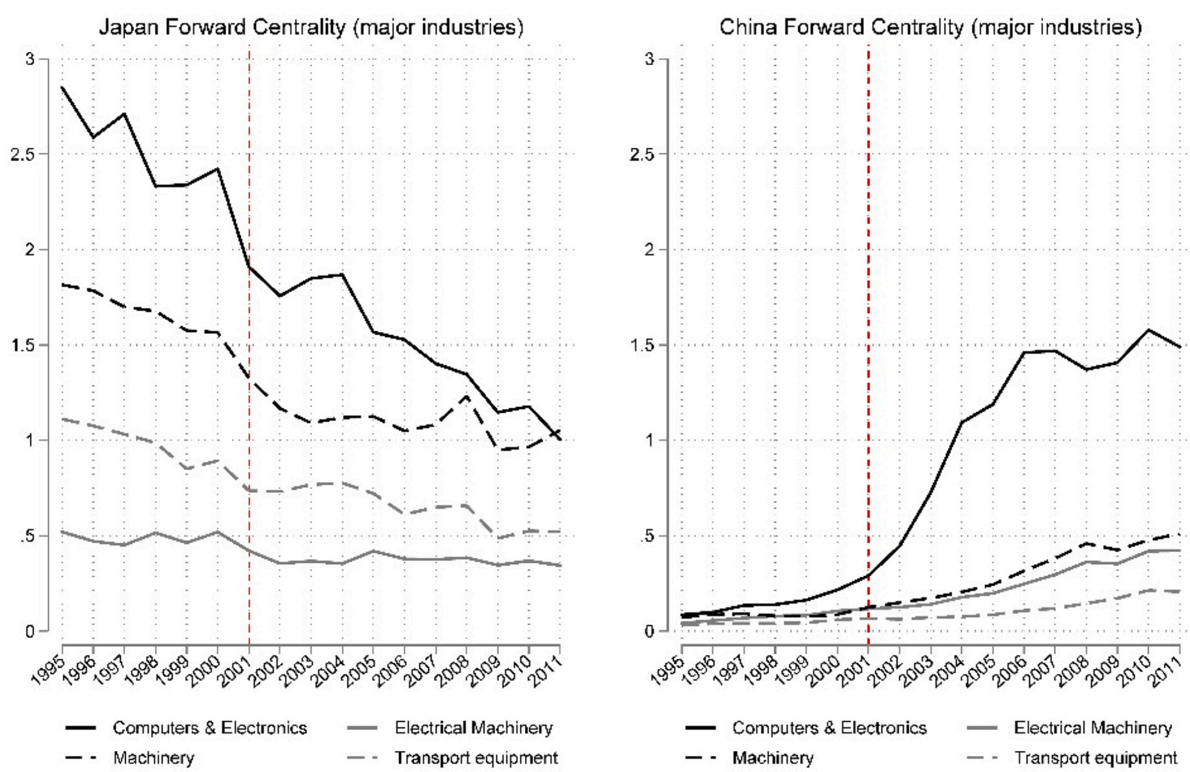


Appendix Fig. A1. Japan's GVC centrality and participation overtime: Manufacturing sector, 1995 to 2011.
Note: The centrality measures denote the weighted average of the industry-level centrality measures using the industry gross output as weights. The left panel shows the centrality measures using the annual industry gross output as weights, while the mid panel show the centrality measures using the initial year (1995) industry gross output as weights.

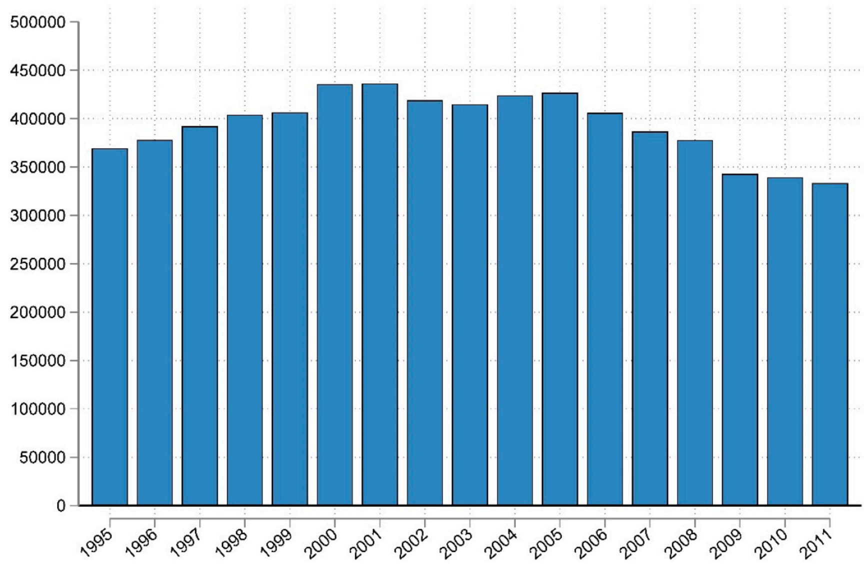
Backward centrality



Forward centrality



Appendix Fig. A2. The trend of GVC centrality for major industries: The comparison for Japan and China.



