Matching and Agglomeration:
Theory and Evidence from Japanese Firm-to-Firm Trade

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Abstract

Why are economic activities geographically concentrated? I argue that matching frictions and increasing returns to scale in firm-to-firm matching for input trade is an important source of agglomeration. Using a yearly panel of firm-to-firm trade in Japan and unanticipated supplier bankruptcies as a natural experiment, I first document that firms rematch with new suppliers at a faster rate in locations and industries with a higher density of alternative suppliers. At the same time, the new supplier matching rate does not decrease with the geographic density of other buyers, hence the matching rate exhibits increasing returns to scale. Motivated by these findings, I develop a structural general equilibrium model of firm-to-firm trade with matching frictions. I structurally estimate the key parameters of the model to precisely replicate the reduced-form estimates, and I show that this agglomeration mechanism explains about a third of the population-density premium in nominal wages in Japan.

1 Introduction

Economic activities are geographically concentrated. While Japan has 47 prefectures, Tokyo Prefecture, which encompasses only 0.5% of the geographic area and 10% of the population of Japan, alone produces 17% of the country's output (in 2008). There is no shortage of theories explaining the agglomeration of economic activity (Duranton and Puga 2004, Head and Mayer 2004, Redding 2013). However, there is limited consensus on the empirical and quantitative relevance of the various mechanisms that the literature proposes.

In this paper, I focus on one such mechanism driving the geographic concentration of economic activity: firms match with input suppliers more easily in denser areas. Although this is a classical idea dating back to Marshall (1890), empirical evidence is limited beyond a suggestive cross-sectional correlation. In this paper, I first provide reduced-form evidence for this agglomeration mechanism. Based on the reduced-form evidence, I develop a new structural model of firm-to-firm trade that micro-founds this agglomeration force. I then use the estimated model to quantify the importance of this mechanism in explaining the spatial distribution of economic activity.

The first part of the paper provides reduced-form evidence for this agglomeration mechanism using a panel of firm-to-firm trade data in Japan. The data exhibits a robust correlation between the number of suppliers per firm and the population density. However, such a cross-sectional correlation may simply reflect that firms with higher demand for external inputs selectively enter in denser areas (Holmes 1999). To deal with this issue, this paper proposes to use unanticipated supplier bankruptcies as a natural experiment. When an unanticipated supplier bankruptcy occurs, the firm's buyers (downstream firms) must find new suppliers. However, a downstream firm may face frictions in matching with a new supplier. Hence, a robust test for the proposed agglomeration benefit is whether the matching rate with a new supplier after an unexpected supplier bankruptcy is increasing in the geographic density of alternative suppliers.

Japanese firm-to-firm trade data provides an excellent opportunity to carry out this test empirically. Aside from the list of the main suppliers and buyers reported by each firm in each year, it provides a comprehensive list of bankruptcies, including the main reasons for each bankruptcy. I focus on "unanticipated bankruptcies" – the death of representatives, natural disaster, etc. – and study the impact of these bankruptcies on their buyers' subsequent matching rates with a new alternative supplier.[1]

The empirical results are summarized as follows. First, I find supportive evidence of the advantage in supplier matching in denser areas. Firms facing unanticipated supplier bankruptcies only gradually rematch with alternative suppliers. At the same time, rematching with an alternative supplier is faster when there are more alternative suppliers selling in the buyer's location. This difference is sizable; the matching rate with new supplier at the 95th percentile of the supplier density distribution is almost twice as fast as the average matching rate.

One concern about this result is that this pattern may be driven by unobserved heterogeneity of firms across locations. For example, firms which use less specialized inputs may selectively enter in denser areas (Holmes and Stevens 2014), and firms find these types of alternative suppliers more easily. Alternatively, firms with a higher ability to find a supplier may selectively enter in denser locations. I resolve this concern in two ways. First, I take advantage of the fact that firms *in the same location and industry* may face unanticipated supplier bankruptcies *in different supplier industries.* This variation allows me to study how the

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[1]According to an internal document from the data source (Tokyo Shoko Research), "unanticipated reasons" cover "unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc." See Table 1 for other reasons of bankruptcies reported in this data set.

new supplier matching rate depends on the density of suppliers conditional on the same location and industry. I operationalize this intuition by including firm's location and industry fixed effects in the regression specification. Second, I exploit firm CEOs' birth places as a plausibly exogenous variation for the supplier density. In the data, there is a strong tendency that CEOs run businesses at their birth locations. This suggests that the supplier density *evaluated at the CEO's birth location* is an arguably exogenous instrument for the supplier density of the firm's location, under the exclusion restriction that the birth place of the CEO affects the new supplier matching rate only through the density of suppliers at the firm's location.

Second, I find that the geographic density of other buyers in the same location does *not* decrease the supplier matching rate. In other words, buyers do not crowd out each other's matching with suppliers. This result is robust to the definition of buyer density. Combined with the evidence that supplier density increases the matching rates, this implies that the new supplier matching rates exhibit *increasing* returns to scale.

The finding of no crowding-out is in stark contrast to firm-to-*worker* matching in the labor market context. The literature typically finds constant returns to scale in firm-to-worker matching, i.e., while unemployed workers' reemployment rate increases in the available job vacancies, it decreases at a similar rate in the number of other unemployed workers.[2] The difference is intuitive. In the context of firm-to-*firm* matching, suppliers can simultaneously serve multiple buyers. On the other hand, in the context of firm-to-*worker* matching, only one unemployed worker can fill a job vacancy, necessarily inducing crowding-out.

Third, I find that firm sales and revenue productivity per worker decrease after an unanticipated supplier bankruptcy. Interestingly, while the matching rate responds to supplier density, the reduction of sales *per matched supplier* does not depend on the geographic density of suppliers. This implies that, in this context, supplier density benefits firms by *more frequent* supplier matching, rather than *better* supplier matches.

In the second part of the paper, I study how the reduced-form estimates translate to the geographic concentration of economic activity in the general equilibrium. To do so, I develop a structural model of firm-to-firm matching and trade, which precisely maps to the reduced-form findings. The model incorporates matching frictions in firm-to-firm input trade in a version of a multi-location multi-sector Melitz model (Melitz 2003). As in a standard Melitz model, firms producing in each location must pay a fixed cost if they decide to sell their intermediate inputs in each of various locations. Each firm also requires intermediate inputs for production. A firm can source intermediate inputs either by directly matching with a supplier or by the more costly means of purchasing through an intermediary. There are frictions in matching with a supplier, and the matching rates increase in the density of input sellers.

The model exhibits an agglomeration force through circular causation between the entry of input sellers and the aggregate input demand. In a location with more input sellers, input buyers enjoy a higher supplier matching rate and hence a cost advantage, i.e., a "forward linkage." This, in turn, creates a larger market for suppliers and encourages more suppliers to sell in the location, i.e., a "backward linkage." This circular causation is governed by two key structural parameters: (1) the elasticity of the supplier matching rate with respect to the geographic density of input sellers, and (2) the production benefit of directly matching with a supplier (as opposed to sourcing from an intermediary).

These key structural parameters are intuitively connected to the reduced-form findings of unanticipated supplier bankruptcies. I use this tight connection to recover the parameters. More specifically, I use the model to simulate the same "natural experiment" of unanticipated supplier bankruptcies (mod-

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[2] An example includes Petrongolo (2001). See Petrongolo and Pissarides (2001) for a survey of this literature.

eled as exogenous separations with a supplier), and obtain the resulting supplier matching patterns and sales growth. I choose the values of the structural parameters that most closely replicate the difference-in-difference estimates from the first part of the paper.

Using the calibrated model, I conduct two counterfactual simulation exercises to quantify the highlighted agglomeration force. In the first counterfactual exercise, I quantify the extent to which the geographic concentration of economic activities in Japan can be explained by the firm-to-firm matching channel of agglomeration force. To do so, I simulate the counterfactual equilibrium by hypothetically shutting down the increasing returns to scale in matching, i.e., assuming that the elasticity of the supplier matching rate with respect to the supplier density is zero (rather than the estimated value of 0.36). I find that, in this counterfactual world, the correlation between nominal wages and population density is smaller by 30%. This large magnitude is in line with Ellison, Glaeser, and Kerr (2010), who find that the proxies for input-output linkages are the most important determinants of coagglomeration of firms in different industries in the US (among proxies that capture other agglomeration forces and natural advantages).

In the second counterfactual exercise, I study the welfare implications of the agglomeration force for existing nominal income redistribution policies in Japan. Due largely to pension payments and medical benefits, there is a steady flow of nominal income from urban to rural locations in Japan (Fukao and Makino 2015). The redistributional impact of these transfers on real income is amplified in the presence of the agglomeration force presented above. By counterfactually simulating a shutdown of existing income transfers, I find that this amplification effect accounts for about 8 percent of the total welfare impact of the redistribution of real income from urban to rural locations in Japan.

The rest of the paper is organized as follows. Section 2 describes the main data set used in this paper. Section 3 provides reduced-form evidence of matching frictions and the increasing returns in firm-to-firm matching using unanticipated supplier bankruptcies as a natural experiment. Section 4 develops a structural model of firm-to-firm trade under matching frictions. Section 5 calibrates the model and presents the counterfactual simulation results. Section 6 concludes.

Related Literature. The idea that agglomeration of economic activity is driven by firm-to-firm matching, or input-output linkages more broadly, is a classical agglomeration mechanism proposed by Marshall (1890). Empirically, Holmes (1999) documents that firms in denser areas tend to have higher shares of input purchase from external suppliers. However, this pattern may be also driven by the fact that firms in denser areas have idiosyncratically stronger tendencies to rely on external inputs (Holmes 1999, Rosenthal and Strange 2004). In this paper, I go beyond the cross-sectional evidence by studying the dynamics of supplier matching by using unanticipated supplier bankruptcies as a natural experiment.

On the theoretical front, Krugman and Venables (1995) and Venables (1996) propose a two-country model of agglomeration through input-output linkages. In their model, suppliers decide their production locations based on market size. In addition, the production function exhibits love-of-variety in intermediate inputs. This creates incentive for input buyers to locate in areas with high density of suppliers. The circular causation between supplier's location decision and input buyers' location decision creates an agglomeration force. The model developed in this paper is distinct from Krugman and Venables (1995) and Venables (1996) in two important ways. First, the model developed in this paper micro-founds agglomeration benefits through matching frictions and increasing returns to scale in matching, rather than love of varieties in production. The reduced-form evidence in this paper speaks directly to the former channel and allows me to directly map the model to the reduced-form evidence. Second, the model developed here goes beyond a simple two-location model by incorporating many locations with various dimensions of spatial hetero-

geneity (e.g., geography, productivity, and local production factors). This extension allows me to conduct a quantitative evaluation of counterfactual scenarios and policies under real-world geography, something that is not possible with a canonical two-location model.

This paper also builds on the growing literature of quantitative spatial economics (see Redding and Rossi-Hansberg (2016) for a survey). This literature extends canonical economic geography models to allow for many heterogeneous locations with rich dimensions of spatial heterogeneity. While these models often feature agglomeration, they are typically agnostic about its microfoundation. Instead, a typical approach in this literature is to assume that the productivity and amenity values of a location are determined by some function of labor density (e.g., Allen and Arkolakis 2014, Kline and Moretti 2014, Diamond 2016, Nagy 2017, Faber and Gaubert 2019), In this paper, I specify a specific source of agglomeration force, provide reduced-form evidence in favor of this source, and develop a quantitative model that precisely map to the reduced-form evidence.

This paper also contributes to the growing literature modeling firm-to-firm trade network formation, as surveyed in Bernard and Moxnes (2018). The closest previous work to this paper is Eaton, Kortum, and Kramarz (2016), who model firm-to-firm matching in input trade under arbitrary geography. The most important distinction between their model and the model in this paper is that I introduce matching between firms that changes stochastically over time. This feature allows me to explicitly map the reduced-form evidence to the model.[3] My model is also related to other models in the firm-to-firm trade literature that put more emphasis on firm-level heterogeneity and less emphasis on spatial equilibrium (e.g., Oberfield 2018, Lim 2018, Tintelnot, Kikkawa, Mogstad, and Dhyne 2019, Bernard, Dhyne, Magerman, Manova, and Moxnes 2019, Bernard, Moxnes, and Saito 2019).

2 Data and Descriptive Patterns of Japanese Firm-to-Firm Trade

This section briefly describes the paper's main data set, a yearly panel of firm-to-firm trade in Japan.

2.1 Data

The main data set of Japanese firm-to-firm trade comes from Tokyo Shoko Research (TSR), a major credit reporting company in Japan. TSR collects the data through face-to-face or phone interviews, complemented by public resources (financial statements, corporate registrations, and public relations documents). The data is constructed as a yearly panel from 2008 to 2016, covering nearly 70% of all firms in Japan.[4] Unlike existing papers that use data from the same data source (e.g., Nakajima, Saito, and Uesugi 2013, Carvalho, Nirei, Saito, and Tahbaz-Salehi 2016, Furusawa, Inui, Ito, and Tang 2017, Bernard, Moxnes, and Saito 2019), I use a complete yearly panel without missing years.

Firm-to-Firm Trade. The most important feature of the data set is that it contains dynamic transitions of the existence of supplier-to-buyer relationships. In each year, TSR's field surveyors ask each firm to report up to 24 main suppliers and buyers.[5] This paper uses a snapshot of this database at the end of each year.

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[3]Other work modeling two-sided search and matching in international and intranational trade includes Allen (2014), Sugita, Teshima, and Seira (2014), Eaton, Jinkins, Tybout, and Xu (2016), Krolikowski and McCallum (2019), Brancaccio, Kalouptsidi, and Papageorgiou (2019). Compared to this literature, Eaton, Kortum, and Kramarz (2016) and my paper model a multi-sided environment, i.e., the same firm becomes an intermediate goods seller and a buyer at the same time.

[4]Appendix A.1 describes the details of the representativeness of TSR's data set. Importantly for my purpose, the sampling probability of TSR's data set is similar across municipalities with different firm density.

[5]The censoring at 24 is practically not binding; less than 0.1% of firms report 24 suppliers (Appendix Figure A.2).

The main reduced-form exercise in this paper studies the impacts of unanticipated supplier bankruptcies on new supplier matching rates. To define the treatment firms and the outcome variables, I define the supplier linkages as the list of reported main suppliers by each firm. The results of the reduced-form exercise are robust to including the linkages only reported by the suppliers, but not the buyers (Appendix B.4). In addition, I exclude supplier linkages where either of the supplier or the buyer reports the existence of a major ownership linkage (corresponding to 3% of all supplier linkages).

Bankruptcies. The data set contains the list of all bankruptcies of firms covered in the data set. Most importantly for my purpose, the data set reports the main reason for each bankruptcy. This information is identified through TSR's investigation of the related parties. Table 1 reports the list of all reasons recorded in this data set. Importantly, the list of potential reasons includes "unanticipated bankruptcies." An internal TSR document describes "unanticipated bankruptcies" as "bankruptcies due to unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc." My main reduced-form exercise uses these bankruptcies as a natural experiment for the buyer-side firms. To further ensure the validity of these natural experiments, I show that there are no pre-trends in my main outcome variables.[6]

Firm Exit. Separately from the list of bankruptcies, TSR provided me with the information of the status of all firms in their data set at the end of each year. A firm's status is categorized as one of the following: "alive," "exit" (with subcategories of exit due to bankruptcies, temporary closure, permanent closure, being merged, or dissolution), or "no up-to-date information" (with subcategories of unknown existence and out-of-date information).

CEOs' Birth Prefectures. The TSR data set reports the birth prefecture of the CEOs for a major subset of firms. Within the samples used for the reduced-form exercise, about 68% of firm CEOs are born in the firm's headquarter prefecture (out of 47 prefectures in Japan). In Section 3, I exploit firm CEOs' birth location as a possible exogenous variation of the supplier density of the firm's actual location when a firm faces unanticipated supplier bankruptcy.

2.2 Descriptive Patterns of Static and Dynamic Supplier Linkages and Geography

In this subsection, I provide a brief overview of some basic static and dynamic patterns of supplier linkages, as well as the cross-sectional patterns of supplier linkages and geography.

Supplier linkages churn over time. Table 2 shows the aggregate summary statistics of supplier linkages. Panel (A) presents a static picture. The average number of main suppliers reported by the firms is 1.65. The number increases to 3.23 conditional on reporting at least one supplier.[7,8]

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[6]Figure A.3 shows the geographic and time distribution of these unanticipated bankruptcies. The frequency of these bankruptcies is not correlated with geographic firm density (Panel A). These bankruptcies are more frequent in the Tohoku area after 2011 (the Great Tohoku Earthquake; Panel B and C). My main reduced-form results are robust to excluding bankruptcies in the Tohoku area after 2011 (Appendix B.4).

[7]About 45% of firms do not report any suppliers. This subset may include firms with which TSR has difficulty conducting detailed interviews. When I study the impacts of unanticipated supplier bankruptcy, I select out these firms by imposing that both control and treatment firms have to report at least one supplier in the baseline period (right before supplier bankruptcies).

[8]Recent studies in other countries document larger numbers of suppliers per firm using an administrative data set of value-added tax collection. For example, Bernard, Dhyne, Magerman, Manova, and Moxnes (2019) document that the median number of suppliers per firm is 9 in Belgium. It should be noted that TSR data reports main suppliers, so suppliers with small transactions tend to be excluded. Also note that, while this attrition may affect the estimates of the average matching rates upon unanticipated supplier bankruptcies (in Section 3), it is less obvious whether it affects the heterogeneous impacts with respect to geographic density of alternative suppliers, which is the more relevant margin in the structural model (Section 4).

Panel (A) of Table 2 also shows that firms tend to have suppliers from a wide range of sectors. Conditional on having a supplier in the four-digit (two-digit) sector, the average number of suppliers in this sector is 1.19 (1.38).[9] These numbers are substantially smaller than 3.23 (average number of suppliers) and close to one. This indicates that firms tend to have suppliers in a wide range of sectors, rather than multiple suppliers within the same input sector.

Panel (B) of Table 2 shows the net and gross growth rate of the number of reported suppliers. Looking at each of the two consecutive years, surviving firms (firms which exist in both of the years and have a supplier in the first year) acquire 0.02 new suppliers *on net.* This is only an 0.8% fraction of the average number of suppliers, suggesting that net growth of the number of suppliers is slow. However, this small net growth rate hides substantial separation and new supplier matching. Surviving firms on average lose 0.17 suppliers (either because of the exit of the supplier or the discontinuation of the relationship) and add 0.19 new suppliers. Stated differently, surviving firms lose 5.3% of their suppliers and add 6.1% new suppliers as a fraction of the number of suppliers in the previous year. From a simple calculation, these numbers imply that 42% of suppliers are replaced over 10 years.[10]

Geography matters for firm-to-firm trade. Panel (A) of Figure 1 shows the cumulative distribution function of the geographic distance between the headquarters of a supplier and a buyer. The median distance between a supplier and a buyer is 37 kilometers. As is already documented by Nakajima, Saito, and Uesugi (2013) and Bernard, Moxnes, and Saito (2019), this number is by an order of magnitude smaller than the median of all possible pairs of firms in Japan. For example, Bernard, Moxnes, and Saito (2019) note that the median distance would be 172 kilometers if the supplier linkages were randomly drawn. This indicates that there is a strong tendency for firms to source from local suppliers. The figure also shows that these distributions are surprisingly stable over time.

If firms have a tendency to source from local suppliers, do firms in denser areas tend to match with more suppliers? Panel (B) of Figure 1 shows that there is a stark positive correlation between the population density and the number of suppliers per firm at the municipality level.[11] This finding is in line with Holmes (1999), who documents the positive correlation between the fraction of externally purchased inputs per firm and firm density in the United States.

These facts are consistent with the hypothesis that firms in denser areas benefit from more frequent matches with suppliers. At the same time, is is also possible that this pattern is driven by selective firm entry; firms with higher external demand for inputs may selectively enter in a denser location. To resolve this identification concern, one has to identify an occasion where firms in different locations are equally in need of an external supplier, and to track the differential matching rates. Unanticipated supplier bankruptcies represent an ideal natural experiment for this purpose. I explore this idea in the next section.

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[9]The industry classification follows the Japan Standard Industrial Classification (JSIC). There are 1,455 number of four-digit industries and 99 two-digit industries following the JSIC. For each firm, I define the industry of the firm by its reported main industry when the firm first enters in the data set.

[10]Using the value-added tax collection data, Huneeus (2018) documents that about 10% to 40% of transactions disappear each year in Chile, depending on the size of the firm. The slower rate of separation in the TSR data set in Japan is consistent with the possibility that small transactions tend to be dropped from the sample.

[11]Using firm density instead of population density yields a virtually identical result (not reported).

3   Reduced-Form Evidence

3.1   Empirical Strategy

The basic idea of the reduced-form empirical exercise is to estimate how quickly firms match with a new alternative supplier following an unanticipated supplier bankruptcy. I then test whether these new matching rates are higher in locations and industries where the geographic density of alternative suppliers is higher.

To identify the impacts of unanticipated supplier bankruptcies on subsequent supplier matching, I implement a standard difference-in-difference method. For each treatment firm (i.e., firms experiencing unanticipated supplier bankruptcy), I construct a set of comparable control firms (details described in the next paragraph). Each treatment firm and its corresponding control firms are denoted as group g. I run the following regression:

$$Y_{igt} = \beta Post_{gt} \times Trt_i + \eta_{gt} + \xi_{ig} + \epsilon_{igt},\tag{1}$$

where i is the firm, t is the year, Trt_i denotes the dummy that takes one if i is the treatment firm, $Post_{gt}$ is the dummy that takes one if t is after the supplier bankruptcy shock to the treatment firm of group g, and Y_{igt} is the outcome variable.[12] The group and year fixed effects η_{gt} are included to make sure that the average treatment effect β is identified off of the comparison within the same group g in the same year t. Firm fixed effects ξ_{ig} takes out all the firm-level unobserved heterogeneity.[13] Standard errors are clustered at the firm i level. In order to give each natural experiment equal weight, each control firm is weighted by the inverse of the number of control firms of group g. In the regression, I include the observation if t is within three years before and after the supplier bankruptcy shock of the treatment firms.

To assign control firms for each treatment firm i, I choose firms that are headquartered in the same municipality as i and which have a supplier in the same four-digit industry as i's bankrupt supplier in the baseline period (i.e., one year before the bankruptcy). Intuitively, this imposes that treatment and control firms face the same geographic supplier market (i.e., in the same headquarter location and have a demand for a supplier in the same four-digit industry).

To alleviate the concern that control firms are indirectly affected by the supplier bankruptcies through supply-chain linkages, I exclude control firms that are within second-degree proximity to firms experiencing unanticipated bankruptcies at some point in the sample period. I further exclude firms whose reported accounting year is more than one year old at the point of the baseline period. This is because TSR may not keep up-to-date information of these firms. The final sample consists of 421 treatment firms that are connected to 161 bankrupt suppliers, with 10,842 assigned control firms in total.

One should note that the impact of supplier bankruptcy identified by regression (1) is different from that of supplier *separation*. This is true for two reasons. First, not all bankruptcies will lead to an immediate exit of the firm. Second, control firms may also lose suppliers (due to anticipated bankruptcies, exits, or link severances). Below, I present most of the results in terms of the reduced-form impacts of unanticipated supplier bankruptcies (instead of the impacts of supplier separation instrumented by unanticipated supplier

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[12]Unless otherwise stated, I treat the observation as missing after a firm exits (except for exit as an outcome variable). I show that the results are robust by including exiting firms in the samples.

[13]Note that firm i may appear multiple times as control firms in different group g.

bankruptcies), except when I study the impact of sales reduction per matched supplier in Section 3.2.4.[14]

After establishing the average effects of unanticipated supplier bankruptcy, I turn to the question of whether the effects depend on the geographic density of alternative suppliers. The regression is specified as follows:

$$Y_{igt} = Post_{gt} \times Trt_i \times \left(\beta + \gamma \log SellerDensity_g + \theta Z_g\right) + \eta_{gt} + \xi_{ig} + \epsilon_{igt}, \tag{2}$$

where $SellerDensity_g$ is the proxy of the geographic density of alternative suppliers selling to firm i's location. In the baseline specification, I define $SellerDensity_g$ as the number of firms in the bankrupting suppliers' four-digit industry which has at least one buyer in firm i's prefecture in 2008 divided by the geographic area of i's prefecture. Note that these "alternative suppliers" can be located outside i's prefecture. This notion of "alternative suppliers" provide a tight mapping to the model in Section 4. In the model, I assume that each supplier pays a fixed cost to enter as a seller in each location (regardless of its production location), which determines the pool of suppliers active as a seller.[15] Z_g represents some controls and fixed effects.

