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

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Abstract

Why are economic activities geographically concentrated? In this paper, I argue that increasing returns to scale in firm-to-firm matching for input trade is an important source of agglomeration. I open by providing its reduced-form evidence with a yearly panel of firm-to-firm trade in Japan. Using unanticipated supplier bankruptcies as natural experiments, I show that firms rematch with new suppliers at a faster rate in locations and industries when there are more alternative suppliers selling in the buyer's location. At the same time, supplier bankruptcies do *not* decrease the supplier matching rate *of other buyers* in near geographic proximity. Based on the reduced-form findings, I develop a new structural model of firm-to-firm trade under matching frictions. In this economy, the presence of more input sellers increases input buyers' aggregate sales by improving the supplier matching rates and hence giving an input cost advantage; this, in turn, attracts more suppliers to sell in the location. I structurally estimate the key parameters to match the reduced-form estimates, and I show that this type of circular causation explains one-third of the population-density premium in output-per-worker, and 12% of the welfare gains of a new bullet train.

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1 Introduction

Economic activities are geographically concentrated. Out of 47 prefectures in Japan, Tokyo Prefecture, which consists of only 0.5% of the geographic area and 7% of the population of Japan alone produces 18% of the country's output.[1] There is no shortage of theories of why the agglomeration of economic activity may occur.[2] However, there is much less consensus about the empirical and quantitative relevance of the various mechanisms that the literature proposes.

In this paper, I focus on one such mechanism of geographic concentration of economic activity: firms find input suppliers more easily in denser areas. Although this is one of the most classical ideas dating back to Marshall (1890), empirical evidence is limited beyond a cross-sectional correlation (Holmes (1999)). In this paper, I first provide new reduced-form evidence of this agglomeration mechanism based on new supplier matching patterns upon unanticipated supplier bankruptcies. Based on the reduced-form evidence, I develop a new structural model of firm-to-firm trade that micro-found this agglomeration force. I then use the estimated model to quantify the importance of this mechanism in explaining the spatial distribution of economic activities.

The first part of the paper provides new reduced-form evidence of this agglomeration mechanism using a panel of firm-to-firm trade data in Japan. The data exhibits a robust correlation between the number of suppliers per firm and the population density, supporting the earlier evidence provided in the United States (Holmes (1999)). However, such a cross-sectional correlation may suffer at least two types of endogeneity issues: First, firms in denser areas may have higher demand for external inputs, due for example to unobserved differences in production processes. Second, firms who are good at finding external suppliers may selectively locate in denser areas.

To overcome the first issue, I use unanticipated supplier bankruptcies as natural experiments to estimate the matching rate with new suppliers. This strategy allows me to focus on firms which are in need of alternative suppliers, regardless of where they locate. To overcome the second endogeneity issue that firms which are good at finding external suppliers may selectively enter in denser locations, I take two strategies. First, I use a *within-location across-industry variation* of a supplier density, i.e., I compare two firms in the *same* location which face a supplier bankruptcy in a *different* supplier industry. Second, I instrument the supplier density of the bankrupting supplier industry by that of the *CEO's birthplace*. This strategy solves the endogeneity concern that CEOs who are good at matching with suppliers start a business in denser locations.[3]

To implement the idea, I use a yearly panel of firm-to-firm trade covering nearly 70% of all Japanese firms.[4] Aside from the comprehensive information of the major suppliers and buyers

[1] According to the number in 2014 by Economic and Social Research Institute (http://www.esri.cao.go.jp/jp/sna/data/data_list/kenmin/files/contents/pdf/gaiyou.pdf).

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

[3] Bleakley and Lin (2012) employ a similar idea of using birthplaces as an instrument in the context of firm-to-worker matching.

[4] A fraction of the same data set, with less time coverage and variables, 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).

reported by each firm in each year, the data set also provides a comprehensive list of bankruptcies with their main reasons. From there, I pick "unanticipated bankruptcy" – the death of representatives, natural disaster, etc. – and study the impact of these bankruptcies on their buyers.[5] The data set also reports the CEO's birth prefecture (out of 47 prefectures in Japan). With this information, I create the density of suppliers of their birthplaces as an instrument for that in their current locations.

To identify the impacts of unanticipated supplier bankruptcies on the subsequent supplier matching, I implement the difference-in-difference method between the treatment firms (firms facing an unanticipated supplier bankruptcy) with comparable control firms. Various characteristics of treatment and control firms before the supplier bankruptcy are similar; this confirms that these bankruptcies are indeed "unanticipated" from the perspective of their buyers.

The results are summarized as follows. First, I find evidence of matching frictions. Treatment firms only gradually recover alternative suppliers. The recovery is imperfect even in the long run. For one unanticipated supplier bankruptcy, treatment firms only rematch with 0.2 new suppliers even after three years following the event.

Second, I find that firms tend to match with new suppliers in near geographic proximity. About one-third of newly matched supplies are headquartered in the same municipality of the treatment firms (out of 1,719 municipalities in Japan in 2013). Interestingly, another one-third of newly matched suppliers are those who are headquartered in a different municipality *but have another existing buyer in the same municipality.* This suggests that the presence of *sales activity* of suppliers is equally important for supplier matching as the physical locations of the suppliers.

Third, I show that this recovery of a supplier is more pronounced in a location and industry where there are more alternative suppliers selling in the buyer's location. The magnitude is sizable; a one-standard-deviation increase of the supplier density doubles the new supplier matching rate, particularly in the short run. These patterns are unlikely to be driven by the fact that firms in denser areas are good at supplier matching; I show that the results remain robust by controlling for the treatment dummy interacted with firm's location to extrapolate *within-location-across-industry variation.* Furthermore, these patterns remain robust by instrumenting the supplier density by that of the CEO's birthplace.

Fourth, the supplier bankruptcies have significant implications on firm production. After three years since the supplier bankruptcy, treatment firms are three percentage points more likely to exit, relative to the control mean of eight percentage points. Interestingly, there is no impact on sales conditional on survival; indicating that exit is a primary margin that supplier bankruptcy affects buyer's production.

Fifth, I find that the higher supplier matching rate of treatment firms does *not* slow down

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

the supplier matching rate *of other buyers* in near geographic proximity. These zero impacts are estimated with tight standard errors. This finding of no crowding-out is in stark contrast to firm-to-*worker* matching in the labor market context, where the presence of unemployed workers is often found to decrease other unemployed workers' reemployment rate (Petrongolo and Pissarides (2001)). These differences are intuitive. In the context of firm-to-firm matching, suppliers can simultaneously serve multiple buyers without inducing crowding out among buyers. On the other hand, in the labor market, a vacant job can be filled by only one unemployed worker, necessarily creating crowding-out.

The reduced-form findings together provide evidence for the increasing returns to scale in firm-to-firm matching. The finding of higher supplier matching rate in a location and industry with higher supplier density, and the finding of no crowding-out, together imply that there are *increasing* returns to scale in matching; increasing both suppliers and buyers improves the supplier matching rate. The finding that matching with suppliers is important in production (i.e., supplier bankruptcy induces buyer's exit) implies that the increasing returns to scale *in matching* implies the increasing returns to scale *in aggregate production.*

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 incorporates matching frictions in firm-to-firm input trade in a version of a multi-location multi-sector Melitz model (Melitz (2003)). As in a standard Melitz model, firms producing in each location decide to sell in various locations by paying a fixed cost. In addition to this standard assumption, firms require inputs for production, which they can source from matched suppliers. The matching rate with a supplier increases in the number of input 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 an agglomeration force through circular causation between the measure of input sellers and downstream market size. In a location with more input sellers, input buyers enjoy a higher supplier matching rate and hence a cost advantage, i.e., a "forward linkage." This, in turn, creates a larger market for suppliers and encourages more supplier to sell in the location, i.e., a "backward linkage." The key parameters that govern this circular causation are two-folds: The elasticity of supplier matching rate with respect to the geographic density of input sellers, and the cost advantage of matching with a supplier. I estimate these structural parameters to replicate the reduced-form impacts of unanticipated supplier bankruptcies on new supplier matching rate and exit probability, as presented in the first part of the paper.

Equipped with the estimated structural model, I ask how much the increasing returns to scale in firm-to-firm matching can explain the geographic concentration of economic activities in Japan. To do so, I simulate the counterfactual equilibrium by hypothetically shutting down the increasing returns to scale in matching, i.e., assuming that the elasticity of the supplier matching rate with respect to the supplier density is 0, unlike the estimates of 0.40 from the structural estimation.

I find that, under this counterfactual world, the density premiums of output per worker and the real wage are smaller by 29% of and 15%, respectively.

To understand the policy implication of this agglomeration force, I next conduct a counterfactual simulation of improving within-country transportation access. Improvement of transportation access may improve the production and welfare in remote areas by increasing the density of input sellers.[6] These welfare effects arise on top of the traditional gains of within-country transportation infrastructure pointed out in the literature (i.e., input price reduction).[7] Taking a bullet train between Hokkaido Island and mainland Japan planned to fully open in 2030 as a case study, I estimate that 12% of welfare gains incurred by Hokkaido Island comes from the increasing returns to scale in matching.

The rest of the paper is organized as follows. Section 2 describes the main data set used in this paper, as well as the suggestive evidence of agglomeration benefit through improved supplier matching. Section 3 provides the reduced-form evidence of matching frictions and increasing returns in firm-to-firm matching using unanticipated supplier bankruptcies as a natural experiment. Section 4 develops a structural trade model of firm-to-firm trade under matching frictions. Section 5 structurally estimates the key parameters of the model, and Section 6 presents the counterfactual equilibrium simulations to understand how much the increasing returns to scale in matching can explain the observed agglomeration patterns of economic activity. Section 7 concludes.

Literature. Agglomeration is a core issue intersecting in urban economics, economic geography, and international trade, and this paper contributes to these strands of the literature. First, this paper is directly related to the literature of the micro-foundation of the agglomeration from increasing returns to scale in matching. Regarding empirics, the closest evidence is limited to a cross-sectional correlation between a fraction of purchased inputs per firm and spatial firm density in the United States (Holmes (1999)). Regarding theory, some papers embed increasing returns to scale in matching as a source of agglomeration (i.e., Diamond (1982); Helsley and Strange (1990)). However, no models have accommodated realistic geography, as well as the presence of cross-locational trade and firm-to-firm matching, both of which are important for quantitative assessment.

Second, this paper contributes to the literature of economic geography. There is a recent wave of quantitative spatial economic models to incorporate realistic geography in theoretical

[6] This point also highlights the difference between the agglomeration mechanism presented in this paper and other types of agglomeration mechanisms. Perhaps most distinctively from other sources of agglomeration mechanisms, this agglomeration mechanism arises from the geographic concentration of suppliers *selling in the location* à la Melitz model, not from the density of firms *producing in the location*. Hence, improving the transportation access between central and remote areas of Japan may increase economic welfare in remote areas, even without relocating firms to produce in remote areas.

[7] See Donaldson (2015) for the literature of welfare gains of within-country transportation infrastructure.

models developed in the New Economic Geography (NEG) literature.[8] This paper's contribution is to explicitly model a particular micro-foundation of agglomeration and study its quantitative 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)).

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

In this section, I briefly describe this paper's main data set, a panel of firm-to-firm trade in Japan. I also document a cross-sectional correlation between local population density and number of suppliers per firm, which suggests an agglomeration benefit through supplier matching. I conclude this section by discussing the confounding factor of this cross-sectional correlation, and how I solve the endogeneity issue using unanticipated supplier bankruptcies as natural experiments in Section 3.

2.1 Data from Tokyo Shoko Research (TSR) Ltd.

The main data set utilized in this paper comes from a major credit reporting agency in Japan, Tokyo Shoko Research (TSR). The data is collected based on face-to-face and phone interviews, as well as public resources such as financial statements, corporate registrations, and public relations documents. The data is a yearly panel starting from 2007 until 2016, and it contains basic firm-level characteristics as well as the precise locations of firm headquarters and establishments. The coverage of the data set is high; in aggregate, the data covers 68% of firms and 70% of total employment in Japan.[9] Several previous papers have used a part of the same data set with limited time coverage and variables, including Nakajima et al. (2012); Bernard et al. (2015); Carvalho et al. (2016), and Furusawa et al. (2017).[10] Below, I describe several important features of the

[8]See Krugman (1991); Krugman and Venables (1995); Fujita et al. (1999) for the theoretical literature of the New Economic Geography, and Allen and Arkolakis (2014); Kline and Moretti (2014); Monte et al. (2015); Ahlfeldt et al. (2015); Faber and Gaubert (2016); Nagy (2017) for the recent quantitative models of economic geography. Redding and Rossi-Hansberg (2016) provide a survey on this literature.

[9]Based on the comparison with the Economic Census in 2009.

[10]The main difference of the data is that it covers every non-missing year from 2007 until 2016, unlike the data from previous research that only covers 2006, 2011, 2012 and 2014. I also make use of some variables that were not available in previous research, including the list of bankruptcies with the main reasons.

data set.

Firm-to-Firm Trade. The most important feature of the data set is that it contains dynamic transitions of supplier-to-buyer relationships. The information is collected by field surveyors through annual face-to-face or phone interviews of TSR by asking up to 24 main suppliers and buyers. Interviews may occur at any point during the year, and I construct a yearly panel of firm-to-firm trade based on the snapshot of the data at the end of each year.[11]

List of Bankruptcies. The data set contains the list of all firms that claimed bankruptcy at some point in the sample period. Most importantly for my purpose, the data set reports the main reason for bankruptcy, identified through TSR's investigation to related parties. Table 1 reports the list of all reasons recorded in this data set. Importantly for my purpose, the list of reasons contains "unanticipated bankruptcies," which is described as "bankruptcies due to unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc.," in an internal document from TSR. In Section 3, I confirm that the outcome variables of firms who face "unanticipated bankruptcies" of suppliers before the event follow a similar trajectory as firms who do not, confirming that these bankruptcies are indeed "unanticipated" from the perspective of their buyers.[12]

Representativeness of TSR Data Across Space. Given that geography is an important focus of this paper, it is important to understand the coverage pattern of TSR data across locations. Figure B.4 plots the fraction of the number firms and total employment in TSR data set out of those numbers in the Economic Census in 2009 for each municipality. The proportion of firms sampled in TSR data set is overall decreasing with some U-shaped pattern in firm density based on Economic Census 2009 (Panel A), while this pattern does not exist for the proportion of total employment relative to the economic census (Panel B). These patterns suggest a tendency that relatively small firms in denser areas, particularly in its intermediate range, are dropped from the TSR data set. In the following analysis, I show that my results are robust by adjusting these municipality-level sampling rates when computing the number of suppliers per firm in Section 3.[13]

[11]One may worry that the threshold of 24 suppliers may be binding. Figure B.2 shows that it is actually not a concern for most of the cases; less than 0.1% of firms have listed 24 firms in 2007. At the same time, there are non-trivial cases where the supplier-side firm reports that the firm is its buyer, even though the buyer-side firm does not report the other way around. In my baseline specification, I do not count these "reverse reporting" cases as the matched suppliers, and I show that my results are robust to the inclusion of these "reverse reporting".

[12]See Table B.1 for more detail. Figure B.3 also shows that this accidental bankruptcy happens equally across all prefectures in Japan. There is also a pattern that these bankruptices are concentrated after 2011 in Tohoku Area, suggesting that the Great Tohoku Earthquake drives non-trivial fraction of "unanticipated accidental bankruptcies." Carvalho et al. (2016) provide related evidence of this finding.

[13]More concretely, I show that my results are not affected by redefining the number of suppliers by weighting by the inverse of the sampling rate at each municipality of supplier's headquarter location. Namely, I define the adjusted number of suppliers of firm i as $\sum_{s\in Supplier(i)} 1/SampleRate_m$, where $SampleRate_m$ is the sampling rate of TSR data set (as appears in Figure B.4) of the headquarter municipality m of supplier s reported by firm i.

2.2 Suggestive Evidence of Supplier Matching Benefit in Denser Areas

Economic output is geographically concentrated in Japan. Panel (A) of Figure 1 shows a positive correlation between aggregate revenue per worker and the population density. The existence of such a density premium has been already documented in various countries, and the figure confirms that the same is true in Japan.[14]

There is also a stark positive correlation between population density and the number of suppliers per firm (weighted by sales size; Panel (B) of Figure 1). This finding is in line with Holmes (1999), who documents the positive correlation between the fraction of externally purchased inputs per firm and spatial firm density in the United States.

As Holmes (1999) also argues, this positive correlation is only suggestive of the agglomeration benefit due to improved supplier matching. Most importantly, firms in denser areas may match with more suppliers because of the unobserved differences in external input demand and production function. Then, the patterns documented in Figure 1 is a reflection of different unobserved firm types and does not imply for an agglomeration benefit.

To address this concern, in Section 3, I use unanticipated supplier bankruptcies as natural experiments to estimate the matching rate with new suppliers. Firms are likely to be in need of an alternative supplier after unanticipated supplier bankruptcies. Hence, these natural experiments allow me to effectively eliminate the confounding factor in the cross-sectional correlation that firms in denser areas simply demand more external suppliers. In fact, the counterfactual simulation with the estimated model (Section 6) reveals that about two thirds of the slope in Panel (B) of Figure 1 still remains in the absence of agglomeration benefit of improved supplier matching rate; confirming that taking this cross-sectional correlation directly as agglomeration benefit leads to substantial overestimation of this agglomeration mechanism.[15]

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

This section provides reduced-form evidence of matching frictions and its increasing returns to scale in firm-to-firm trade by using unanticipated supplier bankruptcy as a natural experiment. The results are summarized as follows: First, firms only imperfectly recover suppliers upon supplier bankruptcy (Section 3.2.1). Second, this recovery is more pronounced in a location and indus-

[14] See, for example, Ciccone and Hall (1996) in the US, and Combes et al. (2012); Gaubert (2015) in France.

