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

Yuhei Miyauchi

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Abstract

Why are economic activities geographically concentrated? In this paper, I argue that increasing returns in firm-to-firm matching is an important source of agglomeration. I open by providing reduced-form evidence of increasing returns in matching using a panel of firm-to-firm trade data covering over a million Japanese firms. Using unexpected supplier bankruptcies as an instrument, I show that the new supplier matching rate upon a supplier loss increases in locations and industries when there are more potential suppliers, while this rate remains stable in the presence of other downstream firms. I then develop a structural trade model with dynamic firm-to-firm matching in input trade. In this economy, the presence of more suppliers increases downstream aggregate sales, as improved supplier matching rates generate cost advantages; this, in turn, attracts more suppliers and leads to geographic concentration. I calibrate the model to match the reduced-form estimates, and I show that this type of circular causation explains a large part of the spatial disparity in Japan's economic activity. The estimated model also predicts that while subsidies for supplier market penetration in peripheral regions improves the welfare of these regions, improving transportation infrastructure between peripheral and central regions sometimes harms the periphery.

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1 Introduction

Economic activities are geographically concentrated. In the case of Japan, 50% of the firms are concentrated in only 3% of the usable area, as observed in Figure 1. There is no shortage of theories that explain why agglomeration may occur.[1] However, there is much less consensus about the empirical relevance of the various mechanisms that the literature proposes.

In this paper, I focus on one such mechanism for agglomeration: increasing returns in firm-to-firm matching in input trade. The idea is simple. In a location with more suppliers, downstream firms have a better chance of finding suitable suppliers for their production, which gives downstream firms a cost advantage and increases aggregate downstream sales. This, in turn, creates a larger market for upstream industries and thereby encourages more suppliers to sell in the location. While simple, the mechanism has important policy implications distinct from other sources of agglomeration. If agglomeration arises from local production externalities as is commonly assumed, the reallocation of productive resources is the key margin that policies should target. Here, however, it may be sufficient to simply improve the access to potential trading partners in distant locations; for example, by providing business matching opportunities or improving transportation access.

The first part of this paper uses a panel of firm-to-firm trade data for over one million Japanese firms to provide reduced-form evidence of increasing returns in firm-to-firm matching.[2] These data allow me to estimate the matching rate with new suppliers upon a supplier loss. If the matching rate improves in the presence of more potential suppliers, but does not decrease as much by the presence of other buyers, there is evidence of increasing returns in matching. To ensure the exogeneity of a supplier loss, I select plausibly unexpected bankruptcies of suppliers – accidental reasons (CEO death, naural disaster, etc.,) and spillovers from other bankruptcies – that are reported in the data set, and use them as instruments for a supplier loss.

The results are summarized as follows. First, I find that the matching rate increases in the number of potential suppliers that already serve other firms in the buyer's location. The magnitude is large: while a loss of one supplier leads to 0.16 new supplier matching per year within the same input sector on average, the matching rate is as high as 0.24 at the 75th percentile and as low as 0.08 at the 25th percentile of the number of potential suppliers. One may worry that these differential matching rates arise because of the selective entry of firms; firms in denser locations are better at matching with new suppliers by nature regardless of the number of potential suppliers they face. I address this concern by controlling for location

[1] Duranton and Puga (2004); Rosenthal and Strange (2004) and Head and Mayer (2004) provide a review.

[2] The data set has been used by several previous papers, including Nakajima et al. (2012); Bernard et al. (2015); Carvalho et al. (2016), and Furusawa et al. (2017).

and industry fixed effects interacted with a supplier loss. This ensures that the differential matching rates are identified by the *within-location-and-buyer-industry* variation, i.e., by the comparison between firms in the same location and industry that loses a supplier in different input industries with a varying number of potential suppliers. I also show that my proxy for the number of potential suppliers – the number of suppliers *established anywhere* that already serve some firms in the buyer's location – matters for the matching rate, rather than a simple count of the number of local suppliers. This suggests that the supplier matching benefits are not simply summarized by the number of local firms, and the presence of cross-location trade is critical for understanding such benefits.

Second, I find that the matching rate remains stable in the presence of other downstream firms. This is in a stark contrast to worker-to-firm matching in the labor market context, where the presence of unemployed workers is often found to decrease other unemployed workers' reemployment rate.[3] These differences are intuitive. In the context of firm-to-firm matching, suppliers can simultaneously serve multiple buyers without inducing crowding out among buyers, while in the labor market, a vacant job can be filled by only one unemployed worker, necessarily creating crowding out. Taking the two findings together, there is evidence of increasing returns in matching: the presence of more suppliers and more buyers improves the firm-to-firm matching rate. Additional findings confirm that such firm-to-firm matching is important for firm production: I find that a supplier bankruptcy leads to a lower sales growth and a higher exit probability of buyer-side firms through an imperfect supplier recovery, and firms do not cope with these supplier bankruptcies by substituting inputs from other existing suppliers.

The second part of the paper develops a structural model to quantify the importance of increasing returns in matching as a source of agglomeration. The model extends a multi-location multi-sector Melitz model (Melitz (2003)) to incorporate dynamic firm-to-firm matching in input trade. As in a standard Melitz model, potential producers enter in each location by paying a fixed cost and draw an idiosyncratic productivity; upon the realization of this productivity draw, they make a decision to sell into various locations by paying a fixed marketing cost. In addition to these standard assumptions, firms require inputs for production, which they can source from matched suppliers. The matching rate with a supplier increases in the number of suppliers selling in the location but it is unaffected by the number of input buyers in the location; this assumption is in line with the empirical findings of increasing returns in matching in the first part of the paper.

The model exhibits agglomeration through circular causation between supplier market penetration and downstream market size. A higher supplier matching rate in a location with

[3]See Petrongolo and Pissarides (2001) for a survey on this literature.

more suppliers gives a cost advantage to downstream firms and hence increases aggregate sales, i.e., a "forward linkage". This, in turn, creates a larger market for suppliers and encourages more supplier entry à la the Melitz model, i.e., a "backward linkage." The spatial distribution of firms and economic activity is consequently determined by the interaction of these two forces on top of the forces in the standard Melitz model (i.e., the population distribution, exogenous productivity, and trade costs). The key parameter that governs the circular causation is the elasticity of the supplier matching rate with respect to the number of potential suppliers. I estimate this parameter to match the reduced-form estimates from the first part of the paper to quantify the agglomeration forces and various policy implications.

The first counterfactual simulation quantifies how much the increasing returns in matching explain the observed geographic concentration patterns of economic activity and welfare in Japan. To understand this, I compute an equilibrium by hypothetically assuming that the elasticity of the supplier matching rate with respect to the number of potential suppliers is 0, unlike the estimates of 0.62 from the structural estimation. I find that, under this counterfactual, the variance of firm density across space would be 45% smaller and the variance of real wages would be 66% smaller. The remaining geographic variations are induced by the exogenous population distribution and the location and sector-specific productivity heterogeneity, including natural advantages. These results imply that a large part of the geographic concentration of firms can be explained by increasing returns in firm-to-firm matching.

In the second counterfactual simulation, I consider the role of policies in promoting economic welfare in geographically disadvantaged locations. In particular, I consider two distinct types of subsidy: subsidies for supplier market penetration and entry subsidies. The former are given to suppliers conditional on serving the location as input sellers *regardless of their production location*, and the latter is given to suppliers *who produce in these locations*. The former subsidies are commonly implemented in the form of trade exhibitions or business matching events, and the latter in the form of tax exemptions or subsidies for new business establishment. I find that the marginal impacts of subsidies on the targeted location's welfare are 6.5 times larger for the former than the latter. This implies that simply subsidizing the outreach of suppliers producing outside, rather than encouraging local inputs production, is more cost efficient. The results have strong implications on the recent discussions of place-based policies that only address the second type of subsidy. The discussion of the first type of subsidy is limited because of a common presumption that agglomeration benefits arise in the form of local production externality; this assumption implies that the relocation of

production resources are required for promoting disadvantaged locations.[4]

In the third counterfactual simulation, I analyze the impacts of transportation infrastructure that improves the access between peripheral and central locations. One may expect that such policy would benefit peripheral locations in a similar way as the subsidies for supplier market penetration. In fact, this motivation has become a substantial driver of the development of Japanese highway networks over the last 50 years. Surprisingly, I find that the reduction of transportation costs may *harm* peripheral regions in realistic scenarios of past and future transportation infrastructure improvements. Whether such improvements help or harm depends on the balances of two counter-forces: On one hand, the reduction of transportation costs benefits the periphery through the relative improvements of supplier matching. On the other hand, reducing transportation costs increases the competition between local suppliers in peripheral regions and suppliers from central regions. If the latter force is stronger, the reduction of transportation costs on net shifts the production resources from peripheral regions to the central regions, harming the periphery. While the possibilities that transportation cost reduction may harm peripheral locations under a sufficiently strong agglomeration force has been theoretically pointed out by the New Economic Geography literature (Krugman (1991); Fujita et al. (1999)) and has been empirically documented in some contexts (e.g., Faber (2014)), this paper is the first to make an empirical connection between this phenomena and the micro-founded agglomeration force.

Agglomeration is a core issue intersecting in urban economics, economic geography, and international trade, and this paper contributes to these strands of the literature. In urban economics, understanding the micro-foundations of agglomeration is one central issue. While theories of micro-foundations of agglomeration are abundant, as reviewed in Duranton and Puga (2004), direct empirical evidence of each mechanism is relatively scarce (Rosenthal and Strange (2004)). In terms of increasing returns in firm-to-firm matching as a source of agglomeration, the closest evidence is limited to the cross-sectional correlation between a fraction of purchased inputs per firm and spatial firm density in the United States (Holmes (1999)).[5]

Second, this paper contributes to the literature of economic geography. There is a recent

[4]See Kline and Moretti (2014b) and Glaeser and Gottlieb (2008) for a review of recent discussions on place-based policies. The assumptions of agglomeration benefits arise in the form of local production externality are common among the early literature of estimating the industry-level returns to scale in production (e.g., Ciccone and Hall (1996)), as well as the recent wave of structural models of urban economics and economic geography geared toward answering counterfactual policy questions (e.g., Allen and Arkolakis (2014); Kline and Moretti (2014a); Monte et al. (2015); **?**); Faber and Gaubert (2016); Nagy (2017). Redding and Rossi-Hansberg (2016) provide a nice survey on this literature).

[5]There are also indirect approaches to infer mechanisms of agglomeration; for example, Ellison et al. (2010) correlate industry co-agglomeration patterns and proxies of different micro-foundations, including the strength of input-output linkages.

wave of quantitative spatial economic models to incorporate realistic geography in theoretical models of the New Economic Geography (NEG) literature (Krugman (1991); Krugman and Venables (1995); Fujita et al. (1999)) as surveyed in Redding and Rossi-Hansberg (2016). This paper's contribution is to explicitly model a particular micro-foundation of agglomeration and study its distinct policy implications.

Third, this paper is related to several sub-fields of international trade. First, this paper is related to the literature of firm sourcing behavior, with particular emphasis on geographic proximity (Antràs et al. (2014); Bernard et al. (2015, 2016); Blaum et al. (2016); Furusawa et al. (2017)). Second, this paper is related to the literature on firm-to-firm trade network formation (Oberfield (2013); Eaton et al. (2016b); Lim (2016); Tintelnot et al. (2017)). Third, it is related to the literature that studies search and matching frictions in trade relationships (Allen (2014); Startz (2016); Eaton et al. (2016a); Krolikowski and McCallum (2017); Brancaccio et al. (2017)).

The rest of the paper is organized as follows. Section 2 provides the description of the main data set used in this paper, a panel of firm-to-firm trade of over a million Japanese firms. Section 3 provides reduced-form evidence of increasing returns in firm-to-firm matching. Section 4 develops a structural trade model to understand the implications of increasing returns in matching for agglomeration patterns. Section 5 structurally estimates the key parameters of the model and presents the procedures for computing counterfactual equilibrium. Section 6 presents three counterfactual simulations to illustrate the quantitative implication of the agglomeration forces. Section 7 concludes.

2 Data and Descriptive Facts

In this section, I briefly describe this paper's main data set, a panel of firm-to-firm trade between over one million Japanese firms. I also document a set of descriptive facts that motivates the empirical exercise in Section 3 and the structural model in Section 4.

2.1 Firm-to-Firm Trade Data in Japan

The main data set utilized in this paper comes from a major credit reporting agency, Tokyo Shoko Research (TSR). The data is based on face-to-face and phone interviews, as well as public resources such as financial statements, corporate registrations, and public relations documents. The panel covers three waves, 2006, 2011, and 2014, and it contains basic firm-

level characteristics as well as the precise locations of firm headquarters.[6]

The most important feature of the data set is that it contains dynamic transitions of supplier-buyer relationships. In each period and for each firm, the data reports up to 24 suppliers and buyers for each firm. The information is collected in annual interviews by field surveyors of TSR by asking whether the relationship from previous years continues to exist or whether a new relationship has been initiated. Figure A.1 reports that, while the upper-bound of 24 suppliers is not binding for most firms, there are a non-negligible number of cases with more than 24 suppliers once I include the number of supplier-buyer relationships reported by supplier-side firms (but not by buyer-side firms). Following other recent papers that utilize the same data set (e.g., Carvalho et al. (2016); Bernard et al. (2016)), I define a supplier-buyer relationship to exist if *either* the supplier-side or the buyer-side firm reports a relationship in each period.

Another important feature of the data set is that it reports the main reasons for bankruptcy in each case. This information is also collected through the interviews by TSR. Table 1 reports the list of reasons recorded in this data set. In Section 3, I make use of this information as an instrument when estimating matching rate with new suppliers upon a supplier loss

2.2 Descriptive Patterns of Firm-to-Firm Matching

This section provides a brief overview of the descriptive patterns of the data that motivates the empirical exercise and the structural model in the subsequent sections.

First, an extensive margin of firm-to-firm trade is geographically concentrated, with non-negligible long-distance trade. As is already documented in Nakajima et al. (2013) and Bernard et al. (2016), who use the same data set, and as is replicated in Figure 2, the median of the geodesic distances between buyers and suppliers across all three years is about 25 km, which is much smaller than that of all possible pairs of firms in Japan (464 km). At the same time, the 75th percentile of the geodesic distances of firm-to-firm trade is about 250 km, suggesting that firms are not constrained to trade within locations. These observations are naturally modeled by market penetration decisions à la Melitz (2003) as pursued in Section 4; firms decide their production locations, and based on the production locations, firms engage in input sales in various locations under geographic frictions.

Second, firms in denser areas have more suppliers. Figure 3 shows that it is true, and Table A.1 further confirms that this correlation is robust to various controls, including

[6]For the empirical analysis of this paper, I define the location of the firm by its headquarter location. I show robustness by restricting the samples to firms with few establishments to minimize the mismeasurement of firm locations.

industry fixed effects and employment size fixed effects.[7] Together with the strong cross-sectional correlation between number of suppliers and revenue productivity per worker,[8] the results are at least consistent with increasing returns in matching; in denser areas where there are more potential supplier and buyers, the probability that downstream firms match with suppliers for each input sector is high.[9] At the same time, the patterns may be driven by endogenous firm entry resulting from unobserved input demand; i.e., firms who unobservably demand more input goods for production may selectively enter in denser locations.

Third, firms in denser areas have a higher rate of matching with new suppliers, while the separation rate with existing suppliers does not decrease with firm density. From a dynamic point of view, the cross-sectional correlation between the number of suppliers and firm density can be driven either by a higher rate of matching with suppliers or a lower rate of separation with existing suppliers in denser areas.[10] Figure 4 shows that the former is increasing in firm density while the latter is flatter (with a U-shape), indicating that the new matching rate is the key driving force of cross-sectional correlation between the number of suppliers per firm and firm density.

In sum, the descriptive patterns are consistent with agglomeration benefits from increasing returns in firm-to-firm matching; in denser areas there are more buyers and suppliers, giving a better chance of matching with a supplier for each input sector. At the same time, the patterns may be driven by endogenous firm entry resulting from unobserved demand for supplier matching. Testing increasing returns in matching requires, to a first order, identifying a case where firms in different locations are equally in search of suppliers. Section 3 explores this point by studying the matching rate with new suppliers upon an exogenous loss of a supplier.

[7] A similar finding has been documented in the literature, i.e., externally sourced input share of firms is positively correlated with firm density in the United States (Holmes (1999)).

[8] Figure A.2 provides a raw correlation; Table A.2 shows that the correlation is not driven by various controls. A similar cross-sectional correlation has been documented by Bernard et al. (2016).

[9] Firms have suppliers in various input sectors. On average firms have 4.6 suppliers across all three years, and they have suppliers in 2.3 two-digit input sectors and 3.1 four-digit input sectors (Panel (A) of Table 2). There is also a wide dispersion in the number of suppliers and input sectors across firms, as shown in Figure A.3.

[10] To see this point more formally, note that the following accounting relationship holds at the firm-level:

$$\begin{aligned}\text{Number of Suppliers}_{t+1} =& \text{Number of Suppliers}_t \times (1 - \text{Probability of Supplier Separation}_t) \\ &+ \text{Number of New Suppliers}_t.\end{aligned}$$

If a firm has a steady-state number of suppliers, i.e., $\text{Number of Suppliers}_{t+1} = \text{Number of Suppliers}_t$, then it follows that

$$\text{Number of Suppliers}_t = \frac{\text{Number of New Suppliers}_t}{\text{Probability of Supplier Separation}_t}, \tag{1}$$

hence, the variation in the number of suppliers per firm is decomposed into number of new suppliers and probability of supplier separation.

3 Reduced-Form Evidence of Increasing Returns in Firm-to-Firm Matching

This section provides reduced-form evidence of increasing returns in firm-to-firm matching. Section 3.1 discusses the main empirical strategy; estimating the new supplier matching rate upon a supplier loss instrumented by unexpected supplier bankruptcies. Section 3.2 presents the main results, and Section 3.3 shows additional results on other outcome variables to confirm the importance of matching frictions in this context.

