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

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Abstract

This paper shows that matching frictions and thick market externality in firm-to-firm trade shape the agglomeration of economic activity. Using panel data of firm-to-firm trade in Japan, I demonstrate that firms gradually match with alternative suppliers following an unanticipated supplier bankruptcy, and that the rate of rematching increases in the geographic density of alternative suppliers. Motivated by these empirical findings, I develop a general equilibrium model of firm-to-firm matching in input trade across space. The model reveals that the thick market externality gives rise to agglomeration externalities affecting regional production and welfare. Using the calibrated model to the reduced-form patterns of firm-to-firm matching, I estimate that the elasticity of a region's real wage with respect to population density due to thick market externalities is approximately 0.02. This finding highlights the substantial impact of thick market externality on the overall agglomeration benefit.

Keywords: Agglomeration, Production Networks, Thick Market Externality

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"When an industry has thus chosen a locality for itself, it is likely to stay there long: so great are the advantages which people following the same skilled trade get from near neighbourhood to one another... And presently subsidiary trades grow up in the neighbourhood, supplying it with implements and materials, organizing its traffic, and in many ways conducing to the economy of its material." – Alfred Marshall (1890) "Principles of Economics"

1 Introduction

Firms are more productive in more densely populated areas. Scholars widely agree that a substantial portion of this productivity pattern can be attributed to agglomeration externalities. In an influential book, Marshall (1890) argues that one important reason behind the agglomeration externality is the presence of matching frictions and thick market externality in firm-to-firm trade; i.e., suppliers and buyers in densely-populated areas have more opportunities to interact and engage in trade. However, despite the recognition of these mechanisms, our understanding of how these forces shape the spatial distribution of economic activity remains limited due to insufficient data and theoretical frameworks pertaining to firm-to-firm trade within and across regions.

This paper investigates how matching frictions and thick market externality in firm-to-firm trade shape the agglomeration of economic activity. Leveraging a unique panel dataset of firm-to-firm trade in Japan in conjunction with unanticipated supplier bankruptcies as a natural experiment, I empirically examine the dynamics of firm-to-firm matching following supplier bankruptcies. I find that firms gradually match with an alternative supplier after the suppliers' bankruptcy, and that the rate of rematching increases in the geographic density of alternative suppliers. Building upon these empirical findings, I develop a general equilibrium model that captures the dynamics of firm-to-firm matching in input trade across space. I demonstrate that thick market externalities give rise to agglomeration externalities, impacting aggregate regional production and welfare. By calibrating the model to the reduced-form patterns of firm-to-firm matching, I estimate that the elasticity of a region's real wage to population density due to thick market externalities is approximately 0.02. By comparing this value to existing estimates of overall agglomeration spillovers, I conclude that thick market externalities substantially contribute to the overall agglomeration benefits experienced in the economy.

This paper is structured into three main parts. In the first part, I provide reduced-form evidence of matching frictions and thick market externality in firm-to-firm trade. Identifying matching frictions in this context poses a significant challenge, as observational data alone does not reveal which input buyer is in need of a supplier, and if so, what type of suppliers. Therefore, a simple comparison of observed matching patterns across locations is insufficient to establish the presence of matching frictions and thick market externality. To overcome this challenge, I leverage unanticipated supplier bankruptcies as a natural experiment. After these shocks, firms are plausibly in need of alternative suppliers. The rate at which firms match with new suppliers provides insight into the severity of matching frictions. Moreover, to what extent the matching rates increase in the density of suppliers provides information about the thick market externality.

To implement this idea, I leverage a rich panel dataset of firm-to-firm trade in Japan, complemented by a comprehensive list of bankruptcies. A crucial aspect of this dataset is that it provides information on the primary causes leading to bankruptcy. Within this dataset, I focus specifically on supplier bankruptcies categorized as "unanticipated reasons," which encompass events like the death of company representatives or natural disasters.