To resolve the concern that γ may capture unobserved heterogeneity of firms due to selective firm entry, I implement two strategies. First, I include firm's location and industry fixed effects in Z_g. This is possible because firms *in the same location and industry* may face unanticipated supplier bankruptcies *in different supplier industries*. Second, I instrument $\log SellerDensity_g$ by the density of suppliers *evaluated at the birth prefecture of the CEO* of the treatment firm of group g (as an interaction with $Post_{gt} \times Trt_i$). The instrument is valid under the exclusion restriction that the birth place of the CEO affects the new supplier matching rate only through the density of suppliers at the firm's location.[16]

Appendix B.1 describes the characteristics of treatment firms and control firms. The median treatment firm has four suppliers. The characteristics of control firms are broadly similar with treatment firms. This indicates that the unanticipated supplier bankruptcies are indeed orthogonal to the observable characteristics of the buyer-side firms. Below, we further show that there are no differential pre-trends in the outcome variables between treatment and control firms.[17]

3.2 Empirical Results

This subsection is organized as follows: First, I show that firms only imperfectly recover suppliers upon supplier bankruptcy (Section 3.2.1). Second, I show that this recovery is stronger in locations and industries for which the geographic density of alternative suppliers is higher (Section 3.2.2). Third, I show that the matching rates are not affected by the geographic density of other buyers in the same location (Section 3.2.3). Fourth, I show that supplier bankruptcies reduce sales growth (Section 3.2.4). Taken together, these

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[14]The primary reason of showing the results in the reduced-form is because of the concern that the exclusion restriction of instrumental variable approach is violated, i.e., firms that are hit by a supplier bankruptcy may be affected even without supplier separation. Appendix B.2 shows that one unanticipated supplier bankruptcy results in an average of 0.75 to 0.8 supplier separations. Hence, in practice, the reduced-form impacts of unanticipated supplier bankruptcies and the impacts of supplier separation instrumented by unanticipated supplier bankruptcies are very close in magnitudes.

[15]At the same time, I show that my reduced-form empirical results are robust to restricting the suppliers producing locally (Appendix B.4.2).

[16]Bleakley and Lin (2012) also exploit individuals' birth place as an exogenous variation to look at the impacts of population density on the rate of occupation switching.

[17]Appendix B.1 also discusses how the characteristics of treatment firms in this natural experiment compare with those of a typical firm in Japan. Treatment firms are slightly larger than a typical firm in Japan. This difference is a result of how the treatment group is constructed; firms that have more suppliers are mechanically more likely to face a supplier bankruptcy and are also likely to have more employees. While the difference is not large in magnitude, some caution is needed for external validity.

results are evidence of matching frictions and increasing returns to scale in firm-to-firm matching.

3.2.1 Average Impacts of Unanticipated Supplier Bankruptcies on Supplier Matching

I first investigate the average impact of an unanticipated supplier bankruptcy on new supplier matching following regression (1). Table 3 shows the results. Appendix Figure B.2 plots the coefficients of the same regression in the standard event-study format.

Column (1) of Table 3 shows that the treatment firms have about 0.6 fewer suppliers right after the supplier bankruptcy. This is less than one, partly because not all supplier bankruptcies lead to an immediate exit of the supplier, and partly because control firms also lose suppliers at the same time (see Appendix B.2). The decreased number of suppliers persists even after three years from the supplier bankruptcies, indicating that the supplier bankruptcy leads to a long-term reduction in the number of suppliers.

At the same time, while matching is imperfect, treatment firms do rematch with new suppliers (Column (2)). The new supplier matching happens gradually; treatment firms match with 0.17 new suppliers up to one year after the shock and with 0.29 new suppliers in two or three years.[18] These patterns are not affected by how I treat firms that exit at some point after the supplier bankruptcy shock. In Column (3), if the firm exits, I insert the value of the outcome variable from the last period in which the firm is observed. The results are quantitatively similar to Column (2). These results are also not driven by the differential pre-trends between the control and treatment firms.

Appendix Table B.3 shows that these newly matched suppliers are concentrated within the same industry of the bankrupting suppliers. It also shows that treatment firms tend to rematch with suppliers which already serve some buyers in the treatment firms' headquarter location. The next section investigates whether the new supplier matching rates increase in the geographic density of the alternative suppliers.[19]

3.2.2 Supplier Matching Rate Increases in Geographic Density of Suppliers

Do firms recover new alternative suppliers more quickly in locations and industries which have higher density of alternative suppliers? I investigate this question by studying the heterogeneous effects of unanticipated supplier bankruptcies on new supplier matching. The regression specification follows equation (2), reproduced here:

$$Y_{igt} \;\;=\;\; Post_{gt} \times Trt_i \times \left(\beta + \gamma \log SellerDensity_g + \theta Z_g \right) + \eta_{gt} + \xi_{ig} + \epsilon_{igt}.$$

In my baseline specification, I define the supplier density as the geographic density of firms in the bankrupt supplier's four-digit industry that already had a buyer in the treatment firm's headquarter prefecture in 2008. In other words, $SellerDensity_g$ captures the density of alternative suppliers already selling to the treatment firm's location. To avoid the possibility that the heterogeneous effects are driven by the geographic area of the prefecture (denominator) rather than the number of alternative suppliers (numerator), I always include log of the geographic area as Z_g.[20] To ease the interpretation of the coefficients,

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[18]Subtracting coefficients of Column (2) from those of Column (1) of Table 3 does not give -1. As explained earlier, this is because not all bankrupt firms immediately exit, and control firms lose the supplier at the same time (see Appendix B.2). The fact that control firms keep losing the supplier also explains why the effect on the number of matched suppliers are stable over time (Column 1), even though the effect on the number of new suppliers increases over time (Column 2).

[19]Another possible response following unanticipated supplier bankruptcy is to substitute from suppliers that treatment firms are already matched. Appendix Table B.4 shows that this is not a significant margin in this context. Column (1) shows that treatment firms are no more or less likely to retain other existing supplier relationships. I also do not find effects on exit and sales growth of other existing suppliers of the treatment firms (Columns 2 and 3).

[20]Note that this treatment becomes irrelevant once I control for prefecture fixed effects in Z_g.

I standardize log $SellerDensity_g$ to be mean zero (within each bankruptcy year) and standard deviation one after residualizing Z_g. Hence, β captures the average treatment effects, and γ captures how much the treatment effect increases with a one-standard-deviation increase in the supplier density.

Table 4 presents the results. Column (1) shows that the effect of unanticipated supplier bankruptcies on new suppliers is significantly higher when the density of alternative suppliers is higher. The magnitude of this difference is sizable; a one-standard-deviation increase in the seller density proxy increases the effect by 0.16. This implies that the treatment effect at the 95th percentile of the supplier density distribution is almost twice the average treatment effect, while it is almost zero at the 5th percentile.

Selective entry of firms. One concern of Column (1) is that γ may capture unobserved heterogeneity of firms in denser and less dense areas due to selective firm entry. The remaining columns of Table 4 resolve this concern.

Column (2) starts by including prefecture fixed effects in Z_g. These fixed effects deal with the most obvious concern that firms in denser areas are unobservably different in supplier matching rates from less dense areas. Including prefecture fixed effects is possible because firms *in the same location and industry* may face unanticipated supplier bankruptcies *in different supplier industries*. In other words, this specification exploits a within-prefecture, across-supplier-sector variation.

Column (3) further includes fixed effects for the bankrupt supplier's two-digit industry in Z_g. This robustness test deals with the concern that the results are driven by the heterogeneity of industries of bankrupt suppliers. For example, firms may be able to find an alternative supplier more quickly for a less specialized input. In a similar spirit, in Column (4), I further control for the employment sizes of the treatment firm and of the bankrupt suppliers in Z_g. This is motivated by the observation by Holmes and Stevens (2014) that firm size captures the degree of input specificity within a narrowly defined industry.

Column (5) further includes the buyer-side firm's prefecture *and* its two-digit industry fixed effects in Z_g. In this specification, I estimate the effect of supplier density only using within-prefecture-and-industry, across-supplier-industry variation.[21] These results further alleviate the concern that innate differences in the ability to find alternative suppliers across locations and sectors drive the results.

While the results in Columns (2) to (5) alleviate the concern of selection to a large degree, one may still worry about the unobserved heterogeneity not swiped by the fixed effects. In particular, they do not address the concern that firms in different locations and sectors have different *comparative* advantages in finding suppliers in different supplier sectors. To alleviate this concern, Column (6) instruments supplier density proxy by the supplier density evaluated at the birth prefecture of the firm CEOs. The instruments are valid under the exclusion restriction that the birth place of the CEO only affects the new supplier matching rate through the density of suppliers at the firm's location. This exclusion restriction may be violated, for example, if the early-life education may affect firm CEO's (comparative) advantage in the ability to find a supplier. While I cannot fully rule out this possibility, this strategy at least deals with the most straightforward concern that firm location choice may be driven by the density of alternative suppliers.

Robustness. Appendix B.4 reports a number of other robustness checks. The results are robust by including exiting firms in the sample, excluding samples which may be directly affected by the Great Tohoku Earthquake in 2011 and the Great Financial Crisis in 2007-08, excluding multi-establishment firms, excluding firms headquartered in Tokyo, excluding firms whose accounting information is outdated, and by adjusting the TSR sampling rate (Appendix B.4.1). It is also robust to alternative definitions of supplier

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[21] The sample size of Column (5) drops compared to other specifications. This is because control firms that are in a different two-digit industry as treatment firms for each group g are dropped in this specification.

density (Appendix B.4.2), dividing samples to manufacturing and non-manufacturing supplier bankruptcies (Appendix B.4.3), and including supplier-reported linkages when constructing the outcome variables (Appendix B.4.4).

3.2.3 Other Buyers Do *Not* Decrease Supplier Matching Rates

The results in Section 3.2.2 show that the supplier matching rate is increasing in the geographic density of suppliers. This subsection investigates whether the matching rate decreases in the presence of more buyers.

This exercise is motivated by the labor search and matching literature. In this literature, it is common to find that the presence of more unemployed workers decreases other unemployed workers' reemployment rate (Petrongolo and Pissarides 2001). In other words, if there are more unemployed workers, the probability of each worker matching with a job vacancy is reduced. If this crowding-out effect is strong, the benefit of a higher density of job vacancies may be offset. One may think that crowding-out is less plausible in the context of supplier-to-buyer matching since suppliers can supply to multiple buyers simultaneously. However, there may still be a crowding-out effect if suppliers face capacity constraints.[22] It is, therefore, worth studying empirically whether the presence of more buyers decreases the matching rate.

The empirical specification follows regression (2), where I include a proxy of buyer density in Z_g. Relative to the proxies of supplier density, it is less straightforward to define the density of relevant buyers (i.e., buyers that are looking for a supplier in the same supplier industry). Here, I try three alternative measures of buyer density and show that the results are robust to the choice of the definition. The first measure defines relevant buyers as the firms in the treatment firm's prefecture that faced an unanticipated supplier bankruptcy in the same four-digit industry in the same year. The second measure defines buyers as firms facing *any types* of supplier separation in the same four-digit supplier industry in the same year. (This includes cases of discontinuation of the relationship without supplier bankruptcies.) The third measure defines buyers by firms that belong to the same two-digit industry and prefecture as the treatment firm.

Table 5 shows the results of the regression (2), with each column corresponding to a different one of the three measures of the buyer density in Z_g. Prefecture fixed effects are included in Z_g (corresponding to Column 2 of Table 4). Both supplier density and buyer density are normalized to be mean zero and standard deviation one after residualizing other covariates included in Z_g.

Irrespective of how buyer density is defined, I find no evidence that the treatment effect on new supplier matching rates significantly decreases in the buyer density. The heterogeneous effects with respect to the buyer density are small and close to zero. Note that the lack of statistical significance of the former is not the result of imprecise estimates; the standard errors are of similar magnitude to that of the supplier density. The fact that the new supplier matching rates increase in the supplier density, but not in buyer density, implies that the matching rates exhibit increasing returns to scale. As already stated, this is a sharp contrast to the typical findings of constant returns to scale in the labor search and matching literature (Petrongolo and Pissarides 2001). In Section 4, I build a model in which the increasing returns to scale in firm-to-firm matching generates an agglomeration force of economic activity.

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[22] See Almunia, Antras, Lopez Rodriguez, and Morales (2018) for the evidence of capacity constraints of exporters in the context of international trade.

3.2.4 Impacts of Supplier Matching on Sales and Revenue Productivity

I now turn to an investigation of how unanticipated supplier bankruptcies affect a firm's sales and revenue productivity. Even if firms face frictions in matching with suppliers, an unanticipated supplier bankruptcy may have limited firm-level implications if firms do not incur a loss from the supplier bankruptcy. The magnitude of the effect of supplier bankruptcies on firm production is also quantitatively important for the strength of the agglomeration force in the model in Section 4.

Table 6 shows that there is a short and long-run reduction in sales and revenue productivity. Column (1) shows the average effect on the sales growth following regression (1). Sales growth is defined as the sales in each period t divided by the sales in the baseline period.[23] Relative to the control mean, treatment firms face a 3 percentage point reduction of the sales growth within one year from the bankruptcy. After two years, the magnitude of the effect stays at a similar level, although significance is lost due to the increased standard error.[24]

Column (2) shows the effect on the growth of revenue per worker. There is a statistically significant effect in revenue per worker after two or three years from a supplier bankruptcy. This magnitude is larger compared to the sales growth, potentially suggesting that firms deal with the loss of suppliers by substituting by hiring new workers in the long run. Column (3) shows that the supplier bankruptcy increases the probability of exit by 0.9 percentage point, yet insignificant.

The model developed in Section 4 can successfully capture these facts. In the model, a loss of a supplier leads to an increased unit cost of production, which leads to the reduction of sales. At the same time, sales requires a payment of fixed cost by labor. This leads to the decrease of the revenue per worker upon a supplier loss. I follow this intuition to structurally estimate a key parameter of the model (cost advantage of matching with a supplier) in Section 5.

Heterogeneous effects. Column (4) of Table 6 investigates the heterogeneous effects with respect to the geographic density of suppliers following the regression equation (2). The heterogeneous effects are insignificant but positive. This is consistent with the fact that firms facing higher supplier density rematch with new suppliers more frequently (Section 3.2.2).

One important question here is whether there is a heterogeneity *in the benefit per supplier*. For example, firms in denser areas may rely on less specialized inputs (Holmes and Stevens 2014), hence production benefit of one additional supplier may be lower in denser areas. If this is the case, the heterogeneity in matching rate documented in Section 3.2.2 does not summarize the agglomeration benefit from firm-to-firm matching in denser areas.

To investigate the heterogeneity of the benefits per supplier, Column (5) report the IV estimates of the total number of matched suppliers on the sales growth (instrumented by unanticipated supplier bankruptcy). More specifically, I run the following IV regression:

$$Y_{it} = \beta \text{NumberSuppliers}_{it} + \gamma \text{NumberSuppliers}_{it} \times \log SellerDensity_g + \epsilon_{it}, \tag{3}$$

where $\text{NumberSuppliers}_{it}$ is the number of suppliers of firm i in period t, and Y_{it} is the sales growth. I instrument $\text{NumberSuppliers}_{it}$ and $\text{NumberSuppliers}_{it} \times \log SellerDensity_g$ by $Trt_i \times Post_{gt}$ and $Trt_i \times Post_{gt} \times \log SellerDensity_g$ to extrapolate the variation induced by the unanticipated supplier bankrupt-

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[23]Sales and revenue productivity growth are windsorized at the 95 percentile (separately for treatment and control firms and for each year since the shock).

[24]Recall that the median treatment firm has four suppliers (Appendix Table B.1), so the magnitude of the shock is interpreted as one supplier bankruptcy out of four.

cies.

Column (5) shows that having one fewer supplier leads to a 5.8 percentage point reduction in sales growth, with no significant heterogeneity in the effect with respect to supplier density. In other words, in this context, supplier density benefits firms by *more frequent* supplier matching, rather than *better* supplier matches.[25]

4   A Model of Firm-to-Firm Matching and Agglomeration

How important is the pattern of firm-to-firm matching documented in Section 3 for the geographic concentration of economic activity in the spatial general equilibrium? To answer this question, this section develops a new structural model of firm-to-firm trade and geography.

In the model, potential producers are distributed over space and sectors. All producers can produce both final goods and intermediate inputs, and all producers use intermediate inputs for production. Hence, all firms can be an intermediate input seller and a buyer simultaneously. The intermediate inputs can be purchased either from stochastically matched suppliers or from fringe intermediaries. A firm that purchases from the fringe intermediaries incurs an additional iceberg cost. Directly matching with a supplier, therefore, gives an input cost advantage.[26] Depending on the realized unit cost of production, each firm decides to enter in various locations as an intermediate seller by paying a fixed cost (i.e., Melitz 2003). From the perspective of input buyers, the matching rate increases with the measure of intermediate inputs sellers, but is unaffected by the presence of other buyers in the location. This assumption is in line with the empirical findings of increasing returns to scale in matching in Section 3.

The main goal of the model is to provide a formal mapping between the magnitudes of the reduced-form estimates in Section 3 and the aggregate equilibrium, while retaining the realistic heterogeneity in places and spatial linkages in input trade. In Section 5, I structurally estimate the key structural parameters of the model to precisely replicate the reduced-form findings, and conduct several counterfactual simulations to highlight the general equilibrium implications.

4.1   Model Set-up

Space is partitioned into a discrete number of locations, denoted by $i, j, n \in N$. Each location is endowed with L_i measure of workers who consume final goods. I assume workers are immobile (Appendix C.3.1 relaxes this assumption). Time is continuous and denoted by t. In this paper, I only consider a steady-state equilibrium in which aggregate variables are constant (e.g., wages, output). Only firm-level variables such as supplier matching status vary by t. Without a risk of confusion, the subscript t is therefore omitted from the aggregate variables.

In each location, there is a continuum of potential producers in each sector. Sectors are denoted by $k, m \in K$. All firms produce both final goods, consumed by final goods consumers, and intermediate inputs, used in production by other firms. In this sense, each firm can be simultaneously a buyer and a supplier in intermediate input trade.

As in a standard Melitz model, each firm produces a differentiated final good. Intermediate inputs, on the other hand, are homogeneous within each input sector. Intermediate input trade is possible only when

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[25]See Helsley and Strange (1990) for a model where the latter force drives the agglomeration benefits (in the context of firm-to-worker matching) and Duranton and Puga (2004) for conceptual distinctions about these two types of channels.

[26]For example, one can interpret the iceberg cost as the limit of customization. Input goods supplied through fringe intermediaries are not customized, and hence the efficiency unit of the inputs are lower than that from directly matched suppliers.

two firms stochastically match as a supplier and a buyer. I assume that each buyer-side firm can be matched with at most one supplier in each intermediate input sector at a time, though suppliers can be matched with multiple buyers simultaneously.

4.1.1 Technology

Each firm can produce both final goods and intermediate inputs with a Cobb-Douglas production technology.[27] The unit cost (for both final goods and intermediate inputs) by firm ω in location i in sector m is

$$c_{\omega t} = \frac{1}{\varphi_\omega} w_i^{\gamma_{L,m}} \prod_{k \in K} p_{\omega t,k}{}^{\gamma_{km}}, \tag{4}$$

where w_i is the wage in ω's production location i, $p_{\omega t,k}$ is the unit cost of intermediate inputs that firm ω has access to in period t, φ_ω is the exogenous productivity of firm ω, $\gamma_{L,m}$ is the labor share in production for sector m, and $\gamma_{k,m}$ is the sector-k intermediate inputs share for sector m's production. I assume that production function exhibits constant returns to scale, i.e., $\gamma_{L,m} + \sum_k \gamma_{km} = 1$ for all $m \in K$.

There are two possible ways to source input goods: directly match with a supplier or purchase through fringe intermediaries. Input prices depend on time t because whether and which supplier each firm is matched with evolves over time.

To derive a closed-form solution, I impose a parametric assumption on the distribution of firm productivity. Following Eaton, Kortum, and Kramarz (2016), I assume that the measure of firms whose productivity is above φ is

$$\mu_{i,m}(\varphi) = \tilde{A}_{i,m} \varphi^{-\theta}. \tag{5}$$

Here, $\tilde{A}_{i,m}$ is interpreted as the exogenous productivity of the location.[28],[29]

4.1.2 Matching between Input Sellers and Buyers

As in Melitz (2003), each firm decides whether to enter as an intermediate input seller in each location in each instantaneous period. I also allow for cross-location trade, i.e., firms can sell their intermediate goods outside their production location by paying a fixed cost at each sales location. However, unlike in Melitz (2003), input sellers only stochastically match with input buyers, i.e., firms producing in the sales location. Below, I describe this process in detail.

To enter in location j, a potential input seller in sector k pays a fixed entry cost at a flow rate of $f_{j,k}^I$ units of location j's labor (regardless of the firm's production location). Stochastic matching occurs between these input sellers that have entered and firms producing in location j. If matched, the seller can sell its intermediate inputs to the buyer until the relationship ends. The seller producing in location i incurs

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[27]The primary reason why I introduce Cobb-Douglas production technology, rather than a more general production technology such as constant elasticity of substitution (CES) production technology, is because the latter poses a challenge in parameter estimation. With Cobb-Douglas production technology, the effect of a supplier match on firms' unit cost is multiplicatively separable across different supplier sectors. This feature provides a direct mapping between a supplier separation (induced by unanticipated supplier bankruptcy) and a supplier match benefit, independent of the presence and the quality of other suppliers. It should be also noted that generalizing the production technology to CES does not change the key logic of the model, except that the benefit of supplier density may exhibit diminishing returns to scale (with the elasticity of substitution above one).

[28]One can potentially interpret $\tilde{A}_{i,m}$ as the combination of exogenous production and other agglomeration benefit of production. Note that, when I conduct a counterfactual simulation of shutting down the agglomeration force due to increasing returns to matching (Section 5.2.1), I fix the values of $\tilde{A}_{i,m}$.

[29]In Appendix C.3.2, I consider an extension of the model in which entrepreneurs enter in each location subject to free entry condition. In this extension, the measure of entrepreneurs also enters in equation (5). This extension adds an additional layer of agglomeration force through the home market effect, similar to the one illustrated in Krugman and Venables (1995).

iceberg trade cost $\tau_{ij,k}$. The iceberg trade cost captures the combination of shipment cost, transaction cost, and other sources of geographic frictions.

Upon entry, the seller posts a price. These posted prices are specific to the sales location and the buyer's sector, but they cannot vary with each specific buyer after the realization of the match. For all buyers matched at this instantaneous period, this price will be applied over the course of the relationship. Input sellers post a price that ex-ante maximizes the expected profit.[30]

I now describe the matching process from the perspective of an input buyer. Among all firms producing in location i, $\delta_{i,km}$ fraction of sector m firms ever match with a supplier in input sector k. $\delta_{i,km}$ can depend on a location and a sector, capturing the possibility that firms in different locations have heterogeneous demand for external input suppliers.

If a potential input buyer (i.e., $\delta_{i,km}$ fraction of firms producing in location i) does not currently have a supplier in input sector k, it stochastically meets with an input seller. The buyer then decides to form a relationship. I discuss the buyer's decision to form a relationship or not after I explain the outside option for the buyer in the next section. If the buyer decides to form a relationship, it can purchase input goods at the price posted by the seller until the relationship ends. While the relationship continues, the input buyer cannot start a new relationship with another supplier in the same input sector.

Following the approach of the labor search and matching literature, I assume that the rate at which the input buyer meets with a supplier is determined by a matching technology. More specifically, I assume that the Poisson rate at which a potential input buyer matches with a new supplier is determined by $v\left(S_{j,k}^I/Z_j\right)$, where $S_{j,k}^I$ is the measure of input sellers, Z_j is the geographic area of location j, and $v\left(\cdot\right)$ is an exogenous function. $v\left(\cdot\right)$ captures the technological relationships between the density of suppliers and the matching rate arising from various frictions, including information imperfections about potential trading partners, heterogeneities, and the necessity of customization.[31] I assume that $v\left(\cdot\right)$ is an increasing function in the density of input sellers but that it does not depend on the density of input buyers.[32] These two assumptions directly follow the reduced-form results in Section 3. For tractability, I assume that $v\left(\cdot\right)$ takes a Cobb-Douglas form, i.e., $v\left(x\right) \equiv \eta x^\lambda$ where η and λ are exogenous parameters.

Conditional on drawing an opportunity to match with a supplier, the input buyer randomly matches with a supplier from the pool of input sellers that enter in location j. In other words, the probability of meeting with a supplier does not depend on where the supplier produces *conditional on entering in location j* as a seller. I also assume that, in case a firm matches with suppliers in multiple sectors, the matching rate with a supplier is independent across different input sectors k.

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[30]It is important to note that input sellers cannot adjust the price after the realization of the match for each buyer. This pricing assumption is different from the Nash bargaining environment, standard in the labor search and matching literature (Diamond 1982, Mortensen and Pissarides 1994). Introducing Nash bargaining in the environment of multi-sided firm-to-firm matching implies that the seller's profit depends on the complete structure of the realized firm-to-firm trade networks and its stochastic evolution over time. To avoid solving such a complex high-dimensional dynamic problem, here I take an approach of ex-ante pricing.

