Production Networks, Geography, and Firm Performance

Andrew B. Bernard

Dartmouth College, Centre for Economic Policy Research, and National Bureau of Economic Research

Andreas Moxnes

University of Oslo and Centre for Economic Policy Research

Yukiko U. Saito

Waseda University and Research Institute of Economy, Trade, and Industry

This paper examines the importance of buyer-supplier relationships for firm performance. We develop a model in which firms outsource tasks and search for suppliers. Lower search and outsourcing costs lead firms to search more and find better suppliers, which in turn drives down marginal costs. We test the theory by exploiting the opening of a high-speed train line in Japan, which lowered the cost of passenger travel but left shipping costs unchanged. Using an exhaustive data set on firms' buyer-seller linkages, we find significant improvements in firm performance as well as creation of buyer-seller links, consistent with the model.

I. Introduction

In spite of the widespread perception that firms' success in part depends on their connections with suppliers, relatively little work has been done on the structure, performance, and importance of production networks.

Thanks go to Adam Kleinbaum, Yaniv Dover, Jonathan Dingel, and Masahisa Fujita as well as seminar participants at Centre for Economic Policy Research European Research

Electronically published February 19, 2019
[*Journal of Political Economy*, 2019, vol. 127, no. 2]

Even less is known about how geography and trade costs affect links in production networks. Finally, in spite of a large literature on the role of infrastructure on economic outcomes, there is almost no evidence on how infrastructure affects supply chains and firm-level productivity. This paper examines the importance of buyer-supplier relationships and the structure of the production network in firm performance.

While there has been an explosion of research on social and economic networks and their formation, to date little of that work has considered supplier-customer relations between firms. In addition, existing studies are often limited to a particular industry or geography within a country (see, e.g., the seminal work of Uzzi [1996]). In this paper we use a comprehensive, unique data set on the production network in Japan. Our data provide supplier-customer links for about 800,000 firms. This set of firms accounts for the large majority of private-sector economic activity in the country. For most of the firms in Japan, we can determine their location, suppliers, customers, and measures of performance.

We develop a set of stylized facts about the Japanese production network to guide our model. Large and productive firms have more suppliers than small firms. Geographic proximity plays an important role in the matching of suppliers and customers. Most connections are local; the median distance to a supplier is 30 kilometers. Larger firms not only have more suppliers but, on average, have suppliers that are farther away. The production network displays negative degree assortativity; the trading partners of well-connected firms, on average, are less well connected themselves. Consider two firms, one with many suppliers, the other with few. The suppliers to the well-connected firm have, on average, relatively few customers. The suppliers to the less connected firm have, on average, many customers. Many of these facts are also present in cross-border trade networks; for example, negative degree assortativity is also found in exporter-importer networks in international trade (see Bernard, Moxnes, and Ulltveit-Moe 2018).

We build a parsimonious model of a domestic economy motivated by the stylized facts. Downstream firms require a continuum of tasks as in-

Workshop in International Trade, Dartmouth Interdisciplinary Network Research Group, Nordic International Trade Seminars, National Bureau of Economic Research International Trade and Investment, Research Institute of Economy, Trade, and Industry, World Bank, and Empirical Investigations in Trade and Investment—Phuket for helpful comments and Yuta Suzuki for great support as a research assistant. We gratefully acknowledge the financial support from the Japan Society for the Promotion of Science (no. 25780181). We thank the Center for Spatial Information Science, University of Tokyo, for its address matching service. This study is conducted as a part of the project "Inter-organizational and Inter-inventors Geographical Proximity and Networks" undertaken at the Research Institute of Economy, Trade, and Industry. This project has received funding from the European Research Council under the European Union's Horizon 2020 research and innovation program (grant agreement 715147). Matlab and Stata codes and documentation are provided as supplementary material online.

puts into the production process, for example, materials processing, accounting, printing, and distribution services. They can produce the tasks themselves or outsource them. Finding suppliers is costly, however, and therefore, it may not be profitable for all firms to outsource a given task, even if the market price of a task is lower than the firm's marginal cost of supplying the same task. Our model is closely related to the international sourcing framework in Antràs, Fort, and Tintelnot (2014), but we modify it to allow for the possibility that firms can supply a given task within the boundary of the firm. Downstream firms can observe broad characteristics of potential upstream locations, that is, average productivity and trade costs, but need to expend resources to observe the prices of individual tasks in a location. In addition, outsourcing is costly because of trade costs. Trade costs are here broadly defined; we have in mind both shipping costs and efficiency losses in the buyer-supplier relationship. In equilibrium, a higher-efficiency firm will search across more locations, source more inputs, and have better performance. If variable trade costs or the fixed costs of search fall, firms will search more, they will source more inputs from more distant locations, and firm sales will rise. These effects will be larger in input-intensive industries in which the marginal benefit of finding better suppliers is greater. For the aggregate economy, locations with low trade and search costs will have higher-performing firms, even if productivity is ex ante identical across all locations. Our framework therefore offers a supply-side microfoundation for why measured productivity varies widely across locations, as documented in Sveikauskas (1975), Glaeser and Maré (2001), and Combes et al. (2012).

To examine the predictions of the model we use the 2004 opening of the southern portion of the high-speed rail lines in Japan (Kyushu Shinkansen) as a quasi natural experiment. The route of this particular extension had been planned at least since 1973, but the actual construction was subject to substantial timing uncertainty due to numerous budgetary and administrative delays, thus limiting the scope for anticipation effects. We examine whether firms near new Shinkansen stations improved their performance after the opening. Estimating a triple difference specification, we find that performance is better for firms near the new stations after the opening and that firms in industries with greater purchased input shares perform better compared to firms in industries with lower purchased input shares.

The model suggests that the firm-level performance improvement is due to changes in the set of suppliers and sourcing locations. We draw on a second cross section of the Japanese production network in 2010 to examine whether firms in localities near the new stations get suppliers from new locations and whether these suppliers themselves are located near newly opened Shinkansen stations. Estimating a similar triple difference specification, the results support the mechanisms emphasized in the model; the number of sourcing locations and the share of suppliers located near a new station both increase for firms also located close to a new station. Our results therefore suggest that face-to-face interaction between individuals across the supply chain improves firm outcomes because firms are more likely to find a good supplier and/or because firms work more efficiently with their existing suppliers. This mirrors the findings in management literature, where research suggests that groups using computer-mediated communication systems communicate less effectively than groups meeting face to face (Hightower and Sayeed 1995, 1996; Warkentin, Sayeed, and Hightower 1997).

This paper is naturally related to a growing literature on the determinants of domestic and foreign sourcing and the impact on firms. Amiti and Konings (2007), Goldberg et al. (2010), Bøler, Moxnes, and Ulltveit-Moe (2015), and Halpern, Koren, and Szeidl (2015) examine the role of imported inputs in firm productivity where foreign and domestic inputs are imperfect substitutes. Our work is closer to that of Antràs et al. (2014), who develop and structurally estimate a model in which firm performance is positively related to the intensive and extensive margins of purchased imported inputs. In the domestic production network, we find systematic relationships between distance to domestic suppliers and firm performance that are analogous to those in the international trade context. In this regard our work is related to that of Fort (2017), who finds an important role for firm heterogeneity and location in the decision to use domestic contract manufacturing services.

The paper is also related to a large literature on the effects of infrastructure on economic development. Governments typically allocate a large fraction of their budgets to infrastructure projects, and multilateral institutions similarly emphasize infrastructure in the expenditure allocation. Most research on the effects of infrastructure concentrates on the location of economic activity, income, and aggregate welfare effects. For example, Donaldson (2018) examines the effects of railroads on income and welfare in India, while Duranton, Morrow, and Turner (2014) consider the effects of interstate highways on the level and composition of trade for US cities. Redding and Turner (2015) survey the literature on the effects of infrastructure on economic activity. This area of research focuses on the role of infrastructure in reducing transport time and costs for goods between cities and in reducing the travel time for individuals within a city, that is, commuting time. Our research points to another role for infrastructure in reducing travel time for individuals (as opposed to goods) between regions and the resulting firm-level improvements coming from the supply chain.

Another related strand of recent work studies the geography of knowledge transmission across locations. Davis and Dingel (2012) model costly idea exchange as the agglomeration force in a system of cities. Our framework focuses on the cost of connecting to others (firms) and the resulting improvements in performance. Cristea (2011) considers the importance of face-to-face meetings in international trade and finds that increased exports raise the demand for business class air travel. Comin, Dmitriev, and Rossi-Hansberg (2012) study technology diffusion over time and find that technology diffuses more slowly to locations that are farther away from technology leaders. Keller and Yeaple (2013) measure the cross-country spatial barriers to the transmission of embodied or disembodied knowledge. They find that person-to-person communication costs increase in distance. Hillberry and Hummels (2008) examine trade in intermediate goods as an explanation for highly localized shipments in the United States.

Our work is also related to that of Giroud (2013), who examines the effect of new airline connections on within-firm performance of and investment in manufacturing plants. Related work in finance argues that proximity matters for monitoring and relationships (see Lerner 1995; Coval and Moskowitz 1999, 2001; Petersen and Rajan 2002). In contrast to his study, which examines reductions in travel costs between headquarters and plants for multiplant firms, we broaden the scope by exploring all buyer-supplier connections among all firms in the economy. Moreover, our model and empirical strategy emphasize the creation and destruction of linkages in response to infrastructure shocks.

In the literature on firm-to-firm connections, Oberfield (2013) develops a network theory of search and production in which producers potentially sell to many customers but have only one supplier. Downstream firms consider match-specific productivity and price when choosing among available techniques. As in our model, the share of purchased inputs matters for the propagation of shocks in the economy, although our focus is on the supplier side rather than the downstream links. Acemoglu et al. (2012) relate these types of microeconomic shocks to aggregate fluctuations in a model of sectoral input-output linkages, while Carvalho, Nirei, and Saito (2014) use the Japanese production network to study the supply chain disruptions occurring in the aftermath of the 2011 earthquake in Japan. Nayar, Flaaen, and Boehm (2015) and Barrot and Sauvagnat (2016) also study supply chain disruptions using natural disasters as exogenous shocks.

While our focus is on buyer-supplier matches in the domestic supply network, it is closely related to the nascent literature using matched importer-exporter data. Bernard et al. (2018) consider exporter-importer connections using Norwegian transaction trade data. They find, as we do, negative assortativity in buyer-seller matches and in-degree and out-degree distributions that largely follow power laws. Blum, Claro, and Horstmann (2012) examine characteristics of trade transactions for the exporter-importer pairs of Chile-Colombia and Argentina-Chile and also find that small suppliers (exporters) typically sell to large (importers) suppliers and small importers (buyers) source from large suppliers (exporters).

The rest of the paper is structured as follows. We describe the data in Section II and develop a set of stylized facts about buyer-supplier relationships in Section III. In Section IV, we develop our multilocation model of domestic sourcing. We describe and estimate our natural experiment along with various robustness checks in Section V and provide concluding remarks in Section VI.

II. Data

The data employed in this paper come from two main sources. First, production network data for two moments in time, 2005 and 2010, are assembled by Tokyo Shoko Research, Ltd. (TSR). TSR is a credit reporting agency, and firms provide information to TSR in the course of obtaining credit reports on potential suppliers and customers or when attempting to qualify as a supplier. The resulting database contains information on more than 950,000 firms in each cross section, represents more than half of all the firms in Japan, and covers all sectors of the economy. The TSR sample is close to the full population of firms with more than four employees.[1]

Each firm provides rank-ordered lists of the most important suppliers (up to 24) and customers (up to 24). TSR also collects information on employment, the number of establishments, the number of factories, up to three (four-digit) industries, sales, profits, and a physical address. In addition, the database records TSR's credit score for the firm. Using an address matching service provided by the Center for Spatial Information Science at the University of Tokyo, we are able to match a firm's address to longitude and latitude data.[2] We use the geocoded data to create a measure of great circle distance between firms. The top three prefectures by counts of firms are Tokyo, Osaka, and Aichi (Nagoya), while the top three two-digit industries by counts are general construction work, specialist construction work, and equipment installation.

Second, firm-level balance sheet data come from Kigyou Katsudou Kihon Chousa Houkokusho (The Results of the Basic Survey of Japanese Business Structure and Activities), henceforth Kikatsu, for the period 1998–2008. Kikatsu is an annual survey that gives detailed information about firm activities such as sales, employment, capital stock, intermedi-

[1] Firms with one to four employees are underrepresented in TSR compared to census data, while for firms with five or more employees, the firm size distribution in TSR is very similar to the distribution in census data.

[2] As each firm reports only one address, the geographic information for multiestablishment firms is likely to reflect the location of the headquarters.

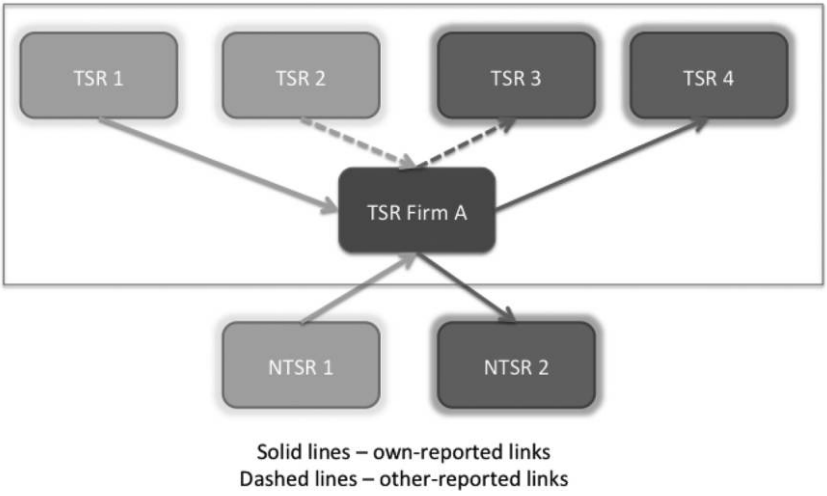

FIG. 1.—Supplier and customer connections: an example. Color version available as an online enhancement.

ate purchases, and industry affiliation. It covers the full population of manufacturing and nonmanufacturing firms with more than 50 employees and with capital of more than ¥30 million.

Supplier and customer connections.—The TSR data have both advantages and disadvantages relative to other production network data sets. Among the advantages is the inclusion of firms of all sizes and industries including both publicly listed and unlisted firms. In addition, the TSR firms self-report their most important suppliers and customers; there is no cutoff in terms of sales or purchases.[3] However, the 24-firm limit for suppliers and customers potentially causes a truncation in the number of relationships in the self-reported data relative to the actual number of such connections.

To mitigate this issue, we combine both self-reported and other-reported information for each firm in the data and use the union of own-reported and other-reported information. For firms A and B, we consider A to be a supplier of B if both firms are in the TSR data and either (i) A reports B as a customer or (ii) B reports A as a supplier. Note that some firms that are reported as suppliers and customers are outside the TSR set of firms (NTSR); that is, they are domestic Japanese firms but are not surveyed by TSR.

In figure 1 we show possible suppliers and customers for a firm (firm A) in the TSR database. Firm A reports that it has two customers, TSR4 and

[3] In their analysis of US production networks, Atalay et al. (2011) use Compustat data on publicly listed firms and their major customers defined as firms that purchase more than 10 percent of the seller's revenue.

NTSR2, and two suppliers, TSR1 and NTSR1. Other firms also report connections to firm A: TSR2 reports firm A as a customer while TSR3 reports firm A as a supplier. In determining firm A's in-degree, the number of suppliers, and its out-degree, the number of customers, we ignore the NTSR links and include both own-reported and other-reported connections. Thus, firm A has an in-degree of 2 (TSR1 and TSR2) and an out-degree of 2 (TSR3 and TSR4).