3.1 Empirical Strategy

While no formal test of increasing returns in matching has been conducted in the context of firm-to-firm matching in input trade, that of the labor market has been studied extensively. As reviewed in Petrongolo and Pissarides (2001), early literature uses aggregate relationship between the number of unemployed workers and the job vacancies,[11] while more recent literature uses micro data and estimates reemployment probabilities as a function of the number of job vacancies and unemployed workers in their local areas. For example, Petrongolo (2001) finds that while more job vacancies increase the reemployment rates, more unemployed workers crowd out the reemployment rates at a similar magnitude, supporting the constant returns in matching.[12]

Testing increasing returns in firm-to-firm matching follows the same idea. I estimate the matching rate with new suppliers upon an exogenous supplier loss. If the matching rate improves in the presence of more potential suppliers, but does not decrease as much by the presence of other buyers, there is evidence of increasing returns in matching. Exogeneity of a supplier loss is important; if the separation is initiated by the downstream firm, it may not be in need and search of alternative suppliers, which biases the matching rate estimates. For this purpose, I instrument a supplier loss by unexpected supplier bankruptcies – accidental reasons (CEO death, naural disaster, etc.,) and spillovers from other bankruptcies – from the

[11] See, for example, Blanchard and Diamond (1989b,a) for an early attempt to estimate matching functions using aggregate data.

[12] Other papers that study reemployment probability as a relationship with local market conditions include Bleakley and Lin (2012) and Macaluso (2016). In a similar vein, Jäger (2016) estimates the implication of an unexpected worker death on new hires and demonstrates how it depends on the presence of alternative workers with similar skill sets.

reasons of bankruptcies reported in the data.[13] The validity of these instruments is further confirmed by testing the absence of pre-trends in the outcome variables.

The number of potential suppliers is proxied by the number of firms for each input industry that supply to some firms in the buyer's location in the baseline period (2006). Reflecting the nonnegligible presence of long-distance trade as reported in Section 2.2, the proxy includes firms which are *established anywhere* and does not restrict to local suppliers; in fact, I show that the matching rate is affected by this proxy but not by the simple count of local suppliers. It should be also stressed that the proxy provides a location and input sector level variation. Such variation allows me to address the concern that firms in a particular location and sector are good at supplier matching in nature, by controlling for the buyer's location and industry specific heterogeneous effects. Figure 5 provides visual illustrations of this proxy for two industries, the forestry industry and the steel industry; while the forestry industry has more potential suppliers in the northern part of Japan, the steel industry has more suppliers in the south.

In turn, I examine various proxies for the number of buyers due to the lack of theoretical guidance on how to identify plausible competitors for supplier matching. The proxies considered include the number of firms in buyer's industry and location, the number of firms in buyer's industry and location facing supplier separation in the same input sector, and the number of firms in buyers industry in any locations. The last proxy allows for the possibility that buyers compete with nonlocal firms to match with a supplier.

3.2 Main Results

This section presents the evidence of increasing returns in firm-to-firm matching; the new supplier matching rate upon a supplier loss increases in locations and industries when there are more potential suppliers, while this rate remains stable in the presence of other downstream firms.

[13] Table 1 lists the full reasons of the bankruptcies. "Spillover from other bankruptcies" are those caused by management difficulties due to chain reactions such as business partners, subsidiary companies, related bankruptcies, voluntary liquidation, etc. "Accidental reasons" include those with unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc. For "spillovers from other bankruptcies," I omit the cases in which the buyer-side firms go bankrupt before the suppliers, thereby avoiding cases in which the "spillover" comes from the buyer-side firms in focus.

3.2.1 Matching Rate Increases with the Number of Potential Suppliers

I first show that the new supplier matching rate upon an exogenous separation is higher with more potential suppliers. To show this, I run the following regression:

$$\begin{aligned} NewSupplier_{fkt} =& \beta_1 Separation_{fkt} + \beta_2 Separation_{fkt} \times \log PotentialSupplier_{loc(f),k} \\ &+ \delta_{loc(f),ind(f),k,t} + \varphi_t(BaselineSupplier_{fkt}) + \epsilon_{fkt}, \end{aligned} \tag{2}$$

where f is the firm, k is the two-digit input sector of the JSIC industry classification,[14] and t is year (2006 and 2011). $NewSupplier_{fkt}$ is the number of new suppliers that firm f matches per year from t to the next period (2006 to 2011 or 2011 to 2014), and $Separation_{fkt}$ is the number of suppliers that firm f loses per year between t and the next period, including supplier exits and the dissolution of supplier-buyer relationships. $PotentialSupplier_{loc(f),k}$ is the proxy for the number of potential suppliers as discussed in Section 3.1; the number of firms in input sector k that supply to any firms in firm f's headquarter location $loc(f)$ (defined by 0.5 degree grid cell) at the baseline year (2006). $\delta_{loc(f),ind(f),k,t}$ is the fixed effects at the level of the location and sector of firm f, input sector k, and year t, to make sure that the new supplier matching rate is identified as a comparison between firms in the same location and industry with a same-input-sector supplier with and without a supplier loss.[15] $\varphi_t(BaselineSupplier_{fkt})$ are the flexible controls for $BaselineSupplier_{fkt}$, included as fixed effects, to control for the fact that firms with more baseline suppliers mechanically face a higher rate of supplier separation. $Separation_{fkt}$ and its interaction with $\log PotentialSupplier_{loc(f),k}$ are instrumented by $UnexpBankruptcy_{fkt}$, the number of unexpected supplier bankruptcies that firm f faces in input sector k per year from t to the next period, and its interaction with $\log PotentialSupplier_{loc(f),k}$. As reported in Table A.3, the first stage is strongly significant and is not driven by the pre-trends.[16] Standard errors are clustered at the firm level, and the regressions are weighted to equalize the weight at the firm and year level. To avoid the case that the results are solely driven by extremely large firms, I take out firms whose baseline number of suppliers is above the 99th percentile for each year.

Table 3 reports the baseline results. Column (1) starts with the specification without

[14] The industry classification follows the Japan Standard Industrial Classification (JSIC). There are 98 two-digit sectors and 1248 four-digit sectors in JSIC classification. JSIC roughly corresponds to International Standard Industrial Classification (ISIC), although they do not uniquely match. For more detail on JSIC, see http://www.soumu.go.jp/english/dgpp_ss/seido/sangyo/index.htm. Table A.5 reports the robustness checks for different levels of industry classification.

[15] Note that the fixed effects $\delta_{loc(f),ind(f),k,t}$ saturate $PotentialSupplier_{loc(f),k}$, so β_2 is identified only off of the interaction, not by the baseline effects of $PotentialSupplier_{loc(f),k}$.

[16] The reason why the first stage coefficient is less than 1 is because control firms lose suppliers at some rate at the same time as treated firms face a supplier bankruptcy.

the heterogeneous effects. The point estimate indicates that a loss of one supplier per year leads to 0.16 more new supplier matching per year in the same two-digit input industry. The fact that it is significantly above 0 implies that firms recover suppliers; the fact that it is significantly below 1 implies that the recovery is far from perfect. Columns (2) reports the results with heterogeneous impacts with respect to the number of potential suppliers.[17] The inter-quartile range of the log number of potential suppliers is 2.6, implying that the impact of supplier separation increases by $0.06 \times 2.6 = 0.156$ by going from the 25th percentile to 75th percentile of the log number of potential suppliers. The magnitude is large relative to the average impact of supplier separation; it implies that the yearly recovery rate ranges from 24% to 8% by going from the 75th percentile to 25th percentile of the number of potential suppliers.

The rest of the columns show that the positive heterogeneous effects with respect to the number of potential suppliers are robust. One may worry that these differential matching rates arise because firms in denser locations are better at matching with new suppliers by nature and not because they face more potential suppliers. To deal with these concerns, in Column (3), I add the interaction between the number of separated suppliers and the log firm density of firm f's location (i.e., the number of firms in the same 0.5 degree grids as firm f). The heterogeneous effect of the number of potential suppliers is robust and positively significant, while that of the firm density is insignificant. To further ensure that the results are not simply driven by the types of firms in each location, in Column (4), I include the interaction between unexpected supplier bankruptcies (instruments) and firm f's location and year fixed effects. The regression now utilize the *within-location* variation; two firms in the same location face an unexpected supplier bankruptcy in two different input industries. The results show that the heterogeneous effects with respect to the number of potential suppliers are robust and still significant.[18] In a similar vein, Column (5) shows that the differential matching rates are not driven by the firm sizes by controlling for the heterogeneous effects with respect to firm's baseline employment size. Column (6) further controls for the heterogeneous effects at the level of regions and buyer's industry for each year.[19]The heterogeneous effects with respect to the number of potential suppliers are now identified by the *within-location-and-buyer-industry* variation, further ensuring that the results are not

[17]The log number of potential suppliers is normalized to be mean 0, hence the coefficients on the number of separated suppliers roughly reflect the average impacts of the supplier separation. The same is true for other interactions with the supplier separation.

[18]Because these added fixed effects saturate the number of unexpected supplier bankruptcy that is used for supplier separation, the average effects of supplier separation are not identified and omitted from the table.

[19]Region is a geographic administrative unit in Japan, with 8 regions in total. I take regions, rather than the 0.5 degree grid cells, to control for the heterogeneous effects at the level of region, buyer industry and year due to the lack of power by using the latter geographic unit.

driven by the selective entry of firms.

Column (7), in turn, investigates the validity of the proxy of the number of potential suppliers relative to a simple count of local suppliers (i.e., number of firms in firm f's location in input sector k). I find the positive significant heterogeneous effects with respect to my proxy and insignificant heterogeneous effects with respect to the number of local suppliers. Further investigation in Table A.4 shows that this pattern is mainly driven by the new supplier matching in far distances; more than half of the new matched suppliers are outside the 0.5 degree grid cells, and they drive this pattern of heterogeneous effects. The fact that the new supplier matching rate is affected by the number of potential suppliers, not by the number of local suppliers, implies that the agglomeration benefits from firm-to-firm matching are not simply summarized by the number of local firms as is commonly assumed. Section 4 discusses the theoretical implications of this observation in further detail.

Lastly, I argue that the results are not driven by the correlated shocks over the supply chain, i.e., firms which face unexpected supplier bankruptcy are on a differential trend for supplier matching patterns. For example, if the underlying reason of the supplier bankruptcy is a natural disaster, it is plausible that the natural disaster also hits their buyers directly. To deal with this concern, Column (8) shows that the results are robust to controlling for the firm and year fixed effects to use only the within-firm-across-input-industry variation; i.e., the new supplier matching rate is identified as a comparison within a firm across different input sectors with and without a supplier loss. In addition, Columns (9) and (10) show that firms which face unexpected supplier bankruptcies from 2011 to 2014 do not show differentially higher rates of supplier matching from 2006 to 2011, and this lack of pre-trends hold for the heterogeneous effects. Hence, the results are not driven by the pre-trends.

Other robustness results. Table A.5 discusses additional robustness results. One remaining concern is that the supplier matching rate depends on the importance of input sectors for each firm's production, and firms tend to locate where there are more important suppliers for their production.[20] To address this concern, Column (1) shows that the results are robust to controlling for the supplier separation interacted with the input coefficients of the IO matrix (at the two-digit industry pair level) as a proxy for the importance of input sectors. Along the same line, Column (2) shows that the results are robust to omitting

[20]This concern does not immediately invalidate the hypothesis of improved supplier matching rate with more potential suppliers if the improved supplier matching rate is the reason for firms' location decisions. To see this, note that under the null hypothesis that the number of potential suppliers does not matter, these firm sorting patterns do not arise anyways. However, this concern invalidates the hypothesis if two industries with strong input-output linkages tend to co-locate for reasons unrelated to input-output linkages, such as similar natural advantages. In such a case, higher matching rates in between these industries are not caused by the presence of more upstream firms but rather caused by the strength of input-output linkages. The robustness exercise presented here rules out this concern.

up to three most important input sectors for each buyer sector, which are likely to be the primary factors of location decisions.[21] Column (3) further addresses the concern due to selective entry of firms by only taking firms whose CEO's birth location is the same as the current firm headquarter location, as these firms are less likely to have made location decisions based on the availability of potential suppliers. The table reports other robustness checks; Columns (4) and (5) show that the results are robust to restricting the instruments for separated suppliers to be unexpected supplier bankruptcy due to accidental reasons and due to other bankruptcy spillovers separately, Columns (6) and (7) show the robustness by excluding the results are robust to excluding Tokyo prefecture and firms with more than 5 establishments, and Columns (8) and (9) show the robustness by finer industry classification at the three-digit and four-digit industries.

Another potential concern is the external validity; unexpected supplier bankruptcies are not representative of the supplier separation. To address this concern, Table A.6 shows the results by using supplier exits for any reasons as an instrument for supplier separation, rather than unexpected supplier bankruptcies. Although the presence of pre-trends makes it hard to draw precise causal estimates, the qualitative patterns are consistent with the results using unexpected supplier bankruptcies as an instrument; firms match more with new suppliers upon separation, and they do so more in the presence of more suppliers.[22]

3.2.2 Matching Rate Does Not Decrease with the Number of Buyers

In this section, I test whether the matching rate decreases with the number of other buyers. The specification is as follows:

$$\begin{aligned} NewSupplier_{fkt} =& \beta_1 Separation_{fkt} + \beta_2 Separation_{fkt} \times \log PotentialSupplier_{loc(f),k} \\ &+ \beta_3 Separation_{fkt} \times \log Buyers_{loc(f),ind(f)} \\ &+ \delta_{loc(f),ind(f),k,t} + \varphi_t(BaselineSupplier_{fkt}) + \epsilon_{fkt}, \end{aligned} \tag{3}$$

where $Buyers_{loc(f),ind(f)}$ are various proxies of the number of buyers. One would expect $\beta_3 < 0$ if downstream firms crowd out each other for supplier matching. As in regression (2),

[21] Importance here is ranked by the baseline probability that firms in buyer industries match with suppliers in each input sector.

[22] Using supplier exits for all reasons, rather than restricting to unexpected supplier bankruptcies, allows me to control for firm, year, and supplier-exit fixed effects (Column (3) for the main specification, Column (6) for the pre-trends). This specification compares firms who face a supplier exit in two different input industries with a different number of potential suppliers, hence controling for any firm-level unobserved characteristics that affect new supplier matching patterns upon a supplier loss. This specification is not possible with unexpected supplier bankruptcies because of the infrequency of the cases that the same firms face two unexpected supplier bankruptcies in different input sectors.

$Separation_{fkt}$ and all of its interactions are instrumented by $UnexpBankruptcy_{fkt}$ and its relevant interactions.

The results reported in Table 4 indicate that there is no evidence of crowding out by other buyers. Using the number of firms in the same two-digit industry in firm f's location (0.5 degree grid cells) as a proxy for the number of buyers (Column 1), as well as those in the same four-digit industries (Column 2), the coefficients β_3 are precisely estimated and close to 0, while β_2 remains significantly positive. In Column (3), I show that the results remain unchanged by taking the number of firms in firm f's industry that also faced an unexpected supplier bankruptcy in the same input sector, exploiting the plausibly exogenous variation in the number of other buyers searching for suppliers. Column (4) shows that the results are also unchanged by counting the buyers in any industry, rather than restricting to those within firm f's industry, as long as they face unexpected supplier bankruptcy in the same input sector k. Furthermore, Columns (5) and (6) demonstrate that these results are unchanged when I count firms that faced supplier separation in input sector k, not only those with unexpected supplier bankruptcies. Lastly, one may worry that buyers may be under competition with nonlocal buyers for matching with suppliers. Columns (7) and (8) show that the results are unchanged by defining the buyers as firms in firm f's industry *located anywhere* that also faced an unexpected supplier bankruptcy in the same input sector.

The findings of no crowding out is in a stark contrast to worker-to-firm matching in the labor market context, where the presence of unemployed workers is often found to decrease other unemployed workers' reemployment rate.[23] The differences come from the fact that, in firm-to-firm matching, suppliers can simultaneously serve multiple buyers without inducing crowding out among buyers; in the labor market, a vacant job can be filled by only one unemployed worker, necessarily creating crowding out. In other words, the fact that firms can share suppliers limits crowding-out by other buyers.[24] In the model, the differences can be expressed that suppliers can simultaneously serve multiple buyers (i.e., *many-to-one* matching), unlike the *one-to-one* matching between a vacant job and an unemployed worker.

3.3 Additional Results

This section briefly presents additional results that confirm the importance of matching frictions. Section 3.3.1 demonstrates that a supplier loss leads to lower sales growth and a higher exit probability. Section 3.3.2 illustrates that there is no evidence that firms cope

[23] See Petrongolo and Pissarides (2001) for a survey on this literature.

[24] In this sense, the increasing returns in matching documented here is related to "sharing," in addition to "matching," among the three classifications of agglomeration mechanisms as introduced in Duranton and Puga (2004).

with a loss of supplier by substituting inputs from other existing suppliers.

3.3.1 Sales Growth and Exit Upon Unexpected Supplier Bankruptcy

In this section, I investigate the impacts of unexpected supplier bankruptcy on sales growth and exit. The specification is as follows:

$$\begin{aligned}\Delta Y_{ft} =&\beta_1 UnexpBankruptcy_{fkt} + \beta_2 UnexpBankruptcy_{fkt} \times \log PotentialSuppliers_{loc(f),k} \\ &+ \delta_{loc(f),ind(f),k,t} + \varphi_t(BaselineSupplier_{fkt}) + \epsilon_{fkt}. \end{aligned} \tag{4}$$

The results are presented in the reduced form rather than the IV form, mainly because the supplier separation cannot be defined when firm f exits. Compared to regression (2), the outcome variables ΔY_{ft} are defined at the firm and year level, but not at the input sector k level. Kaido and Miyauchi (in progress) show that even if the outcome variables do not depend on k, above regression consistently estimates average and heterogeneous treatment effects.