[31]While introducing matching technology in this reduced-form manner makes the underlying nature of matching frictions a black box, it allows for tractably analyzing how the degree of matching frictions affects aggregate spatial equilibrium. See Petrongolo and Pissarides (2001) and Pissarides (2011) for a related discussion in the context of matching function approach in the labor search and matching.

[32]It is straightforward to see that the independence of $v\left(\cdot\right)$ in the number of buyers is mapped to the increasing returns to scale in total matches created in the economy. To see this, assume that the flow rate of total match creation between suppliers in sector k and location j, and any subset of buyers with measure $B_{j,l}^I$ in location j and industry l, is given by $M(S_{j,k}^I, B_{j,l}^I) = \eta\left(S_{j,k}^I/Z_j\right)^\lambda\left(B_{j,l}^I\right)^\iota$. The Poisson rate of matching from the perspective of a buyer is given by $M(S_{j,k}^I, B_{j,l}^I)/B_{j,l}^I$. If $\iota = 1$ and $\lambda > 0$ we have the expression of $v\left(\cdot\right)$ as in the main text. Note that $\iota + \lambda > 1$ implies the increasing returns to scale in total matches created in the economy.

The relationship is exogenously destroyed at the Poisson rate $\rho_{i,km}$. Immediately after the relationship ends, the buyer loses access to the intermediate goods from the supplier for its final goods production.[33]

In order to be able to tractably characterize the aggregate steady-state equilibrium, I make two additional assumptions. First, I assume that the unit cost of intermediate input goods production sold to buyers matched at period t is held fixed at the level when the relationship was first formed (in period t). This assumption ensures that the seller's entry and pricing decision depends only on the *contemporaneous* unit cost, not the future evolution of the unit cost. Second, I assume that the payment for the supplier-buyer relationship happens in the beginning of the relationship, where the transfer from the buyer to supplier is equal to the discounted sum of future expected profit. Together, the per-period intermediate goods sales of a firm depends only on its contemporaneous unit cost, not the expected future evolution of the unit cost. This characterization helps me to aggregate the firm-level sales to the aggregate trade flows, and derive the explicit aggregate equilibrium conditions.

4.1.3   Fringe Intermediaries

If a firm does not have a directly matched intermediate input seller, it can source intermediate inputs from local fringe intermediaries. The fringe intermediaries connect these firms with a randomly chosen input seller that has entered in each location in each instantaneous period. The input seller charges the same posted price to the intermediaries, and the intermediaries then incur χ ad-valorem cost to sell the intermediate inputs to the input buyer. I assume that the fringe intermediaries are perfectly competitive and hence make no profit.

The main role of parameter χ is to capture the (average) differences in unit cost of production when a firm is directly matched with a supplier and when it is not. In reality, the magnitude of χ may depend on the role of customizing specialized inputs for each firm, as well as the returns from long-run relationship-specific investment. Here, I am agnostic about where χ comes from, and focus my analysis on how it affects the aggregate equilibrium. I also assume that χ does not depend on locations or sectors, and importantly, on the density of suppliers. This is motivated by the reduced-form finding in Section 3.2.4 that the reduction of sales *per matched supplier* does not depend on the geographic density of suppliers.

4.1.4   Steady-State Probability of Matching with a Supplier

I now revisit the decision of whether the buyer decides to form a relationship upon drawing a particular supplier (Section 4.1.2). When the buyer draws a supplier, the buyer may in principle decide to forgo the relationship if the supplier's price is too high relative to the outside option (which depends on the option value of drawing a supplier in the future, as well as the price from fringe intermediaries). I exclude the possibility of rejection by assuming that χ is sufficiently large (fringe intermediaries are sufficiently costly) and buyers are sufficiently risk-averse. Hence, the Poisson rate of meeting with a supplier (described in Section 4.1.2) directly maps to the observed matching rate (Section 3).[34]

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[33]While I allow for the general heterogeneity of $\rho_{i,km}$ in location and industry, it is unlikely to be important for quantification. Table A.4 shows that the separation rate with a supplier is only marginally increasing in population density. Importantly, the implied elasticity is much smaller than my estimate of the elasticity of matching rate, $\hat{\lambda}$ (Section 5). This result does not rule out the possibility that the *endogenous* separation could be an important factor outside the model to affect the spatial equilibrium.

[34]My structural estimation results in Section 5 yields the estimate of $\chi = 1.51$. This indicates that matching with the most costly supplier is still significantly less costly than the expected price from fringe intermediaries. To see this, note that the expected price through fringe intermediaries is $\chi \frac{\theta-1}{\theta}$ times the price of the most costly supplier entering in the market. With a reasonable value of θ (4.3 in my baseline calibration; see Table 7), it is greater than one. This calculation does not include the option value of matching with another supplier in the future, but a long as buyers are sufficiently risk-averse, the option value does not overturn this result.

Together with the assumptions in Section 4.1.2, this implies that the steady state probability that a firm in location j and sector m is matched with a supplier in sector k is

$$\Lambda_{j,km} = \delta_{j,km} \frac{\eta \left(S_{j,k}^I / Z_j \right)^\lambda}{\eta \left(S_{j,k}^I / Z_j \right)^\lambda + \rho_{j,km}}, \tag{6}$$

where $\delta_{j,km}$ is the fraction of firms that can match with an external supplier, $\eta \left(S_{j,k}^I / Z_j \right)^\lambda$ is the matching rate with a new supplier, and $\rho_{j,km}$ is the exogenous separation rate. $1 - \Lambda_{j,km}$ is the steady state probability that the firm sources through fringe intermediaries.

4.1.5 Final Goods Market

In addition to intermediate goods, all firms can also produce and sell final goods. Each firm produces a differentiated variety of the final good. Similarly with Caliendo and Parro (2014), I assume that the final goods are not tradable across locations. Firms in production location j and sector k have to pay a fixed cost $f_{j,k}^F$ to sell their final goods in each instantaneous period. There are no matching frictions in the final goods market, and firms can access all potential final goods consumers once paying a fixed cost.

There are two sources of final goods demand: workers and firm owners. I assume that firm owners consume final goods at their production location.[35] Workers and firm owners have the same preferences for final goods consumption. The representative final goods consumer has a CES utility function:

$$U = \prod_{k \in K} \left(\int_{\omega \in \Omega_{i,k}} q_k(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1} \alpha_k}, \tag{7}$$

where $q_k(\omega)$ is the consumption of the goods produced by firm ω, α_k is the consumption share of sector k final goods, $\Omega_{i,k}$ is the set of varieties available for final goods consumers in location i, and $\sigma > 1$ is the elasticity of substitution.

4.1.6 Total Expenditure and Trade Balance

Aggregate intermediate input sales by firms producing in location i and sector k, $X_{i,k}^I$, obeys the following accounting relationship:

$$X_{i,k}^I = \sum_{j \in N} \sum_{m \in K} Y_{j,km}^I \pi_{ij,k}, \tag{8}$$

where $Y_{j,km}^I$ is the aggregate input goods expenditure by firms in sector m and location j for input sector k, and $\pi_{ij,k}$ is location j's input goods expenditure share of goods in sector k from location i.

Aggregate final goods sales by firms producing in location i and sector k, $X_{i,k}^F$, are equal to the final goods demand in location i (as final goods are not tradable). Hence,

$$X_{i,k}^F = Y_{i,k}^F, \tag{9}$$

where $Y_{i,k}^F$ is the final goods demand.

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[35] See Caliendo, Parro, Rossi-Hansberg, and Sarte (2018) for alternative assumptions on firm owners' consumption locations and their implications.

Final goods demand is the sum of labor income $w_i L_i$ and firm profit $\sum_{m \in K} \Pi_{i,m}$, where $\Pi_{i,m}$ indicates the aggregate profit net of fixed cost payments by firms producing in location i in sector m. In addition, I allow for the presence of cross-location income transfer and denote T_i as the net current transfer to location i. From the Cobb-Douglas utility function (equation 7), the final goods demand in sector k is α_k fraction of the effective income of the location:

$$Y_{i,k}^F = \alpha_k \left(w_i L_i + \sum_{m \in K} \Pi_{i,m} + T_i \right). \tag{10}$$

From the Cobb-Douglas production function, the input goods demand $Y_{i,k}^I$ in each location is a constant fraction of total input purchase by the firms producing in each location.

For intermediate goods, I incorporate the possibility that trade is not balanced. Denoting the trade deficit of location i by D_i, the aggregate intermediate goods sales from location i has to balance the aggregate intermediate input purchase up to the trade deficit, i.e.,

$$\sum_{k \in K} X_{i,k}^I = \sum_{k,m \in K} Y_{i,km}^I - D_i. \tag{11}$$

Following the approach of Caliendo and Parro (2014), I take D_i as an exogenous parameter, rather than specifying the sources of trade deficit.

4.2 Steady-State Equilibrium

The model yields closed-form conditions that characterize the aggregate equilibrium. Here, I describe the key logic of the equilibrium characterization and define the steady-state spatial equilibrium. Appendix C.1 describes the full derivations.

I first note that the distribution of the unit cost of firms in each location follows a power law in the steady state (Appendix C.1.1 and C.1.4). Following Section 4.1.1, the unit cost of production follows a convolution of firm-level productivity (φ_ω), which follows a power law (equation 5), and the intermediate input prices $p_{\omega t}$ in each sector k, which depend on whether and which supplier the firm is matched with at period t. A standard result of the power law distribution suggests that this convolution also follows a power law (i.e., Gabaix 2009, Eaton, Kortum, and Kramarz 2016). More concretely, Appendix C.1.1 and C.1.4 shows that the unit cost production is distributed according to $H_{i,m}(c) = \Gamma_{i,m} c^{-\theta}$, where

$$\Gamma_{i,m} = A_{i,m} w_i^{-\theta \gamma_{L,m}} \prod_{k \in K} \left(\bar{c}_{i,k}^I \right)^{-\gamma_{km}\theta} \left\{ 1 - \Lambda_{i,km} + \Lambda_{i,km} \chi^{\gamma_{km}\theta} \right\}, \tag{12}$$

where $A_{i,m} \equiv \tilde{A}_{i,m} \prod_{k \in K} \frac{(\psi_{km}\chi_{i,k})^{-\gamma_{km}\theta}}{1-\gamma_{km}}$, and $\Lambda_{i,km}$ is the steady-state probability of matching with a supplier. Note that $\Gamma_{i,m}$ is increasing in $\Lambda_{i,km}$, because directly matching with a supplier is less costly. For the same reason, it is also increasing in χ, the iceberg cost of buying from fringe intermediaries.

Second, I show that there is an equilibrium where input sellers post prices following a simple constant markup rule. In this equilibrium, an input seller in sector k posts a price $p = \psi_{km} c$ to buyers in sector m, where $\psi_{km} \equiv 1 + (\gamma_{km}\theta)^{-1}$, and c is its contemporaneous unit cost net of iceberg trade cost (Appendix C.1.2). The constant markup result arises because the expected input demand is iso-elastic in posted prices. The fact that the markup ratio is decreasing in γ_{km} and θ is intuitive. Input sellers rationally take into account that their price p affects the sales of the matched input buyers, and hence the input revenue. If

γ_{km} is larger, the input buyers' unit costs are more sensitive to p, so the input seller marks p down more. If θ is larger, a small decrease in p pushes more input buyers to start making sales in different locations. Hence, the input seller marks p down more. In this paper, I focus on this constant markup equilibrium.[36]

Third, the cross-location trade in intermediate inputs is characterized by the gravity equation (Appendix C.1.3). This follows immediately from the constant markup and the power-law distribution of the unit cost. Formally, the fraction of the expenditure of intermediate goods in sector m and location j that comes from location i is

$$\pi_{ij,m} = \frac{\Gamma_{i,m} \left(\tau_{ij,m} \right)^{\theta}}{\sum_{i' \in N} \Gamma_{i',m} \left(\tau_{i'j,m} \right)^{\theta}}. \tag{13}$$

Moreover, this proportion is the same as the extensive margin share of input trade, i.e., the fraction of intermediate goods sellers in location j that are producing in location i. This is a direct implication of the power-law distribution of the unit cost (similar to Chaney 2008) and the random matching assumption (the matching probability with a supplier does not depend on the seller's production location conditional on seller's entry).

Fourth, the free entry condition of a marginal input seller determines the measure of sellers in each location (Appendix C.1.5). As stated in the end of Section 4.1.2, the intermediate input seller's entry decision only depends on the *contemporaneous* unit cost. Hence, given the power law distribution of the unit cost, one can derive the explicit expression for the measure of input sellers and the entry cutoff of the unit cost, similarly to a standard Melitz model with power law distribution (Chaney 2008). Denoting the measure of intermediate input sellers as $S_{j,k}^{I}$, the measure of input sellers is

$$S_{j,k}^{I} = \frac{1}{f_{j,k}^{I} w_j} \sum_{m \in K} \frac{1 - \gamma_{km}}{1 + \gamma_{km}\theta} Y_{j,km}^{I}. \tag{14}$$

This is decreasing in $f_{j,k}^{I} w_j$ (fixed cost of entry), increasing in $Y_{j,km}^{I}$ (input demand), and decreasing in $1/(1 + \gamma_{km}\theta)$ (profit margin).[37] Together with equation (12), the entry cutoff of the unit cost for intermediate input sellers is

$$\bar{c}_{j,k}^{I} = \left(\frac{S_{j,k}^{I}}{\sum_{i' \in N} \Gamma_{i',k} \left(\tau_{i'j,k} \right)^{\theta}} \right)^{1/\theta}. \tag{15}$$

Lastly, Appendix C.1.7 shows that the aggregate profit of firms in location i in sector k, both from the intermediate goods sales and final goods sales, is derived as:

$$\Pi_{i,k} = \sum_{j \in N} \sum_{m \in K} \frac{\gamma_{km}}{1 + \gamma_{km}\theta} Y_{j,km}^{I} \pi_{ij,k} + \frac{\sigma - 1}{\theta\sigma} Y_{i,k}^{F}, \tag{16}$$

Furthermore, from the Cobb-Douglas production function assumption, intermediate input expenditure is a constant fraction of total input purchased by the firms in each location. Appendix C.1.7 shows that, $Y_{i,km}^{I}$,

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[36]The most significant implication of the constant markup result is that the model exhibits no pro-competitive effects of denser locations (i.e., markups are lower in denser areas). While absent in my model, it is not clear whether such a force generates additional agglomeration force. While the pro-competitive effect benefits buyers for cheaper inputs, it discourages supplier entry, which eventually hurts buyers due to decreased supplier matching rates. See Kikkawa, Magerman, and Dhyne (2018) for recent evidence where firms' profit margins depend on the presence of competitors in Belgium.

[37]The term $1 - \gamma_{km}$ arises as the difference between the marginal seller and average seller. See Appendix C.1.5.

the intermediate input demand by firms in location i and sector m toward input sector k, is given by

$$Y_{i,km}^I = \gamma_{km} \left\{ \sum_{j \in N} \sum_{l \in K} \frac{\gamma_{ml}\theta}{1 + \gamma_{ml}\theta} Y_{j,ml}^I \pi_{ij,m} + \frac{\sigma - 1}{\sigma} Y_{i,m}^F \right\}. \tag{17}$$

The steady-state equilibrium is defined by the aggregate intermediate goods sales $\{X_{i,k}^I\}$ and final goods sales $\{X_{i,k}^F\}$, aggregate intermediate goods demand $\{Y_{i,km}^I\}$ and final goods demand $\{Y_{i,k}^F\}$, intermediate goods expenditure shares $\{\pi_{i,k}\}$, unit cost distribution $\{\Gamma_{i,m}\}$, steady-state probability of matching with a supplier $\{\Lambda_{i,km}\}$, wages $\{w_i\}$, measure of intermediate goods sellers $\{S_{i,k}^I\}$, unit cost cut-off for input sellers $\{\bar{c}_{j,k}^I\}$, and firm profit $\{\Pi_{i,k}\}$, which satisfy total expenditure conditions (8), (9), (10) and (17), trade balancing conditions (11), gravity equations of intermediate goods (13), free entry condition for marginal input sellers (14) and (15), firm profit (16), the steady-state matching probability (6), and the endogenous unit cost distributions due to input cost advantage terms (12).

Compared to the standard multi-location multi-sector Melitz model (e.g., Chaney 2008, Arkolakis, Demidova, Klenow, and Rodríguez-clare 2008, Costinot and Rodríguez-Clare 2015), the unit cost of production depends endogenously on the measure of input sellers $S_{j,k}^I$ through the input cost advantage term (equations (6) and (12)). In the next subsection, I discuss how this feature generates an agglomeration force in the model.

4.3   Discussions

4.3.1   Agglomeration Force in the Model

In this subsection, I briefly discuss the main agglomeration force of the model: circular causation between the measure of input sellers, $S_{j,k}^I$, and intermediate input goods demand, $Y_{j,km}^I$.

To see this circular causation, I first discuss how $Y_{j,km}^I$ responds to $S_{j,k}^I$. Recall equation (17), reproduced below:

$$Y_{i,km}^I = \gamma_{km} \left\{ \sum_{j \in N} \sum_{l \in K} \frac{\gamma_{ml}\theta}{1 + \gamma_{ml}\theta} Y_{j,ml}^I \pi_{ij,m}\left(S_{j,k}^I\right) + \frac{\sigma - 1}{\sigma} Y_{i,m}^F \right\}.$$

Here, with a slight abuse of notation, I denote $\pi_{ij,m}\left(S_{j,k}^I\right)$ to highlight the dependency of $\pi_{ij,m}$ on $S_{j,k}^I$ (see equations (6), (12) and (13)). $\pi_{ij,m}\left(S_{j,k}^I\right)$ is increasing in $S_{j,k}^I$, because an increase of $S_{j,k}^I$ increases the probability of matching with a supplier $\Lambda_{j,km}$, which then reduces the input cost of production in location i. This corresponds to the "forward linkage."

The number of sellers, in turn, increases in the aggregate input demand. This can be seen from the free entry condition of a marginal input seller (14), reproduced here:

$$S_{j,k}^I = \frac{1}{f_{j,k}^I w_j} \sum_{m \in K} \frac{1 - \gamma_{km}}{1 + \gamma_{km}\theta} Y_{j,km}^I.$$

This corresponds to a "backward linkage." The "forward linkage" and "backward linkage" constitute a positive feedback loop, reinforcing each other to create a force toward agglomeration of economic activity.

Two structural parameters are particularly relevant in the forward linkage condition. First, it depends on λ, the elasticity of the supplier matching rate with respect to the density of input sellers $S_{j,k}^I$. If λ is large, the steady-state probability of matching with a supplier $\Lambda_{j,km}$ responds more to a small increase of

$S_{j,k}^I$ (equation 6), conveying a greater input cost advantage. Second, the forward linkage depends on χ, the iceberg cost of buying from fringe intermediaries. If χ is larger, location-and-sector input cost advantage term $\Gamma_{j,k}$ responds more strongly to the increase of $\Lambda_{j,km}$ (equation 12).

On top of this circular causation, it is well known that the exponent of the power-law productivity distribution, θ, crucially governs the welfare implications of Melitz model (Arkolakis, Costinot, and Rodríguez-clare 2012). In Section 5.2, I illustrate precisely how θ affects the counterfactual spatial equilibrium.[38]

4.3.2 Mapping the Model to Reduced-Form Facts

Section 4.3.1 highlighted that λ and χ crucially govern the strength of the agglomeration force. I now discuss how these two parameters are strongly related to the reduced-form results in Section 3.

First, Section 3 documents that, upon an unanticipated supplier bankruptcy, firms match with a new supplier at a faster rate in a sector and a location where the geographic density of alternative suppliers is higher. By interpreting an unanticipated supplier bankruptcy as an exogenous supplier separation in the model, the reduced-form finding directly captures the magnitude of the matching rate elasticity λ. The baseline proxy for the density of alternative suppliers used in Section 3 (*SellerDensity*) is also closely related to the supplier density in the model ($S_{i,k}^I / Z_i$). In the model, $S_{i,k}^I$ is defined by the pool of suppliers paying a fixed cost to sell in location i regardless of their production location. In the reduced-form exercise, the definition of *SellerDensity* incorporates these suppliers selling from other locations by counting the number of suppliers *which have at least one buyer in location i* in the baseline period.[39]

Second, Section 3 documents that firms' sales and revenue productivity per worker decline when the firm is hit by an unanticipated supplier bankruptcy. In the model, when a firm faces an exogenous separation with a supplier, its unit cost increases depending on the magnitude of χ, which leads to the reduction of final and intermediate goods sales. At the same time, sales requires a payment of fixed cost by labor. This also leads to the decrease of the revenue per worker upon a supplier loss.

The above discussion implies that there is a transparent mapping between the reduced-form estimates in Section 3 and the key model parameters, λ and χ. In Section 5, I structurally estimate λ and χ to precisely replicate the reduced-form findings following this idea.

It is worth stressing again that, by taking a matching function approach, I do not microfound the matching function itself. In other words, I do not microfound where the matching rate elasticity (λ) and the benefit of a supplier match (χ) come from, out of various possible explanations (e.g., information imperfection of potential trading partners, the importance of customization of specialized inputs). This modeling strategy is motivated by the literature of labor search and matching, which formalize the relationship between matching function and aggregate equilibrium objects (e.g., unemployment rate, production). In a similar vein, I mainly use the model to formally map the reduced-form estimates in Section 3 to the aggregate equilibrium.

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[38]The discussion in this section also highlights that my model does not reduce to a typical model in the literature of quantitative spatial economics (Redding and Rossi-Hansberg 2016), which assume that the productivity is an exogenous function of labor density. To see this, note that the agglomeration feedback loop illustrated above does not rely on movement of labor.

[39]It should be noted that there is still a small difference between the supplier density measure in the reduced-form section (*SellerDensity*) and the supplier density in the model ($S_{i,k}^I / Z_i$). The difference arises because the former includes suppliers that enter as a seller in location i in the past (and matched with a buyer), but do not currently enter as a seller in location i (recall that each firm's marginal cost evolves over time due to supplier matching and separation). When I structurally estimate λ, I obtain the model-consistent $S_{i,k}$ by excluding suppliers that do not acquire any new buyers between 2008 to 2009 from *SellerDensity* to eliminate "inactive" sellers. See Section 5 and Appendix D.1 for more detail.

5 Quantification

In this section, I investigate the quantitative equilibrium implications of the agglomeration force through firm-to-firm matching. I first discuss how I calibrate the model. Importantly, the key structural parameters are recovered to precisely replicate the reduced-form estimates in Section 3. I then illustrate the quantitative equilibrium implications through two counterfactual equilibrium simulations.

5.1 Calibration

When computing the counterfactual equilibrium, it is convenient to solve the model in changes rather than in levels. This approach, often referred to as "exact hat algebra," reduces the set of parameters one needs to know to compute the equilibrium (Dekle, Eaton, and Kortum 2008, Caliendo and Parro 2014). In my context, it is sufficient to calibrate the baseline variables $\{\{\Lambda_{i,km}\}, \{\pi_{ij,k}\}, \{L_i\}, \{Y^I_{j,m}\}, \{T_i\}\}$ and the parameters $\{\theta, \sigma, \lambda, \chi, \{\delta_{i,km}\}, \{\alpha_k\}, \{\gamma_{L,m}\}, \{\gamma_{km}\}\}$ to compute counterfactual equilibrium. The calibrated structural parameters are described in Table 7. Below, I first discuss how the calibration of $\{\lambda, \chi\}$, the key parameters governing the strength of agglomeration force through firm-to-firm matching. Later, I describe how I calibrate the remaining parameters.

Before proceeding, I briefly describe how locations and sectors are matched to the data. Locations in the model correspond to the 47 prefectures in Japan. For sectors, I take 33 two-digit sectors in manufacturing, commerce (wholesale and retail), and construction/equipment services sectors. These 33 two-digit sectors together represent about 80% of all firms in Japan (see Appendix Table B.2).

5.1.1 Matching Rate Elasticity λ and Input Cost Advantage of a Direct Supplier Match χ

As discussed in Section 4.3.1, λ and χ are the key structural parameters that govern the strength of the agglomeration force. I estimate these parameters to precisely replicate the empirical results from Section 3.

The reduced-form results in Section 3 are intuitively informative about λ and χ. In Section 3, I document that (1) upon an unanticipated supplier bankruptcy, firms match with a new supplier at a faster rate in a sector and a location where the geographic density of suppliers is higher, and (2) firms' sales decline when the firm is hit by a unanticipated supplier bankruptcy. By interpreting unanticipated supplier bankruptcies as an exogenous supplier separation of the model, the magnitude of (1) contains information about the matching rate elasticity λ, and the magnitude of (2) contains information about the input cost advantage of directly matching with a supplier χ.