I uncover the following patterns of firms' responses to unanticipated supplier bankruptcies. First, I demonstrate that firms only gradually match with alternative suppliers following unanticipated supplier bankruptcies. At the same time, these firms experience a significant decline in production. These facts suggest the presence of matching friction in firm-to-firm trade. Second, I find a robust positive correlation between matching rates with new suppliers and the geographic density of alternative suppliers. This evidence provides support for the thick market externality. To address the potential concern about selective firm entry, such as firms adept at finding alternative suppliers tending to locate in areas with higher supplier densities, I show that this correlation is robust to controlling for location fixed effects and various firm characteristics, using the birth location of the CEO as exogenous variation for a firm's location, and focusing specifically on the bankruptcies of non-primary suppliers. Third, I do not find a significant correlation between matching rates and the density of other buyers. Therefore, there is no strong evidence that the congestion externality stemming from other input buyers plays a role in the market of firm-to-firm matching.

Drawing upon these empirical patterns, the second part of the paper develops a quantitative theoretical framework that captures the dynamics of firm-to-firm matching in input trade across space. The primary objective of this model is to establish a clear link between the thick market externality and the resulting agglomeration externality. Firms undertake production activities utilizing intermediate goods, which can be sourced either through direct matches with suppliers or through indirect sourcing from costly intermediaries. Due to the presence of matching frictions, matching with suppliers occurs gradually over time. At the same time, the thick market externality enhances the rate at which firms establish supplier linkages in locations and sectors served by a larger number of suppliers. I show that this thick market externality gives rise to agglomeration externalities that impact regional aggregate productivity and welfare. Moreover, when accounting for population mobility, this agglomeration externality generates a force driving population concentration.

In the third part of the paper, I use the developed theoretical model in conjunction with the reduced-form evidence to quantitatively assess the magnitude of the agglomeration benefit resulting from the thick market externality in firm-to-firm trade. To achieve this goal, I utilize the exact-hat algebra approach proposed by Dekle, Eaton, and Kortum (2008) to calibrate the model to the data encompassing multiple heterogeneous locations and cross-regional firm-to-firm trade. An essential aspect of this calibration process involves determining the values of key structural parameters: the elasticity of matching functions and the iceberg cost associated with indirect sourcing. I calibrate these parameters using the reduced-form effects of unanticipated supplier bankruptcies on new supplier matching rates and sales reduction.

Using the calibrated model, I conduct two sets of counterfactual simulations to examine the magnitude of the agglomeration force resulting from the thick market externality. In the first set of simulations, I analyze the impacts of an increase in the population size of the Tokyo prefecture. In the baseline model, I observe that Tokyo's real wage increases in its population size, with an elasticity of 0.137. When I abstract the thick market externality, this elasticity decreases to 0.118. Therefore, the elasticity of agglomeration benefit attributed to the thick market externality is approximately 0.02 ($\approx 0.137 - 0.118$). To provide a benchmark for this result, I also undertake the same counterfactual simulation under an alternate value of productivity spillovers from local population density (modeled as a separate agglomeration externality). I find that abstracting the thick market externality yields a reduction in agglomeration benefit comparable to decreasing the elasticity of local productivity spillovers by 0.03. Although on the lower end, this value is within the range of existing estimates for agglomeration productivity spillovers (from 0.02 to 0.1; i.e., Melo, Graham, and Noland 2009). These findings suggest that a significant proportion of the overall agglomeration benefit can be attributed to the thick market externality in input trade.

In the second set of counterfactual simulations, I investigate how these agglomeration externalities amplify the effects of exogenous productivity increases in the Tokyo prefecture. In the baseline model, I observe that Tokyo's real wage responds to productivity growth with an elasticity of 2.5. This high elasticity is primarily driven by cost propagation effects through sectoral input-output linkages. When I abstract the thick market externality in firm-to-firm matching, this elasticity decreases to 0.241. Therefore, the presence of the thick market externality amplifies the impacts of productivity shocks on local real wages. Furthermore, I observe that abstracting the thick market externality leads to a comparable decrease in the amplification of productivity shocks as reducing the elasticity of local productivity spillovers by 0.03-0.04. Therefore, the thick market externality plays a crucial role in amplifying regional productivity shocks, and its significance is comparable to typical estimates of agglomeration productivity spillovers.