[15] One may think that firms can trade in far locations, and hence there is no reason to expect that matching frictions generate the pattern as in Panel (B) of Figure 1. In Figure B.5, I show that there is a strong tendency that firms trade in close geographic proximity. More concretely, the median geodesic distance between suppliers and buyers is about 38 kilometers. As is already documented by Nakajima et al. (2013) and Bernard et al. (2015), this number is much smaller than the median of all possible pairs of firms in Japan. That being said, the presence of cross-locational trade cannot be ignored both quantitatively and economically, and the structural model developed in Section 4 embraces the possibility of cross-location trade.

try where a geographic density of alternative suppliers is higher (Section 3.2.2). Third, supplier bankruptcies affect firm production through increased exit probability (Section 3.2.3). Fourth, I find that the higher supplier matching rate of treatment firms does *not* slow down the supplier matching rate *of other buyers* in near geographic proximity; suggesting that the geographic concentration of *buyers* does not crowd out matching (Section 3.2.4). Together, there is evidence of matching frictions and increasing returns to scale in matching.

3.1 Empirical Strategy

The basic empirical idea of the reduced-form empirical exercise is to estimate whether and how quickly firms can rematch with a new supplier upon an unanticipated supplier bankruptcy. I then compare these impacts across locations and industries with a different geographic density of alternative suppliers. As explained by Section 2.2, such evidence addresses the concern associated with a simple cross-sectional correlation (Figure 1) that firms in denser areas may be simply more likely to be in demand of external suppliers.[16]

I implement this idea with a difference-in-difference method by comparing firms facing an unanticipated supplier bankruptcy with comparable control firms. Denoting the group of control and treatment firms as g (I describe how to assign control firms for each treatment firm later), I run the standard event-study regression:

$$Y_{igt} = \sum_{s=\dots,-2,0,1,\dots} \beta^s 1\left[s = t - BankruptYear_g\right] \times Trt_i + \eta_{gt} + \xi_{ig} + \epsilon_{igt}, \tag{1}$$

where i is the firm, t is the year, $BankruptYear_g$ is the year of unanticipated supplier bankruptcy for the treatment firm in group g, Trt_i denotes the dummy that i is a treatment firm (i.e., faces unanticipated supplier bankruptcy), and Y_{it} is the outcome variable. The group and year fixed effects η_{gt} make sure that $\{\beta^s\}$ are identified off of the comparison within the same group g in the same year, and the firm fixed effects ξ_{ig} takes out all the firm-level unobserved heterogeneity.[17] Coefficients β^s for $s < 0$ captures the differential pre-trends between treatment and control groups, which serves as an assessment that the differential pre-trends do not drive the treatment effects (β^s for $s \geq 0$).[18] Standard errors are clustered at the supplier level. For each control firm in group g, I impose the inverse of the number of control firms within group g as the regression weight, which effectively equates the weight for each g.

To assign control firms for each treatment firm i, I select control firms to be headquartered in the

[16]This empirical strategy echos the recent literature of testing matching frictions in labor market using micro data. Most notably, 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. Other related papers include Petrongolo (2001), Bleakley and Lin (2012) and Macaluso (2016).

[17]Firm i may appear multiple times as control firms for different treatment firms.

[18] I normalize $\beta^s = 0$ for $s = -1$ because it is saturated by the firm fixed effects ξ_{ig}.

same municipality as treatment firm i,[19] and have to have a supplier in i's bankrupting supplier's four-digit industry in the baseline period (i.e., one year before the bankruptcy). Intuitively, this is imposing that treatment and control firms face the same geographic supplier market (i.e., in the same headquarter location and have a demand for a supplier in the same four-digit industry).[20] [21] [22]

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

$$Y_{igt} = \sum_{s=\dots,-2,0,1,\dots} 1\left[s = t - BankruptYear_g\right] \times Trt_i \times \left(\beta^s + \gamma^s \log SellerDensity_g\right) + \eta_{gt} + \xi_{ig} + \epsilon_{igt}, \tag{2}$$

where $\log SellerDensity_g$ is the proxy of a geographic supplier density selling to i's location. In the baseline specification, I define $SellerDensity_g$ as the geographic density of suppliers in the bankrupting suppliers' four-digit industry who have at least one buyer in firm i's prefecture in 2007 (in the beginning of the data set).[23] To deal with the endogeneity of location choice of firm i, I also run a IV specification where I instrument the terms "$1\left[s = t - BankruptYear_g\right] \times Trt_i \times \log SellerDensity_g$" by "$1\left[s = t - BankruptYear_g\right] \times Trt_i \times \log BirthSellerDensity_g$," where $\log BirthSellerDensity_g$ is the supplier density of the birth prefecture of the CEO of the treatment firm i. To ease the interpretation of the coefficients, I standardize $\log SellerDensity_g$ to be mean zero and standard deviation one; hence β^s for $s \geq 0$ captures the average treatment effects, and γ^s captures the increase of treatment effects by changing the supplier density by one standard deviation.

The identifying assumption of the difference-in-difference method is that there are no differences in the pre-trends between control and treatment firms. The lack of pre-trends must hold if the

[19] There are 1719 municipalities in Japan in 2013.

[20] One concern of choosing control firms located in the same municipality is that the supplier bankruptcy may have spillover effects to control firms. Section 3.2.4 imposes a different assignment scheme of control firms without imposing that control firms are in the same location, and investigate this spillover effect. The results show that there is no evidence of crowding-out, confirming the validity of selecting treatment and control firms using the same headquarter locations. The no-presence of spillover is an economically important finding, and discussed in detail in Section 3.2.4.

[21] Since control firms may also lose suppliers (due to non-unanticipated bankruptcies, exit, or link severance), the impact of unanticipated supplier bankruptcies identified with regression (1) is different from the impacts of a supplier *loss*. Figure B.7 illustrates this point by showing the impact of unanticipated supplier bankruptcy on the probability of separation with the supplier used for assigning control firms to treatment firms (i.e., bankrupting supplier for the treatment firm; randomly-picked supplier within the same four-digit supplier industry for control firms). Results in Panel (B) indicates that unanticipated supplier leads to about 0.75 supplier loss in the year of supplier bankruptcy and about 0.6 supplier loss in three years after the supplier bankruptcy.

[22] In case that firms appear both control and treatment firms, which may happen when a firm has multiple suppliers in the same four-digit industry, I eliminate them from both control and treatment groups. I also exclude firms which face multiple unanticipated supplier bankruptcies from the treatment firms, and exclude firms which face at least one unanticipated supplier bankruptcy from the control firms.

[23] Note that $SellerDensity_g$ is defined at the level of group g and does not depend on firm i, because I assign control firms which locate in the same municipality as the treatment firms.

unanticipated accidental bankruptcies are indeed unanticipated from the perspective of buyer-side firms. While I report the lack of such pre-trends along with the main results for important outcome variables, Table B.1 also summarize the lack of pre-period differences in levels and trends of various characteristics.

3.2 Results

3.2.1 Average Impacts of Unanticipated Supplier Bankruptcies on Supplier Matching

Panel (A) of Figure 2 shows that the treatment firms have about 0.7 less number of suppliers in the year of the supplier bankruptcy. These differences gradually decrease over time, but the difference remains about 0.6 even after two years, indicating that the supplier bankruptcy leads to a long-term reduction of the number of suppliers of treated firms.

While imperfect, treatment firms do rematch with new suppliers (Panel (B) of Figure 2). After three years, treatment firms match with 0.25 more suppliers than control firms. Interestingly, there is no impact on the number of retained suppliers. This indicates that that matching with a new supplier is a more important margin than retaining suppliers as a response to supplier bankruptcies.[24]Panel (A) of Table 2 summarizes the same results in a table form.

The newly matched suppliers after the supplier bankruptcy is concentrated around the industry of the bankrupting supplier. Columns (1) and (2) of Panel (B) of Table 2 show that in the long run (two or three years after the supplier bankruptcy), nearly a half of the newly matched supplier is within the same four-digit industry of the bankrupting suppliers out of 1265 four-digit industries. Hence, there is a clear tendency that firms recover a replacement of the bankrupting suppliers within the same supplier industry.

The newly matched suppliers are also concentrated in near geographic proximity. Columns (3) of Panel (B) of Table 2 show that about one-third of the newly matched suppliers occur within the same municipality (out of 1,719 municipalities in Japan in 2013). Interestingly, another one-third of newly matched suppliers are those who are headquartered in a different municipality *but have another existing buyer in the same municipality.* This suggests that the presence of sales activity of suppliers are equally important for supplier matching as the physical locations of the suppliers.

3.2.2 Supplier Matching Rate Increases with Geographic Density of Input Sellers

Having established that firms imperfectly rematch with suppliers following unanticipated supplier bankruptcies, particularly from firms that have existing buyers in the near geographic proximity, I now investigate whether the rematching with new suppliers is more salient in a location and industry where the geographic density of suppliers is higher.

[24]Table B.4 show that these patterns are robust to the inclusion of exiting firms after the supplier bankruptcies.

Panel (A) of Table 3 shows the results following the regression specification (2).[25] Column (1) show that the new supplier matching upon unanticipated bankruptcies are more pronounced if the geographic supplier density is higher. Column (2) show the results where I instrument the supplier density by that defined at the birth prefecture of the CEO. The magnitude is sizable; one standard deviation decrease of the supplier density more than halves the new matching rate.

To confirm that other heterogeneous characteristics of treatment firms do not drive these heterogeneous responses on new supplier matching rate, the remaining columns of Table 3 show the heterogeneous impacts by including the interaction of treatment and the fixed effects of bankruptcy year, birthplace area of CEO, and the supplier industry. The heterogeneous impacts with respect to the supplier density are robust, confirming the importance of the geographic supplier density on the new supplier matching rate.

Appendix Table B.3 and B.4 shows further robustness of the results, including different definitions of the density of input sellers, excluding firms in Tokyo Prefecture, and adjusting for sampling of firms in TSR data set.

3.2.3 Impact of Supplier Matching on Firm Exit and Sales

Unanticipated supplier bankruptcies not only affect subsequent supplier matching but also affect firm production. Column (1) of Table 4, Panel (A) shows that treatment firms are about 3 percentage point more likely to exit than control firms after three years from supplier bankruptcy. The magnitude is large relative to the control mean of 8 percentage point for the same time span. Column (2) shows that the impact on the log of sales is small and not statistically significantly different from 0 *conditional on survival.* Column (3) shows that the inclusion of existing firms as 0 (in log scale) leads to a large and significant negative impact. The results together confirms an importance of losing a supplier for firm production.

Panel (B) of Table 4 shows the decomposition of the impact on exits by the form of firm exits. The main driving force is the bankruptcy (Column 1), indicating that spillovers of bankruptcies is an important concern. There is also impacts on the case where the treatment firm is merged by another firm (Column 3), whose magnitude is large relative to control mean.

Table 5 in turn investigates the heterogeneous impacts of supplier bankruptcies on exit and sales. Due to the noise in the outcome variables, the heterogeneous impacts are not statistically significant. The point estimates are also small relative to average effects. This is partially driven by the fact that, while firms in denser areas benefit by faster supplier matching, the matching rate

[25] Table B.2 shows that there are no pre-trends, and the pre-trends are also not correlated with the measure of input seller density.

is in any ways low on average, and most firms do not rematch with suppliers (i.e., Section 3.2.1)[26]

3.2.4 Buyers Do *Not* Crowd Out Geographic Neighbors' Supplier Matching

While the supplier density improves supplier matching, it may not necessarily imply for the agglomeration benefit if buyers crowd out each other for supplier matching. To test this crowding-out effect, I analyze the impacts of unanticipated supplier bankruptcies on firms in the geographic neighborhoods of the treatment firms. If buyers crowd out each other, these neighboring firms face a reduction of a number of suppliers; this may happen if suppliers are capacity constrained and cannot supply to multiple buyers in the same location simultaneously.

More specifically, I run the following difference-in-difference specification:

$$Y_{jt} = \sum_{s=\ldots,-2,0,1,\ldots} \beta^s 1\left[s = t - BankruptYear_g\right] \times NeighborTrt_i + \eta_{gt} + \xi_{ig} + \epsilon_{igt}, \qquad (4)$$

where $NeighborTrt_i$ is the firm which are in a near geographic proximity (headquartered in the same 0.005, 0.01, 0.05 degree grids of the firms which are hit by unanticipated supplier bankruptcies; roughly corresponding to 0.5 km, 1 km and 5 km radius). From this regression, I omit firms which are directly hit by unanticipated supplier bankruptcies. I take the same grouping (firms which are in the same municipality and have a same four-digit industry supplier in the baseline period). Hence, the control firms of this regression are those within the same municipality, but not as close to the firms which are directly hit by unanticipated supplier bankruptcy.

Columns (1) to (3) of Table 6 show the impact of the number of suppliers. There are no impacts; and these impacts are precisely estimated, by comparing with firms which are directly hit by (Table 2). There are also no statistically significant impacts on the number of suppliers conditional on the same supplier industry (Column 4), as well as exit and sales (Columns 5 and 6).

The findings of no crowding out are 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.[27] 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

[26]This observation also implies that one can quantify the impacts of supplier bankruptcies on exit and sales *per supplier lost.* This is an important question as the match *quality* can be an important and distinct margin where agglomeration benefit arises through matching (Duranton and Puga (2004); Helsley and Strange (1990)). To explicitly test this, I estimate the following IV regression:

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

where $\text{NumberSuppliers}_{it}$ and $\text{NumberSuppliers}_{it} \times \log SellerDensity_g$ are instrumented by $Trt_i \times Post_{gt}$ and $Trt_i \times Post_{gt} \times \log SellerDensity_g$. Table B.5 investigates this point by studying the heterogeneous IV impacts of an supplier on exit and sales. I find no statistically significant heterogeneity in the "quality" of match.

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

crowding out. In other words, the fact that firms can share suppliers limits crowding-out by other buyers.[28] 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.

4 Model of Firm-to-Firm Matching and Agglomeration

This section develops a new structural model building on the reduced-form evidence in Section 3. The model captures the basic facts in Section 3, and allows me to theoretically analyze how the increasing returns to scale in matching leads to agglomeration of economic activity (Section 4.3).

The model is briefly summarized as follows. Potential producers, which can produce both final goods and input goods, are distributed over space and sectors. Both final goods and input goods production requires usage of inputs, which can be either purchased from stochastically matched suppliers or purchasing from fringe intermediaries. Depending on the realized input cost, each firm decides to enter in various locations as input and final goods sellers by paying a fixed cost (i.e., Melitz (2003)). From the perspective of input buyers, the matching rate increases with the measure of input sellers, but is unaffected by the presence of other buyers in the location; this assumption is in line with the empirical findings of increasing returns in matching in Section 3.

4.1 Model Set-up

Space is partitioned into a discrete number of locations (municipalities), denoted by $i, j, n \in N$. Each location is endowed with L_i measure of workers who consume final goods. I assume workers are immobile, while I relax this assumption in Appendix A.2. Time is continuous and denoted by t. In this paper, I only consider a steady-state equilibrium in which aggregate variables (e.g., wages, output) 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.

In each location, there is a continuum of potential producers in each sector, where sector is denoted by $k, m \in K$. 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 possible when two firms stochastically match as a supplier and a buyer. I assume that each buyer-side firm can be matched with at most one supplier in each input sector at a time, though suppliers can be matched with multiple buyers simultaneously.

[28] 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).

4.1.1 Technology

Each firm can produce both final goods and input goods with the Cobb-Douglas production function. By solving for the cost minimization problem, the unit cost for both final goods and input goods by firm ω in location i in sector m is written as follows:

$$c_{\omega t} = \frac{1}{\varphi_\omega} w_i^{\gamma_{L,m}} \prod_{k \in K} p_{\omega t,k}{}^{\gamma_{km}}, \tag{5}$$

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

There are two possible ways to source input goods: match with a supplier for customized input goods, or purchase from local fringe intermediaries. The input prices depend on time t, because whether and which supplier each firm is matched with evolves over time. I will describe the input prices $p_{\omega t,k}$ in Section 4.1.3 in detail. For now, I simply mention that purchasing from local fringe intermediaries are generically more costly.[29]

To derive the closed-form solution in the steady state, I impose a parametric assumption on the distribution of firm-level exogenous productivity. I follow the assumption of Eaton et al. (2016b) and assume that the measure of firms whose productivity is above φ as

$$\mu_{i,m}(\varphi) = \tilde{A}_{i,m} \varphi^{-\theta} \tag{6}$$

where $\tilde{A}_{i,m}$ is the exogenous location-sector level productivity, which can be interpreted as natural advantages or other production benefits of agglomeration.

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 entry cost at a flow rate $f^F_{j,k}$ in the unit of labor in location j. For shipping goods from production location n to j, the firm incurs an iceberg trade cost $\tau_{nj,k}$. The iceberg trade cost captures the combination of shipment cost, transaction cost, and other sources of geographic frictions. Each seller provides a differentiated variety of final goods in a monopolistically competitive manner.