The 24-firm limit will be binding for very large firms, and therefore, most of their customers and suppliers are other-reported. One may suspect that this implies that large-to-large linkages are underreported because both firms may not report the other. Recall, however, that firms provide a rank-ordered list of their connections; connections to large firms are therefore likely to end up high on the list. Moreover, the degree distributions reported in the next section (fig. 2) do not indicate any discontinuity around the 24-firm threshold.

A number of firms report no suppliers and/or no customers among the TSR firms. This does not mean they recorded no suppliers or customers on their forms, but instead all their reported connections are outside the TSR set of firms. A report of no TSR suppliers or no TSR customers might occur for several reasons. A firm might appear to have no TSR customers because all the domestic firms that are customers are outside the TSR database, all its customers are foreign firms, or all its customers are non-firms, for example, the public or government. A firm might appear to have no TSR suppliers because all the domestic firms that are suppliers are outside the TSR database or all its suppliers are foreign.[4] We choose to work only with the set of TSR firms with a positive in-degree or positive out-degree (links to other TSR firms) and find no evidence of systematic bias in the sample of firms with positive TSR degree. Using NTSR + TSR data, the distribution of firms with TSR degree equal to zero is virtually identical to the overall sample of firms; that is, the mean and variance of NTSR + TSR out-degree and in-degree distributions are the same.

III. The Production Network: Stylized Facts

In this section we begin to explore the domestic production network in Japan.[5] There are 785,939 firms (nodes) in the TSR production network with 3,338,319 supplier-customer connections (directed edges). Of those nodes, 654,588 (568,197) nodes have positive in-degree (out-degree)

[4] It seems implausible to imagine that an operating firm has no actual domestic suppliers. This is supported by the fact that more TSR firms report no customers than report no suppliers.

[5] All descriptive statistics refer to the 2005 cross section. Some of these network characteristics are also presented in Saito, Watanabe, and Iwamura (2007) and Ohnishi, Takayasu, and Takayasu (2010).

among TSR firms. For firms with positive in-degree, the mean number of suppliers is 5.1 and the median is 3. For firms with positive out-degree, the mean number of customers is 5.9 and the median is 3.

The cumulative distribution functions (cdfs) of the in-degree and out-degree distributions are given in figure 2. The distributions are well approximated by a Pareto (power law) distribution. The estimated Pareto shape parameter is −1.37 for the in-degree distribution and −1.46 for the out-degree distribution. Deviations from the Pareto are found in the extreme tails of the distribution. Firms with a very large number of connections are somewhat underrepresented while firms with few connections appear in greater numbers. These deviations from a power law distribution are comparable to those found in exporter-importer degree distributions by Bernard et al. (2018) but are much smaller in magnitude compared to those found by Atalay et al. (2011) for supplier-customer connections derived from data on large US firms and their large customers.

In this section, we document four facts from the data that will guide the development of the model in Section IV. We explore the relationship between firm characteristics, connections in the production network, and geography.

Fact 1. Larger firms have more suppliers.

Higher sales are associated with a larger number of supplier connections. Figure 3 plots the kernel-weighted local polynomial regression of a firm's in-degree (vertical axis) on sales (horizontal axis), both in logs. The linear regression slope is 0.33, meaning that a 10 percent increase in sales is asso-

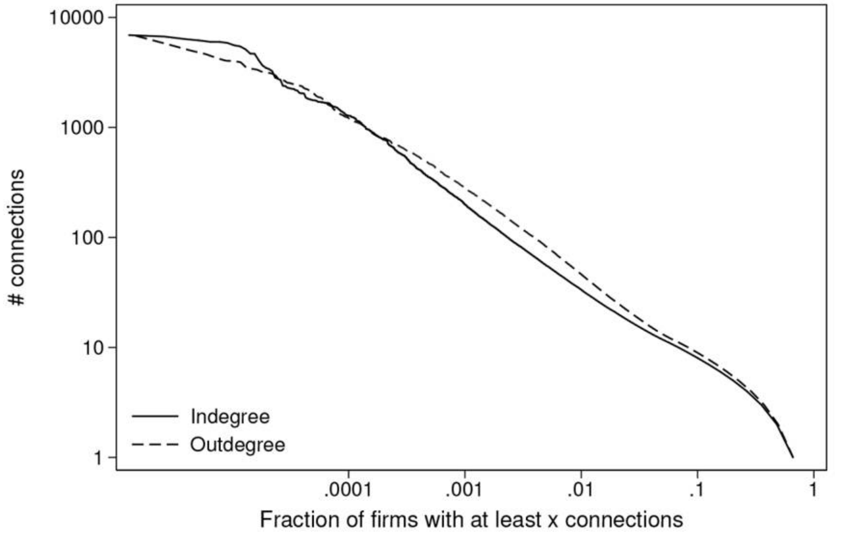

Fig. 2.—In-degree and out-degree cdfs: 2005 data, log scales

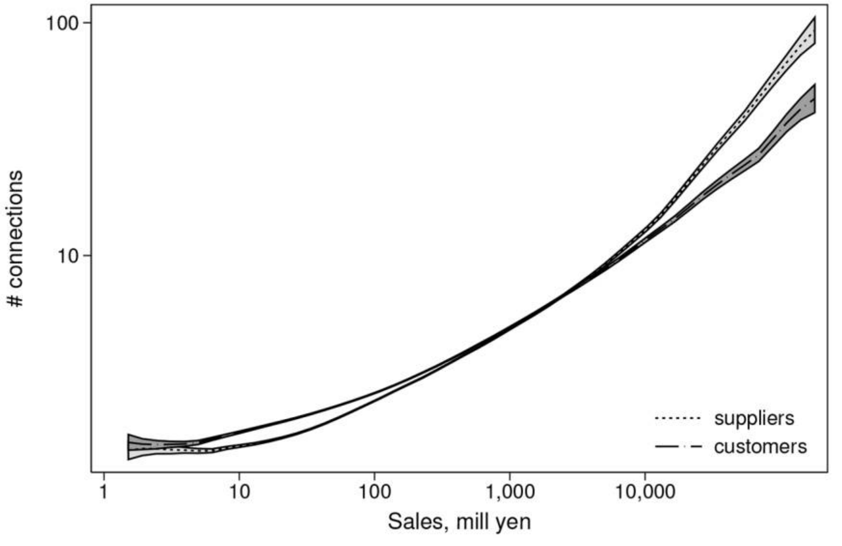

FIG. 3.—Size, in-degree, and out-degree: 2005 data. The figure shows the kernel-weighted local polynomial regression of firm-level log degree (vertical axis) on log sales (horizontal axis). The two lines represent in-degree and out-degree as separate regressions. The gray area denotes the 95 percent confidence bands. The sample is first trimmed by excluding the 0.1 percent lowest and highest observations of sales.

ciated with a 3.3 percent increase in the number of suppliers. A similar positive relationship exists between a firm's sales and out-degree, mirroring the findings in Bernard et al. (2018).

FACT 2. Larger firms have suppliers in more locations and their distance to suppliers is greater.

Figure 4 shows that larger firms tend to have suppliers in more municipalities. A firm in the 1st decile of the sales distribution has suppliers in 1.7 locations while a firm in the 9th decile has suppliers in 3.9 locations.[6] At the same time, larger firms have more remote connections; figure 5 plots the fitted values from a kernel-weighted local polynomial regression of a firm's median distance to its suppliers on its sales (both in logs). The median distance to suppliers is 23.7 km for firms in the 1st decile of the sales distribution, while median distance is roughly 30 percent higher (30.1 km) for firms in the 9th decile of the sales distribution. A similar positive relationship also exists between a firm's sales and median distance to its customers, as well as between distance and the number of municipalities a firm is supplying. These empirical patterns are reminiscent of the evidence from Chaney (2014). In particular, he finds that firms exporting to more countries also have a higher average squared distance to the firms' export destinations.

[6] There are in total 2,180 municipalities in our data set; see also Sec. V.A.

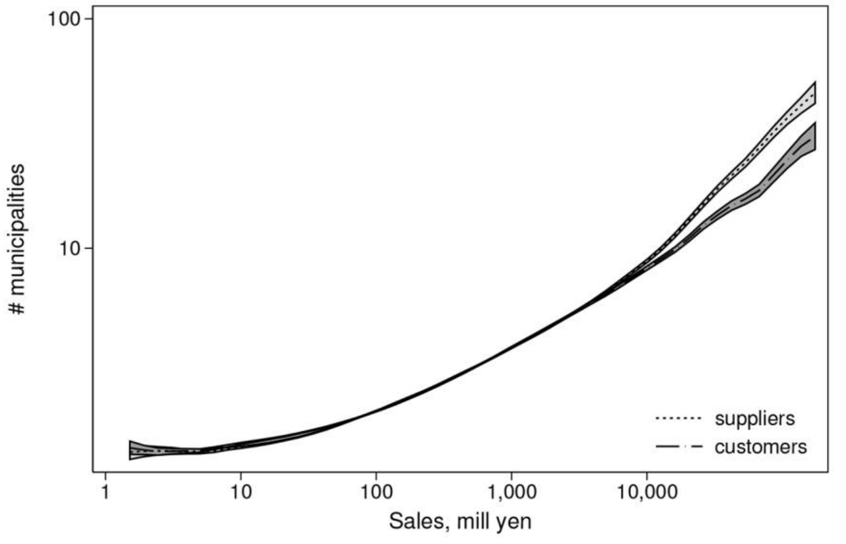

Fig. 4.—Size and number of supplier and customer locations: 2005 data. The figure shows the kernel-weighted local polynomial regression of firm-level log number of municipalities with connections (vertical axis) on log sales (horizontal axis). The two lines represent the supplier and customer side as separate regressions. The gray area denotes the 95 percent confidence bands. The sample is first trimmed by excluding the 0.1 percent lowest and highest observations of sales.

We also compare buyers that have matched to the same supplier. The same pattern arises here; the distance to the supplier is increasing in the performance of the customer. Table 1 reports results from a regression of firm performance (in-degree, sales, employment, and labor productivity) on distance to the supplier, controlling for supplier fixed effects and seller prefecture fixed effects. The relationship is strongly positive; increasing distance by 10 percent to the supplier is associated with 1.9 percent higher sales in the buyer firm.

Robustness.—A potential concern is that facts 1 and 2 are partly driven by differences across industries. For example, large firms may belong to certain types of industries that for various reasons require many suppliers. Hence, we also explore within-industry correlations between size and our various outcome variables. Table 2 shows results when regressing firm characteristics on log size and three-digit Japanese Standard Industrial Code (JSIC) industry fixed effects. The outcome variables are the same as above: in-degree, median distance to suppliers, and number of sourcing municipalities. For completeness, we also report results on the customer side: out-degree, median distance to customers, and number of municipalities with customers.

An additional concern is that larger firms have more plants, so that distance from the relevant plant to a supplier may not be greater for larger firms. We investigate this by including an interaction term between log

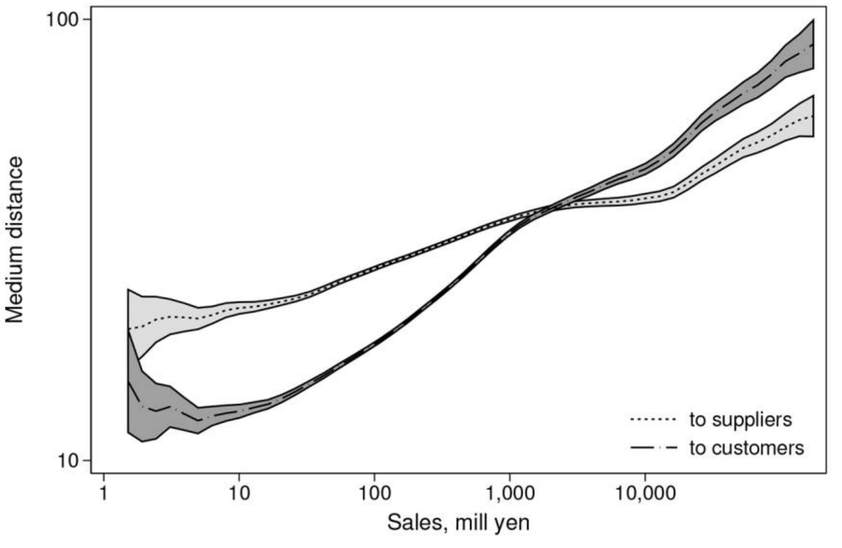

FIG. 5.—Size and median distance to connections: 2005 data. The figure shows the kernel-weighted local polynomial regression of firm-level median log distance to the firm's connections (vertical axis) on log sales (horizontal axis). The two lines represent the distance to suppliers and customers as separate regressions. The gray area denotes the 95 percent confidence bands. The sample is first trimmed by excluding the 0.1 percent lowest and highest observations of sales.

size and a dummy variable for whether the firm is single-plant or not. The interaction is close to zero, indicating that there is a positive relationship also for single-plant firms. We also plot the size–median distance relationship for single-plant firms only; figure G2 in the appendix shows the same polynomial regression plot for this group. Also, the within-supplier relationship between distance and performance continues to be positive when considering single-plant firms only (table 1, rows 5 and 6).

In the model (Sec. IV), small and large firms require the same number of tasks, but large firms optimally decide to outsource more of them. An alternative hypothesis is that large firms offer more products and therefore also require more tasks than smaller firms. We do not observe the tasks performed within the firm, so we cannot directly test this hypothesis. What we can do, however, is to check whether facts 1 and 2 also hold for firms that belong to a single three-digit JSIC industry (in the data, each firm can belong to up to three industries). If the positive relationship between size and in-degree also holds for single-industry firms (within an industry), then this suggests that differences in the range of tasks produced are not driving the empirical relationships. Table 2 includes the interaction between log size and a dummy variable for whether the firm is single-industry or not. The interaction is typically negative but small; hence our results survive when considering this group of firms.

