Global Sourcing and Domestic Production Networks*

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Abstract

This paper studies from both theoretical and empirical perspectives how a country's domestic production networks are shaped by firms' offshoring decisions. We develop a model to study heterogeneous firms' input sourcing from multiple industries, domestic regions, and foreign countries. Input sourcing entails communication with suppliers, which is endogenously increasing in the differentiation of input varieties. The model predicts that firms are less likely to source differentiated inputs, especially from distant domestic and foreign suppliers, due to high communication costs. Triggered by foreign countries' export supply shocks, firms start offshoring inputs from foreign suppliers, which replace their less productive domestic suppliers in the same industry (direct replacement effect). The resulting decline in the marginal costs induces firms to start sourcing from the more productive and distant domestic suppliers (productivity effect), but possibly also from the more proximate ones in the newly sourced differentiated input industries (industry composition effect). The net effect of offshoring on a firm's domestic production networks depends on the relative strength of the three effects, which we verify using data for 4.5 million buyer-seller links in Japan. Based on a firm-level instrument, we find that after offshoring, firms are less likely to drop suppliers, but more so for the larger and more distant ones. They tend to add suppliers that are more proximate and from differentiated input industries. These results imply that firms' offshoring increases the spatial concentration of domestic production networks.

Key Words: production networks; global sourcing, offshoring, face-to-face communication

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1 Introduction

Production has never been more fragmented across countries, thanks to a substantial decline in trade barriers and advances in information, communication and transportation technologies. A growing body of literature studies both the causes and consequences of increasing proliferation of global value chains.[1] The focus of the literature has been the direct effects of global sourcing on the industry or firm that imports intermediate inputs, despite the fact that an economy is an interlinked web of production units, each using inputs from its suppliers to produce goods and services that are sold further downstream. Indeed, recent research has highlighted the importance of considering production networks in studying a wide range of economic issues, such as the propagation and amplification of firm-level shocks to large business-cycle fluctuations (Acemoglu et al., 2012; Carvalho and Gabaix, 2013); knowledge spillover (Javorcik, 2004); the aggregate effects of resource misallocation (Jones, 2011 and 2013); and the gains from trade (Costinot and Rodriguez-Clare, 2014; Caliendo and Parro, 2015). Understanding how global trade reshapes the structure of production networks in a country is clearly important.

This paper studies from both theoretical and empirical perspectives how firms' sourcing of intermediate inputs from foreign suppliers, which we refer to as offshoring, reshapes a country's domestic buyer-supplier networks. Specifically, we examine the effects of offshoring that is triggered by foreign cost shocks on firms' choices of domestic input suppliers. To guide our empirical analysis, we extend the global sourcing model by Antràs, Fort, and Tintelnot (2017, henceforth AFT) to consider multiple domestic source regions, various input industries that differ in product differentiation, and face-to-face communication between heterogeneous buyers and input suppliers. It builds on the premise that trade is more costly over longer distance, and especially so when the success of input production depends on the intensity of communication between buyers and suppliers. Similar to Bernard, Moxnes, and Saito (2016, henceforth BMS), our model features heterogeneous buyers and sellers engaged in costly domestic trade; but we additionally consider firms' sourcing inputs from both domestic and foreign suppliers operating in different input industries. We then empirically examine the theoretical predictions using extensive production network data from Japan.

There are three reasons why we extend the existing models of input sourcing to consider multiple inputs sectors and communication between firms. First, from our Japanese production network data, we observe that the geographic concentration of buyer-seller links is higher for the more differentiated inputs, and is increasing over time. Second, we find that after firms started to offshore inputs, they tend to expand the scope of domestic sourcing by adding suppliers, source regions, and source industries, while dropping suppliers that are on average farther away. A single-sector model

[1] See Feenstra (2008) for a comprehensive summary of the literature. Johnson and Noguera (2016) report that the ratio of value-added to gross exports worldwide declined by about 10 percentage points from 1970 to 2010, suggesting that production depended increasingly more on foreign inputs. Recent studies, which include Antràs, Fort, and Tintelnot (2017) and Blaum, Peters and Lelarge (2016) examine the productivity and welfare effects of firms' importing. There is also a large and growing literature about the effects of offshoring on labor market outcomes (e.g. Ebenstein, et al. 2014; Hummels et al., 2014).

that features only two-sided heterogeneity, standard trade costs, and the scale effect of offshoring would predict instead an increase in the average distance of the domestic buyer-seller links. Third, recent studies in international trade and urban economics emphasize the role of information flows in shaping the patterns of trade and city size distribution (e.g., Keller and Yeaple, 2013; Davis and Dingel, 2016; Redding and Rossi-Hansberg, 2016).[2]

The model features variable trade costs increasing in distance not only because of the standard transport costs but also buyers' costly endogenous communication with suppliers. Buyers choose a higher level of communication with suppliers to safeguard the quality of inputs. Therefore, the elasticity of the variable trade costs with respect to the distance between buyers and suppliers is higher for the more differentiated inputs, encouraging buyers to procure those inputs from the more proximate suppliers.[3] Hence, in addition to productivity sorting in outsourcing as documented in the literature (i.e., the more productive firms self-select into a larger number of source regions, including the more distant domestic regions and foreign countries),[4] our multi-sector model illustrates a pecking order of firms' sourcing across industries–differentiated inputs are less likely to be outsourced, especially from distant or foreign suppliers.

After characterizing firms' equilibrium global production networks, we study how offshoring, triggered by exogenous declines in offshoring costs, affects firms' performance and thus their choices of domestic suppliers. Newly offshoring firms replace the less productive domestic suppliers with foreign suppliers in the same industry (direct displacement effect). In addition, the resulting lower marginal costs as a result of sourcing from more efficient foreign suppliers, as highlighted by AFT, induce firms to expand domestic sourcing by adding the more productive and distant suppliers, while dropping the less productive and closer ones (productivity effect). If the productivity effect is sufficiently pronounced, newly offshoring firms may start paying extra fixed costs to start sourcing in new input industries, which tend to be more differentiated (industry composition effect). The newly added suppliers can thus be more proximate than the existing ones.

The net effect of offshoring on a firm's structure of domestic suppliers is nuanced, as it depends on the relative strength of the direct displacement, productivity, and industry composition effects of offshoring. In particular, offshoring tends to displace generic-input suppliers, which were optimally chosen by buyers to be located farther away. Across industries, newly offshoring firms tend to add differentiated-input suppliers, which are optimally chosen to be located closer by to save communication costs. These patterns of the supplier reorganization may overturn the within-industry productivity effects, resulting in a paradoxical scenario in which firms add closer and possibly smaller domestic suppliers and drop the more distant and possibly larger ones after offshoring. The average

[2] Redding and Rossi-Hansberg (2016) provide a review of the extensive literature on the uneven distribution of economic activities across space, due to exogenous geographic characteristics and endogenous interactions between agents.

[3] The idea that the agency costs of monitoring and communication increase in distance and shape relationship-specific investments has been empirically verified in the finance literature, such as Lerner (1995) and Petersen and Rajan (2002). Cristea (2011) studies the importance of face-to-face meetings in shaping international trade and the demand for business class air travel.

[4] See Bernard et al. (2016) for a unified framework and a literaure review.

distance of a buyer's domestic production networks can drop after its offshoring, strengthening the spatial concentration of firms in related industries.

We empirically examine several theoretical predictions using data for 4.5 million buyer-seller links in Japan.[5] We find evidence largely consistent with BMS's findings on Japan's production networks–the more productive firms source inputs from more suppliers and regions, including the more distant ones. Distant suppliers are more productive on average, while productive firms are more likely to offshore inputs. Above and beyond this spatial pattern of outsourcing, we also uncover evidence about the sectoral pattern of outsourcing, based on the product differentiation of inputs. We find that the negative distance effects on domestic sourcing are stronger for the more differentiated inputs, measured by either Rauch's (1999) product differentiation indicators or the inverse of the elasticity of substitution between input varieties. Hence, firms are less likely to source differentiated inputs from the more distant regions or from foreign countries. Only the relatively more productive firms will outsource differentiated inputs, with the most productive ones offshoring them.

Besides portraying the patterns of firms' global sourcing, we use the network data to examine the model predictions about the effect of offshoring on firms' choices of domestic suppliers. To establish the causal link between firms' offshoring and the pattern of domestic sourcing, we construct a firm-level instrument using information on buyers' initial patterns of domestic sourcing across industries and the corresponding foreign countries' export supply shocks. The idea is that conditional on a firm's sourcing inputs from a domestic input industry, the incremental fixed costs needed for offshoring the same inputs are lower. When positive export supply shocks, due either to reduced trade costs or increased productivity of Japan's trade partners, hit an industry, those that are already sourcing inputs in the same industry should be more likely to start offshoring. Our 2SLS estimates show that offshoring induces firms to drop larger and more distant suppliers, but at the same time add larger suppliers. While the addition of the larger and more distant suppliers is consistent with the productivity effect of offshoring, the dropping of the larger suppliers implies that a sufficiently strong direct replacement effect that many large suppliers in the less differentiated industries were dropped. Indeed, consistent with the theoretical prediction that domestic sourcing of differentiated input suppliers is associated with higher variable trade costs and thus lower profitability, we find that newly offshoring firms are more likely to add suppliers from differentiated input industries. These patterns of the reorganization of supplier relationships offer an explanation for why firms' offshoring can reduce the average distance between buyers and domestic suppliers in the production network. They also shed light on how the trade-induced changes in the production network can affect an economy's aggregate productivity.[6]

[5] The data set is the most comprehensive of all studies that we are aware of on domestic production networks. As will be discussed in Section 2, our network data set covers half of the registered firms in Japan, each of which reports up to 24 suppliers and customers. We use the information reported by both buyers and sellers to maximize the number of links. Recent research by Bernard, Moxnes and Saito (2016) and Carvalho, Nirei, and Saito (2014) use the same network data to study different research questions. The next closest counterpart that we can think of is the paper by Atalay, et al. (2011), who analyze the buyer-seller network in the U.S. using Compustat data that cover only publicly listed firms and their top 5 customers.

[6] Such understanding is particularly important in light of Japanese firms' increasing engagement in global value

Our paper relates to five strands of literature. First, it contributes to the growing cluster of work on networks in international trade, as summarized by Chaney (2016). The literature dates back to the seminal work by Rauch (1999) and Rauch and Trindade (2002), who show that colonial ties, common languages, and the stock of immigrants between two countries are positively related to bilateral trade, especially for differentiated products. The authors relate these findings to the importance of networks, information and search frictions in trade. Recent research seeks to develop models to study the micro foundation of the dynamics and patterns of firms' sorting and matching in international trade networks (e.g., Eaton et al., 2014; Carballo, Ottaviano, and Volpe Martincus, 2016; Bernard, Moxnes and Ulltveit-Moe, 2017; Sugita, Teshima, Seira, 2017). In particular, Bernard, Moxnes and Ulltveit-Moe (2017) build a two-sided heterogeneity model and uncover in Norwegian importer-exporter linked data that matching of trade partners exhibits negative assortativity.[7] They and also Carballo, Ottaviano, and Volpe Martincus (2016) both highlight adjustments on the buyer margin as an important channel through which trade responds to policy shocks. Chaney (2014) develops a model to study how by establishing new contacts and expanding existing trade relationships, firms penetrate into foreign markets and drive aggregate export dynamics.

Second, our paper contributes to the growing literature on the domestic production networks. Oberfield (2013) develops a general-equilibrium model to study how firms' endogenous network formation shapes an economy's productivity and organization of production. Based on recently available buyer-seller linked data, a growing empirical literature documents the pattern and dynamics of domestic production networks. Using the same data set as ours, BMS document important stylized facts, notably the negative assortativity of domestic production networks. Relying on the extension of the high-speed train line as an exogenous shock, the authors find that the average measured productivity of firms near new stations increase due to an expansion of sourcing to more domestic locations. Carvalho, Nirei, and Saito (2014) use the same data set to quantify the propagation of shocks through the domestic input-output linkages, using the Great East Japan Earthquake of 2011 as a case.[8] Using US buyer-seller linked data and a structural model of firms' network formation, Lim (2017) studies the macroeconomic implications of the propagation of firm-level demand and supply shocks through the production networks.

Third, our paper relates to the literature on the relationship between trade and firm performance, other than the traditional concept of firm efficiency. In particular, Holmes and Stevens

chains. For instance, a Nikkei Sangyo Shimbun article on August 31, 2011 reported that Kubota Corporation, a large industry machinery manufacturing firm in Japan, announced the plan to increase its overseas parts and components procurement share form 25% in 2011 to 70% in 2021. A new overseas procurement base will be built in India, in addition to their existing bases in Thailand and China. As part of this offshoring plan, the company would need to reorganize the procurement relationships with the existing domestic suppliers.

[7] Using importer-exporter matched data from Colombia, Eaton et al. (2014) structurally estimate the effects of learning and search costs on aggregate trade. By focusing on a HS 6-digit code within textile/ apparel trade, Sugita, Teshima, Seira (2017) study the rematching of US-Mexican trade relationships after the Multi-Fibre Arrangement quotas on Chinese exporters were removed in 2005. In a sample with mostly one-to-one matches, the authors find evidence of positive assortative matching in trade.

[8] They show that external shocks on downstream firms affect not only the directly linked upstream firms, but also firms that are two or three degrees away from the affected firms.

(2014) build a model that features different product segments within a narrow product category, in which small plants specialize in making specialty goods sold to nearby customers, while large plants specialize in mass production of standardized goods shipped to distant markets. Using plant-level data from the US census, the authors find firms' heterogeneous responses to the China import shocks, as predicted by a model. It is the large plants that were most negatively affected, with some of the smallest specialty firms actually experiencing an increase in market shares. Similarly, we also emphasize the non-efficiency aspect of firms' performance, which determines their responses to globalization. We show that product differentiation of inputs affects not only firms' offshoring decisions but also their domestic sourcing patterns after offshoring.[9] In this regard, our findings are also related to Jensen and Kletzer (2005), who study the tradability of tasks, and Keller and Yeaple (2013), who study the ways multinationals transfer knowledge to their overseas affiliates, either through direct communication or exporting intermediates that embody knowledge. Similar to these studies, we assume in the model and verify in the data that the rate at which trade costs increase in distance varies across industries.

Fourth, our paper relates to the large literature on the geography of trade and economic activities (e.g., Ellison and Glaeser, 1997; Rosenthal and Strange, 2001; Dumais, Ellison, and Glaeser, 2002; Ellison, Glaeser, and Kerr, 2010; and Nakajima, Saito, and Uesugi, 2012; Behrens and Bougna, 2015).[10] It contributes to this literature by showing that offshoring affects coagglomeration of industries through firms' reorganization of their domestic production relationships. It provides evidence that offshoring tends to reinforce coagglomeration, because generic input suppliers, which are on average located farther away, are the ones that tend to be replaced by foreign suppliers while differentiated input suppliers, which are on average located closeby, tend to be added as new suppliers by buyers after offshoring.

Finally, our paper contributes to the extensive literature on the impact of offshoring on labor market (Ebenstein et al., 2014 and Hummels et al., 2014) and firm outcomes (Kasahara and Rodrigue, 2008 and Hijzen, Inui, and Todo, 2010).[11] All these studies examine the direct effect of

[9] Another dimension of firm performance is product quality, which has been studied by a large and growing literature, such as Khandelwal (2010), Baldwin and Harrigan (2011), and Hallak and Sivadasan (2013), among others.

[10] Ellison and Glaeser (1997) propose sectoral measures of the degree of industry agglomeration and coagglomeration, and find evidence of coagglomeration in industry pairs with strong upstream-downstream relationships. Rosenthal and Strange (2001) and Ellison, Glaeser, and Kerr (2010) empirically identify causes of agglomeration and coagglomeration, such as knowledge spillovers, input sharing, product shipping costs, labor market pooling, and natural advantage. Rosenthal and Strange (2001) find that labor market pooling has the most robust effect, while Ellison, Glaeser, and Kerr (2010) find evidence that input-output linkages are particularly important. Using Japanese buyer-seller linked data, Nakajima, Saito, and Uesugi (2012) find evidence that intensity of intra-industry transactions increases industry agglomeration. On the trends of industry agglomeration, Dumais et al. (2002) investigate dynamics of geographic concentration of U.S. manufacturing industries. They find that although the trend of industry agglomeration varies with industries, their average agglomeration levels have slightly declined in recent decades. Behrens and Bougna (2015) also observe a recent decline in the agglomeration in manufacturing industries in Canada.

[11] Ebenstein et al. (2014) and Hummels et al. (2014) examine the effect of offshoring on workers' wages using U.S. and Danish data, respectively. Kasahara and Rodrigue (2008) use Chilean manufacturing plant-level data and find that firms' importing of intermediates improves productivity. Hijzen, Inui, and Todo (2010) find a positive impact of offshoring on Japanese firms' productivity.

offshoring, rather than the effect on other firms through the buyer-supplier networks.

The paper proceeds as follows. Section 2 discusses our data sources. Section 3 presents several stylized facts that motivate our theoretical model. Section 4 introduces our theoretical model. Section 5 presents our empirical design and results. The final section concludes this paper.

2 Data

Our data come from two sources. The first data set, which reports buyer-supplier relationships in Japan for 2005 and 2010, is compiled by the Tokyo Shoko Research, Ltd. (TSR). The network data contain basic firm-level balance sheet information, such as employment, sales, location, main (4-digit) industry (up to 3), founding year, number of establishments, of over 800,000 firms in Japan.[12] Importantly, it also provides information on firm-to-firm relationships. Each firm surveyed by the TSR was asked to report the names of its top 24 suppliers, top 24 customers, and 3 main shareholders. To avoid the "top 24" cutoff from limiting the sample coverage of the production network, we use two-way matching to maximize the number of links. Specifically, we use information reported by a buyer about its sellers and vice versa to maximize the number of buyer-supplier links. Since a buyer of a seller and vice versa can be reported by either end of a relationship, the number of buyers (sellers) of a seller (buyer) can be much greater than 24. In fact, the top seller in our constructed network data in Japan has over 11,000 buyers in 2010, while the top buyer has close to 8,000 suppliers. The distribution of the buyer-supplier links is very skewed, with most of the firms having substantially fewer buyers and sellers (more below). Distance between any pair of buyers and sellers is measured using the geocoded addresses reported by the firms.[13]

We complement the TSR data with the Basic Survey on Japanese Business Structure and Activities (BSJBSA), conducted annually by the country's Ministry of Economy, Trade and Industry (METI). The survey covers all firms that have over 50 employees or 30 million yen of paid-in capital in the country's manufacturing, mining, wholesale and retail, and several service sectors. Firms' responses to the survey are mandatory. The survey data contain detailed information on firms' business activities, such as their main industry (3-digit), number of employees, sales, capital (which is required to compute a firm's total factor productivity), purchases of inputs and materials, exports and imports by continent (e.g., Asia, Europe, etc.). The data set covers 22,939 and 24,892 firms for 2005 and 2010, respectively. We merge the two data sets using firms' names, addresses, and telephone numbers. The merged data contain over 800,000 buyer-supplier pairs.[14] In the regression

[12] The surveys were conducted in 2006 and 2011, respectively. We use both TSR Company Information Database and TSR Company Linkage Database in this paper. According to Carvalho, Nirei and Saito (2014), the TSR data cover more than half of all firms in Japan. According to BMS, the TSR sample covers almost all firms with over 4 employees in Japan.

