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Taiji Furusawa, Tomohiko Inui, Keiko Ito, Heiwai Tang

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Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
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Global Sourcing and Domestic Production Networks

Abstract

This paper studies how firms' offshoring decisions shape a country's domestic production networks. We develop a model in which heterogeneous firms source inputs from multiple industries located in different domestic regions and foreign countries. Input sourcing entails communication with suppliers, which is endogenously increasing in the differentiation of inputs. The model predicts that firms are less likely to source differentiated inputs, especially from distant domestic and foreign suppliers, due to costly communication. Triggered by foreign countries' export supply shocks, firms start offshoring inputs from foreign suppliers, which displace the less productive domestic suppliers in the same industry (the direct displacement effect). The resulting decline in marginal costs induces firms to start sourcing from the more productive and distant domestic suppliers within industries (the within-industry restructuring effect), but possibly also from nearby suppliers that produce inputs that are more differentiated than those supplied by existing suppliers (the 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 on average, but more so for the larger ones. They tend to add nearby suppliers producing differentiated inputs. These results suggest that firms.offshoring may increase the spatial concentration of domestic production networks.

JEL-Codes: D220, D850, F140, L100, L140, R120.

Keywords: production networks, global sourcing, offshoring, face-to-face communication, industry agglomeration.

Taiji Furusawa
Hitotsubashi University
Tokyo / Japan
taiji.furusawa@r.hit-u.ac.jp

Tomohiko Inui
Gakushuin University
Tokyo / Japan
tomohiko.inui@gakushuin.ac.jp

Keiko Ito
Senshu University
Kanagawa / Japan
keiko-i@isc.senshu.u.ac.jp

Heiwai Tang
Johns Hopkins
USA - 20036 Washington DC
hwtang@jhu.edu

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1 Introduction

Substantial declines in trade barriers and advances in information, communication and transportation technologies have encouraged more firms to source inputs from far-away suppliers. A growing body of literature studies both the causes and consequences of increasing global production fragmentation.[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 shown the significance of considering production networks for a wide range of economic topics, 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). How global trade shapes the production networks in a country is an important yet relatively under-explored topic.

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 analyze firms' input sourcing from both domestic and foreign suppliers in different input industries. We then empirically examine the

[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).

theoretical predictions using Japanese extensive production network data.

There are at least three reasons why we extend the existing models of input sourcing to consider multiple input industries and communication between buyers and sellers. 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, especially from the more proximate domestic suppliers, while cutting the ties with existing suppliers that are large. A single-sector model that features only two-sided heterogeneity, standard trade costs, and the scale effect of offshoring would predict the opposite patterns. 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] Studying the relationship between global sourcing and the spatial distribution of economic activities in a country, in relation to information flow, is clearly important.

Our model features variable trade costs increasing in distance not only because of the standard transport costs but also buyers' costly communication with input suppliers. Face-to-face communication can help safeguard the quality of inputs, especially that of differentiated inputs. Buyers' endogenous communication thereby raises the elasticity of the variable trade costs with respect to distance from suppliers, more so for differentiated inputs. Therefore, to save communication costs, buyers will choose to procure differentiated inputs from closer 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—firms are less likely to outsource differentiated inputs, especially from distant or foreign suppliers.

After characterizing firms' equilibrium global production networks, we study how offshoring,

[2] Redding and Rossi-Hansberg (2016) provide a review of the extensive literature on the uneven spatial distribution of economic activities, 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 literature review.

triggered by exogenous increases in the attractiveness of offshoring, affects firms' performance and thus their choices of domestic suppliers. Newly offshoring firms replace the less productive domestic suppliers with foreign suppliers within the same industry (the direct displacement effect). The 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 (the within-industry restructuring 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 (the industry composition effect).

The net effect of offshoring on a firm's structure of domestic suppliers is nuanced, as it depends on the relative strength of the three 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 start sourcing differentiated inputs, which are associated with high communication and thus variable trade costs. As such, to minimize communication costs, newly offshoring firms choose domestic suppliers from the newly added differentiated input industries that are closely located. These patterns of reorganization of supplier relationships may overturn the within-industry restructuring 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 distance from sellers in a buyer's domestic production network 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 about 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 that the negative correlation between distance and the scope of domestic

[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 et al. (2017) 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.

sourcing is stronger for the more differentiated inputs, as measured by 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 spatial and sectoral 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 inputs in the same industry 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 find offshoring relatively more attractive.

The two-stage least squares estimates show that offshoring induces firms to add and drop larger domestic suppliers simultaneously, while adding the more proximate ones. While the addition of the larger suppliers is consistent with the within-industry restructuring effect of offshoring, both dropping of the larger suppliers and adding of the closer suppliers need to be explained by the other two effects. The dropping of the larger suppliers imply a sufficiently strong direct displacement effect, which is stronger in the less differentiated industries; while the adding of the more proximate suppliers is due to the industry composition effect, which implies the addition of suppliers from differentiated industries from which the buyers did not source inputs previously. Consistently, we find that newly offshoring firms are more likely to start sourcing from the more differentiated input industries. These results along with the higher likelihood of adding the more proximate suppliers suggest a strong industry composition effect, and offer an explanation for why offshoring can reduce the average distance between buyers and suppliers in production networks. The documented patterns of supplier reorganization also have implications for analyzing how offshoring affects aggregate productivity.[6]

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

Our paper relates to several strands of literature. First, it contributes to the growing literature on production networks and international trade. The study by Atalay, et al. (2011) is one of the first in the literature to theoretically and empirically describe firms' production networks in a country (the U.S.). Oberfield (2017) develops a model to study the endogenous formation of firms' production networks and its impact on aggregate productivity. Thanks to the recently available buyer-seller linked data, there is a burgeoning literature studying the pattern and dynamics of domestic production networks.[7] Notably, BMS use the same Japanese buyer-seller linked data to highlight the negative assortativity of buyer-supplier links. Based on the extension of the high-speed train line in Japan as an exogenous shock, the authors find that firms near newly built train stations tend to increase sourcing from more domestic locations and thereby experience an increase in measured productivity. Using the same data and exploiting the Great East Japan Earthquake of 2011 as an exogenous shock, Carvalho et al. (2017) quantify the propagation of shocks through the domestic input-output linkages.[8] Tintelnot et al. (2017) develop and estimate a model of firm-to-firm domestic trade, foreign trade, and endogenous network formation. Different from all these studies, our paper focuses on characterizing both the industrial and geographic patterns of domestic production networks. Importantly, we are the first to incorporate both domestic and foreign sourcing in a model to empirically examine how firms' offshoring shapes the domestic production networks across sectors and space.

This paper also contributes to the growing cluster of work on networks in international trade.[9] Recent research seeks to study the micro foundation of the dynamics and patterns of firms' sorting and matching in international trade networks (e.g., Chaney, 2014; Eaton et al., 2014; Carballo, Ottaviano, and Volpe Martincus, 2016; Bernard, Moxnes and Ulltveit-Moe, 2017; Sugita, Teshima, and Seira, 2017).[10] In particular, Bernard, Moxnes and Ulltveit-Moe (2017) build a model that fea-

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 U.S. 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.

[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.

[9] 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. See Chaney (2016) for a literature review.

[10] Using importer-exporter matched data from Colombia, Eaton et al. (2014) structurally estimate the effects of

tures two-sided heterogeneity and uncover in Norwegian importer-exporter linked data the negative assortative matching of trade partners.[11] Chaney (2014) proposes theoretically that a country's aggregate export dynamics are tightly linked to firms' penetration into new foreign markets, through establishing new contacts and expanding existing trade relationships. Different from this literature, which focuses primarily on the patterns of importer-exporter matches, our paper focuses instead on firm-to-firm relationships in the domestic economy, and investigates the impact of firms' offshoring on the evolution of the domestic segment of global value chains.

Our work also contributes to the literature on the interplay between international trade and the non-efficiency aspect of firm performance. In particular, Holmes and Stevens (2014) find in the U.S. manufacturing firm census data that 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. Motivated by these facts, the authors structurally examine firms' heterogeneous responses to import shocks from China, which cannot be explained by a standard heterogeneous-firm model.[12] Relatedly, we show paradoxically that large domestic suppliers are more likely to be dropped, while proximate suppliers are more likely to be added, by the newly offshoring downstream firms.[13] In this regard, this paper shares similar key messages with Jensen and Kletzer (2005), who study the tradability of tasks, and Keller and Yeaple (2013), who examine the ways multinationals transfer knowledge to their overseas affiliates based on sector characteristics. In particular, we show using firm-to-firm linked data that the elasticity of trade costs with respect to distance varies across industries, and thus affects firms' reorganization of domestic production networks upon offshoring.

Finally, 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,

learning and search costs on aggregate trade. By focusing on a HS 6-digit code within textile/ apparel trade, Sugita, Teshima, and 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.

[11] Similar to Carballo, Ottaviano, and Volpe Martincus (2016), the authors also highlight adjustments on the buyer margin as an important channel through which trade responds to policy shocks.

[12] In particular, the authors find that large rather than small plants experience the largest contraction in sales in response to the import shocks, in contrast to the predictions of a standard heterogeneous-firm model.

[13] 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.

2015),[14] and 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; Hijzen, Inui, and Todo, 2010; AFT, 2017).[15] It contributes to the economic geography literature by showing that offshoring can be a source of industry coagglomeration, as generic input suppliers, which are on average located farther away, are the ones that tend to be displaced by foreign suppliers, while differentiated input suppliers, which are on average located nearby, tend to be added as new suppliers by offshoring firms. Contributing to the literature on the (direct) effects of offshoring, our results about the patterns of supplier adding and dropping highlight a previously omitted channel through which offshoring can affect an economy's labor market outcomes and aggregate productivity.

The paper proceeds as follows. Section 2 discusses the data sources. Section 3 presents several stylized facts that motivate a theoretical model, which is introduced in Section 4. Section 5 discusses our empirical design and findings. The final section concludes this paper.

2 Data

Our data come from two sources. The network data for 2005 and 2010 come from Tokyo Shoko Research Ltd. (TSR), a private credit reporting agency. Firms provide information to TSR in order to obtain credit scores for loans. The TSR data contain basic firm-level balance sheet information, such as employment, sales, location, main (4-digit) industry (up to 3), founding year, number of

[14] 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 declined slightly in recent decades. Behrens and Bougna (2015) also observe a recent decline in the agglomeration of manufacturing plants in Canada.