This intuition motivates my use of an indirect inference procedure to estimate λ and χ. Intuitively, I simulate a "natural experiment" of exogenous supplier separation in the model and find the parameter values that most closely replicate the regression results on new supplier matching and sales growth in Section 3. Appendix D.1 and D.2 describe the precise steps for the indirect inference procedure. Table D.1 shows that under the estimated parameters, the model indeed precisely replicate the reduced-form estimates in Section 3.[40]

Using this approach, I obtain the point estimate of 0.36 for λ (with the 90 percent confidence interval

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[40] As noted in Section 3, there are cases where suppliers do not exit immediately after the bankruptcy. When estimating λ and χ, I interpret all unanticipated supplier bankruptcies to correspond to exogenous supplier separation in the model (regardless of their subsequent exit).

of [0.10, 0.74]).[41] In other words, a 100 percent increase in the density of suppliers leads to a 36 percent increase in the matching rate. This large magnitude directly reflects the large heterogeneous effects of unanticipated supplier bankruptcies presented in Table 4. For χ, I obtain a point estimate of 1.51 (with the 90 percent confidence interval of [1.26, 1.90]). This means that firms without a directly matched supplier have to pay 0.51 ad-valorem cost of going through fringe intermediaries to access intermediate goods. With this parameter value, the model matches the reduced-form result that firms facing unanticipated supplier bankruptcy face 3 percent reduction of sales growth (Table 6). In the model, separation with a supplier leads on average to a $\chi^{\gamma_{km}}$ increase in unit cost, where γ_{km} is the Cobb-Douglas input share of the bankrupting supplier's industry k. This change in unit cost leads to a $\chi^{\gamma_{km}\theta}$ proportional decrease in average sales. The parameter θ also matters, as higher θ implies that there are more sellers on the margin of starting to make sales in various sales locations.[42]

5.1.2 Other Parameters and Baseline Variables

Other parameters and baseline variables are either borrowed from the literature or directly obtained from the data.

The intermediate input share $\{\gamma_{L,m}\}$ and labor share of production $\{\gamma_{km}\}$, as well as the final goods consumption share $\{\alpha_m\}$, are taken from the input-output table. Specifically, I use the 2011 input-output table prepared by Japan's Ministry of International Affairs and Communications in Japan.

θ, the parameter of the productivity distribution, and, σ, the elasticity of substitution, are assumed to be 4.3 and 5, values taken from Gaubert and Itskhoki (2019) and Broda and Weinstein (2006), respectively. As noted in Section 4.3.1, θ plays a crucial role in the Melitz model. In the following counterfactual simulations, I discuss how the results depend on these parameters.

The baseline variables $\{\pi_{ij,k}\}$ and $\{\Lambda_{j,km}\}$ are obtained from the TSR data set of firm-to-firm trade. Specifically, $\{\pi_{ij,k}\}$ is obtained from the extensive margin share of input trade, i.e., the fraction of suppliers in sector k that produce in location i, among all sellers in location j.[43] Note that, as discussed in Section 4.2, the extensive margin share of input trade is the same as the total input expenditure share. The steady-state probability of matching with a supplier, $\{\Lambda_{j,km}\}$, is constructed from the fraction of firms in location j and sector m that have a supplier in sector k.[44] For both $\{\pi_{ij,k}\}$ and $\{\Lambda_{j,km}\}$, I use the 2008 data.

The fraction of firms that can ever match with a supplier, $\{\delta_{j,km}\}$, is obtained using equation (6), which describes the relationship between the steady-state matching probability $\Lambda_{j,km}$, the new supplier matching rates $v\left(S_{j,k}^I/Z_j\right) = \eta\left(S_{j,k}^I/Z_j\right)^{\lambda}$, the separation rates $\rho_{j,km}$, and the fraction of firms that can ever match

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[41]I follow a nonparametric bootstrapping procedure to obtain the confidence intervals of $\hat{\lambda}$ and $\hat{\chi}$. More specifically, starting from the data set used in the reduced-form exercise in Section 3, I construct 100 sets of bootstrapped samples by redrawing the data at the group g level. For each bootstrapped data set, I obtain λ and χ that most closely replicate the reduced-form estimates. The 90 percentile confidence sets of the parameters are obtained as the 5-th and 95-th percentiles of the bootstrapped estimates of $\hat{\lambda}$ and $\hat{\chi}$.

[42]See Appendix D.2 for more intuition. Note that the estimate of χ depends on the values of γ_{km} and θ. The estimate of 1.51 is obtained under the value of $\theta = 4.3$ and γ_{km} taken from input-output table (see Table 7).

[43]I assume that the headquarter location is the firm's production location. If there is no supplier in location i that supplies to location j, I set $\pi_{ij,k} = 0$. This effectively assumes that the iceberg trade cost between location i and j for sector k is infinitely high.

[44]I assume that any firm with positive final goods sales appears in the TSR data set (including those who do not report any suppliers). This implies that firms which are matched with a supplier are more likely to be observed in the data, because their unit cost is likely to go below the unit cost threshold. Given that the unit cost of firms that are matched with a supplier in sector k is lower by proportion $\chi^{\gamma_{km}}$, I obtain $\Lambda_{j,km} = \frac{\tilde{\Lambda}_{j,km}\chi^{-\gamma_{km}\theta}}{\tilde{\Lambda}_{j,km}\chi^{-\gamma_{km}\theta}+1}$, where $\tilde{\Lambda}_{j,km}$ is the observed probability that a firm in location j and sector m has a supplier in sector k in TSR data set.

with a supplier $\delta_{j,km}$. Note that I have already estimated the function $v\left(S^I_{j,k}/Z_j\right)$ from the indirect estimation procedure in Section 5.1.1. $\rho_{j,km}$ is set to the average rate at which a firm in location j and sector m is separated with a supplier in sector k in between 2008 and 2016 (including the case where suppliers does not drop out from the sample). Given $\Lambda_{j,km}$, $\eta\left(S^I_{j,k}/Z_j\right)^{\lambda}$ and $\rho_{j,km}$, I back out $\{\delta_{j,km}\}$ using equation (6).

The population size $\{L_i\}$, nominal wages $\{w_i\}$, and the net current transfer $\{T_i\}$ are obtained from prefecture-level accounting data in 2008 (*Kenmin-Keizai-Keisan*). To obtain $\{T_i\}$, I compute the difference between the prefecture's total disposable income and its total earned income.

Finally, I obtain $\{Y^I_{j,km}\}$ for the total expenditure conditions. More specifically, I use equations (10), (16), and (17) to uniquely pin down $\{Y^I_{j,km}\}$ (given $\{L_i\}$, $\{\pi_{ij,k}\}$, $\{T_i\}$ and $\{w_i\}$).

5.2   Counterfactual Simulations

Using the calibrated model, I quantify the equilibrium implications of the agglomeration force through firm-to-firm matching with two counterfactual simulations. In both simulations, I follow the "exact hat algebra" approach to solve for the changes in equilibrium variables between the observed and counterfactual equilibrium (Appendix C.2.1 and Appendix C.2.2).[45]

5.2.1   How Important is Firm-to-Firm Matching for Spatial Economic Inequality?

In the first counterfactual simulation, I quantify the extent to which the agglomeration force highlighted in the paper explains Japan's observed spatial economic disparities.

To do so, I take the calibrated model and shut down the agglomeration force through increasing returns to scale in firm-to-firm matching. This is achieved by setting λ, the elasticity of supplier matching rates with respect to the supplier density, to zero, rather than the actual estimate of 0.36. Under this counterfactual, the new supplier matching rate $v\left(S^I_{j,k}/Z_j\right)$ does not depend on location j and is fixed at the average values in the baseline equilibrium. I then compare spatial inequality of observed nominal wages in Japan in the counterfactual equilibrium vs. the observed data. Appendix C.2.1 provides the exact procedure of computing the counterfactual equilibrium following the exact hat algebra approach.[46]

Note that, in this counterfactual simulation, I keep the exogenous productivity $\tilde{A}_{i,k}$ unchanged. This counterfactual simulation exercise can therefore be understood to isolate the effects of the particular agglomeration force through increasing returns to scale in firm-to-firm matching, with $\tilde{A}_{i,m}$ interpreted as including agglomeration benefits through other mechanisms.

Figure 2 plots the relationship between the nominal labor income per capita (w_i) and population density at the prefecture level, in both baseline and counterfactual equilibria. Both are normalized to be mean zero in log scale. Note that the baseline equilibrium is taken directly from the data (*Kenmin-Keizai-Keisan* in 2008). In the baseline, there is a positive association between the nominal labor income and population density, with the elasticity of about 0.1. The elasticity of 0.1 is within the range of values found in the literature studying population-density premium of production in various countries, including those of Japan

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[45]When implementing the "exact hat algebra" approach, I start from the initial guess of no changes of equilibrium variables, and search for the new equilibrium (in changes) which satisfies the new equilibrium conditions. This procedure effectively picks the counterfactual equilibrium which is on the same bifurcation path if there are potentially multiple equilibria.

[46]More specifically, I solve the model by changing the supplier matching rate by $\hat{v}_{i,k} \equiv \overline{v}_k / v_{i,k}\left(S^I_{j,k}/Z_i\right)$, where $\overline{v}_k$ is the average rate in the baseline equilibrium. To avoid the case that $S^I_{j,k}/Z_i = 0$ in the data and hence $\hat{v}_{i,k}$ is not defined, I obtain $v_{i,k}$ from the zero profit condition (equation 14), with the auxiliary assumption that $f^I_{j,k}$ is proportional to the geographic area of Z_j, i.e., $f^I_{j,k} = f^I_k Z_j$. Appendix C.2.1 provides more detail.

(i.e., Melo, Graham, and Noland 2009).

In the counterfactual equilibrium, the slope is still positive but significantly smaller. The slope in the counterfactual equilibrium is about 0.07 (with 90% confidence interval of [0.047,0.086]).[47] The point estimate implies that about 30% of the population-density premium of labor income is explained by the agglomeration force through firm-to-firm matching. The remaining 70% of the population density premium of wages arises from other heterogeneity across locations, potentially including other agglomeration benefits of production.

Considering that the observed population-density wage premium results from a combination of various agglomeration mechanisms and exogenous productivity differences, the 30% magnitude is quantitatively important. This is consistent with the finding of Ellison, Glaeser, and Kerr (2010), who test the importance of proxies for various agglomeration channels and natural advantages and find that the proxies for input-output linkages are the most important determinants of coagglomeration of different industries.

Sensitivity to Calibrated Parameters and Alternative Specifications. In Appendix Table D.2, I discuss in detail the sensitivity of the results with respect to the values of θ and σ, as well as sensitivity to allowing for labor mobility and free entry of entrepreneurs. Here, I provide an overview of this sensitivity analysis: First, a higher value of θ, the parameter of the productivity distribution, decreases the magnitude of the counterfactual changes in the population-density premium (Row 2). This is explained by the fact that θ governs the strength of the relationship between cost advantage and wages (see equation 12). Note that this is a general observation about the Melitz model with multiple locations (Arkolakis, Costinot, and Rodríguez-clare 2012, Costinot and Rodríguez-Clare 2015). On the other hand, changing σ barely affects the results (Row 3). In my model, σ matters for nominal wages only through the relative profit between intermediate and final goods sales (equation 16).

Incorporating labor mobility decreases the magnitude of the counterfactual changes in the population-density premium (Row 4, see Appendix C.3.1 for this extension). This is due to the fact that labor moves toward prefectures with higher nominal wages, offsetting the changes in nominal wages. Incorporating free entry of entrepreneurs also decreases the magnitude of the counterfactual changes in the population-density premium (Row 5, see Appendix C.3.2 for this extension), as entrepreneurs tend to enter in prefectures with lower wages, offsetting the changes of nominal wages.

5.2.2 How Much Does the Agglomeration Force Amplify the Impacts of Cross-Location Income Redistribution in Japan?

In the second counterfactual exercise, I study the implication of the agglomeration force for income redistribution in Japan.

In Japan, there is a steady transfer of nominal income from urban to rural locations. Panel (A) of Figure 3 shows that there is a a wide heterogeneity of the net current transfer across Japanese prefectures, and they are strongly negatively correlated with the population density. This is largely due to pension payments and medical benefits, along with the fact that rural areas on average have older populations (Fukao and Makino 2015).

The redistributional impacts of these income transfers on regional welfare may be amplified by the agglomeration force. To see this, note that an exogenous increase of T_i increases the final goods demand

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[47]The confidence interval of the slope of the counterfactual equilibrium is obtained as the counterfactual simulations with parameter values of λ and χ at the bottom and top of the 90% confidence intervals. See Table 7 for the confidence intervals of $\hat{\lambda}$ and $\hat{\chi}$.

$Y_{i,k}^{F}$ from equation (10), which then increases input demand Y_i^I from equation (18). This "demand shock" starts the circular causation between input goods demand $Y_{j,km}^I$ and the measure of input sellers $S_{j,k}^I$, as illustrated in Section 4.3.1.

To investigate the real redistributional impacts of these income transfers, I conduct the counterfactual simulation that shuts down the existing nominal income redistribution. Formally, I set the counterfactual level of cross-location income transfer T_i' to be a constant fraction of the baseline nominal labor income ($w_i L_i$), with this fraction being the same across all locations.[48] I conduct the counterfactual simulations under two different values of λ: 0.36 (estimated value) and 0 (assuming no agglomeration force through firm-to-firm matching). The differences in welfare effects of the transfers in these two scenarios are driven by the amplification effect of the income transfer as discussed in Section 4.3.1. Appendix C.2.2 describes the exact procedure of computing the counterfactual equilibrium, which follows the exact hat algebra approach.

Panel (B) of Figure 3 depicts the counterfactual changes in real income in each prefecture under two different values of λ. Real income is defined as the sum of labor income, firm profit, and net current transfer, divided by the price index of the final goods.[49]

The results show that shutting off the cross-location income redistribution favors denser prefectures. This is almost necessarily true since the net current transfer observed in the data is positively correlated with population density (Panel A of Figure 3). With the estimated value of λ (0.36), the slope of the increase in real income with respect to the population density is 0.04. This magnitude is sizable relative to the observed slope of (nominal) labor income with respect to population density (0.10, Figure 2). This indicates that the existing redistribution has a quantitatively large implications.

At the same time, the magnitude of the changes in real income (Panel A) is generally smaller than the changes in nominal income (Panel B). This is due to the fact that nominal wages tend to fall in prefectures that face a net increase in income transfer in the counterfactual equilibrium. The logic follows from a terms-of-trade effect, familiar in the international trade context. An increase in the net current transfer increases the prefecture's intermediate goods demand. This implies that the prefecture's "imports" from other prefectures increases. To satisfy the prefecture's budget constraint (subject to the same level of trade imbalance), the prefecture's "exports" must increase at the same rate. This requires a decrease in nominal wages.

I now return to the question of how much the agglomeration effect amplifies the impacts on real income redistribution. When the agglomeration effect is shut down ($\lambda = 0$), the slope of the real income increase with respect to the population density decreases to 0.037, relative to 0.040 with the estimated value of λ (0.36). In other words, the agglomeration effect amplifies the redistributional impacts of the cross-location transfers by 8 percent (= 0.003 / 0.037). Hence, while a majority of the welfare effect is captured in the model without agglomeration feedback, the agglomeration force adds a non-trivial additional reallocation effect.

To summarize, the results indicate that it is important to take into account the general equilibrium feedback when considering the impacts of nominal income redistribution. Due to terms-of-trade effect, the actual redistributional effect on real income is not as large as the level of the existing nominal net current transfer. At the same time, agglomeration feedback amplifies the redistribution effect by 8 percent.

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[48]Note that in the data, the aggregate current transfer is positive (i.e., $\sum_{i \in N} T_i > 0$). This is mainly driven by transfers from the central government, which do not appear in the prefecture account. When I conduct the counterfactual simulation, I keep the aggregate current transfer unchanged ($\sum_{i \in N} T_i = \sum_{i \in N} T_i'$).

[49]Appendix C.2.3 shows the counterfactual changes in the price index of the final goods consumption.

6 Conclusion

This paper investigates the importance of increasing returns in input trade firm-to-firm matching as a source of agglomeration of economic activity. I first provide reduced-form evidence of this mechanism by using unanticipated supplier bankruptcy as a natural experiment. I document that firms rematch with new suppliers at a faster rate in locations and industries that have more alternative suppliers selling in the buyer's location. At the same time, the new supplier matching rate does not decrease with the geographic density of other buyers. Hence, the matching rate exhibits increasing returns to scale. Based on the reduced-form findings, I develop a new structural model of firm-to-firm trade with matching frictions. The model generates agglomeration feedback through the circular causation between the density of input sellers and the downstream input demand. I structurally estimate the key parameters to precisely replicate the reduced-form effects of unanticipated supplier bankruptcies, and I show that this type of circular causation explains about 30% of the population-density premium in nominal labor income in Japan. The agglomeration force also amplifies the redistribution effect of the existing urban-to-rural income transfer by 8%.

This paper highlights a particular microfoundation for agglomeration forces: firm-to-firm matching in input trade. This is, however, not the only relevant mechanism. Further theoretical and quantitative work in spatial economics is needed to better understand the role of other mechanisms, such as labor market pooling or knowledge spillovers. Increasing availability of microdata at a fine level of spatial disaggregation (e.g. firm-to-firm trade data, satellite images, and mobility and communication information from mobile devices) provide unprecedented opportunities to explore the various mechanisms of agglomeration.

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Table 1: List of Reasons of Bankruptcies

Reason of Bankurptcy	Freq.	Freq. (At Least One Buyer)
Unanticipated Reasons	1589	661
Sales Decline	72483	22775
Accumulation of Debt	10718	5456
Spillovers from Other Bankruptcy	6223	1996
Shortage of Capital	5582	2340
Management Failure	4845	1281
Unknown	3597	929
Over-Investment in Capital	802	368
Deterioration of Credit Conditions	547	282
Difficulty in Collecting Account Receivables	454	237
Over-Accumulation of Inventory	73	38
Total	106913	36363

Note: The table reports the number of bankruptcies reported in the TSR data set, disaggregated by the main reported reasons. "Freq" indicates the number of firms experiencing bankruptcies from 2008 to 2016 for each reason, and "Freq. (At Least One Buyer)" indicates the number of bankrupting firms which are reported by at least one firm as their main suppliers. In an internal document by TSR, "Unanticipated accidental reasons" is described as "unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc."

Table 2: Aggregate Patterns of Static and Dynamic Supplier Linkages

	Number	Percent Change from Previous Year
(A) Static Patterns		
Average Number of Suppliers	1.65	
Average Number of Suppliers (if Positive)	3.23	
Average Number of Suppliers within 4-digit Industry	1.19	
Average Number of Suppliers within 2-digit Industry	1.38	
(B) Dynamic Patterns		
Net Growth of Number of Suppliers	0.02	0.8
Number of Separated Suppliers per Year	0.17	5.3
Number of New Suppliers per Year	0.19	6.1

Note: Each of the statistics in Panel (A) is computed as an average of all years available in the TSR data set (from 2008 to 2016). The third and fourth rows of Panel (A) show the average number of suppliers in each supplier industry conditional on having a supplier in the industry. The industry classification follows the Japan Standard Industrial Classification (JSIC). There are 1,455 four-digit industries and 99 two-digit industries following the JSIC. To compute the statistics in Panel (B), I first take two consecutive years and compute each statistic for the surviving firms (firms that exist in both years), restricting to firms with at least one supplier in the first year. Then I take the average across all pairs of consecutive years in the sample period.

Table 3: Average Impacts of Unanticipated Supplier Bankruptcy on Supplier Matching

	Number of Suppliers	Number of New Suppliers	
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = -2 or -3]	−0.06	0.04	0.01
	(0.05)	(0.04)	(0.04)
Trt x 1[t - BankruptYear = -1]			
	(0.00)	(0.00)	(0.00)
Trt x 1[t - BankruptYear = 0 or 1]	−0.58***	0.18***	0.17***
	(0.05)	(0.05)	(0.05)
Trt x 1[t - BankruptYear = 2 or 3]	−0.56***	0.29***	0.27***
	(0.07)	(0.07)	(0.07)
Include Exiting Firms	No	No	Yes
Control Mean (3 Years After Bankruptcy)	4.81	0.78	0.74
Number of Treatment Firms	421	421	421
Number of Bankrupting Suppliers	161	161	161
Number of Control Firms	10,842	10,842	10,842
Observations	73,422	73,422	76,054

Note: The regression specification follows equation (1). "Number of Suppliers" indicates the total number of suppliers reported by each firm in the TSR data set in each year, and "Number of New Suppliers" indicates the number of reported suppliers which are *not* connected in the baseline period (one year before the bankruptcy). The regression coefficient on "Trt x 1[t - BankruptYear = -1]" is omitted as the baseline. If "Include Exiting Firms" is "No," I treat the observation as missing after the firm exits, and if it is "Yes," I insert the value of the last observation when the firm was alive. For each control firm in group g, I impose the inverse of the number of control firms within group g as the regression weight. Standard errors are clustered at the firm level. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

Table 4: Heterogeneous Impacts of Unanticipated Supplier Bankruptcy on New Supplier Matching

	Number of New Suppliers					
	OLS	OLS	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Trt x 1[t - BankruptYear = 0 or 1]	0.15*** (0.05)					
Trt x 1[t - BankruptYear = 2 or 3]	0.26*** (0.07)					
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.10* (0.05)	0.12** (0.05)	0.12* (0.07)	0.13* (0.07)	0.08 (0.10)	0.14** (0.06)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.16** (0.08)	0.20*** (0.08)	0.23** (0.10)	0.24** (0.09)	0.21* (0.12)	0.28*** (0.10)
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Size (Std.)				−0.07 (0.05)		
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Size (Std.)				−0.01 (0.08)		
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Size (Std.)				−0.04 (0.04)		
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Size (Std.)				−0.001 (0.06)		
Trt x Post x Buyer Prefecture FE		X	X	X	X	X
Trt x Post x Supplier 2-digit Industry FE			X	X	X	
Trt x Post x Buyer Prefecture and 2-digit Industry FE					X	
First-Stage F-Statistics						1920
Number of Treatment Firms	421	421	421	418	260	386
Number of Bankrupting Suppliers	161	161	161	160	117	154
Number of Control Firms	10,842	10,842	10,842	10,798	1,679	9,820
Observations	73,422	73,422	73,422	72,934	12,371	66,280

Note: The regression specification follows equation (2). Seller density is defined as the geographic density of suppliers in the bankrupting suppliers' four-digit industry who have at least one buyer in firm i's prefecture in 2008. The seller density measure is normalized to be mean 0 (within each bankruptcy year) with standard deviation 1 after residualized by other controls Z_g interacted with the treatment dummy. In Column (1), I control for log area of the prefecture of treatment firm i as an interaction with as an interaction with $Post_{gt} \times Trt_i$. Average effects are omitted from Columns (2) to (6), as they are saturated under the fixed effects. Buyer and supplier sizes are defined by the employment size in the baseline period, and it is also normalized to be mean zero and standard deviation one. The sample size of Column (5) drops compared to other specifications, because control firms that are in a different two-digit industry as treatment firms for each group g are dropped in this specification. Column (6) instruments log $SellerDensity_g$ by the density of suppliers evaluated at the birth prefecture of the CEO of the treatment firm of group g (as an interaction with $Post_{gt} \times Trt_i$). Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Heterogeneous Impacts on New Suppliers by Density of Other Buyers

	Number of New Suppliers		
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.08	0.05	0.12**
	(0.05)	(0.05)	(0.05)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.18**	0.18*	0.20***
	(0.09)	(0.10)	(0.08)
Trt x 1[t - BankruptYear = 0 or 1] x log Density of Buyers with Unanticipated Supplier Bankruptcy (Std.)	0.01		
	(0.06)		
Trt x 1[t - BankruptYear = 2 or 3] x log Density of Buyers with Unanticipated Supplier Bankruptcy (Std.)	−0.04		
	(0.09)		
Trt x 1[t - BankruptYear = 0 or 1] x log Density of Buyers with Supplier Separation (Std.)		0.01	
		(0.06)	
Trt x 1[t - BankruptYear = 2 or 3] x log Density of Buyers with Supplier Separation (Std.)		−0.08	
		(0.10)	
Trt x 1[t - BankruptYear = 0 or 1] x log Density of Firms in Same 2-digit Industry (Std.)			−0.02
			(0.05)
Trt x 1[t - BankruptYear = 2 or 3] x log Density of Firms in Same 2-digit Industry (Std.)			−0.06
			(0.08)
Trt x Post x Buyer Prefecture FE	X	X	X
Observations	73,422	73,422	73,422