[13] We use the geocoding service from the Center for Spatial Information Science at the University of Tokyo to first identify the latitude and longitude of each address, and then we compute the distance between any pair of coordinates.

[14] About 52% of the pairs in the balanced TSR sample can be merged to the manufacturing survey data. See Table A3 in the appendix about the summary statistics of the key variables from the BSJBSA data. Importers' average imports-to-intermediate ratio, increases slightly from 18% to 21% from 2005 to 2010. Asia is a very important input source for Japanese importers – among importers, the average share of imports from Asia is over 80% in both 2005

analysis, we focus on the subsample that has manufacturing firms in the downstream.

3 Descriptive Evidence

3.1 Domestic Production Networks

We first describe several key patterns observed in our network data. Table 1 reports the summary statistics on the buyer-supplier links. Panel A reports that the number of buyer-supplier links, based on the TSR sample, is about 3.6 million in 2005 and 4.5 million in 2010. The average number of sellers used by a buyer increased from 4.9 in 2005 to 5.5 in 2010, while the median number increased from 2 to 3. The large difference between the mean and the median numbers of sellers per buyer suggests a highly skewed distribution of buyer-supplier links (i.e., a small number of large buyers having substantially more sellers than other buyers).[15] The increase in the average and median number of buyer-supplier links between 2005 and 2010 implies that the production network in Japan has gotten denser. Notice that the firms' more active self-reporting of sellers may have contributed to the increase in the network density. To mitigate this potential measurement issue, our regression sample includes only buyers and suppliers that operated in both 2005 and 2010.[16]

Panel B reports the summary statistics of the number of links in the regression sample built from merging the BSJBSA firm sample with the TSR network data. Since BSJBSA imposes sampling thresholds based on firms' employment and capital, the mean and the median numbers of sellers linked to a buyer in our regression sample are larger (22 and 10, respectively for the year 2010) than those in the network data.[17] Tables A2 and A3 in the appendix report more detailed statistics by buyers' industry.

Table 2 reports the summary statistics on the number of sellers and domestic regions (prefectures) from which different types of buyers, based on importing statuses, sourced inputs. In 2005, there are altogether 13,784 manufacturing buyers in the regression sample. Of these buyers, 7% did not import in 2005 but started importing by 2010, while 74% continued to be non-importers by 2010. Firms that imported in both 2005 and 2010 accounted for about 13% of the sample.[18]

and 2010.

[15] When we plot the log number of sellers of a buyer against the fraction of buyers having at least that many sellers (Figure A1 in the appendix), we find a power-law distribution, as highlighted by BMS.

[16] The benefit of working on a data set with balanced numbers of buyers and sellers in both years is that biase due to buyers' potentially more comprehensive reporting, which involves suppliers that did not appear in the 2005 cross-section, is alleviated. The cost is that we will not able able to study the entry-exit dynamics in the network.

[17] One may be concerned about the selection biases due to the exclusion of small firms in our regression sample. Three remarks are in order. First, if the goal of the study is to evaluate the effects of firms' offshoring on their domestic supplier choices, our focus on large firms should be fine as large firms tend to engage in offshoring due to the associated high fixed costs (see AFT for the structural estimate of those fixed costs). Second, if there is any effect of offshoring on firms' performance and their choices of domestic suppliers, omitting small firms, which tend to be non-importers, will go against us from finding any effect. Third, even though the fraction of firms that have at least n links is naturally larger derived from a large-firm regression sample, the power-law distribution of the number of sellers per buyer is preserved (see Figure A1 in the appendix), with the slope of the relation based on the regression sample being very close to that derived from the original TSR sample.

[18] Notice that the shares of these firms do not add up to 1 as import stoppers are omitted in the table.

Among the three groups of buyers, continuing importers sourced from more domestic sellers and prefectures than the other two types of firms. They procured inputs from 48.5 domestic sellers in 2005 on average, with the median buyer purchasing inputs from 16 sellers. The mean and median numbers of prefectures from which buyers procure inputs are 7.49 and 5 (out of 47), respectively. While the numbers of sellers and source prefectures are smaller on average compared to continuing importers, they are larger than those of continuing non-importers. Across all groups, the average numbers of suppliers per buyer increased between 2005 and 2010.

Figures 1 and 2 illustrate some patterns that discipline our theoretical model. Both figures show that the number of buyer-seller links is negatively correlated with the distance between the pair. About half of the connections are found within a 25 km radius of buyers. Figure 1 shows that the negative correlation appears to be stronger for differentiated inputs, measured by Rauch's product differentiation indicator. Figure 2 shows that such a negative correlation increased in magnitude since 2005. In Figures 3 and 4, we examine the link between a buyer's sales and its scope of domestic sourcing. Figure 3 shows a positive correlation between a buyer's sales and its number of domestic suppliers, while Figure 4 shows a positive relationship between a buyer's sales and the number of prefectures from which it procures intermediates. These findings reveal the importance of incorporating trade frictions that increase in distance and the degree of product differentiation of inputs in the model.

Regarding the relationship between firms' heterogeneity and their domestic sourcing patterns, we find that more productive buyers have more connected suppliers, within the same 4-digit industry and prefecture (see Table A4 in the appendix for the regression results). Distant suppliers tend to be more productive. These results highlight the significance of considering two-sided heterogeneity across buyers and sellers in the model, as BMS also highlight.

3.2 Firms' Post-Offshoring Outcomes

Let us now present some preliminary empirical results about the correlation between a firm's offshoring (importing) status and its post-offshoring performance. These results will serve as a guide for our theoretical analysis. We estimate the following specification using a simple fixed effects model:

$$\Delta y_i = \alpha + \beta \Delta imp_i + \gamma \ln TFP_i + [FE_s + FE_r] + \varepsilon_i, \tag{1}$$

where Δ is an operator that takes the first difference of the variable y_i between 2005 and 2010, while y_i represents buyer i's log sales and various measures of the scope of domestic sourcing, including log number of domestic suppliers, domestic industries, and domestic regions from which buyer i sources inputs. We also examine the change in the average distance between a buyer and its suppliers, after offshoring. We use three measures of the change in a buyer's average distance from its domestic suppliers. The first one is the Davis-Haltiwanger-Schuh (1998) growth rate of distance, $(dist_{i,10} - dist_{i,05}) / \frac{1}{2} (dist_{i,10} + dist_{i,05})$, which is bounded between -2 and 2 and reduce the impact of a small number of big changes. The second measure is the log difference in distance. The third measure considers the difference between the average distance of the newly added suppliers and that of the dropped suppliers, $\left(dist^{add}_{i,05-10} - dist^{drop}_{i,05-10}\right) / \frac{1}{2}\left(dist^{add}_{i,05-10} + dist^{drop}_{i,05-10}\right)$.

The variable of interest, Δimp_i, represents the change in firm i's import status, which equals 1 if buyer i did not import in 2005 but started to import in 2010, 0 otherwise.[19] We include buyer's (4-digit) industry and region (one for each of the 47 prefectures) fixed effects (FE_s and FE_r) to control for any unobserved determinants of firm outcomes (e.g., firms in certain prefectures are more likely to source inputs and also enjoy a larger extent of positive externalities from other firms because of the high geographic concentration of suppliers). We always control for buyer i's 2005 log total factor productivity, TFP_i, as it is often speculated that ex-ante more productive firms are more likely to import intermediate inputs (e.g., Amiti, Itskhoki, and Konings, 2014).

Table 3 reports the estimates of Equation (1). The regression sample includes manufacturing buyers only, while it includes domestic suppliers from both manufacturing and non-manufacturing industries.[20] Column 1 reports a positive and significant correlation between the change in the firm's import status and the change in its sales. From columns 2 to 4, we find a positive and significant correlation between the change in the firm's import status and its scope of domestic sourcing, in terms of the (log) number of suppliers, the (log) number of industries, and the (log) number of regions from which the firm sources its intermediate inputs. In columns 5 and 6, we find a significant and negative correlation between the firm's offshoring participation and the average distance between the buyer and its domestic suppliers. In column 7, we find that after a firm starts offshoring, the distance from the newly added suppliers is on average less than that of dropped suppliers.[21] All results in this table should not be interpreted as causal, and in Section 5, we will propose a firm-level instrument to gauge the causal effect of offshoring on firms' adding and dropping of suppliers.

While the positive correlation between a firm's import participation and the scope of domestic sourcing is consistent with the main findings by AFT, the negative correlation between offshoring and the average buyer-supplier distance cannot be readily rationalized by their model that only considers one input industry. We therefore develop our own model in the following section.

4 A Model of Firms' Global Sourcing

Motivated by the above preliminary results, we develop a model that features heterogeneous firms' sourcing of intermediate inputs from suppliers located in different domestic and foreign regions.

[19] Recent research shows that many exporters only export for a year and then drop out from exporting (e.g., Blum, Claro, and Horstmann, 2013). To address the issues of occasional importing, we conduct robust checks by defining a new importer as one that imported for at least two years (2010 and 2011), and a non-importer as one that did not import for three consecutive years (2003-2005). The main results remain largely robust and are available upon request.

[20] When constructing the buyer-specific measures of domestic sourcing, parent-child relationships and sellers with fewer than 5 employees are dropped. The regression results remain largely robust when both of these data restrictions are relaxed.

[21] The number of observations in column 7 is significantly smaller because not all buyers added or dropped sellers during the sample period.

4.1 Set-up

We consider a representative industry and build an industry equilibrium model that features global sourcing (domestic sourcing and offshoring). Our model extends AFT to study the pattern of global sourcing and the effect of offshoring on firms' domestic production networks. Similar to BMS, our model considers input suppliers located in multiple domestic regions. Unlike their single-industry models, however, we consider multiple input industries that differ in the degree of product differentiation. We investigate how the differentiation of inputs is related to firms' incentives to outsource inputs, and how it affects the way offshoring firms restructure their individual relationships with suppliers. We also introduce in the model buyers' communication with sellers in an effort to enhance input quality to show that trade costs can endogenously increase with the differentiation of inputs. We first characterize firms' equilibrium global sourcing patterns, before examining how a reduction in foreign input costs affects buyers' choices of domestic suppliers.

4.1.1 Demand

Consider an industry facing only domestic demand.[22] The industry has a continuum set $\mathcal{N}$ of exogenously-given final-good producers of horizontally differentiated products. Consumers have a common love-of-variety utility function that features constant elasticity of substitution (CES), denoted by $\sigma > 1$. Each firm i faces its own demand: $y_i = \frac{p_i^{-\sigma} E}{P^{1-\sigma}}$, where $P = \left[\int_{i \in \mathcal{N}} p_i^{1-\sigma} di\right]^{\frac{1}{1-\sigma}}$ is the price index and E is the total expenditure on the goods. Since final-good producers are the buyers of intermediate inputs in the model, they will be referred to as buyers while input suppliers will often be referred to as sellers.

4.1.2 Final Good Production

Final goods are produced with S different types of inputs, which differ from each other in the degree of product differentiation. The production involves two stages. The first stage is to make S composite inputs, each with a unit mass of differentiated input varieties with the following CES production function:

$$\tilde{x}_{is} = \left[\int_0^1 x_{is}(j)^{\frac{\rho_s - 1}{\rho_s}} dj\right]^{\frac{\rho_s}{\rho_s - 1}},$$

where $\tilde{x}_{is}$ denotes the quantity of composite input $s \in \{1, \cdots, S\}$ that is produced and used by firm i for final-good production, while $x_{is}(j)$ denotes the quantity of variety j of input industry s.

The parameter $\rho_s > 1$, which is the elasticity of substitution between different input varieties in the production of composite input s, is our (inverse) measure of input differentiation. Intuitively, an input is differentiated if it is tailored to the specific needs of a buyer and is therefore difficult to be substituted by other varieties produced by other suppliers. As such, input varieties that are less substitutable are interpreted to be more differentiated. We order input industries such that a

[22] Our empirical analysis will consider multiple buyer industries. Introducing final-good trade would not affect the results qualitatively.

higher index s indicates a higher degree of product differentiation (i.e., $\rho_1 > \rho_2 > \cdots > \rho_S$).

The second stage of the final-good production is to assemble S composite inputs into final goods. The assembly technology of buyer i takes the Cobb-Douglas form:

$$y_i = \varphi_i \prod_{s=1}^{S} \left(\frac{\tilde{x}_{is}}{\beta_s}\right)^{\beta_s},$$

where β_s is the cost share of each input industry in producing final goods while φ_i is buyer i's core productivity.

Each variety j of every input industry s can be insourced or outsourced from a supplier located in one of M domestic regions and M^* foreign regions. In each region $r \in \{1, \cdots, M, M+1, \cdots M+M^*\}$, there are exogenously-given n_{sr} suppliers in each input industry s.[23] A buyer sources each differentiated input variety j from the lowest-cost supplier, which may be the buyer itself (the case represented by $r = 0$) or one of $\sum_{r=1}^{M+M^*} n_{sr}$ input suppliers.

Any input or final-good producer independently draws its input-production productivity z from a Fréchet distribution with a cumulative distribution function defined over $(0, \infty)$ by

$$F_{sr}(z) = e^{-T_{sr} z^{-\theta_s}}, \tag{2}$$

where $T_{sr} > 0$ is positively related with the likelihood of a high-productivity draw while $\theta_s > 1$ governs the variability of the draws. The parameter T_{sr} can vary across final-good producers ($r = 0$) and input producers ($r \neq 0$), as well as across regions.[24]

An input supplier with productivity z has a unit cost of production of $w_r c_s / z$, where w_r is a region-specific cost parameter such as the wage rate while c_s is the cost parameter that is specific to the input industry.

4.1.3 Trade Costs, Buyer-Seller Communication, and Input Quality

Outsourcing involves two types of fixed costs. The first type is the cost to make inputs "outsourceable"(e.g., to codify the design of inputs). Specifically, for each input industry in which a buyer outsources intermediate inputs, it incurs a fixed cost of f, which is assumed to be common across input industries. The second type of fixed costs are those related to searching in a region for the lowest-cost sellers of individual input varieties. Borrowing the insights from AFT, we assume that for every region in which a buyer searches for input suppliers, it incurs an industry-specific fixed cost of f_s. Costly search implies that firms will not source inputs from all regions. With Ω_{is} defined as the set of regions from which firm i sources inputs in industry s, Ω_{is} may be a proper subset of $\{1, \cdots, M, M+1, \cdots, M+M^*\}$. We assume that no fixed cost is required for insourcing, so that a buyer will always insource a fraction of varieties even in the industries that it outsources inputs.

There are also standard iceberg transport costs for domestic and foreign trade of inputs. They

[23] The number of input producers, n_{sr}, is positively correlated with the economic size of region r, and will be absorbed by region and region-sector fixed effects in the regressions below.

[24] Buyers' insourcing is represented by $r = 0$ regardless of the location of the buyer.

take the form $\tau_s(d) = e^{t_s(d)} \geq 1$, where t_s is an industry-specific increasing function of the distance d between a pair of buyer and seller; we measure d by the distance between the buyer's domestic region and the seller's region so that $t_s(0) = 0$.

The transport cost, however, is not the only trade cost that increases with the distance between buyers and sellers. Buyers need to communicate with sellers to make sure that they receive what they want. The cost of face-to-face communication naturally increases with distance, and its benefit clearly depends on the differentiation of the inputs that are traded. Consider a misunderstanding between a pair of buyer and seller about the specification of a product (e.g., size, shape, and color). Low quality parts and components may reduce the quality of final products at the minimum, and can jeopardize the entire production process in the extreme situation.[25] Based on the presumption that the failure of delivering high-quality inputs often arises from miscommunication/misunderstanding between buyers and sellers, we assume that buyers can reduce the probability of failure by engaging in more face-to-face communication.[26]

More specifically, we assume that for each input variety $j \in [0, 1]$ in industry s, a seller's products meet the buyer's expected standard with probability q, and fail to meet the standard with probability $1 - q$. We further assume that in the latter case, all inputs produced by that seller are useless for the buyer. Buyers, however, can affect q by engaging in communication with individual input suppliers, which raises the unit cost of shipped inputs by a multiple of $e^{m(d)q}$, where m is an increasing function of the distance between the buyer and a seller. The marginal communication cost rises with the distance (i.e., face-to-face communication with distant sellers is more costly).

Finally, we assume for simplicity that buyers have all the bargaining power against input suppliers, so that the price of an input equals its unit cost.[27]

This summarizes the setup of the model. Given a productivity distribution $\{\varphi_i\}_{i \in \mathcal{N}}$, each buyer i makes a sequence of decisions as follows:

1. Buyer i as well as each input supplier draws its productivity for input production. Buyer i knows its own productivities for input production for all $j \in [0, 1]$ in every input industry $s = 1, \cdots, S$.

2. In every input industry s, buyer i chooses whether to outsource or not, and pays f for every industry that it has chosen to outsource. In addition, for each industry s that it has chosen to outsource, it selects a set of regions that it searches for input suppliers, and pays f_s for every such region.

[25] Kremer (1993), in his seminal O-ring theory of development, provides several real-world examples about how low-quality inputs can reduce product quality (e.g., garment) at the minimum, and can destroy the final goods completely (e.g., the explosion of the space shuttle Challenger when one of the thousands of the parts, the O-ring, malfunctioned).

[26] Communication involves exchanging ideas about product designs, monitoring the sellers' production processes, among others. There is an extensive literature about how the difficulty of writing complete contracts can result in hold-up and ex-ante underinvestment by both firms. See Antràs (2015) for a book-length analysis of the topic.