Table 5 reports the results. Columns (1) and (2) show the impacts on sales growth, where it is defined as the arc-elasticity (Davis and Haltiwanger (1992)), i.e.,

$$\Delta Y_{ft} = \frac{Sales_{f,t}}{\frac{1}{2}\{Sales_{f,t} + Sales_{f,t+1}\}},$$

where $Sales_{f,t}$ is defined to be 0 if the firm exits in $t+1$. This measure is bounded between 2 and -2, avoids outliers with a large increase in sales from skewing the distribution of percentage changes, and allows inclusion of firms with no sales (i.e., exit). The results show that, while a supplier bankruptcy leads to 3% reduction of sales per year on average relative to control groups, this reduction is mitigated in the presence of more potential suppliers, despite insignificantly. Columns (3) to (6) decompose these impacts in terms of firm f's exit and sales growth conditional on survival. While the average effects are driven more by exit margins (Columns 3 and 5), the heterogeneous effects are driven more by the sales growth conditional on survival (Columns 4 and 6). Lastly, Columns (7) and (8) show that these results are not driven by the pre-trends.[25]

[25]While the lack of significance in heterogeneous effects on sales growth and exits are plausibly driven by the noise, another possibility is that the heterogeneity in the importance of matched suppliers offsets the benefit of improved supplier matching rates. More concretely, if suppliers' productivity is increasing in the proxy of the number of potential suppliers, a loss of these suppliers is more damaging to buyers, which offsets the benefit of a higher recovery rate of suppliers. I show that the structural model in this paper can rationalize this pattern, and I provide suggestive evidence that this is potentially an explanation of the empirical results.

3.3.2 Evidence of Lack of Substitution by Other Existing Suppliers

While a new supplier matching is one way that firms cope with a supplier loss, they can potentially deal with the shock by sourcing more from other existing suppliers. I show that, in this context, there is no such evidence of substitution by other existing suppliers.

To test this, I run the following specification:

$$\begin{aligned}\Delta Y_{fkt} =& \beta_1 UnexpBankruptcy_{fkt} + \beta_2 UnexpBankruptcy_{fkt} \times \log PotentialSuppliers_{loc(f),k} \\ &+ \delta_{loc(f),ind(f),k,t} + \varphi_t(BaselineSupplier_{fkt}) + \epsilon_{fkt}. \end{aligned} \tag{5}$$

The regression specification is the same as regression (4), while now the outcome variables ΔY_{fkt} are various outcomes of other existing suppliers of firm f in input sector k at year t. Samples of the regressions are those with more than one baseline suppliers within the input sector.

Table 6 reports the results. Columns (1) and (2) show the impacts on the probability of separation with other existing suppliers. If firms substitute inputs from other existing suppliers, one would expect that the retention rates of other existing suppliers are higher with unexpected supplier bankruptcies. The results show that there is no such evidence. Columns (3) and (4) show that unexpected supplier bankruptcy actually reduces the sales growth of other existing suppliers on average. The results are in fact the opposite of the prediction under the substitution by other existing suppliers; rather, the results imply that other suppliers are complements of the bankrupting suppliers. This evidence of lack of substitution implies that the shock from a supplier loss cannot be mitigated by the presence of other existing suppliers, confirming the importance of new supplier matching.

4 Model of Firm-to-Firm Matching and Agglomeration

This section develops a model that explains how increasing returns in firm-to-firm matching, as identified in Section 3, leads to agglomeration. The model extends a multi-location multi-sector Melitz model (Melitz (2003)) to incorporate dynamic firm-to-firm matching in input trade. As in a standard Melitz model, potential producers enter in each location by paying a fixed cost and draw an idiosyncratic productivity; upon the realization of this productivity draw, they make a decision to sell into various locations by paying a fixed marketing cost. In addition to these standard assumptions, firms require inputs for production, which they can source from matched suppliers. The matching rate with a supplier increases with the number of suppliers selling in the location, but it is unaffected by the number of buyers at the location; this assumption is in line with the empirical findings of increasing returns in

matching in Section 3.

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. In the baseline, I assume workers are immobile, while I relax this assumption in Appendix C. Time is continuous and denoted by t. In this paper, I only consider a steady-state equilibrium in which aggregate variables (e.g., wages, number of entrants) are constant. Only firm-level variables like supplier matching status vary by t. Without a risk of confusion, the subscript t is omitted from the aggregate variables.

There is a continuum of potential entrants in each location and sector, where sector is denoted by $k, m \in K$. I assume that firms do not change production location over their life-cycles. All firms produce both final goods, consumed by final goods consumers, and input goods, used for production by other firms. In this sense, each firm can be simultaneously a buyer and a supplier in input trade. Input trade is only possible when two firms match as a supplier and a buyer. I assume that each buyer-side firm can be matched with at most one supplier in each 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 input goods with the Cobb-Douglas production function. I assume that the unit cost for producing final goods by firm ω in location i in sector m follows:

$$c^F_{\omega t} = \frac{1}{\varphi_\omega} w_i^{\gamma_{L,m}} \prod_{k \in K} {p_{\omega t,k}}^{\gamma_{k,m}}, \tag{6}$$

where φ_ω is the exogenous productivity of firm ω, $\gamma_{L,m}$ is the labor share in production for sector m, $\gamma_{k,m}$ is the input share of sector k's input goods in sector m's production, w_i is the wage in ω's production location i, and $p_{\omega t,k}$ is the unit cost of input goods that firm ω has access to in period t, which depends on whether or not a firm is matched with a supplier and the price of input goods that the supplier charges. I assume that production function is constant returns to scale, i.e., $\gamma_{L,m} + \sum_k \gamma_{k,m} = 1$ for all $m \in K$.

There are two possible ways to source input goods: match with a supplier for customized input goods or purchase in the generalized input goods market. If firm ω with production location i is matched with supplier υ with production location n in sector k, the unit cost of customized input goods is assumed to be $\psi c^I_\upsilon / \tau_{ni,k}$, where ψ is the constant mark-up ratio charged by supplier υ, c^I_υ is the unit cost of production for firm υ, and $\tau_{ni,k}$ is iceberg

trade cost ($\tau_{ni,k} \leq 1$). The iceberg trade cost captures the combination of shipment cost, transaction cost, and other sources of geographic frictions. If firm ω is not matched with a supplier, the firm can source input goods from the generalized input goods market, where these inputs are produced by perfectly competitive fringe suppliers with linear production technology with labor, charging the unit cost of $\chi_{i,k} w_i$. Taken together, the cost of input goods is written as

$$p_{\omega t,k} = \begin{cases} \min\left\{\psi c_{\upsilon}^{I}/\tau_{ni,k},\ \chi_{i,k} w_i\right\} & \text{if matched with supplier } \upsilon \text{ producing in } n, \\ \chi_{i,k} w_i & \text{otherwise.} \end{cases} \tag{7}$$

As will be stated in Section 4.1.3, I consider an equilibrium where $\chi_{i,k}$ is sufficiently high so that whenever a firm is matched with a supplier, it uses the input goods from the matched supplier rather than sourcing from a generalized input goods market.

For production of input goods, I assume that firms have the same Cobb-Douglas production technology, but regardless of whether the firm is matched with a supplier, they always source input goods from the generalized input goods market. This implies that the unit cost of firm ω to produce input goods is written as

$$c_{\omega}^{I} = \frac{1}{\varphi_{\omega}} w_i \prod_{k \in K} \chi_{i,k}^{\gamma_{k,m}}. \tag{8}$$

One can interpret the assumption that firms do not source input goods from the matched suppliers for their own inputs production as the limit of customization if the supply chain involves more than two firms; suppliers cannot customize input goods that are eventually used for their buyers' buyers' production because they are not directly matched with each other. This assumption implies that firms' decisions for entry as input sellers in various locations, as described in Section 4.1.3, are solely determined by the expected final goods sales of matched buyers, allowing for a tractable characterization of input seller's entry decisions.[26]

4.1.2 Final Goods Demand and Market Structure

As in a standard Melitz model, for firms in sector k to make final goods sales in location j, they have to pay a fixed marketing cost at a flow rate $f_{j,k}^{F}$ regardless of their production location i. Each seller provides a differentiated variety in a monopolistically competitive

[26]Relaxing this assumption to incorporate an input goods usage for the buyers' own inputs production implies that input sellers' entry decisions in various locations depend on how the matched buyers will change their entry decisions for their own input goods sales, which are in turn affected by the expectation of further downstream firms' entry decisions as input sellers, and so on. In other words, input sellers' entry decisions depend on the expectation of the dynamic evolution of the entire network structure through all firms' entry decisions as input sellers, losing tractability of the model.

manner. Representative final goods consumers have a standard CES utility function:

$$U = \prod_{k \in K} \left(\int_{\omega \in \Omega_{i,k}} q_k(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}\alpha_k}, \tag{9}$$

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, $\sigma > 1$ is the elasticity of substitution, and $\Omega_{i,k}$ is the set of varieties available for final goods consumers in location i.

4.1.3 Input Goods Demand, Matching, and Market Structure

For firms in sector k to make input goods sales in location j, they have to pay a fixed marketing cost at flow rate $f^I_{j,k}$ regardless of their production location i. I assume that these decisions are independent of seller entry for final goods sales described in the previous subsection. All producers in location j are potential input buyers. I refer to firms in sector k who pay a fixed marketing cost for input goods sales in location j as "input sellers" in location j, and its measure by $S^I_{j,k}$. I refer to firms producing in location j in sector k as "input buyers" in location j, and its measure by $B_{j,k}$. Due to matching frictions, input sellers can be only stochastically matched with input buyers. If they are matched, I assume that suppliers charge a constant mark-up ratio ψ.

In each period t, firm ω will randomly match with an input seller in location i at the Poisson rate $M_{i,km}\left(S^I_{i,k}\right) \equiv \eta_{i,km} \times \left(S^I_{i,k}\right)^{\lambda}$, where $\eta_{i,km}$ and λ are parameters. Following the reduced-form results in Section 3, I assume that the rate that input buyers match with input sellers does not depend on the number of input buyers, i.e., other buyers do not crowd out matching. Once an input seller and an input buyer match, they decide whether to form a relationship. From the perspective of an input buyer, they match with a supplier at Poisson rate $M_{i,km}\left(S^I_{i,k}\right)/S^I_{i,k}$. I assume that $\chi_{i,k}$, the unit cost of generalized input goods divided by the wage, is sufficiently high so that input buyers and sellers always form a relationship upon a match. Once the relationship is formed, the relationship continues until it is exogenously destroyed at the Poisson rate $\rho_{i,km}$, either because of the bankruptcy of a supplier or because they stop trading with each other. This implies that the steady state probability that firms in production location i in sector m is matched with a supplier in input sector k is

$$\Lambda_{i,km}\left(S^I_{i,k}\right) \equiv \frac{M_{i,km}\left(S^I_{i,k}\right)}{M_{i,km}\left(S^I_{i,k}\right) + \rho_{i,km}}. \tag{10}$$

I also assume that the matching rate with suppliers in input sector k is independent across all input sectors.

Input goods sellers decide to enter in location j as long as the expected benefit of matching with an input buyer is greater than the fixed marketing cost. Denote $\Pi^I_{ij,k}(c^I_k, c)$ as the flow rate of profit that a supplier in sector k who can supply input goods at c^I_k in location j can accrue from a matched buyer whose unit cost for final goods production is c. Then, firm ω with unit cost $c^I_{i,k}$ enters as an input seller in location j if and only if

$$\sum_{m\in M} \frac{M_{i,km}\left(S^I_{i,k}\right)}{S^I_{i,k}} \frac{1}{\xi_k + \rho_{j,km}} \int \Pi^I_{ij,k}(\frac{c^I_{i,k}}{\tau_{ij,k}}, c) \frac{dH^F_{j,m}(c|\frac{c^I_{i,k}}{\tau_{ij,k}})}{B_{j,m}} \geq f^I_{j,k} w_j, \tag{11}$$

where $H^F_{i,m}(c|\tilde{c})$ is the measure of firms in location i and sector m whose unit cost of final goods is below c conditional on having a supplier in sector k with unit cost $\tilde{c}$.[27]The intuition is simple: Upon an entry by paying a fixed marketing cost $f^I_{j,k} w_j$, a supplier matches with an input buyer at Poisson rate $M_{i,km}\left(S^I_{i,k}\right)/S^I_{i,k}$, and the expected flow rate of supplier's profit from a randomly matched input buyer is $\int \Pi^I_{ij,k}(\frac{c^I_{i,k}}{\tau_{ij,k}}, c) \frac{dH^F_{j,m}(c|\frac{c^I_{i,k}}{\tau_{ij,k}})}{B_{j,m}}$. Suppliers incur profit until the relationship is exogenously destroyed at a Poisson rate $\rho_{j,km}$, or the supplier goes bankrupt at rate ξ_k, as specified in the next subsection.

4.1.4 Entry and Exit

Firms in location i in sector m exogenously go bankrupt at rate ξ_m. I consider a steady state where the same flow rate of firms enter so that the number of firms, or equivalently input buyers $B_{i,m}$, is constant over time. Potential entrant ω pays a fixed cost $C_{i,m}$ and draws a productivity $\varphi_\omega \in [0, \infty)$ from a generalized Pareto distribution, where its cumulative distribution function is written as

$$F(\varphi_\omega) = 1 - \left(\frac{\tilde{\varphi}_{i,m}}{\varphi_\omega + \tilde{\varphi}_{i,m}}\right)^\theta, \tag{12}$$

where $\tilde{\varphi}_{i,m}$ and θ are parameters, and $\varphi_\omega \geq 0$. For the purpose of this paper, $\tilde{\varphi}_{i,m}$ is interpreted as the combination of the natural advantage or other unmodeled sources of agglomeration benefit.[28] Such parametrization, together with the approximation that $\tilde{\varphi}_{i,m}$ is sufficiently small, yields tractability in the equilibrium as explained in 4.2. For exposition purposes, I define $\varphi_{i,m}$ by the productivity net of the cost of input goods from the generalized input goods market, i.e. $\varphi_{i,m} \equiv \tilde{\varphi}_{i,m} / \prod_{k\in K} \chi^{\gamma_{k,m}}_{i,k}$.

[27] $H^F_{i,m}(c|\tilde{c})$ depends on $\tilde{c}$, because the fact that an input buyer is matched with a supplier at a certain cost implies that on average their unit cost for production is lower.

[28] To see this, note that the mean of φ_ω is $\frac{1}{\theta-1}\tilde{\varphi}_{i,m}$ for $\theta > 1$.

4.1.5 Total Expenditure and Trade Balance

Aggregate final goods sales from location i is written as

$$X_{i,k}^F = \sum_{j \in N} \alpha_k w_j L_j \pi_{ij,k}^F, \tag{13}$$

where $\pi_{ij,k}^F$ is location j's final goods expenditure share in sector k of goods from location i, and α_k is the final goods consumption share of final goods in sector k. $\pi_{ij,k}^F$ are endogenously determined in the equilibrium and are derived in the next section.

Aggregate input goods sales from location i is written as

$$X_{i,k}^I = \sum_{m \in K} \sum_{j \in N} \gamma_{k,m} \Psi_{j,km} X_{j,m}^F \pi_{ij,k}^I, \tag{14}$$

where $\Psi_{j,km}$ is the share of final goods sales in location j and sector m sold by firms that are matched with a supplier in input sector k, and $\pi_{ij,k}^I$ is location j's input goods expenditure share in sector k of goods from location i.

I assume a steady state where each location i has trade deficit (or deficit if surplus) D_i. Trade balancing condition equates the aggregate sales from location i with the final and input goods purchases in location i net of trade surplus, i.e.,

$$\sum_{k \in K} X_{i,k}^F + \sum_{k \in K} X_{i,k}^I = w_i L_i + \sum_{k,m \in K} \gamma_{k,m} \Psi_{i,km} X_{i,m}^F + D_i. \tag{15}$$

4.2 Characterizing Steady-State Equilibrium

To characterize the steady-state equilibrium, I make use of the parametric assumption that the firm productivity distribution follows a generalized Pareto distribution (i.e., Equation 12). To see why such parametric assumptions are useful, note that the unit cost distributions of final goods in this model depend not only on the wages and firm entry as in a standard Melitz model, but also on the unit cost distributions of input sellers and the match probability with them. This implies that the equilibrium involves a fixed point problem of integral equations with infinite dimensional unknowns, i.e., the unit cost distributions. Here, I show that the dimension of the equilibrium is hugely reduced under the assumption of a generalized Pareto distribution of firm productivity, together with the approximation under sufficiently small $\{\tilde{\varphi}_{i,m}\}$.

Unit Cost Distribution of Input Goods

First, I characterize $H^I_{i,m}(c)$, the measure of producers whose unit cost of input goods is below c in location i in sector m. Appendix B.1.1 shows that

$$H^I_{i,m}(c) = (1 + o(\tilde{\varphi}_{i,m}))^{-\theta} B_{i,m} \varphi^{\theta}_{i,m} w_i^{-\theta} c^{\theta},$$

where $o(\tilde{\varphi}_{i,m})$ is the term that goes to 0 as $\tilde{\varphi}_{i,m} \to 0$. This expression implies that the distribution of the inverse of the unit cost approximately follows a Pareto distribution.

This approximation of $H^I_{i,m}(\cdot)$ implies that $\pi^I_{ij,m}$, the expenditure share of input goods in sector m produced in location i out of total input goods expenditure in location j, follows a gravity equation. To derive this, note that the measure of input sellers who can supply input goods below the unit cost c in location j from location i is $H^I_{i,m}(c\tau_{ij,m})$. From a similar logic as in a standard Melitz model with a Pareto productivity distribution (e.g., Chaney (2008)), $\pi^I_{ij,m}$ corresponds to the extensive margin of trade share, i.e., the share of suppliers selling from location i out of all input sellers in location j.[29] Hence, $\pi^I_{ij,m}$ is derived as

$$\pi^I_{ij,m} = \frac{B_{i,k} \varphi^{\theta}_{i,m} w_i^{-\theta} \tau^{\theta}_{ij,m}}{\sum_{i' \in N} B_{i',m} \varphi^{\theta}_{i',m} w_{i'}^{-\theta} \tau^{\theta}_{i'j,m}}, \tag{16}$$

under the approximation of sufficiently small $\{\tilde{\varphi}_{i,m}\}$.