Appendix Fig. A3. Total number of patent applications to the Japan Patent Office 1995–2011.
Source: Authors' calculation based on the IIP Patent Database 2015.

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 (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, 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 (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
lnRDS	86,320	16.6093	7.6310	0	29.3419
TRADE	109,749	0.3922	0.4882	0	1
IMP	109,749	0.2731	0.4455	0	1
EXP	109,749	0.3376	0.4729	0	1
DAFF	76,486	0.1445	0.3516	0	1
IMP*Centrality (Foreign, Backward)	109,749	0.1735	0.3204	0	1.7003
EXP*Centrality (Foreign, Forward)	109,749	0.3216	0.5599	0	2.8482
IMP*GVC participation (Backward)	109,749	0.0020	0.0048	0	0.0307
EXP*GVC participation (Forward)	109,749	0.0039	0.0079	0	0.0478
Instrumental variables					
China_WTO*Initial_Centrality (Foreign, Backward)	109,749	0.4541	0.4305	0	1.40661
China_WTO*Initial_Centrality (Foreign, Forward)	109,749	0.7008	0.8283	0	2.84824
Initial_IMP*China_WTO*Initial_Centrality (Foreign, Backward)	109,749	0.1091	0.2899	0	1.40661
Initial_EXP*China_WTO*Initial_Centrality (Foreign, Forward)	109,749	0.2515	0.6176	0	2.84824

Appendix Table A2
First stage regression results for Eqs. (3) and (4) in Table 3.

	(3)	(4)
Dependent variable	Backward centrality	Forward centrality
	(Import)	(Export)
IV: China_WTO*Initial_Centrality (foreign)$_i$	−0.3565***	−0.2450***
	(0.117)	(0.034)
GVC participation$_i$	30.6417***	6.3155
	(8.436)	(12.662)
TRADE$_f$	−0.0001	−0.0004
	(0.004)	(0.001)
ln(Employment)$_f$	0.0266*	−0.0002
	(0.016)	(0.006)
lnRDS$_f$	−0.0002	0.0000
	(0.000)	(0.000)
DAFF$_f$	0.0053	0.0004
	(0.004)	(0.004)
Sanderson-Windmeijer multivariate F test of excluded instruments:		
	9.37***	51.74***

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eq. (3) denotes the importer dummy variable, while TRADE in eq. (4) denotes the exporter dummy variable. Note the separate China_WTO and Initial_Centrality terms are collinear with the year and firm fixed effects respectively.
* $p < 0.10$, *** $p < 0.01$.

Appendix Table A3
First stage regression results for Eqs. (3) and (4) in Table 4.

	(3)	(4)
Dependent variable	Backward centrality	Forward centrality
	(Import)	(Export)
IV: China_WTO*Initial_Centrality (foreign)$_i$	−0.3565***	−0.2450***
	(0.116)	(0.034)
Affliate-weighted Centrality$_f$	0.00566**	0.00334
	0.00236	0.00226
GVC participation$_i$	30.6299***	6.3214
	(8.436)	(12.661)
TRADE$_f$	−0.0001	−0.0004
	(0.004)	(0.001)
ln(Employment)$_f$	0.0265*	−0.0002
	(0.016)	(0.006)
lnRDS$_f$	−0.0002	0.0000
	(0.000)	(0.000)
DAFF$_f$	0.0008	−0.0021
	(0.003)	(0.003)
Sanderson-Windmeijer multivariate F test of excluded instruments:		
	9.38***	51.77***

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eq. (3) denotes the importer dummy variable, while TRADE in eq. (4) denotes the exporter dummy variable.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A4
First stage regression results for equations in panel (2) of Table 5.