[27] Introducing explicit negotiation between buyers and sellers would not change the results qualitatively.

3. For each input variety $j \in [0,1]$ of industry s that it has chosen to outsource, buyer i chooses the lowest-price (inclusive of trade costs) supplier of all the input suppliers in regions in Ω_{is} and itself.

4. For each region $r \in \Omega_{is}$, buyer i chooses the optimal sector-specific intensity of communication with the sellers.

5. Buyer i optimally sets its final-good price, which will be a constant mark-up over its marginal cost.

4.2 Optimal Communication Intensity

We now derive each firm i's optimal communication intensity, characterized by the probability $q = q_{isr}$ that firm i receives high-quality inputs, taking its set of source regions, $\{\Omega_{is}\}_{s=1}^{S}$, as given. For a given set of suppliers in the regions in Ω_{is} and hence a given set of prices for the input varieties of industry s, buyer i chooses q_{isr} to minimize the effective unit cost of the composite input s. Let G_{isr} denote the probability distribution of the price of inputs sourced from region r. Also let I_{isr} denote the set of inputs sourced from region r and $\mu(I_{isr})$ its measure. Due to the law of large numbers, the mass $(1 - q_{isr})\mu(I_{isr})$ of the input varieties sourced from region $r \in \Omega_{is}$ is useless, while the prices of remaining $q_{isr}\mu(I_{isr})$ of input varieties are distributed according to the distribution of G_{isr}. There is no such loss for insourced varieties.

Firm i optimally selects how much it purchases from each seller, given the risk of receiving useless inputs with probability $1 - q_{isr}$. As shown in the Appendix, the resulting unit cost for the composite input s, denoted by $\tilde{c}_{is}$, reflects this risk:

$$\tilde{c}_{is} = \left[\mu(I_{is0}) \int_0^\infty p^{1-\rho_s} dG_{is0}(p) + \sum_{r \in \Omega_{is}} \mu(I_{isr}) \int_0^\infty \left(q_{isr}^{\frac{\rho_s}{1-\rho_s}} p \right)^{1-\rho_s} dG_{isr}(p) \right]^{\frac{1}{1-\rho_s}}. \tag{3}$$

Note that for $r \in \Omega_{is}$, unit cost p is multiplied by $q_{isr}^{\frac{\rho_s}{1-\rho_s}} > 1$. This means that the complete loss of a fraction $1 - q_{isr}$ of the input varieties is equivalent to a uniform increase in the unit costs of varieties by the multiple of $q_{isr}^{\frac{\rho_s}{1-\rho_s}}$; the smaller ρ_s (i.e., the higher the product differentiation), the greater the increment of the cost, measured by $q_{isr}^{\frac{\rho_s}{1-\rho_s}}$.

To alleviate the cost of receiving low-quality inputs, buyer i chooses q_{isr} for each $r \in \Omega_{is}$ to minimize $q_{isr}^{\frac{\rho_s}{1-\rho_s}} p$, which can be written as

$$q_{isr}^{\frac{\rho_s}{1-\rho_s}} p = q_{isr}^{\frac{\rho_s}{1-\rho_s}} w_r c_s e^{[m(d_{ir})q_{isr} + t_s(d_{ir})]} / z,$$

where d_{ir} denotes the distance between buyer i and region r. Solving it out yields

$$q_{isr} = \frac{\rho_s}{(\rho_s - 1)m(d_{ir})}. \tag{4}$$

The communication intensity (or the probability of receiving high-quality inputs) and hence the communication costs decrease with ρ_s and d_{ir}. Buyers have more incentive to enhance the communication with sellers of the more differentiated inputs, since failing to obtain high-quality inputs is more costly due to a lower substitutability between input varieties. The communication incentive diminishes with the distance to the supplier because communication, by assumption, is more costly over longer distance.

4.3 Optimal Sourcing Strategies

Let us turn to the stage in which each buyer i selects a seller for each input variety of industry s, taking the set of source regions as given. We will then solve backward for the optimal set of source regions.

Price of inputs firm i buys from a seller, inclusive of trade costs (i.e., transport costs and communication costs), varies with the seller's productivity z and the distance to the seller's location d_{ir}. In the case of insourcing, price, or the unit cost, of an input variety is $p = z^{-1}w_0c_s$. For an input variety sourced from region r, it equals $p = z^{-1}w_r c_s \exp\left[m(d_{ir})q_{isr} + t_s(d_{ir})\right]$. Note that all the price variations within the source regions come from the differences in sellers' productivities. Thus, as shown in the Appendix, we can apply the results of Eaton and Kortum (2002) to obtain buyer i's sourcing pattern and its costs of final-good production as follows.

The share of input varieties in industry s procured from region r is Φ_{isr}/Φ_{is}, with the sourcing potential, as coined by AFT given by

$$\Phi_{isr} = \begin{cases} T_{s0}(w_0c_s)^{-\theta_s} & \text{if } r = 0 \\ n_{sr}T_{sr}(w_rc_s)^{-\theta_s}\left[\frac{\rho_s}{(\rho_s-1)m(d_{ir})}\right]^{\frac{\rho_s\theta_s}{\rho_s-1}} e^{-\theta_s\left[\frac{\rho_s}{\rho_s-1}+t_s(d_{ir})\right]} & \text{if } r = 1,\cdots,M+M^*, \end{cases} \tag{5}$$

while the sourcing capability by $\Phi_{is} \equiv \Phi_{is0} + \sum_{r\in\Omega_{is}}\Phi_{isr}$. The firm-specific unit cost of the composite input s, which is given in (3), can then be rewritten as

$$\tilde{c}_{is} = \gamma_s\Phi_{is}^{-\frac{1}{\theta_s}}, \tag{6}$$

where $\gamma_s \equiv \Gamma\left(\frac{\theta_s+1-\rho_s}{\theta_s}\right)^{\frac{1}{1-\rho_s}}$, with $\Gamma(x) = \int_0^\infty t^{x-1}e^{-t}dt$ being the gamma function, and $\rho_s < 1+\theta_s$ is assumed to hold.

We can now express the profit function for buyer i, still taking the optimal set of source regions as given. As shown in the Appendix, for a given cost profile $\{\tilde{c}_{is}\}_{s=1}^S$, firm i's unit cost of final-good production can be expressed as

$$\psi_i \equiv \varphi_i^{-1}\Pi_{s=1}^S\gamma_s^{\beta_s}\Phi_{is}^{-\frac{\beta_s}{\theta_s}}. \tag{7}$$

Then, it immediately follows that firm i's profits can be expressed as

$$\begin{aligned}\pi_i(\varphi_i) &= B\psi_i^{1-\sigma} - \sum_{s=1}^{S}\delta_{is}\left[f + \sum_{r\in\Omega_{is}} f_s\right] \\ &= B\varphi_i^{\sigma-1}\Pi_{s=1}^{S}\gamma_s^{\beta_s(1-\sigma)}\Phi_{is}^{\frac{\beta_s(\sigma-1)}{\theta_s}} - \sum_{s=1}^{S}\delta_{is}\left[f + \sum_{r\in\Omega_{is}} f_s\right], \end{aligned} \tag{8}$$

where δ_{is} takes 1 if buyer i outsources some inputs in industry s and it takes 0 if it insources all input varieties in industry s, and

$$B = \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} P^{\sigma-1}E;\quad P = \left[\int_{i\in\mathcal{N}}\left(\frac{\sigma\psi_i}{\sigma-1}\right)^{1-\sigma} di\right]^{\frac{1}{1-\sigma}}. \tag{9}$$

The profit function (8) conveys a lot of information about a firm's optimal sourcing. Outsourcing input varieties in any industry s comes with a fixed cost of f, while adding a new region r for sourcing inputs in industry s comes with an additional fixed cost f_s. But they confer a benefit of lowering the marginal cost of production, due to the expansion of the supplier set (i.e., an increase in Φ_{is}). Buyer i makes an optimal choice of the source regions, described by $\{\Omega_{is}\}_{s=1}^{S}$, based on balancing these costs and benefits.[28]

There is no closed-form solution to the firm's optimal choices of outsourcing and source regions. However, we can still describe the buyer's optimal sourcing strategy through the first-order approximation of changes in $\pi_i(\varphi_i)$ as (8). The increment of $\pi_i(\varphi_i)$ when firm i adds a region, say r_1, to $\Omega_{is_1} = \Omega$, for some industry, say s_1, can be approximated as

$$\pi_i(\varphi_i)|_{\Omega_{is_1}=\Omega\cup\{r_1\}} - \pi_i(\varphi_i)|_{\Omega_{is_1}=\Omega} \approx \frac{\beta_s(\sigma-1)}{\theta_s}\tilde{\pi}_i(\varphi_i)\frac{\Phi_{is_1r_1}}{\Phi_{is_10} + \sum_{r\in\Omega}\Phi_{is_1r}} - f_{s_1}, \tag{10}$$

where $\tilde{\pi}_i(\varphi_i) \equiv B\varphi_i^{\sigma-1}\prod_{s=1}^{S}\gamma_s^{\beta_s(1-\sigma)}\Phi_{is}^{\frac{\beta_s(\sigma-1)}{\theta_s}}$ denotes firm i's operating profits. Whereas the increment of $\pi_i(\varphi_i)$ when it outsources inputs of industry s_1 at all can be approximated as

$$\pi_i(\varphi_i)|_{\Omega_{is_1}=\Omega} - \pi_i(\varphi_i)|_{\Omega_{is_1}=\emptyset} \approx \frac{\beta_s(\sigma-1)}{\theta_s}\tilde{\pi}_i(\varphi_i)\frac{\sum_{r\in\Omega}\Phi_{is_1r}}{\Phi_{is_10}} - \left(f + \sum_{r\in\Omega} f_{s_1}\right), \tag{11}$$

where $\Omega \neq \emptyset$. A region is more likely to be added if Φ_{isr} is greater, which is in turn the case if (i) n_s is larger, (ii) T_{sr} is larger, (iii) w_r is smaller, or (iv) d_{ir} is smaller.

In equilibrium, inputs of industry s are outsourced if and only if (11) is nonnegative. Buyer i basically chooses its source regions for each outsourced industry s by selecting the regions in a descending order from the region with the largest Φ_{isr} to the region with the smallest one as long as adding a region gives the buyer a net benefit. However, such monotonicity of adding source regions

[28] $\Omega_{is} = \emptyset$ if buyer i insources all the input varieties of sector s.

may not always hold if $\beta_s(\sigma-1)<\theta_s$, which AFT calls the substitutes case. The Appendix shows some further details of the industry equilibrium, including its existence and uniqueness.

4.4 Testable Predictions

4.4.1 Global Sourcing

Having derived the industry equilibrium, we now discuss some features of global sourcing. We begin with the relationship between global sourcing and the productivity of buyers and sellers. Equation (8) shows that $\pi_i(\varphi_i)$ is supermodular in Φ_{is} and φ_i (because $\tilde{\pi}_i$ is increasing in φ_i), so that the marginal benefit of expanding the search increases with buyer i's core productivity φ_i. The nesting property–the set of source regions weakly expands with the buyer's core productivity–is also obtained in what AFT calls the complements case (i.e., when $\beta_s(\sigma-1)>\theta_s$).[29] Turning to the seller's productivity, our model predicts a negative correlation between the buyer-seller distance and the seller's productivity, which is similar to a finding of BMS. It follows from (4) that the effective price of inputs outsourced from region r can be written as

$$q_{isr}^{\frac{\rho_s}{1-\rho_s}}p=z^{-1}w_r c_s\left[\frac{(\rho_s-1)m(d_{ir})}{\rho_s}\right]^{\frac{\rho_s}{\rho_s-1}}\exp\left[\frac{\rho_s}{\rho_s-1}+t_s(d_{ir})\right].$$

The effective price of inputs sourced from a region increases with its distance from the buyer due to the increasing trade costs, both due to a smaller chance of receiving high-quality inputs and greater transport costs, while the distributions of the effective price of the inputs outsourced are common across the source regions as in Eaton and Kortum (2002). Consequently, inputs supplied from farther regions tend to be produced by more efficient firms than those in closer regions. Interpreting these results from the viewpoint of domestic versus foreign sourcing, we predict that buyers with higher productivity tend to source from foreign suppliers and that foreign trade partners tend to be more productive than the domestic ones.

Let us turn to the examination of how buyers' sourcing strategies depend on the degree of input differentiation. First, we show that the likelihood of outsourcing is negatively related to input differentiation. It follows from (5) that the ratio of region r_1's sourcing potential to firm i's insourcing potential can be expressed as

$$\frac{\Phi_{isr_1}}{\Phi_{is0}}=n_{sr_1}\left(\frac{T_{sr_1}}{T_{s0}}\right)\left(\frac{w_0}{w_{r_1}}\right)^{\theta_s}\left[\frac{\rho_s}{(\rho_s-1)m(d_{ir_1})}\right]^{\frac{\rho_s\theta_s}{\rho_s-1}}e^{-\theta_s\left[\frac{\rho_s}{\rho_s-1}+t_s(d_{ir_1})\right]}. \tag{12}$$

It can be readily shown that Φ_{isr_1}/Φ_{is0} is increasing in ρ_s. Since buyers choose a higher intensity of communication for the more differentiated inputs, insourcing is relatively more appealing to them for such inputs because they need not engage in costly communication in the case of insourcing. Once a buyer chooses to outsource some input varieties, it will then choose the optimal set of source

[29] In the substitutes case, some region may not be included in Ω_{is} even though its Φ_{isr} is greater than $\Phi_{isr'}$ of another region $r'\in\Omega_{is}$, if an inclusion of region r significantly reduces the profitability of keeping other regions in Ω_{is}.

regions. We show next that the negative distance effect on the sourcing potential is greater for the more differentiated inputs. To compare the sourcing potential of region r_1 with that of another region r_2, where $d_{ir_1} > d_{ir_2}$, we obtain from (5) the ratio of the sourcing potentials as

$$\frac{\Phi_{isr_1}}{\Phi_{isr_2}} = \left(\frac{n_{sr_1}}{n_{sr_2}}\right)\left(\frac{T_{sr_1}}{T_{sr_2}}\right)\left(\frac{w_{r_2}}{w_{r_1}}\right)^{\theta_s}\left[\frac{m(d_{ir_2})}{m(d_{ir_1})}\right]^{\frac{\rho_s\theta_s}{\rho_s-1}} e^{-\theta_s[t_s(d_{ir_1})-t_s(d_{ir_2})]}. \tag{13}$$

The multiplicative terms that involve distance, i.e., $[m(d_{ir_2})/m(d_{ir_1})]^{\frac{\rho_s\theta_s}{\rho_s-1}} e^{-\theta_s[t_s(d_{ir_1})-t_s(d_{ir_2})]}$, are less than 1, which implies that the sourcing potential of the farther region r_1 tends to be smaller than that of the closer region r_2. Moreover, $\Phi_{isr_1}/\Phi_{isr_2}$ is smaller, the greater is the input differentiation (i.e., the smaller is ρ_s). Thus, we have shown that the more differentiated inputs are more likely to be completely insourced and that distance matters more for the differentiated inputs in firms' outsourcing decisions.

Proposition 1 *The share of input varieties insourced and the share of input varieties sourced from closer regions are both greater for the more differentiated inputs.*

4.4.2 Reduction in Foreign Input Costs and Restructuring of Production Networks

We now examine how a reduction in foreign input costs affects firms' offshoring decisions and their domestic sourcing strategies. We consider any changes that increase Φ_{isr^*} for some foreign region $r^* \in \{M+1, \cdots, M+M^*\}$, including a fall in w_{r^*} or an increase in T_{sr^*}.

An increase in Φ_{isr^*} makes region r^* more attractive than before for all buyers. Consider the case in which an increase in Φ_{isr^*} induces some buyers to start sourcing inputs from region r^*. Their individual sourcing capabilities, Φ_{is}, increase as a result, leading to lower marginal costs of production. The buyers that have been outsourcing some inputs from region r^* even before a reduction in foreign input costs also enjoy a reduction in their marginal costs, while those that do not source any inputs from region r^* experience no change in their marginal costs.

As the costs of offshoring from region r^* decrease, the marginal costs of production for both continuous importers and import starters from region r^* fall. Consequently, the price index P falls and so does the demand shifter B in (9). Due to this increased intensity of product market competition, not all the firms that import some inputs from region r^* benefit from the reduction in foreign input costs. As shown in (8) and (9), their operating profits increase if and only if the increase in Φ_{is} is large enough that $P^{\sigma-1}\Pi_{s=1}^{S}\Phi_{is}^{\frac{\beta_s(\sigma-1)}{\theta_s}}$ rises despite a fall in P.

Import starters restructure their production networks. In particular, offshoring directly induces them to replace some domestic sellers (and themselves as input producers) with foreign sellers. In addition to this direct effect, the import starters and continuous importers may restructure their production networks as a consequence of the reduction in their marginal costs (which can be referred to as the productivity effect). Their operating profits unambiguously increase relative to those of non-importers, since a reduction in P affects all the final-good producers equally. Thus, it follows from (10) and (11) that the incentive for import starters, in particular, to begin outsourcing inputs in an industry and to expand search regions increases, relative to non-importers. Consequently, for each input industry, some import starters restructure their domestic supplier networks by adding distantly-located and productive sellers while dropping the less productive ones in all other source regions as each region r's share of input varieties, Φ_{isr}/Φ_{is}, decreases when Φ_{is} increases after offshoring.[30] The following proposition summarizes the testable predictions about the effect of a fall in foreign input costs on the structure of import-starters' domestic production networks.

Proposition 2

1. *Relative to non-importers, import starters drop in every source region sellers that are on average less productive than others in the same industries. This extent of dropping is more profound in the newly-offshored industries, since the direct replacement effect that some domestic suppliers are replaced by foreign suppliers is always present. Since offshoring industries tend to be less differentiated, the dropped sellers in offshoring industries tend to be more productive and located farther than sellers in other industries.*

2. *Relative to non-importers, import starters add sellers that are on average more productive and located farther than other firms within each previously-outsourced industry. Some of them add sellers in the newly-outsourced input industries. The sellers added in the newly-outsourced industries tend to be located closer than those in the previously-outsourced industries, since offshoring induces buyers to begin outsourcing inputs that tend to be more differentiated.*

Offshoring leads to the restructuring of domestic production networks, thereby affecting industry coagglomeration. The direct impact of offshoring induces coagglomeration as the sellers directly replaced by foreign sellers tend to be located farther as they produce less differentiated inputs than sellers in other industries. The productivity effects of offshoring on industry coagglomeration are mixed. On the one hand, import starters replace the less productive sellers with the more productive ones, which are located farther than others within the same industries. On the other hand, they may begin outsourcing inputs in the relatively more differentiated industries so that they add sellers located closer than those in other industries. Thus, we have the following proposition.