TABLE 1
FIRM PERFORMANCE AND DISTANCE TO SUPPLIER

	In-Degree	Sales	Employment	Labor Productivity
All firms:				
Distance	.16***	.19***	.16***	.03***
	(320.50)	(261.40)	(264.80)	(99.48)
R^2	.58	.62	.60	.46
Observations	3,302,104	3,298,607	3,297,191	3,294,028
Single-plant firms:				
Distance	.01***	.02***	.01***	.01***
	(7.59)	(8.64)	(5.79)	(7.59)
R^2	.64	.68	.69	.62
Observations	269,761	269,373	269,342	268,975
Buyer-prefecture fixed effects	Yes	Yes	Yes	Yes
Supplier fixed effects	Yes	Yes	Yes	Yes

NOTE.—Each column represents a dependent variable. t-statistics are in parentheses. All variables are in logs. Labor productivity is calculated as sales relative to the number of employees. All firms refers to all firm pairs in the data. Single-plant firms refers to firm-pairs in which both buyer and seller are single-plant.
* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

TABLE 2
FIRM SALES, IN-DEGREE, OUT-DEGREE, AND DISTANCE TO CONNECTIONS

	DEPENDENT VARIABLE					
	No. of Sourcing Cities	No. of Customer Cities	Median Distance to Suppliers	Median Distance to Customers	In-Degree	Out-Degree
Firm sales	.31***	.29***	.02**	.18***	.36***	.31***
	(402.9)	(326.6)	(11.51)	(99.15)	(421.1)	(317.9)
Firm sales × single plant	−.00***	−.00***	−.01***	−.01***	.00	−.00***
	(3.00)	(17.85)	(15.28)	(20.52)	(.37)	(16.80)
Firm sales × single industry	−.01***	−.01***	−.01***	.00***	−.02***	−.01***
	(72.46)	(35.36)	(19.45)	(5.08)	(79.18)	(44.67)
Industries	401	401	401	401	401	403
Observations	435,479	435,479	426,305	426,305	435,479	435,479
R^2	.40	.36	.16	.13	.41	.34

NOTE.—Robust t-statistics are in parentheses. All variables are in logs. Only firms with positive in- and out-degree are included in the sample. JSIC three-digit industry fixed effects are included in all regressions. Single plant = 1 if the firm is a single-plant firm and zero otherwise. Single industry = 1 if the firm belongs to only one three-digit JSIC industry and zero otherwise (the data include up to three three-digit industries per firm).
* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

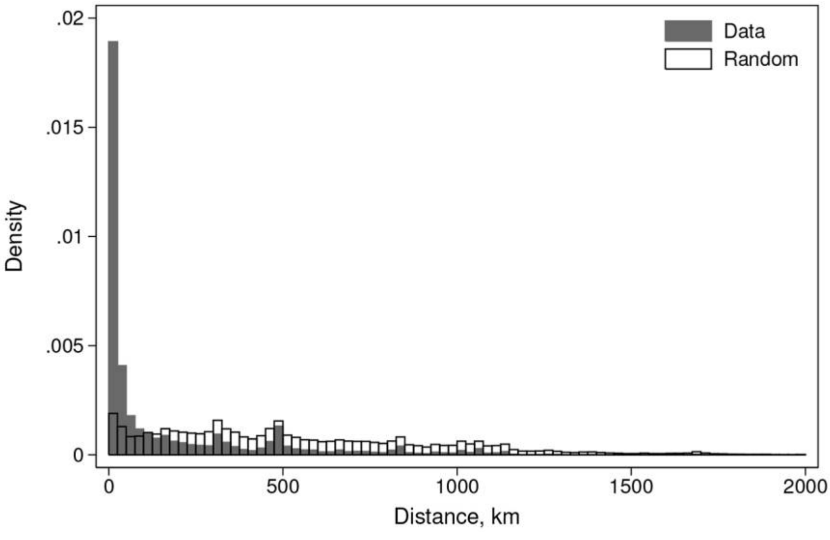

FIG. 6.—Density of distance across buyer-seller pairs: 2005 data. The figure shows the density of distance in kilometers for all buyer-seller pairs. The gray bars represent the density from actual linkages whereas the white bars represent the density from random linkages.

FACT 3. The majority of connections are formed locally.

Distance is important in the formation of links. We start by calculating the distance between any supplier-customer pair ij and show the density of distance in figure 6. As above, geolocation is based on a firm's headquarters, so for multiplant firms the interpretation is distance between headquarters. The gray bars represent the density based on actual linkages. The white bars represent the density based on random linkages.[7] The median (mean) distance is 30 (172) km. Hence, the majority of connections are formed locally. Even so, a few connections span very long distances, so that the average distance is much greater than the median. Moreover, the actual distances between firms are much smaller than what would emerge in a random network. In the network with randomly drawn connections, median (mean) distance is 472 (555) km.

FACT 4. There is negative degree assortativity among sellers and buyers.

One distinguishing feature of networks is the extent to which a well-connected node is linked to other well-connected nodes, known as degree assortativity. While there is an extensive body of research on degree assortativity in technical and social networks, these relationships are less well documented in economics networks. We find that the better con-

[7] A random production network is generated by drawing n_i random customer links for firm i, where n_i is based on the actual out-degree of firm i. Then distances between all random links are calculated on the basis of the geocode of the firms.

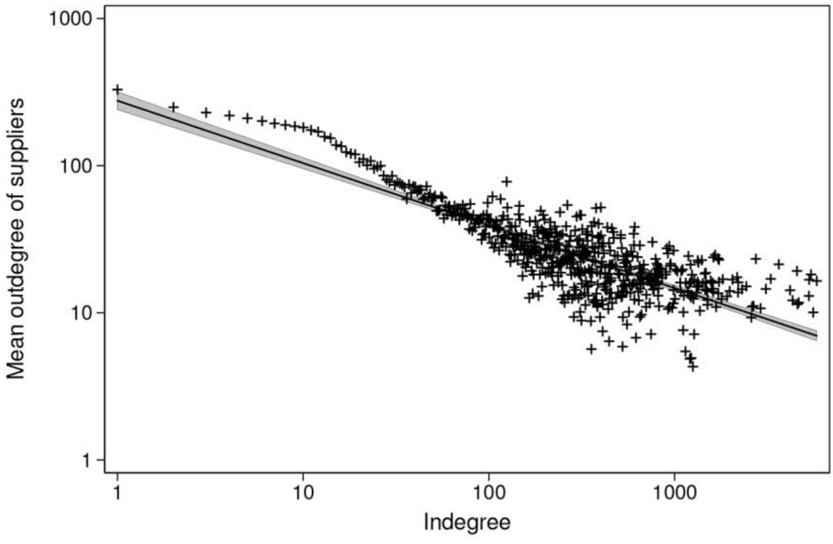

FIG. 7.—Degree assortativity, suppliers and customers of suppliers: 2005 data. The figure shows all possible values of the number of suppliers per firm, a, on the x-axis and the average number of customer connections of these suppliers, $b(a)$, on the y-axis. Axes scales are in logs. The fitted regression line and 95 percent confidence intervals are denoted by the solid line and gray area. The slope coefficient is -0.42.

nected a firm, the less well connected is its average connection. Figure 7 provides an overview of degree assortativity in the Japanese production network. The figure shows all possible values of the number of suppliers per Japanese firm, a, on the x-axis and the average number of (customer) connections of these suppliers, $b(a)$, on the y-axis. The interpretation of a point with the coordinates (10, 1) is as follows: For a Japanese firm sourcing from 10 suppliers, the average supplier has one customer. The fitted regression line has a slope of -0.42, so a 10 percent increase in the number of suppliers is associated with a 4 percent decline in the average supplier's number of customers.[8] Our finding of negative assortativity is not limited to this specific configuration of in- and out-degree. We find similar relationships when using customer out-degree or an undirected measure of the total number of connections.[9]

[8] The correlation between degree and mean degree of connections is a standard measure of assortativity in networks (Jackson and Rogers 2007).

[9] In our data, the correlation is negative and significant for (in-degree, average in-degree of suppliers), (in-degree, average in-degree of customers), (in-degree, average out-degree of customers), (out-degree, average out-degree of suppliers), (out-degree, average in-degree of suppliers), (out-degree, average in-degree of customers), and (out-degree, average out-degree of customers).

This result suggests that the best firms, those with many connections, are selling to firms that, on average, have fewer connections themselves. Interestingly, social networks typically feature positive assortative matching; that is, highly connected nodes tend to attach to other highly connected nodes, while negative correlations are usually found in technical networks such as servers on the internet (Jackson and Rogers 2007).[10] In a recent paper, Bernard et al. (2018) also find negative assortativity between trading firms using Norwegian exporter data matched to foreign importers and Colombian importer trade data matched to foreign exporters. Section IV.C discusses testable predictions on assortativity in the context of our model and provides additional empirical evidence.

IV. The Model

We develop a parsimonious model of outsourcing in a domestic economy motivated by the facts in the previous section. The basic structure is as follows. Firms require a continuum of tasks as inputs into the production process, for example, materials processing, accounting, printing, and mailing services. They can produce the tasks themselves or outsource them. Finding suppliers is costly, however, and therefore, it may not be profitable for all firms to outsource a given task, even though the market price of a task is lower than the firm's marginal cost of supplying the same task. This setup will produce theoretical predictions that are consistent with the empirical regularities documented in Section III and will guide the development of the empirical methodology in Section V. Our model is closely related to the framework in Antràs et al. (2014), but we modify it in several directions. First, we allow for the possibility of in-house production, that is, that firms can supply a given task within the boundary of the firm. This margin of adjustment is crucial in order to match the empirical regularities. Second, geography in the model will be continuous. We combine this with distributional assumptions that allow us to obtain sharp analytical results. Third, our model is a framework for understanding domestic, and not international, sourcing. Since productivity differences are typically much smaller within a country than across countries and since labor is typically much more mobile within a country than across countries, we assume that wages and productivity are common across locations.

[10] In the friendship network among prison inmates considered by Jackson and Rogers (2007), the correlation between a node's in-degree and the average in-degree of its neighbors is .58. The correlation in our data is −.31. Serrano and Boguna (2003) find evidence of negative sorting in the network of trading countries; i.e., highly connected countries, in terms of trading partners, tend to attach to less connected countries.

A. Setup

Geography, sectors, and market structure.—The economy consists of a unit continuum of locations $i \in \mathcal{S}$. Each location consists of an upstream and a downstream sector. Downstream firms combine labor and a unit continuum of tasks and sell their output to final consumers. Upstream firms produce a single task using labor only. Within a location i and for a given task ω, there are many identical firms producing ω at the same marginal cost. Hence, the upstream sector is characterized by perfect competition. Downstream firms are monopolistically competitive and produce a differentiated good with efficiency z, which varies across firms.

Production technology.—The production function of a downstream firm is

$$y = zl^{\alpha}v^{1-\alpha}, \tag{1}$$

where l is labor, α is the labor share, and v is a constant elasticity of substitution (CES) composite of the unit continuum of tasks. The CES price index is

$$P^{1-\rho} = \int_0^1 p_u(\omega)^{1-\rho}\, d\omega,$$

where $p_u(\omega)$ is the price of an individual task ω and ρ is the elasticity of substitution between tasks. The firm can potentially produce all tasks in-house. If so, the firm's efficiency in producing a task ω is a realization of a random variable ϕ from the Frechet distribution $F(\phi) = e^{-T_0\phi^{-\theta}}$, where T_0 determines the average efficiency in producing a task and $\theta > \rho - 1$ is inversely related to dispersion in task productivity. The distribution $F(\phi)$ is identical across all downstream firms; hence, total factor productivity z is the only source of firm-level heterogeneity. As we will see, in equilibrium, the price $p_u(\omega)$ will depend on whether the firm outsources a task or not and, if outsourced, which location it will outsource from.

The production function of an upstream firm in location i is $y_u(\omega, i) = \phi(\omega, i)l$. The efficiency of producing a task ω is a realization of a random variable ϕ from the Frechet distribution $F_u(\phi) = e^{-T\phi^{-\theta}}$. The parameter T governs the average productivity. To keep the model tractable we assume that average productivity T is identical across locations i. Upstream firms in i selling to j are subject to iceberg trade costs $\tau(i, j) \geq 1$. Trade costs are broadly defined here; we have in mind both shipping costs and efficiency losses in the buyer-supplier relationship. The cost of supplying ω from i to j is therefore $w(i)\tau(i, j)/\phi(\omega, i)$, where $w(i)$ is the nominal wage in i. For tractability, we assume that final goods are costlessly traded. This makes the price index of final goods identical in every location.[11]

[11] Without this assumption, nominal wages $w(i)$ would vary across locations because the final goods price index would vary across locations (given that labor mobility equalizes real wages across locations). Costlessly traded final goods allow us to abstract from this.

Labor.—Each location is inhabited by $L(i)$ workers, and the aggregate (exogenous) supply of workers is $\bar{L} = \int_S L(i)\,di$. Consumers derive utility from consumption of the downstream goods. They have identical CES preferences with an elasticity of substitution σ. There is perfect labor mobility across regions. Since final goods are costlessly supplied to consumers across locations, nominal wage equalization is sufficient to leave workers indifferent between locations. Henceforth, we denote the common nominal wage by w.

Entry.—There is a fixed measure of downstream firms in each location, $m(i)$. As there is no free entry, the production of final goods leaves rents. We assume that consumers derive income not only from labor but also from the dividends of a mutual fund. Each consumer owns w shares of the fund, and profits are redistributed to them in units of labor. Total worker income in location i is then $w(1+\psi)L(i)$, where ψ is the dividend per share of the mutual fund.

Outsourcing.—The downstream firm located in j can choose to produce a task ω itself or outsource it. The firm can observe average productivity T and trade costs $\tau(i,j)$ from source i. Observing individual prices for all ω, however, requires effort. Specifically, the firm must incur a fixed cost $f(j)$ paid in terms of labor to observe individual prices in a location i.[12] As we will see, more productive firms find it optimal to search a wider range of locations because the marginal profits from search are higher for high-z firms, while the marginal cost $f(j)$ is constant. Given that $f(j)$ does not vary by source, each location i can be ranked according to its attractiveness as a supplier location, where attractiveness is defined by $\tau(i,j)^{-\theta}$ (see Antràs et al. 2014). A firm in j will therefore search all locations i where $\tau(i,j)$ is lower than some threshold value (to be defined below). As in Eaton and Kortum (2002), conditional on a set of search locations, firm z's share of purchases from location i is

$$\chi(z,i,j) = \frac{T\tau(i,j)^{-\theta}}{\Phi(z,j)}. \tag{2}$$

The function $\Phi(z,j)$ is a measure of market access,

$$\Phi(z,j) = T_0 + \int_1^{\bar{\tau}(z,j)} T\tau^{-\theta} g(\tau,j)\,d\tau, \tag{3}$$

where $\bar{\tau}(z,j)$ is the highest-cost location that z located in j is willing to search, and g is the density of trade costs to location j.

The share of tasks outsourced is

$$o(z,j) = 1 - \frac{T_0}{\Phi(z,j)}.$$

[12] In order to keep the problem tractable, we do not allow an (i,j)–specific f.

Adding more locations to search will raise $\bar{\tau}$ and Φ. More search therefore gives more outsourcing o. As in Eaton and Kortum (2002), the task price index is $P(z, j) = \lambda w \Phi(z, j)^{-1/\theta}$, where λ is a constant.[13] Hence, more outsourcing leads to lower input costs P with an elasticity $1/\theta$. Searching an additional location means that the firm can observe a new set of prices for all tasks ω. The probability of finding at least one task with a lower price than the existing one is strictly positive, and therefore, the price index $P(z, j)$ must go down.

B. *Optimal Search*

The maximization problem of the firm is

$$\max_{\bar{\tau}}\{\pi(z, j) - wf(j)n(z, j)\},$$

where $\pi(z, j)$ is gross profits of firm z located in j and $n(z, j)$ is the measure of locations to search. Total sales of the downstream firm can be written $r = Ap^{1-\sigma}$, where A is a demand shifter and p is the firm's price. Profits are proportional to sales, $\pi = r/\sigma$. Appendix A derives the solution to the problem of the firm as well as the second-order condition. The solution to $\bar{\tau}$ is

$$\bar{\tau}(z, j) = \kappa_1 \left[\frac{T}{w^{\sigma}}\frac{A}{f(j)}\right]^{1/\theta} \Phi(z, j)^{-k/\theta} z^{(\sigma-1)/\theta}, \qquad (4)$$

where $k = 1 - (\sigma - 1)(1 - \alpha)/\theta$ and κ_1 is a constant:

$$\kappa_1 = \left[\frac{(\bar{m}\lambda^{1-\alpha})^{1-\sigma}}{\sigma}\frac{(\sigma - 1)(1 - \alpha)}{\theta}\right]^{1/\theta}.$$

For an arbitrary geography $g(\tau, j)$, one can jointly solve equations (3) and (4), which is a system of two equations and two unknowns $\bar{\tau}(z, j)$ and $\Phi(z, j)$.

The expression for the hurdle $\bar{\tau}$ has a number of interesting features. First, better market access Φ leads to more search when $k < 0$ and less search when $k > 0$. The model of Antràs et al. (2014) has the same property and describes these as the complements and substitutes cases, respectively. Keeping Φ constant, lower search costs $f(j)$ lead to more search (higher $\bar{\tau}$). Higher efficiency z and more demand A also lead to more search (higher $\bar{\tau}$).