Note: The regression specification follows equation (2). In each column, I include the heterogeneous treatment effects with respect to different proxies of buyer density. Column (1) defines relevant buyers as the firms in the treatment firm's prefecture which faced an unanticipated bankruptcy of suppliers in the same four-digit industry in the same year. Column (2) defines buyers as the firms facing supplier separation in the same four-digit supplier industry in the same year. This includes cases of discontinuation of the relationship without supplier exit. Column (3) defines buyers as the firms which belong to the same two-digit industry and prefecture as the treatment firm. Both supplier density and buyer density are normalized to be mean zero and standard deviation one after residualizing other covariates included in Z_g. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Impacts of Unanticipated Supplier Bankruptcy on Sales and Productivity Growth

	Δ Sales	Δ Sales per Worker	Exit	Δ Sales	
	OLS	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)
Trt x 1[t - BankruptYear = 0 or 1]	-0.027^*	-0.011	0.002	-0.027^*	
	(0.015)	(0.013)	(0.010)	(0.016)	
Trt x 1[t - BankruptYear = 2 or 3]	-0.031	-0.058^{***}	0.009	-0.033	
	(0.024)	(0.020)	(0.017)	(0.025)	
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)				0.007	
				(0.014)	
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)				0.023	
				(0.025)	
Number of Suppliers					0.058^*
					(0.033)
Number of Suppliers x log Seller Density (Std.)					0.007
					(0.026)
Control Mean (3 Years After Bankruptcy)	0.933	1.024	0.089	0.933	0.933
Include Exiting Firms	Yes	No	Yes	Yes	Yes
First Stage F-Statistics					14.9
Number of Treatment Firms	420	415	420	420	420
Number of Bankrupting Suppliers	161	160	161	161	161
Number of Control Firms	10,678	10,601	10,678	10,678	10,678
Observations	63,202	60,883	63,202	63,202	63,202

Note: The regression specification follows equations (1) and (2) for Column (1) to (4). Column (5) follows the regression specification (3), where I instrument NumberSuppliers$_{it}$ and NumberSuppliers$_{it} \times \log SellerDensity_g$ by $Trt_i \times Post_{gt}$ and $Trt_i \times Post_{gt} \times \log SellerDensity_g$. Δ Sales is defined by the sales in each period t divided by the sales in the baseline period, windsorized at the 95 percentile (separately for treatment and control groups and the year since the shock). Δ Sales per worker is defined similarly. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Calibrated Structural Parameters

| Parameters	Description	Values
Estimated Parameters from Impacts of Unanticipated Supplier Bankruptcy		
λ	elasticity of supplier matching rate	0.36 (with 90% confidence interval: [0.10, 0.74])
χ	cost advantage of a supplier match	1.51 (with 90% confidence interval: [1.26, 1.90])
Calibrated Parameters		
γ_{km}	intermediate goods share of production	from input-output table (in 2011)
$\gamma_{L,m}$	labor input share of production	from input-output table (in 2011)
α_m	final goods consumption share	from input-output table (in 2011)
θ	exponent of productivity distribution	4.3 (Gaubert and Itskokhi 2018)
σ	elasticity of substitution of final goods	5 (Broda and Weinstein 2006)
$\delta_{i,km}$	fraction of firms which can match with external suppliers	calibrate with equation (6)
Baseline Variables		
$\pi_{ij,k}$	intermediate goods share from each origin	TSR data in 2008
$\Lambda_{i,km}$	steady-state probability of matching with a supplier	TSR data in 2008
L_i	population	from prefecture accounting data in 2008 (*Kenmin-Keizai-Tokei*)
T_i	net current transfer	from prefecture accounting data in 2008 (*Kenmin-Keizai-Tokei*)
w_i	nominal wages	from prefecture accounting data in 2008 (*Kenmin-Keizai-Tokei*)
$Y^I_{i,km}$	aggregate intermediate goods demand	calibrate with equations (10), (16), and (17)

Note: The table reports the set of calibrated parameters for the counterfactual simulation. See Section 5 for the detail of the calibration procedure.

Figure 1: Cross-Sectional Correlation between Number of Suppliers and Population Density

(A) CDF of Geographic Distances between Headquarters of Suppliers and Buyers
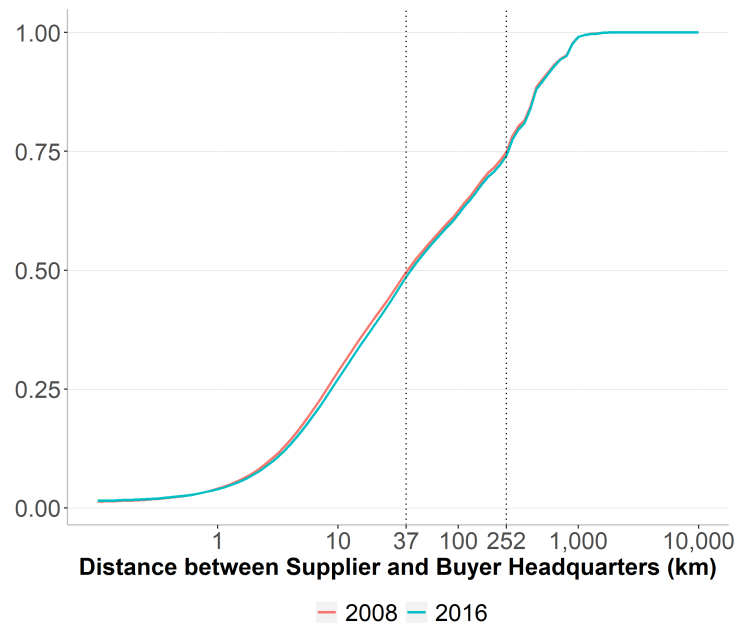
(B) Number of Suppliers per Firm and Population Density
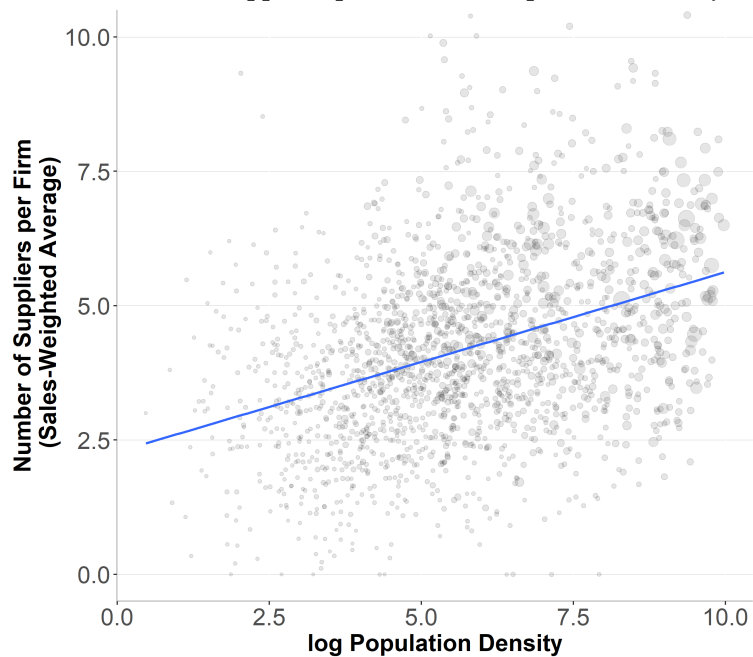
Note: Panel (A) shows the cumulative distribution of the geodesic distances to reported suppliers in 2008 and 2016. The vertical dotted lines (at 37 and 252) correspond to the median and 75th percentile of the distribution in 2008. The same statistics in 2016 are at 40 km and 259 km, respectively. Panel (B) shows the relationship between the population density and the average number of suppliers per firm at the municipality level in 2008. The average number of suppliers is weighted by sales of each firm within each municipality. The size of the dot represents the number of firms in each municipality.

Figure 2: Counterfactual Simulation of Shutting Down Increasing Returns to Scale in Matching
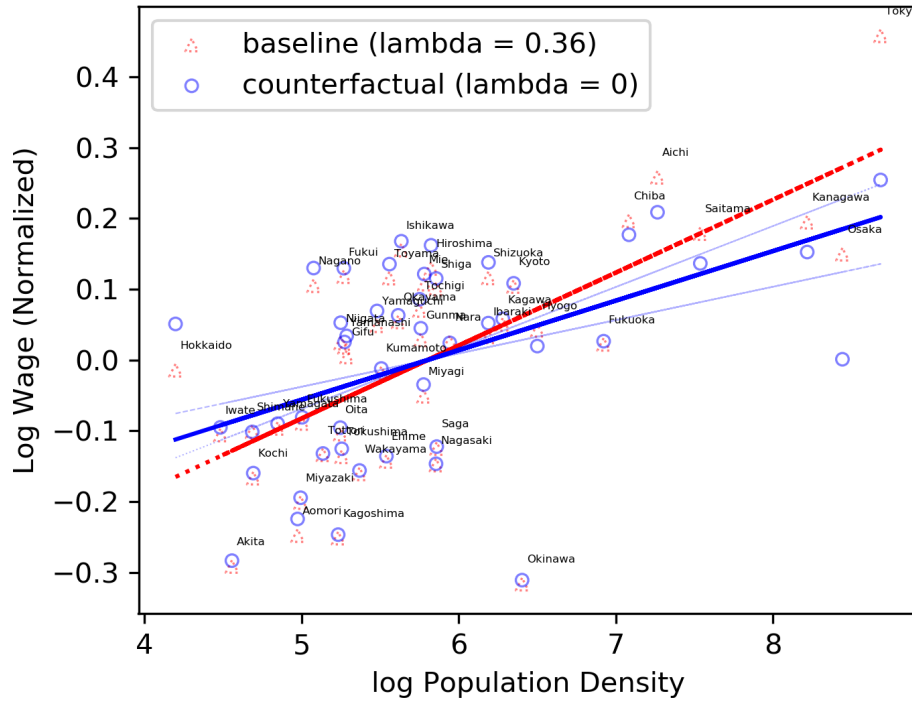

Note: The figure shows the results of the counterfactual simulation of shutting down the increasing returns to scale in firm-to-firm matching ($\lambda = 0$). The figure shows the relationship between the nominal wages and the population density in the baseline equilibrium and counterfactual equilibrium. Wages are normalized to be mean zero in log scale. The two thin lines represent the 90% confidence interval of the counterfactual simulation (i.e., the results of the counterfactual simulation with parameter values of λ and χ at the bottom and top of the 90% confidence intervals). The slope is 0.10 for the baseline equilibrium, and 0.07 for the counterfactual equilibrium (with the 90% confidence interval of [0.047,0.086]). See Section 5.2.1 for more detail about the counterfactual simulation.

Figure 3: Counterfactual Simulation of Shutting Off Existing Cross-Location Income Transfer

(A) Existing Income Transfer in Japan
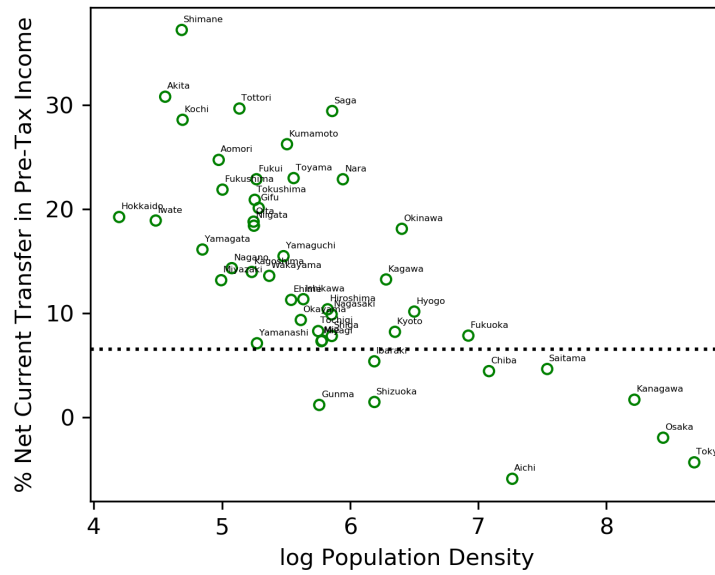
(B) Coutnerfactual Changes of Prefecture Real Income
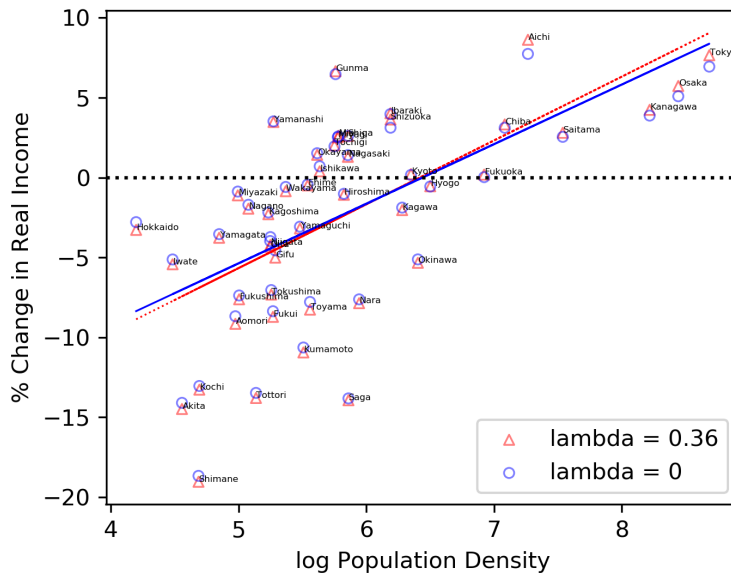
Note: Panel (A) shows the prefecture-level net current transfer as a proportion of total pre-tax income in the prefecture. Net current transfer is obtained from prefecture-level accounting data in 2008 (*Kenmin-Keizai-Keisan*). The dotted horizontal line at 6.5 indicates the average of the net current transfer, weighted by the population size. Panel (B) shows the counterfactual changes in the real income by shutting off the existing net current transfer under two different values of λ: 0.36 (estimated value) and 0 (assuming no agglomeration force through firm-to-firm matching). See Section 5.2.2 for more detail about the counterfactual simulation. Real income is defined by the sum of labor income, firm profit, and net current transfer, divided by the price index of the final goods.

A   Data Appendix

A.1   Coverage of TSR Data Set

The data set has a high coverage of firms in Japan. Table A.1 compares the sample size of the data set in 2009 and 2016, with the official government statistics (the economic censuses). The TSR data set covers 68% of all firms in Japan in 2009, and 89% of firms with at least 5 employees. This indicates that the data set covers most of the economically non-negligible firms in Japan. The coverage increases over time, primarily driven by small firms.

Table A.1: Sample Size and Coverage of TSR Data Sets

		TSR	Economic Census	TSR / Economic Census
2009	All	1,245,726	1,805,545	0.68
	Employment ≤ 4	589,081	1,067,825	0.55
	Employment ≥ 5	656,645	737,720	0.89
2016	All	1,505,497	1,877,438	0.8
	Employment ≤ 4	808,014	1,047,189	0.77
	Employment ≥ 5	697,483	830,249	0.84

Note: This table shows the sample coverage of TSR data sets. The first column reports the number of firms included in the TSR data set in each year and by employment size. The second column reports the number of incorporated firms reported in economic censuses. The last column shows the ratio between the first and second column. Note that the TSR data set potentially includes unincorporated entities.

The data set is also geographically representative. Figure A.1 compares the geographic density of firms in the TSR data set with that in the economic census. The slope of the regression line is 1.04 with an R-squared of 0.98. The fact that the slope is almost one indicates that the sampling rate of firms in the TSR data set is almost orthogonal to the true geographic firm density. At the same time, it is slightly above one, indicating that there is a slight over-representation in denser municipalities. In Appendix B.4, I show that my reduced-form results are robust to adjusting these sampling rates.

Figure A.1: Coverage of TSR data sets relative to Economic Census
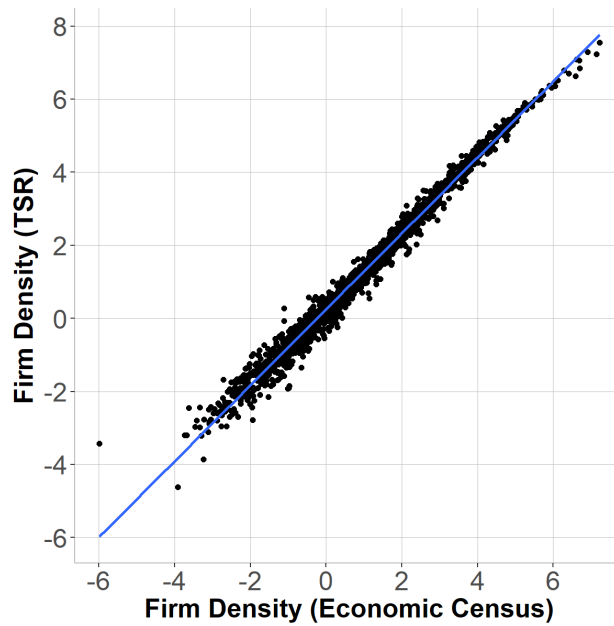
A.2   Additional Figures about TSR Data

Figure A.2: Cumulative Distribution Function of the Number of Suppliers per Firm
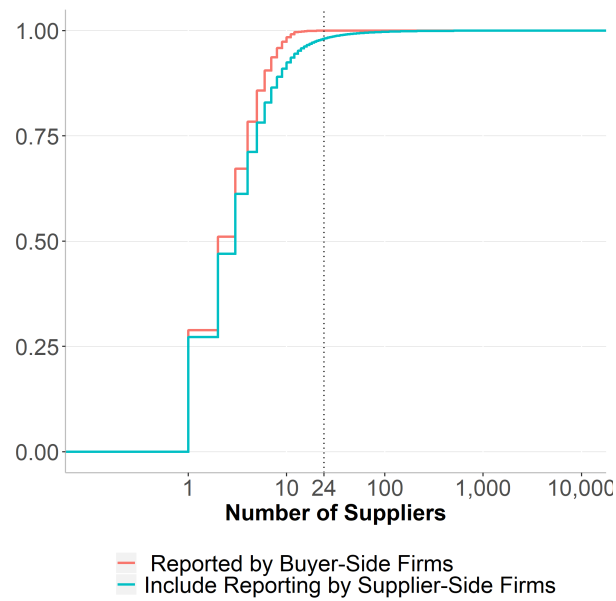
Note: The figure shows the cumulative distribution function of the number of suppliers in the TSR data set in 2008, conditional on having at least one supplier. The first line indicates the number of supplier linkages reported by each firm. Note that 24 is the maximum number of suppliers each firm can report. The second line indicates the number of supplier linkages reported by either the buyer-side firm or the supplier-side firm.

Figure A.3: Geographic and Time Patterns of Unanticipated Accidental Bankruptcies

(A) Probability by Firm Density

(B) Time Trend
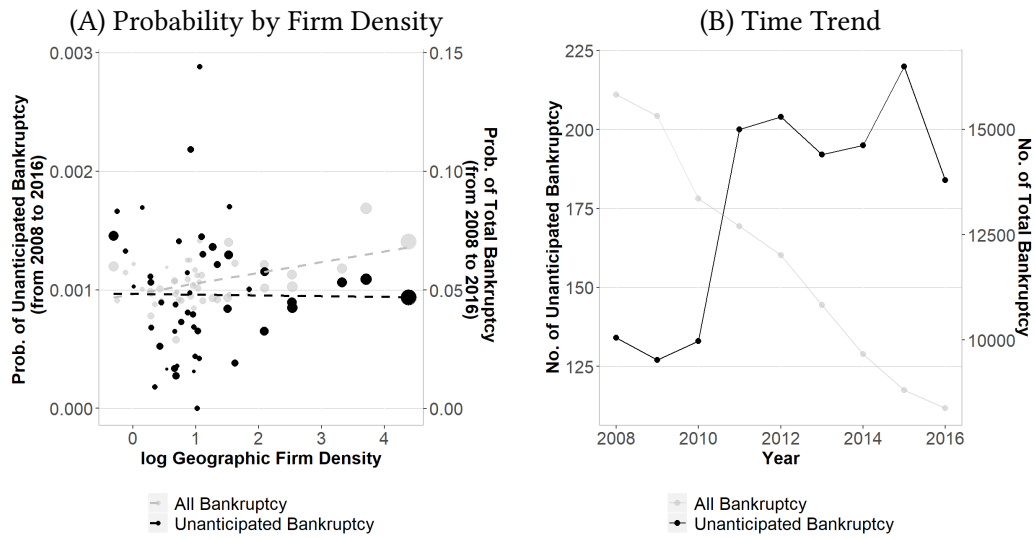
(C) Map of the Probabilities of Unanticipated Bankruptcies
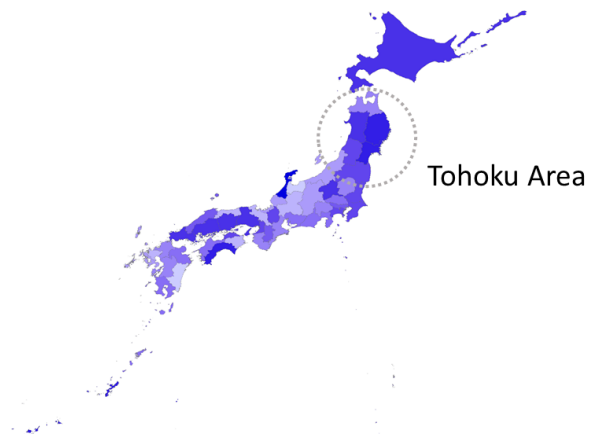
Note: Panel (A) plots the probability of unanticipated bankruptcies by firm density in each prefecture (cumulative over the period between 2008 and 2016). The figure also plots the same statistics of all bankruptcies reported in the data set. See Table 1 for the reported reasons of bankruptcies. Panel (B) plots the number of unanticipated bankruptcies and all bankruptcies over time. The Great Tohoku Earthquake in March 2011 mainly affected the Tohoku Area, shown in Panel (C).

Figure A.4: Separation Rate with a Supplier and Population Density
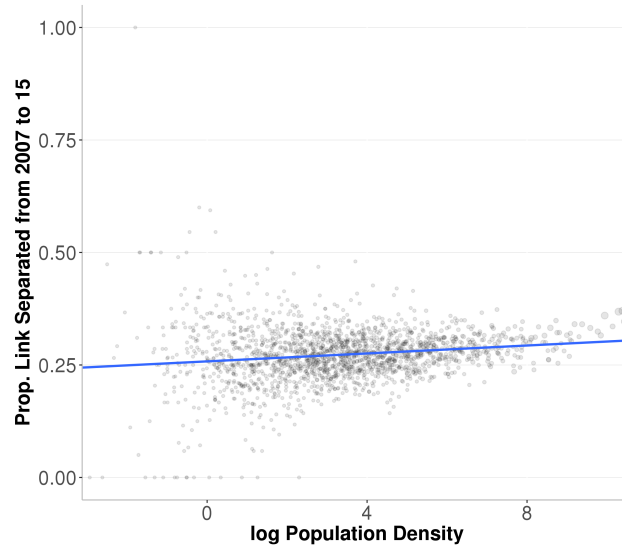
Note: The figure shows the relationship between the proportion of suppliers in 2007 that are separated in 2015, and the population density. Each dot represents a municipality.

B Reduced-Form Appendix

B.1 Basic Characteristics of Treatment Firms

Table B.1 shows the characteristics of the treatment and control firms in 2008. (In 2008, 399 of the 421 treatment firms exist, and 10,272 of the 10,842 control firms exist.)

Panel (i) presents the size of the treatment and control firms. Each row shows the median statistic, as well as the 10th and 90th percentiles (in brackets). The median treatment firm has four suppliers. The median firm has ten employees and has annual sales of 0.28 billion yen (about 2.5 million USD). The characteristics of control firms are broadly similar. It should be stressed that I do not use these characteristics when I assign control firms to each treatment firm. This indicates that the unanticipated supplier bankruptcy is indeed orthogonal to the characteristics of the buyer-side firms.

Panel (ii) shows the distribution of firms across industries. The three major industries are manufacturing, commerce, and construction/equipment services. These three industries together account for more than 80% of the firms in the sample. In the reduced-form exercise, I show that the results are robust by controlling for the buyer and supplier industry interacted with treatment dummy.

Table B.1: Characteristics of Treatment and Control Firms

	Treatment Firms	Control Firms
(i) Firm Size		
Number of Suppliers	4	4
	[0, 9]	[1, 9]
Number of Employees	10	11
	[3, 60.4]	[3, 100]
Annual Sales (Billion Yen)	0.28	0.32
	[0.05, 2.2]	[0.05, 3.95]
(ii) Industry Composition		
Proportion (Manufacturing)	0.29	0.26
Proportion (Commerce)	0.28	0.31
Proportion (Construction / Equipment Services)	0.27	0.25
Proportion (Others)	0.14	0.17
Sample Size	421	10,842

Note: The table shows the characteristics of the treatment firms (firms which face an unanticipated supplier bankruptcy) and the control firms in 2008. 399 out of 421 treatment firms and 10,272 out of 10,842 control firms exist in 2008. Each row of panel (i) shows the median of each statistic, and the bracket shows the 10th and 90th percentile of the statistic. Panel (ii) reports the fraction of firms that fall in each category of industry.