On the demand side, I assume that all labor earnings and firm profit goes to final goods consumption in location i. Representative final goods consumers have a standard CES utility

[29] When mapping the model to the data, I assume that these fringe intermediaries do not appear in the TSR data set.

function:

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

where $q_k(\omega)$ is the consumption of the goods produced by firm ω, α_k is the consumption share of sector k final goods, $\sigma_k > 1$ 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 and Matching

Separately from the decision to sell final goods in location j (Section 4.1.2), each firm in sector k decides to enter as potential input goods sellers in location j at each point in time by paying a fixed entry cost at flow rate f^I in the unit of labor in location j.[30] Shipping input goods from production location n to j requires the same iceberg trade cost $\tau_{nj,k}$ as final goods. I denote the measure of input sellers, i.e., firms in sector k which pay a fixed entry cost for input goods sales in location j, by $S^I_{j,k}$. Due to matching frictions, input sellers only stochastically match with input buyers.

On the demand side of input goods, I first assume that only $\delta_{i,km}$ fraction of firms in location i and sector m ever match with suppliers in sector k; the remaining fraction of firms always source from local fringe intermediaries.[31]If firm ω has a demand for external suppliers, and it is not currently matched with a supplier in sector k, it randomly matches with an input seller at the Poisson rate $v_{i,k}\left(S^I_{i,k}\right)$. Following the reduced-form results in Section 3, I assume that $v_{i,k}\left(S^I_{i,k}\right)$ is increasing in $S^I_{i,k}$, but it does not depend on the number of input buyers, i.e., other buyers do not crowd out matching.[32] The match is also destroyed at the Poisson rate $\rho_{i,km}$, which potentially depends on buyer's location i and sector m, and input sector k.[33] Altogether, the steady-state probability of matching with a supplier in sector k by firms in location i and sector m is written as:

$$\Lambda_{i,km}\left(S^I_{i,k}\right) \equiv \delta_{i,km} \frac{v_{i,km}\left(S^I_{i,k}\right)}{v_{i,km}\left(S^I_{i,k}\right) + \rho_{i,km}}. \tag{8}$$

[30]I assume f^I does not depend on location and sector. This is primarily because of the estimation purposes; since the structural estimation in Section 5 is based on the reduced-form estimates from Section 3 with limited observations, such a treatment is necessary. Introducing heterogeneity in this parameter with respect to location and sector does not affect the logic of the model, and in fact, it does not affect the characterization of the counterfactual equilibrium based on the hat algebra (Proposition 1).

[31]$\delta_{i,km}$ can be interpreted as demand for external suppliers; as discussed in Section 2.2, the positive correlation between this term and the population density may explain the observed cross-sectional correlation between the number of suppliers per firm and population density (Panel B of Figure 1). I do not impose any restrictions in these parameters, and in Section 5, I estimate $\delta_{i,km}$ for each location and sector.

[32]I assume that the matching rates are independent across input sectors within each firm.

[33]To make the analysis of the steady state simple, I do not introduce the process of a "bankruptcy" of a firm. Instead, when taking the model to data, the unanticipated supplier bankruptcy is simply interpreted as an exogenous separation with a supplier. Introducing such a "death" of a firm introduces a life-cycle concern for each firm, which is out of the scope of this paper.

4.1.4 Input Goods Prices

As I briefly mentioned in Section 4.1.1, firms have two possible ways to source input goods: match with a supplier for customized input goods, or purchase from local fringe intermediaries.

The price of input goods is determined as follows. As I already mentioned in Section 4.1.1, the bilateral price p_{ud} is determined when supplier u and buyer d first match (denote this period by t^*) and remains unchanged until the relationship ends. I assume that p_{ud} is determined as a simple mark-up rule: $p_{ud} = \psi c_{\upsilon t^*,i}$, where $c_{\upsilon t^*,i}$ is the unit cost for supplier u at time t^* net of the shipment cost to location i, and ψ is the constant mark-up ratio. I make one more assumption about the input trade and prices: As long as u and d are matched, all the direct and indirect suppliers of u at the point of t^* (i.e., u's suppliers, supplier's suppliers, etc.) keep supplying input goods to u, as long as those goods are used for producing input goods sold to d. Figure B.8 illustrates this point in a simple case where there are only three firms involved.[34]

If firm ω is not matched with a supplier, the firm can purchase input goods from perfectly competitive fringe intermediaries. Each fringe firm can purchase input goods from a random supplier entering in location i at each period, but doing so requires $\chi_{i,k}$ ad-valorem cost for a unit value of input goods. Suppliers charge the mark-up ratio ψ ($\psi \geq 1$) to these fringe intermediaries. Firms do not know ex-ante which input supplier the fringe intermediaries will be able to source from until they decide to purchase from the fringe intermediaries. I further assume that $\chi_{i,k}$ is sufficiently high, so that firms with a directly matched supplier never decides to purchase inputs from these fringe intermediaries.

Taken together, the cost of input goods for firm ω at t is written as

$$p_{\omega t,k} = \begin{cases} p_{\omega \upsilon} & \text{if matched with supplier } \upsilon \text{ ,} \\ \chi_{i,k}\psi\tilde{c} & \text{otherwise,} \end{cases} \tag{9}$$

where $\tilde{c}$ is a random draw from the distribution of unit cost of input sellers in sector k selling in location i.

4.1.5 Total Expenditure and Trade Balance

Aggregate final goods sales by firms in location i and sector k, $X^F_{i,k}$, is expressed by the following accounting relationship:

$$X^F_{i,k} = \sum_{j \in N} Y^F_{j,k} \pi^F_{ij,k}, \tag{10}$$

[34] These two assumptions together imply that the expected profit of a supplier only depends on the firm's *contemporaneous unit cost* $c_{\omega t}$, and it does not depend on the past and future evolution of the unit cost. Importantly, this implies that each firm's decision to enter in a location as an input seller also only depends on the firm's contemporaneous unit cost $c_{\omega t}$.

where $\pi^F_{ij,k}$ is location j's final goods expenditure share in sector k of goods from location i, and $Y^F_{j,k}$ is the aggregate final goods demand in location j and sector k. All $\{X^F_{i,k}, Y^F_{j,k}, \pi^F_{ij,k}\}$ are endogenously determined in the equilibrium.

Aggregate input goods sales by firms in location i and sector k, $X^I_{i,k}$, is also expressed by the following accounting relationship:

$$X^I_{i,k} = \sum_{j \in N} \sum_{m \in K} Y^I_{j,km} \pi^I_{ij,k}, \tag{11}$$

where $Y^I_{j,km}$ is the aggregate input goods expenditure by firms in sector m and location j for input sector k, and$\pi^I_{ij,k}$ is location j's input goods expenditure share in sector k of goods from location i. As is the same with the final goods expenditure, all $\{X^I_{i,k}, Y^I_{j,k}, \pi^I_{ij,k}\}$ are endogenously determined in the equilibrium.

Trade balancing condition equates the aggregate sales from location i with the final and input goods purchases in location i, i.e.,

$$\sum_{k \in K} X^F_{i,k} + \sum_{k \in K} X^I_{i,k} = \sum_{k \in K} Y^F_{i,k} + \sum_{k \in K} \sum_{m \in K} Y^I_{i,km}. \tag{12}$$

4.2 Characterizing Steady-State Equilibrium

In this subsection, I characterize the steady-state equilibrium using aggregate variables. This subsection outlines the main argument to derive equilibrium conditions, and I encourage interested readers to refer to Appendix A.1 for more detailed derivations.

4.2.1 Unit Cost Distribution Given Distribution of Input Costs

I first derive the unit cost distribution of producers at each location. As noted in Section 4.1.1, the unit cost distribution depends on the exogenous productivity, wage and the input cost, where the input cost is stochastically determined through supplier matching. Denote the steady-state distribution of the unit cost of input goods k that buyers in location i and sector m has access to by $\tilde{G}^I_{i,km}(\cdot)$. $\tilde{G}^I_{i,km}(\cdot)$ depends both on the probability of matching with a supplier, as well as the distribution of the unit cost of the suppliers selling in location i. In this subsection, I derive the unit cost distribution of firms in location i and sector m given $\tilde{G}^I_{i,km}(\cdot)$. In Section 4.2.5, I characterize $\tilde{G}^I_{i,km}(\cdot)$ and fully derive the unit cost distribution.

The measure of firms in location i in sector m whose unit cost of input goods is below c, $H_{i,m}(c)$, is derived from equations (5), (6) and (9) as

$$\begin{aligned} H_{i,m}(c) &= \int_{p_1,\ldots,p_K} \mu_{i,m} \left(\frac{c}{w_i^{\gamma_{L,m}} \prod_{k \in K} p_k{}^{\gamma_{km}}} \right) \prod_{k \in K} d\tilde{G}^I_{i,km}(p_k) \\ &= \Gamma_{i,m} c^{-\theta} \end{aligned} \tag{13}$$

where $\Gamma_{i,m} \equiv \tilde{A}_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k\in K} \int_{p_k} p_k{}^{-\theta\gamma_{km}} d\tilde{G}^I_{i,km}(p_k)$.[35] Most importantly, the unit cost distribution also follows the power law under the power law distribution of the exogenous productivity (equation 6), where its scale (i.e., $\Gamma_{i,m}$) depends on the exogenous location and sector productivity ($\tilde{A}_{i,m}$), labor cost (w_i), and the input cost for sector k ($\int_{p_k} p_k{}^{-\theta\gamma_{km}} d\tilde{G}^I_{i,km}(p_k)$).

4.2.2 Gravity Equation of Final Goods Sales

The final goods market clears at each point in time given the unit cost distribution just as in the standard Melitz model. As is well-known in the Melitz model with power law (Pareto) distribution, [36]the trade share follows gravity equation; the share of final goods expenditure in location j and sector m for the goods produced in location i is given by

$$\pi^F_{ij,m} = \frac{\Gamma_{i,m}\left(\tau_{ij,m}\right)^{\theta}}{\sum_{i'\in N}\Gamma_{i',m}\left(\tau_{i'j,m}\right)^{\theta}}. \tag{14}$$

4.2.3 Gravity Equation of Input Goods Sales

In the steady state, the aggregate expenditure share of input goods, $\pi^I_{ij,m}$, follows the same gravity equation as that of the final goods sales (14), i.e., $\pi^I_{ij,m} = \pi^F_{ij,m}$. To see this, first note that just as in the final goods market, there is a unique cut-off of the input cost $\bar{c}^I_{i,k}$ below which firms enter as sellers in location i at each period.[37] The presence of unique cut-off implies that the distribution of the unit cost of input suppliers follows the Pareto distribution. The Pareto distribution implies that the fraction of the measures of input sellers from location j out of all input sellers in location i and sector m is $\pi^F_{ij,m}$, which is the same share as for the final goods market. I then show that the fraction of the *measures* of input sellers is the same as the share of *expenditures*, following a similar logic as for the final goods. Hence, I have [38]

$$\pi^I_{ij,m} = \frac{\Gamma_{i,m}\left(\tau_{ij,m}\right)^{\theta}}{\sum_{i'\in N}\Gamma_{i',m}\left(\tau_{i'j,m}\right)^{\theta}}. \tag{15}$$

4.2.4 Measure and Unit Cost Distribution of Input Sellers

Appendix A.1.3 shows that the free entry condition of a marginal input seller allows me to derive the measure of seller $S^I_{j,k}$ as

[35] Here I also use the assumption that the matching probability with suppliers are independent across input sectors as mentioned in Section 4.1.3.

[36] See, for example, Chaney (2008). Appendix A.1.1 reproduces the same argument in more detail.

[37] Note that this cut-off only depends on the *contemporaneous* unit cost, and it does not depend on the past or future expectation of matching with suppliers. See Section 4.1.3 and Figure B.8.

[38] See Appendix A.1.2 for more detailed discussion. The main logic of the model is unchanged even if we assume that the iceberg trade cost is different between input goods and final goods, in which case $\pi^I_{ij,m}$ and $\pi^F_{ij,m}$ follow different gravity equations. Here, I assume that iceberg trade cost is the same and hence $\pi^I_{ij,m} = \pi^F_{ij,m}$, because the data only allows calibration of $\pi^I_{ij,m}$ from the share of the measure of the matched supplier, but not $\pi^F_{ij,m}$ directly.

$$S^I_{j,k} = \sum_{m \in K} (1 - \gamma_{km}) \frac{\psi Y^I_{j,km}}{f^I w_j} \tag{16}$$

Despite the involved algebra in Appendix A.1.3, the intuition of the expression of $S^I_{j,k}$ is straightforward. It is proportional to the market size $\psi Y^I_{j,km}$, i.e., aggregate profit by firms in sector k from input sales in location j, and inversely proportional to the fixed cost payment for input sales, $f^I w_j$. γ_{km} enters negatively for the following reason: Higher γ_{km} implies that supplier's profit is more sensitive to supplier's unit cost c. Thus, higher γ_{km} decreases the marginal input seller's profit conditional on the same market size, resulting in less input seller entry.[39]

To derive the cut-off of the unit cost for input supplier entry $\bar{c}^I_{j,k}$, note that the measure of input suppliers who can supply goods to location j below cost c is written as $\sum_{i' \in N} \Gamma_{i',k} \left(\tau_{i'j,m}\right)^{\theta} c^{\theta}$. Hence, $\bar{c}^I_{j,k}$ is derived as

$$\bar{c}^I_{j,k} = \left(\frac{S^I_{j,k}}{\sum_{i' \in N} \Gamma_{i',k} \left(\tau_{i'j,m}\right)^{\theta}} \right)^{1/\theta}. \tag{17}$$

4.2.5 Full Characterization of Unit Cost Distribution using the Derived Unit Cost of Input Sellers

Now that I characterize the distribution of unit cost of input sellers in each location as the inverse of Pareto distribution with upper bound $\bar{c}^I_{j,k}$, I now revisit the distribution of unit cost (13) and rewrite the distribution using $S^I_{j,k}$ and $\bar{c}^I_{j,k}$. Following a simple algebra as derived in Appendix A.1.4, the unit cost distribution of production is derived as $H_{i,m}(c) = \Gamma_{i,m} c^{-\theta}$, where

$$\Gamma_{i,m} = A_{i,m} w_i^{-\theta \gamma_{L,m}} \prod_{k \in K} \left(\bar{c}^I_{i,k} \right)^{-\gamma_{km}\theta} \left\{ 1 - \Lambda_{i,km}(S^I_{i,k}) + \Lambda_{i,km}(S^I_{i,k}) \chi_{i,k}^{\gamma_{km}\theta} \right\}, \tag{18}$$

where $A_{i,m}$ is the adjusted exogenous productivity at the location, defined by $A_{i,m} \equiv \tilde{A}_{i,m} \prod_{k \in K} \frac{\left(\psi \chi_{i,k}\right)^{-\gamma_{km}\theta}}{1-\gamma_{km}}$. Here, $\Lambda_{i,km}(S^I_{i,k})$ is the steady-state probability that a firm in sector m and location i is matched with a supplier in sector k, as introduced in (8), and $\chi_{i,k}^{\theta\gamma_{km}}$ governs the relative cost advantage to match with a supplier.

4.2.6 Aggregate Input and Final Goods Demand

Under the Cobb-Douglas production function, the aggregate input demand $Y^I_{i,km}$ is written as

$$Y^I_{i,km} = \gamma_{km} \left(X^F_{i,m} + X^I_{i,m} \right), \tag{19}$$

[39] In fact, Lemma 1 of Appendix A.1.3 shows that the expected profit is proportional to $c^{-\gamma_{km}\theta}$. The fact that the expected profit is proportional to the power function of c is the reason why there is an explicit solution for the measure of input sellers, just as the standard Melitz model with Pareto distribution with CES utility where the profit is proportional to $c^{1-\sigma}$.

where γ_{km} is the Cobb-Douglas share of input in sector k used for production by sector m.

To derive the aggregate input demand, note that there are two sources of demand: demand from workers and demand from firm profit. Appendix A.1.5 shows that the firm profit is $1/\theta$ fraction of aggregate sales,[40] for both input goods and final goods. Thus, the aggregate final goods demand is derived as

$$Y^F_{i,m} = \alpha_m \left(w_i L_i + \frac{1}{\theta} \sum_{k \in K} \left(X^I_{i,k} + X^F_{i,k} \right) \right), \tag{20}$$

where the second part denotes the profit of firms in location i.

4.2.7 Steady-State Equilibrium

Summing up, the equilibrium is defined as follows:

Definition 1. The steady-state equilibrium is defined by steady state aggregate sales$\{X^I_{i,k}, X^F_{i,k}\}$, aggregate demand $\{Y^I_{i,k}, Y^F_{i,k}\}$, expenditure shares $\{\pi^I_{i,k}, \pi^F_{i,k}\}$, input cost advantage $\{\Gamma_{i,m}\}$, wages $\{w_i\}$, measure of input sellers $\{S^I_{i,k}\}$, unit cost cut-off for input sellers $\{\bar{c}^I_{j,k}\}$, which satisfy the total expenditure conditions (10) and (11), trade balancing conditions (12), gravity equations for final goods (14) and input goods (15), input cost advantage (18), free entry condition for marginal input sellers (16) and (17).

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 input goods demand $Y^I_{i,km}$.