C. *Model and Data*

We now return to the stylized facts presented in Section III and relate them to the model. The proofs are found in appendix B.

[13] $\lambda^{1-\rho} = \Gamma([\theta - (\rho - 1)]/\theta)$, where Γ is the gamma function.

First, more productive firms outsource more tasks and therefore have more suppliers:

$$\frac{\partial o(z,j)}{\partial z} > 0,$$

because $\partial\Phi(z,j)/\partial z > 0$. Given that more productive firms search more, they are more likely to find a sourcing option for a given task ω at a lower cost than the cost of producing in-house. This is consistent with the evidence in figure 3, that larger firms tend to have more suppliers. Note that, according to the model, higher efficiency z leads to both increased sales and in-degree, while higher in-degree itself leads to greater sales. Hence, the level of sales for a given firm is determined by both the direct effect of core efficiency z and the indirect effect of in-degree. The positive correlation shown in figure 3 is a result of both the direct and indirect effects.

Second, more productive firms search more and costlier locations:

$$\frac{\partial \bar{\tau}}{\partial z} > 0.$$

High-z firms have a greater incentive to search more locations because the potential cost savings are larger for more productive firms. As a consequence, more productive firms have higher maximum and average trade costs to suppliers. This is consistent with the evidence in figures 4 and 5, that larger firms tend to have suppliers in more locations and greater distance to their suppliers. A corollary is that, when comparing a supplier's customers in different markets, the average customer in a more remote market is more productive than the average customer in a nearby market. This is shown formally in appendix B, Section D, and is consistent with the empirical evidence in table 1, that remote customers of a given supplier tend to be larger and have many connections.

Third, more productive firms in location j reach suppliers in markets that are, on average, less well connected in j. Specifically, consider a firm with efficiency z in location j, sourcing from the marginal location $\bar{\tau}(z,j)$. Denote the expected measure of location j customers among upstream firms in z's marginal location $\bar{c}(z,j)$. Then

$$\frac{\partial \bar{c}(z,j)}{\partial z} < 0.$$

This reflects the fact that higher-z firms reach costlier locations and the suppliers there are, on average, not very competitive in z's home market.

The evidence in figure 7 relates in-degree to the average out-degree of suppliers. However, the theoretical prediction relates productivity of a firm in location j, which is increasing in in-degree, to the average number of location j customers of the suppliers. We therefore calculate the average out-degree of suppliers as

$$\bar{o}_f = \frac{1}{N_f} \sum_{g \in \Omega_f} o_{gj},$$

where o_{gj} is the number of location j customers of firm g, Ω_f is the set of suppliers located in f's marginal location, and N_f is the number of elements in Ω_f. We define a location as either a prefecture or a municipality and define the marginal location as the maximum distance location across all suppliers of firm f. Table 3 shows the correlation between in-degree and $\bar{o}_f$ after controlling for location fixed effects (cols. 1 and 2) or location-industry fixed effects (cols. 3 and 4). In all cases, there is strong evidence of negative assortativity, consistent with the prediction of the model.

D. *The Density of Trade Costs*

So far, we have not imposed any structure on the density of trade costs $g(\tau, j)$. In this section, we will choose a functional form for $g(\ )$ that will allow us to derive closed-form expressions for key relationships in the model (e.g., eqq. [3] and [4]). This in turn helps us to derive theoretical predictions that will later be tested in the data (proposition 1 in the next section).

We assume that $g(\tau, j)$ is inverse Pareto with shape $\gamma > \theta$ and support $[1, \tau_H]$, $g(\tau) = \gamma[\tau_H^{-\gamma}/(1 - \tau_H^{-\gamma})]\tau^{\gamma-1}$. An inverse Pareto captures the notion that a location has few nearby markets and many remote markets. The upper bound τ_H is the maximum trade cost within Japan. One can show that a higher τ_H shifts the trade cost distribution to the right. In other words, a distribution with a high τ_H first-order stochastically dominates a distribution with a low τ_H (app. F). Therefore, τ_H is a convenient metric for average trade costs in the economy. Appendix F provides empirical evidence that

TABLE 3
Assortativity

	(1)	(2)	(3)	(4)
In-degree$_f$	−.75***	−.78***	−.78***	−.85***
	(232.6)	(236.6)	(263.9)	(249.4)
Prefecture (P) or municipality (M)	P	M	P	M
Location fixed effects	Yes	Yes	No	No
Location-industry fixed effects	No	No	Yes	Yes
Observations	433,247	433,247	433,247	433,247
R^2	.21	.29	.37	.62

Note.—t-statistics clustered by firm are in parentheses. The independent variable is firm in-degree and the dependent variable is $\bar{o}_f$ as defined in Sec. IV.C. All variables are in logs.
* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

the inverse Pareto is a good approximation of the empirical distance density in our data set.

E. Testable Predictions

As we discuss later in Section V, we will exploit a natural experiment in which a large shock to infrastructure lowered passenger travel time (but not goods travel time) between many location pairs in Japan. This empirical exercise allows us to quantify the impact of a large-scale infrastructure project on firm performance and to evaluate the importance of the theoretical mechanism emphasized in this paper. In order to guide the subsequent empirical work, this section details the consequences of such a shock according to the model.

First, consider the impact on firm sales of lower search costs $f(j)$. Lower $f(j)$ leads to sales growth of a downstream firm in j. Holding final goods demand A constant,

$$\frac{\partial \ln r(z,j)}{\partial \ln f(j)} = \frac{(\sigma-1)(1-\alpha)}{\theta}\frac{\partial \ln \Phi(z,j)}{\partial \ln f(j)} < 0.$$

The elasticity $\partial \ln \Phi(z,j)/\partial \ln f(j) < 0$ measures the fall in market access from an increase in $f(j)$ (Sec. B in app. B). Now consider how $\partial \ln r(z,j)/\partial \ln f(j)$ varies across industries with different labor intensities α:

$$\frac{\partial^2 \ln r(z,j)}{\partial \ln f(j)\partial\alpha} = \frac{\sigma-1}{\theta}\left[-\frac{\partial \ln \Phi(z,j)}{\partial \ln f(j)} + (1-\alpha)\frac{\partial^2 \ln \Phi(z,j)}{\partial \ln f(j)\partial\alpha}\right].$$

The cross elasticity is the sum of direct and indirect effects. The direct effect is that a percentage reduction in input costs $P(z)$ will have a stronger positive effect on sales in industries in which inputs constitute a large share of total costs. The indirect effect is that input-intensive firms may search more or less intensively relative to labor-intensive firms when $f(j)$ falls (the cross elasticity $\partial^2 \ln \Phi(z,j)/\partial \ln f(j)\partial\alpha$). Appendix D shows that both the direct and indirect effects have the same sign when $g(\tau, j)$ is inverse Pareto. Hence, the total effect is

$$\frac{\partial^2 \ln r(z,j)}{\partial \ln f(j)\partial(1-\alpha)} < 0,$$

so that sales growth is stronger for input-intensive firms relative to labor-intensive firms when search costs fall.

Second, consider the impact on firm sales of lower variable trade costs. Using the same inverse Pareto parameterization of the trade cost distribution $g(\tau, j)$, appendix D shows that $\partial \ln r(z,j)/\partial \ln \tau_H < 0$ and $\partial^2 \ln r(z,j)/\partial \ln \tau_H \partial(1-\alpha) < 0$. Hence, lower variable trade costs (e.g., more efficient buyer-supplier relationships or lower shipping costs) increase sales, and sales growth is stronger for input-intensive firms. We summarize this in the following proposition.

PROPOSITION 1. (i) Lower search costs $f(j)$ and average trade costs lead to growth in sales among downstream firms in j. (ii) Sales growth is stronger in input-intensive (low-α) relative to labor-intensive (high-α) industries.

Proof. See appendix D.

Part ii of proposition 1 forms the basis of our identification strategy in Section V.A.

Third, consider the impact on locations searched among firms in j of lower search costs $f(j)$. Lower $f(j)$ leads to search in new locations and therefore suppliers from new locations among downstream firms in j. Moreover, the response is stronger in input-intensive industries,

$$\frac{\partial \ln \bar{\tau}(z,j)}{\partial \ln f(j)} < 0 \quad \text{and} \quad \frac{\partial^2 \ln \bar{\tau}(z,j)}{\partial \ln f(j) \partial (1-\alpha)} < 0.$$

Lower $f(j)$ means that the cost of obtaining information about prices is lower. Firms therefore search additional locations ($\bar{\tau}$ increases). There is a positive probability of finding a task at a lower price compared to the price of in-house production. Hence, firms will also find new suppliers in those new locations.

Fourth, consider the impact on locations searched when average variable trade costs decline. Again, the cross elasticity is negative, $\partial^2 \ln \bar{\tau}(z,j)/\partial \ln \tau_H \partial(1-\alpha) < 0$. Intuitively, lower average trade costs, for example, due to more efficient buyer-seller relationships, induce firms in input-intensive industries to search more markets. We summarize this in the following proposition.

PROPOSITION 2. (i) Lower search costs and lower average variable trade costs lead to search in, and suppliers from, new locations among downstream firms in j. (ii) The response is stronger in input-intensive (low-α) relative to labor-intensive (high-α) industries.

Proof. See appendix D.

Part ii of proposition 2 forms the basis of our identification strategy in Section V.B.

F. Closing the Model

Given the assumptions above, both product markets and the labor market clear. Labor market clearing can be seen as follows. Expenditure by final consumers, E, equals total wage income plus profits from the monopolistic sector. Moreover, consumer income must equal the value of output in upstream and downstream production, Sales^{Up} and $\text{Sales}^{\text{Down}}$, respectively. Hence, we have

$$\begin{aligned} E &= w(1 + \psi)\bar{L} \\ &= \text{Sales}^{\text{Up}} + \text{Sales}^{\text{Down}}. \end{aligned} \tag{5}$$

The aggregate value of labor demand equals aggregate sales in upstream and downstream production minus aggregate profits. Inserting equation (5) gives us

$$wL^D = \text{Sales}^{\text{Up}} + \text{Sales}^{\text{Down}} - w\psi\bar{L} = w\bar{L}.$$

Therefore, aggregate labor demand L^D equals supply $\bar{L}$.

V. Production Networks and Productivity: A Natural Experiment

This section details our identification strategy for estimating the impact of lower trade and search costs on firm performance and linkages in the production network. We start by providing some background on the natural experiment.

The southern portion of the high-speed (bullet) train network in Japan was expanded in March 2004 (Kyushu Shinkansen). This resulted in a dramatic reduction in travel time between major cities in the area. For example, travel time between Kagoshima and Shin-Yatsushiro declined from 130 minutes to 35 minutes, and travel time between Hakata and Kagoshima declined from 4 hours to just 2 hours. Figure 8 gives an overview of the geography. The black dots are locations within 30 km of a new Shinkansen station, whereas the gray dots are all other localities in the data set.[14] Although the geographical scope is somewhat limited, the new rail line extended Shinkansen service to two prefectures with a total population of 3.5 million, roughly that of Connecticut.

The Shinkansen expansion offers several advantages for assessing the impact on infrastructure on linkages and firm performance. First, the plan of the expansion started already in 1973, making it relatively unlikely that firms in our sample could influence the timing and location of stations. Moreover, the timing of completion was subject to substantial uncertainty starting in 1991, limiting the scope for anticipation effects. Nevertheless, our empirical methodology addresses endogeneity concerns in a variety of ways as discussed below. Second, goods in Japan do not travel on the Shinkansen, and there was no contemporaneous reduction in travel time for goods along this southern route, as discussed in Section V.A.4.

[14] We divide Japan into a grid consisting of 500 × 500 cells (dots in the map); each cell is a square roughly 5.6 km on a side.

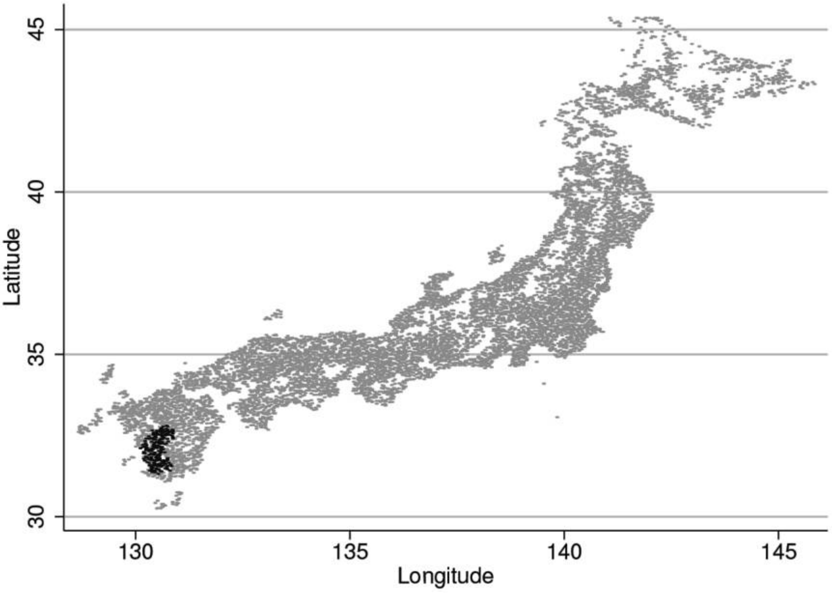

FIG. 8.—Kyushu Shinkansen treated cells

A. *Economic Integration and Firm Performance*

In this section we ask whether and to what extent the Shinkansen expansion improved performance among firms in affected regions. As shown in proposition 1, the model suggests a simple identification strategy. Lower variable trade costs, due to more efficient buyer-supplier relationships, and lower search costs, $f(j)$, improve firm sales because they reduce marginal costs directly and indirectly, by enabling firms to find lower-cost or higher-quality suppliers. Moreover, the impact is greater for input-intensive firms (low-α firms) relative to labor-intensive firms.[15] Intuitively, improved travel time has no impact on marginal costs in an industry that does not rely on inputs, that is, when $\alpha = 1$. Of course, sales may improve in $\alpha = 1$ industries as well, because improved travel time allows firms to find new customers. Our empirical strategy will difference out this mechanism; that is, the methodology identifies only marginal cost effects and not demand-side effects.

[15] A disconnect between the theory and the data is that, in the data, virtually all firms are both suppliers and customers. As such, there is no clear empirical distinction between upstream and downstream firms. One could extend the model to incorporate a roundabout production structure, so that suppliers are themselves sourcing from other firms, with an industry-specific labor share α.

Consider the following regression,

$$\ln y_{fjrt} = \alpha_f^1 + \alpha_{rt}^2 + \beta \text{Station}_f \times H_j \times I[t \geq 2004] + \beta X_{fjrt} + \epsilon_{fjrt}, \quad (6)$$

where y_{fjrt} is a measure of firm performance for firm f in industry j located in region r at time t, relative to average performance in the same industry-year.[16] We focus on the 8-year period 2000–2008, that is, 4 years before and after the infrastructure shock.

In addition to using sales as the outcome variable, we also use sales per employee (LP) and revenue total factor productivity (TFPR). In monopolistic competition models, LP and TFPR are constant across firms within an industry. However, if output prices among treated firms do not adjust immediately in response to the infrastructure shock, then LP and TFPR are expected to increase (see app. E). For TFPR, this occurs because TFPR controls for the firm's value of inputs (in the absence of firm-level input deflators), so that if firm-level input prices decline, then TFPR will rise.[17]

The main independent variable is the interaction between Station_f, which is one if firm f is within 30 km of a new station, H_j, which is the input intensity of the industry in 2003, and $I[t \geq 2004]$, which is an indicator variable taking the value one from 2004 and onward. The 30 km threshold for a station is chosen so that total travel time is significantly affected and Shinkansen dominates alternative modes of transport. For example, for a firm 60 km from a station, car travel time to the station would amount to 40–60 minutes, and hence the percentage drop in total travel time would be significantly less compared to a firm located near the station. We also check the results with other thresholds in Section V.A.2. Input intensity is defined as 1 minus the labor share of the three-digit industry in 2003. The labor share is the industry's wage costs relative to total costs; see appendix G. The terms α_f^1 and α_{rt}^2 are firm and prefecture-year fixed effects. There are 47 prefectures in Japan.