For the purpose of the external validity, it is also useful to discuss how the characteristics of treatment firms in this natural experiment compare with those of a typical firm in Japan. Panel (A) of Appendix Table B.2 shows that treatment firms are slightly larger than a typical firm in the sample (with at least one supplier). For example, the median employment size of treatment firms is 10, while that of a typical firm is 7. This difference is a result of how the treatment group is constructed; firms that have more suppliers are mechanically more likely to face a supplier bankruptcy and are also likely to have more employees. While the difference in size between the treatment firms and typical firms is not large in magnitude, it does suggest that one should think carefully about the external validity of the results. Relatedly, Panel (B) of Appendix Table B.2 shows that the bankrupt suppliers are slightly smaller than a typical supplier in Japan.

Table B.2: Characteristics of Treatment Firms and Suppliers

(A) Treatment Firms (Buyers of Firms facing Unanticipated Bankruptcies)

	Treatment Firms	All Firms (At least One Supplier)
(i) Firm Size		
Number of Suppliers	4	3
	[0, 9]	[1, 7]
Number of Employees	10	7
	[3, 60.4]	[2, 50]
Annual Sales (Billion Yen)	0.28	0.16
	[0.05, 2.2]	[0.02, 1.63]
(ii) Industry Composition		
Proportion (Manufacturing)	0.29	0.19
Proportion (Commerce)	0.28	0.31
Proportion (Construction / Equipment Services)	0.27	0.26
Proportion (Others)	0.14	0.22
Sample Size	421	669,441

(B) Treatment Suppliers (Firms experiencing Unanticipated Bankruptcies)

	Treatment Suppliers	All Firms (At least One Buyer)
(i) Firm Size		
Number of Buyers	2	2
	[0, 6]	[1, 10]
Number of Employees	10	12
	[2, 39.6]	[3, 90]
Annual Sales (Billion Yen)	0.28	0.36
	[0.07, 1.47]	[0.05, 3.95]
(ii) Industry Composition		
Proportion (Manufacturing)	0.31	0.28
Proportion (Commerce)	0.36	0.34
Proportion (Construction / Equipment Services)	0.21	0.2
Proportion (Others)	0.11	0.16
Sample Size	161	287,124

B.2 Impacts on Separation with a Supplier Used for Assigning Treatment Firms and Control Firms

One should note that the impact of supplier bankruptcy identified by regression (1) is different from that of supplier *separation.* This is true for two reasons. First, not all bankruptcies will lead to an immediate exit of the firm. Second, control firms may also lose suppliers (due to anticipated bankruptcies, exits, or link severances). Figure B.1 shows that one unanticipated supplier bankruptcy results in an average of 0.75 to 0.8 supplier separations.

Figure B.1: Separation with a Supplier Used for Assigning Treatment Firms to Control Firms
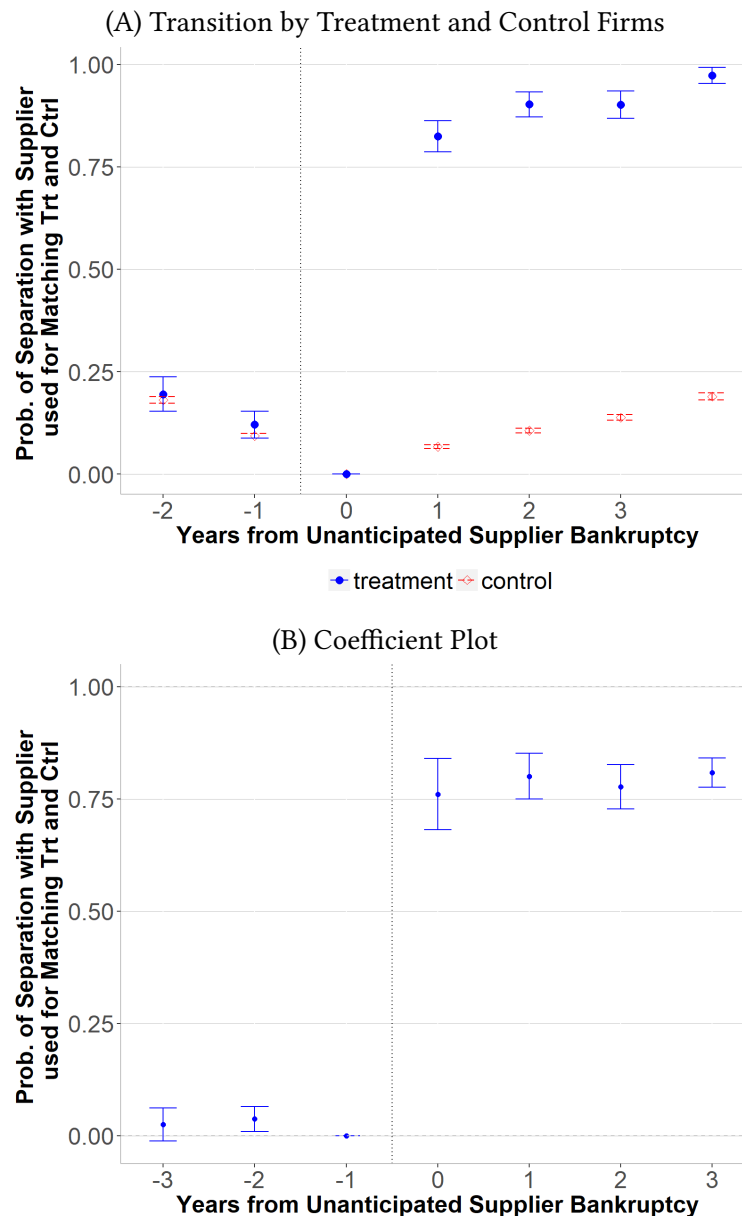
Note: Panel (A) shows the trajectory of the separation probability with the supplier used for assigning treatment firms to control firms. (For treatment firms, it is the bankrupting supplier, and for control firms, it is a randomly-picked supplier within the same four-digit supplier industry). Panel (B) shows the coefficients of the event-study regression (1) on the same outcome variable. See the footnote of Figure B.2 for more detail about the specification.

B.3 Additional Tables and Figures from Reduced-Form Section

Table B.3: Decomposition of Impacts on Newly Matched Suppliers

	Dependent Variable: Number of New Suppliers within Specified Subset				
	All	Within 4-digit Industry	Within 2-digit Industry	Headquarter in Same Prefecture	Has Buyer in Same Prefecture
	(1)	(2)	(3)	(4)	(5)
Trt x 1[t - BankruptYear = 2 or 3]	0.29***	0.07***	0.10***	0.16***	0.16***
	(0.07)	(0.02)	(0.03)	(0.04)	(0.05)
Random Matching Benchmark (Impacts after 2-3 Years)	0.29	0.001	0.007	0.013	0.004
Actual Impacts / Random Matching Benchmark	1	52	14	13	37

Note: The regression specification follows equation (1). The outcome variables are the number of newly matched suppliers (i.e., number of suppliers which are *not* connected in the baseline period) within a specified subset of potential suppliers in each column. Only the impacts after two or three years from the shock are reported. To benchmark the results, Column (1) reproduces the impacts on the number of all new suppliers (Column 2 of Table 3). Columns (2) and (3) report the impacts on the number of newly matched suppliers within the same industry as the bankrupting suppliers. Column (4) reports the impacts on the number of newly matched suppliers whose headquarters are located in the same prefecture as the treatment firms. Column (5) report the impacts on the number of newly matched suppliers that already have existing buyers in the treatment firm's prefecture (at the point of 2008). The row "Random Matching Benchmark" indicates the hypothetical impacts if treatment firms randomly matched with a supplier independent of the supplier's industry or location. The row "Actual Impacts/Random Matching Benchmark" indicates the ratio of the estimated coefficients and the hypothetical impacts under the random matching benchmark. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.4: Impacts on Other Existing Suppliers

	Continued Relationships with Other Suppliers	Proportion of Exit of Other Suppliers	log Sales of Other Surviving Suppliers
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = -2 or -3]	−0.06		−0.01
	(0.06)		(0.01)
Trt x 1[t - BankruptYear = -1]			
	(0.00)		(0.00)
Trt x 1[t - BankruptYear = 0 or 1]	0.02	0.004	0.01
	(0.04)	(0.003)	(0.01)
Trt x 1[t - BankruptYear = 2 or 3]	−0.06	0.01	0.03
	(0.05)	(0.005)	(0.02)
Observations	76,054	67,573	66,784

Note: The regression specification follows equation (1). Column (1) takes the outcome variables as the number of continued relationships with other existing suppliers (i.e., the number of reported suppliers which are connected in the baseline period (one year before the bankruptcy)). In Column (2), the outcome variable is the fraction of suppliers that exit out of the suppliers that firm i has at the point of the baseline period (one year before the shock), excluding the supplier experiencing unanticipated bankruptcies. Treatment firms that have no suppliers other than the bankrupting ones are omitted. In Column (3), the outcome variable is the mean of the log sales of firm i's other suppliers, where other suppliers are defined similarly as in Column (2). For each control firm in group g, I impose the inverse of the number of control firms within group g as the regression weight. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.5: IV Impacts of Number of Suppliers on Sales Growth

| | | ΔSales | |
| | OLS | IV | IV |
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = 0 or 1]	-0.027^*		
	(0.016)		
Trt x 1[t - BankruptYear = 2 or 3]	-0.033		
	(0.025)		
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.007		
	(0.014)		
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.023		
	(0.025)		
Number of Suppliers		0.056	0.058^*
		(0.035)	(0.033)
Number of Suppliers x log Seller Density (Std.)			0.007
			(0.026)
First Stage F-Statistics		14.9	14.9
Observations	63,202	63,202	63,202

Note: The table reports the results of the following IV regression:

$Y_{it} = \beta \text{NumberSuppliers}_{it} + \gamma \text{NumberSuppliers}_{it} \times \log SellerDensity_g + \epsilon_{it}$, where $\text{NumberSuppliers}_{it}$ is the number of suppliers of firm i in period t, and Y_{it} is the sales growth. I instrument $\text{NumberSuppliers}_{it}$ and $\text{NumberSuppliers}_{it} \times \log SellerDensity_g$ by the variation induced by the unanticipated supplier bankruptcies, i.e., $Trt_i \times Post_{gt}$ and $Trt_i \times Post_{gt} \times \log SellerDensity_g$. For each control firm in group g, I impose the inverse of the number of control firms within group g as the regression weight. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.
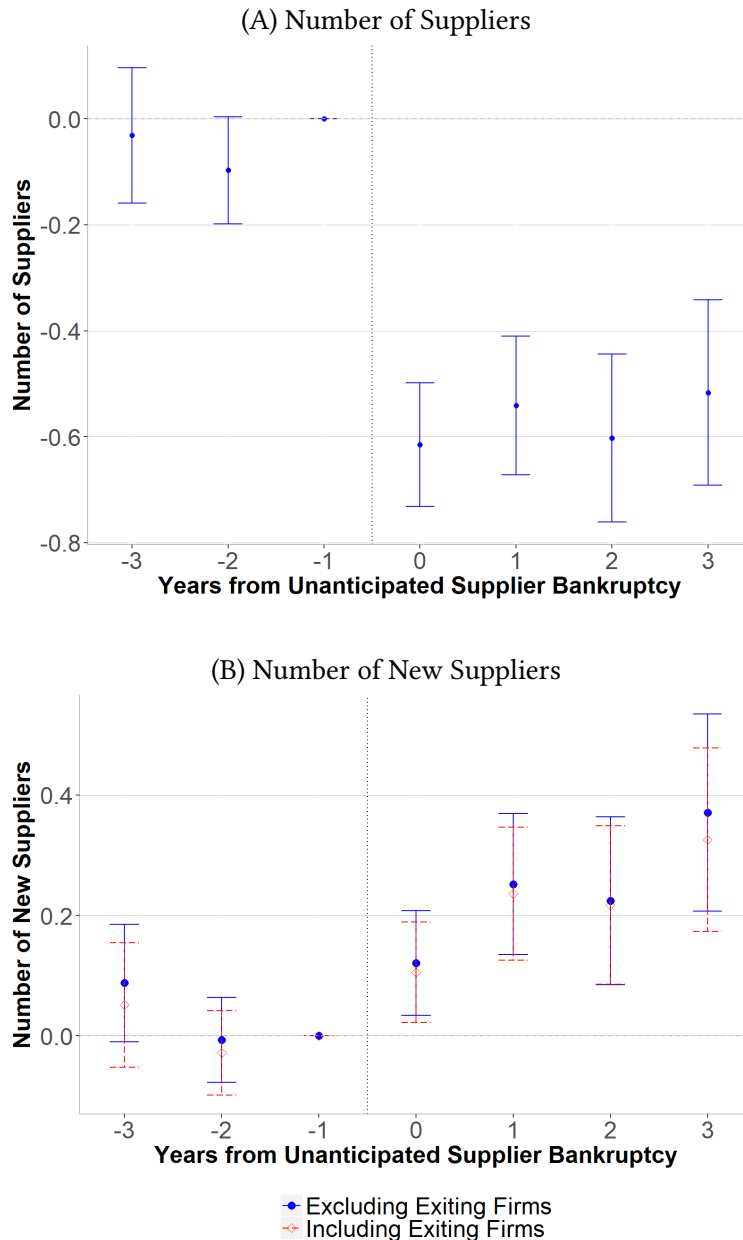
Figure B.2: Average Impacts of Unanticipated Supplier Bankruptcy on Supplier Matching

(A) Number of Suppliers

(B) Number of New Suppliers

- Excluding Exiting Firms
- Including Exiting Firms

Note: The figures plot the coefficients and the 95 percent confidence intervals of the coefficients of the regression (1). See Table 3 for the same results in the regression table format. Panel (A) reports the impacts on the total number of suppliers reported by each firm in the TSR data set in each year. Panel (B) reports the impacts on the number of reported suppliers which are *not* connected in the baseline period (one year before the bankruptcy). In Panel (B), "Excluding Exiting Firms" corresponds to the case in which I treat the observation as missing, and "Including Exiting Firms" corresponds to the case in which I insert the value of the outcome variable at the last time the firm is observed. For each control firm in group g, I impose the inverse of the number of control firms within group g as the regression weight. Standard errors are clustered at the firm level.

B.4 Robustness of the Heterogeneous Effects of Unanticipated Supplier Bankruptcies by Supplier Density

This subsection describes robustness of the results reported in Section 3.2.2.

B.4.1 Baseline Robustness

Table B.6 shows further robustness of the results presented in Table 4 with restricted samples and alternative specifications. Each column corresponds to a different sample restriction. Panel A corresponds to the specification where Z_g is just the geographic area of the prefecture, while Panel B corresponds to the specification where Z_g is a set of prefecture fixed effects.

Column (1) shows that the results are robust by including exiting firms in the sample. For firms that drop out of the sample, missing values of the outcome variable are filled with the value of the outcome variable observed in the last period in which the firm was alive.

Columns (2) and (3) show that the results are robust by dropping the locations and time periods that had large-scale economic disturbances. Column (2) excludes the bankruptcies of suppliers in the Tohoku area after 2011 (the year of the Great Tohoku Earthquake). Column (3) eliminates all supplier bankruptcies in 2009 (the year subsequent to the Financial Crisis). These robustness exercises alleviate the concern that control firms are somehow affected by the underlying shocks.

Column (4) shows that the results are robust to including only firms that do not have establishments outside of their headquarter prefectures. This sample restriction alleviates the concern that, in the main results, supplier density is not evaluated at the relevant location (I observe supplier relationships at the firm level, not at the establishment level). A similar concern is that firms tend to locate their headquarters in Tokyo, regardless of the location of the actual economic activity. Hence, the density of suppliers in Tokyo prefecture may not be accurately measured. Column (5) shows that the results are not driven by samples headquartered in Tokyo prefecture.

In Column (6) and (7), I show that the results are not driven by the particular sampling of the TSR data set. In Column (6), I exclude the samples where the accounting year of the last available financial statement is not updated from the baseline period (one year before the shock). This may happen if TSR has not conducted interviews since the baseline period, and hence supplier information is not updated.[50] Another concern is that the outcome variable (the number of newly matched suppliers) is driven by the probability that the reported supplier is covered in the TSR's data set. As discussed in Section 2, the TSR data set covers nearly 90% of economically non-negligible firms (firms with equal to or more than 5 employees) and has broadly representative patterns across different locations (Appendix Figure A.1). However, to further alleviate this concern, Column (7) shows that the results are robust to adjusting the number of reported suppliers by the sampling probability based on the supplier location.[51]

Lastly, Column (8) uses the birthplace of the representative of the firm as a potential source of exogenous variation of supplier density. The TSR data set reports the birth prefecture of the CEOs. Within the samples used for the reduced-form exercise, about 68% of firm CEOs are born in the firm's headquarter prefecture. This indicates that firm CEOs have high tendency to run businesses in their birth prefectures. To the extent that firm CEOs cannot choose their birth locations, the variation of the CEOs' birthplace gives an

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[50]Another possibility is that TSR conducts interviews but the latest financial account is not ready. Unfortunately, the date when the interview is conducted is not available.

[51]More concretely, I define the outcome variable as $\sum_{s \in NewSupplier(i)} 1/SampleRate_s$, where $NewSupplier(i)$ is the set of new suppliers of firm i. $SampleRate_s$ is the sampling rate of the TSR data set relative to the economic census (see Appendix Figure A.1) evaluated at the supplier s's headquarter municipality.

exogenous variation of supplier density at the point of unanticipated supplier bankruptcies.[52] Following this idea, Column (8) instruments supplier density proxy by the supplier density evaluated at the birth prefecture of the firm CEOs. Panel (A) marginally loses significance at the 10 percent nominal value, but the point estimates are similar to the baseline results. This result alleviates the endogeneity concern that unobserved (comparative) advantage in matching with alternative suppliers is correlated with supplier density proxy.

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[52]Bleakley and Lin (2012) also exploit individuals' birth place as an exogenous variation to separate the agglomeration effect from selection.

Table B.6: New Supplier Matching: Robustness

	Include Exiting Firms	Exclude Tohoku After 2011	Exclude Bankruptcy in 2009	Exclude Multi-Establishment	Exclude Tokyo	Exclude No Update in Accounting Year	Adjust Sampling Rate	IV: Seller Density in Birth Prefecture
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Baseline							
Trt x 1[t - BankruptYear = 0 or 1]	0.16*** (0.05)	0.15*** (0.05)	0.15*** (0.05)	0.15*** (0.05)	0.15*** (0.05)	0.15*** (0.06)	0.27*** (0.07)	0.15*** (0.05)
Trt x 1[t - BankruptYear = 2 or 3]	0.26*** (0.07)	0.23*** (0.08)	0.28*** (0.08)	0.22*** (0.08)	0.26*** (0.08)	0.27*** (0.08)	0.39*** (0.11)	0.25*** (0.08)
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.10** (0.05)	0.10* (0.05)	0.10* (0.05)	0.16*** (0.06)	0.10** (0.05)	0.10* (0.06)	0.16** (0.07)	0.09 (0.05)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.13* (0.07)	0.17** (0.08)	0.13* (0.08)	0.23*** (0.08)	0.15* (0.08)	0.14* (0.08)	0.18 (0.11)	0.14 (0.08)
	Panel B. Include Trt x Post x Prefecture FE							
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.13*** (0.05)	0.12** (0.05)	0.13** (0.05)	0.18*** (0.05)	0.14*** (0.05)	0.13** (0.06)	0.22*** (0.08)	0.14** (0.06)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.21*** (0.07)	0.19** (0.08)	0.14* (0.08)	0.23*** (0.08)	0.22*** (0.08)	0.20** (0.08)	0.33*** (0.11)	0.28*** (0.10)
Number of Treatment Firms	421	400	368	334	374	421	421	386
Number of Bankrupting Suppliers	161	154	138	136	145	161	161	154
Number of Control Firms	10,842	10,613	9,137	7,889	6,625	10,842	10,842	9,820
Observations	76,054	71,676	64,447	53,520	45,727	69,094	76,054	66,280

Note: The regression specification follows equation (2). See the footnote of Table 4 for the details of the specification. Panel A corresponds to the specification in which I control for the geographic area of prefecture as Z_g, and Panel B corresponds to the specification where prefecture fixed effects are included as Z_g. Each column represents a robustness specification indicated at the top row. In Column (1), if firms exit, I insert the value of the outcome variable as the last time when the firm was alive. Column (2) excludes the bankruptcies of suppliers in the Tohoku area after 2011 (the year of the Great Tohoku Earthquake). Column (3) eliminates all supplier bankruptcies in 2009 (the year subsequent to the Financial Crisis). Column (4) only includes firms which do not have establishments outside their headquarter prefecture. Column (5) excludes firms with headquarters in Tokyo prefecture. Column (6) excludes the samples where the accounting year of the last available financial statement is not updated from the baseline period (one year before the shock). Column (7) adjusts the number of reported suppliers by the sampling probability based on the supplier location. More concretely, I define the outcome variable as $\sum_{s \in NewSupplier(i)} 1/SampleRate_s$, where $NewSupplier(i)$ is the set of new suppliers of firm i, and $SampleRate_s$ is the sampling rate of the TSR data set relative to economic census (i.e., Appendix Figure A.1), evaluated at the supplier s's headquarter municipality. Column (8) instruments supplier density proxy by the supplier density evaluated at the birth prefecture of the firm CEO. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

B.4.2 Alternative Definitions of Supplier Density

Appendix Table B.7 shows the robustness of the results to alternative definitions of supplier density. In Column (1), rather than evaluating the supplier density in 2008, I evaluate the supplier density right before each supplier bankruptcy. In Column (2), I define supplier density based on the suppliers' headquarter locations, i.e., I count the suppliers headquartered in the treatment firm's prefecture. The results are robust to these alternative definitions.

Columns (3) and (4) investigate the robustness at different levels of classifications of industry and geography. In Column (3), I show that the results are robust to defining the industry of suppliers at the two-digit level (instead of four-digit level). In Column (4), I specify the geographic unit by municipalities, a finer geographic unit than the baseline definition of prefectures.[53] Column (4) loses significance and the coefficients are much smaller than the baseline specification. This indicates that defining the supplier density at too fine a spatial level results in a noisy proxy.

Table B.7: New Supplier Matching: Alternative Definitions of Supplier Density

	Number of New Suppliers			
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.13***	0.11**	0.10**	0.05
	(0.05)	(0.05)	(0.04)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.22***	0.25***	0.13**	0.09
	(0.07)	(0.07)	(0.06)	(0.06)
Trt x Post x Buyer Prefecture FE	X	X	X	X
Definition of Seller Density	Evaluated Right Before Bankrutpcy	Count Locally-Headquarterd Suppliers	Defined by Two-Digit Supplier Industry	Defined by Municipality
Observations	76,054	76,054	76,054	75,902

Note: Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

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[53]There are 1719 municipalities and 47 prefectures in Japan in 2013. In 2008, 16% of all supplier linkages are within municipalities, and 50% of all supplier linkages are within prefectures.

B.4.3 Dividing Samples to Manufacturing and Non-manufacturing Supplier Bankruptcies

Appendix Table B.8 shows separate results for cases in which bankrupt suppliers are in the manufacturing sector (Columns 1 and 2) and the non-manufacturing sector (Columns 3 and 4). In both cases, the average impacts on the number of new suppliers is significantly positive (Columns 1 and 3). At the same time, the average impact is smaller for the manufacturing sector than for the non-manufacturing sector bankrupt- cies. This suggests that it is harder to replace bankrupt manufacturing suppliers than non-manufacturing suppliers (for instance, commerce or construction/equipment services). In both manufacturing and non-manufacturing supplier bankruptcies, the heterogeneous impacts with respect to supplier density is posi- tive and large relative to the average impacts. However, I lose significance of the heterogeneous effect for manufacturing bankruptcy due to the smaller average impacts and reduced sample size.

Table B.8: New Supplier Matching: Manufacturing vs Non-manufacturing Supplier Bankruptcy

| | Dependent Variable: Number of New Suppliers | | | |
| | Manufacturing Bankruptcy | | Non-manufacturing Bankruptcy | |
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1]	0.08		0.20***	
	(0.08)		(0.07)	
Trt x 1[t - BankruptYear = 2 or 3]	0.21*		0.29***	
	(0.12)		(0.09)	
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.06	0.07	0.08	0.11
	(0.07)	(0.07)	(0.07)	(0.07)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.14	0.12	0.17	0.23**
	(0.11)	(0.10)	(0.10)	(0.09)
Trt x Post x Buyer Prefecture FE		X		X
Number of Treatment Firms	158	158	185	185
Number of Bankrupting Suppliers	49	49	83	83
Number of Control Firms	1,040	1,040	1,451	1,451
Observations	7,533	7,533	65,870	65,870

Note: Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

B.4.4 Reverse Reporting

Table B.9 shows the robustness by including supplier-reported linkages when constructing the outcome variables (the number of newly matched suppliers). Results are qualitatively similar to the baseline specification, as long as the outcome is windsorized at the tail of the distribution. Windsorization is necessary due to the thick-tailed distribution of the outcome variable.