Proposition 3 *Although the effects of offshoring on industry coagglomeration are mixed, it induces industry coagglomeration if the direct replacement effect is greater than the indirect productivity effect.*

As shown in the Appendix, the direct replacement effect is more likely to dominate the productivity effect if the overall and region-specific fixed sourcing costs are large. Whether offshoring entails industry coagglomeration depends on the relative strength of the three effects, which we explore empirically in Section 5.3.

[30] We assume in this section that the distribution of $\{\varphi_i\}_{i\in\mathcal{N}}$ has a support that is wide enough to induce some import starters to restructure their domestic supplier networks as their marginal costs of production decrease.

5 Regression Analyses and Results

In this section, we empirically examine the three testable hypotheses derived in Section 4. For notational clarity, let us denote buyer, seller, industry (3-digit), and region (one of 47 prefectures) by i, j, s, and r, respectively. Notice that when industry and region fixed effects are included, we will be clear about whether they are for the buyer or seller.

5.1 Domestic Sourcing Patterns

We first examine whether our theoretical predictions about the patterns of firms' domestic sourcing are observed in the data. Equation (13) shows that firm i's spatial pattern of domestic sourcing in industry s can be described by $\Phi_{isr_1}/\Phi_{isr_2}$, the ratio of the mass of input varieties procured from region r_1 to that from region r_2. Let us denote firm i's reference region of sourcing in industry s by $r_s(i)$, and use it to define the denominator, $\Phi_{isr_s(i)}$. It can be buyer i's home region or the nearest region from which it sources inputs. We study the determinants of buyer i's sourcing patterns according to the log of (13):

$$\log \frac{\Phi_{isr}}{\Phi_{isr_s(i)}} = \underbrace{-\log n_{sr_s(i)} - \log T_{sr_s(i)} + \theta_s \log w_{r_s(i)} + \frac{\rho_s \theta_s}{\rho_s - 1} \log m(d_{ir_s(i)})}_{\text{input-industry reference-region-specific}} \tag{14}$$

$$+ \underbrace{\log n_{sr} + \log T_{sr} - \theta_s \log w_r}_{\text{input-industry source-region-specific}}$$

$$- \theta_s \frac{\rho_s}{\rho_s - 1} \times \log m(d_{ir}) - \theta_s t_s(d_{ir})$$

We measure $\Phi_{isr}/\Phi_{isr_s(i)}$ by $N^{seller}_{isr}/N^{seller}_{isr_s(i)}$, the ratio of the number of industry-s sellers in region r from which buyer i purchases inputs, relative to the counterpart in buyer i's reference source region. Notice that the first four terms are specific to the pair of an input industry and the buyer's reference source region, while the next three terms are specific to the pair of an input industry and source region. Instead of estimating each individual component (e.g. T_{sr}), we include input-industry buyer-reference-region and input-industry source-region fixed effects to absorb all seven terms in the regressions. The main variable of interest is $\theta_s \frac{\rho_s}{\rho_s - 1} \log m(d_{ir})$, while $\theta_s t_s(d_{ir})$ will be controlled for by an interaction term that proxies for the input-industry-specific variable trade costs.

To quantify the effect of communication costs versus standard trade frictions, we parameterize $\log m(d_{ir})$ and $t_s(d_{ir})$ as follows:

$$\log m(d_{ir}) = \log d_{ir}^{\beta}$$
$$t_s(d_{ir}) = \log d_{ir}^{\gamma \phi_s}$$

where ϕ_s captures the time sensitivity of the delivery of inputs.

With these parametrizations, we can express the empirical counterpart of (14) as[31]

$$\log \frac{N_{irs}^s}{N_{isr(i)}^s} = -\beta \left[\frac{\rho_s \theta_s}{\rho_s - 1} \log(d_{ir})\right] - \gamma \left[\phi_s \theta_s \log(d_{ir})\right] + \left[FE_{sr(i)} + FE_{sr}\right] + \varepsilon_{irs}, \tag{15}$$

where an industry is defined as a JSIC 3-digit category.[32] $FE_{sr_s(i)}$ and FE_{sr} stand for input-industry reference-region and input-industry source-region fixed effects, respectively.[33] With these fixed effects included, we study the relationship between a buyer's scope of domestic sourcing and the proximity of each region (relative to the reference region from which it sources the same type of inputs).

To estimate $-\beta$ and $-\gamma$, we need to construct industry-specific parameter, ρ_s, θ_s and ϕ_s. We measure ρ_s with the estimated elasticity of substitution between varieties in each industry s imported into the US from Soderbery (2015), who improved the parameters originally estimated by Broda and Weinstein (2006). Since the focus of the paper is firms' sourcing of intermediate inputs, we exclude capital and consumption goods according to the United Nations Broad Economic Categories (BEC) list, when constructing $\rho_s/(\rho_s - 1)$. We adopt the estimates of θ_s from Caliendo and Parro (2015), at roughly the 2-digit industry level. Details about the data sources, concordances, definitions and construction of each industry-level variable are described in the data appendix.

Table 4 reports the estimates of $-\beta$ and $-\gamma$, according to (15). Standard errors are clustered at the industry-source-region level. In columns 1 to 3, we use each buyer's nearest source region for each industry as the reference region, while in columns 4 through 6, we use the buyer's home region. As reported in column 1, we find that a buyer procures from fewer sellers from a distant region. Specifically, relative to the nearest region, a 10% increase in the distance will lower the number of sellers by 0.5% for an industry with a median value of θ_s (9.82).[34] Column 2 shows that such negative correlation is more pronounced for the more differentiated inputs, as proxied by $\rho_s/(\rho_s - 1)$. A one standard-deviation increase in $\rho_s/(\rho_s - 1)$ (0.262) from the sectoral mean (1.328) is associated with an additional 0.13% decline in the number of sellers for the same 10% increase in distance, evaluated at the same median value of θ_s. Column 3 shows that the results remain robust after we control for the interaction between $\log(d_{ir})$ and the share of air-transported imports into a US industry, ϕ_s (Hummels and Schaur, 2013). The results remain quantitatively more significant when we use the buyer's home region as the reference region (see columns 4 to 6), or when we use the 2010 sample (see Table A5 in the appendix), or when we include the parent-children relationships (results available upon request).

In Table 5, we empirically examine the pattern of firms' global sourcing at the extensive margin

[31] We use capital city of the prefecture to compute the distance.

[32] We aggregate information from JSIC 4-digit to 3-digit because at the 4-digit level, a firm is unlikely to procure inputs from multiplier prefectures. All our empirical results remain largely robust to including 4-digit input industry and buyer industry fixed effects. Results are available upon request.

[33] These fixed effects can capture any unobserved characteristics of a buyer's location and industry (e.g., infrastructure of agglomeration effects), as well as a seller's location and industry.

[34] $-0.47\% = -0.00535 \times 0.1 \times 9.82$.

(i.e., whether a buyer is sourcing from a region or not). Since we only have information on firms' foreign sourcing at the broad sector level (12 manufacturing sectors) from BSJBSA, we consider a firm's participation in domestic and foreign sourcing respectively at the broad sector level. Information for firms' domestic sourcing at the more disaggregated industry level are aggregated to the broad sector level, accordingly.[35] We also compute the weighted average of input industries' characteristics across 3-digit industries within a broad sector. The procedures are described in detail in the data appendix.

In the first six columns, we empirically examine the extensive-margin version of specification (15), by replacing the dependent variable with a dummy for whether buyer i sources intermediates from source region r in industry s. Since we no longer use information of the reference source region to define the dependent variable, we drop $FE_{sr_s(i)}$ as a regressor. Instead, we include input-industry source-region (FE_{sr}) fixed effects and also buyer fixed effect to control for any unobservable determinants of domestic sourcing. With input-industry source-region fixed effects included, we find in columns 1 through 3 that a buyer's likelihood of sourcing inputs from a prefecture is decreasing in its distance from it (column 1), more so for the more differentiated inputs (columns 2 and 3). These regression results remain robust and quantitatively similar after we control for buyer fixed effects (columns 4 to 6). We find that the cross-industry variation in the "distance effect" on the incidence of domestic sourcing is economically significant. Based on the coefficients reported in column 4, a 10% increase in distance is associated with a 0.1 percentage-point decline in the likelihood of sourcing from the region, evaluated at the mean value of θ_s.[36] Based on the estimates in column 5 and the mean value of θ_s, the same distance is associated with an additional 0.1 percentage-point decline in the likelihood of sourcing for industries with a one standard-deviation larger $\rho_s/(\rho_s-1)$ relative to the sectoral mean.[37]

In columns 7 and 8, we examine the determinants of a firm's engagement in offshoring in an input industry. Without detailed information about the source country of offshoring, we examine Proposition 1 on offshoring by including a buyer's (log) TFP and the interaction term between (log) TFP and $\rho_s/(\rho_s-1)$. Our model predicts that more productive firms will be more likely to incur the fixed costs to offshore intermediates. Given that the trade costs will be increasing in input industry's product differentiation, such positive relationship should be weaker for the more differentiated inputs. We find a positive and significant correlation between a buyer's productivity and the likelihood that it offshores inputs, after controlling for input-industry source-region fixed effects. The productivity effect on offshoring is weakened in the more differentiated input industries. These results remain robust even after we control for buyer fixed effects in column 8. We also find

[35] For instance, the dummy for a firm's domestic sourcing is set equal to 1 for a broad sector if the firm outsources in any 3-digit industry that belongs to the sector.

[36] Using the coefficient on $ln(dist+1)\times\theta_s$ (=−0.001) and the median value of θ_s (=9.82) we come up with $0.098\% = -0.001 \times 0.1 \times 9.82$.

[37] Given that the mean and the standard deviation of $\rho_s/(\rho_s-1)$ are 1.328 and 0.262 (across 3-digit industries, see Table A in the appendix), respectively, the increase in the likelihood of sourcing from a region is $-0.004 \times \underbrace{0.262}_{\text{std of } \rho_s/(\rho_s-1)} \times \underbrace{9.82}_{\overline{\theta}_s} \times 0.1 * 100$.

that a buyer's domestic sourcing in an input industry is positively related to the likelihood of offshoring in the same industry. This result implies that fixed costs to offshore could be lower if a firm already incurs some of them for domestic sourcing. This pattern of sequential sourcing will be the basis for the construction of our instrument discussed in the following section.

5.2 Instruments

To gauge the causal effects of offshoring, we propose a set of instruments at the buyer level. We follow the existing research (e.g., Autor, Dorn, and Hanson (2013); ADH hereafter) to estimate industry-level gravity equations and take the time-varying residuals as export supply shocks from Japan's major trade partners over the period of 2005-2010. We do not aim to distinguish the reasons for why exports increase in certain industries and countries. They could happen because of substantial declines in trade costs and/or increases in productivity of exporting countries.[38] To reduce the dimension of estimation, we estimate the export supply shocks from Japan's top 20 trade partners in 2005 at the SITC (rev. 2) 4-digit level, with the 21st trade partner being the summation of all other trade partners. We also restrict the set of destination countries to EU 15 countries plus the US, similar to ADH and AFT.

To construct the instruments for offshoring at the firm level, we exploit the information about the sectoral pattern of domestic sourcing of each firm. In Table 5, we find that firms are more likely to offshore inputs in an industry if it has already sourced them domestically. These results are suggestive of a lower fixed cost of offshoring in a particular industry, after a firm sourced some inputs in the industry. Foreign countries' export supply shocks in an industry are more likely to induce a Japanese firm to start offshoring if it has already outsourced inputs in the same industry. Based on these findings, we merge a firm's sectoral pattern of domestic outsourcing with that of the vector of estimated export supply shocks.

More specifically, the construction of the firm-level instruments based involves four steps. First, we begin with the estimation of a gravity equation of bilateral exports, relative to Japanese exports, similar to ADH:

$$\ln\left(X_{sck}\right) - \ln\left(X_{sJk}\right) = \ln\left(A_{sc}\right) - \ln\left(A_{sJ}\right) - \left(\sigma_s - 1\right)\left[\ln\left(\tau_{sck}\right) - \ln\left(\tau_{sJk}\right)\right], \tag{16}$$

where X_{sck} and X_{sJk} are dollar value of industry-i exports to country k from country c and Japan (J), respectively. σ_s is the elasticity of substitution between different available varieties in industry s. A_{sc} and A_{sJ} are the export capabilities of country c and Japan in industry s. τ_{sck} and τ_{sJk} are iceberg trade costs facing firms in country c when exporting industry-s goods to country k.

Notice that both A's and τ's vary across time for both countries. To estimate the right hand side of equation (16), we run the following regression:

$$\ln\left(X_{sckt}\right) - \ln\left(X_{sJkt}\right) = \alpha_{sc} + \alpha_{kc} + \varepsilon_{sckt}, \tag{17}$$

[38] Notice that ADH (2013) focus on the trade shocks from China only, while our trade shocks can come from any Japan's major trade partners.

where in theory,

$$\varepsilon_{sckt} = \left[\ln\left(\frac{A_{sct}}{A_{sJt}}\right) - \alpha_{sc}\right] + \left[-(\sigma_s - 1)\ln\left(\frac{\tau_{sckt}}{\tau_{sJkt}}\right) - \alpha_{kc}\right]. \tag{18}$$

In equation (18), the variable α_{sc} captures the initial (log) difference in the comparative advantage in industry s between country c and Japan, while the variable α_{kc} stands for the initial (log) difference in the barriers against exports in industry s to destination k between the two countries, including any geographic and historical factors that affect exports from the two countries to country k. $\ln\left(\frac{A_{sct}}{A_{sJt}}\right)$ and $\ln\left(\frac{\tau_{sckt}}{\tau_{sJkt}}\right)$ are the corresponding time-varying counterparts of these differences. Subtracting these time-varying variables from their corresponding initial values yields ε_{sckt}, which represents a destination-industry-specific export supply shock relative to Japan's. Note that positive export-supply shocks can be due to either an improvement in exporting country c's productivity or a reduction in the trade costs it faces in destination k, including the increase in its demand for goods in industry s. We obtain $\widehat{\varepsilon}_{sckt}$ by estimating equation (17).

The second step of the construction of the instruments takes an average over the export-supply shocks across destinations and years within each origin-country-industry. We then compute the average export supply shocks from each exporting country and industry over the period of 2005-2010 as:

$$\overline{\triangle\varepsilon_{sc}} = \frac{1}{5}\frac{1}{N_{sc}}\sum_{t=2006}^{2010}\sum_{k\in\Psi_{sc}}\triangle\varepsilon_{sckt},$$

where Ψ_{sc} is the set of export destinations of country c in industry s, and N_{sc} is the number of destinations.

In the third step, we compute the weighted average of export supply shocks at the industry level, by using weights, ω_{sc}, equal to the share of imports from country c in total Japanese imports of good s:

$$shock^s = \sum_{c}^{c=N_{s,05}} \omega_{sc}\overline{\triangle\varepsilon_{sc}},$$

where $N_{s,05}$ is the number of Japan's trade partners in industry s and 2005.

Finally, we construct a vector of instruments for each buyer i as

$$shock_i = \begin{pmatrix} \phi_{i1} shock^1 \\ . \\ . \\ \phi_{iN} shock^S \end{pmatrix}, \tag{19}$$

where ϕ_{is} is a dummy, which equals 1 if buyer i outsources industry-s inputs domestically. We construct such instruments at the 2-digit Japanese SIC level. $S = 35$ since there are 35 2-digit SIC categories.[39]

[39] The idea of using a vector of instruments rather than one instrument is inspired by Bastos, Silva, and Verhoogen (2016). Alternatively, we can use the simple average of the $\phi_{is} shock^s$ across industries for each firm as an instrument.

5.3 Relationship between Firms' Global Sourcing and Domestic Supplier Choices

The final part of the paper studies Propositions 2 and 3, which are about the effect of firms' offshoring on their choices of domestic suppliers. We first examine whether the likelihood of a buyer's dropping domestic suppliers is associated with its exogenously induced offshoring decision. To this end, we estimate the following specification using our two-year panel data on Japan's production networks (2005 and 2010):

$$I_{ij} = \beta \Delta imp_i + \gamma \Delta imp_i \times (x_{ij}/\overline{x}_i) + \delta \ln (sales)_i + \left[FE_s^b + FE_r^b + FE_s \right] + \varepsilon_{ij}, \tag{20}$$

where I_{ij} is a dummy variable indicating whether buyer i drops (or adds) seller j between 2005 and 2010. When we run the "drop" regressions, the dependent variable is defined as $I_{ij} = Drop_{ij}$, which is equal to 1 if seller j and buyer i were linked in 2005 but not anymore in 2010, and 0 otherwise (if the relationship continued). When we run the "add" regressions, the dependent variable is defined as $I_{ij} = Add_{ij}$, which is equal to 1 if a link between seller j and buyer i is observed for 2010, but not in 2005, and 0 otherwise (indicating old relationships).[40]

The variable Δimp_i is a change in the importing status to indicate firm i's switching from no offshoring (in 2005) to offshoring (between 2005 and 2010). In other words, this specification requires the use of a sample of firms that did not offshore in 2005 to gauge the effect of the extensive margin of offshoring on the firms' domestic production networks. The regressor of interest is the interaction term $\Delta imp_i \times (x_{ij}/\overline{x}_i)$, where $x_{ij}/\overline{x}_i$ represents a measure of a supplier's characteristic, relative to the average of the buyer's existing (2005) suppliers' characteristics. We consider a relative measure rather than the absolute one since the decisions to add and drop suppliers are buyer-specific. More specifically, when we run the "drop" regressions, $\overline{x}_i$ is constructed using the sample of sellers from which the buyer procured inputs in 2005. On the other hand, when we run the "add" regressions, $\overline{x}_i$ is constructed using sellers from which the buyer procured inputs in 2010 (i.e., those that were dropped since 2005 will not be included in the construction of the buyer's mean). Standard errors are clustered by input industry. We consider two seller characteristics– size (measured by either sales or employment) and distance from a buyer. Input-industry fixed effects (FE_s) are always included in all specifications. We always include buyer-industry (FE_s^b) and buyer-region (FE_r^b) fixed effects to control for any region- and industry-specific trends of supplier adding and dropping, such as external economies of scale for different industries, initial conditions for economic development, or local government policies.[41]

To establish causality, we use the vector $shock_i$ proposed in (19) as a set of instruments for

There are two issues with this approach. First, a larger (more productive) buyer tends to have a larger sectoral scope of sourcing and thus have more ϕ_{is} equal to 1. Second, the dummies do not capture the intensive margin of sourcing or offshoring, implying the simple average may not be informative about the exposure to the export supply shocks.