The covariates in X_{fjrt} are the remaining interactions $\text{Station}_f \times I[t \geq 2004]$ and $H_j \times I[t \geq 2004]$. In addition, since prefectures are relatively large geographic areas, we introduce a second geographic control. Each prefecture is further divided into local administrative units called municipalities. We have in total 1,365 municipalities in the final sample, making the average population of a municipality roughly 60,000 (Japan's total population was 127.8 million in 2005). The high number of municipality-year pairs means that municipality-year fixed effects are computationally infeasible. We can, however, include a variable for average performance in a

[16] Section A in app. G details the construction of the dependent variable.

[17] Firm performance is measured relative to industry (three-digit) year means. There are in total 315 three-digit industries in the data. TFPR is estimated using the Olley and Pakes (1996) methodology; see Sec. A in app. G.

municipality-year.[18] For example, if $\ln y_{fjrt}$ is sales, we include average log sales excluding firm f in the municipality-year as a control variable.

The regression in equation (6) is a triple differences model, and the intuition for identification is as follows. The Shinkansen expansion is expected to bring higher performance gains for an input-intensive firm located close to a new station compared to a labor-intensive firm located close to a new station. The empirical strategy is to compare the growth of input-intensive firms before and after 2004 (first difference) to the growth of labor-intensive firms (second difference) and compare this differential effect in locations with a new station relative to locations without a new station (third difference).

The triple differences approach resolves a number of potential concerns. First, performance growth due to demand-side effects (i.e., growth among labor-intensive firms due to new customers) is differenced out because demand-side effects are expected to affect labor-intensive and input-intensive firms similarly.[19] The demand side could, however, still be a problem if input-intensive industries are typically more tradable than labor-intensive industries. Our data, however, show that this is not the case. The correlation between the average distance to customers (across all firms in a JSIC three-digit industry) and H_j is $-.01$ and is insignificant. Second, a potential concern is that input-intensive firms may grow faster than labor-intensive firms even in the absence of the Shinkansen expansion. The methodology controls for this because the triple interaction coefficient β will capture only the differential impact (input-intensive relative to labor-intensive) for firms close to a station relative to the differential impact for firms that are far from a station. Hence, if input-intensive firms grow faster in every location, then β will be zero. Third, a potential concern is that the new Shinkansen line was introduced in high-growth regions. As we compare the differential growth only for input relative to labor-intensive firms, endogeneity is not a concern as long as the Shinkansen line was not targeted particularly for input-intensive firms.

1. Results

Table 4 shows regression results from estimating equation (6). Column 1 uses log sales relative to the industry-year as the dependent variable. The triple interaction term β is positive and significant at the 5 percent level, indicating that the Shinkansen expansion boosts firm sales for input-intensive firms relative to labor-intensive firms. The magnitudes are economically significant: a coefficient of 0.65 means that a Shinkansen stop increased sales by 0.65 log points more for a firm with $H_j = 1$ relative to a

[18] This approach is similar to that of Giroud (2013).
[19] The common demand-side effect is captured in $\text{Station}_f \times I[t \geq 2004]$.

TABLE 4
Firm Performance

	Sales (1)	Sales/Employee (2)	TFPR (3)
$\text{Station}_f \times H_j \times \text{Post2004}_t$	.65***	.68***	.58***
	(3.08)	(3.06)	(2.87)
Firm and municipality controls	Yes	Yes	Yes
Prefecture-year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	142,989	141,346	138,150
R^2	.97	.92	.97

Note.—t-statistics clustered by firm are in parentheses. Dependent variables are in logs and are measured relative to industry-year means.
* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

firm with $H_j = 0$. A firm in the 9th decile of the H_j distribution ($H_j = 0.92$, e.g., industrial plastic products, JSIC 183) increased sales by roughly 0.14 log points more than a firm in the 1st decile of the H_j distribution ($H_j = 0.70$, e.g., general goods rental and leasing, JSIC 701). Columns 2 and 3 use labor productivity and TFPR as the dependent variable. Again, the triple interaction term is positive and significant, suggesting that the infrastructure shock improved the firm's measured productivity. The magnitudes are slightly smaller compared to sales: a firm in the 9th decile of the H_j distribution improves TFPR by 0.13 log points faster than a firm in the 1st decile.

By using the structure of the model, we can back out the implied reduction in the price index of inputs associated with the bullet train. Recall that TFPR is log revenue minus the estimated production function, $\text{TFPR} = \ln(yp) - \alpha \ln l - (1-\alpha)\ln(vP)$, where vP is materials expenditure.[20] Replacing y with the production function in equation (1) and taking changes yields

$$\Delta\text{TFPR} = \Delta \ln z + \Delta \ln p - (1-\alpha)\Delta \ln P.$$

Given that efficiency z and output prices p are constant, we get $\Delta \ln P = -\Delta\text{TFPR}/(1-\alpha)$. Hence, using the same example as above, a firm in the 9th decile of the H_j distribution would get roughly 14 percent lower input prices than a firm in the 1st decile (0.13/0.92).

The fact that an infrastructure project unrelated to transportation of goods can improve firm performance by this magnitude is indeed remarkable. More broadly, our findings suggest that domestic trade costs dampen economic activity by limiting buyer-supplier linkages and that reducing these barriers will help development and growth. From a policy perspec-

[20] As capital is not part of the model, we abstract from it here.

tive, the results point to important positive effects of large-scale infrastructure projects that are typically neglected from cost-benefit analyses: that infrastructure projects can bring efficiency gains from freer flow of information across firms.

2. Robustness

In this section, we explore a number of robustness checks. First, a potential concern is that input-intensive firms near a new station tend to grow faster than labor-intensive firms near a new station (but not in other locations), that is, that there are pretrends in the treatment relative to the control group. A simple way to check for this is to conduct a falsification test. We estimate equation (6) on the 5-year period 1998–2002 and incorrectly set the Shinkansen expansion to 2000; that is, we replace $I[t \geq 2004]$ with $I[t \geq 2000]$. The results are shown in table 5. For all three dependent variables, the triple interaction term is not significantly different from zero; hence there are no pretrends in the data.

An alternative falsification test is to focus on the set of industries that are geographically close to their suppliers. For these industries, the Shinkansen expansion should have a muted effect because there is less scope

TABLE 5
FIRM PERFORMANCE: ROBUSTNESS I

	Sales (1)	Sales/ Employment (2)	TFPR (3)	Sales (4)	Sales/ Employment (5)	TFPR (6)
$\text{Station}_f \times H_j \times \text{Post2000}_t$	−.26	.10	−.25			
	(.82)	(.46)	(.80)			
$\text{Station}_f \times H_j \times \text{Post2004}_t$				.66***	.69***	.59***
				(3.20)	(3.23)	(2.98)
$\text{Station}_f \times \text{Plants}_f \times \text{Post2004}_t$				.17***	.22	.16***
				(2.69)	(1.34)	(2.63)
Firm and municipality controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,675	68,675	67,289	142,989	141,346	138,150
R^2	.98	.94	.98	.97	.92	.94

NOTE.—Cols. 1–3 are the falsification test using data from 1998–2002. Cols. 4–6 use the main sample and include the number of plants, Plants_f, as well as all interactions with Station_f and Post2004_t. Plants_f is multiplied by 100. t-statistics clustered by firm are in parentheses. Dependent variables are in logs and are measured relative to industry-year means.

* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

to source inputs from remote locations (e.g., because of characteristics of the product being traded). We therefore reestimate the main regression on a subset of industries that are close to their suppliers. Specifically, we calculate the average distance to suppliers for each firm and then take the average across firms within each three-digit industry. Only industries below the median distance are included in the regression sample. The results in table 6 show that, for all three dependent variables, the triple interaction term is not significantly different from zero.

We also test for the possibility that firms in input-intensive industries typically have more plants than in labor-intensive industries. If so, our results could potentially be explained by efficiency improvements taking place within the same firm (across plants), for example, as in Giroud (2013). We first calculate the correlation between H_j and the average number of plants per firm (across firms in a three-digit JSIC industry j). This correlation is $-.13$ and is significant, showing that input-intensive industries, on average, have fewer plants. Next, we add a second triple interaction term to the baseline regression, $\text{Station}_f \times p_f \times I[t > 2004]$, where p_f is the number of plants belonging to firm f. The results in table 5, columns 4–6, show that the main effect is close to the baseline in table 4. Hence, we conclude that this is not driving our results.

Another concern is that the results are sensitive to the chosen 30 km threshold for whether a firm belongs to a new station or not. We therefore estimate the model with Station_f taking the value one if firm f is within 10 km of a new station. Columns 1–3 in table 7 show that the results are relatively close to the baseline: the impact on sales, sales per employee, and TFPR is slightly stronger compared to the baseline. We also investigate whether firms in cities near those served by the Shinkansen were affected.

TABLE 6
Firm Performance: Less Traded Industries

	Sales (1)	Sales/Employee (2)	TFPR (3)
$\text{Station}_f \times H_j \times \text{Post2004}_t$	.32	$-.32$	.29
	(.89)	(.87)	(.87)
Firm and municipality controls	Yes	Yes	Yes
Prefecture-year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	63,316	62,420	61,585
R^2	.97	.90	.97

Note.—t-statistics clustered by firm are in parentheses. The sample is constructed by calculating the average distance to suppliers for each firm and then averaging across firms within each three-digit industry. Only industries below the median distance are included in the regression sample. Dependent variables are in logs and are measured relative to industry-year means.

* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

TABLE 7

FIRM PERFORMANCE: ROBUSTNESS II

	Sales (1)	Sales/Employment (2)	TFPR (3)	Sales (4)	Sales/Employment (5)	TFPR (6)
$\text{Station}_f^{0-10} \times H_j \times \text{Post2004}_t$	.90***	.77***	.85***			
	(3.70)	(4.67)	(3.60)			
$\text{Station}_f^{0-30} \times H_j \times \text{Post2004}_t$				.65***	.68***	.59***
				(3.08)	(3.05)	(2.87)
$\text{Station}_f^{30-60} \times H_j \times \text{Post2004}_t$				.08*	−.16***	.11***
				(1.90)	(2.88)	(2.77)
Firm and municipality controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142,989	141,346	138,150	142,989	141,346	138,150
R^2	.97	.92	.98	.97	.92	.97

NOTE.—*t*-statistics clustered by firm are in parentheses. Dependent variables are in logs and are measured relative to industry-year means. $\text{Station}_f^{x-y} = 1$ if firm f is between x and y km from a new station. Cols. 1–3: as baseline but use 10 km threshold instead of 30 km threshold. Cols. 4–6: as baseline but add interactions with Station_f^{30-60}.

* Significant at the .1 level.

** Significant at the .05 level.

*** Significant at the .01 level.

TABLE 8
Firm Performance: Robustness III

	Sales (1)	Sales/ Employment (2)	TFPR (3)	Sales (4)	Sales/ Employment (5)	TFPR (6)
$\text{Station}_f \times H_j \times \text{Post2004}_t$	.70***	.69***	.63***	.61***	.62***	.54***
	(3.32)	(3.10)	(3.06)	(2.73)	(2.59)	(2.57)
$\text{Station}_f \times \text{R\&D}_j \times \text{Post2004}_t$				−.02	−.03	−.02
				(.68)	(.92)	(.69)
Construction industry	No	No	No	Yes	Yes	Yes
Firm and municipality controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	140,407	138,789	135,611	142,989	141,346	138,150
R^2	.97	.92	.97	.97	.92	.97

Note.—t-statistics clustered by firm are in parentheses. Dependent variables are in logs and are measured relative to industry-year means. Cols. 1–3: construction is excluded. Cols. 4–6: 2003 R&D indicator variable of industry as well as interactions with Station_f and Post2004_t are included.

* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

A common concern is that firms in adjacent cities lose market share because they become less competitive relative to firms in cities with Shinkansen service, the so-called "straw effect." In table 7, columns 4–6, we add an indicator variable for whether a firm is between 30 and 60 km of a new station and the set of interactions with H_j and $I[t \geq 2004]$. The triple interaction terms are still positive, but the magnitudes are smaller compared to the baseline, suggesting that the economic benefits decline with distance from the new stations.

Finally, a potential issue is that the results are primarily driven by the construction sector, possibly because construction firms grow as a result of increased demand related to building the new infrastructure. Note, however, that the triple differences approach should control for this, since identification is based on comparing industries with different input intensities.[21] Nevertheless, we rerun the regression excluding firms belonging to construction industries (table 8, cols. 1–3). Overall the results are very similar to the baseline results in table 4.

[21] Moreover, any potential bias would be negative because the construction demand shock occurred before 2004, not after.

3. Commuting

The infrastructure shock also benefited firms because of more efficient commuting. First, the reduction in travel time for existing commuters benefits both workers and firms by freeing up more time for work and leisure. Second, firms in the treated areas can potentially attract and hire more workers or find workers with skills that are better matched to the firm. Both effects will improve firm sales and performance. If the positive impact coming from commuting is identical across industries, then our results will be unaffected, since changes that affect all industries at the same time are differenced out. Still, it could be that some industries benefit more from commuting than others.

One mechanism might be that labor-intensive industries gain more than input- or capital-intensive industries simply because labor constitutes a larger share of the costs of production. This would mean that the true effect coming from supplier linkages is larger than what we have estimated, because input-intensive industries benefit less from commuting than labor-intensive industries. This would tend to bias our results toward zero.

Another mechanism might be that skilled workers consider the cost of travel time to be higher than unskilled workers, so that a large drop in travel time is more beneficial for skill-intensive industries. We test this hypothesis by constructing a measure of skill intensity for each industry and then including triple interaction terms for skill intensity, in addition to the existing triple interaction terms for input intensity. In the data, there is no direct measure of skill intensity. There is, however, a variable for the number of R&D workers. We define an industry's R&D intensity as the number of R&D workers relative to total workers in the industry. Across JSIC three-digit industries, almost 20 percent of the industries report zero R&D workers. Our preferred measure of skill intensity is therefore an indicator variable equal to one if the industry has higher than median R&D intensity (the median is 0.013). The results are shown in table 8, columns 4–6; the input intensity interaction term is close to the baseline results, while the skill intensity indicator is close to zero. In sum, we conclude that, although commuting is certainly an important factor, it does not significantly affect our estimates of the supply chain effect.

4. Congestion

Because the bullet train line carries only people, the main interpretation of our results is that the infrastructure shock facilitated face-to-face meetings, leading to more suppliers and more efficient buyer-seller relationships. A potential concern, however, is that the bullet train line freed up capacity across other modes of transport, leading to less congestion for trucks and regular trains. If that were the case, then the interpretation of our results would be different. We investigate this by exploring data from the Net Freight Flow Census from Japan's Ministry of Land, Infrastructure, Transport, and Tourism. The census provides data on average freight time across Japan's prefectures. Table 9 shows the percentage change in freight time from 2000 to 2010 across the prefectures on Japan's southern main island (Kyushu). The cells in bold are the prefecture pairs that were affected by the bullet train. Although the data are noisy, there is no evidence that freight times fell, or increased by less, in the affected prefectures relative to the unaffected prefectures. The average (median) increase in freight time across all pairs was 18 (22) percent, while the increase in the affected pairs was 21 and 24 percent (for Kagoshima-Fukuoka and Kagoshima-Kumamoto, respectively).