Unit Cost Distribution of Final Goods

Next, I characterize $H^F_{i,m}(c)$, the measure of producers with unit cost of final goods below c in location i in sector m. Appendix B.1.2 shows that

$$H^I_{i,m}(c) = (1 + o(\tilde{\varphi}_{i,m}))^{-\theta} B_{i,m} \varphi^{\theta}_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k \in K} \Omega_{i,km} \left(S^I_{i,k}, \bar{c}^I_{i,k} \right) c^{\theta},$$

[29] To see this point more formally, note that the expectation of the input goods sales does not depend on the supplier's production location conditional on the unit cost that the supplier can supply input goods to the sales location. By denoting this by $r_{ij,m}(c)$, $\pi^I_{ij,m}$ is derived as

$$\pi^I_{ij,m} = \frac{\int_0^{\bar{c}^I_{j,m}} r_{ij,m}(c) dH^I_{i,m}(c\tau_{ij,m})}{\sum_{i' \in N} \int_0^{\bar{c}^I_{j,m}} r_{i'j,m}(c) dH^I_{i',m}(c\tau_{i'j,m})} \approx \frac{B_{i,m} \varphi^{\theta}_{i,m} w_i^{-\theta} \tau^{\theta}_{ij,m} \int_0^{\bar{c}^I_{j,m}} r_{ij,m}(c) dc^{\theta}}{\sum_{i' \in N} B_{i',m} \varphi^{\theta}_{i',m} w_{i'}^{-\theta} \tau^{\theta}_{i'j,m} \int_0^{\bar{c}^I_{j,m}} r_{i'j,m}(c) dc^{\theta}} = \frac{B_{i,m} \varphi^{\theta}_{i,m} w_i^{-\theta} \tau^{\theta}_{ij,m}}{\sum_{i' \in N} B_{i',m} \varphi^{\theta}_{i',m} w_{i'}^{-\theta} \tau^{\theta}_{i'j,m}},$$

where $\bar{c}^I_{i,m}$ is the entry cutoff of input goods sellers in sector m in location i. Note that, this logic of extensive margin of trade share corresponds to that of the expenditure share is the same as that of a standard Melitz model with a Pareto distribution (e.g., Chaney (2008)). A similar technique has been applied by Eaton et al. (2016b) to derive a gravity equation of input goods trade with static firm-to-firm matching.

where $\prod_{k\in K}\Omega_{i,km}\left(S^I_{i,k},\overline{c}^I_{i,k}\right)$ is the input cost advantage in location i for sector m. In turn, $\Omega_{i,km}\left(S^I_{i,k},\overline{c}^I_{i,k}\right)$ is written as $\Omega_{i,k}\left(S^I_{i,k},\overline{c}^I_{i,k}\right)=1-\Lambda_{i,km}\left(S^I_{i,k}\right)+\Lambda_{i,km}\left(S^I_{i,k}\right)\nu_{i,km}\left(\overline{c}^I_{i,k}\right)$, where $\Lambda_{i,km}\left(S^I_{i,k}\right)$ is the steady state probability of matching with a supplier (Equation 10), and $\nu_{i,km}\left(\overline{c}^I_{i,k}\right)\equiv\frac{1}{\gamma_{k,m}+1}\left(\overline{c}^I_{i,k}/w_i\chi_{i,k}\right)^{-\gamma_{k,m}\theta}$ governs the average cost advantage upon being matched with a supplier. From the same argument as in a standard Melitz model with a Pareto distribution (e.g., Chaney (2008)), location j's final goods expenditure share in sector m of goods from location i is written as

$$\pi^F_{ij,m}=\frac{B_{i,m}\varphi^{\theta}_{i,m}w_i^{-\theta\gamma_{L,m}}\tau^{\theta}_{ij,m}\prod_{k\in K}\Omega_{i,km}\left(S^I_{i,k},\overline{c}^I_{i,k}\right)}{\sum_{i'\in N}B_{i',m}\varphi^{\theta}_{i',m}w_{i'}^{-\theta\gamma_{L,m}}\tau^{\theta}_{i'j,m}\prod_{k\in K}\Omega_{i',km}\left(S^I_{i',k},\overline{c}^I_{i',k}\right)}. \tag{17}$$

Zero Profit Conditions of Input Goods Sellers

Zero-profit conditions of input goods sellers yield the number of input sellers $S^I_{j,k}$ and input seller entry cut-off of unit cost $\overline{c}^I_{j,k}$. Appendix B.1.3 shows that $S^I_{j,k}$ is solved as

$$S^I_{j,k}=\frac{1}{w_j f^I_{j,k}}\psi\sum_{m\in K}\left\{\frac{\theta+\gamma_{k,m}(\sigma-1)}{\theta}\gamma_{k,m}\Psi_{j,km}X^F_{j,km}\right\}, \tag{18}$$

where $\Psi_{j,km}=\frac{\Lambda_{j,km}\left(S^I_{j,k}\right)\nu_{j,km}\left(S^I_{j,k},\overline{c}^I_{j,k}\right)}{1-\Lambda_{j,km}\left(S^I_{j,k}\right)+\Lambda_{j,km}\left(S^I_{j,k}\right)\nu_{j,km}\left(S^I_{j,k},\overline{c}^I_{j,k}\right)}$ is the share of final goods sales in location j and sector m sold by firms that are matched with a supplier in input sector k (also appearing in total expenditure condition in Equation 14).[30] Given the number of sellers S^I_i, the entry cut-off of sellers is derived as

$$\overline{c}^I_{j,k}=\left(\frac{S^I_{j,k}}{\sum_{i'\in N}B_{i',k}\varphi^{\theta}_{i',m}w_{i'}^{-\theta}\tau^{\theta}_{i'j,m}}\right)^{1/\theta}. \tag{19}$$

Free Entry Conditions

The expected profit of firms upon an entry depends both on the final goods profits and input goods profits. Appendix B.1.4 shows that the free entry conditions yield the number of firms,

[30] The intuition of the expression of $\Psi_{j,km}$ is as follows: Firms that are matched with a supplier in input sector k enjoy a cost advantage by $\nu_{j,km}\left(\overline{c}^I_{j,k}\right)$ over unmatched firms. Hence, the sales share of firms with a supplier is expanded from $\Lambda_{j,km}\left(S^I_{j,k}\right)$, the steady state probability of matching with a supplier in input sector k, by the factor of $\nu_{j,km}\left(\overline{c}^I_{j,k}\right)$. $\Psi_{j,km}$ enters in zero-profit conditions, because the aggregate input sales is written as $\gamma_{k,m}\Psi_{j,km}X^F_{j,km}$.

equivalently as input buyers, as

$$B_{i,k} = \frac{1}{\xi_k C_{i,k} w_i} \frac{(\sigma-1)}{\theta} \sum_{j \in N} \left\{ \pi^F_{ij,k} \frac{1}{\sigma} \alpha_k w_j L_j + \psi \pi^I_{ij,k} \sum_{m \in K} \gamma^2_{k,m} \Psi_{j,km} X^F_{j,km} \right\}. \tag{20}$$

Together, the equilibrium is characterized as follows:

Proposition 1. *Under sufficiently small $\varphi_{i,k}$, the steady-state equilibrium is characterized by $\{S^I_{i,k}, B_{i,k}, w_i, X^F_{i,k}, \bar{c}^I_{j,k}, \pi^F_{ij,k}, \pi^I_{ij,k}\}$, which satisfy total expenditure conditions (13, 14), trade balancing conditions (15), gravity equations for input goods (16) and final goods (17), zero profit conditions (18), entry cut-off of input goods sellers (19) and free-entry conditions (20).*

4.3 Matching and Agglomeration in the Model

In this subsection, I briefly discuss the main agglomeration forces of the model: circular causation between the input seller entry $S^I_{j,k}$ and the final goods sales of input buyers $X^F_{i,m}$. For the sake of the discussion of this section, I will ignore the endogeneity of w_i and the number of producers $B_{i,m}$, which constitute a further general equilibrium loop as in the standard Melitz model.

Final goods sales of input buyers in location i in sector m, $X^F_{i,m}$, is determined by the total expenditure condition for final goods (Equation 13). By combining the expenditure share from the gravity equation (16), I have the relationship corresponding to a "forward linkage":

$$X^F_{i,m} = \sum_{j \in N} \alpha_k w_j L_j \frac{B_{i,m} \varphi^{\theta}_{i,m} w_i^{-\theta \gamma_{L,m}} \tau^{\theta}_{ij,m} \prod_{k \in K} \Omega_{i,km} \left(S^I_{i,k}, \bar{c}^I_{i,k} \right)}{\sum_{i' \in N} B_{i',m} \varphi^{\theta}_{i',m} w_{i'}^{-\theta \gamma_{L,m}} \tau^{\theta}_{i'j,m} \prod_{k \in K} \Omega_{i',km} \left(S^I_{i',k}, \bar{c}^I_{i',k} \right)}.$$

The intuition of these equations is simple: If there are more sellers $S^I_{i,k}$, producers have a higher chance of matching with a supplier, which gives a cost advantage to producers in location i (high $\Omega_{i,km} \left(S^I_{i,k}, \bar{c}^I_{i,k} \right)$) and hence increases aggregate final goods sales $X^F_{i,m}$. The number of sellers, in turn, is again derived by the zero profit condition (18), reproduced here:

$$S^I_{j,k} = \frac{1}{w_j f^I_{j,k}} \psi \sum_{m \in K} \left\{ \frac{\theta + \gamma_{k,m}(\sigma-1)}{\theta} \gamma_{k,m} \Psi_{j,km} X^F_{j,km} \right\}.$$

It shows that $S^I_{j,k}$ is increasing in the final goods sales of input buyers, $X^F_{j,m}$. 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.

In this circular causation, the elasticity of supplier matching rate with respect to the

number of input sellers, λ, serve a crucial role. To see this, recall that $\Omega_{i,k}\left(S^I_{i,k}, \overline{c}^I_{i,k}\right) = 1 - \left\{\nu_{i,km}\left(\overline{c}^I_{i,k}\right) - 1\right\} \times \eta_{i,km} \times \left(S^I_{i,k}\right)^{\lambda} / \left\{\eta_{i,km} \times \left(S^I_{i,k}\right)^{\lambda} + \rho_{i,km}\right\}$ by plugging in Equation (10) in the definition of $\Omega_{i,km}$. Hence, the sensitivity of $\Omega_{i,km}$ with respect to $S^I_{i,k}$ is crucially governed by the parameter λ, the elasticity of the supplier matching rate with respect to the number of potential suppliers. In Section 5, I estimate λ to replicate the reduced-form estimates in Section 3.

While related, the circular causation through vertical linkages presented here is somewhat distinct from the theoretical models developed by Krugman and Venables (1995) and Venables (1996). In their models, there are no matching frictions, and firms have access to all producers all across the world. There, the circular causation arises from the production location decision of suppliers and from downstream market size. Here, on the other hand, the circular causation arises from supplier market penetration decision à la Melitz (2003) and from downstream market size. The distinction leads to crucial differences in policy implications, as illustrated in the subsidies for supplier market penetration in Section 6.2.

Just like Krugman and Venables (1995), Venables (1996), and other models of economic geography with agglomeration forces, the circular causation may potentially lead to multiple equilibria. While the presence of multiple equilibria does not cause issues in parameter estimation because the estimation procedure only utilizes the partial equilibrium relationships of the model, it complicates the counterfactual equilibrium simulation. In this paper, I compute counterfactual equilibrium that follow the same bifurcation path as in the observed equilibrium. Section 5 discuss these points further.

5 Equilibrium Computation and Model Estimation

This section discusses the procedure for obtaining counterfactual equilibrium and parameter estimation and calibration. The key parameter is estimated by matching the reduced-form estimates of increasing returns in matching presented in Section 3. The counterfactual equilibrium simulation procedures are implemented to quantify the implied agglomeration forces in Section 6.

5.1 Computation of Counterfactual Equilibrium

To compute the counterfactual equilibrium, I follow the approach of "hat algebra" initiated by Dekle et al. (2008). This procedure allows me to limit the set of parameters and baseline variables required to compute the counterfactual equilibrium. In the following proposition, I describe the conditions of counterfactual equilibrium under two policy counterfactual simu-

lations: Subsidies for supplier market penetration and entry subsidies (Section 6.2), and the change in transportation cost (Section 6.3).

Proposition 2. *Given baseline equilibrium variables* $\{B_{i,k}, w_i, X^F_{i,k}, \pi^F_{ij,k}, \pi^I_{ij,k}, \Lambda_{i,km}, \nu_{i,km}, \Psi_{i,km}\}$, *parameters* $\{\lambda, \psi, \theta, \{\gamma_{L,k}, \gamma_{k,m}, \alpha_k\}\}$, *counterfactual subsidies for supplier market penetration* $\{T^S_{i,k}\}$, *entry subsidies* $\{T^B_{i,k}\}$, *and changes in transportation costs* $\{\hat{\tau}_{ij,k}\}$, *the counterfactual equilibrium is computed by solving the following set of equations with respect to* $\{\hat{S}^I_{i,k}, \hat{B}_{i,k}, \hat{w}_i, \hat{X}^F_{i,k}, \hat{\bar{c}}^I_{j,k}, \hat{\pi}^F_{ij,k}, \hat{\pi}^I_{ij,k}\}$*:*

(i) gravity equation of input goods

$$\hat{\pi}^I_{ij,m} = \frac{\hat{B}_{i,m}\hat{w}_i^{-\theta}\hat{\tau}^{\theta}_{ij,m}}{\sum_{i' \in N} \pi^I_{i'j,m}\hat{B}_{i',m}\hat{w}_{i'}^{-\theta}\hat{\tau}^{\theta}_{i'j,m}},$$

and that of final goods

$$\hat{\pi}^F_{ij,m} = \frac{\hat{B}_{i,m}\hat{w}_i^{-\theta\gamma_{L,m}}\hat{\tau}^{\theta}_{ij,m}\prod_{k\in K}\hat{\Omega}_{i,km}}{\sum_{i' \in N} \pi^F_{i'j,m}\hat{B}_{i',m}\hat{w}_{i'}^{-\theta\gamma_{L,m}}\hat{\tau}^{\theta}_{i'j,m}\prod_{k\in K}\hat{\Omega}_{i',km}}.$$

(ii) zero-profit conditions of input goods sellers

$$\hat{S}^I_{j,k} = \frac{1}{\hat{w}_j}\frac{\sum_{m\in K}\left(\theta + \gamma_{k,m}(\sigma-1)\right)\gamma_{k,m}\Psi_{j,km}X^F_{j,m}\hat{\Psi}_{j,km}\hat{X}^F_{j,m} + \frac{\theta}{\psi}T^S_{i,k}}{\sum_{m\in K}\left(\theta + \gamma_{k,m}(\sigma-1)\right)\gamma_{k,m}\Psi_{j,km}X^F_{j,m}},$$

(iii) free entry conditions

$$\hat{B}_{i,k} = \frac{1}{\hat{w}_i}\frac{\sum_{j\in N}\left\{\pi^F_{ij,k}\hat{\pi}^F_{ij,k}\frac{1}{\sigma}\alpha_k w_j\hat{w}_j L_j + \psi\pi^I_{ij,k}\hat{\pi}^I_{ij,k}\sum_{m\in K}\gamma^2_{k,m}\Psi_{j,km}\hat{\Psi}_{j,km}X^F_{j,km}\hat{X}^F_{j,km}\right\} + \frac{\theta}{\sigma-1}T^B_{i,k}}{\sum_{j\in N}\left\{\pi^F_{ij,k}\frac{1}{\sigma}\alpha_k w_j L_j + \psi\pi^I_{ij,k}\sum_{m\in K}\gamma^2_{k,m}\Psi_{j,km}X^F_{j,km}\right\}}.$$

(iv) cost advantages from supplier matching

$$\hat{\Omega}_{i,km} = \frac{1 - \Lambda_{i,km}\hat{\Lambda}_{i,km} + \Lambda_{i,km}\nu_{i,km}\hat{\Lambda}_{i,km}\hat{\nu}_{i,km}}{1 - \Lambda_{i,km} + \Lambda_{i,km}\nu_{i,km}},$$

where steady state supplier matching probability is $\hat{\Lambda}_{i,km} = 1/\left\{1 - \Lambda_{i,km} + \Lambda_{i,km} \times \left(\hat{S}^I_{i,k}\right)^{-\lambda}\right\}$ *and cost advantage upon a match is* $\hat{\nu}_{i,km} = \left\{\hat{S}^I_{i,k}/\left(\sum_{i'\in N}\pi^I_{i'i,k}\hat{B}_{i',k}\hat{w}_{i'}^{-\theta}\hat{\tau}^{\theta}_{i'i,k}\right)\right\}^{-\gamma_{km}}$.

(v) trade balancing condition (no change in trade surplus)

$$1 = \frac{\sum_{k\in K}X^F_{i,k}\hat{X}^F_{i,k} + \sum_{k\in K}X^I_{i,k}\hat{X}^I_{i,k} - w_i\hat{w}_i L_i - \sum_{k,m\in K}\gamma_{k,m}\Psi_{i,km}\hat{\Psi}_{i,km}X^F_{i,m}\hat{X}^F_{i,m}}{\sum_{k\in K}X^F_{i,k} + \sum_{k\in K}X^I_{i,k} - w_i L_i - \sum_{k,m\in K}\gamma_{k,m}\Psi_{i,km}X^F_{i,m}},$$

where input goods sales is $X^I_{i,k}\hat{X}^I_{i,k} = \sum_{m\in K}\sum_{j\in N}\gamma_{k,m}\Psi_{j,km}\hat{\Psi}_{j,km}X^F_{j,m}\hat{X}^F_{j,m}\pi^I_{ij,k}\hat{\pi}^I_{ij,k}$.