[15] 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. AFT build a multi-country sourcing model to study both theoretically and empirically firms' selection into importing and the resulting cost effects and complementarities between sourcing from different countries.

establishments, of over 800,000 firms in Japan.[16] Crucially, 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 a two-way matching method to maximize the number of links, using information reported by a buyer about its sellers and vice versa. Since a relationship with a buyer or seller 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 addresses reported by the firms, which we geocode.[17]

We complement the TSR data with the Basic Survey of Japanese Business Structure and Activities (BSJBSA), conducted annually by the country's Ministry of Economy, Trade and Industry (METI). The BSJBSA data cover 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.).[18] 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.[19] In the regression analysis, we focus on the subsample that has manufacturing firms on the buyer side of a relationship.

[16] 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 et al. (2017), 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.

[17] 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 compute the distance between any pair of coordinates.

[18] The data set, however, does not provide information on firms' imports by sector.

[19] About half of the observations of the balanced TSR sample have buyers that can be merged to firms included in the manufacturing survey. 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 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 and 2010.

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 links, based on the TSR sample, is about 3.6 millions in 2005 and 4.5 millions in 2010. The average number of sellers for a buyer increased from 4.9 in 2005 to 5.5 in 2010, while the median 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 have substantially more sellers than other buyers).[20] The increases in the average and median numbers of buyer-supplier links since 2005 suggest that the production network in Japan is getting denser. Since the rise in the density of the network may be due to firms' more comprehensive self-reporting of sellers, we use a regression sample that includes only buyers and suppliers that operated in both 2005 and 2010, to mitigate this potential measurement issue.[21]

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 (25 and 10, respectively, for the year 2005) than those in the network data.[22] Tables A1 and A2 in the appendix report more detailed statistics by buyers' main industry.

Table 2 reports the summary statistics on the numbers of sellers and domestic regions (47 prefectures) from which different types of buyers, based on their import statuses, sourced inputs.

[20] 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.

[21] The cost of using a data set with balanced numbers of buyers and sellers in both years is that we cannot study the entries and exits in the network.

[22] One may be concerned about the selection biases arising from 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 choices of domestic suppliers, the focus on large firms should be fine as large firms are more likely to engage in offshoring, which entails 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 therefore their choices of domestic suppliers, omitting small firms, which tend to be non-importers, in our sample will go against us from finding any effect. It is because the variation in firms' participation in offshoring and the associated effects would have been even larger if small firms were included in the sample. Third, even though the fraction of firms that have at least n links is naturally larger based on the regression sample, the power-law distribution of the number of sellers per buyer is preserved (see Figure A1 in the appendix). The slope of the relation based on the regression sample is almost identical to that derived from the original TSR sample.

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.[23] These continuing importers sourced inputs from more domestic sellers and prefectures than new importers and non-importers. They procured inputs from 48.5 domestic sellers in 2005 on average, with the median equal to 16. The mean and median numbers of prefectures from which existing importers procure inputs are 7.49 and 5, respectively. For new importers, while their numbers of sellers and source prefectures are on average smaller than those of continuing importers, they are larger than those of continuing non-importers.

Figures 1-3 illustrate the empirical regularities that discipline our theoretical model. Figure 1 shows that the number of buyer-seller links is negatively correlated with the distance between the pair, and about half of the connections are observed within a 25 km radius of buyers. This negative correlation appears to increase in magnitude since 2005. Figures 2 and 3 reveal the relationship between a buyer's sales and its scope of domestic sourcing. Figure 2 shows a positive correlation between buyers' sales and the number of connected domestic suppliers, while Figure 3 depicts a positive correlation between their sales and the number of prefectures from which they source inputs. We also find that within the same 4-digit industry and prefecture, the more productive buyers use more suppliers, and distant suppliers tend to be more productive (see Table A4 in the appendix for the regression results). These results altogether demonstrate the importance of incorporating trade frictions that are increasing in distance, along with two-sided heterogeneity across buyers and sellers in the model, similar to BMS.

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. We estimate the following specification using a simple fixed effects model:

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

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

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 or various measures of the scope of domestic sourcing, including log numbers of domestic suppliers, domestic industries, and domestic regions respectively from which buyer i sources inputs. We also examine how offshoring changes the average distance between a buyer and its domestic suppliers. We use three measures of the change in a buyer's average distance from its suppliers, represented by $dist_{i,t}$. 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 by construction bounded between -2 and 2 to reduce the impact of outliers. The second measure is the log difference in the average distance. The third measure considers the difference between the average distance of the newly added suppliers and that of the dropped suppliers, $\left(dist_i^{add} - dist_i^{drop}\right)/\frac{1}{2}\left(dist_i^{add} + dist_i^{drop}\right)$.

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.[24] We include buyer's (4-digit) industry and region (prefecture) 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 due to a high geographic concentration of suppliers). We always control for buyer i's 2005 log total factor productivity, TFP_i, as it is well documented in the literature that 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 the construction of a buyer's performance measure uses information of its linked suppliers in both manufacturing and non-manufacturing industries.[25] 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, as measured by the (log) numbers of suppliers, industries, or regions from which the firm sources its intermediate inputs.

In columns 5 and 6, we find a significant and negative correlation between a firm's offshoring

[24] Recent research reveals 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 robustness checks by defining a new importer as one that imported for two consecutive years (2010 and 2011), and a non-importer as one that did not import for three consecutive years (2003-2005). The main results remain robust and are available upon request.

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

participation and the average distance between the firm and its domestic suppliers. In column 7, we find that after a firm starts offshoring, the distance from the newly added suppliers relative to that of the dropped suppliers tends to drop.[26] Figures 4 and 5, which show the links of added and dropped domestic suppliers of electronics firms that started offshoring inputs since 2005, portray a pattern that suggests an increased geographic concentration of domestic production networks. Without any causal implications, the results in Table 3 show insightful correlation between offshoring and firms' domestic sourcing behavior. 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 in AFT, the negative correlation between offshoring and the average buyer-supplier distance cannot be readily rationalized by their model that only considers a single input industry. We therefore develop our own model in the following section.

4 A Model of Firms' Global Sourcing

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

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 changes firms' incentives to outsource inputs and how offshoring affects firms' post-offshoring relationships with individual suppliers. We also introduce in the model buyers' communication with sellers in an effort to enhance input quality to show that the elasticity of trade costs with respect to distance can endogenously increase with the differentiation of inputs. We first characterize firms' spatial and sectoral equilibrium patterns of

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

global sourcing, before examining the effect of a reduction in foreign input costs on buyers' choices of domestic suppliers.

4.1.1 Demand

Consider an industry facing only domestic demand.[27] 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 Goods Production

Final goods are produced with inputs from S different industries, which differ from each other in the degree of product differentiation. Production of final goods involves two stages. The first stage is to make S composite inputs, each with a unit mass of differentiated input varieties, using 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 has to be tailored to the specific needs of a buyer and is therefore difficult to be substituted with other varieties produced by other suppliers. As such, input varieties that are less substitutable are considered more differentiated. We order input industries such that a higher index s indicates a higher degree of product differentiation (i.e., $\rho_1 > \rho_2 > \cdots > \rho_S$).

[27] We focus on the effects of firms' importing decisions. Introducing exports of final goods would complicate the model without affecting the main theoretical results.

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 sourced 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.[28] 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 inverse variability of the draws. A smaller θ_s implies a larger variation of productivity across firms within the sector. The location parameter T_{sr} can vary across final-good producers ($r = 0$) and input producers ($r \neq 0$), as well as across regions.[29]

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 requires a buyer to incur 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

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

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

in which a buyer outsources intermediate inputs, it has to incur a fixed cost of f, which is common across input industries. The second type of fixed costs are those related to search in a region for the lowest-cost sellers of individual input varieties. Borrowing the insight from AFT, we assume that for every region 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. Let Ω_{is} denote the set of regions from which firm i sources inputs in industry s. The set 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 take the form $t_s(d) \geq 1$ and $t_s(0) = 1$, where t_s is an industry-specific increasing function of the distance d between the buyer's region and a seller's region.

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.[30] 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.[31] Based on the presumption that the failure of delivering high-quality inputs often arises from miscommunication or misunderstanding between buyers and sellers, we assume that a buyer can reduce the probability of failure by engaging in face-to-face communication more vigorously.[32]

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

[30] Despite the substantial improvement in information and communication technologies, business travels did not appear to decrease (Liu, Scholnick, and Finn, 2017). A majority of executives surveyed by Harvard Business Review (2009) claimed that in-person meetings are essential for "sealing the deal" and maintaining long-term relationships.

[31] 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).

[32] 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.

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.[33] The marginal communication cost rises with the distance (i.e., face-to-face communication with distant sellers is more costly).

In this model, 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.[34]

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.

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.

[33] By specifying the communication as a variable cost rather than a fixed cost, we assume that the intensity of communication is increasing in the value of transaction. The finding of a positive correlation between the total value of outsourcing and the number of business travels at the industry level for the U.S. offer indirect evidence for that assumption (Liu, Scholnick, and Finn, 2017).

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

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 Appendix A, 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

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

where d_{ir} denotes the distance between buyer i and region r. It can be readily verified that the cost-minimizing q_{isr} is given by

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

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 face-to-face 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.

The 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, the price, or the unit cost, of an input variety is $p = z^{-1}w_0 c_s$. For an input variety sourced from region r, it equals $p = z^{-1}w_r c_s t_s(d_{ir})\exp[m(d_{ir})q_{isr}]$. Note that all the price variations within the source regions come from the differences in sellers' productivities. Thus, as shown in Appendix A, 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 Φ_{isr} given by

$$\Phi_{isr} = \begin{cases} T_{s0}(w_0 c_s)^{-\theta_s} & \text{if } r = 0 \\ n_{sr}T_{sr}(w_r c_s t_s(d_{ir}))^{-\theta_s}\left[\frac{\rho_s}{(\rho_s-1)m(d_{ir})}\right]^{\frac{\rho_s\theta_s}{\rho_s-1}} e^{\frac{\rho_s\theta_s}{1-\rho_s}} & \text{if } r = 1,\cdots,M+M^*, \end{cases} \tag{5}$$

and the sourcing capability by $\Phi_{is} \equiv \Phi_{is0} + \sum_{r\in\Omega_{is}}\Phi_{isr}$. Notice that in the absence of the communication channel, the trade elasticity is only θ_s, as in Eaton and Kortum (2002) and many of its variants. Communication raises the cost of trade, making the trade elasticity also depend on ρ_s. The firm-specific unit cost of the composite input s, which is given by (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 Appendix A, for a given cost profile $\{\tilde{c}_{is}\}_{s=1}^{S}$, firm i's unit cost of final-goods production can be expressed as

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

It immediately follows that firm i's profits can be expressed as

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

where δ_{is} takes 1 if buyer i outsources some inputs in industry s, and 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 entails 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.[35]

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 $\pi_i(\varphi_i)$ in (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

$$\pi_i(\varphi_i)|_{\Omega_{is_1}=\Omega\cup\{r_1\}} - \pi_i(\varphi_i)|_{\Omega_{is_1}=\Omega} \approx \frac{\beta_s(\sigma-1)}{\theta_s} \tilde{\pi}_i(\varphi_i) \frac{\Phi_{is_1 r_1}}{\Phi_{is_1 0} + \sum_{r\in\Omega} \Phi_{is_1 r}} - f_{s_1}, \tag{10}$$

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

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. In principle, buyer i 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 may not always hold if $\beta_s(\sigma-1) < \theta_s$, which AFT call the substitutes case. Appendix A 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 call the complements case (i.e., when $\beta_s(\sigma-1) > \theta_s$).[36] 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 sourced from region r can be written as

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

[36] 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}.