	(1)		(2)	(3)		(4)
Dependent variable	Backward centrality	$TRADE_f$* backward centrality	Backward centrality	Forward centrality	$TRADE_f$* forward centrality	Forward centrality
	(Import)	(Import)	(Import)	(Export)	(Export)	(Export)
IV1: China_WTO*Initial_Centrality $(Foreign)_i$	−0.3493***	−0.0253	−0.3519***	−0.2354***	−0.0036	−0.2446***
	(0.113)	(0.044)	(0.114)	(0.036)	(0.017)	(0.034)
IV2: Initial_TRADE*China_WTO* Initial_Centrality $(Foreign)_i$	−0.0218***	−0.1422***		−0.0179*	−0.2055***	
	(0.008)	(0.036)		(0.011)	(0.032)	
Affliate-weighted $Centrality_f$	0.0054**	0.0034	0.0056**	0.0025	0.0045	0.0032
	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)
GVC $Participation_i$	30.8216***	12.5544***	32.0003***	6.1959	4.2123	7.0466
	(8.380)	(3.375)	(8.314)	(12.440)	(6.151)	(13.008)
$TRADE_f$*GVC $Participation_i$			−2.8009***			−1.2664
			(0.462)			(0.816)
$TRADE_f$	−0.0027	0.6471***	0.017***	−0.0044	0.9307***	0.0130
	(0.005)	(0.076)	(0.005)	(0.003)	(0.166)	(0.009)
$\ln(Employment)_f$	0.0253	0.0041	0.0256	−0.0012	−0.0045	−0.0004
	(0.016)	(0.005)	(0.016)	(0.006)	(0.008)	(0.005)
$lnRDS_f$	−0.0003	0.0003	−0.0003	−0.0002	0.0007***	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$DAFF_f$	0.0021	−0.0040	0.0022	0.0002	−0.0153**	−0.0019
	(0.003)	(0.006)	(0.003)	(0.003)	(0.008)	(0.003)
Sanderson-Windmeijer multivariate F test of excluded instruments						
	22.84***	17.73***	9.46***	56.09***	38.59***	51.56***

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eqs. (1) and (2) denotes the importer dummy variable, while TRADE in eqs. (3) and (4) denotes the exporter dummy variable.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A5
Robustness checks: Direct versus indirect linkages.
Dependent variable: ln(1 + Citation-weighted number of patent applications).

	(1)	(2)	(3)	(4)
	Backward	Forward	Backward	Forward
3-year lagged	(Import)	(Export)	(Import)	(Export)
L3.Direct $(foreign)_i$	0.0102	0.262***		
	(0.241)	(0.079)		
L3.Indirect $(foreign)_i$			0.0244	0.243***
			(0.121)	(0.065)
L3.GVC $participation_i$	−12.61***	5.085*	−12.90***	5.197*
	(3.603)	(2.822)	(3.475)	(2.573)
L3.$TRADE_f$	0.0158**	0.00414	0.0158**	0.00387
	(0.006)	(0.009)	(0.006)	(0.009)
L3.$\ln(Employment)_f$	0.0706***	0.0670***	0.0704***	0.0660***
	(0.017)	(0.020)	(0.017)	(0.020)
L3.$lnRDS_f$	0.00347***	0.00354***	0.00347***	0.00354***
	(0.001)	(0.001)	(0.001)	(0.001)
L3.$DAFF_f$	−0.0201	−0.0203	−0.0202	−0.0203
	(0.012)	(0.012)	(0.012)	(0.012)
Number of observations	63,373	63,373	63,373	63,373
R-squared	0.0865	0.0856	0.0865	0.0859

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eqs. (1) and (3) denotes the importer dummy variable, while TRADE in eqs. (2) and (4) denotes the exporter dummy variable.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A6
Robustness checks: Alternative GVC measures, Manufacturing industries (3-year lagged).
Dependent variable: ln(1 + Citation-weighted number of patent applications).

	(1)	(2)	(3)	(4)
	Backward	Forward	Backward	Forward
3-year lagged	(Import)	(Export)	(Import)	(Export)
L3.Centrality (foreign)$_i$	0.0228	0.136***	−0.0374	0.121***
	(0.074)	(0.037)	(0.156)	(0.037)
L3.GVC participation$_i$	−15.52***	6.326*		
	(4.423)	(3.161)		
L3.TRADE$_f$	0.0164**	0.00449	0.0146**	0.00460
	(0.006)	(0.009)	(0.006)	(0.009)
L3.ln(Employment)$_f$	0.0696***	0.0695***	0.0675***	0.0682***
	(0.018)	(0.019)	(0.020)	(0.019)
L3.lnRDS$_f$	0.00349***	0.00346***	0.00353***	0.00352***
	(0.001)	(0.001)	(0.001)	(0.001)
L3.DAFF$_f$	−0.0197	−0.0194	−0.0207	−0.0200
	(0.012)	(0.012)	(0.012)	(0.012)
L3.lnPROD$_i$	0.0498	−0.0459	−0.0302	−0.0317
	(0.043)	(0.038)	(0.045)	(0.042)
L3.Upstreamness$_i$	0.0824	−0.0378	0.0352	0.00515
	(0.059)	(0.099)	(0.112)	(0.099)
L3.RCA_VA$_i$	−0.118	−0.0822	−0.0734	−0.0907
	(0.075)	(0.083)	(0.100)	(0.089)
Number of observations	63,373	63,373	63,373	63,373
R-squared	0.0841	0.086	0.0841	0.086