[40] Readers are reminded that the results for the add regressions should not be interpreted as the effects on the likelihood of sourcing. The correct way to interpret the results is the difference in the seller characteristics under study between new and continuing relationships.

[41] When we control for buyer fixed effects, the coefficients on the interactions have the same sign and remain significant. The drawback is that we will no longer be able to identify the independent effect of Δimp_i on buyers' supplier adding and dropping.

Δimp_i, and a vector of $shock_i \times (x_{ij}/\overline{x}_i)$ as a set of instruments for $\Delta imp_i \times (x_{ij}/\overline{x}_i)$ to estimate specification (20) via two-stage least squares (2SLS). Table 6 reports both the OLS and 2SLS results of estimating (20), based on the sample of all buyers in the manufacturing sector that sourced inputs only domestically in 2005. As reported in columns 1 to 4, the OLS estimates on Δimp_i and $\Delta imp_i \times (x_{ij}/\overline{x}_i)$ take the expected signs but are all insignificant. The 2SLS estimates in columns 5 to 8 show statistically significant results. In column 5, the estimate on Δimp_i shows that a buyer's offshoring decision reduces the likelihood of dropping suppliers. Within buyer industries, buyer home regions, and input industries, a buyer that started importing since 2005 is on average 8.9% less likely to drop its existing sellers between 2005 and 2010. In column 6, we find that even though newly offshoring firms tend to be less likely to drop domestic suppliers, they are *relatively* more likely to drop the more distant (column 6) and larger (columns 7 and 8) ones. All F statistics for the first stages of these 2SLS estimations suggest that our instruments pass the weak instrument test by a wide margin.

In Table 7, we estimate the "add" regressions based on specification (20). Columns 1 to 4 report the OLS estimates. It is not surprising that there is a positive correlation between a firm's import dummy and likelihood of having a new domestic supplier. For instance, a positive productivity shock will induce a firm to add both domestic and foreign suppliers. As reported in columns 5 to 8, the 2SLS estimates show that the newly offshoring firms are less likely to add distant suppliers (column 6), but more likely to add larger domestic suppliers (columns 7 and 8). The findings that newly offshoring firms are relatively more likely to drop but more likely to add larger suppliers seem to be contradictory. However, through the lens of our model, these results can be rationalized by the joint force of the direct replacement and productivity effects of offshoring. The findings that larger domestic suppliers are more likely to be dropped can be a result of offshoring firms' substituting non-differentiated domestic suppliers, which tend to be larger and more distantly located, with foreign suppliers. The results that larger domestic suppliers are more likely to be added can be due to the productivity effect of offshoring that induces firms to add more productive and distant domestic suppliers within each industry. The fact that more distant suppliers are less likely to be added can be explained by the industry composition effect– differentiated input industries, from which a buyer previously did not source inputs, are now being added to the buyer's sourcing set. To save communication costs, the buyer will source from closer domestic suppliers in the newly added differentiated input industries.

To further study the three effects of offshoring, especially the industry composition effect, we empirically examine the relationship between firms' offshoring and the pattern of adding and dropping input industries. To this end, we estimate the following specification:

$$I_{is} = \beta_s \Delta imp_i \times X_s + [FE_i + FE_s] + \xi_{is}, \tag{21}$$

where I_{is} is a dummy variable indicating whether buyer i drops (or adds) industry s between 2005 and 2010. When we run the "drop" regressions, the dependent variable is defined as $I_{is} = Drop_{is}$, which is equal to 1 if buyer i sourced inputs in industry s in 2005 but stopped sourcing in the same industry in 2010, and 0 otherwise. On the other hand, when we run the "add" regressions, the dependent variable is defined as $I_{is} = Add_{is}$, which is equal to 1 if buyer i did not source in industry s in 2005 but started sourcing in that industry in 2010, and 0 otherwise. The variable of interest, $\Delta imp_i \times X_s$, is an interaction term between the change in buyer i's importing status and industry s's product differentiation, measured by either the Rauch indicator or $\rho_s/(\rho_s - 1)$. The regression sample includes the sample of firms that did not import in 2005. Input-industry fixed effects (FE_s) and buyer fixed effects (FE_i) are always included.

Table 8 presents the estimates of (21) via OLS and 2SLS. The 2SLS estimates show that newly offshoring firms are less likely to drop (as measured by the Rauch indicator in column 3) but more likely to add domestic suppliers in the more differentiated input industries (columns 7 and 8). These pattern of input industry adding and dropping support the model predictions, and are consistent with the findings that distant suppliers are less likely to be added but more likely to be dropped after a firm offshores inputs.

6 Concluding Remarks

In this paper, we study from both theoretical and empirical perspectives the spatial and sectoral patterns of firms' global sourcing, as well as the effect of offshoring on firms' domestic production networks. We develop a multi-region global sourcing model in which firms source inputs from suppliers in various input industries that differ in the degree of product differentiation. Firms choose the optimal level of communication with suppliers, depending on the inputs' product differentiation.

Using exhaustive data on buyer-seller links in Japan, we find that the more productive firms source inputs from more suppliers and domestic regions, including the more distant ones. Distant suppliers are more productive on average, while productive firms are more likely to offshore inputs. The negative distance effects on domestic sourcing are stronger for the more differentiated inputs. Using a firm-level instrument based on buyers' sectoral patterns of domestic sourcing and foreign countries' export supply shocks across industries, we find that offshoring induces firms to add and drop larger domestic suppliers, but drop more distant suppliers on the net. This reorganization of domestic supplier relationships reduces the average distance between buyers and sellers in Japan, increasing the spatial concentration of domestic production networks.

Scholars have postulated that distance has become less relevant for market transactions, thanks to increasing efficiency in information, communication, and transportation (Friedman, 2005). Indeed, firms' global sourcing implies a wider geographic dispersion of production activities. Our paper offers explanations for how market transactions can paradoxically become more localized when markets are more globalized (Baldwin, 2013; World Trade Organization, 2013). Understanding the macroeconomic implications of the localization of production networks is a promising avenue for research.

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A Appendix for the Theory

A.1 Firm's Cost Minimization Problem

Given a distribution function of the prices for the input varieties for every sector s, which is denoted by $G_{isr}(p)$, firm i chooses the input levels $\{x_{isr}(p)\}_{p\in[0,\infty)}$ to minimize the cost of producing composite input s. The unit cost function for firm i is the solution to the minimization problem:

$$\min_{\{x_{isr}(\cdot)\}_{r\in\{0\}\cup\Omega_{is}}} \sum_{r\in\{0\}\cup\Omega_{is}} \mu(I_{isr}) \int_0^\infty p x_{isr}(p) dG_{isr}(p)$$

$$\text{s.t} \left[\mu(I_{is0}) \int_0^\infty x_{is0}(p)^{\frac{\rho_s-1}{\rho_s}} dG_{is0}(p) + \sum_{r\in\Omega_{is}} q_{isr}\mu(I_{isr}) \int_0^\infty x_{isr}(p)^{\frac{\rho_s-1}{\rho_s}} dG_{isr}(p)\right]^{\frac{\rho_s}{\rho_s-1}} \geq 1.$$

By solving this problem, we obtain the optimal input levels as

$$x_{is0}(p) = p^{-\rho_s} \left[\mu(I_{is0}) \int_0^\infty p^{1-\rho_s} dG_{is0}(p) + \sum_{r\in\Omega_{is}} \mu(I_{isr}) \int_0^\infty \left(q_{isr}^{\frac{\rho_s}{1-\rho_s}} p\right)^{1-\rho_s} dG_{is0}(p)\right]^{\frac{\rho_s}{1-\rho_s}},$$

$$x_{isr}(p) = p^{-\rho_s} q_{isr}^{\rho_s} \left[\mu(I_{is0}) \int_0^\infty p^{1-\rho_s} dG_{is0}(p) + \sum_{r'\in\Omega_{is}} \mu(I_{isr'}) \int_0^\infty \left(q_{isr'}^{\frac{\rho_s}{1-\rho_s}} p\right)^{1-\rho_s} dG_{is0}(p)\right]^{\frac{\rho_s}{1-\rho_s}}, \text{ for } r \in \Omega_{is}.$$

Substituting these solutions to $\sum_{r\in\{0\}\cup\Omega_{is}} \mu(I_{isr}) \int_0^\infty p x_{isr}(p) dG_{isr}(p)$ gives us the unit cost $\tilde{c}_{is}$ given in (3).

A.2 Optimal Sourcing and the Unit Cost of Final Good Production for a Given Sets of Source Regions

The unit cost of inputs equals $p = z^{-1} w_0 c_s$ for insourced inputs, while it equals

$$q_{isr}^{\frac{\rho_s}{1-\rho_s}} p = z^{-1} q_{isr}^{\frac{\rho_s}{1-\rho_s}} w_r c_s e^{[m_s(d_{ir})q_{isr}+t_s(d_{ir})]}$$

for inputs outsourced to sellers in region r. Following Eaton and Kortum (2002), therefore, we obtain the distribution function of effective prices, $\tilde{p} \equiv q_{isr}^{\frac{\rho_s}{1-\rho_s}} p$, for each source region r as

$$\tilde{G}_{isr}(\tilde{p}) = 1 - e^{-\Phi_{isr}\tilde{p}^{\theta_s}}, \text{ for } r \in \{0\} \cup \Omega_{is},$$

where Φ_{isr} is defined in (5).

The input-price (or input-cost) probability distribution for every input variety of type s is common across the source regions and can be written as

$$\tilde{G}_{is}(\tilde{p}) = 1 - e^{-\Phi_{is}p^{\theta_s}}, \text{ where } \Phi_{is} = \Phi_{is0} + \sum_{r\in\Omega_{is}} \Phi_{isr};$$

and hence the unit cost of the composite input s is given by $\tilde{c}_{is} = \gamma_s \Phi_{is}^{-\frac{1}{\theta_s}}$, where $\gamma_s \equiv \Gamma\left(\frac{\theta_s+1-\rho_s}{\theta_s}\right)^{\frac{1}{1-\rho_s}}$. For a given cost profile $\{\tilde{c}_{is}\}_{s=1}^{S}$, the optimal level of the composite input s to produce each unit of the final good equals $\tilde{x}_{is} = \frac{\beta_s}{\varphi_i \tilde{c}_{is}} \Pi_{j=1}^{S} \tilde{c}_{ij}^{\beta_j}$. Consequently, the unit cost of a final good is given by

$$\psi_i \equiv \sum_{s=1}^{S} \tilde{c}_{is}\tilde{x}_{is} = \frac{1}{\varphi_i}\Pi_{s=1}^{S}\tilde{c}_{is}^{\beta_s} = \frac{1}{\varphi_i}\Pi_{s=1}^{S}\gamma_s^{\beta_s}\Phi_{is}^{-\frac{\beta_s}{\theta_s}}.$$

A.3 Sourcing Strategy and Industry Equilibrium

As AFT points out, buyers' choice of source regions requires some consideration as to whether the choice of individual source regions exhibits substitutability. To see this, we examine how an addition of a source region, say region r_2, affects the sourcing potential of another source region, say region r_1, within the same input industry by taking a further difference of the expression in (10):

$$\begin{aligned}&[\pi_i(\varphi_i)|_{\Omega_{is}\cup\{r_1,r_2\}} - \pi_i(\varphi_i)|_{\Omega_{is}\cup\{r_2\}}] - [\pi_i(\varphi_i)|_{\Omega_{is}\cup\{r_1\}} - \pi_i(\varphi_i)|_{\Omega_{is}}] \\ &\approx \frac{\beta_s(\sigma-1)}{\theta_s}\left[\frac{\beta_s(\sigma-1)}{\theta_s}-1\right]\tilde{\pi}_i(\varphi_i)\frac{\Phi_{isr_1}}{\Phi_{is0}+\sum_{r\in\Omega_{is}}\Phi_{isr}}\frac{\Phi_{isr_2}}{\Phi_{is0}+\sum_{r\in\Omega_{is}}\Phi_{isr}}. \end{aligned} \quad (22)$$

We see immediately that the profit function is supermodular in Φ_{isr_1} and Φ_{isr_2} if $\beta_s(\sigma-1) > \theta_s$, which AFT call the complements case, while it is submodular if $\beta_s(\sigma-1) < \theta_s$, which is called the substitutes case. Adding a source region increases the sourcing potential of other regions in the complements case, while it decreases the sourcing potential of other regions in the substitutes case.

In contrast, the first-order approximation of the impact of an inclusion of region r_2 as a source region in sector s_2 on the sourcing potential of region r_1 in another input sector, say s_1, is given by

$$\begin{aligned}&[\pi_i(\varphi_i)|_{\Omega_{is_1}\cup\{r_1\},\Omega_{is_2}\cup\{r_2\}} - \pi_i(\varphi_i)|_{\Omega_{is},\Omega_{is_2}\cup\{r_2\}}] - [\pi_i(\varphi_i)|_{\Omega_{is_1}\cup\{r_1\},\Omega_{is_2}} - \pi_i(\varphi_i)|_{\Omega_{is_1},\Omega_{is_2}}] \\ &\approx \frac{\beta_{s_1}(\sigma-1)}{\theta_{s_1}}\frac{\beta_{s_2}(\sigma-1)}{\theta_{s_2}}\tilde{\pi}_i(\varphi_i)\frac{\Phi_{is_1r_1}}{\Phi_{is0}+\sum_{r\in\Omega_{is_1}}\Phi_{is_1r}}\frac{\Phi_{is_2r_2}}{\Phi_{is0}+\sum_{r\in\Omega_{is_2}}\Phi_{is_2r}} > 0.\end{aligned}$$

In this case, the profit function is unambiguously supermodular. Adding a source region always increases the sourcing potential of any region for all other input sectors.

As argued by AFT, buyers' choice of source regions is rather simple if $\beta_s(\sigma-1) > \theta_s$ for all s, since adding a region will never give the buyers incentive to drop any existing source regions. In other cases where $\beta_s(\sigma-1) < \theta_s$ for some s, however, it is possible that $r_1 \notin \Omega_{is}$ while $r_2 \in \Omega_{is}$ even though $\Phi_{isr_1} > \Phi_{isr_2}$; this can arise if an inclusion of r_1 would lead to an exclusion of some other regions from Ω_{is} while an inclusion of r_2 with a small Φ_{isr_2} will not.

There is a unique industry equilibrium in this model. For a given B in (9), each buyer i optimally chooses the set of source regions $\{\Omega_{is}\}_{s=1}^{S}$. The unit cost of final good production is determined accordingly as shown in (7), which in turn determines the price index P and hence an associated value of B, say B', as shown in (9). Let $B' = h(B)$ represent this relationship. Then it is readily verified that h is a decreasing function on $(0, \infty)$.[42] Thus, there exists a unique fixed point of h such that $B^* = h(B^*)$ where B^* is the equilibrium value of B.

A.4 Proof of the Propositions

Potential source regions differ from one another in various aspects such as the number of input-producers, technological level, and wage rate. To isolate the distance effect, we assume here that all parameters other than ρ_s take the same values across different input industries. Omitting the subscript s for those parameters and also omitting the final-good producer index, for notational simplicity, the sourcing potential given in (5) can be written as

$$\Phi_{sr} = \begin{cases} T_0(w_0 c)^{-\theta}, & \text{if } r = 0 \\ n_r T_r (w_r c)^{-\theta} \left[\frac{\rho_s}{(\rho_s-1)m(d_r)}\right]^{\frac{\rho_s\theta}{\rho_s-1}} e^{-\theta\left[\frac{\rho_s}{\rho_s-1}+t(d_r)\right]}, & \text{if } r = 1, \cdots, M+M^*. \end{cases} \tag{23}$$

Furthermore, equations (12) and (13) can be rewritten as

$$\frac{\Phi_{sr}}{\Phi_{s0}} = n_r \left(\frac{T_r}{T_0}\right)\left(\frac{w_0}{w_r}\right)^{\theta} \left[\frac{\rho_s}{(\rho_s-1)m(d_r)}\right]^{\frac{\rho_s\theta}{\rho_s-1}} e^{-\theta\left[\frac{\rho_s}{\rho_s-1}+t(d_r)\right]}, \text{ for any } r, \tag{24}$$

$$\frac{\Phi_{sr_1}}{\Phi_{sr_2}} = \left(\frac{n_{r_1}}{n_{r_2}}\right)\left(\frac{T_{r_1}}{T_{r_2}}\right)\left(\frac{w_{r_2}}{w_{r_1}}\right)^{\theta} \left[\frac{m(d_{r_2})}{m(d_{r_1})}\right]^{\frac{\rho_s\theta_s}{\rho_s-1}} e^{-\theta[t(d_{r_1})-t(d_{r_2})]}. \tag{25}$$

We also assume here that source regions are complements, i.e., $\beta(\sigma-1) > \theta$, to conduct a rigorous analysis. As argued in the previous subsection, we are not able to perfectly predict equilibrium sets of source regions in the substitutes case where $\beta(\sigma-1) < \theta$. In the following analysis, we focus on the complements case and use a nice property that when $\Phi_{sr_1} > \Phi_{sr_2}$, if $\Phi_{sr_2} \in \Omega_s$, so is Φ_{sr_1}.

A.4.1. Proposition 1

We see from (23) that Φ_{sr} falls with d_r for $r \neq 0$. Moreover, the elasticity of Φ_{sr} with respect to $m(d_r)$ and $t(d_r)$ are $\rho_s\theta/(\rho_s-1)$ and $\theta t(d_r)$, respectively, which indicates that the adverse distance effect is greater for the more differentiated inputs.