Table B.9: New Supplier Matching: Include Reverse Reporting

	Number of New Suppliers			
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1]	0.13*		0.22***	
	(0.08)		(0.07)	
Trt x 1[t - BankruptYear = 2 or 3]	0.21		0.49***	
	(0.19)		(0.16)	
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.11	0.24**	0.12*	0.22**
	(0.08)	(0.12)	(0.07)	(0.10)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.25	0.43	0.28	0.32
	(0.28)	(0.44)	(0.23)	(0.35)
Trt x Post x Buyer Prefecture FE		X		X
Windsorize	90 Percentile	90 Percentile	80 Percentile	80 Percentile
Observations	73,422	73,422	73,422	73,422

Note: The table reports the robustness of the results in Table 4 by including the supplier linkages only reported by the supplier-side firms (in addition to the buyer-reported suppliers) in the outcome variable. Due to the thick tail nature of the outcome variable, I windsorize the outcome variables at the 90th and 80th percentiles. See the footnote of Table 4 for other details of the specification. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

C Model Appendix

C.1 Details of Characterizing Steady-State Equilibrium

This appendix provides the details of the equilibrium characterization as outlined in Section 4.2.

C.1.1 Unit Cost Distribution Given Distribution of Intermediate Input Costs

I first derive the unit cost distribution of producers at each location. As noted in Section 4.1.1, the unit cost distribution depends on the exogenous productivity, wage, and the intermediate input cost, where the input cost is stochastically determined through supplier matching.

Denote the steady-state distribution of the unit cost of intermediate input goods in sector k that firms in location i and sector m face as $G^I_{i,km}(\cdot)$. $G^I_{i,km}(\cdot)$ depends both on the probability of matching with a supplier, as well as the distribution of the sales prices of the suppliers selling in location i. In this subsection, I derive the unit cost distribution of firms in location i and sector m given $G^I_{i,km}(\cdot)$. $G^I_{i,km}(\cdot)$ is the mixture of the intermediate input price when a firm is directly matched with a supplier, and also when the firm is going through fringe intermediaries. In Section C.1.4, I characterize $G^I_{i,km}(\cdot)$ and fully derive the unit cost distribution.

Denote the measure of firms in location i in sector m whose unit cost of input goods is below c by $H_{i,m}(c)$. $H_{i,m}(c)$ is derived from equations (4) and (5) as

$$
\begin{aligned}
H_{i,m}(c) &= \int_{p_1,\ldots,p_K} \mu_{i,m}\left(\frac{c}{w_i^{\gamma_{L,m}}\prod_{k\in K}p_k^{\gamma_{km}}}\right)\prod_{k\in K}dG^I_{i,km}(p_k) \\
&= \left(\tilde{A}_{i,m}w_i^{-\theta\gamma_{L,m}}\prod_{k\in K}\int_{p_k}p_k^{-\theta\gamma_{km}}dG^I_{i,km}(p_k)\right)c^{-\theta} \\
&\equiv \Gamma_{i,m}c^{-\theta}.
\end{aligned}
\tag{18}
$$

Here I used the assumption that the matching probability with suppliers are independent across input sectors if a firm matches with a supplier in multiple input sectors (Section 4.1.2). Equation (18) shows that the unit cost distribution also follows the power law. The location of the distribution (i.e., $\Gamma_{i,m}$) depends on the exogenous location and sector productivity ($\tilde{A}_{i,m}$), labor cost (w_i), and the input cost for each input sector ($\int_{p_k}p_k^{-\theta\gamma_{km}}dG^I_{i,km}(p_k)$).

C.1.2 Input Sellers' Pricing Follows a Constant Mark-up Rule

In this subsection, I show that there is an equilibrium where input sellers post prices following a simple constant markup rule. That is, an input seller in sector k posts a price $p = \psi_{km}c$ to buyers in sector m, where $\psi_{km} \equiv 1 + (\gamma_{km}\theta)^{-1}$, and c is its contemporaneous unit cost net of iceberg trade cost.

The argument follows in two steps. In Step 1, I argue that there is a unique cut-off of contemporaneous unit cost c (net of iceberg trade cost) below which firms enter in location j as an input seller. In Step 2, I argue that there is an equilibrium in which input sellers follow constant mark-up pricing.

Step 1. There is a unique entry cut-off of the unit cost c to enter as a seller in each location.

I first define $J_{j,km}(c)$, an instantaneous profit of sector-k firms from intermediate goods sales to buyers in location j and sector m, if the firm's unit cost to sell in location j is c (net of iceberg trade cost). Note that this only depends on the contemporaneous unit cost c, because of the assumption that the unit cost of

intermediate inputs production for matched buyers is held fixed at the point when they match. (See the end of Section 4.1.2). I argue that $J_{j,km}(c)$ is strictly decreasing in c. To see this, consider two firms, firm 1 and 2, with different unit cost c_1 and c_2 ($c_1 > c_2$). Assume that seller 1's optimal price is p_1. Then, by posting the same price, seller 2 obtains strictly higher expected profit. This indicates that $J_{j,km}(c_1) < J_{j,km}(c_2)$. This shows that $J_{j,km}(c)$ is strictly decreasing in c.

Given that $J_{j,km}(c)$ is strictly increasing in c, it is immediately clear that there is a unique cutoff of entry. To see this, note that a potential input seller with a unit sales cost c in location j (net of iceberg trade cost) decide to enter as an input seller if and only if $\sum_{m \in K} J_{j,km}(c) \geq f_{j,k}^I w_j$ (i.e., the sum of the expected profit supersedes the fixed cost payment). Because $J_{j,km}(c)$ is strictly increasing in c for each $m \in K$, this derives the unique cut-off $\bar{c}_{j,k}$ below which all firms enter as a seller.

Step 2. **There is an equilibrium in which input sellers post prices following a constant mark-up ratio**: $p = \psi_{km} c$.

To derive the optimal pricing of input sellers, consider a marginal proportional change of price from p to $p\Delta$ (where $\Delta \approx 1$). I consider how the expected revenue changes by this price change.

Given that the matching rate with buyers is independent of the posted price p, the change of the seller's expected revenue is entirely driven by the input demand from the matched buyer (i.e., intensive margin). From the perspective of the matched buyer, the increase of price from p to $p\Delta$ implies that its input cost increases proportionally by $\Delta^{\gamma_{km}}$, where γ_{km} is the Cobb-Douglas input share of the intermediate goods from the supplier.

Now, I argue that the proportional increase of input cost by $\Delta^{\gamma_{km}}$ leads to a proportional decrease of input demand by $\Delta^{\theta \gamma_{km}}$. To see this, I first assume that firms indeed follow a constant mark-up pricing. Under this assumption, input demand of the matched buyer is a constant fraction of its sales (from Cobb-Douglas production function). Now, given the existence of entry cut-off of unit cost, the proportional increase of unit cost by $\Delta^{\gamma_{km}}$ leads to the reduction of the fraction of firms entering in each market by $\Delta^{\theta \gamma_{km}}$ in proportion, where θ is the exponent of the productivity distribution. Because the expected sales do not depend on the unit cost *conditional on entry* under the power-law distribution of unit cost, the expected sales from matched buyers also increases by $\Delta^{\theta \gamma_{km}}$ in proportion.

The above argument implies that the elasticity of expected revenue with respect to input demand is constant at $-\gamma_{km}\theta$. It then follows from a standard monopoly pricing that the seller charges a price with mark-up ratio with the inverse of this elasticity. This leads to the mark-up ratio stated above.

C.1.3 Gravity Equations of Intermediate Input Goods Markets

First, I argue that the extensive margin share of intermediate goods sourcing, i.e., the fraction of intermediate goods sellers from a particular origin across all source locations, follows the gravity equation specified in equation (13).

Given the presence of unique entry cut-off of the unit cost (Section C.1.2), together with the unit cost distribution of production (Section C.1.1), it is immediately clear that the fraction of input sellers producing in location i among all input sellers which enter in location j is expressed as equation (13), reproduced here:

$$\pi_{ij,m}^I = \frac{\Gamma_{i,m} \left(\tau_{ij,m}\right)^\theta}{\sum_{i' \in N} \Gamma_{i',m} \left(\tau_{ij,m}\right)^\theta}.$$

Furthermore, because of the random matching assumption (the matching probability with a supplier

does not depend on the supplier's production location *conditional on supplier's entry*), the fraction of *matched* intermediate goods sellers from origin i among all *matched* suppliers follows the same gravity equation.

Now, I argue that $\pi_{ij,m}^I$ also corresponds to the intermediate goods expenditure share from a supplier producing in location i out of all input expenditure by firms producing in location j toward input sector m. The logic follows the standard Melitz model with power-law productivity distribution (Chaney 2008). Because of the power-law productivity distribution, the expected profit and revenue from intermediate goods sales *conditional on entry* is independent of the unit cost. Therefore, equation (13) also corresponds to the input expenditure share.

C.1.4 Full Characterization of Unit Cost Distribution

I now revisit Section C.1.1 to fully characterize the distribution of unit cost for production. In Section C.1.1, I derived the unit cost distribution for production given $G_{i,km}^I(\cdot)$, where $G_{i,km}^I(\cdot)$ is the steady-state distribution of input goods prices in sector k that firms in location i and sector m face. As noted already, $G_{i,km}^I(\cdot)$ is the mixture of the intermediate input cost when a firm is directly matched with a supplier, and also when the firm is going through fringe intermediaries.

To explicitly derive $G_{i,km}^I(\cdot)$, I denote the cumulative distribution function of the intermediate goods prices posted by sellers in location i by $F_{i,km}^I(\cdot)$. $G_{i,km}^I(\cdot)$ is then obtained as

$$G_{i,km}^I(c) = \Lambda_{i,km} \times F_{i,km}^I(c\psi_{km}) + \{1 - \Lambda_{i,km}\} \times F_{i,km}^I(c\psi_{km}\chi).$$

where ψ_{km} is the markup ratio, χ is the ad-valorem cost of going through fringe intermediaries, and $\Lambda_{i,km}$ is the steady-state probability of matching with a supplier. By plugging this in to the expression of $\Gamma_{i,m}$ in Section C.1.1, we have

$$\Gamma_{i,m} = \tilde{A}_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k \in K} \int_{p_k} p_k^{-\theta\gamma_{km}} dG_{i,km}^I(p_k)$$

$$= \tilde{A}_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k \in K} [\Lambda_{i,km} \times \int_0^{\bar{c}_{i,k}^I \psi_{km}} (c\psi)^{-\theta\gamma_{km}} dF_{i,km}^I(c\psi_{km}) +$$

$$\{1 - \Lambda_{i,km}\} \times \int_0^{\bar{c}_{i,k}^I \psi_{km}\chi} (c\psi\chi)^{-\theta\gamma_{km}} dF_{i,km}^I(c\psi_{km}\chi)]$$

Now, by noting that $F_{i,km}^I(\cdot)$ is the inverse of the Pareto distribution with exponent θ and the upper bound $\bar{c}_{i,k}^I$,

$$\int_0^{\bar{c}_{i,k}^I \psi_{km}} (c\psi_{km})^{-\theta\gamma_{km}} dF_{i,km}^I(c\psi_{km}) = \int_0^{\bar{c}_{i,k}^I \psi_{km}} z^{-\theta\gamma_{km}} \frac{\theta z^{\theta-1}}{\left(\bar{c}_{i,k}^I \psi_{km}\right)^\theta} dz$$

$$= \frac{1}{1 - \gamma_{km}} \left(\bar{c}_{i,k}^I \psi_{km}\right)^{-\gamma_{km}\theta}$$

Likewise,

$$\int_0^{\bar{c}_{i,k}^I \psi_{km}\chi} (c\psi_{km}\chi)^{-\theta\gamma_{km}} dF_{i,km}^I(c\psi_{km}\chi) = \frac{1}{1 - \gamma_{km}} \left(\bar{c}_{i,k}^I \psi_{km}\chi\right)^{-\gamma_{km}\theta},$$

Hence, $\Gamma_{i,m}$ is obtained as

$$\Gamma_{i,m} = \tilde{A}_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k\in K} \frac{\left(\bar{c}_{i,k}^I \psi_{km}\chi\right)^{-\gamma_{km}\theta}}{1-\gamma_{km}} \left\{1 - \Lambda_{i,km} + \Lambda_{i,km}\chi^{\gamma_{km}\theta}\right\}$$

$$\equiv A_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k\in K} \left(\bar{c}_{i,k}^I\right)^{-\gamma_{km}\theta} \left\{1 - \Lambda_{i,km} + \Lambda_{i,km}\chi^{\gamma_{km}\theta}\right\}$$

by normalizing $A_{i,m} \equiv \tilde{A}_{i,m} \prod_{k\in K} \frac{(\psi_{km}\chi)^{-\gamma_{km}\theta}}{1-\gamma_{km}}$. This is the same expression as given in equation (12).

C.1.5 Measure, Entry Cut-off, and Aggregate Profit of Intermediate Goods Sales

The logic of deriving the measure, entry cut-off, and the aggregate profit follows analogously from a standard Melitz model with power law productivity distribution (Chaney 2008, Arkolakis, Demidova, Klenow, and Rodríguez-clare 2008).

To derive these, I first define $\varphi_{j,km}^I(c)$ as the expected profit by sector-k firms from intermediate input sales in location j and sector m at each instantaneous period (if the firm enters in location j), when the firm's contemporaneous unit cost of selling to location j (net of iceberg trade cost) is c. From the discussion in Section C.1.2, the elasticity of the expected profit with respect to the input price is $-\gamma_{km}\theta$. Given the constant markup, $\varphi_{j,km}^I(c)$ is proportional to $c^{-\gamma_{km}\theta}$.

Now, because of the constant markup, the aggregate profit from the intermediate input sales at each period is a constant fraction $\left(\frac{(\gamma_{km}\theta)-1}{\psi_{km}}\right)$ of the aggregate input demand. This gives the following accounting relationship:

$$\frac{(\gamma_{km}\theta)-1}{\psi_{km}} Y_{j,km}^I = \int_0^{\bar{c}_{j,k}^I} \varphi_{j,km}^I(c) d\Omega_{j,k} c^{\theta},$$

where $\Omega_{j,k} \equiv \sum_{n\in N} \Gamma_{n,k}\tau_{nj,k}$, and $\Omega_{j,k}c^{\theta}$ is the distribution of unit cost (net of iceberg transport cost) by intermediate input sellers in location j. Solving the integration of the right-hand side using the property that $\varphi_{j,km}^I(c)$ is proportional to $c^{-\gamma_{km}\theta}$, I obtain

$$\frac{(\gamma_{km}\theta)-1}{\psi_{km}} Y_{j,km}^I = S_{j,k}^I \varphi_{j,km}^I(\bar{c}_{j,k}^I) \frac{1}{1-\gamma_{km}}, \tag{19}$$

where $\bar{c}_{j,k}^I$ is the entry cutoff of the unit cost in location j and sector k, and $S_{j,k}^I = \Omega_{j,k}\left(\bar{c}_{j,k}^I\right)^{\theta}$ is the measure of input sellers in location j and sector k.

Now, the break-even condition of the marginal sellers is

$$f_{j,k}^I w_j = \sum_{m\in K} \varphi_{j,km}^I(\bar{c}_{j,k}^I). \tag{20}$$

Reformulating equations (19) and (20), I obtain

$$S_{j,k}^I = \frac{1}{f_{j,k}^I w_j} \sum_{m\in K} \frac{1-\gamma_{km}}{1+\gamma_{km}\theta} Y_{j,km}^I, \tag{21}$$

and

$$\bar{c}_{j,k}^{I} = \left(\frac{S_{j,k}^{I}}{\sum_{i' \in N} \Gamma_{i',k} \left(\tau_{i'j,k} \right)^{\theta}} \right)^{1/\theta}, \tag{22}$$

which correspond to equations (14) and (15).

For later purposes, I also derive the aggregate profit for input goods sales in location j. To derive this, note that each firm has to pay $f_{j,k}^{I} w_j$ fixed cost for entry. Then, the aggregate profit net of fixed cost payment is derived as

$$\sum_{m \in K} \frac{(\gamma_{km}\theta)^{-1}}{\psi_{km}} Y_{j,km}^{I} - S_{j,k}^{I} f_{j,k}^{I} w_j = \frac{\gamma_{km}}{1 + \gamma_{km}\theta} Y_{j,km}^{I}, \tag{23}$$

where I use equation (21) for reformulation.

C.1.6 Measure, Entry Cut-off, and Aggregate Profit of Final Goods Sales

The derivation of the final goods seller entry is analogous to the intermediate goods market in Section C.1.5, except that final goods are not tradable across locations.

First, note that the CES utility and monopolistic competition (Section 4.1.5) implies that the mark-up ratio is $1/(\sigma - 1)$. Hence, the aggregate profit (without fixed cost payment) is $\frac{1}{\sigma} Y_{j,k}^{F}$. Denoting the profit from final goods sales (before paying a fixed cost) in location j by firms with unit cost c as $\varphi_{j,m}^{F}(c)$, together with the free entry condition of the marginal seller $\varphi_{j,m}^{F}(\bar{c}_{j,k}^{F}) = f_{j,k}^{F} w_j$,

$$
\begin{aligned}
\frac{1}{\sigma} Y_{j,k}^{F} &= \int_{0}^{\bar{c}_{j,k}^{F}} \varphi_{j,k}^{F}(c) d\Gamma_{i,k} c^{\theta}, \\
&= \Gamma_{j,k} \left(\bar{c}_{j,k}^{F} \right)^{\theta} f_{j,k}^{F} w_j \frac{\theta}{\theta - \sigma + 1}.
\end{aligned} \tag{24}
$$

By noting the measure of final goods sellers $S_{j,k}^{F} = \Gamma_{i,k} \left(\bar{c}_{j,k}^{F} \right)^{\theta}$, we have

$$S_{j,k}^{F} = \frac{\theta - \sigma + 1}{\theta \sigma} \frac{1}{f_{j,k}^{F} w_j} Y_{j,k}^{F}, \tag{25}$$

and

$$\bar{c}_{j,k}^{F} = \left(\frac{S_{j,k}^{F}}{\Gamma_{i,k}} \right)^{1/\theta}. \tag{26}$$

For later purposes, I also derive the aggregate profit for final goods sales in location j. To derive this, note that each firm has to pay $f_{j,k}^{F} w_j$ fixed cost for entry. Then, the aggregate profit net of fixed cost payment is derived as

$$\frac{1}{\sigma} Y_{j,k}^{F} - S_{j,k}^{F} f_{j,k}^{F} w_j = \frac{\sigma - 1}{\theta \sigma} Y_{j,k}^{F}, \tag{27}$$

where I use equation (25) for reformulation.

C.1.7 Aggregate Firm Profit and Total Intermediate Input Expenditure

There are two sources of firm profit: intermediate goods sales from various sales locations, and local final goods sales. From equations (23) and (27), aggregate profit by firms producing in location i and sector k is

given by

$$\Pi_{i,k} = \sum_{j \in N} \sum_{m \in K} \frac{\gamma_{km}}{1 + \gamma_{km}\theta} Y^I_{j,km} \pi_{ij,k} + \frac{\sigma - 1}{\theta\sigma} Y^F_{i,k},$$ (28)

which is the same expression as equation (16).

Now, I also derive the total intermediate input expenditure $Y^I_{i,km}$ by firms producing in location i and sector m toward input sector k. From Cobb-Douglas production function, $Y^I_{i,km}$ is a constant fraction of total input expenditure (including labor payment) excluding fixed cost payment. Hence,

$$
\begin{aligned}
Y^I_{i,km} &= \gamma_{km} \left\{ X^F_{i,m} + X^I_{i,m} - S^I_{j,m} f^I_{j,m} w_j - S^F_{j,m} f^F_{j,m} w_j - \Pi_{i,m} \right\}, \\
&= \gamma_{km} \left\{ \sum_{j \in N} \sum_{l \in K} \frac{\gamma_{ml}\theta}{1 + \gamma_{ml}\theta} Y^I_{j,ml} \pi_{ij,m} + \frac{\sigma - 1}{\sigma} Y^F_{i,m} \right\},
\end{aligned}
$$ (29)

where I used equations (9), (8), (23), (27) and (28).

C.1.8 Steady-State Equilibrium

The steady-state equilibrium is defined in Section 4.2. Here, I reproduce all the relevant equilibrium conditions. To minimize the number of endogenous variables, I use total expenditure conditions (8) and (9) to drop the aggregate intermediate goods sales $\{X_{i,k}^I\}$ and final goods sales $\{X_{i,k}^F\}$ from the equilibrium conditions. Then, the steady-state equilibrium is defined by aggregate intermediate goods demand $\{Y_{i,km}^I\}$ and final goods demand $\{Y_{i,k}^F\}$, intermediate goods expenditure shares $\{\pi_{i,k}\}$, unit cost distribution $\{\Gamma_{i,m}\}$, steady-state probability of matching with a supplier $\{\Lambda_{i,km}\}$, wages $\{w_i\}$, measure of intermediate goods sellers $\{S_{i,k}^I\}$, unit cost cut-off for input sellers $\{\bar{c}_{j,k}^I\}$, and firm profit $\{\Pi_{i,k}\}$, which satisfy:

(i) steady state probability of supplier matching (equation 6)

$$\Lambda_{j,km} = \delta_{j,km} \frac{\eta \left(S_{j,k}^I / Z_j\right)^\lambda}{\eta \left(S_{j,k}^I / Z_j\right)^\lambda + \rho_{j,km}},$$

(ii) gravity equations of intermediate goods trade (equation 13) and input cost advantage (equation 12),

$$\pi_{ij,km} = \frac{\Gamma_{i,m} \left(\tau_{ij,m}\right)^\theta}{\sum_{i' \in N} \Gamma_{i',m} \left(\tau_{i'j,m}\right)^\theta}$$

$$\Gamma_{i,m} = A_{i,m} w_i^{-\theta \gamma_{L,m}} \prod_{k \in K} \left(\bar{c}_{i,k}^I\right)^{-\gamma_{km}\theta} \left\{1 - \Lambda_{i,km} + \Lambda_{i,km}\chi^{\gamma_{km}\theta}\right\}$$

(iii) measures and the cutoff of input sellers (equations 14 and 15)

$$S_{j,k}^I = \frac{1}{f_{j,k}^I w_j} \sum_{m \in K} \frac{1 - \gamma_{km}}{1 + \gamma_{km}\theta} Y_{j,km}^I$$

$$\bar{c}_{j,k}^I = \left(\frac{S_{j,k}^I}{\sum_{i' \in N} \Gamma_{i',k} \left(\tau_{i'j,k}\right)^\theta}\right)^{1/\theta}$$

(iv) input goods demand (from equation 17)

$$Y_{i,km}^I = \gamma_{km} \left\{\sum_{j \in N} \sum_{l \in K} \frac{\gamma_{ml}\theta}{1 + \gamma_{ml}\theta} Y_{j,ml}^I \pi_{ij,m} + \frac{\sigma - 1}{\sigma} Y_{i,m}^F\right\}$$

(v) final goods demand (from equation 10) and firm profit (from equation 16)

$$Y_{i,k}^F = \alpha_k \left(w_i L_i + \sum_{m \in K} \Pi_{i,m} + T_i\right)$$

$$\Pi_{i,k} = \sum_{j \in N} \sum_{m \in K} \frac{\gamma_{km}}{1 + \gamma_{km}\theta} Y_{j,km}^I \pi_{ij,k} + \frac{\sigma - 1}{\theta\sigma} Y_{i,k}^F$$

(vi) trade balancing condition (from equations 8 and 11)

$$\sum_{k,m \in K} \sum_{j \in N} Y_{j,km}^I \pi_{ij,k} = \sum_{k,m \in K} Y_{i,km}^I - D_i$$

C.2 Computing counterfactual equilibrium

C.2.1 Shutting Down Increasing Returns to Scale in Matching

In this counterfactual simulation, I obtain the equilibrium configuration under a hypothetical scenario where the matching rate with a supplier $v\left(S_{j,k}^I/Z_i\right)$ is equalized across locations. To do this, I fix the counterfactual matching rate to be equalized at the average rate in the baseline equilibrium $\overline{v}_k$, and it does not depend on locations (i.e., set $\lambda = 0$). I denote $\hat{v}_{i,k} \equiv \overline{v}_k/v_{i,k}\left(S_{j,k}^I/Z_i\right)$, i.e., the proportional change of matching rate in this counterfactual simulation.[54]