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eqs. (1) and (3) denotes the importer dummy variable, while TRADE in eqs. (2) and (4) denotes the exporter dummy variable. lnPROD denotes sector output, Upstreamness denotes the measure of GVC upstreamness, and RCA_VA denotes sector revealed comparative advantage based on the trade in value added.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A7
Robustness checks: Manufacturing industries except computer & electronics industry, (3-year lagged).
Dependent variable: ln(1 + Citation-weighted number of patent applications).

	(1)	(2)	(3)	(4)
	Fixed-effect panel estimation		IV	
	Backward	Forward	Backward	Forward
3-year lagged	(Import)	(Export)	(Import)	(Export)
L3.Centrality (foreign)$_i$	−0.0565	0.159**	−0.372***	0.207***
	(0.088)	(0.060)	(0.135)	(0.080)
L3.GVC participation$_i$	−13.61***	7.810	−1.052	7.055
	(4.011)	(5.771)	(7.351)	(5.317)
L3.TRADE$_f$	0.0116**	0.00364	0.0140***	0.00380
	(0.005)	(0.010)	(0.004)	(0.009)
L3.ln (Employment)$_f$	0.0685***	0.0626**	0.0681***	0.0639***
	(0.018)	(0.021)	(0.019)	(0.019)
L3.lnRDS$_f$	0.00324***	0.00330***	0.00334***	0.00326***
	(0.001)	(0.001)	(0.001)	(0.001)
L3.DAFF$_f$	−0.0253**	−0.0259**	−0.0250**	−0.0254**
	(0.011)	(0.011)	(0.011)	(0.010)
Number of observations	59,607	59,607	59,278	59,278
Number of firms	6266	6266	5937	5937
R-squared	0.0876	0.0861	0.0849	0.0859
Kleibergen-Paap rk LM statistic			2.726*	5.004**
Kleibergen-Paap rk Wald F statistic			70.264	40.906

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eqs. (1) and (3) denotes the importer dummy variable, while TRADE in eqs. (2) and (4) denotes the exporter dummy variable.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A8
Robustness checks: manufacturing industries (1-year lagged).
Dependent variable: ln(1 + Citation-weighted number of patent applications).

	(1)	(2)	(3)	(4)
	Fixed-effect panel estimation		IV	
	Backward	Forward	Backward	Forward
1-year lagged	(Import)	(Export)	(Import)	(Export)
L.Centrality (foreign)$_i$	−0.0154	0.0489*	−0.138*	0.0649
	(0.047)	(0.025)	(0.075)	(0.045)
L.GVC participation$_i$	−2.494	7.325***	0.550	7.515***
	(4.118)	(1.213)	(2.805)	(1.076)
L.TRADE$_f$	0.0132**	0.0134	0.0135***	0.0135*
	(0.005)	(0.008)	(0.005)	(0.008)
L.ln(Employment)$_f$	0.0897***	0.0894***	0.0915***	0.0897***
	(0.018)	(0.019)	(0.018)	(0.018)
L.lnRDS$_f$	0.00260**	0.00256***	0.00257***	0.00255***
	(0.001)	(0.001)	(0.001)	(0.001)
L.DAFF$_f$	−0.00902	−0.00889	−0.00810	−0.00883
	(0.011)	(0.011)	(0.011)	(0.010)
Number of observations	71,493	71,493	71,235	71,235
Number of firms	6924	6924	6666	6666
R-squared	0.0532	0.0542	0.0522	0.0542
Kleibergen-Paap rk LM statistic			2.644	5.120**
Kleibergen-Paap rk Wald F statistic			8.592	52.422

Notes: Standard errors clustered at the 2-digit industry level in parentheses. Firm fixed effects and year fixed effects are included. TRADE in eqs. (1) and (3) denotes the importer dummy variable, while TRADE in eqs. (2) and (4) denotes the exporter dummy variable.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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