To see how the distance effect on the ranking of potential source regions varies with the degree of input differentiation, we find from (25) that the distance plays a bigger role for the more differentiated inputs, i.e., the inputs associated with a greater $\rho_s/(\rho_s-1)$, in ranking the regions. At the one extreme where $\rho_s/(\rho_s-1) \to 1$, (25) shows that distance is just one of the factors that affect relative attractiveness of a region. At the other extreme where $\rho_s/(\rho_s-1) \to \infty$, we see that distance is the only factor that affects the ranking of the source regions. So we infer that close regions are more likely to be ranked higher than farther regions. Letting $k_s(r)$ denote region r's ranking as a source region in industry s, we indeed have that if $k_{s_1}(r_1) < k_{s_1}(r_2)$ and $k_{s_2}(r_1) > k_{s_2}(r_2)$ for some

[42] It follows from (7), (8), and (9) that an increase in B induces a firm, say i, to expand Ω_{is} for some s, which reduces ψ_i and P, and hence B.

r_1 and r_2 and for some s_1 and s_2 such that $s_1 < s_2$ (i.e., inputs in industry s_1 are less differentiated than those in industry s_2), then we have $d_{r_1} > d_{r_2}$. Close regions are more likely to ranked higher so that more likely to be chosen as source regions in industries for the more differentiated inputs.

The share of region r_1 relative to insourcing and that of region r_1 relative to region r_2 are given by (24) and (25), respectively. To see how they vary with the degree of inputs differentiation, we take a logarithm and differentiate them with respect to $\rho_s/(\rho_s - 1)$:

$$\frac{\partial \log(\Phi_{sr_1}/\Phi_{s0})}{\partial(\rho_s/(\rho_s-1))} = \theta\left[\log\frac{\rho_s}{\rho_s-1} - \log m(d_{r_1})\right] < 0, \tag{26}$$

$$\frac{\partial \log(\Phi_{sr_1}/\Phi_{sr_2})}{\partial(\rho_s/(\rho_s-1))} = \theta\left[\log m(d_{r_2}) - \log m(d_{r_1})\right] < 0, \text{ if } d_{r_1} > d_{r_2}, \tag{27}$$

where the first inequality obtains since $\rho_s/[(\rho_s-1)m(d_{r_1})] = q_{sr_1}$ is a probability and hence is less than 1. These suggest that the share of insourcing relative to any source region and the share of a region relative to another, farther region are both higher for the more differentiated inputs.

Indeed, we can further show that the share of insourcing itself is higher for the more differentiated inputs. To this end, we define r_j^s and $\bar{k}_s$ as the j-th region in the ranking and the optimal number of source regions for industry s, respectively, and rewrite (10) and (11) as

$$\pi(\varphi)|_{\Omega_s=\{r_1^s,\cdots,r_{k+1}^s\}} - \pi(\varphi)|_{\Omega_s=\{r_1^s,\cdots,r_k^s\}} \approx \frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\frac{\Phi_{sr_{k+1}}/\Phi_{s0}}{1+\sum_{j=1}^{k}(\Phi_{sr_j^s}/\Phi_{s0})} - f_s, \tag{28}$$

$$\pi(\varphi)|_{\Omega_s=\{r_1^s,\cdots,r_{\bar{k}_s}^s\}} - \pi(\varphi)|_{\Omega_s=\emptyset} \approx \frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\sum_{j=1}^{\bar{k}_s}\frac{\Phi_{sr_j^s}}{\Phi_{s0}} - \left(f + \bar{k}_s f_s\right). \tag{29}$$

Figure A2 shows how the optimal sets of source regions are determined for industries s_1 and s_2, where $s_1 < s_2$. It follows from (28) that the intersections, illustrated as s_1 and s_2 in the figure, give us the optimal sourcing decision of the firm for the two input industries, ignoring the integer problem (which can be justified especially when the number of source regions is large so that smallest sourcing potential Φ_{sr} in Ω_s is small). If both upward-sloping and downward-sloping curves for industry s_1 are located above those for industry s_2, as illustrated in the figure, the optimal sourcing capability for s_1 is greater than that for s_2, i.e., $\Phi_{s_1} = \Phi_{s_1 0} + \sum_{j=1}^{\bar{k}_{s_1}} \Phi_{s_1 r_j^{s_1}} > \Phi_{s_2 0} + \sum_{j=1}^{\bar{k}_{s_2}} \Phi_{s_2 r_j^{s_1}} = \Phi_{s_2}$, since $\Phi_{s_1 0} = \Phi_{s_2 0}$ as indicated in (23). It is easy to see that this will be the case if $\Phi_{s_1 r_j^{s_1}} > \Phi_{s_2 r_j^{s_2}}$ for any j.

The inequality $\Phi_{s_1 r_j^{s_1}} > \Phi_{s_2 r_j^{s_2}}$ can be shown from the observation that $\Phi_{s_1 r} > \Phi_{s_2 r}$ for any r, which in turn follows from (26). To this end, we consider a series of rankings for industry s_2, where any consecutive rankings are different in a permutation of two regions, such that the region with a larger sourcing potential moves up in ranking while the one with a smaller sourcing potential moves down. The series starts with the ranking for industry s_1 and ends with the ranking for industry s_2: we start with $\{r_{j(0)}\}_{j(0)=1}^{M+M^*} = \{r_j^{s_1}\}_{j=1}^{M+M^*}$, followed by $\{r_{j(1)}\}_{j(1)=1}^{M+M^*}$, and so forth, and end with $\{r_{j(n(s_1,s_2))}\}_{j(n(s_1,s_2))=1}^{M+M^*} = \{r_j^{s_2}\}_{j=1}^{M+M^*}$, where $n(s_1,s_2)$ denotes the number of permutations necessary to reach from $\{r_j^{s_1}\}_{j=1}^{M+M^*}$ to $\{r_j^{s_2}\}_{j=1}^{M+M^*}$. We shall show $\Phi_{s_1 r_j^{s_1}}/\Phi_{s_1 0} > \Phi_{s_2 r_{j(h)}}/\Phi_{s_2 0}$

for any $h \in \{0, 1, \cdots, n(s_1, s_2)\}$. We begin with the observation, from (26), that $\Phi_{s_1 r_{j(0)}}/\Phi_{s_1 0} > \Phi_{s_2 r_{j(0)}}/\Phi_{s_2 0}$. Suppose then that $\Phi_{s_1 r_j^{s_1}}/\Phi_{s_1 0} > \Phi_{s_2 r_{j(h)}}/\Phi_{s_2 0}$ for any h, and show that the counterpart inequality also holds for $h+1$. In the $(h+1)$-th step, the permutation of region r, which used to be in the l-th place, and region r', which used to be in the l'-th place, occurs such that $l \equiv k_{j(h)}(r) = k_{j(h+1)(r')} < k_{j(h)}(r') = k_{j(h+1)}(r) \equiv l'$. Now, for the comparison for the l-th place between the two industries, we have

$$\frac{\Phi_{s_1 r_l^{s_1}}}{\Phi_{s_1 0}} > \frac{\Phi_{s_1 r_{l'}^{s_1}}}{\Phi_{s_1 0}} > \frac{\Phi_{s_2 r'}}{\Phi_{s_2 0}},$$

where the first inequality follows from $l < l'$ while the second inequality follows from the supposition for the h-th step. As for the l'-th place, we have

$$\frac{\Phi_{s_1 r_{l'}^{s_1}}}{\Phi_{s_1 0}} > \frac{\Phi_{s_2 r'}}{\Phi_{s_2 0}} > \frac{\Phi_{s_2 r}}{\Phi_{s_2 0}},$$

where the first inequality follows from the supposition while the second inequality follows from the very reason why region r' took region r's place in the $(h+1)$-th step. These two series of inequalities show that $\Phi_{s_1 r_j^{s_1}}/\Phi_{s_1 0} > \Phi_{s_2 r_{j(h)}}/\Phi_{s_2 0}$ for any step. Thus, we have established $\Phi_{s_1 r_j^{s_1}} > \Phi_{s_2 r_j^{s_2}}$ for any j, and hence $\Phi_{s_1} = \Phi_{s_1 0} + \sum_{j=1}^{\bar{k}_{s_1}} \Phi_{s_1 r_j^{s_1}} > \Phi_{s_2 0} + \sum_{j=1}^{\bar{k}_{s_2}} \Phi_{s_2 r_j^{s_1}} = \Phi_{s_2}$.

Having established $\Phi_{s_1} > \Phi_{s_2}$, it follows immediately from $\Phi_{s_1 0} = \Phi_{s_2 0}$ that $\Phi_{s_1 0}/\Phi_{s_1} < \Phi_{s_2 0}/\Phi_{s_2}$, i.e., the share of insourcing is greater for the industry with higher inputs differentiation. This ends the proof of Proposition 1.

A.4.2 Proposition 2

We shall show that the less differentiated inputs are more likely to be outsourced and then show the direct and indirect impacts of offshoring on dropping and adding of input sellers.

We show here that for $s_1 < s_2$, if the firm outsources in industry s_2, it also outsources in industry s_1. The converse is not true. To show this claim, we use

$$\sum_{j=1}^{\bar{k}_{s_1}} \frac{\Phi_{s_1 r_j^{s_1}}}{\Phi_{s_1 0}} > \sum_{j=1}^{\bar{k}_{s_2}} \frac{\Phi_{s_2 r_j^{s_2}}}{\Phi_{s_2 0}}, \tag{30}$$

which has been established in the proof of Proposition 1. If $\bar{k}_{s_1} \leq \bar{k}_{s_2}$, on the one hand, then we have

$$\begin{aligned} \frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\sum_{j=1}^{\bar{k}_{s_1}} \frac{\Phi_{s_1 r_j^{s_1}}}{\Phi_{s_1 0}} - \bar{k}_{s_1} f_s &> \frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\sum_{j=1}^{\bar{k}_{s_2}} \frac{\Phi_{s_2 r_j^{s_2}}}{\Phi_{s_2 0}} - \bar{k}_{s_1} f_s \\ &\geq \frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\sum_{j=1}^{\bar{k}_{s_2}} \frac{\Phi_{s_2 r_j^{s_2}}}{\Phi_{s_2 0}} - \bar{k}_{s_2} f_s, \end{aligned}$$

where the first inquality follows from (30) while the second inequality follows from $\bar{k}_{s_1} \leq \bar{k}_{s_2}$. If $\bar{k}_{s_1} > \bar{k}_{s_2}$, on the other hand, we have

$$\frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\sum_{j=1}^{\bar{k}_{s_1}}\frac{\Phi_{s_1 r_j^{s_1}}}{\Phi_{s_1 0}} - \bar{k}_{s_1} f_s > \frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\sum_{j=1}^{\bar{k}_{s_2}}\frac{\Phi_{s_1 r_j^{s_1}}}{\Phi_{s_1 0}} - \bar{k}_{s_2} f_s$$
$$> \frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\sum_{j=1}^{\bar{k}_{s_2}}\frac{\Phi_{s_2 r_j^{s_2}}}{\Phi_{s_2 0}} - \bar{k}_{s_2} f_s,$$

where the first inequality follows from $\bar{k}_{s_1} > \bar{k}_{s_2}$ and $(\Phi_{s_1 r_j^{s_1}}/\Phi_{s_1 0}) - f_s > 0$ for any $j \leq \bar{k}_{s_1}$ while the second inequality follows from $\frac{\Phi_{s_1 r_j^{s_1}}}{\Phi_{s_1 0}} > \frac{\Phi_{s_2 r_j^{s_2}}}{\Phi_{s_2 0}}$ for any j. Thus, we have established the claim.

Now, consider the case where the firm begins importing some of the inputs in some industry, say s_1, from a foreign region, say r^*. The direct consequence of this is a rise in Φ_{s_1}. As a result, the share of input varieties sourced from every other source region, $\Phi_{s_1 r}/\Phi_{s_1}$, drops. The dropped input suppliers tend to be less efficient.

As Φ_{s_1} increases due to offshoring, the unit cost of the final good decreases for all import starters, as shown in (7). As (8) indicates, this gives all the import starters incentive to expand the set of source regions and also to expand the industries in which the firms outsource some of the inputs. Although the demand shifter B is negatively affected, as shown in (9), the import starters have incentive to expand the search for input suppliers relative to the non-importers, since a decline in B affects all final-good producers equally. Therefore, the import starters add some regions to the set of source regions for some industries, while they drop, as a consequence, inefficient suppliers from all the existing source regions in those industries. Since newly-added regions are associated with the smallest sourcing potentials compared with the existing source regions within the industries, the newly-added sellers tend to be distantly located and more productive. If an import starter begins outsourcing some of the inputs in an industry, then we know from the above claim that the industry produces the most differentiated inputs of all the industries in which the firm outsources. Proposition 1 tells us that the sellers in that industry tend to be closer than sellers in other industries. This ends the proof of Proposition 2.

A.4.3 Proposition 3

Proposition 3 and the discussion that follows claim that if the fixed costs of outsourcing and those of searching regions for input suppliers are large, the offshoring tend to result in industry coagglomeration.

Proposition 2 shows that firms tend to offshore less differentiated inputs. Those inputs tend to be outsourced from distant regions, so import starters tend to replace distant suppliers with foreign sellers. Thus, the direct replacement induces industry coagglomeration. Proposition 2 also shows two indirect channels through which the average distance between buyers and sellers is affected. The first channel is the reshuffling of input suppliers within the industries. The import starters tend to add suppliers in distant regions while dropping firms in every existing source regions, so that the reshuffling induces dispersion within the industries. The other channel, however, is for industry coagglomeration. It is the channel of adding new ones in the list of the outsourcing industries. As we have seen, such industries tend to produce the more differentiated inputs, and hence the sellers, which are newly-added, are located closer than those in other industries on average.

If f and f_s are large, the indirect effect tends to be for industry coagglomeration, since then the number of outsourcing industries is small so that the dispersion effect is relatively small. In addition, the indirect effect itself becomes small relative to the direct effect, since the import starters tend to expand the search for new input suppliers less aggressively in that case, as we can see from (8). Thus, if f and f_s are large enough, offshoring induces industry coagglomeration. This completes the proof of Proposition 3.

B Appendix for the Empirical Analysis

B.1 Measures of Industry Characteristics

Product Differentiation

Source: Rauch (1999). Description: a dummy variable that takes value equal to 1 for differentiated products, and 0 for homogeneous products. There are two versions of the differentiation indicator–"conservative" and "liberal". In the main regressions, we use the "conservative" version, which has a lower number of commodities classified as either organized exchange or reference priced. Since industries are originally defined at the 4-digit level based on the ISIC (revision 3) classification, we use the following procedures to construct the differentiation dummies for each industry in Japan's Standard Industrial Classification (JSIC) 3-digit classification.[43]

1. We first map each ISIC 4-digit code (292 categories) to multiple JSIC (rev. 11) 4-digit code (1261 categories, with 563 manufacturing industries), using the concordance file constructed by the Statistics Bureau of Japan. Since the matching is many-to-one, we use the simple average of the Rauch indicator across all ISIC codes within each JSIC. To define the Rauch dummy at the JSIC level, we replace computed averages that are strictly greater than 0.5 with 1, and 0 otherwise.

2. To construct the Rauch differentiation indicator at the JSIC 3-digit and the broad BSJBSA sectors (12 manufacturing product groups), we compute the weighted average of the indicators across all corresponding 4-digit codes, with weight equal to the share of each 4-digit code in the total sales of the 3-digit and the BSJBSA sector, respectively. Sales data by 4-digit industry for 2005 are obtained from the Census of Manufactures published from the Ministry of Economy, Trade, and Industry (METI). Once again, we replace computed averages that are strictly greater than 0.5 with 1, and 0 otherwise.

[43] According to the official document by Japan's Statistics Bureau, there are 420 3-digit categories and 1269 4-digit categories for the JSIC2002 (Revision 11). For JSIC2007 (Revision 12), there are 529 3-digit categories and 1455 4-digit categories.

3. For 2005, we obtain 148 Rauch dummies (out of 150 JSIC (rev. 11) 3-digit manufacturing industries); while for 2010, we obtain 153 Rauch dummies (out of 177 JSIC (rev. 12) manufacturing industries).

Elasticity of Substitution

Source: Soderbery (2015). Description: refined estimates of the demand elasticity for US imported varieties (1993-2007), originally constructed by Broda and Weinstein (2006). Since product categories are originally classified at the HS 6-digit, we use the following procedures to construct the elasticity measure for each JSIC 3-digit industry.

1. We first keep only intermediate inputs in the data set, based on the United Nations Broad Economic Categories (BEC) list.

2. We then merge the list of intermediate inputs at the HS 6-digit level (2617 categories) with the industry list of the Japanese Input-Output (IO) Table from 2005 (361 categories), using the concordance file from the Statistics Bureau of Japan. The mapping is not unique–an HS code can be mapped to multiple IO industry code, and vice versa.

3. We then map each IO code to a JSIC 4-digit code, using the concordance file from the Statistics Bureau of Japan.

4. To construct the elasticity measure at the JSIC 3-digit and the broad BSJBSA sectors (12 manufacturing product groups), we compute the weighted average of $\rho_s/(\rho_s - 1)$ across all corresponding 4-digit categories, with weight equal to the share of each 4-digit category in the total sales of the 3-digit and BSJBSA broad sector, respectively. Sales data by 4-digit industry for 2005 are obtained from the Census of Manufactures published from the Ministry of Economy, Trade, and Industry (METI).

5. We obtain 144 elasticity measures for 2005 (out of 150 JSIC (rev. 11) 3-digit manufacturing industries), and 150 elasticity measures for 2010 (out of 177 JSIC2007 (rev. 12) manufacturing industries).

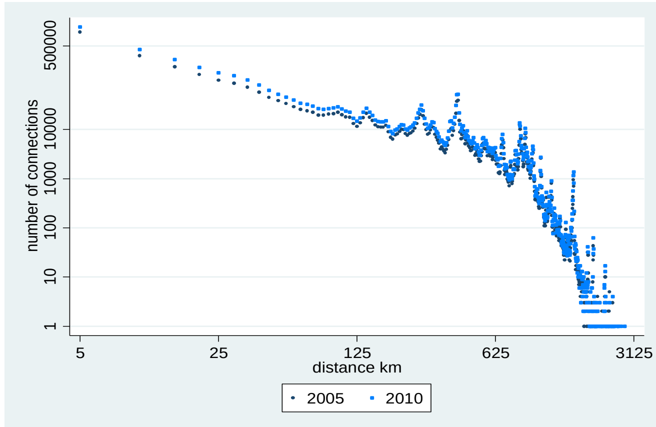
Air Freight Cost

Source: Hummels and Shaur (2013). Description: the cost of air freight for imports in each US industry, measured in ad-valorem terms (i.e., the percentage of the total value of shipment). Purpose: We use it as a proxy for the timeliness of trade for each product. The concordance procedure is identical to that used to construct the elasticity measures, as the air-freight measure is originally available at the HS 6-digit (2002) level. 180 and 188 air-freight measures are available for 2005 and 2010, respectively, at the JSIC 3-digit level.