The primary contribution of this paper is to provide an empirical and theoretical analysis of thick market externality in firm-to-firm trade as a source of agglomeration externality. This mechanism aligns with one of the core agglomeration theories put forth by Marshall (1890). More recently, Duranton and Puga (2004) underscores the significance of matching between different agents as one important mechanism behind agglomeration externalities. However, the empirical and theoretical exploration of this specific agglomeration mechanism has been limited due to a lack of data and theoretical framework. The closest empirical evidence to this paper is provided by Holmes (1999), who finds that firms located in denser areas tend to rely more on external suppliers for their input purchases. In contrast, this paper goes beyond cross-sectional evidence by examining the dynamics of supplier matching using detailed dynamic firm-to-firm trade data. Theoretically, Krugman and Venables (1995) and Venables (1996) propose models of agglomeration based on the love of varieties in intermediate inputs. My focus is instead on exploring matching frictions and thick market externality in firm-to-firm trade.

Outside the context of firm-to-firm trade, the concept of thick market externality has been extensively studied in the context of the labor market. Drawing on the theoretical framework of search and matching frictions in the labor market (Diamond 1982, Pissarides 1985, Mortensen 1986), this body of literature has sought to estimate matching frictions and the thick market externality using aggregate data (see Petrongolo and Pissarides (2001) for a comprehensive survey) or by analyzing the reemployment patterns of unemployed individuals using micro data (Petrongolo 2001). More recent papers in this literature, such as Bleakley and Lin (2012), Jäger and Heining (2022), and Macaluso (2023), have utilized exogenous separations between workers and firms, such as worker displacement or mortality, to provide empirical evidence for matching frictions and the presence of thick market externality. In this paper, I employ similar empirical and theoretical approaches in the context of firm-to-firm matching in input trade.

Besides the agglomeration literature, this paper contributes to the broader body of research on production networks, trade, and economic geography. First, this paper contributes to the literature on the endogenous formation of production networks across regions and countries (see Bernard and Moxnes (2018) and Antràs and Chor (2021) for recent surveys). Closest to this paper is Eaton, Kortum, and Kramarz (2022), who develop a theoretical framework where firms in different regions endogenously establish production linkages within a general equilibrium framework.[1] Building upon Eaton et al. (2022), I extend their theoretical framework in two important ways. First, I incorporate dynamic matching and separation. This feature allows me to explicitly connect reduced-form evidence on dynamic supplier matching after unanticpated supplier bankruptcy to my theoretical framework. Second, I incorporate worker mobility, following the recent literature on quantitative spatial models (Allen and Arkolakis 2014, Redding and Rossi-Hansberg 2017). This extension enables me to establish a link between thick market externality in firm-to-firm trade and agglomeration phenomena.[2]

This paper also contributes to the literature on the disruption of production networks. In particular, Barrot and Sauvagnat (2016), Boehm, Flaaen, and Pandalai-Nayar (2019) and Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021) document how natural disaster shocks to firms or regions propagate through firm-to-firm trade networks and impact connected firms. Jacobson and Von Schedvin (2015) shows that the impact of firm bankruptcy propagates through trade credit relationships. This paper contributes to this literature by examining the process of production network recovery following an unanticipated supplier bankruptcy.

[1] See Oberfield (2018) for a model with a similar aggregation property as Eaton et al. (2022) without the spatial dimension of trade, and Panigrahi (2022) for an extension of Eaton et al. (2022) to incorporate multiple dimensions of firm heterogeneity.

[2] Other recent papers on endogenous firm-to-firm trade networks focus on the role of domestic and international sourcing decisions (Furusawa, Inui, Ito, and Tang 2017), transportation infrastructure (Bernard, Moxnes, and Saito 2019), propagation of shocks across production networks (Dhyne, Kikkawa, Mogstad, and Tintelnot 2020, Lim 2018 and Huneeus 2018), firm size distribution (Bernard, Dhyne, Magerman, Manova, and Moxnes 2022), misallocation of production resources (Boehm and Oberfield 2020), market power distortions (Dhyne, Kikkawa, and Magerman 2022), effects of supplying to multinational companies (Alfaro-Urena, Manelici, and Vasquez 2022), and firms' quality choices (Demir, Fieler, Xu, and Yang 2023).