B. Economic Integration and Firm Linkages

The empirical results from Section V.A show that the infrastructure shock improves firm performance and that the performance effects are stronger among input-intensive firms, consistent with the model. In this section, we explore in more detail the economic mechanism behind this decline in marginal costs. Our model suggests that the input price index of the firm, $P(z)$, falls because treated firms work more efficiently with existing suppliers, outsource more tasks, and find better suppliers for existing tasks (Secs. IV.C and IV.E). This section provides firm-level evidence that the performance gains are driven by the supplier channel. As shown in proposition 2, the model has the testable prediction that the search intensity, as measured by the cutoff location $\bar{\tau}(z, j)$, is increasing faster for input- relative to labor-intensive industries when fixed or variable trade costs decline. Hence, input-intensive firms should add more supplying municipalities than labor-intensive firms when infrastructure improves.

Data.—We proceed by employing both 2005 and 2010 cross sections of the TSR data. A potential problem is that the sample of firms is not iden-

TABLE 9
Freight Time, Percentage Change 2000–2010

	Saga	Nagasaki	Kumamoto	Oita	Miyazaki	Kagoshima
Fukuoka	4	28	27	58	−25	**21**
Saga		−8	30	4	−52	5
Nagasaki			72	54	9	20
Kumamoto				88	− 38	**24**
Oita					22	32
Miyazaki						−6

Note.—The table shows the percentage change in freight time from 2000 to 2010 from the Net Freight Flow Census collected by the Ministry of Land, Infrastructure, Transport, and Tourism. Numbers refer to average freight time across different modes (train, truck, air, and sea).

tical in 2005 and 2010. The calculation of, for example, the number of municipalities is therefore sensitive to this sampling issue. We solve this by first constructing a balanced panel of firms that are in the data in both 2005 and 2010. This rules out the possibility that differences in sampling across 2005 and 2010 affect our measurement. Note that there is no need to merge the TSR data to Kikatsu in this section. Hence, the number of firms increases substantially compared to the sample in Section V.A.

The timing of the two TSR cross sections of 2005 and 2010 is not ideal for our purposes, because the Shinkansen extension occurred in March 2004. The underlying assumption is therefore that the impact of the train had not fully materialized when firms were surveyed in 2005. Our hypothesis is that finding new suppliers is a slow and costly process, so that it is unlikely that firms had fully adjusted after 1 year. Therefore, our estimates are biased toward zero if firms partially adjusted before 2005.

Methodology.—As in Section V.A, we investigate whether there is a stronger response among input-intensive firms than labor-intensive firms in treated locations. We estimate an identical triple differences equation; the only difference is that there are now only two years, 2005 and 2010, in the panel. Exactly as in Section V.A, we control for geographic trends at the municipality level by including the leave-out mean of y_{fjrt} across all firms in the same municipality, as well as by including prefecture-year fixed effects.

Results.—Table 10 shows the results. The dependent variable in column 1 is the number of sourcing municipalities. We find a significant increase in sourcing municipalities caused by the Shinkansen. According to our estimates, a fully input-intensive firm adds one more sourcing municipality

TABLE 10
FIRM CONNECTIONS, 2005–10

	No. of Municipalities (1)	χ (2)	No. of Suppliers (3)
$\text{Station}_f \times H_j \times 2010_t$	1.16**	.13**	.97
	(2.25)	(2.00)	(1.17)
Firm and municipality controls	Yes	Yes	Yes
Prefecture-year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	610,948	610,948	610,948
R^2	.97	.97	.98

NOTE.—The symbol χ refers to the share of suppliers located in treated locations, where treatment is defined as being <30 km from a new Shinkansen station. t-statistics clustered by firm are in parentheses. Dependent variables are measured relative to industry-year means.
* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

compared to a fully labor-intensive firm. Next, we ask whether the portfolio of suppliers is being shifted toward suppliers located close to a new train station. The dependent variable in column 2 is therefore the share of suppliers located 30 km from a new station. Here we also see a significant effect, suggesting that the infrastructure shock caused a reallocation in the production network. Finally, the dependent variable in column 3 is the number of suppliers. While the point estimate is positive, we cannot reject the null hypothesis of no change. Interestingly, this is also consistent with the predictions of the model. Specifically, appendix D shows that while the infrastructure shock will lead to more suppliers, the magnitude is not necessarily greater in input-intensive industries. The reason is that input-intensive firms may already outsource a large share of the unit continuum of tasks, implying that the scope for further outsourcing is limited.

The triple difference specification is preferred because it allows us to control for regional trends in a flexible way. However, one may wonder whether firms in locations that get a new station become more connected relative to firms in other locations, irrespective of the input intensity of the industry. Table 11 shows the results of a difference-in-difference model in which only the interaction between Station_f and a 2010 dummy is included. While the statistical significance is weaker compared to the baseline specification, we find that firms near new stations increase their connectedness as measured by the number of municipalities with active suppliers.

In a final test, we go back to our main regression in Section V.A and ask whether those firm performance results are driven by firms that add suppliers between 2005 and 2010. Columns 1–3 in table 12 show results when repeating the baseline specification, but using only firms that did not add suppliers over this period. Columns 4–6 use only firms that added

TABLE 11
FIRM CONNECTIONS, 2005–10

	No. of Municipalities (1)	χ (2)	No. of Suppliers (3)
$\text{Station}_f \times 2010_t$	.08*	.00	.13
	(1.71)	(.25)	(1.54)
Firm and municipality controls	No	No	No
Prefecture-year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	610,948	610,948	611,119
R^2	.97	.97	.98

NOTE.—The symbol χ refers to the share of suppliers located in treated locations, where treatment is defined as being <30 km from a new Shinkansen station. t-statistics clustered by firm are in parentheses. Dependent variables are measured relative to industry-year means.

* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

TABLE 12
FIRM PERFORMANCE: NEW SUPPLIERS VERSUS NO NEW SUPPLIERS

	Sales (1)	Sales/ Employment (2)	TFPR (3)	Sales (4)	Sales/ Employment (5)	TFPR (6)
$\text{Station}_f \times H_j \times \text{Post2004}_t$	−.08	.07	−.06	.60**	.72***	.54**
	(.19)	(.26)	(.12)	(2.48)	(2.74)	(2.31)
Firm and municipality controls	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,392	4,303	4,109	107,825	106,540	104,149
R^2	.94	.91	.94	.97	.92	.97

NOTE.—Cols. 1–3 use the sample of firms with no new suppliers from 2005 to 2010. Cols. 4–6 use the sample of firms with new suppliers from 2005 to 2010. t-statistics clustered by firm are in parentheses. Dependent variables are in logs and are measured relative to industry-year means.
* Significant at the .1 level.
** Significant at the .05 level.
*** Significant at the .01 level.

suppliers over the period. While the results for non-adders are noisy and insignificant, the results for adders are positive and robust.

Summing up, we find significant growth in sourcing localities and a reallocation of the supply chain consistent with the model. Moreover, these reallocation effects are consistent with the firm performance gains found in Section V.A.

VI. Conclusions

This paper examines how firm performance is related to the characteristics of the supply network with a special focus on geography. Using a comprehensive, unique data set on supplier-customer links among 950,000 Japanese firms, we develop a set of facts about the production network. Geographic proximity plays a key role for the matching of suppliers and customers as most connections cover relatively short distances. Large, more productive firms both have more suppliers and, on average, have suppliers that are farther away. While large firms have more suppliers, the trading partners of those large, well-connected firms, on average, are less well connected themselves.

Guided by these facts, we develop a simple model in which firms can outsource tasks and search for suppliers in different locations. Firms located in close proximity to other markets, and firms that face low search costs, will search more and find better suppliers. This in turn drives down the firm's marginal production costs. We test the theory by exploiting the opening of a high-speed train line in Japan, which lowered the cost of passenger travel but left shipping costs unchanged.

We find compelling evidence that the supply network matters for firm performance. The infrastructure shock generated significant performance gains, especially for firms in industries that have large shares of purchased inputs. We also provide evidence that these gains are related to changes in buyer-seller linkages as predicted by the model.

While there is a large literature on the link between infrastructure and improvements in regional economic outcomes, this paper provides the first direct evidence on the role of infrastructure on supply chains and firm performance. We highlight a novel transmission mechanism for the effects of improved infrastructure in which reductions in search costs and buyer-seller inefficiencies allow firms to match with more and better suppliers, thus lowering the marginal cost of production. The resulting geographic variation in marginal costs for otherwise ex ante identical firms yields systematic differences in economic activity across space. Firms in more geographically central locations have lower marginal costs and produce more.

This work has emphasized the role of domestic suppliers in explaining firm performance. Our results suggest that future research might fruitfully focus on how heterogeneous firms sort into locations, how reduced travel time affects intensive and extensive margins in both domestic and international buyer-supplier relationships, and how firm linkages form and evolve over time.

Appendix A

Optimal Search

The solution for $\bar{\tau}$ is

$$\bar{\tau}(z,j) = \kappa_1 \left[\frac{T}{w^{\sigma}}\frac{A}{f(j)}\right]^{1/\theta} \Phi(z,j)^{-k/\theta} z^{(\sigma-1)/\theta}.$$

Proof. The maximization problem of the firm is

$$\max_{\bar{\tau}} \{\pi(z,j) - wf(j)n(z,j)\},$$

where $\pi(z,j) = Ap(z,j)^{1-\sigma}/\sigma$. The term A is the demand shifter for final goods, $A = w(1+\psi)\bar{L}Q^{\sigma-1}$, where Q is the CES price index for final goods. Given monopolistic competition and CES preferences, the firm charges a price that is a constant markup over marginal costs: $p(z,j) = \bar{m}w^{\alpha}P(z,j)^{1-\alpha}/z$, where $\bar{m} = \sigma/(\sigma-1)$. Inserting p and P into the profit function then yields

$$\pi(z,j) = \frac{(\bar{m}\lambda^{1-\alpha})^{1-\sigma}}{\sigma} Aw^{1-\sigma}\Phi(z,j)^{(\sigma-1)(1-\alpha)/\theta} z^{\sigma-1}.$$

The expressions for Φ and n are

$$\Phi(z,j) = T_0 + \int_1^{\bar{\tau}(z,j)} T\tau^{-\theta} g(\tau,j)\,d\tau,$$
$$n(z,j) = \int_1^{\bar{\tau}(z,j)} g(\tau,j)\,d\tau.$$

Differentiating with respect to $\bar{\tau}$ yields

$$\frac{\partial\Phi(z,j)}{\partial\bar{\tau}} = T\bar{\tau}^{-\theta} g(\bar{\tau},j),$$
$$\frac{\partial n(z,j)}{\partial\bar{\tau}} = g(\bar{\tau},j).$$

The first-order condition is then

$$\frac{(\bar{m}\lambda^{1-\alpha})^{1-\sigma}}{\sigma} A \frac{(\sigma-1)(1-\alpha)}{\theta} w^{1-\sigma}\Phi(z,j)^{(\sigma-1)(1-\alpha)/\theta-1} z^{\sigma-1} T\bar{\tau}^{-\theta} = wf(j).$$

Rearranging,

$$\bar{\tau}(z,j) = \kappa_1\left[\frac{T}{w^{\sigma}}\frac{A}{f(j)}\right]^{1/\theta}\Phi(z,j)^{-k/\theta} z^{(\sigma-1)/\theta},$$

where

$$\kappa_1 = \left[\frac{(\bar{m}\lambda^{1-\alpha})^{1-\sigma}}{\sigma}\frac{(\sigma-1)(1-\alpha)}{\theta}\right]^{1/\theta}$$

and $k = 1-(\sigma-1)(1-\alpha)/\theta$.

The second-order condition is

$$\frac{(\bar{m}\lambda^{1-\alpha})^{1-\sigma}}{\sigma} A \frac{(\sigma-1)(1-\alpha)}{\theta} z^{\sigma-1} w^{1-\sigma}$$
$$\times\left\{-k\Phi^{-k-1}\left[\frac{\partial\Phi(z,j)}{\partial\bar{\tau}}\right]^2 + \frac{\partial^2\Phi(z,j)}{\partial\bar{\tau}^2}\Phi(z,j)^{-k}\right\} - wf(j)\frac{\partial^2 n(z,j)}{\partial\bar{\tau}^2} < 0.$$

Inserting the expressions for $\partial^2\Phi/\partial\bar{\tau}^2$ and $\partial n/\partial n^2$, this can be rewritten as

$$\frac{(\bar{m}\lambda^{1-\alpha})^{1-\sigma}}{\sigma} A \frac{(\sigma-1)(1-\alpha)}{\theta} z^{\sigma-1} w^{1-\sigma}\Phi^{1-k}\frac{T\bar{\tau}^{-\theta}}{\Phi}\left(-\frac{k}{\Phi}T\bar{\tau}^{-\theta}g^2 - \theta\bar{\tau}^{-1}g + g'\right)$$
$$- wf(j)g' < 0.$$

Using the first-order condition, we know that the following must hold in optimum:

$$\pi(z,j)\underline{\chi}(z,j) = wf\frac{\theta}{(\sigma-1)(1-\alpha)},$$

where $\underline{\chi}$ is the trade share from the marginal location $\bar{\tau}$, $\underline{\chi}(z,j) = T\bar{\tau}(z,j)^{-\theta}/\Phi(z,j)$. This tells us that gross profits from the marginal location $\bar{\tau}$ equal the fixed search cost f multiplied by the factor $\theta/(\sigma-1)(1-\alpha)$. Exploiting this relationship gives us the second-order condition

$$k\underline{\chi}(z,j)g(\bar{\tau},j) + \frac{\theta}{\bar{\tau}} > 0.$$

QED

Appendix B

Predictions of the Model

This appendix derives implications of the model described in Sections IV.C and IV.E of the main text.

A. The Relationship between $\bar{\tau}$ and z

The cutoff $\bar{\tau}$ is increasing in z, $\partial\bar{\tau}/\partial z > 0$.

Proof. Using equation (3), we have

$$\frac{\partial \Phi}{\partial z} = \frac{\partial \bar{\tau}}{\partial z} T\bar{\tau}^{-\theta} g(\bar{\tau}, j).$$

Using equation (4), we have

$$\frac{\partial \bar{\tau}}{\partial z} = \kappa_1 \left[\frac{T}{w^\sigma}\frac{A}{f(j)}\right]^{1/\theta} \Phi(z,j)^{-k/\theta} z^{(\sigma-1)/\theta}\left[-\frac{k}{\theta}\Phi(z,j)^{-1}\frac{\partial \Phi}{\partial z} + \frac{\sigma-1}{\theta}z^{-1}\right].$$

Substituting in $\partial\Phi/\partial z$ and rearranging yields

$$\frac{\partial \bar{\tau}}{\partial z} = \frac{(\sigma-1)/z}{\theta/\bar{\tau} + k\bar{\chi}(z,j)g(\bar{\tau},j)},$$

which is positive given that the regularity condition $\theta/\bar{\tau} + k\bar{\chi}(z,j)g(\bar{\tau},j) > 0$ holds. QED

This also implies that $\partial o/\partial z > 0$ because $\partial\Phi/\partial z > 0$.

B. The Relationship between $\bar{\tau}$ and $f(j)$

The cutoff $\bar{\tau}$ is decreasing in costs $f(j)$, $\partial\bar{\tau}/\partial f(j) < 0$.