Input goods demand in location i in sector m for input sector k, $Y^I_{i,km}$, is determined by the aggregate sales at location i which use sector k as inputs (equation 19). Together with the total expenditure conditions (equations 10 and 20), I have

$$Y^I_{i,km} = \gamma_{km} \sum_{j \in N} \left(Y^F_{j,m} + \sum_{l \in K} Y^I_{j,ml} \right) \pi_{ij,m},$$

where $\pi_{ij,m} = \frac{\Gamma_{i,m}(\tau_{ij,m})^{\theta}}{\sum_{i' \in N} \Gamma_{i',m}\left(\tau_{i'j,m}\right)^{\theta}}$ and $\Gamma_{i,m} \equiv A_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k \in K} \left(\bar{c}^I_{i,k}\right)^{-\gamma_{km}\theta} \left\{1 - \Lambda_{i,km}(S^I_{i,k}) + \Lambda_{i,km}(S^I_{i,k}) \chi_{i,k}^{\gamma_{km}\theta}\right\}$ (from equations 14 and 15). Importantly, $Y^I_{i,km}$ is increasing in $S^I_{i,k}$ through increasing the matching rate $\Lambda_{i,km}(S^I_{i,k})$ (i.e., equation 8); If there are more sellers $S^I_{i,k}$, producers in location i have a higher chance of matching with a supplier, which gives them a cost advantage. Also, the degree to

[40]Note that it is different from the mark-up ratio ($\frac{1}{\sigma-1}$ for final goods, and ψ for input goods), because of the presence of fixed cost of entry.

which the increase of $S^I_{i,k}$ increases $Y^I_{i,km}$ also depends on $\chi_{i,k}$, i.e., the cost advantage of matching with a supplier relative to unmatched. This corresponds to the "forward linkage."[41]

The number of sellers, in turn, depends on the aggregate input demand linearly following the free entry condition of a marginal seller (16), reproduced here:

$$S^I_{i,k} = \sum_{m \in K} (1 - \gamma_{km}) \frac{\psi Y^I_{i,km}}{f^I w_i}.$$

It shows that $S^I_{i,k}$ is increasing in the final goods sales of input buyers, $Y^I_{i,km}$. 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.

From the discussion of "forward linkages," the two parameters that are particularly important is the sensitivity of $\Lambda_{i,km}(S^I_{i,k})$ with respect to $S^I_{i,k}$, and the productivity advantage of matching with a supplier, $\chi_{i,k}$. These parameters are structurally estimated in Section 5 to replicate the reduced-form results using unanticipated supplier bankruptcies as presented in Section 3.

While closely 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). First, the "forward linkage" in their models arise from the love of variety in input goods for production. Here, it comes from the matching frictions and the increasing returns to scale, which have a closer mapping to the reduced-form exercise in Section 3. Second, the "backward linkage" in Krugman and Venables (1995) and Venables (1996) affects a firm's *production* location decision. Here, it affects a firm's *sales* entry decision à la Melitz (2003). This distinction leads to differences in implication for transportation improvement as discussed in Section 6.2.

5 Structural Estimation

This section estimates the key structural parameters of the model presented in Section 4. As discussed in Section 4.3, the elasticity of supplier matching rate with respect to the measure of input sellers and the degree of production benefit of matching with a supplier are the two key parameters that govern the agglomeration benefit. I estimate these parameters to replicate the reduced-form estimates of the impacts of unanticipated supplier bankruptcies presented in Section 3.

[41]There is also a counter-force that the increase of $S^I_{j,k}$ implies that the average cost of input suppliers become higher through the increase of the cut-off value $\bar{c}^I_{i,k}$. This type of counter force exists in any Melitz model that incorporates intermediate goods.

5.1 Estimation Procedure

5.1.1 Matching Rate Elasticity

To estimate the elasticity of matching rate with respect to the number of suppliers, I first parametrize the matching rate with a supplier as follows:

$$v_{i,km}\left(S_{i,k}^{I}\right)=\eta\left(\frac{S_{i,k}^{I}}{Z_{i}}\right)^{\lambda},$$

where Z_i is the geographic area of municipality i, λ is the elasticity of matching rate with respect to $S_{i,k}^{I}$, i.e., the measure of input sellers in location i and sector k, and η is the structural parameter governing the average matching rate. The basic idea of estimating λ and η is to use the parametrized matching rate to simulate the impacts of unanticipated supplier bankruptcy given λ and η, and match these model prediction with the reduced-form estimates in Section 3.

More precisely, I compute the difference of the probability that a firm is matched with a new supplier after t years from an exogenous separation with a supplier (i.e., treatment firms) and that for a firm which do not face a supplier separation (i.e., control firms). Computing this number requires $\{S_{i,k}^{I}\}$ which is not directly observed; I use the model equation (16), i.e., $S_{j,k}^{I}=\frac{\psi}{f_{i,k}^{I}}\sum_{m\in K}\left(1-\gamma_{km}\right)\frac{Y_{j,km}^{I}}{w_{j}}$ to obtain $S_{j,k}^{I}$ up to scale.[42]Denoting this number as $NewSupplier_{i,k}^{t}(\eta,\lambda)$, the model-predicted value of the event-study regression coefficients (equation 2) are obtained by running the following OLS regression:

$$NewSupplier_{i,k}^{t}(\eta,\lambda)=\tilde{\beta}_{NewSupplier}^{t}+\tilde{\gamma}_{NewSupplier}^{t}\log\text{SellerDensity}_{i,k}+\epsilon_{i,k}.$$

Denoting the OLS estimators of these regression coefficients as $\tilde{\beta}_{NewSupplier}^{t}(\eta,\lambda)$ and $\tilde{\gamma}_{NewSupplier}^{t}(\eta,\lambda)$, the structural parameters (η,λ) are then estimated by minimizing the squared distance between the model-predicted regression coefficients and the reduced-form regression coefficients using actual unanticipated bankruptcies $\{\hat{\beta}_{NewSupplier}^{t},\hat{\gamma}_{NewSupplier}^{t}\}$ (i.e., Table 3), weighted by the variance of the reduced-form regression coefficients:

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

To obtain the standard errors of these parameters, I bootstrap the reduced-form regression coefficients $\{\hat{\beta}_{NewSupplier}^{t},\hat{\gamma}_{NewSupplier}^{t}\}$ and take the 95% confidence interval for the structural parameters $(\hat{\eta},\hat{\lambda})$.

[42] $Y_{j,km}^{I}$ is obtained from the relationship $Y_{j,km}^{I}=\gamma_{km}\left(X_{i,m}^{I}+X_{i,m}^{F}\right)$, where $X_{i,m}^{I}+X_{i,m}^{F}$ correspond to the aggregate purchase made by firms in location i and sector m, and γ_{km} are taken from the input-output coefficients, as described in Section 5.1.4. Since the value of $\frac{\psi}{f_{i,k}^{I}}$ is not identified, the reported value of η is under the normalization that $\frac{\psi}{f_{i,k}^{I}}=1$.

5.1.2 Production Benefit per Match

The degree of production benefit of having a supplier is governed by $\chi_{i,k}$, and I estimate this parameter using the impacts of accidental supplier bankruptcies on exit.[43] I assume in the baseline specification that $\chi_{i,k}$ is the same across location and sector, i.e., $\chi = \chi_{i,k}$.[44]

To map the "exit" in the data to the model, I assume that a firm "exits" in the model if the firm stops entering in any final and input goods market; the unit cost goes below the threshold of the entry cut-off of all markets. Under this assumption, I simulate the differential exit probability between treatment and control firms $Exit^t(\chi, \eta, \lambda)$ as a function of χ and the parameters related to the matching rate (η, λ).[45]

Denoting this value as , I follow the same procedure as in Section 5.1.1 to estimate the parameter χ; that is, I first obtain the model-predicted event-study regression coefficients $\tilde{\beta}^t_{Exit}(\chi, \hat{\eta}, \hat{\lambda})$ and $\tilde{\gamma}^t_{Exit}(\chi, \hat{\eta}, \hat{\lambda})$ from the following regression, where $(\hat{\eta}, \hat{\lambda})$ are already estimated in Section 5.1.1:

$$Exit^t_{i,k}(\chi, \hat{\eta}, \hat{\lambda}) = \tilde{\beta}^t_{Exit} + \tilde{\gamma}^t_{Exit} \log \text{SupplierDensity}_{i,k} + \epsilon_{i,k},$$

and χ is estimated by minimizing the squared distance between $\{\tilde{\beta}^t_{Exit}(\chi, \eta, \lambda), \tilde{\gamma}^t_{Exit}(\chi, \eta, \lambda)\}$ and the reduced-form regression coefficients using actual unanticipated bankruptcies $\{\hat{\beta}^t_{Exit}, \hat{\gamma}^t_{Exit}\}$ from Table 5, i.e.,

$$\hat{\chi} \equiv \arg\min_{\chi_0, \varepsilon} \sum_{t=0,1,\ldots} \frac{\left(Exit^t(\chi, \hat{\eta}, \hat{\lambda}) - \hat{\beta}^t_{Exit}\right)^2}{\widehat{Var(\hat{\beta}^t_{Exit})}} + \frac{\left(Exit^t(\chi, \hat{\eta}, \hat{\lambda}) - \hat{\gamma}^t_{Exit}\right)^2}{\widehat{Var(\hat{\gamma}^t_{Exit})}}.$$

5.1.3 Fraction of Firms with Supplier Matching Demand

$\delta_{i,km}$, the fraction of firms in location i and sector m which ever match with suppliers in sector k, can be estimated using equation (8), i.e., $\Lambda_{i,km} \equiv \delta_{i,km} \frac{v_{i,k}\left(S^I_{i,k}\right)}{v_{i,k}\left(S^I_{i,k}\right) + \rho_{i,km}}$. Here, $v_{i,k}\left(S^I_{i,k}\right)$ are estimated in Section 5.1.1, $\rho_{i,km}$ are estimated as the rate of separation with a supplier in sector k by firms in sector m and municipality i, and $\Lambda_{i,km}$ are the steady-state probability that a firm in location i and sector m are matched with a supplier.[46]

[43] I choose to target the response to exit rather than sales on conditional on survival based on the observation that the large fraction of firm-level impact of supplier bankruptcies arises on exit margin than sales reduction conditional on survival, as reported in Table 4.

[44] A future robustness exercise will include allowing the correlation between $\chi_{i,k}$ and the population density.

[45] The matching rate matters because firm's unit cost may again go below the threshold if it matches with a new supplier.

[46] More precisely, $\Lambda_{i,km}$ is defined by the average of the number of suppliers held by firms in municipality i and industry m in supplier sector k in 2007, weighted by firm sales. The model predicts that the weight does not affect this value, but in the data, this treatment allows me to avoid that the results rely on firms which are economically negligible. It should be noted that in some cases firms have multiple suppliers in the same four-digit industry, but it happens less than 10% of the cases of firm and industry pair.

5.1.4 Other Parameters

Several other parameters that are required for computing a counterfactual equilibrium. I obtain the Cobb-Douglas share of input goods $\{\gamma_{km}\}$ and the Cobb-Douglas share of final goods consumption $\{\alpha_m\}$ from the input coefficients and final goods expenditure share in the input-output matrix created by the Ministry of Internal Affairs and Communications of Japan in 2011. The exponent of the power law of the production distribution, θ, is calibrated to be 5 following the standard estimates of trade elasticity (i.e., Head and Mayer (2014)).

There are several other structural parameters in the model, but I argue in Section 6 that these parameters are *not* required for computing the counterfactual equilibrium. More concretely, I do not need to know the markup ratio for input goods ψ, the elasticity of substitution of consumption$\{\sigma_k\}$, the trade cost $\{\tau_{ij,m}\}$, fixed cost of entry as final goods sellers$\{f^F_{j,k}\}$ and input goods sellers f^I. The basic logic follows the "hat-algebra" approach (Dekle et al. (2008)), which I will describe in detail in Section 6.

5.2 Estimation Results

Table 7 shows the list of the estimated and calibrated structural parameters. λ is estimated to be 0.40 reflecting the quantitatively large magnitude that the new supplier matching rate depends on the geographic density of suppliers, as documented in Section 3.2.2. χ is greater than 1, reflecting the large impacts of unanticipated supplier bankruptcies on exit. The magnitudes of these parameters are interpreted through a counterfactual equilibrium simulation of shutting down the increasing returns to scale in matching in Section 6.

6 Counterfactual Simulations

6.1 How Important is Increasing Returns to Scale for Agglomeration of Economic Activity?

To assess the importance of the estimated degree of increasing returns to scale in firm-to-firm matching, I hypothetically shut down the increasing returns to scale in matching, i.e., compute the equilibrium under $\lambda = 0$ rather than the estimated value of $\lambda = 0.40$, and study how the equilibrium changes. More specifically, I assume that the Poisson rate of matching with a supplier is $\overline{v}_k$, and it does not depend on $S^I_{i,k}$. The following proposition provides the set of equations that the counterfactual equilibrium have to satisfy, as well as the required parameters and baseline variables necessary for computing the counterfactual equilibrium, based on the standard "hat-algebra" approach (Dekle et al. (2008)):[47]

Proposition 1. *Assume that under the counterfactual equilibrium, the Poisson rate of matching with a supplier in sector k is exogenously given at the level of $\overline{v}_k$. Then, probability of matching with a supplier $\{\Lambda_{i,km}\}$, the expenditure share of input goods and final goods $\{\pi_{ij,k}\}$, the input demand for input goods $\{Y^I_{i,km}\}$, together with parameters $\{\lambda, \chi, \theta, \{\gamma_{L,m}\}, \{\gamma_{km}\}, \{\alpha_m\}\}$ and exogenous variables $\{L_i\}$, the counterfactual equilibrium is obtained by solving the following equations with respect to $\{Y^{I'}_{i,km}, Y^{F'}_{i,k}\}$, $\{\pi'_{i,k}\}$ $\{\hat{S}^I_{i,k}\}, \{w'_i\}, \{\hat{\overline{c}}^I_{j,k}\}$.*

(i) steady state probability of supplier matching

$$\Lambda'_{i,km} = \delta_{i,km} \frac{\overline{v}_k}{\overline{v}_k + \rho_{i,km}}.$$

(ii) gravity equation and input cost advantage

$$\hat{\pi}_{ij,k} = \frac{\hat{\Gamma}_{i,k}}{\sum_{i' \in N} \pi_{i'j,k} \hat{\Gamma}_{i',k}}$$

where

$$\hat{\Gamma}_{i,m} \equiv \hat{w}_i^{-\theta\gamma_{L,m}} \prod_{k \in K} \left(\hat{\overline{c}}^I_{j,k}\right)^{-\theta\gamma_{km}} \frac{1 - \Lambda'_{i,km} + \Lambda'_{i,km}\chi^{\gamma_{km}\theta}}{1 - \Lambda_{i,km} + \Lambda_{i,km}\chi^{\gamma_{km}\theta}}.$$

(iii) measures of sellers and the cutoff of input sellers

$$\hat{\overline{c}}^I_{j,k} = \left(\frac{\hat{S}^I_{j,k}}{\hat{\Gamma}_{j,k}/\hat{\pi}_{jj,k}}\right)^{1/\theta}$$

and

$$\hat{S}^I_{j,k} = \frac{1}{\hat{w}_j} \frac{\sum_{m \in K} (1 - \gamma_{km}) Y^{I'}_{j,km}}{\sum_{m \in K} (1 - \gamma_{km}) Y^I_{j,km}}$$

(iv) total expenditure conditions

$$Y^{I'}_{i,km} = \gamma_{km} \sum_{j \in N} \left(Y^{F'}_{j,m} + \sum_{l \in K} Y^{I'}_{j,ml} \right) \pi'_{ij,m}$$

and

$$Y^{F'}_{i,m} = \alpha_m \left(w'_i L_i + \frac{1}{\theta} \sum_{k \in K} \frac{1}{\gamma_{km}} Y^{I'}_{i,km} \right)$$

[47] As usual, variables with hat indicate the proportional change of the variables in the counterfactual equilibrium relative to the baseline, and variables with prime indicate the level of these variables under the counterfactual. Variables without hat or prime indicate the levels of these variables in the baseline (i.e., observed equilibrium).

(v) trade balancing condition

$$\sum_{k\in K}\sum_{j\in N} Y_{j,k}^{F'}\pi_{ij,k}\hat{\pi}_{ij,k} + \sum_{k,m\in K^2}\sum_{j\in N} Y_{j,km}^{I'}\pi_{ij,k}\hat{\pi}_{ij,k} = \sum_{k\in K} Y_{i,k}^{F'} + \sum_{k,m\in K^2} Y_{i,km}^{I'}$$

Aside from the structural parameters $\{\lambda, \chi, \theta, \{\gamma_{km}\}, \{\alpha_m\}\}$, I obtain the baseline variables required to conduct a counterfactual equilibrium in the following manner. $\{\tau_{ij,m}\}$ are calibrated to match the probability that a firm in location j and sector m source from a firm located in municipality i, conditional on sourcing in sector m.[48] $\{\Lambda_{i,km}\}$ are the steady-state probability that a firm in location i and sector m are matched with a supplier, as already obtained to estimate $\{\delta_{i,km}\}$. Note the mark-up ratio for input goods ψ, elasticity of substitution of consumers$\{\sigma_k\}$, the trade cost $\{\tau_{ij,m}\}$, fixed cost of entry as final goods sellers $\{f_{j,k}^F\}$ and input goods sellers f^I, are *not* required for computing the counterfactual equilibrium.

To illustrate how much shutting down the increasing returns to scale would weaken the geographic concentration of economic activity, Figure 3 show the correlation between the population density (L_i/Z_i) and various outcome variables in the baseline equilibrium and the counterfactual equilibrium.