Finally, this paper contributes to the literature on search and matching frictions in domestic and international trade. In particular, Allen (2014) and Krolikowski and McCallum (2021) develop dynamic frameworks that incorporate search and matching frictions in the formation of trade relationships. In contrast to these studies, this paper empirically and theoretically studies matching frictions in the context of production networks, where firms and industries are interconnected through input-output linkages.[3]

The rest of the paper is organized as follows. Section 2 describes the main dataset. Section 3 presents reduced-form evidence of matching frictions and thick market externality using unanticipated supplier bankruptcies as a natural experiment. Section 4 develops a general equilibrium model of firm-to-firm matching across space. Section 5 calibrates my model to reduced-form patterns and quantifies the agglomeration externality arising from thick market externality. Section 6 concludes.

2 Data

Data Sources. This paper utilizes a primary dataset obtained from Tokyo Shoko Research (TSR), a major credit reporting company in Japan. TSR collects comprehensive panel data of firms through personal interviews or phone surveys, supplemented by public resources such as financial statements, corporate registrations, and public relations documents. Most importantly for my purpose, this dataset reports up to 24 main suppliers and buyers.[4] Firms also report the ranking of their suppliers and buyers based on the transaction amount. The dataset constitutes a yearly panel spanning from 2008 to 2016, covering nearly 70% of all firms in Japan.[5] I use this dataset to track the dynamic evolution of supplier-to-buyer (or firm-to-firm) trade linkages.

In my analysis, I exclude supplier linkages if the firms have a major ownership linkage, which corresponds to 1.5% of all supplier linkages. In the baseline analysis, I define supplier linkages based on reports from the buyer-side firms. I demonstrate that my empirical results remain robust when including linkages reported by the supplier-side firms.

The dataset provides the headquarters' address for each firm and the addresses of

[3]Other papers that embed search frictions in international trade include Chaney (2014), Brancaccio, Kalouptsidi, and Papageorgiou (2020), Dasgupta and Mondria (2018), Eaton, Jinkins, Tybout, and Xu (2022), Startz (2021), Lenoir, Martin, and Mejean (2023).

[4]The censoring at 24 is practically not binding; fewer than 0.1% of firms report exactly 24 suppliers.

[5]Appendix Table A.1 provides additional details of the coverage of the dataset. Appendix Figure A.1 shows that the TSR dataset exhibits similar coverage rates across different municipalities in Japan.

all its establishments, including their prefectures and municipalities.[6] At the same time, supplier-to-buyer linkages are reported at the firm level rather than the establishment level. In my main analysis below, I proxy firms' location using the address of their headquarters. I show that the main reduced-form empirical results hold when restricting the analysis to firms with establishments concentrated in a single prefecture to address potential mismeasurement of the transaction location. The dataset also includes information on the CEO's name and characteristics, including birth prefecture, graduation school, age, and gender.

I merge this firm-to-firm dataset with the list of bankruptcies and their main documented causes. TSR compiles this data through their investigation of the parties involved. About 2 percent of bankruptcies are categorized as "unanticipated reasons," which TSR's internal document describes as "bankruptcies due to unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc." In the next section, I leverage these unanticipated supplier bankruptcies as a natural experiment to offer evidence of matching frictions.[7]

I use this firm-to-firm trade data to provide reduced-form evidence for matching frictions and thick-market externality in Section 3 and to calibrate the quantitative general equilibrium model in Section 5. For the latter, I augment the dataset with official government statistics. First, I use population size across 47 prefectures in Japan from the Population Census, conducted by the Ministry of Internal Affairs of Japan in 2010. Second, I use input-output table at the two-digit sector level, which was created by Japan's Ministry of International Affairs and Communications in Japan in 2011.

Descriptive Patterns of Firm-to-firm Trade and Geography. Before delving into the main empirical analysis using unanticipated supplier bankruptcy, I present suggestive evidence for the thick market externality in firm-to-firm matching. First, firm-to-firm trade linkages are geographically concentrated. Panel (A) of Figure 1 illustrates the cumulative distribution function of the geographic distance between the headquarters of a supplier and a buyer. The median distance between them is 37 kilometers, significantly shorter than the median distance for all potential pairs in Japan (172 kilometers; Bernard et al.