Proposition 2 states that computing an equilibrium does not require all the parameters in the model; rather, a subset of parameters $\{\lambda, \psi, \{\gamma_{L,m}, \gamma_{k,m}, \alpha_k\}, \theta, \sigma\}$ and baseline variables $\{B_{i,k}, w_i, X^F_{i,k}, \pi^F_{ij,k}, \pi^I_{ij,k}, \Lambda_{i,km}, \nu_{i,km}, \Psi_{i,km}\}$ are sufficient. These parameters and baseline variables are either estimated, calibrated, or directly obtained from the data. Next subsection is devoted to the discussion.

As noted in Section 4.3, there may be multiple equilibria, i.e., there may be multiple set of endogenous variables that solve the system of equations in Proposition 2. For the counterfactual simulations provided later, I obtain the coutnerfactual equilibrium by gradually changing the subsidies ($\{T^S_{i,k}, T^B_{i,k}\}$) or transportation cost ($\{\hat{\tau}_{ij,k}\}$); in this sense, the obtained counterfactual equilibrium follows the same bifurcation paths as in the observed equilibrium. This is an intuitive equilibrium selection rule under the counterfactual policies, particularly when the policies are at a relatively small scale and are unlikely to induce switching to equilibria on a different bifurcation path.

In the counterfactual simulation exercise, I mostly focus on the change in the firm density $B_{j,k}$ and the real wages $\frac{w_j}{P_j}$, where P_j is the consumer price index. The following proposition is useful for characterizing the changes in real wages in each location.

Proposition 3. *The change in real wages are derived as*

$$\widehat{\left(\frac{w_i}{P_i}\right)} = \prod_{m\in K}\left(\frac{\hat{\pi}^F_{ii,m}}{\hat{B}_{i,m}\hat{\tau}^{\theta}_{ii,m}\hat{w}_i^{-\theta\gamma_{L,m}}\prod_{k\in K}\hat{\Omega}_{i,km}}\right)^{\frac{\alpha_m}{\theta}}.$$

Proof. See Appendix B.2. □

5.2 Parameter Estimation and Calibration

As explained in the previous section, the knowledge of $\{\lambda, \psi, \{\gamma_{L,m}, \gamma_{k,m}, \alpha_k\}, \theta, \sigma\}$ and baseline variables $\{B_{i,k}, w_i, X^F_{i,k}, \pi^F_{ij,k}, \pi^I_{ij,k}, \Lambda_{i,km}, \nu_{i,km}, \Psi_{i,km}\}$ are sufficient for computing counterfactual equilibrium. Below, I discuss the estimation and calibration of these parameters and variables in turn.

5.2.1 Elasticity of Supplier Matching Rate λ

As discussed in Section 4.3, the elasticity of supplier matching rate λ is a particularly important parameter that governs the degree of agglomeration. Below, I illustrate the estimation procedure of λ to match the reduced-form estimates presented in Section 3.

In the model introduced in Section 4, input buyers in location i in sector m who lost a supplier in sector k matches with a new supplier at Poisson rate $\eta_{i,km} \times \left(S^I_{i,k}\right)^\lambda$. This implies that the probability that the firm matches with an alternative supplier after one year is approximated by $1 - \exp(-\eta_{i,km} \times \left(S^I_{i,k}\right)^\lambda)$. This object is directly mapped to the data to estimate λ, i.e.,

$$\hat{\lambda} = \min_{\lambda} || \left\{ 1 - \exp(-\eta_{i,km} \times \left(S^I_{i,k}\right)^\lambda) \right\} - \left\{ \hat{\beta}_1 + \hat{\beta}_2 \times \log PotentialSuppliers_{ik} \right\} ||^2$$

where $\hat{\beta}_1$ and $\hat{\beta}_2$ are the reduced-form estimates of Equation (2), where we choose $\hat{\beta}_1 = 0.175$ and $\hat{\beta}_2 = 0.059$ from Column (3) of Table 3.

In order to estimate λ, further parametric assumptions are required for $\eta_{i,km}$ and $S^I_{i,k}$. By noting the relationship $\eta_{i,km} \times \left(S^I_{i,k}\right)^\lambda = \eta_{i,km} \left(\frac{\psi}{f^I_{j,k}}\right)^\lambda \left[\frac{1}{w_j} \sum_{m \in K} \left\{ \frac{\theta + \gamma_{k,m}(\sigma-1)}{\theta} \gamma_{k,m} \Psi_{j,km} X^F_{j,km} \right\}\right]^\lambda$, I parametrize that $\eta_{i,km} \left(\frac{\psi}{f^I_{j,k}}\right)^\lambda \sim \log \mathcal{N}(\mu_{\eta,km}, \sigma^2_\eta)$ and $\mu_{km} \sim \mathcal{N}(\overline{\mu}_\eta, \overline{\sigma}^2_\eta)$. The estimation results suggest the value of λ =0.62, implying that 1 percent increase of $S^I_{i,k}$ leads to 0.62 percent higher rate of supplier matching.

It should be noted that the multiplicity of equilibria, as discussed in Section 4.3, does not cause issues in the estimation of parameter λ. This is because the estimation of the parameter is conducted by just using the partial equilibrium relationship of a model without using an entire equilibrium structure. The same argument applies to markup ratio of input sales ψ, and other baseline parameters explained below.

5.2.2 Mark-up Ratio of Input Sales ψ

I estimate ψ using the free entry condition. Intuitively, firms earn profits from two sources of demand: final goods sales and input sales. The profit margin of final goods sales is calibrated from the substitution of CES utility function from the literature. Hence, the extent to which firms are likely to locate close to input demands, relative to final goods consumers, informs the value of mark-up ratio charged for the input sales.

To see this more formally, the free entry conditions are reproduced here:

$$B_{i,k} = \frac{1}{\zeta_{i,k} C_{i,k} w_i} \frac{(\sigma - 1)}{\theta} \sum_{j \in N} \left\{ \pi^F_{ij,k} \frac{1}{\sigma} \alpha_k w_j L_j + \psi \pi^I_{ij,k} \sum_{m \in K} \gamma^2_{k,m} \Psi_{j,km} X^F_{j,km} \right\},$$

Together with the calibrated parameters $(\{\alpha_k\}, \sigma, \theta, \{\gamma_{k,m}\}, \xi_{i,k})$ and the baseline variables $(\pi^F_{ij,k}, \pi^I_{ij,k}, w_j, \Psi_{j,km}, X^F_{j,km})$, the only unobserved parameters in this equation are the input sales mark-up ratio ψ and the fixed entry cost $C_{i,k}$. I parametrize $C_{i,k} \sim \mathcal{N}(\mu_{C,k}, \sigma^2_C)$ and $\mu_{C,k} \sim \mathcal{N}(\overline{\mu}_C, \overline{\sigma}^2_C)$. The estimated ψ is 0.05, indicating the profit margin is somewhat smaller

than that of the final goods, $\frac{1}{\sigma} \approx 0.15$.[31]

5.2.3 Other Parameters and Baseline Variables

Table 7 provides the remaining list of estimated and calibrated parameters and variables required for computing counterfactual equilibrium following Proposition 2. In terms of parameters, I calibrate $\{\alpha_k, \gamma_{k,m}\}$ from the input-output matrix and σ, θ from the literature (Broda and Weinstein (2006); Head and Mayer (2014)). While some variables are directly obtained from the data ($B_{i,k}, w_i, \Lambda_{i,km}, \Psi_{i,km}$), others are obtained indirectly from the model relationships. Appendix D further discusses the detailed procedure.[32]

6 Counterfactual Simulations

This section presents three counterfactual simulations to illustrate the quantitative implications of the agglomeration forces from increasing returns in matching. Section 6.1 computes the equilibrium by hypothetically shutting off the increasing returns in matching. In Sections 6.2 and 6.3, I investigate two policy counterfactual simulations that may improve the welfare of peripheral locations in Japan: subsidies for supplier market penetration and entry subsidies and transportation infrastructure.

6.1 How Much Do Increasing Returns in Matching Explain Geographic Concentration of Economic Activity in Japan?

Section 5.2 estimates λ to be 0.62 by matching the reduced-form estimates in Section 3. As discussed in Section 4.3, the magnitude of λ crucially governs the degree of circular causation between supplier market penetration and downstream market size, creating agglomeration feedback. Then, what does $\lambda = 0.62$ imply for the real world agglomeration patterns in Japan?

To answer this question, I compute the counterfactual equilibrium under the assumption that $\lambda = 0$. More specifically, I assume that the Poisson rate that input buyers match

[31] The idea of inferring profit margins from firm entry decisions are commonly implemented in the literature of industrial organization; e.g., Bresnahan and Reiss (1991).

[32] The cost advantages upon matching with a supplier $\nu_{i,km}$ are calibrated from the cross-sectional sales premium of matching with a supplier (see Appendix D.2 for further discussion). As discussed in Section 3.3.1, such heterogeneity may be a part of the explanation of the lack of statistical significance of the heterogeneous impacts on sales growth and exit probability of unexpected supplier bankruptcy with respect to the number of potential suppliers. To investigate this point further, Table A.7 shows the correlation between the calibrated $\nu_{i,km}$ and the proxy for the number of potential suppliers as defined in Section 3. The positive correlation implies that the cost advantage upon a match is higher with more potential suppliers, consistent with the explanation in Footnote 25.

with suppliers is $\eta_{i,km} \times \left(\overline{S}^I_{i,k}\right)^{\lambda}$, where $\overline{S}^I_{i,k} \equiv \frac{1}{N}\sum_{j\in N} S^I_{j,k}$, i.e., the average number of input sellers in sector k in the baseline equilibrium. These matching rates are assumed to be unchanged under the counterfactual equilibrium and they do not depend on $\hat{S}^I_{i,k}$. Hence, the equilibrium is computed following Proposition 2, except that $\hat{S}^I_{j,k}$ are exogenously specified as $\hat{S}^I_{j,k} = \overline{S}^I_{j,k}/S^I_{j,k}$ rather than zero profit conditions.

Figure 6 shows that counterfactually assuming that $\lambda = 0$ significantly reduces the variance of the firm density and real wages across space. Quantitatively, Panel (A) of Table 8 shows that the variance of firm density decreases to 55% of the baseline, while the variance of real wages decreases to about a third. The remaining geographic variations are induced by the exogenous population distribution, L_i, and the heterogeneity of productivity across locations and sectors, $\varphi_{i,m}$, which include natural advantages. The results confirm that a significant part of geographic inequality in firm density and real wages are attributed to the increasing returns in matching.

6.2 Supplier Marketing Subsidies and Entry Subsidies

In this section, I study the impacts of subsidies to promote geographically disadvantaged areas. Throughout the world, policies targeting the improvements of disadvantaged locations are common and are often refereed as place-based policies (Kline and Moretti (2014b)). A widespread concern associated with favoring disadvantaged locations is that these policies may reallocate resources from productive locations to non-productive locations, potentially harming aggregate welfare (Glaeser and Gottlieb (2008); Kline and Moretti (2014b); Fajgelbaum et al. (2016)). While the policies are associated with such a trade-off if the agglomeration benefits arise from local production spillovers, they may not be if agglomeration force arises from an increased number of input sellers; in such a case, improving the welfare of disadvantaged locations is possible without a large shift of production resources to these locations.

More concretely, I study two types of subsidies to target a periphery location: subsidies for supplier market penetration and entry subsidy in peripheral areas. The former are given to suppliers conditional on serving the location as input sellers *regardless of their production location*, and the latter are given to suppliers who produce in these locations. The former subsidies are commonly implemented in the form of trade exhibitions or business matching events, and the latter in the form of tax exemptions or subsidies for new business establishment. In the model, these are translated as $T^S_{i,k}$ and $T^B_{i,k}$ in Proposition 2.

Panel (B) of Table 8 presents the results where the two types of subsidies are given to one location that lies in the periphery of Japan, Hokkaido. In both cases, the amount of

total subsidy is equal to the input sales from Hokkaido in the baseline ($X^I_{i,k}$) to allow me to compare the marginal returns of the two different subsidy schemes. While both are effective in improving the real wages of Hokkaido, the improvements in Hokkaido from the subsidy for supplier market penetration is by far larger in magnitude than the entry subsidy; it is 6.5 times larger. Interestingly, I find that the firm density *decreases* due to the subsidies for supplier market penetration. This is because the improved productivity due to supplier matching pushes up labor demand and hence wages, increasing the fixed entry cost.

6.3 Transportation Infrastructure

In this subsection, I study the impacts of transportation infrastructure to reduce the trade cost between central and peripheral locations. One may expect that the transportation infrastructure would benefit peripheral locations in a similar way as the subsidy for supplier market penetration by improving supplier access from central to peripheral locations. In fact, this motivation has become a driver of the development of the Japanese highway network after World War II. To test whether this conjecture is true, I study the implications of counterfactually improving the transportation infrastructure between Hokkaido to the rest of Japan. That is, I assume that the iceberg trade cost decreases $\hat{\tau}_{ij,k} = 1.5\tau_{ij,k}$ if i or j is Hokkaido for all $k \in K$. Similarly, I consider the increase of iceberg trade cost, i.e., $\hat{\tau}_{ij,k} = 0.5\tau_{ij,k}$.

Panel (C) of Table 8 shows that the decrease of transportation cost *reduces* the welfare of Hokkaido and *improves* peripheral regions for a decrease of transportation cost. In other words, transportation infrastructure harms the periphery. The intuition is as follows: While the reduction of transportation costs increases the benefits of supplier matching in peripheral regions relative to central regions, it also increases the competition between local suppliers in peripheral regions and from central regions. The increased competition creates a force that on net shifts the production resources from peripheral regions to the central regions.

7 Conclusion

This paper investigates the importance of increasing returns in firm-to-firm matching in input trade as a source of agglomeration. In the first part of the paper, I provide reduced-form evidence of increasing returns in firm-to-firm matching. Using unexpected supplier bankruptcies as an instrument, I show that the new supplier matching rate upon a supplier loss increases in locations and industries when there are more potential suppliers, while this rate remains stable in the presence of other downstream firms. In the second part of the paper,

I build a structural trade model to quantify the importance of increasing returns in firm-to-firm matching for the geographic concentration patterns of economic activity in Japan. The structural model highlights distinct policy implications compared to other commonly assumed agglomeration forces, i.e., those based on local production externalities. In particular, I find that the marginal impacts of subsidies for supplier market penetration are much larger than entry subsidies. I also find that transportation infrastructure development sometimes harms the periphery by shifting production resources to the central regions.

There are several important directions for future work. First, further understanding of why matching frictions exist and how the policies can reduce such frictions is important. To understand this, Daisuke Miyakawa and I are partnering with Tokyo Shoko Research to conduct a randomized control trial to provide information about potential transaction partners. Such an RCT will reveal how information frictions interact with geographic space and how reducing such frictions improves firm production. Second, dynamic implications of matching frictions and increasing returns in firm-to-firm matching for regional business cycles and long-term growth should be studied both theoretically and empirically. Lastly, other microfoundations of agglomeration should be studied empirically, theoretically and quantitatively. By no means does this paper claim that increasing returns in firm-to-firm matching is the *only* source of agglomeration. Reflecting Marshall (1890), labor market pooling and knowledge spillovers may be equally important forces that drive agglomeration. With this respect, a general key message of this paper is that both theoretical and empirical understandings of different microfoundations of agglomeration are important for proper understanding of policy consequences, and further research is awaited.