The results suggest that the increasing returns to scale in matching is a quantitatively important factor that explains the observed density premium in economic activity. First, the density premium in the number of suppliers per firm (Panel A of Figure 3) would decrease to 65% under the counterfactual equilibrium.[49] This is a significant reduction, confirming the importance of increasing returns to scale in matching, but it also implies that 65% of density premium attributes to the heterogeneity in demand for external suppliers $(\delta_{i,m})$.[50] This confirms that focusing on unanticipated supplier bankruptcies would be important for an accurate assessment of the agglomeration benefit, as motivated in Section 2.2.

As for the other variables that are more directly related to the agglomeration of economic activity, Panel (C) shows the change in total revenue per capita $(\sum_{k\in K}\left(X_{i,k}^F + X_{i,k}^I\right)/L_i)$.[51] The results show that 29% of the density premium is explained by the increasing returns to scale. Finally, Panel (D) shows that about 15% of density premium in real wages attribute to the increasing

[48] Note that this extensive margin of the share of sourcing input goods are the same as that of the input goods expenditure as discussed in Section 4.2. Furthermore, it is the same as the expenditure share for final goods, as argued also in Section 4.2.

[49] Note that the baseline relationship in Panel (A) of Figure 3 is exactly the same as Panel (B) of Figure 1. More precisely, the number of suppliers per firm is defined as $\sum_{k\in K}\frac{Y_{i,k}}{\sum_{m\in K}Y_{i,m}}\Lambda_{i,km}$, where $\frac{Y_{i,k}}{\sum_{m\in K}Y_{i,m}}$ enters because of the sales weight. In the baseline, $\Lambda_{i,km}$ is defined by the average of the number of suppliers held by firms in municipality i and industry m in supplier sector k in 2007, weighted by firm sales. The model predicts that the weight does not affect this value, but in the data, this treatment allows me to avoid that the results rely on firms which are economically negligible. It should be noted that in some cases firms have multiple suppliers in the same four-digit industry, but it happens less than 10% of the cases of firm and industry pair.

[50] Although the exogenous separation rate, $\rho_{i,km}$, is another factor that affects the density premium under the counterfactual, it is not quantitatively an important factor, because it is flat in population density (See Figure B.9).

[51] The plots for the baseline equilibrium is exactly the same as Panel (A) of Figure 1.

returns to scale.[52]

6.2 Welfare Impact of Hokkaido Bullet Train

The estimated model also highlights the importance of within-country transportation improvement as a strategy to improve regional economic welfare, particularly in remote places. Improvement of transportation access may improve the production and welfare in remote areas by increasing the density of input sellers.[53] These welfare effects arise on top of the traditional gains of within-country transportation infrastructure through input price reduction (Donaldson (2015)).

To understand this point, I simulate the welfare impacts of a new bullet train in a northern part of Japan. The bullet train, *Hokkaido-Shinkansen*, is planned to connect Hokkaido Island and the main island Japan, and it is expected to fully open in 2030 (a part of it is opened in 2016). The bullet train is predicted to reduce the estimated travel time between Tokyo and Sapporo City, the center of Hokkaido, from 8.5 hours to 5 hours (about 40% reduction in travel time).

Figure 4 shows the impact on real wages in Hokkaido as a function of the change in travel time (affecting iceberg trade cost for input goods) from and to other parts of Japan. The welfare gains are higher with the estimated degree of increasing returns to scale in matching ($\lambda = 0.4$) relative to the world where there is no increasing returns to scale in matching ($\lambda = 0$). Under the predicted travel time reduction of 40% by Hokkaido bullet train, the additional gains of transportation cost reduction amounts to the 12% of total welfare gains incurred by Hokkaido Island.

7 Conclusion

This paper investigates the importance of increasing returns in firm-to-firm matching in input trade as a source of agglomeration. I first provide reduced-form evidence of increasing returns to scale in firm-to-firm matching. I find that firms only imperfectly recover suppliers upon unanticipated supplier bankruptcy, but this recovery rate is more pronounced in a location and industry where a geographic density of alternative suppliers is higher. I also find that supplier bankruptcies do not decrease the supplier matching rate *of other buyers* in near geographic proximity; suggesting that the geographic concentration of *buyers* does not crowd out matching. To quantify the importance of this increasing returns to scale in matching in observed agglomeration patterns in Japan, I

[52] To compute the change in real wage, I make use of a simple welfare expression following Proposition 2. The baseline real wages are obtained from nominal wage divided by the price index, both taken from the website of the Ministry of Internal Affairs and Communications of Japan.

[53] This point also highlights the difference between the agglomeration mechanism presented in this paper and other types of agglomeration mechanisms. Perhaps most distinctively from other sources of agglomeration mechanisms, this agglomeration mechanism arises from the geographic concentration of suppliers *selling in the location* à la Melitz model, not from the density of firms *producing in the location.* Hence, improving the transportation access between central and remote areas of Japan may increase economic welfare in remote areas, even without relocating firms to produce in remote areas.

develop a new structural model of firm-to-firm trade under matching frictions. In this economy, a higher geographic density of suppliers gives firms an input cost advantage through improved supplier matching, which increases aggregate sales; this, in turn, attracts more suppliers to sell in the location. I structurally estimate the key parameters to match the reduced-form estimates, and I show that this type of circular causation explains nearly one third of the population density premium in output per worker.

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Table 1: List of Reasons of Bankruptcies

Reason of Bankurptcy	Freq.	Freq. (At Least One Buyer)
Unanticipated Reasons	1548	325
Sales Decline	75492	12861
Accumulation of Debt	11111	2851
Spillovers from Other Bankruptcy	6793	1519
Shortage of Capital	6038	1371
Management Failure	5346	894
Unknown	4184	694
Over-Investment in Capital	875	280
Deterioration of Credit Conditions	589	229
Difficulty in Collecting Account Receivables	543	162
Over-Accumulation of Inventory	98	36
Total	112617	21222

Note: The table reports the distribution of the main reasons of bankruptcies reported in the TSR data set. “Freq” indicates the number of firms experiencing bankruptcies from 2007 to 2016 for each reason, and “Freq. (At Least One Buyer)” indicates the number of bankrupting firms with at least one buyer. “Unanticipated accidental reasons” is described as “unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc,” in an internal document by TSR.

Table 2: Average Impacts of Unanticipated Supplier Bankruptcy on Supplier Matching

(A) Net and Gross Supplier Matching

	Number of Suppliers	New Suppliers	Retained Suppliers
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = -2 or -3]	-0.10^{*}	-0.02	-0.07
	(0.05)	(0.04)	(0.05)
Trt x 1[t - BankruptYear = -1]			
	(0.00)	(0.00)	(0.00)
Trt x 1[t - BankruptYear = 0 or 1]	-0.64^{***}	0.05	0.04
	(0.05)	(0.04)	(0.03)
Trt x 1[t - BankruptYear = 2 or 3]	-0.58^{***}	0.20^{***}	-0.03
	(0.07)	(0.07)	(0.05)
Control Mean 3 Years After Bankruptcy	5.04	0.79	3.37
Number of Treated Firms	447	447	447
Number of Bankrupting Suppliers	167	167	167
Number of Control Firms	14,630	14,630	14,630
Observations	99,447	99,447	99,447

(B) New Supplier Matching by Industry and Geography

	New Suppliers			
	Within 4-digit Ind.	Within 2-digit Ind.	Locate Same Mun.	Supply to Same Mun.
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = -2 or -3]	0.02^{**}	0.01	0.03	-0.02
	(0.01)	(0.01)	(0.02)	(0.04)
Trt x 1[t - BankruptYear = -1]				
	(0.00)	(0.00)	(0.00)	(0.00)
Trt x 1[t - BankruptYear = 0 or 1]	0.04^{***}	0.04^{**}	0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)
Trt x 1[t - BankruptYear = 2 or 3]	0.08^{***}	0.11^{***}	0.07^{***}	0.12^{***}
	(0.02)	(0.04)	(0.02)	(0.04)
Control Mean 3 Years After Bankruptcy	0.08	0.17	0.08	0.30
Number of Treated Firms	447	447	447	447
Number of Bankrupting Suppliers	167	167	167	167
Number of Control Firms	14,630	14,630	14,630	14,630
Observations	94,794	94,794	94,794	94,794

Note: The coefficients of the event-study regression (1) are reported. In Panel (A), "Number of Suppliers" indicates the total number of suppliers reported by each firm in TSR data set, "New suppliers" indicate the number of suppliers that each firm has which are *not* connected in the baseline period (one year before the bankruptcy), and "Retained suppliers" indicate the number of suppliers that each firm has which *are* connected in the baseline period, excluding the supplier used for matching treatment and control firms. In Panel (B), (3) takes the number of new suppliers who are headquartered in the same municipality, and (4) takes that among those who have existing buyers in the same municipality within three years prior to the supplier bankruptcy. If a firm exits and drops out from the sample, I fill in the outcome variables from the last year of the observation; see Table B.4 for the robustness of this treatment. For each control firm in group g, I impose the inverse of the number of control firms within group g as the regression weight. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table 3: Heterogeneous Impacts of Unanticipated Supplier Bankruptcy on New Supplier Matching

	New Suppliers				
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Trt x 1[t - BankruptYear = 0 or 1]	0.06	0.06			
	(0.04)	(0.04)			
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.10**	0.09**	0.09**	0.10**	0.09*
	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)
Trt x 1[t - BankruptYear = 2 or 3]	0.22***	0.22***			
	(0.07)	(0.07)			
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.12*	0.10	0.10	0.10	0.10
	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)
Trt x Post x Bankrupt Year FE			X	X	X
Trt x Post x Birthplace Area FE				X	X
Trt x Post x 1-digit Ind. FE					X
Observations	99,447	99,436	99,436	88,332	88,332

Note: The coefficients of the event-study regression with heterogeneous impacts (2) are reported. See the footnote of Figure 2 for the outcome variables. Seller density is defined as the geographic density of suppliers in the bankrupting suppliers' four-digit industry who have at least one buyer in firm i's prefecture in 2007, and it is normalized to be mean 0 with standard deviation 1 in log scale. IV specification instruments seller density by that of the birthplace prefecture of the CEO of treatment firms. See Table B.2 for the lack of pre-trends for the same specification. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Average Impacts of Unanticipated Supplier Bankruptcy on Exit and Sales Growth

(A) Exit and Sales

	Exit	log Sales	log Sales (incl. Exit)
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = -2 or -3]		0.01	−0.05
		(0.01)	(0.04)
Trt x 1[t - BankruptYear = -1]			
		(0.00)	(0.00)
Trt x 1[t - BankruptYear = 0 or 1]	0.01	−0.01	−0.20*
	(0.01)	(0.01)	(0.11)
Trt x 1[t - BankruptYear = 2 or 3]	0.03*	0.001	−0.38*
	(0.02)	(0.02)	(0.20)
Control Mean 3 Years After Bankruptcy	0.087	12.582	11.443
Number of Treated Firms	447	447	447
Number of Bankrupting Suppliers	167	167	167
Number of Control Firms	14,630	14,630	14,630
Observations	99,447	93,848	96,913

(B) Decomposition of Exit

	Bankruptcy	Voluntary Exit	Merged	Existence Unknown
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1]	0.01*	−0.01	0.004*	−0.0001
	(0.01)	(0.004)	(0.002)	(0.003)
Trt x 1[t - BankruptYear = 2 or 3]	0.02*	−0.001	0.01	0.01
	(0.01)	(0.01)	(0.004)	(0.01)
Control Mean 3 Years After Bankruptcy	0.034	0.033	0.005	0.015
Number of Treated Firms	447	447	447	447
Number of Bankrupting Suppliers	167	167	167	167
Number of Control Firms	14,630	14,630	14,630	14,630
Observations	99,447	99,447	99,447	99,447

Note: The coefficients of the event-study regression (1) is reported. Column (3) of Panel (A) includes firms which exit in the sample, inserting 0 for log sales. Panel (B) shows the impacts of different forms of exit as in Column (1) of Panel (A). Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Heterogeneous Impacts of Unanticipated Supplier Bankruptcy on Exit and Sales

	Exit		log Sales (incl. Exit)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1]	0.01	0.01	−0.16	−0.16
	(0.01)	(0.01)	(0.11)	(0.11)
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.001	−0.002	0.02	0.03
	(0.01)	(0.01)	(0.11)	(0.11)
Trt x 1[t - BankruptYear = 2 or 3]	0.03*	0.03*	−0.35*	−0.35*
	(0.02)	(0.02)	(0.20)	(0.20)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	−0.003	−0.001	0.06	−0.02
	(0.02)	(0.02)	(0.22)	(0.24)
Observations	99,447	99,436	96,913	96,902

Note: The table reports coefficients of the event-study regression with heterogeneous impacts (2). IV specification instruments seller density by that of the birthplace prefecture of the CEO of treatment firms. See the footnote of Table 3 for other comments about the specification. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Evidence of No Crowding-out

	Number of Suppliers			Number of Suppliers (Within 4-digit Ind.)	Exit	log Sales
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor Trt x 1[t - BankruptYear = -2 or -3]	0.06	0.004	0.02	−0.003	−0.005	0.05
	(0.10)	(0.07)	(0.05)	(0.02)	(0.004)	(0.05)
Neighbor Trt x 1[t - BankruptYear = -1]						
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Neighbor Trt x 1[t - BankruptYear = 0 or 1]	−0.02	−0.04	−0.002	0.02	0.002	−0.02
	(0.06)	(0.05)	(0.04)	(0.02)	(0.01)	(0.10)
Neighbor Trt x 1[t - BankruptYear = 2 or 3]	0.06	0.01	0.05	0.02	0.01	−0.14
	(0.10)	(0.08)	(0.06)	(0.02)	(0.01)	(0.16)
Degree Grid Size for Defining Neighbor Trt	0.005	0.01	0.05	0.01	0.01	0.01
Observations	95,050	95,050	95,050	95,050	95,050	92,619

Note: The coefficients of the the event-study regression (4) are reported. Neighbor Trt indicates a dummy that takes 1 if their geographic neighbors (defined by the grid cells specified in the bottom of the table) face unanticipated supplier bankruptcy. From these regressions, firms which are directly hit by unanticipated supplier bankruptcies are excluded. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Estimated and Calibrated Structural Parameters

Parameters	Values
Estimated Parameters	
λ	0.40
η	0.052
χ	1.85
Calibrated Parameters	
θ	5 (Head and Mayer (2013))
γ_{km}, α_m	From Input-Output Matrix

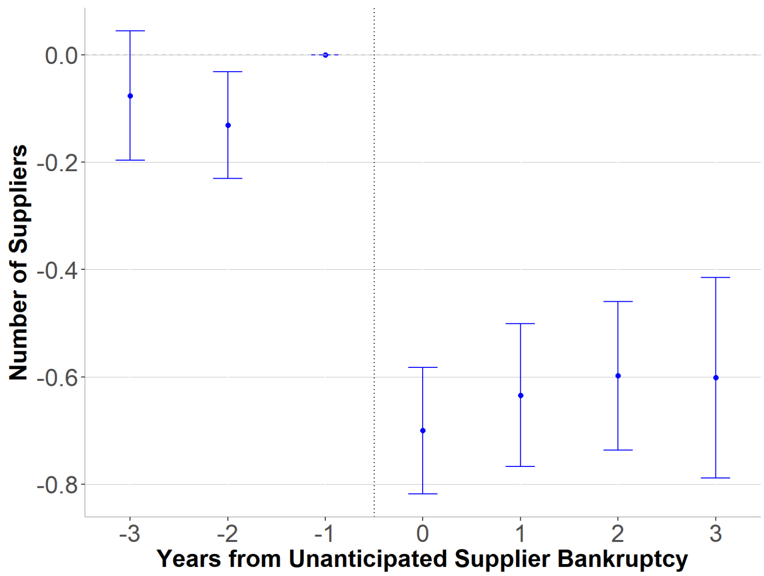
Note: The table reports the estimates of the structural parameters of the model. See Section 5 for the estimation procedure.

Figure 1: Cross-Sectional Correlation between Supplier Matching and Population Density

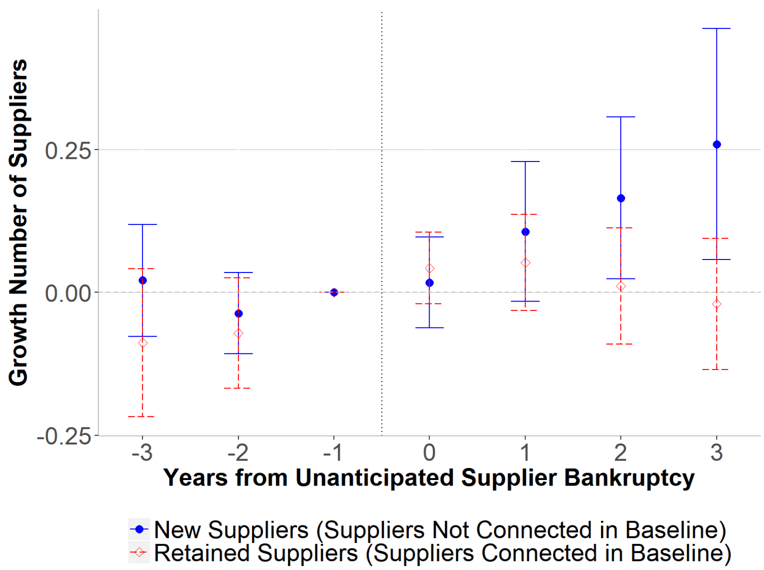
Note: Based on the TSR data set in 2007. Each dot represents a municipality. The size of the dots reflects the number of firms in each municipality.