[6]There are 47 prefectures and 1719 municipalities in Japan in 2014.

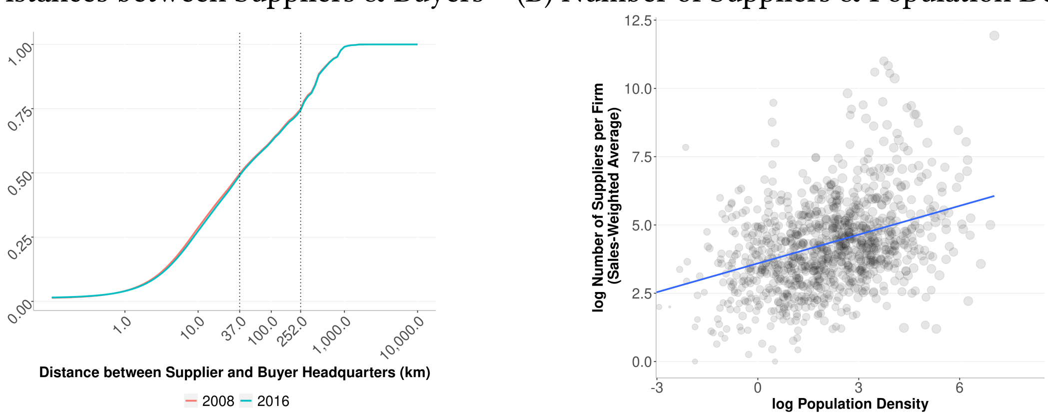
[7]Appendix Table A.2 reports the list of all reasons and their proportion among reported bankruptcies. Appendix Figure A.2 shows that these unanticipated bankruptcies occur uniformly across space, suggesting that these bankruptcies are not driven by a single regional shock such as the Great Tohoku Earthquake. I also confirm the robustness of my results by excluding firms in the Tohoku and Hokkaido regions.

2019). These findings indicate a strong tendency for firms to engage with local suppliers, although a notable fraction of trade occurs across regions.

If firms tend to source from local suppliers, do firms in denser areas tend to have a higher number of suppliers? Panel (B) of Figure 1 reveals a clear positive correlation between the population density and the number of suppliers per firm at the municipality level. This finding aligns with Holmes (1999), who documents the positive correlation between the fraction of externally purchased inputs per firm and firm density in the United States. These pieces of evidence suggest the presence of matching frictions and thick market externality in firm-to-firm trade. However, they are also consistent with an alternative hypothesis that firms in different locations have varying demands for external suppliers. In the next section, I provide more direct evidence of matching frictions and thick-market externality using unanticipated supplier bankruptcy as a natural experiment.

Figure 1: Spatial Patterns of Firm-to-Firm Trade

(A) Distances between Suppliers & Buyers (B) Number of Suppliers & Population Density



Note: Panel (A) shows the cumulative distribution functions of the geodesic headquarter distances to reported suppliers in 2008 and 2016 from TSR data. Panel (B) shows the relationship between the population density and the average number of reported suppliers per firm at the municipality level in 2008 (weighted by the buyer-side firms' sales).

3 Reduced-Form Evidence

3.1 Empirical Strategy

The primary approach for examining matching frictions and thick market externality is to analyze firms' reactions to unanticipated supplier bankruptcies. When faced with these shocks, firms are plausibly in need of alternative suppliers. The rate at which firms establish new matches with suppliers indicates the level of matching frictions. Moreover, the extent to which matching rates increase in relation to supplier density provides insights into the presence of thick market externality. In this section, I formalize these ideas using a simple model of supplier-to-buyer matching to derive a specification for empirical analysis.