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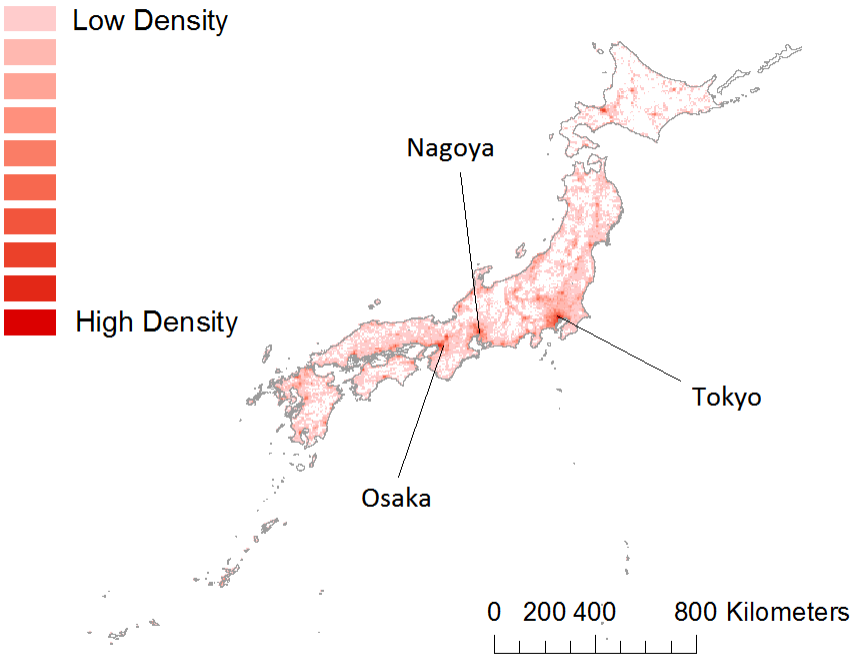
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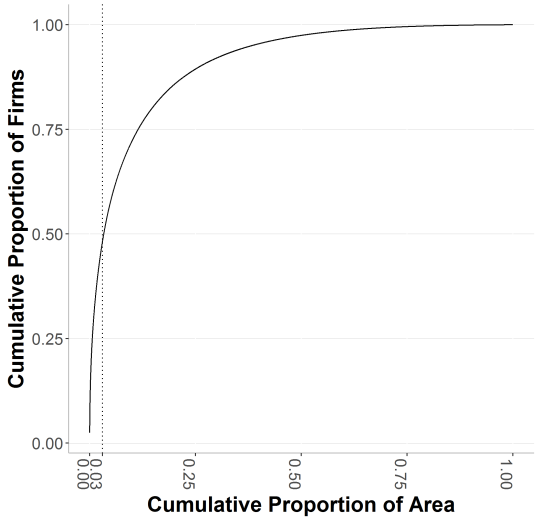
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Figure 1: Geographic Distribution of Firms in Japan

(A) Map of Japan

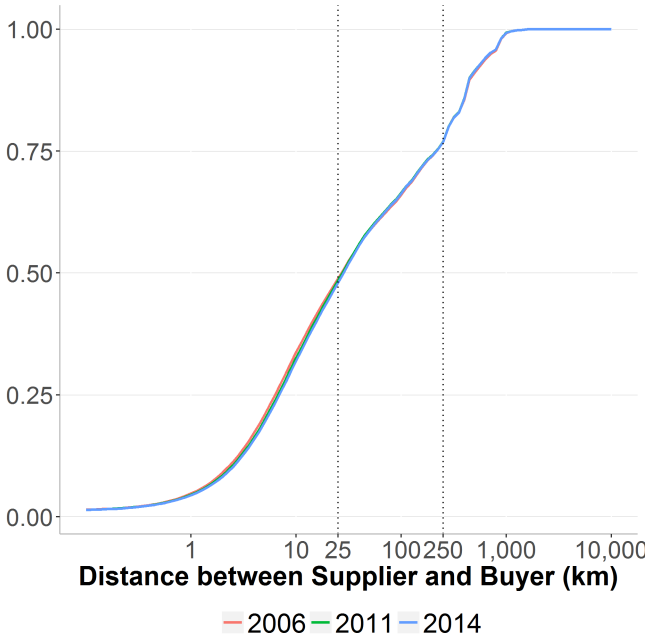


(B) Cumulative Distribution of Firms by Local Firm Density



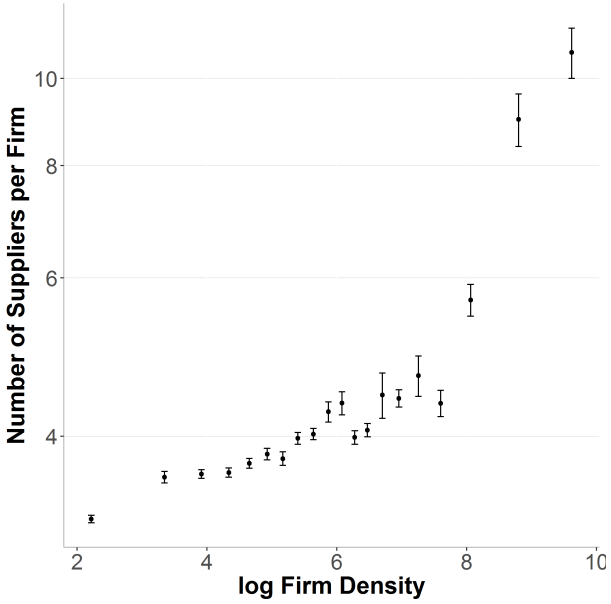
Note: Local firm density is defined by the density of firm headquarters in 2006, evaluated at each grid cell of 0.05 degree latitude by 0.05 degree longitude (approximately 5.5 km by 4.5 km).

Figure 2: Cumulative Distribution of Geodesic Distances between Supplier and Buyers



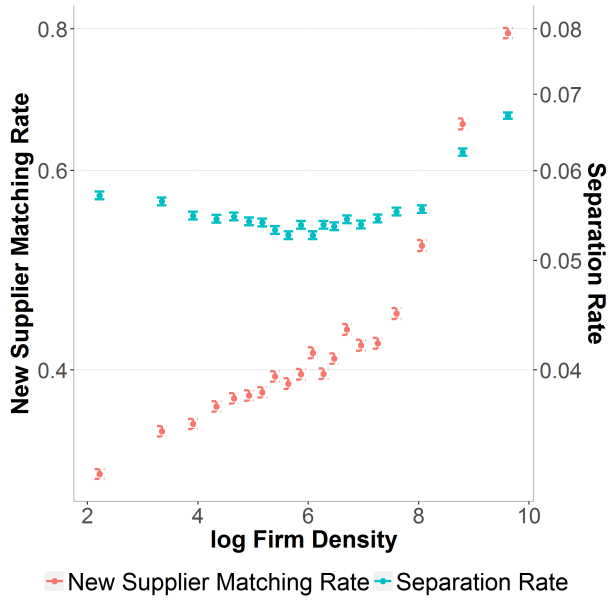
Note: The graph shows the cumulative distributions of geodesic distance between supplier and buyer's headquarter locations for the years of 2006, 2011, and 2014.

Figure 3: Number of Suppliers per Firm and Local Firm Density



Note: Samples are firms in the data set from 2006. Firm density is defined by the density of firm headquarters in 2006, evaluated at each grid cell of 0.05 degree latitude by 0.05 degree longitude (approximately 5.5 km by 4.5 km).

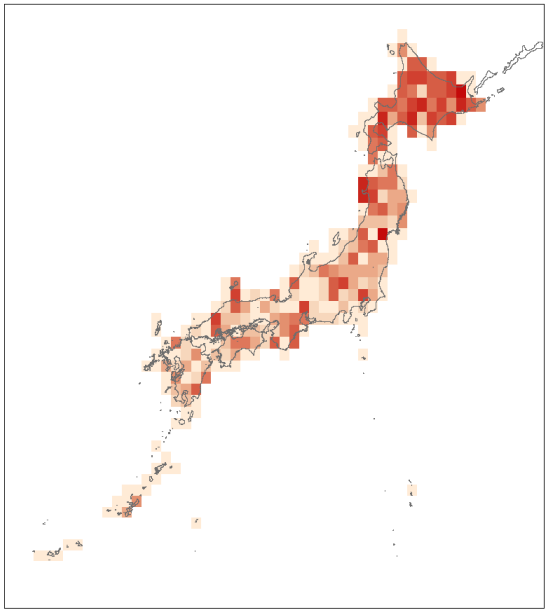
Figure 4: New Supplier Matching Rate and Separation Rate by Local Firm Density



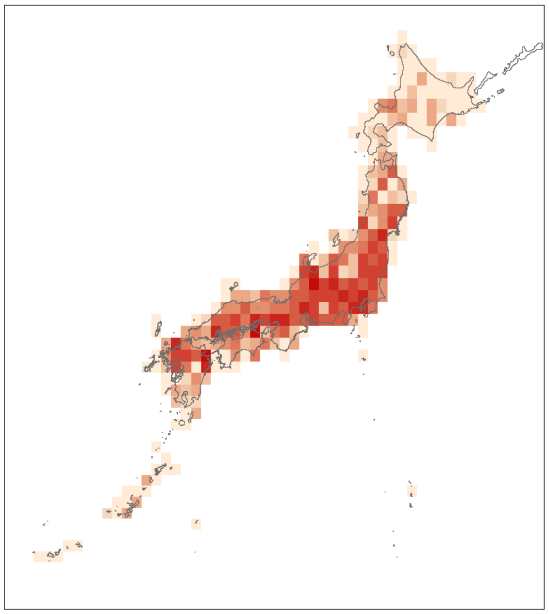
Note: "New Supplier Matching Rate" is the number of suppliers that firms gain per year (averaged across 2006 to 11 and 2011 to 14), and "Separation Rate" is the probability that firms lose suppliers per year, including both the exits of suppliers and dissolution of trading relationships.

Figure 5: Examples of Geographic Variation of the Proxy of Potential Suppliers

(A) Forestry Industry



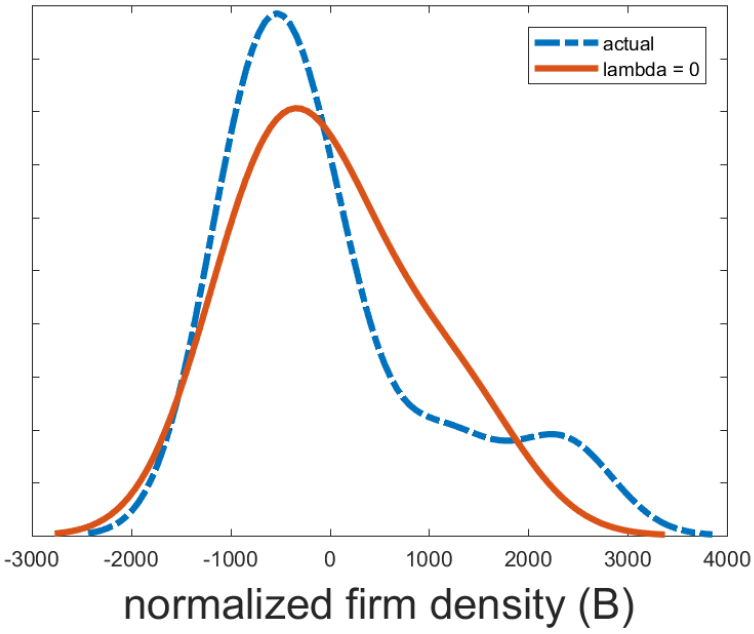
(B) Steel Industry



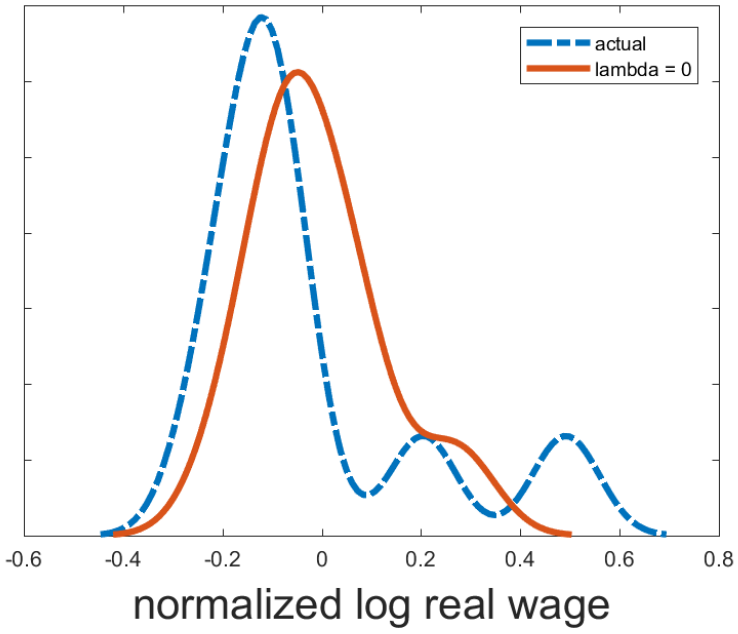
Note: See Section 3 for the definition of the number of potential suppliers.

Figure 6: Counterfactual Simulation: Shutting Off Increasing Returns in Matching

(A) PDF of firm density (normalized)



(B) PDF of log real wages (normalized)



Note: The graphs show the results from the counterfactual simulations in Section 6.1. Panel (A) shows the distribution of firm density in the observation (in dotted blue lines) and that under the counterfactual equilibrium with $\lambda = 0$ (in solid red lines). Panel (B) shows the same objects for the real wages. In both graphs, firm density and log real wages are normalized to be mean 0.

Table 1: Main Reasons of Bankruptcies

Reasons of Bankruptcies	Number of Bankruptcies 06-14	Percentage
reasons used for IV		
spillover from other bankruptcy	2,310	5.8%
accidental reansons	615	1.5%
reasons NOT used for IV		
non-performing sales	26,073	65.4%
accumulation of debt	5,614	14.1%
insufficient capital	2,791	7.0%
management failure	1,311	3.3%
overinvestment in capital	438	1.1%
difficulty in collecting account receivable	249	0.6%
non-project related failure	232	0.6%
issuance of accomodation debt	155	0.4%
over-accumulation of inventory	51	0.1%
Total	39,839	100.0%

Note: The frequency of the bankruptcies assigned to each main reason of bankruptcies is reported. "Spillover from other bankruptcy" and "accidental reasons" are the two categories of bankruptcies used for an instrument for a supplier loss in Section 3. "Spillover from other bankruptcies" are those caused by management difficulties due to chain reactions such as business partners, subsidiary companies, related bankruptcies, voluntary liquidation, etc. "Accidental reasons" include those with unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc.

Table 2: Summary Statistics of Japanese Firm-to-Firm Matching in Input Trade

(A) Cross-Sectional Patterns

	years		
	2006	2011	2014
(i) Number of Suppliers per Firm			
mean	4.65	4.63	4.62
median	2	2	2
5 percentile	0	0	0
95 percentile	12	12	13
99 percentile	33	35	37
(ii) Number of 2-digit Input Sectors with a Supplier per Firm			
mean	2.39	2.34	2.33
median	2	2	2
(iii) Number of 4-digit Input Sectors with a Supplier per Firm			
mean	3.16	3.11	3.10
median	2	2	2
(iv) Number of Buyers per Firm			
mean	4.64	4.66	4.65
median	2	2	2
5 percentile	0	0	0
95 percentile	13	12	13
99 percentile	42	40	41
(v) Number of Firms	695,418	1,030,965	1,095,617

(B) Dynamic Patterns

	years		per-year average
	2006 to 11	2011 to 14	
(i) Probability of Exit	0.099	0.053	0.019
(ii) Change of Suppliers (Conditional on Survival)			
Proportion of Exiting Suppliers	0.10	0.05	0.018
Proportion of Lost Supplier Relationships	0.37	0.24	0.077
No. of New Suppliers / No. of Baseline Suppliers	0.54	0.24	0.094
(iii) Relocation Probability of Firm Headquarters	0.014	0.008	0.003

Note: Proportion of lost suppliers in Row (ii) of Panel (B) includes both the cases of supplier exits and dissolution of trading relationships in the specified time interval. Relocation of firm headquarters in Row (iii) of Panel (B) is defined by the relocation outside the grid cell of 0.5 degree latitude by 0.5 degree longitude. The two-digit and four-digit sectors follow the Japan Standard Industrial Classification (JSIC) with 98 two-digit sectors and 1248 four-digit sectors in JSIC classification. For more detail on JSIC, see http://www.soumu.go.jp/english/dgpp_ss/seido/sangyo/index.htm .

Table 3: Evidence of New Supplier Matching Rate Increasing in Potential Suppliers

	New Suppliers								Pretrend	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Separated Suppliers	0.156***	0.160***	0.156***				0.171***	0.145	−0.027	−0.027
	(0.054)	(0.054)	(0.060)				(0.061)	(0.090)	(0.035)	(0.035)
Sep. S. x log Potential Suppliers		0.066**	0.078*	0.104***	0.155***	0.155***	0.085*	0.077*		0.005
		(0.026)	(0.040)	(0.040)	(0.041)	(0.041)	(0.050)	(0.042)		(0.015)
Sep. S. x log Firm Density			−0.014							
			(0.045)							
Sep. S. x log Local Suppliers							−0.018			
							(0.034)			
Unexp. S. Bankruptcy x Location x Year FE				X	X	X				
Unexp. S. B. x log Employment Size					X	X				
Unexp. S. B. x Buyer Industry x Region x Year FE						X				
Firm x Year FE								X		
Observations	2,288,793	2,288,793	2,288,793	2,288,793	2,285,126	2,285,126	2,288,793	2,288,793	989,957	989,957

Note: Regression specification follows Equation (2). The regression is run at the firm, input sector, and year level. The outcome variable is the number of new suppliers per year, and "Separated Suppliers" indicates the number of lost suppliers per year. "Potential Suppliers" are defined as the number of firms in input sector that supply to some firms in the same location (0.5 degree grid cells) in the baseline period (2006). "Separated Suppliers" and its interactions are instrumented by "Unexpected Supplier Bankruptcy" and its relevant interactions. All regressions control for the buyer's location, buyer's sector, input sector and year fixed effects, as well as the fixed effects for the baseline number of suppliers. "log Potential Suppliers" are normalized to be mean 0, and the inter-quartile range is 2.6. Region is a geographic administrative unit in Japan, with 8 regions in total. "log Local Suppliers" indicate the number of firms in each input sector in the buyer's location. Standard errors are clustered at the firm level, and regressions are weighted to equalize the weight at the firm and year level. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Evidence of New Supplier Matching Rate Not Decreasing in Buyers

	New Suppliers							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Supplier Separation	0.179***	0.165***	0.152**	0.120	0.174***	0.124**	0.193***	0.108
	(0.054)	(0.049)	(0.061)	(0.083)	(0.064)	(0.059)	(0.055)	(0.066)
Sep. S. x log Potential Suppliers	0.091***	0.071***	0.063***	0.060**	0.054**	0.049**	0.066**	0.066**
	(0.032)	(0.027)	(0.023)	(0.024)	(0.025)	(0.025)	(0.026)	(0.026)
Sep. S. x log Buyers (Same 2-digit Industry)	−0.036							
	(0.033)							
Sep. S. x log Buyers (Same 4-digit Industry)		−0.008						
		(0.020)						
Sep. S. x log Buyers (Same 2-digit Industry) with Unexp. S. Bankruptcy			0.012					
			(0.049)					
Sep. S. x log Buyers (all) with Unexp. S. Bankruptcy				0.027				
				(0.046)				
Sep. S. x log Buyers (Same 2-digit Industry) with Supplier Separation					0.019			
					(0.031)			
Sep. S. x log Buyers (all) with Supplier Separation						0.028		
						(0.030)		
Sep. S. x log Buyers Anywhere (Same 2-digit Industry) with Unexp. S. Bankruptcy							0.032	
							(0.022)	
Sep. S. x log Buyers Anywhere (all) with Unexp. S. Bankruptcy								0.035*
								(0.021)
Observations	2,288,793	2,288,793	2,288,793	2,288,793	2,288,793	2,288,793	2,288,793	2,288,793