Figure 2: Average Impacts of Unanticipated Supplier Bankruptcy on Supplier Matching

(A) Number of Suppliers



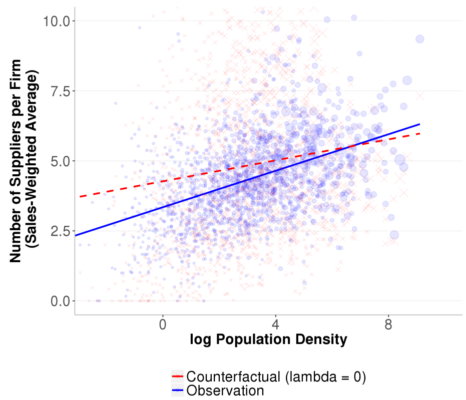
(B) New Supplier Matching and Supplier Retention



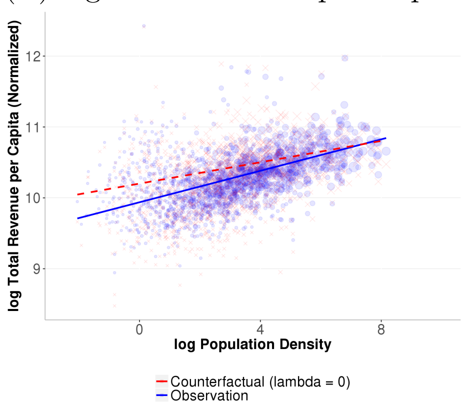
Note: The coefficients of the event-study regression (1) are reported. "Number of Suppliers" indicates the total number of suppliers reported by each firm in TSR data set, "New suppliers" indicate the number of suppliers that each firm has which are *not* connected in the baseline period (one year before the bankruptcy), and "Retained suppliers" indicate the number of suppliers that each firm has which *are* connected in the baseline period, excluding the supplier used for matching treatment and control firms. For both panels, I treat the outcome variables as missing in case the firm goes exit; see Table B.4 for the robustness of this treatment. For each control firm in group g, I impose the inverse of the number of control firms within group g as the regression weight. Standard errors are clustered at the supplier level.

Figure 3: Counterfactual Simulation Under No Increasing Returns to Scale in Matching

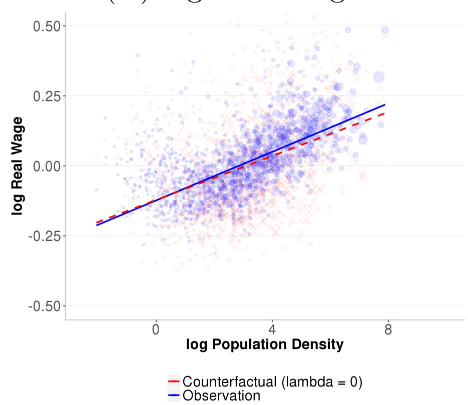
(A) Number of Suppliers per Firm



(C) log Total Revenue per Capita

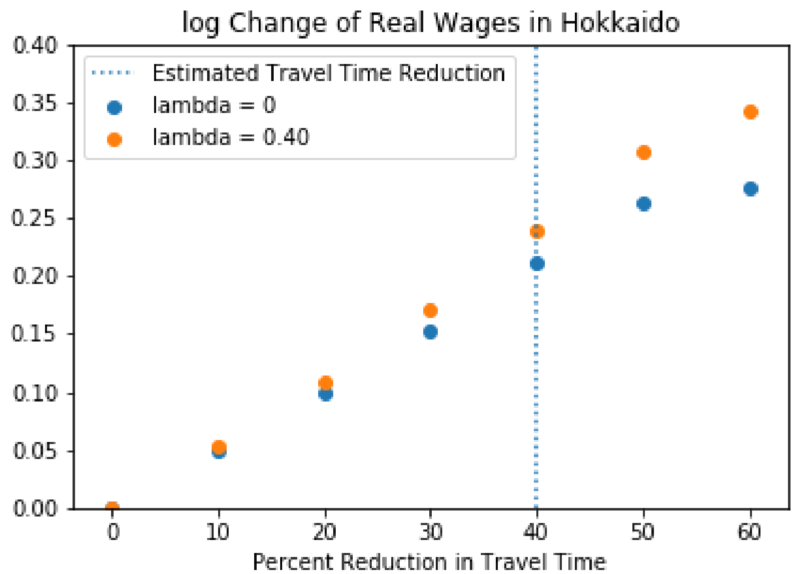


(D) log Real Wages



Note: The figures show the scatter plots of each outcome variables observed in the data (with Specification as "Baseline") and those in the counterfactual simulation under $\lambda = 0$ (with Specification as "Counterfactual") in the y-axis, against log population density in the x-axis. See Section 6.1 for more detail about the counterfactual simulation.

Figure 4: Welfare Impact of Hokkaido Bullet Train



Note: The figure shows the impact on real wages in Hokkaido as a function of the change in travel time (affecting iceberg trade cost for input goods) from and to other parts of Japan. As a reference, the bullet train planned to open in 2030 is estimated to reduce the travel time from 8.5 hours to 5 hours (about 40% reduction) between Tokyo and Sapporo. See Section 6.2 for more detail about the counterfactual simulation.

A Model Appendix

A.1 Details of Characterizing Steady-State Equilibrium

This appendix provides a more detailed derivation of the equilibrium characterization as outlined in Section 4.2.

A.1.1 Gravity Equation of Final Goods Sales

The final goods market clears at each point in time given the unit cost distribution just as in the Melitz model.As is well-known in the the Melitz model with power law (Pareto) distribution, [54]the trade share follows gravity equation. Here I reproduce the logic behind this argument.

From the utility maximization problem of final goods consumers with preferences (7) and the static profit maximization problem by producers, a firm which faces unit cost c to sell a good in location i charges the mark-up ratio $\frac{\sigma}{\sigma-1}$, and the profit is proportional to $c^{1-\sigma}$. Hence, there is a unique cutoff value of the unit cost $\bar{c}^F_{j,k}$ below which firms in sector k enter as a final goods seller in location j.

Now, note that the measure of firms who can supply goods from location i to location j above unit cost c is given by $H_{i,m}(c/\tau_{ij,k}) = \Gamma_{i,m}\tau^{\theta}_{ij,k}c^{-\theta}$. Hence, the fraction of the expenditure of final goods in sector m consumed in location j that come from location i is

$$\pi^F_{ij,m} = \frac{\int_0^{\bar{c}^F_{j,k}} c^{1-\sigma}\Gamma_{i,m}\left(\tau_{ij,m}\right)^{\theta} dc}{\sum_{i'\in N}\int_0^{\bar{c}^F_{j,k}} c^{1-\sigma}\Gamma_{i',m}\left(\tau_{i'j,m}\right)^{\theta} dc} = \frac{\Gamma_{i,m}\left(\tau_{ij,m}\right)^{\theta}}{\sum_{i'\in N}\Gamma_{i',m}\left(\tau_{i'j,m}\right)^{\theta}}.$$

Note that this is also the proportion of firms in sector m, producing in i entering in as input sellers in location j, i.e., the extensive margin of trade.

A.1.2 Gravity Equation of Input Goods Sales

In the steady state, the aggregate expenditure share of input goods, $\pi^I_{ij,m}$, follows the same gravity equation as that of the final goods sales (14), i.e., $\pi^I_{ij,m} = \pi^F_{ij,m}$. To see this, first note that just as in the final goods market, there is a unique cut-off of the input cost $\bar{c}^I_{i,k}$ below which firms enter as sellers in location i at each period.[55] The presence of unique cut-off implies that the distribution of unit cost of input suppliers follows the Pareto distribution with the same share of the *measures* of input sellers as in final goods market $\pi^F_{ij,m}$.

[54]See, for example, Chaney (2008). Appendix A.1.1 reproduces the same argument in more detail.

[55]Note that this cut-off only depends on the *contemporaneous* unit cost, and it does not depend on the past or future expectation of matching with suppliers. This is because if a firm u matches with an input buyer d at some time period t, firm u can write a contract that bind all directly and indirectly connected suppliers at the point of t for providing input goods supply for d, as described in Section 4.1.3 and Figure B.8.

Next, I show that the share of the *measures* of input sellers is the same as the share of *expenditures.* To show this, denote the average input sales of firms in sector k, location i in sales to location j and sector m, conditional on the relationship between supplier and buyer is t^*(i.e., period since they get matched), and the supplier's unit cost is c (at the point of being matched), by $R_{ij,km}(t^*, c)$. Generally, $R_{ij,km}(t^*, c)$ is increasing in t^* as buyers also start entering various locations as input sellers to take advantaged of the cost advantage; likewise, $R_{ij,km}(t^*, c)$ is decreasing in c. However, $R_{ij,km}(t^*, c)$ does *not* depend on the location of the supplier i conditional on c, the supplier's unit cost at location j. Then, the input expenditure share conditional on the relationship length t^*, $\pi^I_{ij,k}(t^*)$, is derived as

$$\pi^I_{ij,k}(t^*) = \frac{\int_0^{\bar{c}^I_{j,k}} R_{ij,km}(t^*, c)\Gamma_{i,k}\left(\tau_{ij,k}\right)^\theta dc}{\sum_{i'\in N}\int_0^{\bar{c}^I_{j,k}} R_{ij,km}(t^*, c)\Gamma_{i',k}\left(\tau_{i'j,k}\right)^\theta dc} = \frac{\Gamma_{i,k}\left(\tau_{ij,k}\right)^\theta}{\sum_{i'\in N}\Gamma_{i',k}\left(\tau_{i'j,k}\right)^\theta},$$

which does not depend on t^*. Hence, the aggregate expenditure share, by integrating $\pi^I_{ij,k}(t^*)$ with respect to the distribution of the relationship duration, also gives the same expression.

A.1.3 Measure and Unit Cost Distribution of Input Sellers

To derive the measure of input sellers, I first show the following lemma.

Lemma 1. *$R_{ij,km}(t^*, c)$, as defined in Appendix A.1.2, is proportional to $c^{-\gamma_{km}\theta}$.*

Proof. First, I decompose $R_{ij,km}(t^*, c)$ as follows:

$$R_{ij,km}(t^*, c) = \sum_{n\in N} R^F_{ijn,km}(t^*, c) + \sum_{n\in N} R^I_{ijn,km}(t^*, c),$$

where $R^F_{ijn,km}(t^*, c)$ is the input purchase for buyers used for *final* goods production sold in location n by the matched buyer, $R^I_{ijn,km}(t^*, c)$ is the input purchase for buyers used for *input* goods production sold in location n by the matched buyer. Below, I show that both $R^F_{ij,km}(t^*, c)$ and $R^I_{ij,km}(t^*, c)$ are proportional to $c^{-\gamma_{km}\theta}$.

To show that $R^F_{ijn,km}(t^*, c)$ is proportional to $c^{-\gamma_{km}\theta}$, recall that there is a unique cut-off of entry for final goods sales. Together with the fact that the buyer's unit cost is proportional to $c^{-\gamma_{km}}$, a small decrease of supplier's cost Δc increases the probability that the matched buyer's unit cost goes below the threshold by $c^{-\gamma_{km}\theta} - (c + \Delta c)^{-\gamma_{km}\theta}$. From the logic of the Pareto distribution in Melitz model (i.e., Chaney (2008)), conditional on entry as final goods market by buyers, the average sales does not depend on the supplier's cost c. It follows that $R^F_{ijn,km}(t^*, c)$ is proportional to the proportion of firms which enter in various locations, hence proportional to $c^{-\gamma_{km}\theta}$.

To show that $R^I_{ijn,km}(t^*, c)$ is proportional to $c^{-\gamma_{km}\theta}$, from the same logic as $R^F_{ijn,km}(t^*, c)$, the matched buyers have $c^{-\gamma_{km}\theta}$ higher probability of entering in location n as input sellers for the over the past t^* period of time. From the same logic, $R^I_{ijn,km}(t^*, c)$ is proportional to $c^{-\gamma_{km}\theta}$. $\square$

With Lemma 1, the measure of seller is derived as follows. First, I define $R_{ij,km}(c) = \int R_{ij,km}(t^*, c) \exp(-\rho t^*$ the sum of the expected sales of the supplier until the relationship breaks down. Note that under Lemma 1, $R_{ij,km}(c)$ is also proportional to $c^{-\gamma_{km}\theta}$, and hence I write $R_{ij,km}(c) = c^{-\gamma_{km}\theta} R^*_{ij,km}$

The zero profit condition of the marginal supplier to enter in location j as input seller can be written as

$$f_{j,k} w_j = \psi(\bar{c}^I_{j,k})^{-\gamma_{km}\theta} R^*_{ij,km}.$$

Furthermore, at each period, the rent from the newly created matches are $Y^I_{j,km} = Y^I_{j,km} \frac{1}{\rho} \int_0^\infty \exp(-\rho t) dt$. Hence, the aggregate demand condition should satisfy

$$Y^I_{j,km} = \int_0^{\bar{c}^I_{j,k}} (c)^{-\gamma_{km}\theta} R^*_{ij,km} \times \left(\sum_{i' \in N} \Gamma_{i',k} \left(\tau_{i;j,m} \right)^\theta \theta c^{\theta - 1} \right) dc$$

By solving these two equations, the desired results are obtained.

A.1.4 Full Characterization of Unit Cost Distribution using the Derived Unit Cost of Input Sellers

Now that I characterize the distribution of unit cost of input sellers in each location as the inverse of Pareto distribution with upper bound $\bar{c}^I_{j,k}$, I now revisit the distribution of unit cost and rewrite the distribution using $S^I_{j,k}$ and $\bar{c}^I_{j,k}$.

Denoting the CDF of the unit cost of input suppliers as $G^I_{i,km}(\cdot)$, the CDF of the unit cost $\tilde{G}^I_{i,km}(\cdot)$ is written as

$$\tilde{G}^I_{i,km}(c) = \Lambda_{i,km} \left(S^I_{i,k} \right) \times G^I_{i,km}(c\psi) + \left\{ 1 - \Lambda_{i,km} \left(S^I_{i,k} \right) \right\} \times G^I_{i,km}(c\psi\chi_{i,k}).$$

This follows from the fact that if a firm is not directly matched with a supplier, it has to go through a fringe intermediary firms, which incurs $\chi_{i,k}$ ad-valorem cost (Section 4.1.1). By plugging this in to the expression of $\Gamma_{i,m}$ in equation (6), we have

$$\begin{aligned}
\Gamma_{i,m} &= \tilde{A}_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k \in K} \int_{p_k} {p_k}^{-\theta\gamma_{km}} d\tilde{G}^I_{i,km}(p_k) \\
&= \tilde{A}_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k \in K} [\Lambda_{i,km} \left(S^I_{i,k} \right) \times \int_0^{\bar{c}^I_{i,k}\psi} (c\psi)^{-\theta\gamma_{km}} dG^I_{i,km}(c\psi) + \\
&\qquad \left\{ 1 - \Lambda_{i,km} \left(S^I_{i,k} \right) \right\} \times \int_0^{\bar{c}^I_{i,k}\psi\chi_{i,k}} (c\psi\chi_{i,k})^{-\theta\gamma_{km}} dG^I_{i,km}(c\psi\chi_{i,k})]
\end{aligned}$$

Now,

$$\begin{aligned}
\int_0^{\bar{c}^I_{i,k}\psi} (c\psi)^{-\theta\gamma_{km}} dG^I_{i,km}(c\psi) &= \int_0^{\bar{c}^I_{i,k}\psi} z^{-\theta\gamma_{km}} \frac{\theta z^{\theta-1}}{\left(\bar{c}^I_{i,k}\psi\right)^\theta} dz \\
&= \frac{1}{\left(\bar{c}^I_{i,k}\psi\right)^\theta} \frac{\theta}{\theta-\theta\gamma_{km}} \left(\bar{c}^I_{i,k}\psi\right)^{\theta(1-\gamma_{km})} \\
&= \frac{1}{1-\gamma_{km}} \left(\bar{c}^I_{i,k}\psi\right)^{-\gamma_{km}\theta}
\end{aligned}$$

Likewise,

$$\int_0^{\bar{c}^I_{i,k}\psi\chi_{i,k}} (c\psi\chi_{i,k})^{-\theta\gamma_{km}} dG^I_{i,km}(c\psi\chi_{i,k}) = \frac{1}{1-\gamma_{km}} \left(\bar{c}^I_{i,k}\psi\chi_{i,k}\right)^{-\gamma_{km}\theta},$$

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

$$\begin{aligned}
\Gamma_{i,m} &= \tilde{A}_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k\in K} \frac{\left(\bar{c}^I_{i,k}\psi\chi_{i,k}\right)^{-\gamma_{km}\theta}}{1-\gamma_{km}} \left\{1-\Lambda_{i,km}\left(S^I_{i,k}\right)+\Lambda_{i,km}\left(S^I_{i,k}\right)\chi_{i,k}^{\gamma_{km}\theta}\right\} \\
&= A_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k\in K} \bar{c}^I_{i,k} \left\{1-\Lambda_{i,km}\left(S^I_{i,k}\right)+\Lambda_{i,km}\left(S^I_{i,k}\right)\chi_{i,k}^{\gamma_{km}\theta}\right\},
\end{aligned}$$

by normalizing $A_{i,m} \equiv \tilde{A}_{i,m} \prod_{k\in K} \frac{\left(\psi\chi_{i,k}\right)^{-\gamma_{km}\theta}}{1-\gamma_{km}}$.

A.1.5 Aggregate Input and Final Goods Demand

Under the Cobb-Douglas production function, the aggregate input demand $Y^I_{i,km}$ is simply written as

$$Y^I_{i,km} = \gamma_{km}\left(X^F_{i,m}+X^I_{i,m}\right),$$

where γ_{km} is the Cobb-Douglas share of input in sector k used for production of goods in sector m.