3.1.1 A Model of Firm-to-Firm Matching

Consider a firm in region j and sector m that is looking for a supplier in sector k. Due to matching frictions, it takes some time for the firm to find a suitable supplier and establish a transactional relationship. The rate at which successful matches are formed may depend on the number of potential suppliers and the number of buyers in search of suppliers. Building on the labor search and matching literature (Diamond 1982, Pissarides 1985, Mortensen 1986), I adopt a Cobb-Douglas matching function to capture these relationships. In particular, I assume that the Poisson rate at which a link between suppliers in sector k and buyers in sector m is created per unit of geographic area in location j follows:

$$M\left(S_{j,k}^{*}, B_{j,m}^{*}\right) = \eta \left(S_{j,k}^{*}\right)^{\lambda^{S}} \left(B_{j,m}^{*}\right)^{\lambda^{B}}, \quad S_{j,k}^{*} = \sum_{n \in \mathcal{N}} S_{nj,k}^{*} \tag{1}$$

where $S_{nj,k}^{*}$ represents the geographic density of suppliers producing in location n who can supply intermediate inputs to buyers in location j (the asterisk denotes geographic density); $S_{j,k}^{*}$ sums these up across all supplier locations n (to account for inter-region trade); $B_{j,m}^{*}$ is the geographic density of input buyers in location j and sector m; η is a parameter governing the efficiency of the matching process; and λ^S and λ^B represent the elasticities of the matching function. The Poisson rate at which a buyer matches with a supplier is given by $M\left(S_{j,k}^{*}, B_{j,m}^{*}\right) / B_{j,m}^{*} = \eta \left(S_{j,k}^{*}\right)^{\lambda^{S}} \left(B_{j,m}^{*}\right)^{\lambda^{B}-1}$.

The elasticities of the matching function, λ^S and λ^B, capture the key externalities in the matching process. A positive value of λ^S indicates that a buyer's matching rate with a supplier increases with the geographic density of suppliers, capturing the "thick market externality" (Petrongolo and Pissarides 2001). Similarly, a negative value of $\lambda^B - 1$ implies that a buyer's matching rate with a supplier decreases with the geographic density of buyers, capturing the "congestion externality." In Section 4, I show that these externalities give rise to agglomeration externality for regional production and welfare in general equilibrium.

3.1.2 Empirical Specification using Unanticipated Supplier Bankruptcies

I now derive the empirical specification to test matching frictions as well as thick market and congestion externality. Consider a buyer f in sector m and location j who is searching for a supplier in sector k. Based on the matching function (1), I can approximate the probability that the buyer matches with a supplier within Δ years as follows:[8]

$$\text{NewSuppliers}_{fjkm\Delta} \approx \eta\Delta \times \left(1 + \lambda^S \log S^*_{j,k} + \left(\lambda^B - 1\right) \log B^*_{j,m}\right). \tag{2}$$

If $\text{NewSuppliers}_{fjkm\Delta}$ is directly observed, one can estimate equation (2) to test for thick market and congestion externality. In fact, previous studies in the labor search and matching literature estimate a version of this equation using the observed data on employment status (e.g., Petrongolo 2001). However, in the context of supplier-to-buyer matching, researchers do not directly observe $\text{NewSuppliers}_{fjkm\Delta}$. This is because observational data does not reveal which buyer is in need of a supplier, and if so, what type of suppliers.

To overcome this challenge, I focus on the event where a buyer loses a supplier due to an unanticipated bankruptcy. Following such a loss, buyers are likely to require an alternative supplier. Therefore, the speed at which firms match with a new supplier after an unanticipated supplier bankruptcy provides information about the magnitude of matching frictions. In other words, the causal effect of supplier bankruptcy on new supplier matching reveals the presence of matching frictions in firm-to-firm trade.

I implement this idea empirically using a stacked-by-event difference-in-difference method. For each "event" of an unanticipated supplier bankruptcy, I define their input buyers as "treatment firms" (i.e., firms that report the bankrupt firm as a supplier one year prior to its bankruptcy). I also select "control firms" that are comparable to the treatment firms but whose suppliers do not go bankrupt. In particular, I select control firms such that their headquarters are located in the same municipality as the treatment firms and they have a supplier in the same four-digit industry as the treatment firms' bankrupt supplier prior to the bankruptcy. Finally, I stack observations from all bankruptcy events. Adapting equation (2) in the difference-in-difference framework, the regression specification is given as follows:

[8] Using the properties of a Poisson process, $\text{NewSuppliers}_{fjkm\Delta} = 1 - \exp\left(-\eta S^{*\lambda^S}_{j,k} B^{*\lambda^B - 1}_{j,m} \Delta\right)$. Taking the first-order approximation around $\Delta \approx 0$ and then around $\log S_{j,k} \approx \log B_{j,m} \approx 0$ gives equation (2).

$$\text{NewSuppliers}_{fjkmgt} = \sum_{\Delta=\cdots-2,0,\cdots} Trt_f \times 1[t - \text{BankruptYear}_g = \Delta] \times \left(\tilde{\eta}_\Delta + \tilde{\lambda}^S_\Delta \log S^*_{j,k} + \tilde{\lambda}^B_\Delta \log B^*_{j,m} + \theta_\Delta X_{fjkmg}\right) + \xi_{fg} + \zeta_{gt} + \epsilon_{fjkmgt}, \quad (3)$$

where f denotes the firm, t denotes the year, Trt_f denotes a dummy variable for the treatment firm, g represents the bankruptcy event (i.e., the set of control and treatment firms associated with the same bankruptcy event), BankruptYear_g is the year of supplier bankruptcy in event g, and $\tilde{\eta}_\Delta$, and $\tilde{\lambda}^S_\Delta$, $\tilde{\lambda}^B_\Delta$ are regression coefficients Δ years after the supplier bankruptcy shock. The event-year fixed effects ζ_{gt} ensure that the treatment effect is identified by comparing the treatment and control firms within the same event, and the firm-event fixed effects ξ_{fg} account for time-invariant firm heterogeneity.[9] X_{fjkmg} includes a series of fixed effects and firm characteristics that control for other dimensions of treatment heterogeneity, as I further discuss in Section 3.1.3. Notice that I normalize the event-study coefficients by one year prior to the bankruptcy, i.e, $\tilde{\eta}_\Delta = \tilde{\lambda}^S_\Delta = \tilde{\lambda}^B_\Delta = 0$ for $\Delta = -1$. I cluster the standard errors at the firm f level.[10]

A key advantage of the stacked-by-event difference-in-difference method is that the treatment effects $\{\tilde{\eta}_\Delta, \tilde{\lambda}^S_\Delta, \tilde{\lambda}^B_\Delta\}$ are identified solely through the comparison between treatment firms and control firms for each period *within each bankruptcy event*. This specification avoids the potential bias in the conventional two-way fixed-effects (TWFE) difference-in-difference framework, which includes post-treatment observations of treatment units as a part of the control group.[11] The stacked-by-event difference-in-difference design is a recommended approach to address this issue (Roth et al. 2023).

The regression equation (3) identifies $\tilde{\eta}_\Delta$ as the average effect of unanticipated supplier bankruptcy (when $\log S^*_{j,k}$, $\log B^*_{j,m}$, and X_{fjkmg} are excluded from the regression), and $\tilde{\lambda}^S_\Delta$, $\tilde{\lambda}^B_\Delta$ as the heterogeneous effects of supplier bankruptcy with respect to $\log S^*_{j,k}$ and $\log B^*_{j,m}$, respectively. Under the first-order approximation of the matching function

[9] Note that firm f may appear multiple times as control firms in different groups g.

[10] If the treatment assignment (i.e., unanticipated supplier bankruptcy) is independent between treatment and control firms, clustering standard errors at the firm level yields asymptotically consistent standard errors (Abadie, Athey, Imbens, and Wooldridge 2023).

[11] The conventional TWFE regression in this context corresponds to a specification where the regression unit is a firm-and-year combination with firm and year fixed effects, without including for event-year fixed effects. de Chaisemartin and D'Haultfoeuille (2022) and Roth, Sant'Anna, Bilinski, and Poe (2023) provide recent surveys for the biases in TWFE specifications and alternative difference-in-difference specifications to overcome them.

(equation 2), these regression coefficients correspond to $\tilde{\eta}_\Delta \approx \eta\Delta$, $\tilde{\lambda}^S_\Delta \approx \eta\Delta\lambda^S$, and $\tilde{\lambda}^B_\Delta \approx \eta\Delta(\lambda^B - 1)$. Therefore, one can infer the elasticity of matching function with supplier density (i.e., thick market externality) from $\lambda^S \approx \tilde{\lambda}^S_\Delta / \tilde{\eta}_\Delta$ and the elasticity of matching function with supplier density (i.e., congestion externality) from $\lambda^B \approx \tilde{\lambda}^B_\Delta / \tilde{\eta}_\Delta + 1$. I use these relationships to calibrate λ^S and λ^B in the quantitative analysis in Section 5.