The effective price of inputs sourced from a region increases with its distance from the buyer due to the increasing trade costs, arising from 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 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 show that buyers with higher productivity tend to source from foreign suppliers and that foreign trade partners tend to be more cost-effective 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

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

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 regions. We show next that the negative correlation between distance and 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

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

The multiplicative terms that involve distance, i.e., $[t_s(d_{ir_2})/t_s(d_{ir_1})]^{\theta_s}\,[m(d_{ir_2})/m(d_{ir_1})]^{\frac{\rho_s\theta_s}{\rho_s-1}}$, 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^*} and 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 lower 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 (including themselves as input producers) with foreign sellers (an effect that we refer to as the *direct displacement effect*). From Proposition 1, we learn that these newly added foreign sellers tend to produce the less differentiated inputs. Thus, the displaced domestic sellers tend to be from the less differentiated industries. In addition, import starters and continuous importers may restructure their production networks as a consequence of the reduction in their marginal costs (an effect that we refer to as the *productivity effect*). Their operating profits unambiguously increase relative to those of non-importers, since a reduction in P affects all final-good producers equally.

The productivity effect in turn affects a firm's domestic production networks through two channels. First, it follows from (10) that import starters have a greater incentive to expand search regions, relative to non-importers. Offshoring entails a rise in Φ_{is} so that each region r's share of input varieties, given by Φ_{isr}/Φ_{is}, drops. 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 (an effect that we refer to as the *within-industry restructuring effect*).[37] Second, it follows from (11) that import starters also have a greater incentive to begin outsourcing inputs in a new industry, particularly the differentiated one that was not being sourced previously due to high variable trade costs (an effect that we refer to as the *industry composition effect*). The following proposition summarizes the testable predictions about the various effects of a fall in foreign input costs on the structure of newly offshoring firms' 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 displacement effect that some domestic suppliers are displaced by foreign suppliers is always present. Since the newly offshored industries tend to be less differentiated, the dropped sellers in those industries tend to be located farther and more productive than those 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. In addition, some import starters add sellers in industries from which they previously did not outsource inputs. Since such newly-outsourced industries tend to be more differentiated and thus entail higher communication costs, the sellers added in the newly-outsourced industries tend to be located closer than those in the previously-outsourced industries.*

Offshoring leads to the restructuring of firms' domestic production networks, thereby affecting industry coagglomeration. The direct displacement effect induces coagglomeration as the sellers that are directly replaced by foreign sellers tend to be located farther as they produce inputs that are

[37] 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.

less differentiated than sellers in other industries. The two types of productivity effects of offshoring on industry coagglomeration are mixed. On the one hand, the within-industry restructuring effect implies that 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, the industry composition effect induces them to begin outsourcing inputs in the relatively more differentiated industries so that they add sellers located closer than those in other industries. The following proposition summarizes these possibilities.

Proposition 3 *Although the effects of offshoring on industry coagglomeration are mixed, offshoring induces industry coagglomeration if the within-industry restructuring effect is small relative to the direct displacement and industry composition effects.*

The proof of Proposition 3 is relegated to Appendix A. The basic idea is that if the fixed sourcing costs are large so that within-industry restructuring in the newly offshored industries is limited, the direct replacement and industry composition effects tend to dominate. Whether offshoring leads to industry coagglomeration depends on the relative strength of the three effects of offshoring, which we examine empirically in Section 5.3.

5 Regression Analyses and Results

In this section, we empirically examine using the network data 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. When industry and region fixed effects are included in the regressions, we will be clear about whether they are for the buyer or seller.

5.1 Domestic Sourcing Patterns

We first examine Proposition 1, which is about the patterns of firms' domestic sourcing. 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 input s. We study the determinants of buyer i's sourcing patterns according to the log of (13):

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

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

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

We measure $\Phi_{isr}/\Phi_{isr_s(i)}$ by $N_{isr}/N_{isr_s(i)}$, 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 a source region. Instead of estimating each individual component (e.g. T_{sr}) on the right hand side of (14), we include input-industry 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 $\theta_s \log t_s(d_{ir})$ will be controlled for by an interaction term that proxies for the input-industry specific variable trade cost that increases in distance.

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

$$m(d_{ir}) = d_{ir}^{\beta}$$

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

where ϕ_s captures the time sensitivity of the delivery of inputs (which gives the cross-industry variation of transport costs).

With these parameterizations, we can express the empirical counterpart of (14) as

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

where an industry is defined as a JSIC 3-digit category.[38] $FE_{sr_s(i)}$ and FE_{sr} stand for input-industry reference-region and input-industry source-region fixed effects, respectively.[39] With these fixed effects included, we study the relationship between a buyer's scope of domestic sourcing in a region and the proximity of the source region (relative to the reference region from which it sources the same type of inputs).[40]

To estimate β and γ, we need estimates of the model's key parameters: ρ_s, θ_s and ϕ_s. We measure ρ_s by the estimated elasticity of substitution between *imported* varieties in each industry s in the U.S. from Soderbery (2015), who has improved the original estimates by Broda and Weinstein (2006). The original estimates are at the HS 6-digit level, we use two concordance files and average the estimates up to the JSIC 3-digit level, using sales weights obtained from Japan's Census of Manufacturers (see the Appendix for details). Since the focus of the paper is firms' sourcing of intermediate inputs, when constructing $\rho_s/(\rho_s-1)$, we exclude capital and consumption goods according to the United Nations Broad Economic Categories (BEC) list.

We use two sets of estimates of θ_s. The first set is from Caliendo and Parro (2015), who estimate θ_s using data on bilateral trade between 16 economies for 20 ISIC sectors. The second set of θ_s is obtained from our own estimation using firm revenue data. In Section B.3 in the appendix, we show how one can use the empirical distribution of firms' revenue to estimate θ_s. We show that if a firm's core productivity is distributed Fréchet with parameters T and θ, its revenue is also distributed Fréchet, with the location parameter equal to $TA^{\frac{\theta}{\rho-1}}$ and the shape parameter equal to $\theta/(\rho-1)$, where A is a sector-specific variable. Therefore, we can use the mean and the standard deviation of firm revenue in the TSR data to back out θ_s (at the 3-digit JSIC level), given ρ_s. For ϕ_s, we use the share of air freight costs in U.S. imports in industry s to proxy for the importance of timely delivery (see the Appendix for details). The idea is that if the delivery of a good is time sensitive, the slope of the variable trade cost with respect to distance is steeper.

Table 4 reports the estimates of β and γ, according to (15). Standard errors are clustered at the input-industry-source-region level. In columns 1 to 6, we use a buyer's nearest source region for

[38] 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. The results are available upon request.

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

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

each industry as the reference region, while in columns 7 through 9, we use a buyer's home region as the reference point. The cost of using a buyer's home region as the reference point is that not all buyers procure inputs in each sector from its home region. Thus, the number of observations will be smaller in the last three columns. When using the estimated θ_s from Caliendo and Parro (2014), we find in columns 1 to 3 that a buyer's scope of domestic sourcing is decreasing in distance, more so for differentiated inputs. Specifically, as reported in column 1, a 10% increase in the distance relative to the nearest region is associated with a 0.5% drop in the number of sellers for an industry that has the mean value of θ_s (=9.82).[41] Column 2 shows that such negative correlation is more pronounced for the more differentiated inputs, as proxied by $\rho_s/(\rho_s-1)$. Sectors that have a one standard-deviation larger $\rho_s/(\rho_s-1)$ (=0.26), compared to the mean value of 1.33, is associated with an additional 0.15% drop in the number of sellers from a region that is 10% farther away compared to the reference region, evaluated at the same mean value of θ_s.[42] Column 3 shows that the results remain robust after we control for the interaction between $\log d_{ir}$ and the share of air freight cost in imports of the corresponding U.S. industry, ϕ_s (Hummels and Schaur, 2013).

In columns 4 to 6, when we use the firm-based estimate of θ_s, we find quantitatively larger effects. According to the coefficient on $\frac{\rho_s\theta_s}{\rho_s-1}\log(d_{ir})$ in column 6, sectors that have one standard-deviation larger $\rho_s/(\rho_s-1)$ compared to the sectoral mean are associated with an additional 0.19% drop in the number of sellers from a region that is 10% away in distance relative to the reference region, evaluated at the mean value of θ_s (=13.72).[43] The results become quantitatively more significant when we use the buyer's home region as the reference region (see columns 7 to 9), 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' domestic sourcing at the extensive margin, by replacing the dependent variable in specification (15) with a dummy for whether buyer i sources intermediates in industry s from source region r 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 on firms' domestic sourcing at the more disaggregated industry level is aggregated

[41] $-0.47\% = -0.00535 \times 10 \times 9.82\%$
[42] $-0.145\% = -0.00565 \times 10 \times 9.82 \times 0.262\%$
[43] $-0.188\% = -0.00524 \times 10 \times 13.717 \times 0.262\%$

to the broad sector level.[44] Accordingly, we compute the weighted average of input industries' characteristics across 3-digit industries within a broad sector. The procedures of aggregation are described in detail in the data appendix. 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, while retaining input-industry source-region (FE_{sr}) fixed effects. We sometimes include buyer fixed effects as well to control for any unobservable determinants of domestic sourcing (e.g., buyer's productivity).

We use the estimated θ_s from Caliendo and Parro (2014) in Panel A, and our own estimates using firm-level data in Panel B. Regardless of the estimates, we find that a buyer's likelihood of sourcing inputs from a prefecture is decreasing in the bilateral distance (columns 1 and 7), after controlling for input-industry source-region fixed effects. The negative correlation is stronger for the more differentiated inputs (columns 2-3 and columns 8-9, respectively). These regression results remain robust and quantitatively similar after we control for buyer fixed effects (columns 4-6 and columns 10-12, respectively). We find that the differential effect of distance on the incidence of domestic sourcing across industries is economically significant. Based on the coefficients reported in column 4, a 10% increase in distance relative to the home region 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.[45] 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.[46]

In Table 6, we study the determinants of a firm's decision to offshore inputs in an 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 are more likely to incur the fixed costs to offshore intermediates. Given that trade costs will be increasing in input industry's product differentiation, such positive relationship should be weaker for the more differentiated inputs. Re-

[44] 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.