Note: Regression specification follows Equation (3). See the footnote of Table 3 for the definitions of samples, outcome variables, other controls, and the variable "Potential Suppliers". "log Buyers (Same 2-digit Industry)" indicates the number of firms in the same 2-digit industry in firm f's location. "log Buyers (Same 2-digit Industry) with Unexp. S. Bankruptcy" indicates the number of firms in the same 2-digit industry in f's location that faced unexpected supplier bankruptcy in the same 2-digit input sector, while "log Buyers (Same 2-digit Industry) with Supplier Sepaeation" follows the same definition except that firms are counted if they faced any supplier separation (including supplier exits and dissolution of trade relationships) in the same 2-digit sector. "log Buyers (Same 2-digit Industry) Anywhere with Unexp. S. Bankruptcy" follows the same definition as "log Buyers (Same 2-digit Industry) with Unexp. S. Bankruptcy," except firms in any locations are counted as long as they face unexpected supplier bankruptcy in the same input sector. Standard errors are clustered at the firm level, and regressions are weighted to equalize the weight at the firm and year level. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Impacts of Unexpected Supplier Bankruptcy on Sales Growth and Exit

	Sales Growth		Exit		Sales Growth (Surviving)		Sales Growth (Pretrend)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unexpected Supplier Bankruptcy	−0.031*	−0.036*	0.007*	0.007*	−0.005	−0.009	−0.012	−0.013
	(0.018)	(0.019)	(0.004)	(0.004)	(0.012)	(0.012)	(0.016)	(0.016)
Unexp. S. Bankruptcy x log Potential Suppliers		0.013		−0.0005		0.011		0.008
		(0.011)		(0.003)		(0.007)		(0.008)
Observations	2,496,861	2,496,861	2,496,861	2,496,861	2,309,804	2,309,804	1,017,393	1,017,393

Note: The regression specification follows Equation (4). See the footnote of Table 3 for the definitions of samples, outcome variables, other controls, and the variable "Potential Suppliers". Sales growth is defined by the arc-elasticity (Davis and Haltiwanger (1992)). Standard errors are clustered at the firm level, and regressions are weighted to equalize the weight at the firm and year level. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Impacts of Unexpected Supplier Bankruptcy on Other Existing Suppliers

	Pr[Other Supplier Separation]		Other Supplier Sales Growth	
	(1)	(2)	(3)	(4)
Unexpected Supplier Bankruptcy	0.002	−0.002	−0.020**	−0.024***
	(0.006)	(0.007)	(0.008)	(0.008)
Unexp. S. Bankruptcy x log Potential Suppliers		0.007		0.006
		(0.004)		(0.005)
Observations	870,764	870,764	865,615	865,615

Note: The regression specification follows Equation (5). See the footnote of Table 3 for the definitions of samples, outcome variables, other controls, and the variable "Potential Suppliers". Sales growth is defined by the arc-elasticity (Davis and Haltiwanger (1992)). Standard errors are clustered at the firm level, and regressions are weighted to equalize the weight at the firm and year level. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Estimated and Calibrated Parameters

	value	source
(A) Estimated Parameters		
Elasticity of supplier matching rate λ	0.62	Section 5.2.1
Mark-up ratio of input sales ϕ	0.05	Section 5.2.2
(B) Calibrated Parameters		
Input share in production $\gamma_{L,m}, \gamma_{km}$		IO table
Final goods expenditure share α_k		IO table
Productivity distribution shape parameter θ	5	Head and Mayer (2006)
Elasticity of substitution σ	5	Broda and Weinstein (2006)
(C) Baseline Variables		
Number of producers $B_{i,k}$		data
Wages w_i		data
Steady state supplier matching probability $\Lambda_{i,km}$		data
Market share of firms with a supplier $\Psi_{i,km}$		data
Probability of sourcing input goods from i in j $\pi^I_{ij,k}$		Smoothed with gravity equation; See Appendix D.1
Cost advantage upon supplier matching $\nu_{i,km}$		Use $\Psi_{i,km}$ and $\Lambda_{i,km}$; See Appendix D.2
Expenditure share of final goods from i in j $\pi^F_{ij,k}$		Use gravity equation of final and input goods; See Appendix D.3
Final goods sales $X^F_{i,k}$		Use total expenditure condition (Equation 13)
Input goods sales $X^I_{i,k}$		Use total expenditure condition (Equation 14)

Table 8: Results from Counterfactual Simulations

(A) Counterfactually Assume $\lambda = 0$

	$\lambda = 0.62$ (observed equilibrium)	$\lambda = 0$ (counterfactual)
variance of log real wages	1 (normalized)	0.36
variance of firm density	1 (normalized)	0.55

(B) Subsidies for Supplier Marketing Penetration and Entry subsidies

	no subsidy (observed equilibrium)	subsidy for supplier penetration (T^S) (counterfactual)	entry subsidy (T^B) (counterfactual)
real wages in Hokkaido	1 (normalized)	1.13	1.02
real wages in Other Locations	1 (normalized)	1.02	0.99
firm density in Hokkaido	1 (normalized)	0.86	1.11
firm density in Other Locations	1 (normalized)	1.32	1.00

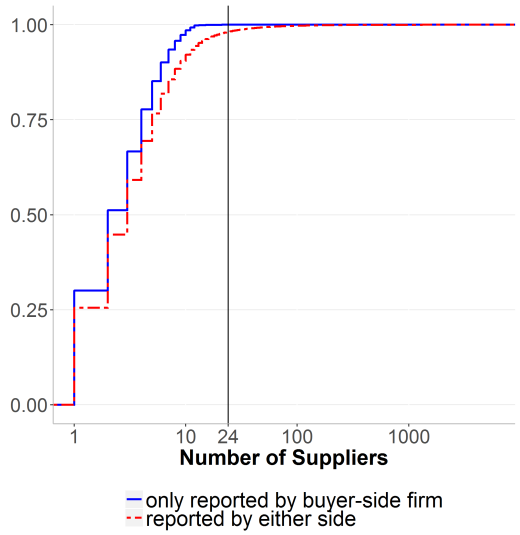
(C) Changes in Transportation Cost

	observed equilibrium	$\hat{\tau}_{ij,k} = 0.5\tau_{ij,k}$ for i or j = Hokkaido (transportation cost increase)	$\hat{\tau}_{ij,k} = 1.5\tau_{ij,k}$ for i or j = Hokkaido (transportation cost decrease)
real wages in Hokkaido	1 (normalized)	0.99	0.97
real wages in Other Locations	1 (normalized)	0.93	1.12
firm density in Hokkaido	1 (normalized)	1.00	0.98
firm density in Other Locations	1 (normalized)	0.88	1.07

Note: See Section 6 for the details of the counterfactual simulations.

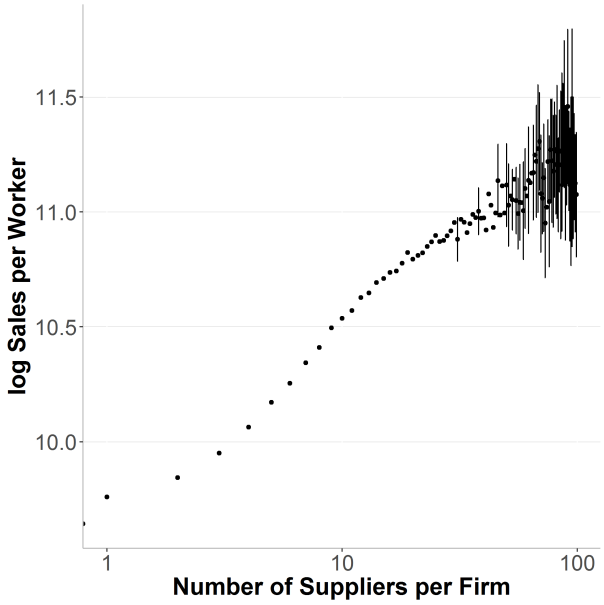
A Additional Figures and Tables

Figure A.1: CDF of Number of Suppliers



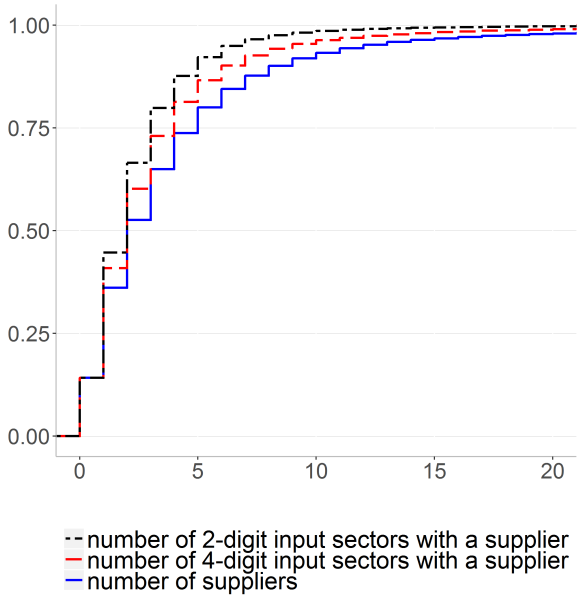
Note: Cumulative distribution of the number of suppliers under two definitions. "Only reported by buyer-side firm" defines the existence of a link if only buyer-side firms report. "Reported by either side" defines the existence of a link if either party reports that the relationship exists.

Figure A.2: Per-Worker Revenue Productivity and Number of Suppliers per Firm



Note: Samples are based on the data from 2006. The graph shows the average log sales per worker for each number of suppliers, censored at 100.

Figure A.3: Distribution of Suppliers and Input Sectors per Firm



Note: Samples are based on the data from 2006. The graph shows the CDF of the number of suppliers and number of input sectors with a supplier at the firm level, censored at 20.

Table A.1: Number of Suppliers per Firm and Firm Density

	No. of Suppliers					log No. of Suppliers
	(1)	(2)	(3)	(4)	(5)	(6)
log Firm Density	0.784***	0.956***	0.100***	0.268***	0.228***	0.025***
	(0.193)	(0.218)	(0.023)	(0.020)	(0.010)	(0.002)
Sample					excl. Tokyo	
4-digit Industry FE		X	X	X	X	X
Employment Size FE			X	X	X	X
Prefecture FE				X	X	X
Observations	696,454	696,453	670,740	670,740	591,312	670,740
R^2	0.002	0.034	0.928	0.929	0.895	0.447

Note: Samples are firms in the data set from 2006. Firm density is defined by the density of firm headquarters in 2006, evaluated at each grid cell of 0.05 degree latitude by 0.05 degree longitude (approximately 5.5 km by 4.5 km). Prefecture is a geographic administrative unit in Japan, with 47 prefectures in total. Standard errors are clustered at the grid cell level. *p<0.1; **p<0.05; ***p<0.01.

Table A.2: Revenue Productivity and Number of Suppliers per Firm

	log Sales per Worker		
	(1)	(2)	(3)
log (Supplier Number + 1)	0.373***	0.305***	0.340***
	(0.001)	(0.001)	(0.001)
4-digit Industry FE		X	X
Employment Size FE			X
Observations	670,092	670,091	670,091
R^2	0.107	0.313	0.324

Note: Samples are firms in the data set from 2006. Firm density is defined by the density of firm headquarters in 2006, evaluated at each grid cell of 0.05 degree latitude by 0.05 degree longitude (approximately 5.5 km by 4.5 km). Robust standard errors are reported. *p<0.1; **p<0.05; ***p<0.01.

Table A.3: First Stages of New Supplier Matching Regression

	Supplier Separation			
			Pretrend	
	(1)	(2)	(3)	(4)
Unexpected Supplier Bankruptcy	0.864***	0.861***	0.028	0.034
	(0.023)	(0.023)	(0.025)	(0.026)
Unexp. Sup. Bankruptcy x log Potential Suppliers		0.007		−0.011
		(0.012)		(0.011)
Observations	2,288,793	2,288,793	989,957	989,957
R^2	0.367	0.367	0.243	0.243

Note: The first stage regression of Equation (3) are reported. See the footnote of Table 3 for the definitions of samples, outcome variables, other controls, and the variable "Potential Suppliers". Standard errors are clustered at the firm level, and regressions are weighted to equalize the weight at the firm and year level. *p<0.1; **p<0.05; ***p<0.01.

Table A.4: New Supplier Matching Within and Outside Locations

	New Suppliers			
	(Local)	(Nonlocal)	(Local)	(Nonlocal)
	(1)	(2)	(3)	(4)
Supplier Separation	0.063*	0.093**	0.020	0.151***
	(0.037)	(0.037)	(0.037)	(0.046)
Sep. S. x log Potential Suppliers			−0.041	0.126***
			(0.034)	(0.038)
Sep. S. x log Local Suppliers			0.077***	−0.095***
			(0.023)	(0.027)
Observations	2,288,793	2,288,793	2,288,793	2,288,793

Note: The specification follows that of Table 3. "Local" indicates the number of new suppliers within the same 0.5 degree grids, and "Nonlocal" indicates that outside the grids.

Table A.5: Additional Robustness on New Supplier Matching Regression

	New Suppliers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Separated Suppliers	0.177***	0.082*	0.122**	0.359**	0.157***	0.169***	0.149**	0.096*	0.065
	(0.058)	(0.048)	(0.050)	(0.156)	(0.060)	(0.046)	(0.062)	(0.054)	(0.071)
Sep. S. x log Potential Suppliers	0.087***	0.048**	0.054**	0.100*	0.080***	0.043**	0.048	0.043	0.050*
	(0.026)	(0.023)	(0.025)	(0.058)	(0.028)	(0.021)	(0.029)	(0.028)	(0.030)
Sample		excl. top 3 input sector	CEO born locally	only accidental	only bankruptcy spillover	excl. Tokyo	est. size <= 5	3-digit	4-digit
Unexp. S. Bankruptcy x Input Coef	X								
Observations	2,288,793	1,211,769	1,657,981	2,288,793	2,288,793	2,040,504	1,766,340	2,676,549	2,853,765

Note: The specification follows that of Table 3. Column (1) controls for the interaction between unexpected supplier bankruptcy and the input coefficients of the IO matrix. In Column (2), the ranking of industry pair is based on the baseline probability that firms in buyer industries match with suppliers in each input sector. Columns (4) and (5) restrict the instruments for separated suppliers to be unexpected supplier bankruptcy due to accidental reasons and due to other bankruptcy spillovers, respectively. Column (8) and (9) indicate the regressions run at the three digits and four digits industry classification levels, respectively.

Table A.6: New Supplier Matching Regression with All Supplier Exits as an Instrument

	New Suppliers			Pretrend		
	(1)	(2)	(3)	(4)	(5)	(6)
Separated Suppliers	0.125***	0.127***		−0.038***	−0.039***	
	(0.007)	(0.007)		(0.005)	(0.005)	
Sep. S. x log Potential Suppliers		0.053***	0.062***		0.031***	0.027***
		(0.005)	(0.005)		(0.003)	(0.003)
Firm x Year x Supplier Exit FE			X			X
Observations	2,288,793	2,288,793	2,288,793	989,957	989,957	989,957

Note: The specification follows that of Table 3, except that the instruments are supplier exits for any reasons, not unexpected supplier bankruptcies as in Table 3.

Table A.7: Correlation between $\nu_{i,km}$ and Proxy of Potential Suppliers in Reduced-Form Regression

	$\log \nu$		
	(1)	(2)	(3)
log Potential Suppliers	0.029***	0.031***	0.074***
	(0.002)	(0.003)	(0.009)
Input Sector FE		X	X
Buyer Sector FE		X	X
Buyer Location FE			X
Observations	89,739	89,739	89,739

Note: See Appendix D.2 for the calibration of $\nu_{i,km}$, i.e., the cost advantage upon supplier matching in the structural model, and Section 3 for the definition of the proxy for the number of potential suppliers in the reduced-form exercise. *p<0.1; **p<0.05; ***p<0.01.

B Proofs and Derivations

B.1 Proof of Proposition 1

This section provides a proof of Proposition 1, following in the order of Section 4.2 by filling the detailed algebraic derivations.

B.1.1 Unit Cost Distribution and a Gravity Equation of Input Goods

The unit cost of firm ω in production location i in sector m is reproduced from equation (8) as

$$c^I_\omega = \frac{1}{\varphi_\omega} w_i \prod_{k \in K} \chi_{i,k}^{\gamma_{k,m}},$$

The measure of firms whose unit cost is below c is derived as

$$\begin{aligned}
H^I_{i,m}(c) &= B_{i,m} Pr[c \geq \frac{1}{\varphi_\omega} w_i \prod_{k \in K} \chi_{i,k}^{\gamma_{k,m}}] \\
&= B_{i,m} \left(\frac{\frac{1}{c} w_i \prod_{k \in K} \chi_{i,k}^{\gamma_{k,m}} + \tilde{\varphi}_{i,m}}{\tilde{\varphi}_{i,m}} \right)^{-\theta} \\
&= B_{i,m} \left(\frac{\frac{1}{c} w_i \prod_{k \in K} \chi_{i,k}^{\gamma_{k,m}}}{\tilde{\varphi}_{i,m}} \right)^{-\theta} \left(1 + \frac{\tilde{\varphi}_{i,m}}{\frac{1}{c} w_i^{\gamma_{L,m}} \prod_{k \in K} g_{i,k}^{\gamma_{k,m}}} \right)^{-\theta} \\
&= (1 + o(\tilde{\varphi}_{i,m}))^{-\theta} B_{i,m} \varphi^\theta_{i,m} w_i^{-\theta} c^\theta
\end{aligned}$$

where $o(\tilde{\varphi}_{i,m})$ is the term that goes to 0 as $\tilde{\varphi}_{i,m} \to 0$.