B.2 Instruments

[tbc]

Figure 1. Distance and Number of Links (2005 & 2010)



Source: Tokyo Shoko Research

Figure 2. Number of sellers by buyer sales

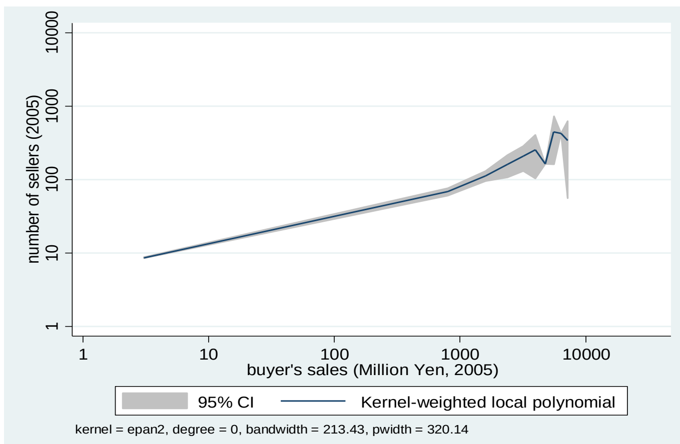


Figure 3. Number of prefectures sourced by buyer sales

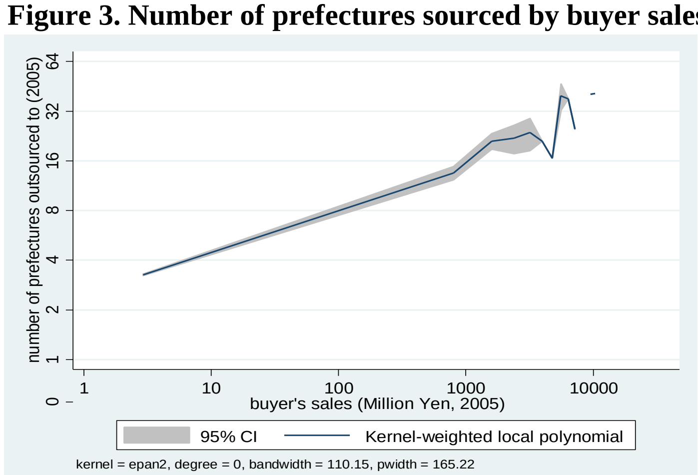
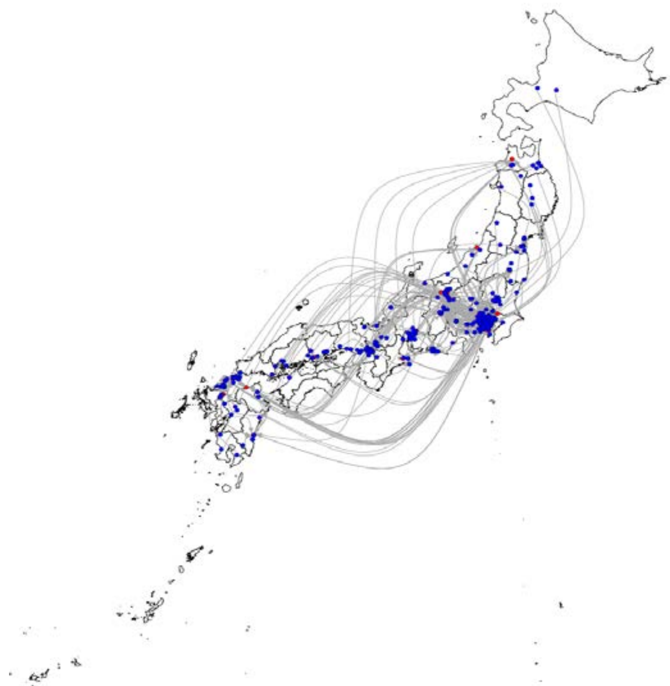
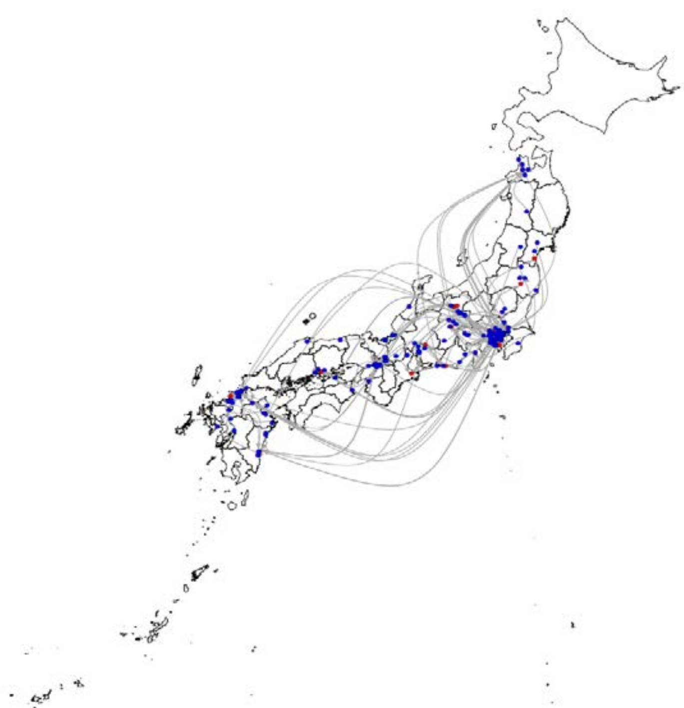


Figure 4. Sellers that were added by newly offshoring electronic producers (2005-2010)



Note: Buyers (electronic producers) are represented by red dots, while their new sellers in blue dots.

Figure 5. Sellers that were dropped by newly offshoring electronic producers (2005-2010)



Note: Buyers (electronic producers) are represented by red dots, while their dropped sellers in blue dots.

Table 1: Summary Statistics of the Network Data and the Regression Sample

A. Network Data from Tokyo Shoko Research (TSR)

	Nb. of Observations	Mean Nb. of Sellers	Median Nb. of Sellers
2005	3,586,090	4.89	2
2010	4,463,168	5.47	3

B. Regression Samples Merged with Basic Survey Data (BSJBSA)

	Nb Obs	Mean nb of sellers	Median nb of sellers
2005	345,352	25.05	10
2010	433,586	31.11	13

Note: All samples decribed include buyers in the manufacturing sector but sellers from both manufacturing and non-manufacturing sectors.

Table 2: Summary Statistics (Number of Buyers and Sellers)

Sample:	All mfg. buyers	Continuing importers 2005-2010	Import starters between 2005-2010	Continuing Non-importers 2005-2010
A. Number of buyers in 2005				
Count	13,784	1,807	1,024	10,135
Share	1.00	0.13	0.07	0.74
B. Number of sellers per buyer in 2005				
Mean	25.05	48.50	22.47	20.58
Median	10	16	11	9
Max.	4,724	4,026	1,471	4,724
C. Number of sellers' prefectures per buyer in 2005				
Mean	5.17	7.49	5.34	4.62
Median	4	5	4	4
Max.	47	47	40	46
D. Number of sellers per buyer in 2010				
Mean	32.07	60.91	30.32	26.36
Median	14	22.5	10	12
Max.	4,746	3,639	1,852	4,746
E. Number of sellers' prefectures per buyer in 2010				
Mean	6.14	8.80	6.49	5.49
Median	5	7	5	4
Max.	47	47	41	47

Note: Only manufacturing buyers are included. Continuous importers: firms with positive imports in 2005 and 2010. Importer starters: firms without imports in 2005 and with positive imports in 2010. Non-imporers: firms reporting no import in 2005 and 2010.

Table 3: Buyer's Offshoring and Changes in the Pattern of Domestic Outsourcing

Dep. Var.: First Difference beween 2005 and 2010	Δln(Sales)	Δln(Nb. Sellers)	Δln(Nb. Input Industries)	Δln(Nb. Source Regions)	$\frac{\Delta \text{dist}}{\text{avg(dist)}}$	Δln(dist)	$\frac{\text{dist}^{\text{add}} - \text{dist}^{\text{drop}}}{1/2(\text{distadd} + \text{dist}^{\text{drop}})}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Imp Starter $\text{Dummy}_{\text{buyer}}$	0.0572***	0.0677***	0.0422***	0.0413**	-0.0336*	-0.0405*	-0.0794**
	(0.017)	(0.016)	(0.015)	(0.016)	(0.017)	(0.023)	(0.035)
$\ln(\text{TFP})_{\text{buyer,2005}}$	0.00627	0.0279**	0.0204**	0.0104	-0.00401	-0.00369	-0.0156
	(0.011)	(0.011)	(0.009)	(0.009)	(0.011)	(0.015)	(0.027)
Fixed Effects	Buyer (4-digit) Industry and Buyer Region						
R-sq	.161	.125	.128	.103	.0971	.104	.107
Nb Obs	4881	4765	4765	4765	4740	4739	3338

Note: The regression sample includes manufacturing buyers only and domestic suppliers from both manufacturing and non-manufacturing industries. Each observation is a buyer. When constructing the buyer-specific measures of domestic sourcing, parent-child relationships and sellers with fewer than 5 employees are dropped. The number of observations in column 7 is significantlly smaller because not all buyers added or dropped sellers during the sample period. A buyer's TFP is estimated using the Olley-Pakes method with the buyer's value added as the dependent variable. Robust standard errors, clustered by the buyer's region, are used. All existing importers in 2005 are excluded in the sample, so only import starters and non-importers are included. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Distance, Scope of Domestic Outsourcing, and Product Differentiation of Inputs

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$\ln(N_{\text{source pref}}/N_{\text{nearest pref}})_{\text{input ind}}$			$\ln(N_{\text{source pref}}/N_{\text{home pref}})_{\text{input ind}}$		
$\ln(\text{dist})_{i,\text{source pref}} \times \theta_{\text{input-ind}}$	-0.00535***	0.00262		-0.00819***	0.00214	
	(0.001)	(0.002)		(0.001)	(0.003)	
$\ln(\text{dist})_{i,\text{ source pref}} \times \theta\rho/(\rho-1)_{\text{input-ind}}$		-0.00565***	-0.00516***		-0.00727***	-0.00712***
		(0.002)	(0.002)		(0.002)	(0.002)
$\ln(\text{dist})_{i,\text{source pref}} \times \theta_{\text{input-ind}} \times \text{air}_{\text{input-ind}}$			-0.000379			-0.000388
			(0.000)			(0.000)
Input Ind FE x Closest Region FE	√	√	√			
Input Ind FE x Source Region FE	√	√	√	√	√	√
Input Ind FE x Buyer Region FE				√	√	√
R-sq	.278	.275	.274	.302	.299	.297
Nb of Obs	49485	48735	48550	36560	36013	35860

Note: The regression sample includes manufacturing buyers only and domestic suppliers from both manufacturing and non-manufacturing sectors. Parent-child relationships are removed from the sample. Data for 2005 are used while the results based on 2010 data are reported in Table A5 in the appendix. The unit of observation in all columns is at the buyer-source-region-sector level. All regressions include input-industry-closest-region and input-industry-source-region fixed effects, where the closest region is the closest prefecture from which firm i sources intermediate inputs in a particular industry. Standard errors, clustered at the industry-source-region level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Global Sourcing and Product Differentiation of Inputs (Extensive Margin)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:			$\text{Dummy}_{\text{source pref, input industry}}$				$\text{Dummy}_{\text{off, input industry}}$	
$\ln(\text{dist}+1)_{\text{from seller's pref}} \times \theta_{\text{input-ind}}$	-0.0010***	0.00403***		-0.00100***	0.00402***			
	(0.000)	(0.000)		(0.000)	(0.000)			
$\ln(\text{dist}+1)_{\text{from seller's pref}} \times \theta\rho/(\rho-1)_{\text{input-ind}}$		-0.00399***	-0.00156***		-0.00401***	-0.00158***		
		(0.000)	(0.000)		(0.000)	(0.000)		
$\ln(\text{dist} + 1)_{\text{i,source pref}} \times \theta_{\text{input-ind}} \times \text{air}_{\text{input-ind}}$			-0.000194***			-0.000195***		
			(0.000)			(0.000)		
Domestic sourcing (yes=1)							0.0747***	0.0681***
							(0.002)	(0.002)
$\text{TFP}_{\text{buyer,2005}}$							0.0109***	
							(0.001)	
$\text{TFP}_{\text{buyer,2005}} \times \theta\rho/(\rho-1)_{\text{input-ind}}$							-0.000414***	-0.000408***
							(0.000)	(0.000)
Buyer FE	-	-	-	√	√	√	-	√
Input Ind (12) FE x Source Region FE	√	√	√	√	√	√		
Input Ind (12) FE							√	√
R-sq	0.052	0.056	0.055	0.087	0.092	0.09	.03	0.136
Nb of Obs	7773612	7773612	7773612	7773612	7773612	7773612	257208	257208

Note: The regression sample includes manufacturing buyers only and domestic suppliers from both manufacturing and non-manufacturing sectors. Data for 2005 are used. The unit of observation in all columns is at the buyer-source-region-sector level. Parent-child relationships are removed from the sample. Columns 1-6 include input-sector-source-region fixed effects, while columns 4-6 include also buyer fixed effects. Columns 7-8 include input-sector fixed effects, while column 8 also includes buyer fixed effects. Standard errors, clustered at the buyer level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Offshoring and Supplier Dropping (Seller Characteristics)

Dependent Variable	$Drop_{ij}$							
	OLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Seller's Characteristics		dist	sales	emp		dist	sales	emp
Imp $Starter_i$	0.00246	-0.00438	-0.00929	-0.00552	-0.0888***	-0.179***	-0.474***	-0.223***
	(0.005)	(0.011)	(0.026)	(0.009)	(0.021)	(0.039)	(0.109)	(0.036)
Imp $Starter_i$ x (x_j / x_{i05})		0.00682	0.0117	0.00802		0.0936**	0.384***	0.134***
		(0.010)	(0.027)	(0.009)		(0.037)	(0.108)	(0.032)
x_j / x_{i05}		0.0241***	0.0925***	0.0305***		0.0156**	0.0427**	0.0133**
		(0.006)	(0.014)	(0.005)		(0.006)	(0.021)	(0.006)
Input Industry FE	√	√	√	√	√	√	√	√
Buyer Industry FE	√	√	√	√	√	√	√	√
Buyer Home Region FE	√	√	√	√	√	√	√	√
Buyer's $\ln(sales)_{2005}$	√	√	√	√	√	√	√	√
Nb of Buyers	4866	4841	4863	4859	4866	4841	4863	4859
Nb of Buyers that Offshore	508	506	508	508	508	506	508	508
Nb of Observations	88442	87698	88442	88439	88442	87698	88442	88439
R-sq	.119	.122	.12	.12	.119	.122	.12	.12
			First Stage					
			Kleibergen-Paap F statistic		150.78	78.96	78.04	78.762

The sample includes only manufacturing buyers that did not import in 2005. Newly added sellers are removed from the sample. The unit of observation is a buyer-seller pair. Parent-child relationships are removed from the sample. The dependent variable of the first stage of the 2SLS model is the buyer's import starting dummy, with various firm-industry-specific export supply shocks interacted with the seller characteristics as regressors. Robust standard errors, clustered at the input-industry level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Offshoring and Supplier Adding (Seller Characteristics)

Dependent Variable	Add_{ij}							
	OLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Seller's Characteristics		dist	sales	emp		dist	sales	emp
$Imp\ Starter_i$	0.0448***	0.0707***	0.0373	0.0498***	0.0404	0.119**	-0.523***	-0.0837*
	(0.005)	(0.013)	(0.025)	(0.010)	(0.027)	(0.046)	(0.114)	(0.045)
$Imp\ Starter_i$ x (x_j / x_{i05})		-0.0254**	0.00748	-0.00452		-0.0768**	0.552***	0.118***
		(0.011)	(0.023)	(0.008)		(0.033)	(0.109)	(0.034)
x_j / x_{i05}		0.0686***	-0.0699***	-0.0180***		0.0762***	-0.146***	-0.0355***
		(0.005)	(0.025)	(0.006)		(0.007)	(0.026)	(0.007)
Input Industry FE	√	√	√	√	√	√	√	√
Buyer Industry FE	√	√	√	√	√	√	√	√
Buyer Home Region FE	√	√	√	√	√	√	√	√
Buyer's $\ln(sales)_{2005}$	√	√	√	√	√	√	√	√
Nb of Buyers	4926	4901	4925	4923	4926	4901	4925	4923
Nb of Buyers that Offshore	513	511	513	513	513	511	513	513
Nb of Observations	110682	110208	110682	110682	110682	110208	110682	110682
R-sq	.0428	.0463	.0432	.0431	.0428	.046	.0392	.041
			First Stage					
			Kleibergen-Paap F statistic		158.14	82.57	46.20	80.301

The sample includes only manufacturing buyers that did not import in 2005. Dropped sellers are removed from the sample, so that the comparison is between new suppliers and continuing suppliers. The unit of observation is a buyer-seller pair. Parent-child relationships are removed from the sample. The dependent variable of the first stage of the 2SLS model is the buyer's import starting dummy, with various firm-industry-specific export supply shocks interacted with the seller characteristics as regressors. Robust standard errors, clustered at the input-industry level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Offshoring and Industry Adding and Dropping

Dependent Variable	$Drop_{is}$				Add_{is}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS		2SLS		OLS		2SLS	
Imp $Starter_i$ x Rauch	-0.000418		-0.268**		0.00485***		0.133***	
	(0.023)		(0.131)		(0.001)		(0.019)	
Imp $Starter_i$ x $\rho/(\rho-1)_{input\text{-}ind}$		-0.00979		-0.109		0.00374*		0.115***
		(0.033)		(0.102)		(0.002)		(0.020)
Input Industry FE	√	√	√	√	√	√	√	√
Buyer FE	√	√	√	√	√	√	√	√
Number of Obs.	21230	20880	20882	20880	701632	687784	701632	687784
R-sq	.273	.274	.266	.273	.0718	.0723	.0718	.0723
		KP F stat:	10.40	32.873		KP F stat:	3.385	3.385