[45] Using the coefficient on $ln(dist+1)\times\theta_s$ (=−0.001) and the mean value of θ_s (=9.82) we come up with $-0.098\% = -0.001 \times 10 \times 9.82\%$.

[46] 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 A9 in the appendix), respectively, the increase in the likelihood of sourcing from a region is $-0.004 \times \underbrace{0.262}_{\text{std of } \rho_s/(\rho_s-1)} \times 10 \times \underbrace{9.82}_{\overline{\theta}_s}\%$.

gardless of which estimated θ_s used, we find a positive and significant correlation between a buyer's likelihood of offshoring inputs and its productivity, after controlling for input-industry source-region fixed effects. Such correlation is weaker for the more differentiated input industries (see columns 1 and 3). These results remain robust even after we control for buyer fixed effects in columns 2 and 4. We also find 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.

5.2 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 and adding domestic suppliers is associated with an 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):

$$I_{ij} = \beta \Delta imp_i + \gamma \Delta imp_i \times \log\left(\frac{x_{ij}}{\overline{x}_i}\right) + \delta \log sales_i + \left[FE_{s(i)} + FE_{r(i)} + FE_{s(j)} + FE_{r(j)}\right] + \varepsilon_{ij}, \quad (16)$$

where I_{ij} is a dummy variable indicating whether buyer i drops (or adds) seller j between 2005 and 2010. Each unit of observation is a buyer-seller link. The regression sample excludes all existing importers in 2005, as our goal is to study the effect of the participation in offshoring, rather than that of the extent of offshoring.

When we run the "drop" regressions, we further restrict the sample by excluding each buyer's newly added seller links, such that we can gauge the effect of offshoring on a firm's decisions of dropping an *existing* domestic seller. In particular, the dependent variable of the "drop" regressions 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, on the other hand, we restrict the sample by excluding each buyer's dropped seller links, such that we can empirically compare the characteristics between the buyer's continuing suppliers with those of its newly added suppliers, after it offshores inputs. The dependent variable of the "add" regressions is defined as $I_{ij} = Add_{ij}$, which is equal to 1 if a new link between buyer i and seller j is observed in the 2010 sample but not in 2005, and 0 otherwise (indicating an old relationship).[47]

The variable Δimp_i is a dummy indicating firm i's switching from no offshoring in 2005 to offshoring any inputs between 2005 and 2010.[48] The regressor of interest is the interaction term $\Delta imp_i \times \log\left(\frac{x_{ij}}{\overline{x}_i}\right)$, where $\frac{x_{ij}}{\overline{x}_i}$ represents a measure of a supplier's characteristic, relative to the average characteristics of the sellers used by buyer i in 2005. We use a demeaned measure since a buyer compares the candidate supplier with its existing suppliers when making decisions to add or drop suppliers. For instance, a supplier considered to be large by a firm may not be considered large by another firm. More specifically, in 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, in 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). We consider two seller characteristics—log size (measured by either sales or employment) and log distance from a buyer. Buyer-industry ($FE_{s(j)}$), buyer-region ($FE_{r(i)}$), input-industry ($FE_{s(j)}$), and source-region ($FE_{r(j)}$) fixed effects are always included to control for any region- and industry-specific trends of supplier adding and dropping, such as external economies of scale for different industries, initial levels of economic development, or local government policies.[49]

To establish causality, we estimate specification (16) via two-stage least squares (2SLS). We construct an instrument at the buyer level. We first follow Hummels et al. (2014) to measure the world export supply (WES) shocks in each industry s during our sample period as:

$$WES_s = \ln\left(exp_{s,2010}\right) - \ln\left(exp_{s,2005}\right), \tag{17}$$

where $exp_{s,t}$ is the global exports to all destination countries in the world except Japan.[50]

[47] Notice that the results for the "add" regressions should not be interpreted as the effects on the likelihood of sourcing. The coefficient on the interaction term shows the difference in the average seller's characteristics between new and continuing relationships.

[48] Recall that we do not have information on firms' imports by sector.

[49] 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.

[50] The regression results are robust to alternative measures of WES using only data from exporting countries that were Japan's top trade partners in 2005 or those from destination countries that are either OECD or advanced economies.

To construct the instruments for offshoring at the firm level, we exploit the information about a firm's sectoral pattern of domestic sourcing. In Table 5, we find that firms are more likely to offshore inputs in an industry in which it has already sourced inputs domestically. These results are suggestive of a lower fixed cost of offshoring, conditional on the firm's domestic sourcing in the same industry. Thus, foreign countries' export supply shocks in an industry are more likely to induce a Japanese firm to start offshoring if it has already sourced 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, and compute firm i's exposure to the world export supply shocks as

$$shock_i = \sum_{s=1}^{S} \phi_{is} WES_s, \tag{18}$$

where ϕ_{is} is a dummy, which equals 1 if buyer i outsources industry-s inputs domestically in 2005, and 0 otherwise. We construct such dummies at the Japanese 4-digit SIC level (i.e., $S = 563$ manufacturing industries).

We use $shock_i$ specified in (18) as an instrument for Δimp_i, and $shock_i \times \log \frac{x_{ij}}{\overline{x}_i}$ as an instrument for $\Delta imp_i \times \log \frac{x_{ij}}{\overline{x}_i}$, as suggested by Wooldridge (2010). Table 7 reports both the OLS and 2SLS results of estimating (16) for dropping, based on the sample of all buyers in the manufacturing sector that sourced inputs domestically but not from foreign suppliers in 2005. As reported in columns 1 to 4, while the OLS estimated coefficient on Δimp_i and $\Delta imp_i \times \log \frac{x_{ij}}{\overline{x}_i}$ take the expected signs, they are all insignificant.[51] The 2SLS estimates in columns 5 to 8, however, show statistically significant effects of offshoring on firms' dropping of domestic suppliers. In column 5, the estimated coefficient on Δimp_i shows that a buyer's offshoring decision *reduces* the likelihood of dropping domestic suppliers. Within buyer industries, buyer home regions, input industries, and source regions, a buyer that started importing since 2005 is on average 65% 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 larger one (columns 7 and 8). In particular, the coefficient of 0.087 on the interaction term in column 7 implies that an existing supplier that is 50% larger than the mean supplier of a buyer is 4.3% relatively

[51] The main endogeneity that we aim to tackle is a firm's positive supply shock that may trigger its offshoring on the one hand, but affect the probability of dropping domestic suppliers in either direction on the other. The insignificant results based via OLS do not contradict our significant 2SLS results.

more likely to be dropped on average. If we measure firm size by employment, the differential effect would be 6.5% according to the coefficient of 0.129 on the interaction term reported in column 8. All F statistics for the first stages of these 2SLS estimations suggest that our instruments pass the weak instrument test by a wide margin. Table A6 in the Appendix reports the regression results of the first stage. The coefficients on the instrument and its interaction with seller characteristics are statistically significant when the corresponding endogenous variables are used as the dependent variables of the first stage.

Table 8 reports the estimates of the "add" regressions based on specification (16). 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 simultaneously. As reported in columns 5 to 8, the 2SLS estimates show that the newly offshoring firms are less likely to add the relatively more distant domestic suppliers (column 6), but more likely to add the larger ones (columns 7 and 8).

The findings that newly offshoring firms are more likely to add larger suppliers seem to contradict the earlier findings that they are also more likely to drop larger suppliers, as reported in Table 7. However, through the lens of our model, these results can be rationalized by the joint force of the direct displacement, within-industry restructuring and industry composition effects of offshoring. The findings that larger domestic suppliers are more likely to be dropped are consistent with the direct displacement effect. Offshoring firms' substitute domestic generic-input suppliers, which tend to be larger and more distantly located, with foreign suppliers producing similar inputs. The results that larger domestic suppliers are more likely to be added can be due to the within-industry restructuring 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. Considering the rise in communication costs, the buyer will source inputs from closer domestic suppliers in the newly added, differentiated industries. Table A7 in the Appendix shows that the coefficients on the instrument and its interaction with seller characteristics are statistically significant in the corresponding first-stage regressions.

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

$$I_{is} = \beta_s \Delta imp_i + \gamma_s \Delta imp_i \times X_s + \left[FE_{s(i)} + FE_{r(i)} + FE_{s(j)}\right] + \xi_{is}, \tag{19}$$

where I_{is} is a dummy variable indicating whether buyer i drops (or adds) industry s between 2005 and 2010. Each unit of observation is a buyer-input-industry pair. Similar to the sample we used to estimate (16), the regression sample excludes all buyers that already imported inputs in 2005.

When we run the "drop" regressions, we further restrict the sample by excluding each buyer's newly added input industries, such that we can gauge the effect of offshoring on a firm's decisions of dropping an *existing* input industry. 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.

When we run the "add" regressions, we restrict the sample by excluding each buyer's dropped input industries since 2005, such that we can gauge the effect of offshoring on a firm's decisions to add new industries, based on their industry characteristics compared to *continuing* input industries. To consider a full matrix of industries that a buyer can consider adding, we create a regression sample by setting $I_{is} = Add_{is} = 0$ for all input industries from which buyer i did not source inputs in both 2005 and 2010, but equal to 1 for those from which buyer i did not source inputs in 2005 but started sourcing inputs in or before 2010.

The variable of interest, $\Delta imp_i \times X_s$, is an interaction term between the change in buyer i's import status and industry s's product differentiation (X_s), measured by either $\rho_s / (\rho_s - 1)$ or the Rauch indicator, which equals 1 for differentiated goods, and 0 otherwise (see Section B.1 in the Appendix for details). Buyer industry ($FE_{s(i)}$), home region ($FE_{r(i)}$), and input industry fixed effects ($FE_{s(j)}$) are always included.

Table 9 presents the estimates of (19) via OLS and 2SLS. By using $shock_i$ as an instrument for Δimp_i, and $shock_i \times X_s$ as an instrument for $\Delta imp_i \times X_s$, we find in our 2SLS regressions that newly offshoring firms are less likely to drop (as measured by the Rauch indicator in column 5) but more likely to add the more differentiated industries for domestic sourcing (both columns 7 and 8). These patterns of input industry adding and dropping support the model predictions, and are consistent with the hypothesis that the industry composition effect and the direct displacement effect are the main reasons for why closer suppliers are more likely to be added, while larger suppliers are more likely to be dropped, after a firm offshores inputs. Table A8 in the Appendix reports the regression results of the first stage.