B.1.2 Unit Cost Distribution of Final Goods

The unit cost of firm ω in production location i in sector m is reproduced from equation (6) as

$$c^F_{\omega t} = \frac{1}{\varphi_\omega} w_i^{\gamma_{L,m}} \prod_{k \in K} {p_{\omega t,k}}^{\gamma_{k,m}},$$

where, for each k independently,

$$\begin{cases} p_{\omega t,k} = \chi_{i,k} w_i & \text{w.p. } 1 - \Lambda_{i,km}\left(S^I_{i,k}\right) \\ p_{\omega t,k} \sim G^I_{i,k}(\cdot) & \text{w.p. } \Lambda_{i,km}\left(S^I_{i,k}\right) \end{cases}$$

hold in the steady state, where $G^I_{i,k}(\cdot)$ is the probability distribution of unit cost of input goods in location i in sector k. From the argument in Section 4.2, $G^I_{i,k}(\cdot)$ is approximated by the inverse of the Pareto distribution with upper bound $\overline{c}^I_{i,k}$, where $\overline{c}^I_{i,k}$ is the entry cutoff of

input goods sellers in sector k in location i. The measure of firms whose unit cost is below c is derived as

$$\begin{aligned}
H_{i,m}^F(c) &= \int_{p_1,\ldots,p_N} B_{i,m} Pr[c \geq \frac{1}{\varphi_\omega} w_i^{\gamma_{L,m}} \prod_{k\in K} {p_k}^{\gamma_{km}}] \prod_{k\in K} dG_{i,k}^I(p_k) \\
&= \int_{p_1,\ldots,p_N} B_{i,m} \left(\frac{\frac{1}{c} w_i^{\gamma_{L,m}} \prod_{k\in K} {p_k}^{\gamma_{km}} + \tilde{\varphi}_{i,m}}{\tilde{\varphi}_{i,m}} \right)^{-\theta} \prod_{k\in K} dG_{i,k}^I(p_k) \\
&= \int_{p_1,\ldots,p_N} B_{i,m} \left(\frac{\frac{1}{c} w_i^{\gamma_{L,m}} \prod_{k\in K} {p_k}^{\gamma_{km}}}{\tilde{\varphi}_{i,m}} \right)^{-\theta} (1 + o(\tilde{\varphi}_{i,m}))^{-\theta} \prod_{k\in K} dG_{i,k}^I(p_k) \\
&= (1 + o(\tilde{\varphi}_{i,m}))^{-\theta} B_{i,m} \varphi_{i,m}^{\theta} w_i^{-\theta\gamma_{L,m}} c^{\theta} \\
&\qquad \times \prod_{k\in K} \left\{ \left(1 - \Lambda_{i,km}\left(S_{i,k}^I\right)\right) + \Lambda_{i,km}\left(S_{i,k}^I\right) \int_{p_k} \left(\frac{p_k}{w_i \chi_{i,k}} \right)^{-\theta\gamma_{km}} dG_{i,k}^I(p_k) \right\} \\
&= (1 + o(\tilde{\varphi}_{i,m}))^{-\theta} B_{i,m} \varphi_{i,m}^{\theta} w_i^{-\theta\gamma_{L,m}} c^{\theta} \\
&\qquad \times \prod_{k\in K} \left\{ \left(1 - \Lambda_{i,km}\left(S_{i,k}^I\right)\right) + \Lambda_{i,km}\left(S_{i,k}^I\right) \frac{1}{\gamma_{km}+1} \left(\frac{\overline{c}_{i,k}^I}{w_i \chi_{i,k}} \right)^{-\theta\gamma_{km}} \right\} \\
&\equiv (1 + o(\tilde{\varphi}_{i,m}))^{-\theta} B_{i,m} \varphi_{i,m}^{\theta} w_i^{-\theta\gamma_{L,m}} \prod_{k\in K} \Omega_{i,km}\left(S_{i,k}^I, \overline{c}_{i,k}^I\right) c^{\theta}
\end{aligned}$$

where $o(\tilde{\varphi}_{i,m})$ is again the term that goes to 0 as $\tilde{\varphi}_{i,m} \to 0$. $\Omega_{i,km}\left(S_{i,k}^I, \overline{c}_{i,k}^I\right)$ represents the cost advantage from supplier matching, i.e.,

$$\Omega_{i,km}\left(S_{i,k}^I, \overline{c}_{i,k}^I\right) = 1 - \Lambda_{i,km}\left(S_{i,k}^I\right) + \Lambda_{i,km}\left(S_{i,k}^I\right) \nu_{i,km}\left(\overline{c}_{i,k}^I\right), \tag{21}$$

where $\Lambda_{i,km}\left(S_{i,k}^I\right)$ is the steady state probability of matching with a supplier (Equation 10), and $\nu_{i,km}\left(\overline{c}_{i,k}^I\right) \equiv \frac{1}{\gamma_{k,m}+1}\left(\overline{c}_{i,k}^I / w_i \chi_{i,k}\right)^{-\gamma_{k,m}\theta}$ governs the average cost advantage upon being matched with a supplier.

B.1.3 Zero Profit Condition of Input Goods Sellers

Zero-profit conditions of input goods sellers yield the number of input sellers $S_{j,k}^I$ and input seller entry cut-off of unit cost $\overline{c}_{j,k}^I$. To see this, first observe that aggregate profit from input sales in location j by sector k to sector m is $\psi\gamma_{k,m}\Psi_{j,km}X_{j,m}$, where $\Psi_{j,km}$ is the share of final goods sales in location j and sector m sold by firms with a supplier in input sector k, out of total sales by firms in location j and sector m (introduced in Equation (14)). I first derive $\Psi_{j,km}$ as a function of $\nu_{i,km}\left(\overline{c}_{i,k}^I\right)$ and $\Lambda_{i,km}\left(S_{i,k}^I\right)$. To see this, note that conditional on being matched, the probability of making a sale is $\nu_{i,km}\left(\overline{c}_{i,k}^I\right)$ times the unmatched one.

This yields

$$\Psi_{j,km}\left(S^I_{j,k},\bar{c}^I_{j,k}\right)=\frac{\Lambda_{j,km}\left(S^I_{j,k}\right)\nu_{j,km}\left(\bar{c}^I_{j,k}\right)}{1-\Lambda_{j,km}\left(S^I_{j,k}\right)+\Lambda_{j,km}\left(S^I_{j,k}\right)\nu_{j,km}\left(\bar{c}^I_{j,k}\right)}.$$

Now, the ratio of the profit from input goods of two firms with unit cost c and c' is written as $\frac{\Pi^I_{j,km}(c')}{\Pi^I_{j,km}(c)}=\left(\frac{c'}{c}\right)^{\gamma_{k,m}(1-\sigma)}$, by noting that the unit cost differences translates to downstream final goods sales by the factor of $\gamma_{k,m}$. Furthermore, the measure of input goods suppliers whose unit cost is below c is approximated by $\sum_{i'\in N}B_{i',m}\varphi^{\theta}_{i',m}w_{i'}^{-\theta}\tau^{\theta}_{i'j,m}c^{\theta}\equiv\Gamma^I_{j,k}c^{\theta}$. From these relationships, I solve for the cut-off value of unit cost $\bar{c}^I{}_{j,k}$:

$$\begin{aligned}
\psi\gamma_{k,m}\Psi_{j,km}X_{j,m} &= \int_0^{\bar{c}^I{}_{j,k}}\Pi^I_{j,km}(c)d\Gamma^I_{j,k}c^{\theta}\\
&= \int_0^{\bar{c}^I{}_{j,k}}\Pi^I_{j,km}(\bar{c}^I_{j,k})\left(\frac{\bar{c}^I_{j,k}}{c}\right)^{\gamma_{k,m}(1-\sigma)}\Gamma^I_{j,k}\theta c^{\theta-1}dc\\
&= \Pi^I_{j,km}(\bar{c}^I_{j,k})\frac{\theta}{\theta+\gamma_{k,m}(\sigma-1)}\Gamma^I_{j,k}\bar{c}^{I\theta}_{j,k}\\
&= \Pi^I_{j,km}(\bar{c}^I_{j,k})\frac{\theta}{\theta+\gamma_{k,m}(\sigma-1)}S^I_{j,km}.
\end{aligned}$$

By noting that the zero profit condition is derived as $f^s_j w_j=\sum_{m\in K}\Pi^I_{j,km}(\bar{c}^I_{j,k})$, I have

$$S^I_{j,k}=\frac{1}{w_j f^I_{j,k}}\sum_{m\in K}\left\{\frac{\theta+\gamma_{k,m}(\sigma-1)}{\theta}\psi\gamma_{k,m}\Psi_{j,km}X_{j,km}\right\}.$$

Recalling again that the measure of input goods suppliers whose unit cost is below c is approximated by $\sum_{i'\in N}B_{i',m}\varphi^{\theta}_{i',m}w_{i'}^{-\theta}\tau^{\theta}_{i'j,m}c^{\theta}\equiv\Gamma^I_{j,k}c^{\theta}$, the entry cut-off of unit cost is derived as

$$\bar{c}^I_{j,k}=\left(\frac{S^I_{j,k}}{\sum_{i'\in N}B_{i',k}\tau^{\theta}_{i'j,m}\varphi^{\theta}_{i',m}w^{\theta}_{i'}}\right)^{1/\theta}.$$

B.1.4 Free Entry Conditions

Total input goods profit of firms in location j, net of the fixed marketing cost, is written as

$$\begin{aligned}
&\sum_{m\in K}\int_0^{\bar{c}^I_{j,k}}\left(\Pi^I_{j,km}(c)-w_j f^I_{j,k}\right)d\Gamma^I_{j,k}c^{\theta}\\
&=\sum_{m\in K}\psi\gamma_{k,m}\Psi_{j,km}X_{j,m}-\left\{\frac{\theta+\gamma_{k,m}(\sigma-1)}{\theta}\psi\gamma_{k,m}\Psi_{j,km}X_{j,km}\right\}\\
&=\sum_{m\in K}\frac{\gamma_{k,m}(\sigma-1)}{\theta}\psi\gamma_{k,m}\Psi_{j,km}X_{j,m}
\end{aligned}$$

Total final goods profit of firms in location j, net of fixed marketing cost, is similarly derived as

$$\int_0^{\bar{c}^F_{j,k}} \left(\Pi^F_{j,km}(c) - w_j f^F_{j,k}\right) d\Gamma^F_{j,k} c^\theta = \frac{\sigma-1}{\sigma\theta}\alpha_k w_j L_j.$$

Hence, the free entry condition to enter in location i is written as

$$B_{i,k} = \frac{1}{\xi_k C_{i,k} w_i} \sum_{j\in N} \left\{ \pi^F_{ij,k} \frac{\sigma-1}{\sigma\theta}\alpha_k w_j L_j + \psi \sum_{m\in K} \frac{\gamma_{k,m}(\sigma-1)}{\theta} \gamma_{k,m} \Psi_{j,km} X_{j,m} \right\},$$

where ξ_k is the bankruptcy rate, and $C_{i,k}w_i$ is the fixed entry cost.

B.2 Proof of Proposition 3

From the definition of CES consumer utility and pareto distribution of unit cost of final goods sellers, the consumer price index in location i is written as

$$\begin{aligned}
P_i &\propto \prod_{m\in K} \left(S^F_{i,m}\right)^{\frac{\alpha_m}{1-\sigma}} \left(\bar{c}^F_{j,m}\right)^{\alpha_m} \\
&= \prod_{m\in K} \left(S^F_{i,m}\right)^{\frac{\alpha_m}{1-\sigma}} \left(\frac{S^F_{i,m}}{\sum_{i'} B_{i',m} \varphi^\theta_{i',m} w_{i'}^{-\theta\gamma_{L,m}} \tau^\theta_{i'i,m} \prod_{k\in K} \Omega_{i',km}} \right)^{\frac{\alpha_m}{\theta}} \\
&= \prod_{m\in K} \left(S^F_{i,k}\right)^{\frac{\alpha_k(1-\sigma+\theta)}{\theta(1-\sigma)}} \left(\frac{\pi^F_{ii,m}}{B_{i,m} \varphi^\theta_{i,m} w_i^{-\theta\gamma_{L,m}} \tau^\theta_{ii,m} \prod_{k\in K} \Omega_{i,km}} \right)^{\frac{\alpha_m}{\theta}}
\end{aligned}$$

Note that under the Pareto distribution $S^F_{i,k}$ only depends on L_i, hence the values are unchanged under the counterfactual simulations. Therefore, the change of real wages is written as

$$\left(\widehat{\frac{w_i}{P_i}}\right) = \prod_{m\in K} \left(\frac{\hat{\pi}^F_{ii,m}}{\hat{B}_{i,m} \hat{w}_i^{-\theta\gamma_{L,m}} \hat{\tau}^\theta_{ii,m} \prod_{k\in K} \hat{\Omega}_{i,km}} \right)^{\frac{\alpha_m}{\theta}}$$

C Model Extension to Incorporating Labor Mobility

To incorporate labor mobility, I make a following additional assumption. I assume that workers also consume housing goods in addition to final goods, with Cobb-Douglas utility with share β. In addition, each worker has heterogeneous preferences for locations, $\boldsymbol{\epsilon} = \{\epsilon_1, \ldots, \epsilon_N\}$. Together, the utility of a worker that draws preference shock $\boldsymbol{\epsilon}$ is written as

$$U_i(\boldsymbol{\epsilon}) = A_i \frac{w_i}{P_i^{1-\beta} R_i^\beta} \epsilon_i,$$

where A_i is the exogenous amenity level of the locations and R_i is the rent in location i. I assume that housing supply in each location is fixed to 1 at each location. From the land market clearing condition, the rent is determined as $R_i = w_i L_i$ hence the utility function $U_i(\epsilon) = A_i \left(\frac{w_i}{P_i}\right)^{1-\beta} (L_i)^{-\beta} \epsilon_i$. Assuming that ϵ_i is drawn from Fréchet distribution with scale parameter ν independently for each worker and location, and normalizing the total population $\overline{L} = \sum_i L_i = 1$, I have free labor mobility conditions:

$$L_i = \frac{A_i^{\nu} \left(\frac{w_i}{P_i}\right)^{(1-\beta)\nu} (L_i)^{-\beta\nu}}{\sum_{i'} A_{i'}^{\nu} \left(\frac{w_{i'}}{P_{i'}}\right)^{(1-\beta)\nu} (L_i)^{-\beta\nu}}. \tag{22}$$

The equilibrium with free labor mobility is simply characterized by just adding free labor mobility conditions in the characterization of Proposition 1 and including L_i as an additional endogenous variables.

Proposition 4. *Under sufficiently small $\varphi_{i,k}$, the steady-state equilibrium with free labor mobility is characterized by $\{S^I_{i,k}, B_{i,k}, w_i, X^F_{i,k}, \overline{c}^I_{j,k}, \pi^F_{ij,k}, \pi^I_{ij,k}, L_i\}$ that satisfy total expenditure conditions (13, 14), trade balancing condition (15), gravity equations for input goods (16) and final goods (17), zero profit conditions (18), entry cut-off of input goods sellers (19), free-entry conditions (20), and free labor mobility (22).*

D Calibration of Parameters and Baseline Variables

D.1 Expenditure Share of Input Goods from Different Locations $\pi^I_{ij,k}$

By noting that $\pi^I_{ij,k}$ also corresponds to the extensive margin of trade, empirical frequency of the probability of sourcing input goods from location i in sector k, $\pi^I_{ij,k}$, can be in principle directly obtained from the data set by counting the fraction of sector k suppliers producing in location j from location i. However, this measure is noisy due to the sparseness of the data and involves many zeros. To deal with this, I first estimate the parametrized gravity equation (16) to obtain the smoothed predictor of $\pi^I_{ij,k}$. To implement this, I estimate the following model

$$\tilde{\pi}^I_{ij,k} = \frac{\delta_{i,k}\tau^\theta_{ij,k}}{\sum_{i' \in N} \delta_{i',k}\tau^\theta_{ij,k}}$$

where I parametrize $\tau^\theta_{ij,k} = (D_{ij})^{\kappa_k}$ and D_{ij} is the straight line distance between i and j. $\delta_{i,k}$ is the location fixed effects, defined as $\delta_{i,k} \equiv B_{i,k}\varphi^\theta_{i,k}w_i^{-\theta}$. The model is estimated by a Poisson regression as suggested by Santos Silva and Tenreyro (2006). I use the predictor of the model

$$\tilde{\pi}^I_{ij,k} = \frac{\hat{\delta}_i\hat{\tau}^\theta_{ij,k}}{\sum_{i' \in N} \hat{\delta}_{i'}\hat{\tau}^\theta_{ij,k}},$$

for the baseline $\pi^I_{ij,k}$.

D.2 Cost Advantages upon Supplier Matching $\nu_{i,km}$

As derived in Appendix B.1.3, I use the following relationship to obtain $\nu_{j,km}$,

$$\Psi_{j,km} = \frac{\Lambda_{j,km}\nu_{j,km}}{1 - \Lambda_{j,km} + \Lambda_{j,km}\nu_{j,km}},$$

where $\Lambda_{j,km}$ and $\Psi_{j,km}$ are directly obtained from the data. Intuitively, $\nu_{j,km}$ is identified from the magnitude that firms in location j in sector m that are matched with a supplier in input sector k have a higher sales than unmatched firms.

D.3 Expenditure Share of Final Goods $\pi^F_{ij,k}$

Since the data does not directly provide the final goods flow, I infer it from the gravity equations of final goods (17). Together with the gravity equations of input goods (16),

$$\pi^F_{ij,m} = \frac{\pi^I_{ij,m} \prod_{k \in K} \Omega_{i,km}}{\sum_{i' \in N} \pi^I_{i'j,m} \prod_{k \in K} \Omega_{i',km}},$$

where $\Omega_{i,km}$ is obtained as $\Omega_{i,km} = 1 - \Lambda_{i,km} + \Lambda_{i,km}\nu_{i,km}$.