To derive the aggregate input demand, note that there are two sources of demand: demand from workers and demand from firm profit. I show that for both terms, firm profit is $1/\theta$ fraction of aggregate sales.

Lemma 2. *The profit generated by the final goods sales by firms in location i, sector m is $Y^F_{j,k}/\theta$, where $Y^F_{j,k}$ is the aggregate sales by the same firms.*

Proof. To solve the aggregate profit retained at each firm, I first obtain the cutoff value, $\bar{c}^F_{j,k}$. To derive this, first note that the profit from the final goods sales in location j and sector m whose unit cost at location j is c before paying fixed cost, $\Pi^F_{j,m}(c)$, is proportional to $c^{(1-\sigma)}$, which gives me the relationship $\Pi^F_{j,m}(c) = \Pi^F_{j,m}(\bar{c}^F_{j,k})\left(\frac{\bar{c}^F_{j,k}}{c}\right)^{(\sigma-1)}$. Also, define $\Omega_{i,k} \equiv \sum_{i'\in N}\Gamma_{i',k}\left(\tau_{i'j,k}\right)^\theta$, hence the measure of firms whose unit cost at location i is below c is $\Omega_{i,k}c^\theta$. Then, the aggregate profit from sales in location j, $\frac{1}{\sigma-1}Y^F_{j,k}$, has to equate with the integration of $\Pi^F_{j,m}(c)$, which yields

$$\begin{aligned}\frac{1}{\sigma-1}Y^F_{j,k} &= \int_0^{\overline{c}^F_{j,k}} \Pi^F_{j,km}(c)d\Omega_{i,k}c^\theta, \\ &= \Omega_{i,k}\int_0^{\overline{c}^F_{j,k}} \Pi^F_{j,km}(\overline{c}^F_{j,k})\left(\frac{\overline{c}^F_{j,k}}{c}\right)^{(\sigma-1)} \theta c^{\theta-1}dc, \\ &= \Omega_{i,k}\left(\overline{c}^F_{j,k}\right)^\theta \Pi^F_{j,km}(\overline{c}^F_{j,k})\frac{\theta}{\theta-\sigma+1}. \end{aligned} \tag{21}$$

Now, by noting that the measure of final goods sellers in j is derived as $S^F_{j,k} = \Omega_{j,k}\left(\overline{c}^F_{j,k}\right)^\theta$, the profit net of fixed cost is

$$\begin{aligned}\frac{1}{\sigma-1}Y^F_{j,k} - S^F_{j,k}f^F_{j,k}w_j &= \Omega_{i,k}\left(\overline{c}^F_{j,k}\right)^\theta \left\{\Pi^F_{j,km}(\overline{c}^F_{j,k})\frac{\theta}{\theta-\sigma+1} - f^F_{j,k}w_j\right\}, \\ &= \Omega_{i,k}\left(\overline{c}^F_{j,k}\right)^\theta \left\{\Pi^F_{j,km}(\overline{c}^F_{j,k})\frac{\theta}{\theta-\sigma+1} - \Pi^F_{j,km}(\overline{c}^F_{j,k})\right\}, \\ &= \Omega_{i,k}\left(\overline{c}^F_{j,k}\right)^\theta \left\{\Pi^F_{j,km}(\overline{c}^F_{j,k})\frac{\sigma-1}{\theta-\sigma+1}\right\}, \end{aligned} \tag{22}$$

where the second transformation used tthe zero-profit condition of the marginal final goods sellers $\Pi^F_{j,km}(\overline{c}^F_{j,k}) = f^F_{j,k}w_j$. Taken equations (21) and (22) together, I have

$$\frac{1}{\sigma-1}Y^F_{j,k} - S^F_{j,k}f^F_{j,k}w_j = \frac{Y^F_{j,k}}{\theta},$$

which is the desired result. □

Lemma 3. *The profit generated by the final goods sales by firms in location i, sector m is $Y^I_{j,k}/\theta$, where $Y^I_{j,k}$ is the aggregate sales by the same firms..*

Proof. I show that the above statement is true conditional on the relationship duration t^*. From the proof of Lemma 1, for each relationship duration, sales is proportional to $c^{-\gamma_{km}\theta}$. Because of the fixed mark-up ratio ψ, the profit is written as $\Pi^I_{j,m}(c,t^*) = \Pi^F_{j,m}(\overline{c}^I_{j,k},t^*)\left(\frac{\overline{c}^I_{j,k}}{c}\right)^{\gamma_{km}\theta}$. Also, define $\Pi^I_{j,m}(c) = \int \Pi^I_{j,m}(c,t^*)\exp(-\rho t^*)dt*$.

Then, the aggregate profit from sales in location j, $\psi Y^F_{j,k}h(t^*)$, has to equate with the integration of $\Pi^I_{j,m}(c,t^*)$, which yields

$$\begin{aligned}\psi Y^I_{j,k} &= \int_0^{\overline{c}^I_{j,k}} \Pi^I_{j,m}(c)d\Omega_{i,k}c^\theta, \\ &= \Omega_{i,k}\int_0^{\overline{c}^I_{j,k}} \Pi^I_{j,m}(\overline{c}^I_{j,k})\left(\frac{\overline{c}^F_{j,k}}{c}\right)^{\gamma_{km}\theta} \theta c^{\theta-1}dc, \\ &= \Omega_{i,k}\left(\overline{c}^F_{j,k}\right)^\theta \Pi^I_{j,m}(\overline{c}^I_{j,k})\frac{\theta}{1-\gamma_{km}}. \end{aligned} \tag{23}$$

Now, by noting that the measure of final goods sellers in j is derived as $S^I_{j,k} = \Omega_{j,k}\left(\overline{c}^I_{j,k}\right)^\theta$, the profit net of fixed cost is

$$\begin{aligned}
\psi Y^I_{j,k} - S^I_{j,k} f^I_{j,k} w_j &= \Omega_{i,k}\left(\overline{c}^I_{j,k}\right)^\theta \left\{\Pi^I_{j,km}(\overline{c}^I_{j,k})\frac{1}{1-\gamma_{km}} - f^I_{j,k} w_j\right\}, \\
&= \Omega_{i,k}\left(\overline{c}^I_{j,k}\right)^\theta \left\{\Pi^I_{j,km}(\overline{c}^I_{j,k})\frac{1}{1-\gamma_{km}} - \Pi^I_{j,km}(\overline{c}^I_{j,k})\right\}, \\
&= \Omega_{i,k}\left(\overline{c}^I_{j,k}\right)^\theta \left\{\Pi^I_{j,km}(\overline{c}^I_{j,k})\frac{1}{1-\gamma_{km}}\right\}, \qquad (24)
\end{aligned}$$

where the second transformation used tthe zero-profit condition of the marginal final goods sellers $\Pi^I_{j,km}(\overline{c}^I_{j,k}) = f^I_{j,k} w_j$. Taken equations (23) and (24) together, I have

$$\frac{1}{\sigma-1} Y^I_{j,k} - S^I_{j,k} f^I_{j,k} w_j = \frac{Y^I_{j,k}}{\theta}.$$

□

A.2 Model Extension to Incorporating Labor Mobility

To incorporate labor mobility, I make a following additional assumption. I assume that workers also consumw_{i}e 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

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

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 exogenously fixed. From the land market clearing condition, the rent is determined as $R_i = \beta w_i L_i$, hence the utility function is rewritten as $U_i(\epsilon) = \mathcal{A}_i \left(\frac{w_i}{P_i}\right)^{1-\beta} (L_i)^{-\beta} \epsilon_i$. 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 the free labor mobility condition:

$$L_i = \frac{\mathcal{A}_i^\nu \left(\frac{w_i}{P_i}\right)^{(1-\beta)\nu} (L_i)^{-\beta\nu}}{\sum_{i'} \mathcal{A}_{i'}^\nu \left(\frac{w_{i'}}{P_{i'}}\right)^{(1-\beta)\nu} (L_i)^{-\beta\nu}}. \qquad (25)$$

The equilibrium with labor mobility is simply characterized by just adding free labor mobility conditions in Definition 1, and including L_i as an additional endogenous variable.

Definition 2. The steady-state equilibrium is defined by steady state aggregate sales$\{X^I_{i,k}, X^F_{i,k}\}$, aggregate demand $\{Y^I_{i,k}, Y^F_{i,k}\}$, expenditure shares $\{\pi^I_{i,k}, \pi^F_{i,k}\}$, input cost advantage $\{\Gamma_{i,m}\}$, wages $\{w_i\}$, measure of input sellers $\{S^I_{i,k}\}$, unit cost cut-off for input sellers $\{\bar{c}^I_{j,k}\}$, and the labor allocation $\{L_i\}$, which satisfy the total expenditure conditions (10) and (11), trade balancing conditions (12), gravity equations for final goods (14) and input goods (15), input cost advantage (18), free entry condition for marginal input sellers (16) and (17), and free labor mobility (25).

A.3 Obtaining Counterfactual Welfare Change

Proposition 2. *The change in real wages are derived as*

$$\widehat{\left(\frac{w_i}{P_i}\right)} = \hat{w}_i \prod_{k \in K} \left(\frac{\hat{\pi}_{ii,k}}{\hat{\Gamma}_{i,k}}\right)^{-\frac{\alpha_m}{\theta}}.$$

This expression is similar to the general counterfactual welfare formula (i.e., Arkolakis et al. (2012)), except that I have to adjust for the change of productivity of each location $\hat{\Gamma}_{i,k}$.

B Additional Tables and Figures

Table B.1: Balancing between Control and Treatment Firms

Variable	Control	Treatment	p-value of diff.
Growth Number of Suppliers	0.19	0.31	0.06 *
log Sales	12.60	12.43	0.07 *
log Sales Growth	-0.01	-0.01	0.96
log Employment	2.60	2.48	0.1
log Employment Growth	-0.01	-0.01	0.93
Solvency Score	49.04	48.36	0.07 *

Note: "Control" and "Treatment" indicate the average value for control and treatment firms, weighted by the inverse of the number of control firms in each group. "p-value of diff." indicates the p-value of the difference between control and treatment firms. *p<0.1; **p<0.05; ***p<0.01.

Table B.2: No Heterogeneous Pretrends upon Unanticipated Supplier Bankruptcy by Supplier Density

	New Suppliers		log Sales	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = -1 or -2]	−0.003	−0.003	0.02	0.02
	(0.04)	(0.04)	(0.01)	(0.01)
Trt x 1[t - BankruptYear = -1 or -2] x log Seller Density (Std.)	−0.004	0.03	−0.02	−0.03
	(0.04)	(0.04)	(0.02)	(0.02)
Observations	44,028	44,023	43,633	43,628

Note: The coefficients of the event-study regression with heterogeneous impacts (2) are reported. The regression is the same as in Table 3, except that I include per-period terms. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table B.3: Heterogeneous Impacts on New Supplier Matching upon Unanticipated Supplier Bankruptcy by Different Definition of Supplier Density

	New Suppliers					
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Trt x 1[t - BankruptYear = 0 or 1]	0.06	0.06	0.06	0.06	0.06	0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.09**	0.11**	0.08**	0.13**	0.10**	0.10**
	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)
Trt x 1[t - BankruptYear = 2 or 3]	0.22***	0.22***	0.22***	0.22***	0.22***	0.22***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.09	0.09	0.11	0.13	0.15**	0.11
	(0.06)	(0.07)	(0.07)	(0.10)	(0.07)	(0.08)
Definition of Seller Density	2-digit Ind.	2-digit Ind.	Municipality	Municipality	Local Headquarters	Local Headquarters
Observations	99,447	99,436	99,447	99,436	99,447	99,436

Note: The coefficients of the event-study regression with heterogeneous impacts (2) are reported. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table B.4: Robustness of Heterogeneous Impacts of Unanticipated Supplier Bankruptcyy

	New Suppliers		
	IV	IV	IV
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = 0 or 1]	0.06 (0.04)	0.07 (0.05)	0.09 (0.06)
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.09* (0.05)	0.10* (0.06)	0.13** (0.07)
Trt x 1[t - BankruptYear = 2 or 3]	0.20*** (0.08)	0.24*** (0.08)	0.31*** (0.10)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.11 (0.08)	0.09 (0.09)	0.14 (0.10)
Specification	Excl. Exiting Firms	Excl. Tokyo	Sampling Adjustment
Observations	94,783	67,584	99,436

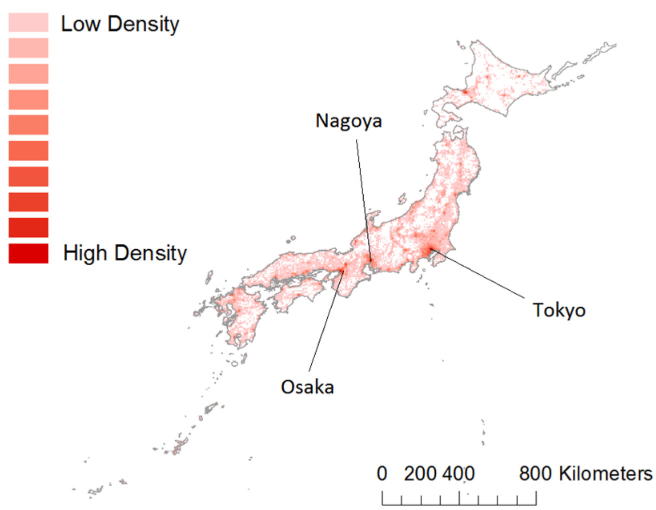
Note: The coefficients of the event-study regression with heterogeneous impacts (2) are reported. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table B.5: IV impacts on Exit and Sales of Number of Suppliers

	Exit		log Sales (incl. Exit)	
	(1)	(2)	(3)	(4)
Number of Suppliers	−0.06	−0.07*	0.75	0.87*
	(0.04)	(0.04)	(0.47)	(0.51)
Number of Suppliers x log Seller Density (Std.)		−0.01		0.33
		(0.05)		(0.62)
Observations	29,576	29,572	28,886	28,882

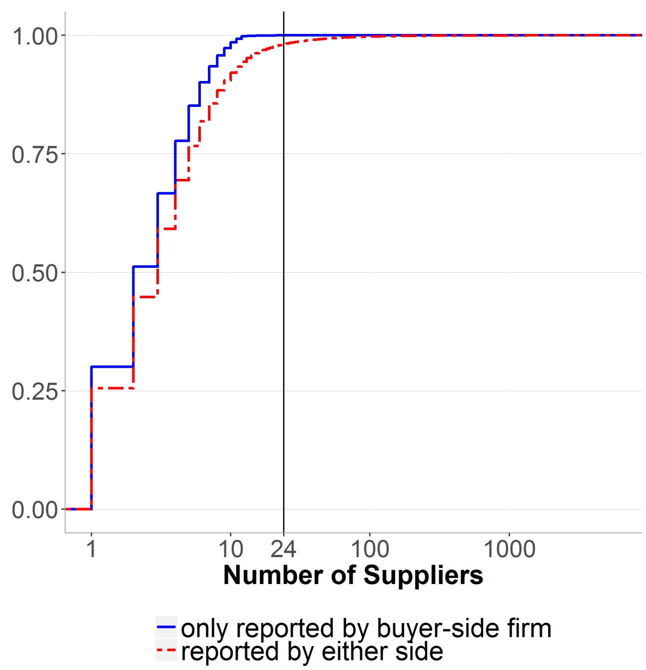
Note: The table reports the results of the IV regression (3) in footnote 26. In these regressions, I only include where t is either one year before the supplier bankruptcy or three years after the supplier bankruptcy. In case firm i exit at period t, "Number of Suppliers" is defined as the value of the last year before the firm goes exit. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Figure B.1: Geographic Population Density in Japan



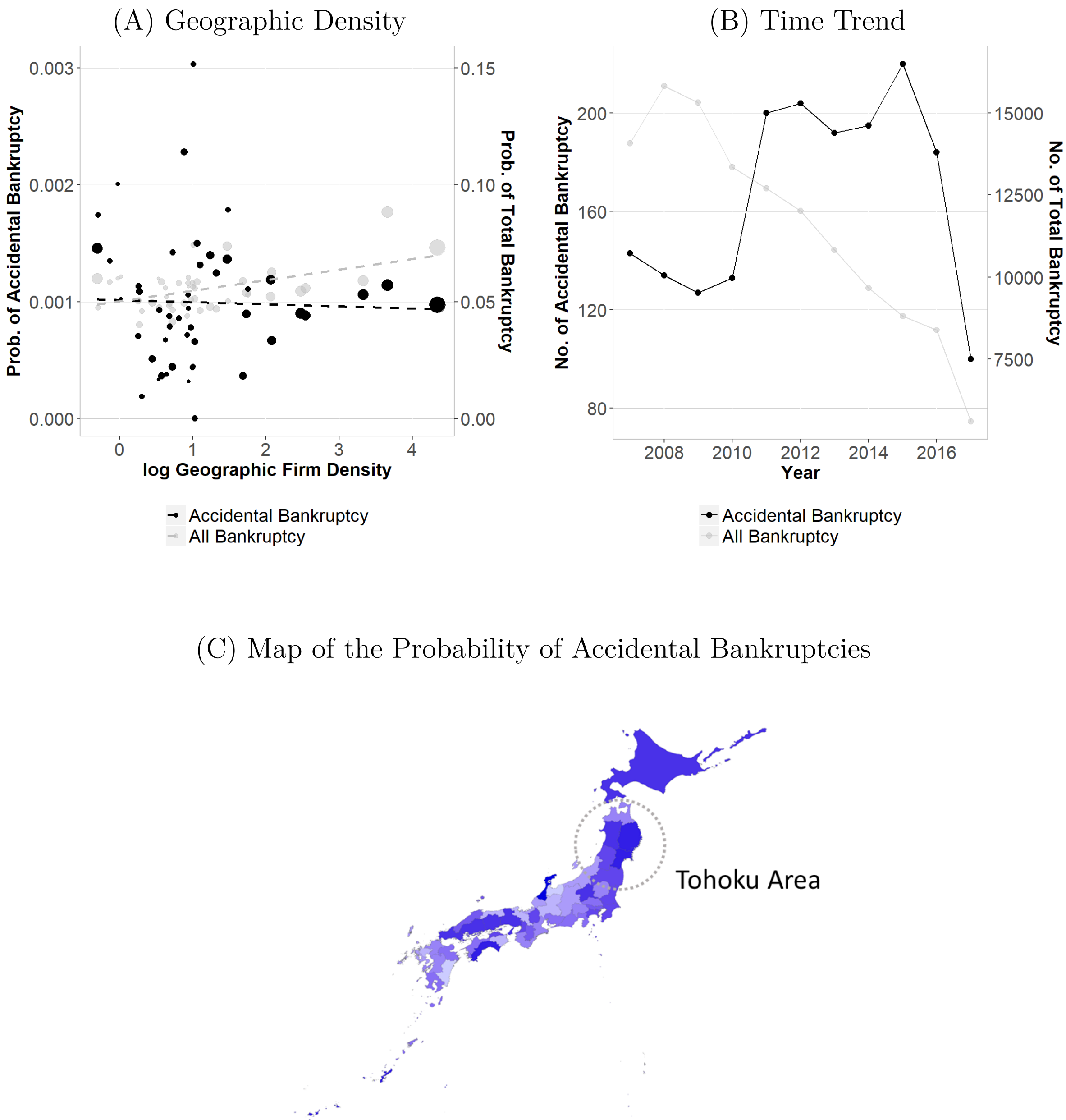
Note: Based on Population Census in 2010.