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 correlation between distance and the extent of domestic sourcing is stronger for differentiated inputs. Using a firm-level instrument based on the sectoral patterns of buyers' initial domestic sourcing and global export supply shocks, we study the causal impact of a firm's offshoring on its choices of domestic suppliers. We find that upon offshoring, firms are less likely to drop domestic suppliers on average, but are relatively more likely to drop the larger ones. Newly offshoring firms tend to add domestic suppliers that are relatively larger but also those that are more proximate. These findings suggest that the within-industry restructuring and industry composition effects of offshoring, both arising from declines in marginal costs, play important roles in shaping firms' domestic production networks. The resulting reorganization of firms' domestic supplier relationships reduces the average distance between buyers and sellers, increasing the spatial concentration of production clusters in Japan.

Lower communication and transportation costs obviously have made production more global. Our paper shows that while input sourcing has become more spatially dispersed across countries, it may lead to localization of production within a nation or region. These results echo the World

Trade Organization's (2013) findings about the increasingly regionalized global value chains. We leave the analysis about the macroeconomic implications of the increasing localization of production networks for future research.

Hitotsubashi University

Gakushuin University

Senshu University

Johns Hopkins University and CESIfo

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

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

for inputs outsourced to sellers in region r. Following Eaton and Kortum (2002), 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 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):

$$\begin{aligned}&[\pi_i(\varphi_i)|_{\Omega_{is}\cup\{r_1,r_2\}} - \pi_i(\varphi_i)|_{\Omega_{is}\cup\{r_2\}}] - [\pi_i(\varphi_i)|_{\Omega_{is}\cup\{r_1\}} - \pi_i(\varphi_i)|_{\Omega_{is}}] \\ &\approx \frac{\beta_s(\sigma-1)}{\theta_s}\left[\frac{\beta_s(\sigma-1)}{\theta_s} - 1\right]\tilde{\pi}_i(\varphi_i)\frac{\Phi_{isr_1}}{\Phi_{is0}+\sum_{r\in\Omega_{is}}\Phi_{isr}}\frac{\Phi_{isr_2}}{\Phi_{is0}+\sum_{r\in\Omega_{is}}\Phi_{isr}}.\end{aligned} \tag{20}$$

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 $(0,\infty)$.[52] 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

$$\Phi_{sr} = \begin{cases} T_0(w_0c)^{-\theta}, & \text{if } r = 0 \\ n_rT_r(w_rct(d_r))^{-\theta}\left[\frac{\rho_s}{(\rho_s-1)m(d_r)}\right]^{\frac{\rho_s\theta}{\rho_s-1}}e^{\frac{\rho_s\theta}{1-\rho_s}}, & \text{if } r = 1,\cdots,M+M^*. \end{cases} \tag{21}$$

[52]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.

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

$$\frac{\Phi_{sr}}{\Phi_{s0}} = n_r \left(\frac{T_r}{T_0}\right) \left(\frac{w_0}{w_r t(d_r)}\right)^{\theta} \left[\frac{\rho_s}{(\rho_s - 1)m(d_r)}\right]^{\frac{\rho_s \theta}{\rho_s - 1}} e^{\frac{\rho_s \theta}{1-\rho_s}}, \text{ for any } r, \tag{22}$$

$$\frac{\Phi_{sr_1}}{\Phi_{sr_2}} = \left(\frac{n_{r_1}}{n_{r_2}}\right) \left(\frac{T_{r_1}}{T_{r_2}}\right) \left(\frac{w_{r_2} t(d_{r_2})}{w_{r_1} t(d_{r_1})}\right)^{\theta} \left[\frac{m(d_{r_2})}{m(d_{r_1})}\right]^{\frac{\rho_s \theta_s}{\rho_s - 1}}. \tag{23}$$

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 (21) 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 (23) 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 $\rho_s/(\rho_s - 1) \to 1$, (23) 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 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 (22) and (23), respectively. To see how they vary with the degree of inputs differentiation, we take a logarithm and differentiate them with respect to $\rho_s/(\rho_s-1)$:

$$\frac{\partial \log(\Phi_{sr_1}/\Phi_{s0})}{\partial(\rho_s/(\rho_s-1))} = \theta \left[\log \frac{\rho_s}{\rho_s-1} - \log m(d_{r_1})\right] < 0, \tag{24}$$

$$\frac{\partial \log(\Phi_{sr_1}/\Phi_{sr_2})}{\partial(\rho_s/(\rho_s-1))} = \theta \left[\log m(d_{r_2}) - \log m(d_{r_1})\right] < 0, \text{ if } d_{r_1} > d_{r_2}, \tag{25}$$

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

$$\pi(\varphi)|_{\Omega_s=\{r_1^s,\cdots,r_{k+1}^s\}} - \pi(\varphi)|_{\Omega_s=\{r_1^s,\cdots,r_k^s\}} \approx \frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\frac{\Phi_{sr_{k+1}}/\Phi_{s0}}{1+\sum_{j=1}^{k}(\Phi_{sr_j^s}/\Phi_{s0})} - f_s, \tag{26}$$

$$\pi(\varphi)|_{\Omega_s=\{r_1^s,\cdots,r_{\bar{k}_s}^s\}} - \pi(\varphi)|_{\Omega_s=\emptyset} \approx \frac{\beta(\sigma-1)}{\theta}\tilde{\pi}(\varphi)\sum_{j=1}^{\bar{k}_s}\frac{\Phi_{sr_j^s}}{\Phi_{s0}} - \left(f + \bar{k}_s f_s\right). \tag{27}$$

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 (26) 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 (21). 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 (24). 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 (24), 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

$$\sum_{j=1}^{\bar{k}_{s_1}} \frac{\Phi_{s_1 r_j^{s_1}}}{\Phi_{s_1 0}} > \sum_{j=1}^{\bar{k}_{s_2}} \frac{\Phi_{s_2 r_j^{s_2}}}{\Phi_{s_2 0}}, \tag{28}$$

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 inequality follows from (28) 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

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

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 displacement 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 within-industry restructuring effect. 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, which we have referred to as the industry composition effect. 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

Elasticity of Substitution

Source: Soderbery (2015). Description: refined estimates of the demand elasticity of U.S. 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 Japan's Standard Industrial Classification (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 weights 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).

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 JSIC 3-digit category.[53]

1. We first map each ISIC 4-digit code (292 categories) to multiple JSIC (rev. 11) 4-digit codes (1261 categories, with 563 manufacturing industries), using the concordance file from 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 the computed averages that are strictly greater than 0.5 with 1, and 0 otherwise.

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

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

Air Freight Cost

Source: Hummels and Shaur (2013). Description: the cost of air freight for imports in each U.S. 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

[53] 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.

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 Construction of the Instrument

To compute the growth rate of global exports at the JSIC 3-digit level, we first compute the US dollar value of global exports to all countries expect Japan at the SITC (revision 2) 5-digit level using Comtrade data (2005-2010). We then use a concordance file from the United Nations Statistical Division to match a unique HS 4-digit (2002 version) category to a unique SITC code. The unique match is determined based on the number of HS 10-digit categories shared between a pair of SITC and HS code. For a handful of cases that a unique match cannot be determined because there are multiple pairs that tie in terms of the number of HS 10-digit categories shared, we will pick the smaller SITC in terms of the numeral value, albeit arbitrarily. Since a SITC may be split into multiple HS 4-digit category, we will split the export value of a SITC category using the number of HS 10-digit categories shared with each HS 4-digit as weight. We then repeat the same procedure to match export values at the HS 4-digit levels to each IO code (361 of them), using the concordance file from the Statistics Bureau of Japan, and finally map export values from IO categories to JSIC (rev. 11) 4-digit categories, using another concordance file from the Statistics Bureau. We then construct a firm-level instrument as specified in Equations (17) and (18) in the main text.

B.3 New Method to Estimate the Dispersion of Firm Productivity (θ)

Firm i's revenue can be written as $R(z_i) = Az_i^{\rho-1}$, where A is a constant that is common across all firms in the industry.[54] The distribution of a firm's revenue, R, can be written as

$$\begin{aligned} G(R) &= Prob\{R_i < R\} \\ &= Prob\{Az_i^{\rho-1} < R\} \\ &= Prob\{z_i < (R/A)^{\frac{1}{\rho-1}}\} \\ &= F\left((R/A)^{\frac{1}{\rho-1}}\right) \\ &= e^{-TA^{\frac{\theta}{\rho-1}}R^{\frac{\theta}{1-\rho}}}, \end{aligned}$$

where F denotes the cumulative distribution function of Fréchet(T,θ), implying that R is also distributed Fréchet with the location parameter equal to $T' = TA^{\frac{\theta}{\rho-1}}$ and the shape parameter equal to $\theta' = \theta/(\rho-1)$.

Now, the mean and variance of Frechet is given by

$$\begin{aligned} \mu &= \frac{1}{T'}\Gamma\left(1-\frac{1}{\theta'}\right), \\ \sigma^2 &= \frac{1}{T'^2}\left[\Gamma\left(1-\frac{2}{\theta'}\right) - \Gamma\left(1-\frac{1}{\theta'}\right)^2\right], \end{aligned}$$

where $\Gamma_x = \int_0^\infty t^{x-1}e^{-t}dt$ is the gamma function.

Consequently, we have

$$\frac{\sigma^2}{\mu^2} = \frac{\Gamma\left(1-\frac{2}{\theta'}\right)}{\Gamma\left(1-\frac{1}{\theta'}\right)^2} - 1.$$

Using Mathematica, we can identify θ' using σ^2 and μ^2 for each 3-digit JSIC industry, each computed using firm revenue data from TSR Company Information Database. Given estimates of ρ_s from Soderbery (2015), we can then compute θ_s as $(\rho_s - 1)\theta'_s$, for each industry s.

[54] $A = \left(\frac{\frac{\rho}{\rho-1}wc}{P}\right)^{1-\rho} E.$

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Table 1: Summary Statistics of the Origianl Network and Regression Samples

A. Samples from Tokyo Shoko Research (TSR) Network Data			
	Nb. of Obs.	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			
	Nb. of Obs.	Mean Nb. of Sellers	Median Nb. of Sellers
2005	345,352	25.05	10
2010	433,586	31.11	13

Note: All samples include buyers in the manufacturing sector but their sellers in both manufacturing and non-manufacturing sectors. The regression samples reported in Panel B is constructed with the TSR data, after removing buyers or sellers that appear only in one year of the panel, merged with data from the Basic Survey of Japanese Business Structure and Activities (BSJBSA).

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. Import starters: firms without imports in 2005 and with positive imports in 2010. Non-importers: firms reporting no import in both 2005 and 2010.