The sample includes only manufacturing firms that did not import in 2005. The unit of observation is at the buyer-input-industry level. The dependent variable of all regressions is a dummy variable equal to 1 if a 3-digit industry was dropped by a buyer between 2005 and 2010, 0 otherwise. The dependent variable of the first stage of the 2SLS model (columns 5-8) is the buyer's import starting dummy, with various firm-industry-specific export supply shocks interacted with the input industry characteristics as regressors. Robust standard errors, clustered at the buyer level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Tables

Table A1: Summary Statistics of the Original TSR Data and the Merged Sample

	TSR sample (Panel A in Table 1)					
	2005			2010		
	Nb Obs	Nb of Sellers		Nb Obs	Nb of Sellers	
		mean	median		mean	median
Agriculture and forestry	8,888	2.77	2	13,476	2.85	2
Fishing	2,668	3.68	2	2,708	3.48	2
Mining	5,762	5.21	3	6,176	5.72	3
Construction	1,013,087	5.27	3	1,242,916	5.46	3
Manufacturing	842,034	7.24	3	1,002,775	7.57	3
Electricity, gas, and water supply	13,349	32.48	4	14,548	27.87	4
Information services	56,181	5.10	2	91,822	6.03	2
Transportation	106,034	4.65	3	152,774	5.53	3
Wholesale and retail trade	959,720	5.11	3	1,159,663	5.33	3
Finance and insutrance	29,675	7.48	2	30,492	6.12	2
Housing and real estate	50,687	3.86	2	117,443	4.83	2
Research	49,521	3.61	2	91,459	4.46	2
Hotels and accomodation	37,103	3.86	2	53,122	4.10	2
Living service	48,824	4.24	2	60,287	4.41	2
Education	9,068	3.87	2	18,530	5.59	2
Medical services	19,660	3.07	2	45,096	3.88	3
Miscellaneous services	25,967	6.20	3	34,252	7.31	3
Services, not elsewhere classified	95,950	3.61	2	117,521	3.70	2
Public servies	34	8.50	5.5	6	3.00	3
Not available	211,878	2.00	1	208,102	3.41	2

Source: Japan's TSR

Table A2: Summary Statistics of the Original TSR Data and the Merged Sample

	Sample Merged the Basic Survey (Panel B in Table 1)			
	Nb Obs	% pair merged	Nb of Sellers	
			mean	median
	2005			
Food products and beverages	35,953	45.21	20.34	11
Textiles	10,278	38.41	15.91	8
Lumber and wood products	7,206	24.43	19.91	11
Pulp, paper and paper products	10,450	51.64	23.17	10
Printing	9,922	40.42	18.17	8
Chemical products	27,440	72.74	27.49	12
Petroleum and coal products	1,743	65.55	27.67	14
Plastic products	12,223	44.82	17.39	10
Rubber products	5,129	58.82	26.71	9.5
Ceramic, stone and clay products	13,227	42.01	24.14	11
Iron and steel	12,706	61.90	27.15	11
Non-ferrous metals	9,536	68.01	27.32	10
Fabricated metal products	20,045	33.59	16.46	9
Machinery	57,877	53.07	25.36	12
Electrical machinery and appliances	38,395	69.59	38.09	10
Computer and electronic equipment	15,717	79.19	45.96	11
Electronic parts and devices	11,707	66.18	18.85	9
Transportation equipment	36,752	75.47	44.93	13
Miscellaneous mfg. industries	9,046	40.67	22.56	8
	2010			
Food products and beverages	39,776	44.89	23.89	13
Textiles	14,538	32.49	19.33	11
Lumber and wood products	17,478	46.93	29.18	13
Pulp, paper and paper products	11,915	39.79	22.96	10
Printing	33,752	73.61	36.33	16
Chemical products	1,831	62.83	31.57	16.5
Petroleum and coal products	16,305	46.84	23.73	13
Plastic products	6,162	58.24	34.42	12
Rubber products	537	23.58	12.20	8
Ceramic, stone and clay products	15,955	63.06	36.10	15
Iron and steel	9,747	63.99	29.10	12
Non-ferrous metals	24,094	34.10	21.19	12
Fabricated metal products	24,550	57.48	40.92	16.5
Machinery	81,398	61.14	41.96	16
Electrical machinery and appliances	16,815	68.47	40.81	15.5
Computer and electronic equipment	13,144	64.40	21.87	12
Electronic parts and devices	35,060	66.61	37.82	13
Transportation equipment	28,801	81.21	92.91	17
Miscellaneous mfg. industries	25,369	41.68	29.03	14
Non-manufacturing industries	16,359	28.08	17.63	9

Source: Japan's TSR

Table A3: Characteristics of Downstream Firms (Buyers) in the Basic Survey

All industries	2005	2010
No. of firms in the BSJBSA	22,939	24,892
Nb. of importers	5,344	5,659
Nb. of importers from Asia	4,315	4,786
Fraction of firms that import	0.233	0.227
Fraction of firms that import from Asia	0.188	0.192
Average importer's import intensity		
(imports/ total purchases)	0.183	0.212
Aveage firms' shares of imports from Asia		
(imports from Asia / total imports)	0.795	0.821
Manufacturing industries		
Nb. of firms in the BSJBSA	11,021	11,361
Nb. of importers	3,270	3,494
Nb. of importers from Asia	2,747	3,082
Fraction of firms that import	0.297	0.308
Fraction of firms that import from Asia	0.249	0.271
Average importer's import intensity	0.163	0.192
(imports/ total purchases)		
Aveage firms' shares of imports from Asia		
(imports from Asia / total imports)	0.824	0.846

Source: BSJBSA (2005, 2010)

Table A4: Firm Productivity, Distance, and the Scope of Domestic Sourcing (2010)

Dependent Variable	ln(# sellers' prefectures)$_{buyer}$		ln(# sellers)$_{buyer}$		ln(# jsic 4-digit outsourced)$_{buyer}$		ln(Sales/Emp)$_{seller}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Measure of Buyer's Productivitiy	TFP (OP)	VA/Emp	TFP (OP)	VA/Emp	TFP (OP)	VA/Emp	-
Productivity$_{buyer}$	0.104***	0.344***	0.141***	0.553***	0.110***	0.485***	
	(0.021)	(0.016)	(0.027)	(0.025)	(0.023)	(0.021)	
ln(distance)							0.0543***
							(0.001)
Buyers' (4-digit) Industry FE	√	√	√	√	√	√	
Buyer's Prefecture FE	√	√	√	√	√	√	
Buyer FE							√
Sellers' (4-digit) Industry FE							√
Sellers' Prefecture FE							√
Parent-subsidiary dummy							√
Distance							b/w buyer-seller
SE clustering	Buyers' (4-digit) Industry						Buyer
R-sq	.191	.247	.191	.261	.2	.271	.646
Nb of Obs	8701	8742	8701	8742	8701	8742	598946

Note: The regression sample includes manufacturing buyers only and domestic suppliers that are either manufacturing or non-manufacturing. The unit of observation is at the buyer level from columns (1) to (6), and at the buyer-seller level in columns (7). All regressions include the most exhaustive set of fixed effects possible. Standard errors, clustered at the buyer's industry level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Distance, Scope of Domestic Outsourcing, and Product Differentiation of Inputs (2010)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$\ln(N_{source\ pref}/N_{nearest\ pref})_{input\ ind}$			$\ln(N_{source\ pref}/N_{home\ pref})_{input\ ind}$		
$\ln(dist)_{i,source\ pref} \times \theta_{input\text{-}ind}$	-0.00447***	-0.00198		-0.00732***	-0.00264	
	(0.001)	(0.002)		(0.001)	(0.002)	
$\ln(dist)_{i,\ source\ pref} \times \theta\rho/(\rho\text{-}1)_{input\text{-}ind}$		-0.00177	-0.00331***		-0.00330**	-0.00539***
		(0.001)	(0.001)		(0.002)	(0.001)
$\ln(dist)_{i,source\ pref} \times \theta_{input\text{-}ind} \times air_{input\text{-}ind}$			0.0000203			0.0000203
			(0.000)			(0.000)
Input Ind FE x Closest Region FE	√	√	√			
Input Ind FE x Source Region FE	√	√	√	√	√	√
Input Ind FE x Buyer Region FE				√	√	√
R-sq	.262	.261	.266	.29	.288	.294
Nb of Obs	65498	64967	59172	47543	47148	42889

Note: The regression sample includes manufacturing buyers only and domestic suppliers from both manufacturing and non-manufacturing sectors. Parent-child relationships are removed from the sample. Data for 2010 are used. The unit of observation in all columns is at the buyer-source-region-sector level. All regressions include input-industry-closest-region (or input-industry-home-region in columns (4)-(6)) and input-industry-source-region fixed effects, where the closest region is the closest prefecture from which firm i sources intermediate inputs in a particular industry. Standard errors, clustered at the industry-source-region level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Top 20 Input Industries by Buyer-Seller Distance (2005)

Seller Industry (out of 150)		Nb. of links	Distance (km) Median	Mean	25th pct	75th pct	ρ/(ρ-1)	Rauch	θ
453	Harbor and river transport	11	408.1	572.9	405.5	927.8	-	-	
731	Hospitals	22	341.1	319.5	25.3	466.8	-	-	
31	Marine fisheries	131	280.1	325.9	23.8	557.9	-	-	
214	Leather footwear	126	269.1	249.1	7.7	395.7	1.186	1	
105	Cigarettes, cigars and tobacco	47	265.2	352.1	92.0	539.3	1.117	0	
98	Vegitable oils, animal oils, and fats	674	247.3	273.9	28.7	409.8	1.046	1	
649	Non-deposit money corporations engaged in the provision of finance, credit, n.e.c.	899	217.9	263.1	33.1	401.9	-	-	
176	Medical products	1866	210.2	238.9	23.3	395.4	1.089	1	
117	Rope and netting	381	209.7	256.6	36.1	395.4	1.369	1	
51	Metal mining	121	206.4	264.3	13.8	407.8	-	-	
491	Wholesale trade, general merchandise	13014	193.6	239.9	14.6	400.2	-	-	
102	Wine, sake, liquors	775	189.3	267.1	36.3	401.2	1.330	0	
261	Boilers, engines, and turbines	566	185.0	251.5	27.8	406.2	1.040	1	
225	Clay refractories	360	181.7	246.1	25.2	415.6	1.326	1	
106	Feeds and fertiliers	554	181.1	302.2	43.2	481.6	1.198	0	
181	Petroleum refining	423	171.9	250.4	12.8	403.3	1.060	1	
101	Soft drinks and carbonated water	623	170.8	253.9	34.7	387.7	1.090	1	
174	Rayon, acetate fibers, and synthetic fibers	386	168.1	217.0	16.9	398.1	1.101	0	
241	Primary smelting and refining of non-ferrous metals	611	167.6	230.1	21.7	396.8	1.495	1	
304	Aircraft	575	166.0	234.5	23.2	398.2	1.027	1	

Table A7: Bottom 20 Input Industries by Buyer-Seller Distance (2005)

326	Lacquer ware	97	8.4	86.0	2.1	111.0	1.382	1	
891	Advertising agencies	1972	8.2	125.1	3.4	164.0	-	-	
905	Private employment services	71	8.1	122.2	3.3	368.9	-	-	
831	Travel agency	235	7.9	102.8	2.7	61.4	-	-	
754	Welfare services for the aged and care services, except home care help services	11	7.9	37.6	2.2	33.6	-	-	
316	Ophthalmic goods, including frames	207	7.8	75.0	3.1	140.1	1.618	1	
808	Photographic studios	122	7.8	176.6	3.1	369.5	-	-	
372	Fixed telecommunications	15	7.8	66.4	4.2	42.1	-	-	
574	Fresh fish stores	22	7.6	98.7	4.2	45.0	-	-	
412	Recording and disk production	40	7.4	70.4	3.2	109.1	-	-	
829	Laundry, beauty and bath services, n.e.c.	35	7.2	49.2	1.3	18.3	-	-	
771	Social education	26	5.8	91.9	3.5	14.4	-	-	
803	Certified public accountants' and auditors' offices	14	5.6	40.4	2.4	11.4	-	-	
413	Newspaper publishers	160	5.3	104.7	3.0	218.8	-	-	
382	Private broadcasting	57	5.3	62.0	1.8	16.4	-	-	
53	Crude petroleum and natural gas production	13	5.1	84.9	2.5	7.8	-	-	
169	Service industries related to printing trade	28	4.6	51.9	2.4	17.2	1.648	1	
939	Other services	24	4.3	15.6	1.6	25.6	-	-	
674	Life insurance agents and brokers	175	2.8	61.0	0.0	20.2	-	-	
564	Shoe stores	36	1.3	88.5	0.4	35.9	-	-	
				Mean across Industries			1.328	0.770	9.820
				Median across Industries			1.228	1.000	8.871
				Standard Deviation across Industries			0.262	0.422	5.805

Note: Only manufacturing buyers are used in the construction of these measures

Figure A1. Distribution of Buyers with Different Number of Suppliers

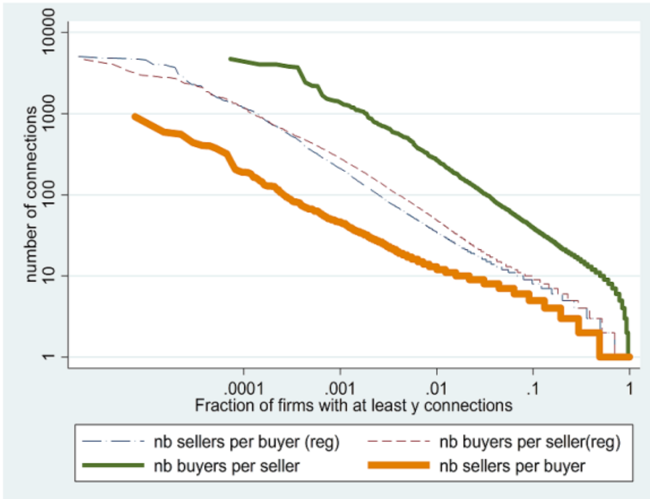


Figure A2: Optimal sourcing capabilities

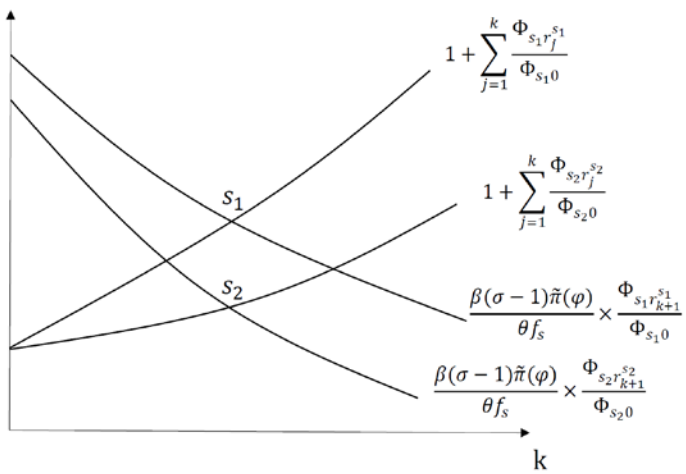


Figure A3. Export Supply Shocks from Japan's Major Trade Partners

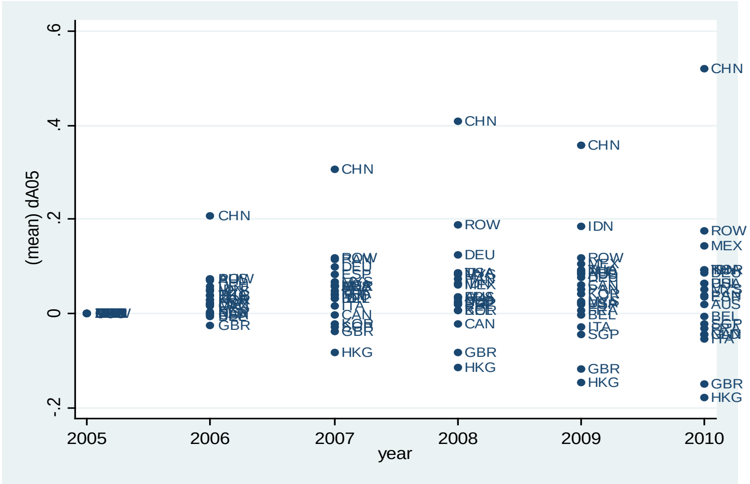


Figure A4: Number of buyers per sq km by prefecture

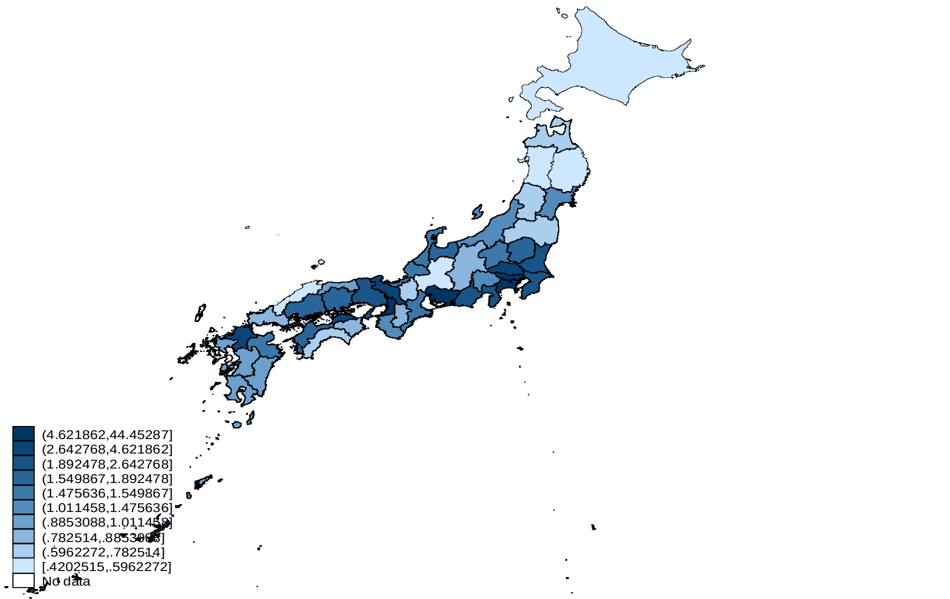


Figure A5: Number of sellers per sq km by prefecture