Figure B.2: Distribution of Number of Suppliers per Firm



Note: Based on TSR data in 2007.

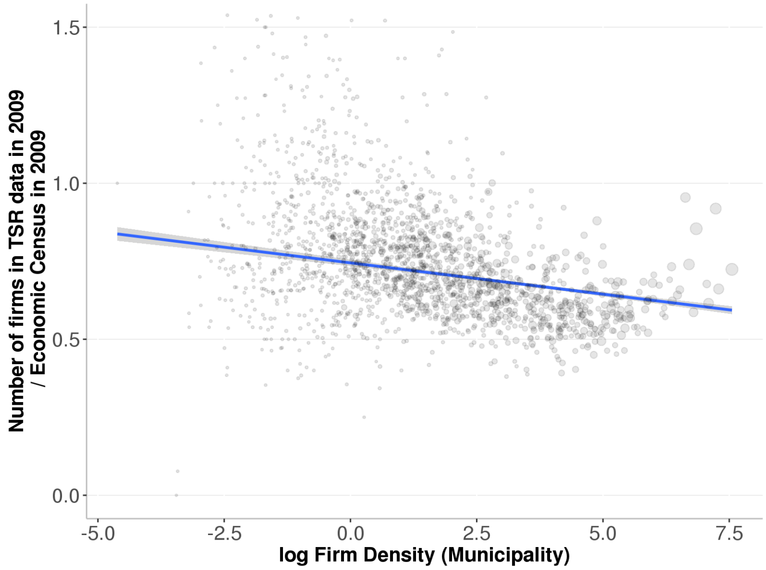
Figure B.3: Geographic and Time Patterns of Unanticipated Accidental Bankruptcies



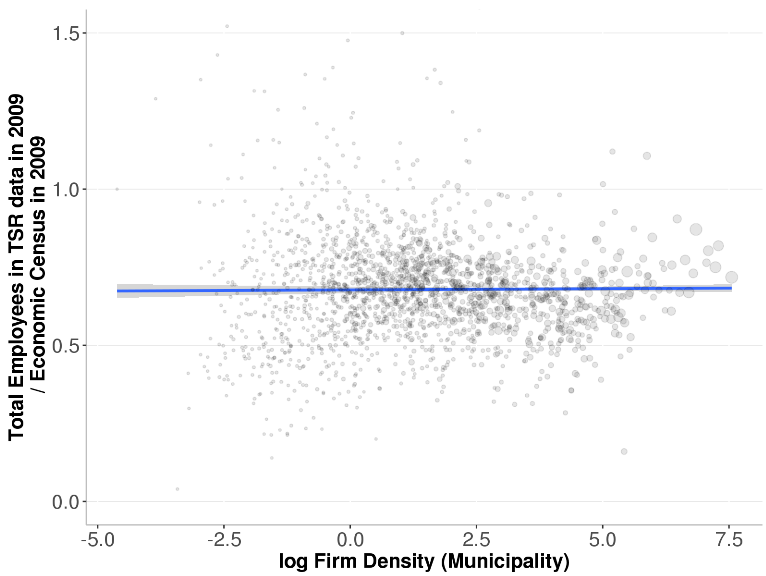
Note: Based on the bankruptcy data set provided by TSR. The Great Tohoku Earthquake happened in Tohoku Area as shown in Panel (C) in March 2011.

Figure B.4: Representativeness and Sampling Patterns of TSR data set

(A) Proportion of Firms in TSR dataset

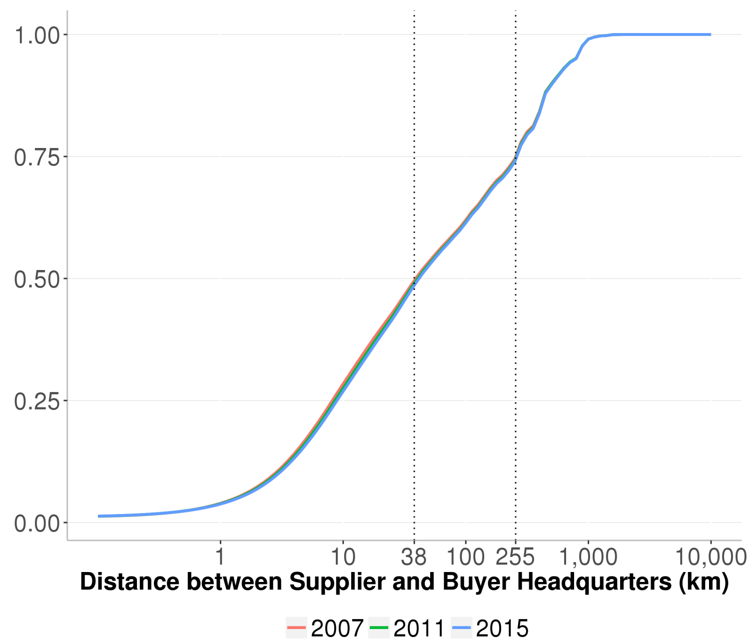


(B) Proportion of Covered Employment in TSR dataset



Note: Based on TSR data in 2009 and economic census in 2009. log Firm Density in the x-axis is defined by the economic census in 2009. In aggregate, the data covers on average 68% of firms and 70% of total employments of Japan.

Figure B.5: Distribution of Geographic Distances between Suppliers and Buyers



Note: The graph shows the cumulative distributions of geodesic distance between supplier and buyer's headquarter locations for the years of 2007, 2011, and 2015.

Figure B.6: Representativeness of Firms facing Unanticipated Supplier Bankruptcy

(A) Sales Distribution of Firms experiencing Unanticipated Bankruptcies

(B) Sales Distribution of Firms facing Unanticipated Supplier Bankruptcies

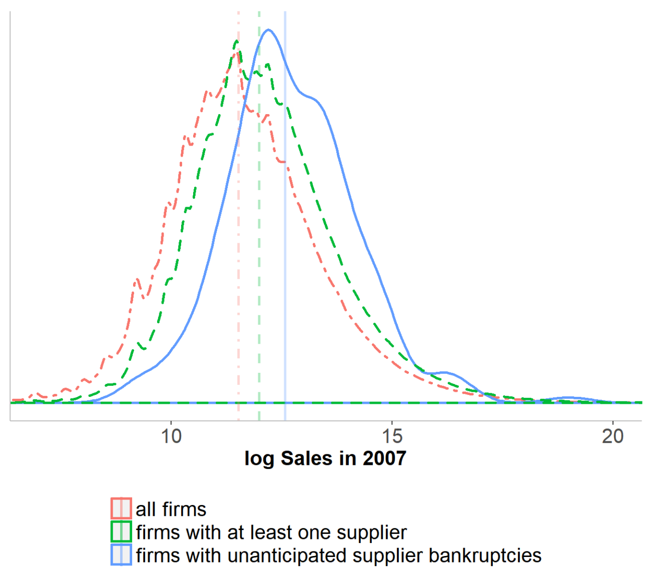
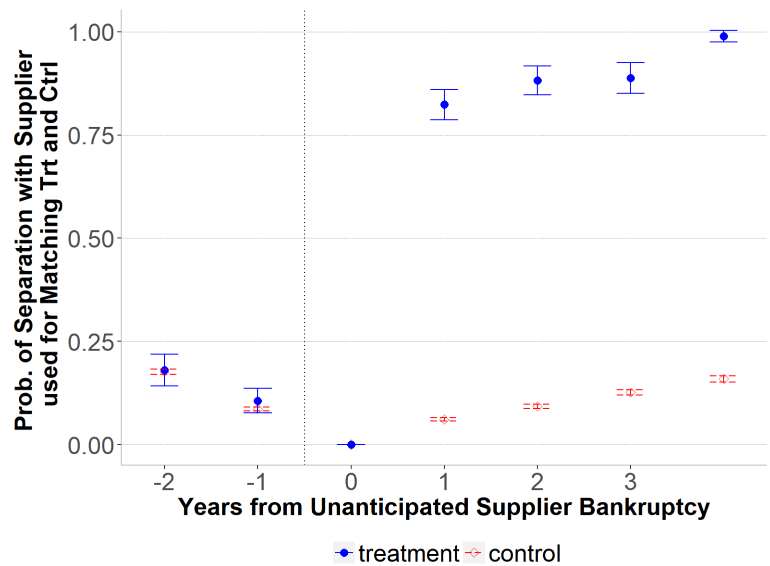
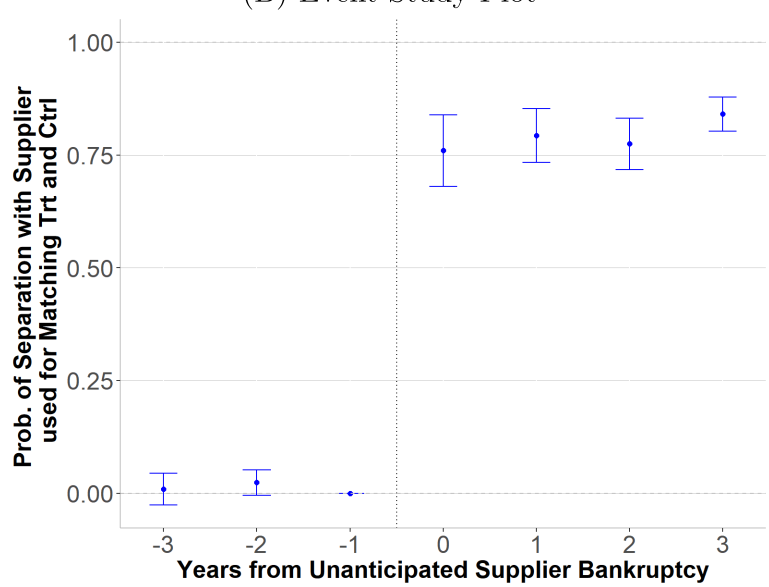


Figure B.7: Separation with a Supplier Used for Matching Control and Treatment Firms

(A) Trajectory by Control and Treatment

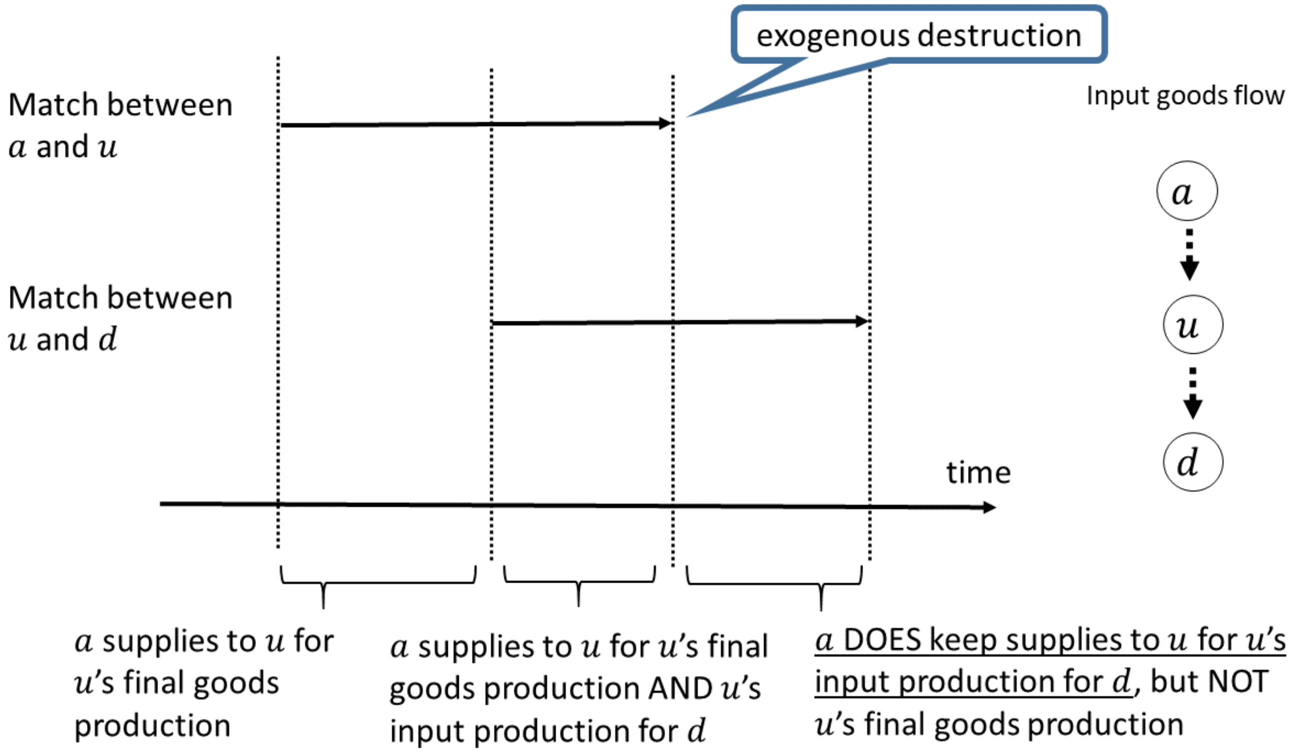


(B) Event Study Plot



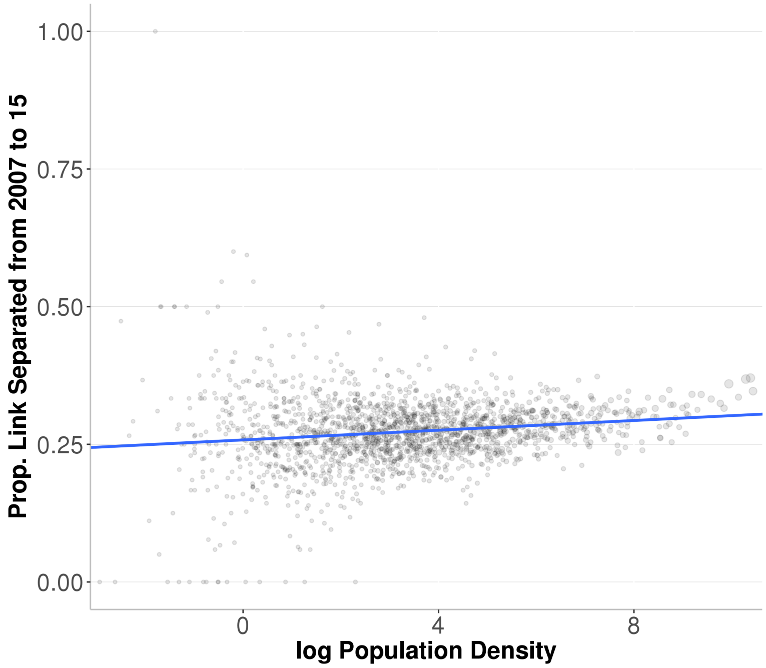
Note: Panel (A) shows the trajectory of the probability of separation with the supplier used for assigning control firms to treatment firms (i.e., bankrupting supplier for the treatment firm; randomly-picked supplier within the same four-digit supplier industry for control firms). Panel (B) shows the coefficients of the event-study regression (1) on the same outcome variable. See the footnote of Figure 2 for more detail about the specification.

Figure B.8: Timing of the Matching and Input Goods Sales in the Model



Note: The figure illustrates the timing of firm-to-firm matching and input goods sales as explained in Section 4.1.3.

Figure B.9: Probability of Separation and Population Density



Note: y-axis shows the probability that a supplier-link that each firm in a municipality has in 2007 is separated in 2015. Each dot represents the municipality.