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

Dep. Var.:	Δlog(Sales)	Δlog(Nb. Sellers)	Δlog(Nb. Input Industries)	Δlog(Nb. Source Regions)	$\frac{dist_{10} - dist_{05}}{\frac{1}{2}(dist_{10} + dist_{05})}$	Δlog(dist)	$\frac{dist^{add} - dist^{drop}}{\frac{1}{2}(dist^{add} + dist^{drop})}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Imp Starter	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)
$\log(\text{TFP})_{t\text{-}1}$	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)
Buyer (4-digit) Industry FE	√	√	√	√	√	√	√
Buyer Region FE	√	√	√	√	√	√	√
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 significantly 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)	(7)	(8)	(9)
Dependent Variable:	$\ln(N_{i,source\ pref}/N_{i,nearest\ pref})_{input\ ind}$						$\ln(N_{i,source\ pref}/N_{i,home\ pref})_{input\ ind}$		
Estimated θ:	Caliendo-Parro			Estimates using Firm Data			Caliendo-Parro		
$\ln(dist)_{i,source\ pref} \times \theta$	-0.00535***	0.00262		-0.00386***	0.00215		-0.00819***	0.00214	
	(0.001)	(0.002)		(0.001)	(0.002)		(0.001)	(0.003)	
$\ln(dist)_{i,\ source\ pref} \times \theta \times \rho/(\rho-1)$		-0.00565***	-0.00516***		-0.00441***	-0.00524***		-0.00727***	-0.00712***
		(0.002)	(0.002)		(0.001)	(0.001)		(0.002)	(0.002)
$\ln(dist)_{i,source\ pref} \times \theta \times air$			-0.000379			-0.000651**			-0.000388
			(0.000)			(0.000)			(0.000)
Input Ind × Closest Region FE	√	√	√	√	√	√	-	-	-
Input Ind × Source Region FE	√	√	√	√	√	√	√	√	√
Input Ind × Buyer Region FE	-	-	-	-	-	-	√	√	√
R-sq	.278	.275	.274	.325	.275	.274	.302	.299	.297
Nb of Obs	49485	48735	48550	55609	49668	49483	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. Observations are at the buyer input-industry source-region 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 input-industry-source-region level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: The Incidence of Domestic Sourcing and Product Differentiation of Inputs

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			$\text{Outsource}_{\text{source pref, input industry}}$			
Estimated θ:			Caliendo-Parro Estimates			
$\ln(\text{dist}+1)_{\text{i, source pref}} \times \theta$	-0.0010***	0.00403***		-0.00100***	0.00402***	
	(0.000)	(0.000)		(0.000)	(0.000)	
$\ln(\text{dist}+1)_{\text{i,source pref}} \times \theta \times \rho/(\rho-1)$		-0.00399***	-0.00156***		-0.00401***	-0.00158***
		(0.000)	(0.000)		(0.000)	(0.000)
$\ln(\text{dist} + 1)_{\text{i,source pref}} \times \theta \times \text{air}$			-0.000194***			-0.000195***
			(0.000)			(0.000)
Buyer FE	-	-	-	√	√	√
Input Sector (12) × Source Region FE	√	√	√	√	√	√
R-sq	0.052	0.056	0.055	0.087	0.092	0.09
Nb of Obs	7773612	7773612	7773612	7773612	7773612	7773612

Panel B	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable:			$\text{Outsource}_{\text{source pref, input industry}}$			
Estimated θ:			Estimates using Firm Data			
$\ln(\text{dist}+1)_{\text{i, source pref}} \times \theta$	-0.00064***	0.00334***		-0.00065***	0.00334***	
	(0.000)	(0.000)		(0.000)	(0.000)	
$\ln(\text{dist}+1)_{\text{i,source pref}} \times \theta \times \rho/(\rho-1)$		-0.00320***	-0.000836***		-0.00321***	-0.000842***
		(0.000)	(0.000)		(0.000)	(0.000)
$\ln(\text{dist} + 1)_{\text{i,source pref}} \times \theta \times \text{air}$			-0.0000827***			-0.0000813***
			(0.000)			(0.000)
Buyer FE	-	-	-	√	√	√
Input Sector (12) × Source Region FE	√	√	√	√	√	√
R-sq	.0517	.0566	.0535	.0869	.0918	.0887
Nb of Obs	7773612	7773612	7773612	7773612	7773612	7773612

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. Regressions in Panel A use the estimated θ from Caliendo and Parro (2014), while those in Panel B use our own firm-based estimates of θ. See Section B.5 in the appendix for the detailed estimation procedures. All columns include input-sector-source-region fixed effects, while columns 4-6 and 10-12 include buyer fixed effects as well. Standard errors, clustered at the buyer level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6: The Incidence of Offshoring and Product Differentiation of Inputs

	(1)	(2)	(3)	(4)
Dependent Variable:		$\text{Offshore}_{\text{input industry}}$		
Estimated θ:	Caliendo-Parro Estimates		Estimates using Firm Data	
Domestic sourcing dummy	0.0747***	0.0681***	0.0748***	0.0683***
	(0.002)	(0.002)	(0.002)	(0.002)
$\text{TFP}_{\text{buyer,2005}}$	0.0109***		0.00962***	
	(0.001)		(0.001)	
$\text{TFP}_{\text{buyer,2005}} \times \theta \times \rho/(\rho-1)$	-0.000414***	-0.000408***	-0.000193***	-0.000176***
	(0.000)	(0.000)	(0.000)	(0.000)
Input Sector (12) FE	√	√	√	√
Buyer FE	-	√	-	√
R-sq	.03	0.136	.0297	.136
Nb of Obs	257208	257208	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 and 2 use the estimated θ from Caliendo and Parro (2014), while columns 3 and 4 use our own firm-based estimates of θ. All columns include input-sector fixed effects, while columns 2 and 4 include buyer fixed effects as well. Standard errors, clustered at the buyer level, are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Offshoring and Supplier Dropping

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	$Drop_{ij}$							
	OLS				2SLS			
Seller's Characteristics (x_j)	-	dist	sales	emp	-	dist	sales	emp
Imp Starter_i	0.00218	0.00226	0.00224	0.00227	-0.653***	-0.696***	-0.667***	-0.674***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.222)	(0.238)	(0.225)	(0.226)
$\text{Imp Starter}_i \times \log(x_j/x_{i05})$		0.000773	0.000762	0.00232		-0.0298	0.0873***	0.129**
		(0.002)	(0.002)	(0.003)		(0.059)	(0.030)	(0.052)
$\log(x_j/x_{i05})$		0.0104***	0.00522***	0.00685***		0.0141*	-0.00676	-0.0110
		(0.001)	(0.001)	(0.001)		(0.008)	(0.004)	(0.007)
Input Industry FE	√	√	√	√	√	√	√	√
Buyer Industry FE	√	√	√	√	√	√	√	√
Source Region FE	√	√	√	√	√	√	√	√
Buyer Home Region FE	√	√	√	√	√	√	√	√
Buyer's $\ln(\text{sales})_{2005}$	√	√	√	√	√	√	√	√
Nb of Buyers	4375	4354	4375	4375	4375	4354	4375	4375
Nb of Buyers that Offshore	477	476	477	477	477	476	477	477
Nb of Obs	86716	86019	86716	86716	86716	86019	86716	86716
R-squared	.047	.0491	.0476	.0477				
Kleibergen-Paap F statistic					41.697	18.588	20.880	20.875

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. In column 5, the dependent variable of the first stage is a buyer's import starting dummy. For each regression in columns 6 to 8, there are two first stages, with the dependent variable being a buyer's import starter dummy or its interaction with a seller characteristic. The instrument for a buyer's import starter dummy is the variable $shock_i$ constructed based on Equation (18) in the text, while the instrument for the import starter interaction is $shock_i$ interacted with the corresponding seller characteristic. See Table A6 for the regression results of the first stage. Robust standard errors are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Offshoring and Supplier Adding

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Add_{ij}							
	OLS				2SLS			
Seller's Characteristics (x_j)	-	dist	sales	emp	-	dist	sales	emp
Imp $Starter_i$	0.0439***	0.0447***	0.0438***	0.0438***	0.112	0.125	0.0917	0.0950
	(0.005)	(0.005)	(0.005)	(0.005)	(0.178)	(0.182)	(0.180)	(0.181)
Imp $Starter_i \times \log(x_j/x_{i10})$		-0.00475**	0.0005	-0.0006		-0.123***	0.167***	0.252***
		(0.002)	(0.002)	(0.003)		(0.037)	(0.025)	(0.039)
$\log(x_j/x_{i10})$		0.0160***	-0.0087***	-0.00945***		0.0337***	-0.0321***	-0.0460***
		(0.001)	(0.001)	(0.001)		(0.006)	(0.004)	(0.006)
Input Industry FE	√	√	√	√	√	√	√	√
Buyer Industry FE	√	√	√	√	√	√	√	√
Source Region FE	√	√	√	√	√	√	√	√
Buyer Home Region FE	√	√	√	√	√	√	√	√
Buyer's $\ln(\text{sales})_{2005}$	√	√	√	√	√	√	√	√
Nb of Buyers	4995	4903	4995	4995	4995	4903	4995	4995
Nb of Buyers that Offshore	516	509	516	516	516	509	516	516
Nb of Obs	109407	108520	109407	109407	109407	108520	109407	109407
R-squared	.0513	.0546	.0524	.0521				
Kleibergen-Paap F statistic					95.897	45.412	47.947	47.916

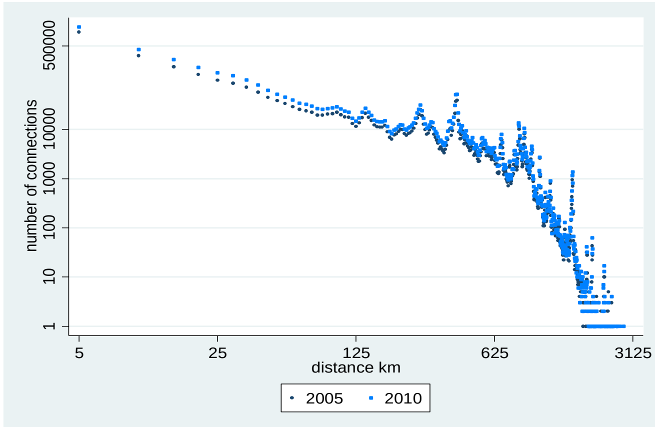
The sample includes only manufacturing buyers that did not import in 2005. Dropped sellers are removed from the sample, so that the comparison is between new suppliers and continuing suppliers. The unit of observation is a buyer-seller pair. Parent-child relationships are removed from the sample. In column 5, the dependent variable of the first stage is a buyer's import starting dummy. For each regression in columns 6 to 8, there are two first stages, with the dependent variable being a buyer's import starter dummy or its interaction with a seller characteristic. The instrument for a buyer's import starter dummy is the variable $shock_i$ constructed based on Equation (18) in the text, while the instrument for the import starter interaction is $shock_i$ interacted with the corresponding seller characteristic. See Table A7 for the regression results of the first stage. Robust standard errors are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Offshoring and Industry Adding and Dropping