Following the convention of exact hat algebra, I denote the proportional changes in equilibrium objects with hat, and the its level in the counterfactual equilibrium with prime. Then, given the baseline variables $\{\{\Lambda_{i,km}\}, \{\pi_{ij,k}\}, \{L_i\}, \{Y_{j,m}^I\}, \{T_i\}\}$, changes in the matching rate $\{\hat{v}_{i,k}\}$, and the structural parameters $\{\theta, \sigma, \lambda, \chi, \{\delta_{i,km}\}, \{\alpha_k\}, \{\gamma_{L,m}\}, \{\gamma_{km}\}\}$, the counterfactual equilibrium is solved as a solution to the following set of equations:

(i) steady state probability of supplier matching

$$\hat{\Lambda}_{i,km} = \frac{\hat{v}_{i,k}}{\hat{v}_{i,k}\Lambda_{i,km}/\delta_{i,km} + 1 - \Lambda_{i,km}/\delta_{i,km}}$$

(ii) gravity equations of intermediate goods trade and input cost advantage

$$\hat{\pi}_{ij,m} = \frac{\hat{\Gamma}_{i,m}}{\sum_{i'\in N}\hat{\Gamma}_{i',m}\pi_{ij,m}}, \quad \hat{\Gamma}_{i,m} = \hat{w}_i^{-\theta\gamma_{L,m}}\prod_{k\in K}\left(\hat{\tilde{c}}_{i,k}^I\right)^{-\gamma_{km}\theta}\left\{\frac{1 - \Lambda_{i,km}' + \Lambda_{i,km}'\chi^{\gamma_{km}\theta}}{1 - \Lambda_{i,km} + \Lambda_{i,km}\chi^{\gamma_{km}\theta}}\right\}$$

(iii) measures and the cutoff of input sellers

$$\hat{S}_{j,k}^I = \frac{1}{\hat{\tilde{c}}_{j,k}^I}\frac{\sum_{m\in K}(1-\gamma_{km})Y_{j,km}^{I'}/(1+\gamma_{km}\theta)}{\sum_{m\in K}(1-\gamma_{km})Y_{j,km}^I/(1+\gamma_{km}\theta)}, \quad \hat{\tilde{c}}_{j,k}^I = \left(\frac{\hat{S}_{j,k}^I}{\hat{\Gamma}_{j,k}/\hat{\pi}_{jj,k}^I}\right)^{1/\theta}$$

(iv) input goods demand

$$Y_{j,km}^{I'} = \gamma_{km}\left\{\sum_{j\in N}\sum_{l\in K}\frac{\gamma_{ml}\theta}{1+\gamma_{ml}\theta}Y_{j,ml}^{I'}\pi_{ij,m}' + \frac{\sigma-1}{\sigma}Y_{i,m}^{F'}\right\}$$

(v) final goods demand and firm profit

$$Y_{i,k}^{F'} = \alpha_k\left(w_i'L_i + \sum_{m\in K}\Pi_{i,m}' + T_i\right)$$

$$\Pi_{i,k}' = \sum_{j\in N}\sum_{m\in K}\frac{\gamma_{km}}{1+\gamma_{km}\theta}Y_{j,km}^{I'}\pi_{ij,k}' + \frac{\sigma-1}{\theta\sigma}Y_{i,k}^{F'}$$

---

[54]To avoid the case that $S_{j,k}^I/Z_i = 0$ in the data and hence $\hat{v}_{i,k}$ is not defined, I obtain $v_{i,k}$ from the zero profit condition (equation 14). This requires an auxiliary assumptions of $f_{j,k}^I$. Here, I assume that it is proportional to the geographic area of Z_j, i.e., $f_{j,k}^I = f_k^I Z_j$. This yields $\hat{v}_{i,k} = \left(\frac{1}{|N|}\sum_{j'\in N}\frac{1}{w_{j'}}\sum_{m\in K}\frac{1-\gamma_{km}}{1+\gamma_{km}\theta}Y_{j',km}^I/Z_j\right)^\lambda / \left(\frac{1}{w_j}\sum_{m\in K}\frac{1-\gamma_{km}}{1+\gamma_{km}\theta}Y_{j,km}^I/Z_j\right)^\lambda$ following equation (14).

(vi) trade balancing condition

$$\sum_{k,m \in K} \sum_{j \in N} Y_{j,km}^{I'} \pi_{ij,k}' - \sum_{k,m \in K} Y_{i,km}^{I'} = \sum_{k,m \in K} \sum_{j \in N} Y_{j,km}^{I} \pi_{ij,k} - \sum_{k,m \in K} Y_{i,km}^{I}$$

C.2.2   Change of Cross-Location Income Transfer

Denote the counterfactual configuration of income transfer $\{T_i'\}$. Given baseline variables $\{\{\Lambda_{i,km}\}, \{\pi_{ij,k}\}, \{L_i\}, \{Y_{j,m}^{I}\}\}$ and the parameters $\{\theta, \sigma, \lambda, \chi, \{\delta_{i,km}\}, \{\alpha_k\}, \{\gamma_{L,m}\}, \{\gamma_{km}\}\}$, the counterfactual equilibrium is solved as a solution to the following set of equations:

(i) steady state probability of supplier matching

$$\hat{\Lambda}_{i,km} = \frac{\left(\hat{S}_{i,k}^{I}\right)^{\lambda}}{\left(\hat{S}_{i,k}^{I}\right)^{\lambda} \Lambda_{i,km}/\delta_{i,km} + 1 - \Lambda_{i,km}/\delta_{i,km}}$$

(ii) gravity equations of intermediate goods trade and input cost advantage

$$\hat{\pi}_{ij,m} = \frac{\hat{\Gamma}_{i,m}}{\sum_{i' \in N} \hat{\Gamma}_{i',m} \pi_{ij,m}}, \quad \hat{\Gamma}_{i,m} = \hat{w}_i^{-\theta\gamma_{L,m}} \prod_{k \in K} \left(\hat{\hat{c}}_{i,k}^{I}\right)^{-\gamma_{km}\theta} \left\{ \frac{1 - \Lambda_{i,km}' + \Lambda_{i,km}' \chi^{\gamma_{km}\theta}}{1 - \Lambda_{i,km} + \Lambda_{i,km} \chi^{\gamma_{km}\theta}} \right\}$$

(iii) measures and the cutoff of input sellers

$$\hat{S}_{j,k}^{I} = \frac{1}{\hat{\hat{c}}_{j,k}^{I}} \frac{\sum_{m \in K}(1 - \gamma_{km})Y_{j,km}^{I'}/(1 + \gamma_{km}\theta)}{\sum_{m \in K}(1 - \gamma_{km})Y_{j,km}^{I}/(1 + \gamma_{km}\theta)}, \quad \hat{\hat{c}}_{j,k}^{I} = \left(\frac{\hat{S}_{j,k}^{I}}{\hat{\Gamma}_{j,k}/\hat{\pi}_{jj,k}^{I}}\right)^{1/\theta}$$

(iv) input goods demand

$$Y_{j,km}^{I'} = \gamma_{km} \left\{ \sum_{j \in N} \sum_{l \in K} \frac{\gamma_{ml}\theta}{1 + \gamma_{ml}\theta} Y_{j,ml}^{I'} \pi_{ij,m}' + \frac{\sigma - 1}{\sigma} Y_{i,m}^{F'} \right\}$$

(v) final goods demand and firm profit

$$Y_{i,k}^{F'} = \alpha_k \left(w_i' L_i + \sum_{m \in K} \Pi_{i,m}' + T_i' \right)$$

$$\Pi_{i,k}' = \sum_{j \in N} \sum_{m \in K} \frac{\gamma_{km}}{1 + \gamma_{km}\theta} Y_{j,km}^{I'} \pi_{ij,k}' + \frac{\sigma - 1}{\theta\sigma} Y_{i,k}^{F'}$$

(vi) trade balancing condition

$$\sum_{k,m \in K} \sum_{j \in N} Y_{j,km}^{I'} \pi_{ij,k}' - \sum_{k,m \in K} Y_{i,km}^{I'} = \sum_{k,m \in K} \sum_{j \in N} Y_{j,km}^{I} \pi_{ij,k} - \sum_{k,m \in K} Y_{i,km}^{I}$$

C.2.3 Counterfactual Changes in Consumer Price Index

In this subsection, I derive the expression for the counterfactual changes in consumer price index. Given the CES utility of consumers (Section 4.1.5), the counterfactual changes in final goods consumer price index is written as

$$
\begin{aligned}
\hat{P}_i &= \prod_{k \in K} \left((\hat{S}_{i,k}^F)^{\frac{1}{1-\sigma}} \hat{c}_{i,k}^F \right)^{\alpha_k} \\
&= \prod_{k \in K} \left((\frac{\hat{Y}_{i,k}^F}{\hat{w}_i})^{\frac{1}{\theta} - \frac{1}{\sigma - 1}} \hat{\Gamma}_{i,k}^{-\frac{1}{\theta}} \right)^{\alpha_k},
\end{aligned}
$$

where the transformation use the relationships in Section C.1.6.

C.3 Model Extensions

C.3.1 Labor Mobility

In this subsection, I consider an extension of the model where workers are mobile across locations. I assume that workers consume housing goods in addition to final goods, with Cobb-Douglas utility share β. In addition, each worker receives a preference shock to live in each location, $\epsilon = \{\epsilon_1, \ldots, \epsilon_N\}$. Together, the utility of a worker with shock ϵ by residing in location i is written as

$$
U_i(\epsilon) = \mathcal{A}_i \frac{w_i}{P_i^{1-\beta} R_i^{\beta}} \epsilon_i,
$$

where $\mathcal{A}_i$ is the exogenous amenity level of location i, P_i is the price index of final goods, and R_i is the rent in location i. For simplicity, I assume that the net current transfer T_i accrues to firm owners, and hence it does not enter in worker's location decision. I assume that housing supply in each location is exogenously fixed. From the land market clearing condition, the rent per area is determined as $R_i = \beta w_i L_i / Z_i$. Plugging this condition into the utility function, I obtain the indirect utility function $U_i(\epsilon) = \tilde{\mathcal{A}}_i Z_i^{-\beta} \left(\frac{w_i}{P_i} \right)^{1-\beta} (L_i)^{-\beta} \epsilon_i$, where $\tilde{\mathcal{A}}_i \equiv \mathcal{A}_i (Z_i / \beta)^{\beta}$.

I assume that ϵ_i is drawn from independent Fréchet distribution with dispersion parameter ν. By normalizing the total population $\overline{L} = \sum_i L_i = 1$, workers' optimal residential location choice problem yields the following condition:

$$
L_i = \frac{\tilde{\mathcal{A}}_i^{\frac{\nu}{1+\beta\nu}} \left(\frac{w_i}{P_i} \right)^{\upsilon}}{\sum_{i'} \tilde{\mathcal{A}}_{i'}^{\frac{\nu}{1+\beta\nu}} \left(\frac{w_{i'}}{P_{i'}} \right)^{\upsilon}}, \tag{30}
$$

where $\upsilon \equiv \frac{(1-\beta)\nu}{1+\beta\nu}$. The steady-state equilibrium with labor mobility is then defined by adding condition (30) to endogeneize $\{L_i\}$ in the set of equilibrium conditions presented in Section 4.2.

When conducting a counterfactual simulation, I need the value of υ, the elasticity of migration with respect to real labor income υ. I set this parameter to be 2, which is within the range of values in the previous estimates in Japan (Kondo and Okubo 2015).

C.3.2 Free Entry of Entrepreneurs

In this subsection, I discuss the extension of the model to incorporate entrepreneurs' free entry. As discussed in Section 4.3.1, this extension adds an additional layer of agglomeration feedback due to a home

market effect that is similar to the one presented by Krugman and Venables (1995).

In this extension, I first modify the measure of firms in each location (equation 5). I assume that the measure of firms in location i whose productivity is above φ is written as

$$\mu_{i,m}(\varphi) = B_i \tilde{A}_{i,m} \varphi^{-\theta},$$

where B_i is the measure of entrepreneurs who jointly own firms in location i. Following this modification, the measure of firms with unit cost below c is now modified to be $H_{i,m}(c) = \Gamma_{i,m} c^{-\theta}$, where

$$\Gamma_{i,m} = B_i A_{i,m} w_i^{-\theta \gamma_{L,m}} \prod_{k \in K} \left(\bar{c}_{i,k}^I \right)^{-\gamma_{km}\theta} \left\{ 1 - \Lambda_{i,km} + \Lambda_{i,km} \chi^{\gamma_{km}\theta} \right\}. \tag{31}$$

Entrepreneurs enter in various locations by paying a fixed cost F_i in the unit of local labor. The free-entry condition of the entrepreneurs is written as

$$B_i w_i F_i = \sum_{m \in K} \Pi_{i,m}. \tag{32}$$

where $\Pi_{i,m}$ is the aggregate firm profit given by equation (10).

Lastly, the total expenditure condition of final goods are now modified as

$$Y_{i,k}^F = \alpha_k \left(w_i L_i + T_i \right). \tag{33}$$

Unlike equation (10), firm profit $\Pi_{i,m}$ does not enter in this expression. This is because all firm profit is used to pay local labor through entrepreneurs' free-entry condition (32).

Together, the steady-state equilibrium with free entry of entrepreneurs is defined by the aggregate intermediate goods sales $\{X_{i,k}^I\}$ and final goods sales $\{X_{i,k}^F\}$, aggregate intermediate goods demand $\{Y_{i,km}^I\}$ and final goods demand $\{Y_{i,k}^F\}$, intermediate goods expenditure shares $\{\pi_{i,k}\}$, unit cost distribution $\{\Gamma_{i,m}\}$, steady-state probability of matching with a supplier $\{\Lambda_{i,km}\}$, wages $\{w_i\}$, measure of intermediate goods sellers $\{S_{i,k}^I\}$, unit cost cut-off for input sellers $\{\bar{c}_{j,k}^I\}$, firm profit $\{\Pi_{i,k}\}$, and the measure of entrepreneurs $\{B_i\}$, which satisfy total expenditure conditions (8), (9), (33) and (17), trade balancing conditions (11), gravity equations of intermediate goods (13), free entry condition for marginal input sellers (14) and (15), firm profit (16), the steady-state matching probability (6), the endogenous unit cost distributions due to input cost advantage terms (31), and the entrepreneurs' free-entry conditions (32).

D   Quantification Appendix

In this appendix, I describe the details of the estimation procedures of the key structural parameters governing the agglomeration force of the model. I first estimate the matching technology parameters (λ and η). After that, I estimate the input cost advantage of a direct supplier match (χ).

Before describing the estimation procedures, I make several comments about the mapping between the model and the data. First, I interpret all unanticipated supplier bankruptcies to correspond to exogenous supplier separation in the model. This includes cases where suppliers do not immediately exit after an unanticipated bankruptcy.

Second, I assume that a supplier linkage is observed in the data if a firm is directly matched with a supplier in the model. If the link is not reported in the data in each of the two-digit input sectors, I interpret that the firm is sourcing through fringe intermediaries.

Third, note that the supplier density measure in the reduced-form section ($SellerDensity$) is not exactly the same as the supplier density in the model ($S_{i,k}^{I}/Z_i$). Recall that the former is defined as the density of suppliers in sector k which have at least one buyer in location i in 2008. Through the lens of the model, these two measures are different, because the former includes suppliers that enter as a seller in location i in the past (and matched with a buyer), but do not currently enter as a seller. To obtain the model-consistent $S_{i,k}$, I exclude suppliers that do not acquire any new buyers until 2009 from the definition of supplier density in Section 3. When I simulate the "natural experiment" in the model, I use the above-mentioned definition of $S_{i,k}/Z_i$. In practice, these two measures are highly correlated with a correlation coefficient of over 0.9.

D.1   Estimation of Matching Technology Parameters λ and η

I denote the reduced-form estimates of the average and heterogeneous impacts of unanticipated supplier bankruptcies on the number of new suppliers by $\{\hat{\beta}^s, \hat{\gamma}^s\}$ (corresponding to the coefficients of regression 2), where s indicates the years from the supplier bankruptcy. I also denote the model prediction of these terms as $\{\tilde{\beta}^s(\eta,\lambda), \tilde{\gamma}^s(\eta,\lambda)\}$. I describe how I obtain these terms in the next paragraph. I estimate (η,λ) by minimizing the squared distance between $\{\hat{\beta}^s, \hat{\gamma}^s\}$ and $\{\tilde{\beta}^s(\eta,\lambda), \tilde{\gamma}^s(\eta,\lambda)\}$. Formally, the estimators of (η,λ) are defined as:

$$(\hat{\eta}, \hat{\lambda}) \equiv \arg\min_{\eta,\lambda} \sum_{s=0,1,2,3} \frac{\left(\tilde{\beta}^s(\eta,\lambda) - \hat{\beta}^s\right)^2}{\widehat{Var(\hat{\beta}^s)}} + \frac{\left(\tilde{\gamma}^s(\eta,\lambda) - \hat{\gamma}^s\right)^2}{\widehat{Var(\hat{\gamma}^s)}},$$

where $\widehat{Var(\hat{\beta}^s)}$ and $\widehat{Var(\hat{\gamma}^s)}$ correspond to the variance of the regression coefficients from the reduced-form regression (2) in Section 3.[55]

To obtain the model predicted values ($\{\tilde{\beta}^s(\eta,\lambda), \tilde{\gamma}^s(\eta,\lambda)\}$) for each value of (η,λ), I take the following steps. For each of the treatment firm ω, I first obtain the model-predicted probability that firm ω is matched with a new supplier in the bankrupting supplier's industry after s years from the supplier bankruptcy, $Match_{\omega,s}$. Within a reasonably small s, it is approximated by $Match_{\omega,s} = 1 - \exp(-\eta(S_{i,k}^{I}/Z_i)^\lambda s)$, where k is the industry of the bankrupting supplier. I use this expression for $Match_{\omega,s}$. Furthermore, within a

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[55]To obtain $\{\hat{\beta}^s, \hat{\gamma}^s\}$, I define the outcome variable to be the number of newly matched suppliers, without restricting the suppliers to be within the same sector as the bankrupting suppliers. Through the lens of the model, there is no difference in the matching rates with a supplier in other sectors between treatment and control firms (the matching rates are independent across input sectors within a firm). Empirically, while treatment firms have strong tendency to rematch within the bankrupting supplier's sector, they also rematch with suppliers in other sectors (Appendix Table B.3). The most plausible reason for this is due to the industry classification errors of the matched suppliers.

small s, control firms do not start to match with a new supplier. Hence, the model-predicted values of the regression coefficients ($\{\tilde{\beta}^s(\eta,\lambda),\tilde{\gamma}^s(\eta,\lambda)\}$) are obtained by running the following regression:

$$Match_{\omega,s} = \tilde{\beta}^s + \tilde{\gamma}^s \log SellerDensity_{\omega} + \epsilon_{\omega,s}. \tag{34}$$

It is intuitive that λ and η are uniquely identified by this procedure. To see this, note that $\tilde{\gamma}^s(\eta,\lambda)$ is monotonically increasing in λ from the expression of $Match_{\omega,s}$ (as long as $S^I_{i,k}/Z_i$ and $SellerDensity_{\omega}$ are sufficiently strongly correlated). Similarly, $\tilde{\beta}^s(\eta,\lambda)$ is increasing in η.

Following the procedure, I obtain the estimates of $\hat{\lambda} = 0.36$ and $\hat{\eta} = 0.026$. Column (1) and (2) of Table D.1 shows how these estimated values of $\hat{\lambda}$ and $\hat{\eta}$ replicate the reduced-form regression results. Column (1) is the estimates from the actual data, and Column (2) is the model prediction under the estimated parameters.

I follow a nonparametric bootstrapping procedure to obtain the confidence intervals of the estimated parameters $(\hat{\eta}, \hat{\lambda})$. More specifically, starting from the data set used in the reduced-form exercise in Section 3, I construct 100 sets of bootstrapped samples by redrawing the data at the group g level. For each bootstrapped data set, I follow the above procedure to obtain $(\hat{\eta}, \hat{\lambda})$. The 90 percentile confidence set of the parameters is obtained as the 5-th and 95-th percentiles of the estimated $(\hat{\eta}, \hat{\lambda})$. With this procedure, the confidence interval of $\hat{\lambda}$ is obtained as $[0.10, 0.74]$.

D.2 Input Cost Advantage of a Direct Supplier Match χ

I estimate χ after estimating λ and η. I choose χ that most closely replicates the average impacts on sales growth in Section 3. Denote the actual impact on sales growth following regression (1) by $\hat{\beta}^s$, and the model prediction of the equivalent as $\tilde{\beta}^s(\chi)$. The estimator of $\hat{\chi}$ is defined as:

$$\hat{\chi} \equiv \arg\min_{\chi} \sum_{s=0,1,2,3} \frac{\left(\tilde{\beta}^s(\chi) - \hat{\beta}^s\right)^2}{\widehat{Var(\hat{\beta}^s)}}.$$

To obtain $\tilde{\beta}^s(\chi)$, I take the following steps. Given the already estimated values of λ and η, I first obtain the difference of the probabilities that a firm ω has a supplier in sector k if treated and if untreated. If treated, firms lose all suppliers, but rematch with a new supplier with probability $Match_{\omega,s}$ (as defined in Appendix Section D.1). Hence, the desired probability is obtained as $1 - Match_{\omega,s}$.

I then obtain the model-predicted ratio in the expected sales between the treatment firm and control firm. To obtain this, first note that the ratio of the average unit cost between firms with and without a supplier in sector k is $\chi^{\gamma_{km}}$, where γ_{km} is the Cobb-Douglas input share of the bankrupting supplier's industry k. This translates to $\chi^{-\gamma_{km}\theta}$ ratio of the expected sales.[56] Given that treatment firms are $1 - Match_{\omega,s}$ less likely to be matched with a supplier than control firms, the ratio of the expected sales between the treatment and control firms is $(1 - Match_{\omega,s})\chi^{-\gamma_{km}\theta}$. Together, $\tilde{\beta}^s(\chi)$ is given as $(1 - Match_{\omega,s})\chi^{-\gamma_{km}\theta}E[Sales^{CTRL}_{\omega,s}]$, where $E[Sales^{CTRL}_{\omega,s}]$ is the control mean of the data.

It is intuitive that χ is uniquely identified by this procedure. This is because $\tilde{\beta}^s(\chi)$ is monotonically decreasing in χ given its expression (conditional on λ and η).

The above procedure obtains the estimates of $\hat{\chi} = 1.51$. Column (3) and (4) of Table D.1 shows how this estimated value replicates the reduced-form regression results. Column (3) is the estimates from the

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[56] θ matters, because higher θ implies that there are more sellers on the margin of starting to make sales in various sales locations. This follows from a standard logic of a Melitz model with power-law distribution (Chaney 2008).

actual data, and Column (4) is the model prediction under the estimated parameters.

The confidence set of $\hat{\chi}$ is obtained following the same bootstrapping procedure as in Section D.1. I obtain the 90% confidence interval of $[1.26, 1.90]$.

Table D.1: Reduced-Form Results of Unanticipated Supplier Bankruptcy and Model Prediction of the Response to Supplier Separation (Targeted Moments)

| | Number of New Suppliers | | Δ Sales | |
	Data	Model	Data	Model
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1]	0.152***	0.113	−0.027*	−0.035
	(0.049)		(0.016)	
Trt x 1[t - BankruptYear = 2 or 3]	0.263***	0.276	−0.031	−0.032
	(0.073)		(0.025)	
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.099*	0.088		
	(0.051)			
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.156**	0.186		
	(0.076)			
Observations	73,422		63,202	

D.3 Robustness Results of Counterfactual Simulation

Table D.2: Counterfactual Simulation Of Shutting Down Increasing Returns to Scale in Matching: Alternative Specifications

Specification	Percent Reduction in Population Density Premium in Wages
(1) $\theta = 4.3$, $\sigma = 5$ (Baseline Calibration)	32 %
(2) $\theta = 7.3$, $\sigma = 5$	20 %
(3) $\theta = 7.3$, $\sigma = 8$	20 %
(4) Incorporate Labor Mobility ($\theta = 4.3$, $\sigma = 5$, $v = 2$)	7 %
(5) Incorporate Free-Entry ($\theta = 4.3$, $\sigma = 5$)	21 %

Note: The table shows the percent reduction of the slope between log of nominal wages and log of population density under the counterfactual simulation of shutting down the increasing returns to scale in firm-to-firm matching ($\lambda = 0$). See Section 5.2.1 for more detail about the counterfactual simulation. Row (1) corresponds to the baseline specification, corresponding to Figure 2. Rows (2) and (3) change the values of θ and σ. Row (4) incorporates labor mobility following Appendix C.3.1. I set the parameter governing the elasticity of migration with respect to real labor income v as 2, which is within the range of values in the previous estimates in Japan (Kondo and Okubo 2015). Row (5) incorporates the free entry of entrepreneurs following Appendix C.3.2.