Proof. Using equation (3), we have

$$\frac{\partial \Phi(z,j)}{\partial f(j)} = \frac{\partial \bar{\tau}}{\partial f} T\bar{\tau}^{-\theta} g(\bar{\tau}, j).$$

Using equation (4), we have

$$\frac{\partial \bar{\tau}(z,j)}{\partial f(j)} = -\frac{1}{\theta}\bar{\tau}(z,j)\frac{1}{f}\left[1 + k\frac{\partial \Phi}{\partial f}\frac{f}{\Phi(z,j)}\right].$$

Substituting in $\partial\Phi/\partial f$ and rearranging yields

$$\frac{\partial\bar{\tau}(z,j)}{\partial f(j)} = \frac{-1/f}{\theta/\bar{\tau} + k\bar{\chi}(z,j)g(\bar{\tau},j)},$$

which is negative given that the regularity condition $\theta/\bar{\tau} + k\bar{\chi}(z,j)g(\bar{\tau},j) > 0$ holds. This means that

$$\frac{\partial n(z,j)}{\partial f(j)} = \frac{\partial\bar{\tau}(z,j)}{\partial f(j)} g(\bar{\tau},j) < 0.$$

QED

Note that we can also express

$$\frac{\partial\Phi(z,j)}{\partial f(j)}\frac{f(j)}{\Phi(z,j)} = -\frac{\underline{\chi}(z,j)g(\bar{\tau},j)}{\theta/\bar{\tau} + k\underline{\chi}(z,j)g(\bar{\tau},j)} < 0.$$

Furthermore, $\partial o/\partial f < 0$ because $\partial\Phi/\partial f < 0$.

C. *Assortativity*

The expected measure of buyers from j among suppliers in z's marginal market is decreasing in efficiency z.

Proof. The expected measure of buyers from j for a task ω in a location with trade costs τ (given the assumption of a unit continuum of tasks) is

$$\begin{aligned} c(\tau,j) &= m(j)\int_{\underline{z}(\tau,j)} \frac{T\tau^{-\theta}}{\Phi(z,j)}\lambda(z,j)\,dz \\ &= m(j)T\tau^{-\theta}\int_{\underline{z}(\tau,j)} \frac{\lambda(z,j)}{\Phi(z,j)}\,dz, \end{aligned}$$

where $\lambda(z,j)$ is the density of productivity in location j, $m(j)$ is the mass of firms in j, and $\underline{z}(\tau,j)$ is the minimum efficiency z required in order to source from a location with trade costs τ. The expected measure of buyers from j among suppliers in z_0's marginal market is therefore

$$\bar{c}(z_0,j) = m(j)T\bar{\tau}(z_0)^{-\theta}\int_{z_0} \frac{\lambda(z,j)}{\Phi(z,j)}\,dz.$$

We get

$$\frac{\partial\bar{c}(z_0,j)}{\partial z_0} = -m(j)T\bar{\tau}(z_0)^{-\theta}\left[\frac{\theta}{\bar{\tau}(z_0)}\frac{\partial\bar{\tau}}{\partial z_0}\int_{z_0}\frac{\lambda(z,j)}{\Phi(z,j)}\,dz + \frac{\lambda(z_0,j)}{\Phi(z_0,j)}\right],$$

which is negative because $\partial\bar{\tau}/\partial z_0 > 0$ (see Sec. A). QED

Hence, the average supplier in a downstream firm's marginal market is less well connected if downstream productivity z_0 is higher.

D. *The Relationship between Trade Costs and Expected Productivity of a Buyer*

The expected productivity of a downstream buyer from j is increasing in trade costs between supplier and buyer.

Proof. The expected productivity of buyers from j for a task ω is

$$E[z(j,\tau)] = \int_{\underline{z}(\tau,j)} v(z) z \lambda(z,j)\, dz,$$

with weights

$$v(z) = \frac{\frac{T\tau^{-\theta}}{\Phi(z,j)}}{\int_{\underline{z}(\tau,j)} \frac{T\tau^{-\theta}}{\Phi(z,j)} \lambda(z,j)\, dz} = \frac{\Phi(z,j)^{-1}}{\int_{\underline{z}(\tau,j)} \Phi(z,j)^{-1} \lambda(z,j)\, dz}.$$

Differentiating with respect to τ yields

$$\frac{E[z(j,\tau)]}{\partial \tau} = \frac{\partial \underline{z}}{\partial \tau} \frac{\lambda(\underline{z},j)}{\Phi(\underline{z},j)} \frac{\int_{\underline{z}(\tau,j)} z \frac{\lambda(z,j)}{\Phi(z,j)}\, dz - \int_{\underline{z}(\tau,j)} \underline{z} \frac{\lambda(z,j)}{\Phi(z,j)}\, dz}{\left[\int_{\underline{z}(\tau,j)} \frac{\lambda(z,j)}{\Phi(z,j)}\, dz\right]^2}.$$

The sum of the two integrals in the numerator is positive because we integrate over $z > \underline{z}$. Moreover, $\partial \underline{z}/\partial \tau = 1/(\partial \bar{\tau}/\partial z) > 0$, so that $E[z(j,\tau)]/\partial \tau > 0$. QED

Hence, when comparing a supplier's connections in different markets, the expected productivity of a buyer is higher in markets with higher trade costs.

Appendix C

Distributional Assumptions

Assume that τ is inversely Pareto distributed with support $[1, \tau_H]$ and shape $\gamma > \theta$: The density is $g(\tau) = \gamma[\tau_H^{-\gamma}/(1 - \tau_H^{-\gamma})]\tau^{\gamma-1}$ and the cdf is $G(\tau) = [\tau_H^{-\gamma}/(1 - \tau_H^{-\gamma})](\tau^\gamma - 1)$. An inverse Pareto captures the empirical fact that a location j has few nearby markets and many remote markets; we show in appendix F that the inverse Pareto is a reasonable approximation of the empirical distribution of distance in our data. Note that a distribution with high upper bound τ_H first-order stochastically dominates a distribution with a low upper bound. Denote the two distributions (i) and (ii); then for $\tau_H^{(i)} > \tau_H^{(ii)}$, we have $G^{(i)}(\tau) < G^{(ii)}(\tau)$. This can be seen by differentiating the cdf:

$$\frac{\partial G}{\partial \tau_H} = -\frac{\gamma \tau_H^{-\gamma-1}}{(1 - \tau_H^{-\gamma})^2}(\tau^\gamma - 1) < 0.$$

In addition, we assume that a downstream firm's average productivity in task production, T_0, is related to the average cost of purchasing tasks in the marketplace as follows:[22]

[22] Note that

$$\int_1^{\tau_H} T\tau^{-\theta} g(\tau,j)\, d\tau = \frac{T\tau_H^{-\gamma}}{1 - \tau_H^{-\gamma}} \frac{\gamma}{\gamma - \theta}(\tau_H^{\gamma-\theta} - 1),$$

so T_0 equals $\int_1^{\tau_H} T\tau^{-\theta} g(\tau,j)\, d\tau/(\tau_H^{\gamma-\theta} - 1)$.

$$T_0 = \frac{T\tau_H^{-\gamma}}{1-\tau_H^{-\gamma}}\frac{\gamma}{\gamma-\theta}.$$

Hence, a downstream firm cannot be too efficient in producing tasks itself, otherwise there would be no incentive to outsource. Given these additional assumptions, the hurdle $\bar{\tau}$, equilibrium market access Φ, and measure of searched locations n are

$$\bar{\tau}(z,j) = \kappa_2\left[\frac{A}{w^\sigma f(j)}\right]^{1/\omega} T^{(1-k)/\omega} z^{(\sigma-1)/\omega}, \tag{C1}$$

$$\Phi(z,j) = \frac{T\tau_H^{-\gamma}}{1-\tau_H^{-\gamma}}\frac{\gamma}{\gamma-\theta}\bar{\tau}(z,j)^{\gamma-\theta}, \tag{C2}$$

$$n(z,j) = \frac{\tau_H^{-\gamma}}{1-\tau_H^{-\gamma}}[\bar{\tau}(z,j)^\gamma - 1], \tag{C3}$$

where $\omega = \theta + k(\gamma-\theta)$ and κ_2 is a constant:

$$\kappa_2 = \kappa_1^{\theta/\omega}\left(\frac{\tau_H^{-\gamma}}{1-\tau_H^{-\gamma}}\frac{\gamma}{\gamma-\theta}\right)^{-k/\omega}.$$

The sourcing problem has an interior solution only if the second-order condition, $\omega > 0$, is satisfied. Henceforth, we focus exclusively on the interior solution, that is, $\omega > 0$.

Appendix D

Propositions

Proposition 1 states as follows: (i) Lower search costs $f(j)$ and trade costs τ_H lead to growth in sales among downstream firms in j. (ii) Sales growth is stronger in input-intensive (low-α) relative to labor-intensive (high-α) industries.

Proof. Under the distributional assumption for $g(\tau, j)$, we get

$$\frac{\partial \ln r(z,j)}{\partial \ln f(j)} = -\frac{(\sigma-1)(1-\alpha)}{\theta}\frac{\gamma-\theta}{\omega} < 0,$$
$$\frac{\partial \ln r(z,j)}{\partial \ln \tau_H} = -\frac{(\sigma-1)(1-\alpha)}{\theta}\frac{\gamma}{1-\tau_H^{-\gamma}}\frac{\theta}{\omega} < 0,$$

and

$$\frac{\partial^2 \ln r(z,j)}{\partial \ln f(j)\partial(1-\alpha)} = -\frac{\sigma-1}{\theta}\frac{\gamma(\gamma-\theta)}{\omega^2} < 0,$$
$$\frac{\partial^2 \ln r(z,j)}{\partial \ln \tau_H\partial(1-\alpha)} = -\frac{\sigma-1}{1-\tau_H^{-\gamma}}\left(\frac{\gamma}{\omega}\right)^2 < 0;$$

hence the elasticity of sales with respect to both fixed costs $f(j)$ and variable costs τ_H is negative, and the elasticity is more negative when $1-\alpha$ is high. QED

Proposition 2 states that lower search costs $f(j)$ and variable costs τ_H lead to an increase in the number of locations searched among downstream firms in j. Moreover, the response is stronger in input- (low-α) relative to labor-intensive (high-α) industries.

Proof. Under the distributional assumption for $g(\tau, j)$, we get

$$\frac{\partial \ln \bar{\tau}(z,j)}{\partial \ln f(j)} = -\frac{1}{\omega} < 0,$$

$$\frac{\partial^2 \ln \bar{\tau}(z,j)}{\partial \ln f(j) \partial(1-\alpha)} = -\omega^{-2}\frac{(\gamma-\theta)(\sigma-1)}{\theta} < 0.$$

Hence, the search intensity, as measured by the cutoff $\bar{\tau}(z,j)$, is always increasing faster for input- relative to labor-intensive firms when search costs fall. Also, the cross elasticity is negative when average variable trade costs change:

$$\frac{\partial \ln \bar{\tau}(z,j)}{\partial \ln \tau_H} = \frac{k}{\omega}\frac{\gamma}{1-\tau_H^{-\gamma}},$$

$$\frac{\partial^2 \ln \bar{\tau}(z,j)}{\partial \ln \tau_H \partial(1-\alpha)} = -\frac{\gamma}{1-\tau_H^{-\gamma}}\frac{\sigma-1}{\omega^2} < 0.$$

Note that $\partial \ln \bar{\tau}(z,j)/\partial \ln \tau_H$ in general depends on the sign of k (which can be either positive or negative), while the cross elasticity is always negative and is not a function of k. QED

The model has no clear prediction about the magnitudes of $\partial o/\partial \ln f$ and $\partial o/\partial \ln \tau_H$ in input- relative to labor-intensive industries. This can be seen by the following expressions:

$$\frac{\partial \ln \Phi(z,j)}{\partial \ln f} = -\frac{\gamma-\theta}{\omega} < 0,$$

$$\frac{\partial \ln \Phi(z,j)}{\partial \ln \tau_H} = -\frac{\gamma}{1-\tau_H^{-\gamma}}\frac{\theta}{\omega} < 0.$$

Because $o(z,j) = 1 - T_0/\Phi(z,j)$, we also get $\partial o/\partial \ln f = (1-o)\partial \ln \Phi/\partial \ln f < 0$ and $\partial o/\partial \ln \tau_H = (1-o)\partial \ln \Phi/\partial \ln \tau_H < 0$; that is, lower search or variable trade costs yield more outsourcing. However, the cross elasticity is

$$\frac{\partial^2 o}{\partial \ln f \partial(1-\alpha)} = -\frac{\partial o}{\partial(1-\alpha)}\frac{\partial \ln \Phi}{\partial \ln f} + (1-o)\frac{\partial^2 \ln \Phi}{\partial \ln f \partial(1-\alpha)}$$

$$= (1-o)\left[-\frac{\partial \ln \Phi}{\partial(1-\alpha)}\frac{\partial \ln \Phi}{\partial \ln f} + \frac{\partial^2 \ln \Phi}{\partial \ln f \partial(1-\alpha)}\right],$$

where the first term in the brackets is positive while the second is negative. Hence, there is no clear prediction from the model about the outsourcing response across industries.

Appendix E

Sales per Employee and TFPR

This appendix discusses the use of sales per employee (LP) and revenue productivity (TFPR) in the context of the model.

We start with sales per employee. By using the expression for the production function, sales per employee can be written as

$$LP = \frac{py}{l} = pz\left(\frac{v}{l}\right)^{1-\alpha}.$$

Inserting the first-order condition, $v/l = [(1-\alpha)/\alpha]w/P$, we get

$$LP = \left(\frac{1-\alpha}{\alpha}\right)^{1-\alpha} pz\left(\frac{w}{P}\right)^{1-\alpha}.$$

Inserting the expression for prices, $p = \bar{m}kw^{\alpha}P^{1-\alpha}/z$, where $k = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}$, we get

$$LP = \frac{\bar{m}w}{\alpha}.$$

Hence, sales per employee is constant across firms within the same industry. Note that if output prices p are sticky, then a fall in sourcing costs P leads to a rise in LP.

Revenue productivity is defined as

$$\begin{aligned}\text{TFPR} &= \frac{py}{(vP)^{1-\alpha}l^{\alpha}} \\ &= \frac{pz}{P^{1-\alpha}},\end{aligned}$$

where in the second equality we inserted the production function.[23] Inserting prices yields

$$\text{TFPR} = \bar{m}kw^{\alpha},$$

which is also constant across firms within the same industry. Note that if output prices p are sticky, then a fall in sourcing costs P leads to a rise in TFPR. Intuitively, this occurs because TFPR controls for the value of inputs vP, instead of the quantity of inputs v, so that a fall in P translates into a rise in TFPR.

[23] We have omitted capital in the definition of TFPR because capital is not in the model. The analysis in this appendix would be similar if we included capital. When estimating TFPR, capital is controlled for; see Sec. A in app. G.

Appendix F

The Distribution of Trade Costs

This appendix provides empirical support for the assumption that trade costs are inversely Pareto distributed with density

$$g(\tau) = \gamma \frac{\tau_H^{-\gamma}}{1 - \tau_H^{-\gamma}} \tau_0^{\gamma - 1}. \tag{F1}$$

Let distance d from location i be inversely Pareto distributed with support $[0, d_{Hi}]$ and shape parameter $\kappa > 0$. The cdf is

$$H_i(d) = \left(\frac{d}{d_{Hi}}\right)^{\kappa}.$$

Consider the 500×500 grid data set described in Section V. We calculate distance for every location pair ij and the empirical distribution of distance for each location i. Because of the large number of location-pairs, we limit the calculations to the 1st, 2nd, …, 9th deciles of the distance distribution. From this, we obtain the kth decile in location i, d_{ik}. If the distribution is inverse Pareto, the following must hold:

$$\ln H_{ik} = -\kappa \ln d_{iH} + \kappa \ln d_{ik}, \tag{F2}$$

where H_{ik} takes the values 0.1 for $k = 1$, 0.2 for $k = 2$, and so on. The inverse Pareto should fit the data well if the relationship between H_{ik} and the d_{ik} is approximately log linear. Figure F1 plots H_{ik} against $d_{ik} - \bar{d}_i$, where $\bar{d}_i = (1/9)\Sigma_{k=1}^{9} d_{ik}$, on log axes. The normalization removes the constant term d_{iH}, which may vary across locations. Overall, the relationship is close to linear, although there is clearly heterogeneity in the distribution across locations. Estimating equation (F2) with location fixed effects produces a slope coefficient κ of 1.07.