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	$Drop_{is}$		Add_{is}		$Drop_{is}$		Add_{is}	
	OLS				2SLS			
Imp Starter_i	0.0117	0.00121	-0.00008	-0.00185	0.625	0.440	-0.197***	-0.143**
	(0.019)	(0.041)	(0.001)	(0.003)	(0.466)	(0.823)	(0.046)	(0.056)
Imp Starter_i x Rauch	-0.00730		0.00448***		-0.516***		0.168***	
	(0.020)		(0.001)		(0.198)		(0.018)	
Imp Starter_i x $\rho/(\rho\text{-}1)$		0.00350		0.00402**		-0.189		0.0652**
		(0.029)		(0.002)		(0.339)		(0.026)
Input Industry FE	√	√	√	√	√	√	√	√
Buyer Industry FE	√	√	√	√	√	√	√	√
Buyer Home Region FE	√	√	√	√	√	√	√	√
Buyer's $\ln(\text{sales})_{2005}$	√	√	√	√	√	√	√	√
Number of Obs.	21992	21653	699504	659984	21891	21552	659984	646958
R-squared	.0368	.0374	.0501	.0097				
Kleibergen-Paap F statistic					4.567	4.437	55.4	54.306

The sample includes only manufacturing firms that did not import in 2005. The unit of observation is a buyer-input-industry pair. The dependent variable of the regressions in columns (1), (2), (5) and (6) 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 regressions in columns (3), (4), (7) and (8) is a dummy variable equal to 1 if a 3-digit industry was added by a buyer between 2005 and 2010, 0 otherwise. For each regression in columns 5 to 8, there are two first stages, with the dependent variable being a buyer's import starter dummy or its interaction with the input industry's characteristic. The instrument for a buyer's import starter dummy is the variable $shock_i$ constructed based on Equation (18) in the text, while the instrument for the import starter interaction is $shock_i$ interacted with the corresponding input industry's characteristic. See Table A8 for the regression results of the first stages. Robust standard errors are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

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



Source: Tokyo Shoko Research

Figure 2. Number of Sellers and Buyers' Sales

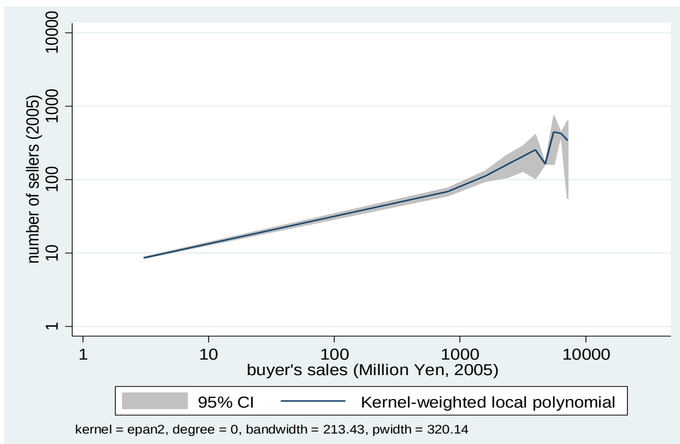


Figure 3. Number of Prefectures Sourced and Buyer Sales

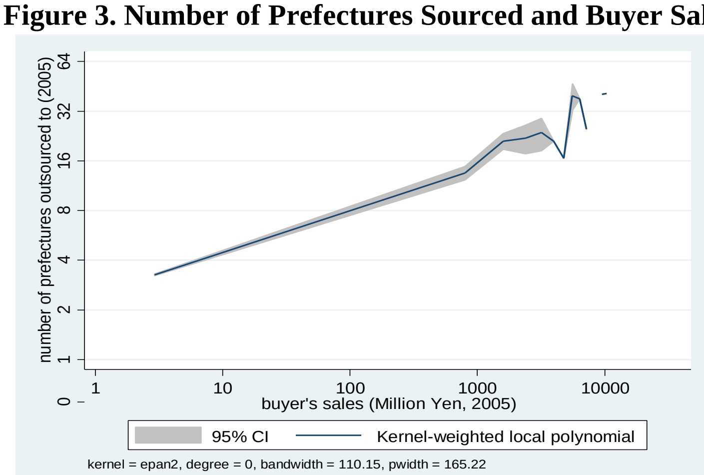
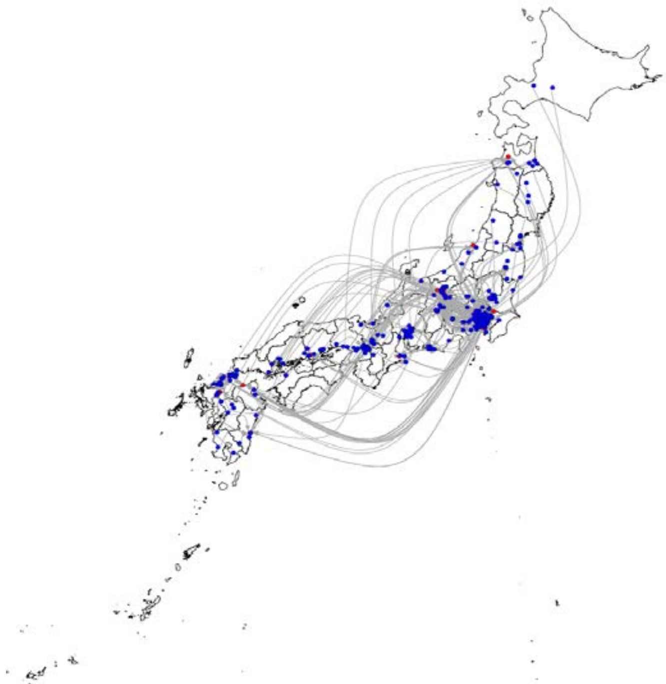
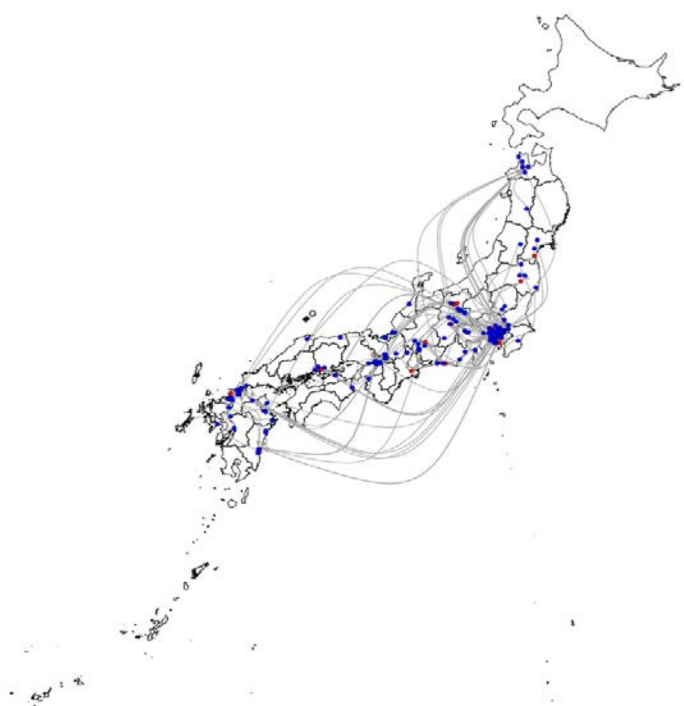


Figure 4. Sellers that were added by newly offshoring electronics producers (2005-2010)



Note: Buyers (electronics producers) are represented by red dots, with their new suppliers represented in blue dots.

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



Note: Buyers (electronics producers) are represented by red dots, with their dropped suppliers represented in blue dots.

Appendix Figures and Tables

Table A1: Summary Statistics of the Original TSR and Regression Samples

	TSR sample (Panel A in Table 1)					
	2005			2010		
	Nb. of Obs.	Nb. of Sellers		Nb. of 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 Tokyo Shoko Research Ltd. (TSR).

Table A2: Summary Statistics of the Original TSR and Regression Samples

	Regression Samples (Panel B in Table 1)			
	Nb Obs	% pair merged	Nb of Sellers	
			mean	median
<u>2005</u>				
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
<u>2010</u>				
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 Tokyo Shoko Research Ltd. (TSR).

Table A3: Firm Characteristics in the Basic Survey on Japanese Business Structure and Activities

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 (imports/ total purchases)	0.163	0.192
Aveage firms' shares of imports from Asia (imports from Asia / total imports)	0.824	0.846

Source: Basic Survey on Japanese Business Structure and Activities (BSJBSA 2005, 2010)

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	ln(# sellers' prefectures)$_{buyer}$		ln(# sellers)$_{buyer}$		ln(# jsic 4-digit outsourced)$_{buyer}$		ln(Sales/Emp)$_{seller}$
Measure of Buyer's Productivity	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)	(7)	(8)	(9)
Dependent Variable:	$\ln(N_{\text{source pref}}/N_{\text{nearest pref}})_{\text{input ind}}$						$\ln(N_{\text{source pref}}/N_{\text{home pref}})_{\text{input ind}}$		
Source of Estimated θ	Caliendo-Parro Estimates			Our Esimates based on Firm Data			Caliendo-Parro Estimates		
$\ln(\text{dist})_{i,\text{source pref}} \times \theta$	-0.00447***	-0.00198		-0.00325***	-0.00122		-0.00732***	-0.00264	
	(0.001)	(0.002)		(0.000)	(0.001)		(0.001)	(0.002)	
$\ln(\text{dist})_{i,\text{ source pref}} \times \theta \times \rho/(\rho-1)$		-0.00177	-0.00331***		-0.00151	-0.00251***		-0.00330**	-0.00539***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.002)	(0.001)
$\ln(\text{dist})_{i,\text{source pref}} \times \theta \times \text{air}$			0.00002			-4.19e-08			0.00002
			(0.000)			(0.000)			(0.000)
Input Ind × Closest Region FE	√	√	√	√	√	√			
Input Ind × Source Region FE	√	√	√	√	√	√	√	√	√
Input Ind × Buyer Region FE							√	√	√
R-sq	.262	.261	.266	.315	.26	.265	.29	.288	.294
Nb of Obs	65498	64967	59172	73493	65829	59920	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: First-Stage of the FE-IV Regressions Reported in Table 7