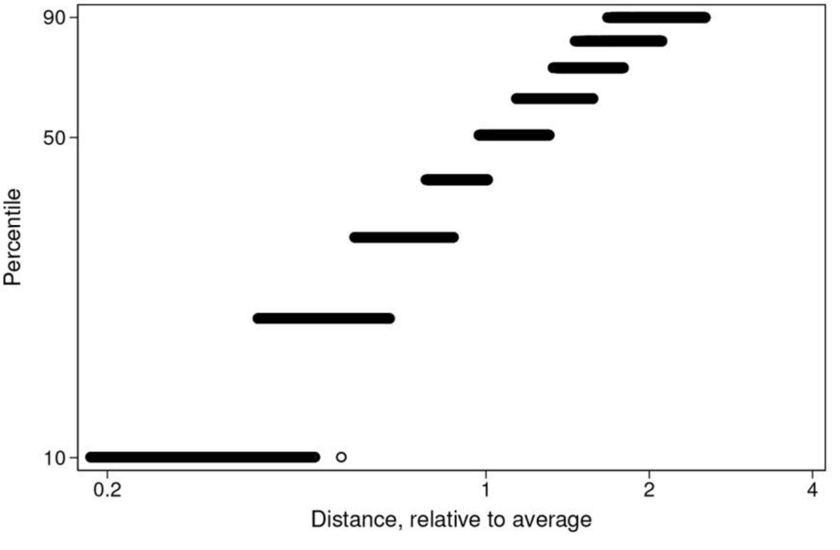

Fig. F1.—The cdf of distance across locations. Axes are on log scales.

As is common in the literature, we assume that for large d, $\tau(d)$ is well approximated by the power law $\tau = (\alpha d)^{\rho}$ with $\alpha > 0$ and $\rho > 0$. Then τ inherits the distribution of d with shape parameter $\gamma = \kappa/\rho$. Because $\tau \geq 1$, the τ density has support $[1, \tau_H]$, which yields the expression of $g(\tau)$ given in equation (F1).

Appendix G

Data

A. *Firm Performance*

This section describes the measures of firm performance used in Section V.A. As in Klette (1999), all firm-level variables are demeaned relative to industry-year means, $\ln \hat{y}_{ijt} = \ln y_{ijt} - \overline{\ln y_{jt}}$, where $\ln \hat{y}_{ijt}$ refers to the demeaned variable for firm i in industry j at time t, $\ln y_{ijt}$ refers to the original log variable, and $\overline{\ln y_{jt}}$ refers to the mean of the log variable in industry-year jt. The industry classification is three-digit JSIC. Demeaning by industry-year has the benefit that it eliminates the need for deflating nominal variables; moreover, it allows the technology of an industry to move freely over time.

TFPR is estimated by the Olley and Pakes (1996) procedure. We estimate the gross production function

$$\ln \text{Revenue}_{it} = \beta_l \ln \text{Labor}_{it} + \beta_m \ln \text{Materials}_{it} + \beta_k \ln \text{Capital}_{it} + \omega_{it} + \eta_{it}, \quad \text{(G1)}$$

where ω_{it} is total factor productivity of the firm and η_{it} is either measurement error or a shock to productivity that is not forecastable during the period in which labor can be adjusted. After obtaining the estimates $\hat{\beta}_l$, $\hat{\beta}_m$, and $\hat{\beta}_k$, TFPR is calculated by subtracting predicted output from actual output:

$$\text{TFPR}_{it} = \hat{\omega}_{it} = \ln \text{Revenue}_{it} - \hat{\beta}_l \ln \text{Labor}_{it} - \hat{\beta}_m \ln \text{Materials}_{it} - \hat{\beta}_k \ln \text{Capital}_{it}.$$

B. *Input Intensity*

Input intensity H_j is calculated as input costs relative to total costs for each JSIC three-digit industry j in year 2003. Specifically, denote WC_j total wage costs for industry j, $WC_j = \Sigma_{i\in j}\text{wage costs}_i$, and total costs $TC_j = \Sigma_{i\in j}\text{total costs}_i$. Then H_j is $H_j = 1 - WC_j/TC_j$. Figure G1 shows the density of H_j across all 315 JSIC industries.

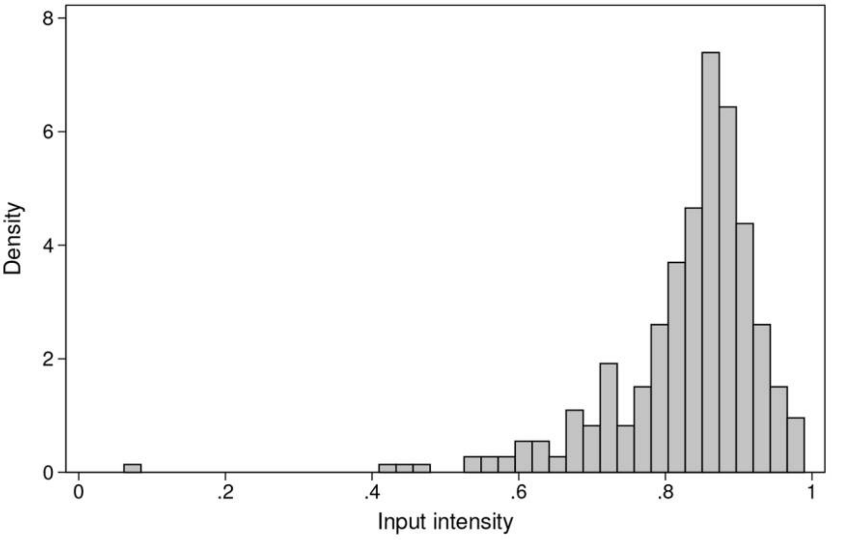

FIG. G1.—Density of input intensity H_j across industries: 2003 data

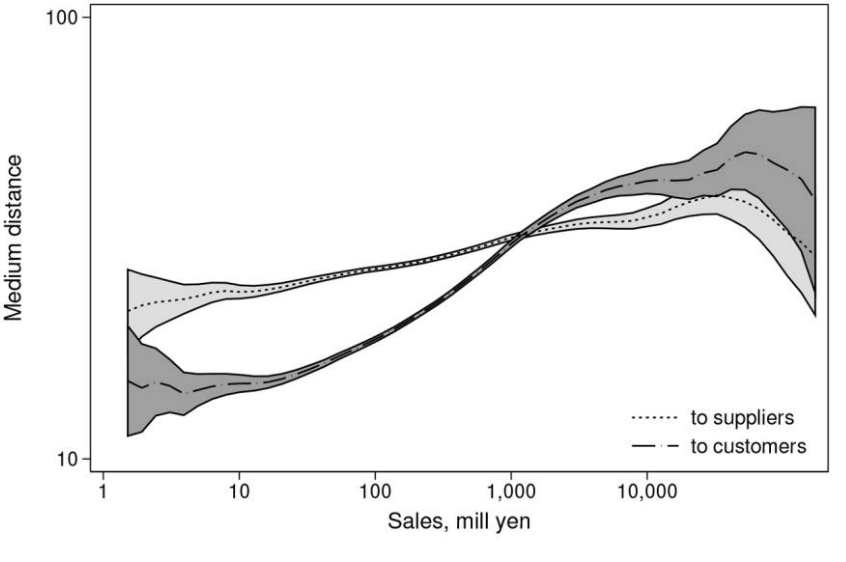

FIG. G2.—Size and median distance to connections: single-plant firms, 2005 data. The figure shows the kernel-weighted local polynomial regression of firm-level median log distance to the firm's connections (vertical axis) on log sales (horizontal axis). Firms with more than one plant are excluded. The two lines represent distance to suppliers and customers as separate regressions. The gray area denotes the 95 percent confidence bands. The sample is first trimmed by excluding the 0.1 percent lowest and highest observations of sales.

References

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. "The Network Origins of Aggregate Fluctuations." *Econometrica* 80 (September): 1977–2016.

Amiti, Mary, and Jozef Konings. 2007. "Trade Liberalization, Intermediate Inputs and Productivity: Evidence from Indonesia." *A.E.R.* 97 (5): 1611–38.

Antràs, Pol, Teresa C. Fort, and Felix Tintelnot. 2014. "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms." Working Paper no. 20772, NBER, Cambridge, MA.

Atalay, Enghin, Ali Hortacsu, James Roberts, and Chad Syverson. 2011. "Network Structure of Production." *Proc. Nat. Acad. Sci.* 108 (13): 5199–5202.

Barrot, Jean-Noël, and Julien Sauvagnat. 2016. "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks." *Q.J.E.* 131 (3): 1543–92.

Bernard, Andrew B., Andreas Moxnes, and Karen Helene Ulltveit-Moe. 2018. "Two-Sided Heterogeneity and Trade." *Rev. Econ. and Statis.* 100 (3): 424–39.

Blum, Bernardo S., Sebastian Claro, and Ignatius J. Horstmann. 2012. "Import Intermediaries and Trade Costs: Theory and Evidence." Manuscript, Univ. Toronto.

Bøler, Esther Ann, Andreas Moxnes, and Karen Helene Ulltveit-Moe. 2015. "R&D, International Sourcing, and the Joint Impact on Firm Performance." *A.E.R.* 105 (12): 3704–39.

Carvalho, Vasco M., Makoto Nirei, and Yukiko U. Saito. 2014. "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake." Discussion paper, Res. Inst. Economy, Trade, and Industry, Tokyo.

Chaney, Thomas. 2014. "The Network Structure of International Trade." *A.E.R.* 104 (11): 3600–3634.

Combes, Pierre-Philippe, Gilles Duranton, Laurent Gobillon, Diego Puga, and Sébastien Roux. 2012. "The Productivity Advantages of Large Cities: Distinguishing Agglomeration from Firm Selection." *Econometrica* 80 (6): 2543–94.

Comin, Diego, Mikhail A. Dmitriev, and Esteban Rossi-Hansberg. 2012. "The Spatial Diffusion of Technology." Working Paper no. 18534, NBER, Cambridge, MA.

Coval, Joshua D., and Tobias J. Moskowitz. 1999. "Home Bias at Home: Local Equity Preference in Domestic Portfolios." *J. Finance* 54 (December): 2045–73.

———. 2001. "The Geography of Investment: Informed Trading and Asset Prices." *J.P.E.* 109 (August): 811–41.

Cristea, Anca. 2011. "Buyer-Seller Relationships in International Trade: Evidence from U.S. States' Exports and Business-Class Travel." *J. Internat. Econ.* 84:207–20.

Davis, Donald R., and Jonathan I. Dingel. 2012. "A Spatial Knowledge Economy." Working Paper no. 18188, NBER, Cambridge, MA.

Donaldson, Dave. 2018. "Railroads of the Raj: Estimating the Impact of Transportation Infrastructure." *A.E.R.* 108 (4–5): 899–934.

Duranton, Gilles, Peter Morrow, and Matthew A. Turner. 2014. "Roads and Trade: Evidence from the US." *Rev. Econ. Studies* 81 (2): 681–724.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, Geography, and Trade." *Econometrica* 70 (September): 1741–79.

Fort, Teresa C. 2017. "Technology and Production Fragmentation: Domestic versus Foreign Sourcing." *Rev. Econ. Studies* 84 (2): 650–87.

Giroud, Xavier. 2013. "Proximity and Investment: Evidence from Plant-Level Data." *Q.J.E.* 128:861–915.

Glaeser, Edward L., and David C. Maré. 2001. "Cities and Skills." *J. Labor Econ.* 19 (2): 316–42.

Goldberg, Pinelopi Koujianou, Amit Kumar Khandelwal, Nina Pavcnik, and Petia Topalova. 2010. "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India." *Q.J.E.* 125 (November): 1727–67.

Halpern, Lazlo, Miklos Koren, and Adam Szeidl. 2015. "Imported Inputs and Productivity." *A.E.R.* 105 (12): 3660–3703.

Hightower, R. T., and L. Sayeed. 1995. "The Impact of Computer-Mediated Communication Systems on Biased Group Discussion." *Computers in Human Behavior* 11 (1): 33–44.

———. 1996. "Effects of Communication Mode and Prediscussion Information Distribution Characteristics on Information Exchange in Groups." *Information Systems Res.* 7 (4): 451–65.

Hillberry, Russell, and David Hummels. 2008. "Trade Responses to Geographic Frictions: A Decomposition Using Micro-Data." *European Econ. Rev.* 52 (3): 527–50.

Jackson, Matthew O., and Brian W. Rogers. 2007. "Meeting Strangers and Friends of Friends: How Random Are Social Networks?" *A.E.R.* 97 (3): 890–915.

Keller, Wolfgang, and Stephen R. Yeaple. 2013. "The Gravity of Knowledge." *A.E.R.* 103 (4): 1414–44.

Klette, Tor Jakob. 1999. "Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data." *J. Indus. Econ.* 47 (4): 451–76.

Lerner, Josh. 1995. "Venture Capitalists and the Oversight of Private Firms." *J. Finance* 50 (March): 301–18.

Nayar, Nitya Pandalai, Aaron Flaaen, and Christoph Boehm. 2015. "Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tohoku Earthquake." Paper no. CES-WP-15-28, Center Econ. Studies, US Census Bur., Washington, DC.

Oberfield, Ezra. 2013. "Business Networks, Production Chains, and Productivity: A Theory of Input-Output Architecture." Technical report, Princeton Univ.

Ohnishi, T., H. Takayasu, and M. Takayasu. 2010. "Network Motifs in Inter-firm Network." *J. Econ. Interaction and Coordination* 5 (2): 171–80.

Olley, G. S., and A. Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64:1263–97.

Petersen, Mitchell A., and Raghuram G. Rajan. 2002. "Does Distance Still Matter? The Information Revolution in Small Business Lending." *J. Finance* 57 (December): 2533–70.

Redding, Stephen J., and Matthew A. Turner. 2015. "Transportation Costs and the Spatial Organization of Economic Activity." In *Handbook of Urban and Regional Economics*, vol. 5, edited by Gilles Duranton, J. Vernon Henderson, and William Strange, chap. 20. Amsterdam: North-Holland.

Saito, Yukiko U., Tsutomu Watanabe, and Mitsuru Iwamura. 2007. "Do Larger Firms Have More Interfirm Relationships?" *Physica A: Statistical Mechanics and Its Applications* 383 (1): 158–63.

Serrano, Ma Ángeles, and Marián Boguñá. 2003. "Topology of the World Trade Web." *Physical Rev. E.* 68 (1).

Sveikauskas, Leo. 1975. "The Productivity of Cities." *Q.J.E.* 89 (3): 393–413.

Uzzi, Brian. 1996. "The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect." *American Sociological Rev.* 61 (4): 674–98.

Warkentin, Merrill E., Lutfus Sayeed, and Ross Hightower. 1997. "Virtual Teams versus Face-to-Face Teams: An Exploratory Study of a Web-Based Conference System." *Decision Sci.* 28 (4): 975–96.