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Imp $Starter_i$	Imp $Starter_i$	Imp $Starter_i$ × $\log(dist_j/dist_{05})$	Imp $Starter_i$	Imp $Starter_i$ × $\ln(sales_j/sales_{05})$	Imp $Starter_i$	Imp $Starter_i$ × $\ln(emp_j/emp_{05})$
Seller's Characteristics (x_j)	-	dist	dist	sales	sales	emp	emp
$shock_i$	0.117***	0.112***	-0.007	0.117***	0.011	0.117***	0.011
	(0.018)	(0.018)	(0.031)	(0.018)	(0.044)	(0.018)	(0.033)
$shock_i \times \log(x_j/x_{i05})$		-0.006	0.497***	-0.003	0.781***	0.001	0.575***
		(0.018)	(0.058)	(0.014)	(0.071)	(0.018)	(0.065)
$\log(x_j$ -$/x_{i05})$		0.000	0.052	0.000	0.000	-0.000	0.037***
		(0.003)	(0.010)	(0.003)	(0.012)	(0.003)	(0.012)
Input Industry FE	√	√	√	√	√	√	√
Buyer Industry FE	√	√	√	√	√	√	√
Buyer Home Region FE	√	√	√	√	√	√	√
Buyer's $\ln(sales)_{2005}$	√	√	√	√	√	√	√
Nb of Obs	86716	86716	86716	86716	86019	86716	86,716
R-squared	0.1729	0.1736	0.1522	0.1729	0.1392	0.1729	0.1387

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. Robust standard errors are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A7: First-Stage of the FE-IV Regressions Reported in Table 8

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Imp $Starter_i$	Imp $Starter_i$	Imp $Starter_i$ × $\log(dist_j/dist_{10})$	Imp $Starter_i$	Imp $Starter_i$ × $\ln(sales_j/sales_{10})$	Imp $Starter_i$	Imp $Starter_i$ × $\ln(emp_j/emp_{10})$
Seller's Characteristics (x_j)	-	dist	dist	sales	sales	emp	emp
$shock_i$	0.082***	0.079***	-0.0003	0.082***	0.0095	0.082***	0.007
	(0.008)	(0.008)	(0.013)	(0.008)	(0.018)	(0.008)	(0.013)
$shock_i \times (x_j - x_{i05})$		0.0077	0.498***	-0.003	0.838***	0.002	0.689***
		(0.014)	(0.037)	(0.011)	(0.054)	(0.014)	(0.051)
$x_j - x_{i05}$		-0.002	0.051***	0.0004	-0.015	-0.0009	0.015
		(0.003)	(0.005)	(0.002)	(0.010)	(0.003)	(0.010)
Input Industry FE	√	√	√	√	√	√	√
Buyer Industry FE	√	√	√	√	√	√	√
Buyer Home Region FE	√	√	√	√	√	√	√
Buyer's $\ln(sales)_{2005}$	√	√	√	√	√	√	√
Nb of Obs	109407	108520	108520	109407	109407	109407	109407
R-squared	0.1634	0.1638	0.1628	0.1634	0.146	0.1634	0.148

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. Robust standard errors are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A8: First-Stage of the FE-IV Regressions Reported in Table 9

	(1)	(2)	(3)	(4)
Dependent Variable	Imp Starter_i	Imp Starter_i × Rauch	Imp Starter_i	Imp Starter_i × $\rho/(\rho-1)$
shock_i	0.0294***	0.0017	0.0294***	0.0028
	(0.0029)	(0.0025)	(0.0032)	(0.0047)
shock_i × Rauch	0.0000	0.929***		
	(0.0262)	(0.0132)		
$\text{shock}_i \times \rho/(\rho-1)$			0.0000	0.929***
			(0.0381)	(0.0675)
Input Industry FE	√	√	√	√
Buyer Industry FE	√	√	√	√
Buyer Home Region FE	√	√	√	√
Buyer's $\ln(\text{sales})_{2005}$	√	√	√	√
Nb of Obs	659,984	659,984	646,958	646,958
R-squared	0.1011	0.1052	0.1011	0.1024

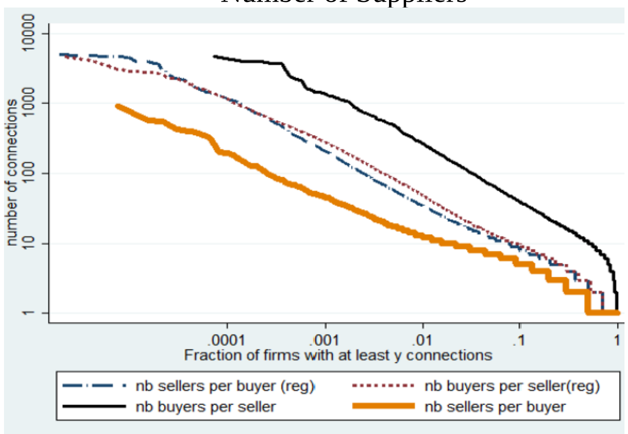
The sample includes only manufacturing firms that did not import in 2005. The unit of observation is at the buyer-input-industry level. Newly added sellers are removed from the sample. The unit of observation is a buyer-seller pair. Parent-child relationships are removed from the sample. Robust standard errors are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A9: Input Industries by Buyer-Seller Distance and Characteristics (2005)

	Seller Industry (out of 150)	Nb. of links	Median	Mean	25th pct	75th pct	ρ/(ρ-1) (Broda-Weinstein)	Rauch	θ (Caliendo-Parro)	θ (Firm-based Est)
	Top 20 Input Industries in terms of Average Distance from Buyers		Distance (km)							
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	-	-	8.871	-
214	Leather footwear	126	269.1	249.1	7.7	395.7	1.186	1	5.732	5.659
105	Cigarettes, cigars and tobacco	47	265.2	352.1	92.0	539.3	1.117	0	8.871	12.862
98	Vegitable oils, animal oils, and fats	674	247.3	273.9	28.7	409.8	1.046	1	9.821	12.837
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	5.160	13.683
117	Rope and netting	381	209.7	256.6	36.1	395.4	1.369	1	5.732	23.820
51	Metal mining	121	206.4	264.3	13.8	407.8	-	-	24.498	9.995
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	9.821	12.862
261	Boilers, engines, and turbines	566	185.0	251.5	27.8	406.2	1.040	1	6.119	17.455
225	Clay refractories	360	181.7	246.1	25.2	415.6	1.326	1	1.713	22.387
106	Feeds and fertiliers	554	181.1	302.2	43.2	481.6	1.198	0	9.821	12.862
181	Petroleum refining	423	171.9	250.4	12.8	403.3	1.060	1		29.622
101	Soft drinks and carbonated water	623	170.8	253.9	34.7	387.7	1.090	1	9.821	12.862
174	Rayon, acetate fibers, and synthetic fibers	386	168.1	217.0	16.9	398.1	1.101	0	5.160	13.683
241	Primary smelting and refining of non-ferrous metals	611	167.6	230.1	21.7	396.8	1.495	1	-	8.250
304	Aircraft	575	166.0	234.5	23.2	398.2	1.027	1	9.917	17.788
	Bottom 20 Input Industries in terms of Average Distance from Buyers									
326	Lacquer ware	97	8.4	86.0	2.1	111.0	1.382	1	7.742	8.223
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	-	-	24.498	9.995
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	13.718
				Median across Industries			1.228	1.000	8.871	12.862
				Standard Deviation across Industries			0.262	0.422	5.805	8.997

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

Figure A1. Distribution of Buyers with Different Number of Suppliers



Note: "reg" denotes the regression sample.

Figure A2: Optimal sourcing capabilities

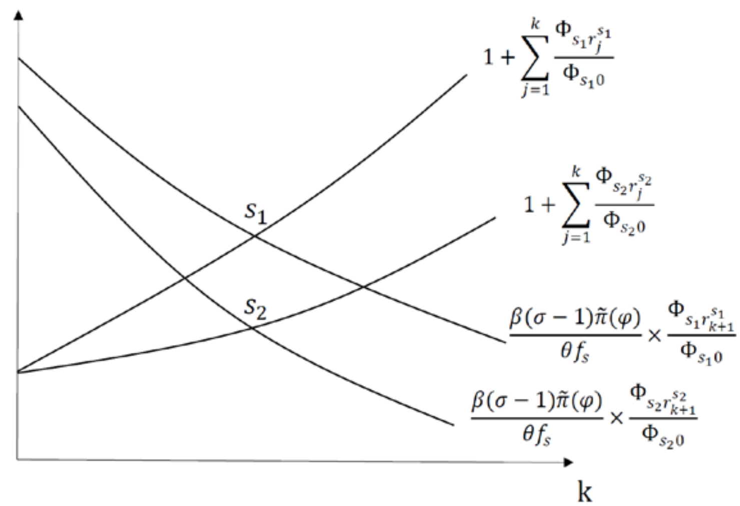


Figure A3: Number of buyers per sq km by prefecture

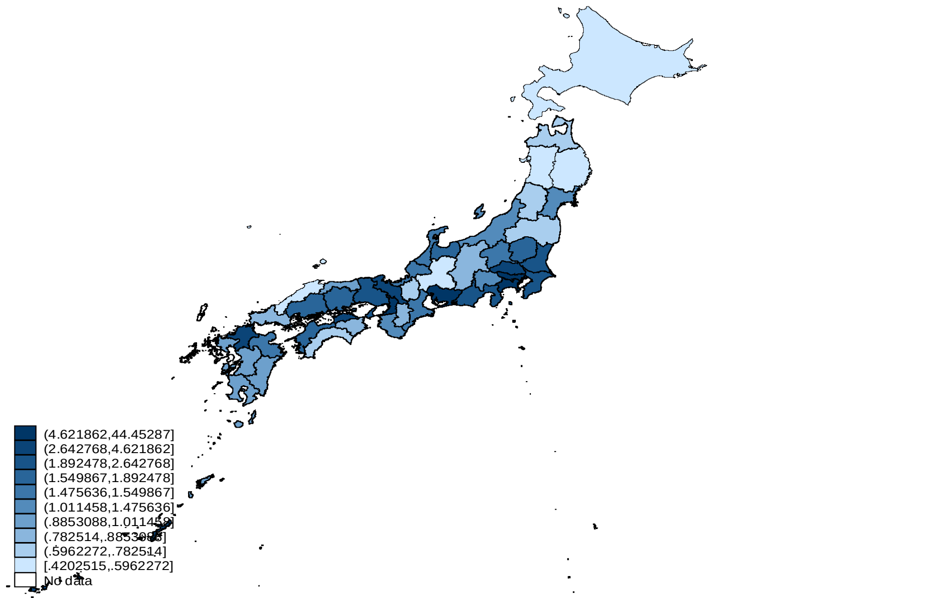


Figure A4: Number of sellers per sq km by prefecture