The empirical implementation of regression (3) requires a proxy for the supplier density, $S^*_{j,k} (= \sum_i S^*_{ij,k})$, and the buyer density, $B^*_{j,m}$. In my baseline analysis, I use the number of firms in the bankrupt supplier's four-digit industry that have at least one buyer in firm f's headquarter prefecture j in 2008 (beginning of the sample) divided by the geographic area of j as a proxy for $S^*_{j,k}$. This definition of supplier density accounts for the possibility that suppliers are located outside the treatment firms' prefecture, as often observed in the data (Figure 1). This choice of $S^*_{j,k}$ aligns with the definition in my structural model in Section 4, where suppliers make entry decisions to each destination market j subject to variable and fixed costs. At the same time, I demonstrate the robustness of my reduced-form results by using alternative proxies, such as counting only local suppliers or taking the distance-weighted sum of the number of suppliers across different locations.

I proxy $B^*_{j,m}$ with the geographic density of firms that belong to the same industry as firm f and whose headquarters are located in prefecture j. Similar to $S^*_{j,k}$, this definition of $B^*_{j,m}$ aligns with my structural model in Section 4. At the same time, I present the robustness of the results by employing alternative proxies, such as the number of firms that experienced supplier bankruptcy or separation in the same input industry as the treatment firms.

3.1.3 Endogeneity Concerns

There are two types of endogeneity concerns: the endogeneity of supplier bankruptcy (Trt_f) and the endogeneity of supplier and buyer densities ($S^*_{j,k}$ and $B^*_{j,m}$). Below I discuss potential threats to these identification assumptions and my strategy to address them.

Endogeneity of Supplier Bankruptcies. A key identification assumption for studying the effects of supplier bankruptcies is that supplier bankruptcy occurs exogenously to the unobserved trends in outcome variables for buyers (new supplier matching rates). An obvious violation of this identification assumption would occur if supplier bankruptcy is caused by a decline in buyers' input demand. To rule out this possibility, I focus solely on supplier bankruptcies that are classified as "unanticipated reasons" as discussed in Section 2. In particular, I exclude supplier bankruptcies classified as "sales decline" or "debt accumulation," as they are unlikely to meet these criteria. To further validate that "unanticipated bankruptcies" indeed occur independently of buyers' characteristics, I show below that the characteristics of treatment and control firms are broadly similar prior to the supplier bankruptcy events.

Even if supplier bankruptcy is exogenous to the treatment firms, identification may still be compromised if the supplier bankruptcy is associated with potential outcomes of *control firms*. One possible scenario is that supplier bankruptcies are induced by aggregate regional shocks. In particular, the Great Tohoku Earthquake in 2012 might have directly affected both treatment and control firms in the region (Carvalho et al. 2021). To address this concern, I conduct robustness checks by excluding firms headquartered in the Tohoku and Hokkaido regions (the most severely affected regions) and firms that had direct trading relationships with these regions before 2011.[12]

Another possible scenario that could lead to identification failure is if supplier bankruptcy directly affects the outcome variables of control firms. For one thing, control firms may be indirectly connected to bankrupt firms through firm-to-firm trade networks. I address this concern by conducting robustness checks by excluding control firms that are within second-degree proximity in the firm-to-firm trade network (e.g., supplier's buyer or buyer's buyer) to firms experiencing unanticipated bankruptcies. For another, control firms may be direct competitors of the treatment firms. I address this concern by conducting robustness checks by excluding control firms belonging to the same two-digit industry as the treatment firms.

Endogeneity of Supplier and Buyer Densities. Even if unanticipated supplier bankruptcies (Trt_f) are exogenous so that their average treatment effects are credibly identified, the heterogeneous effects with respect to supplier and buyer densities ($S^*_{j,k}$ and $B^*_{j,m}$) may be biased if these proxies are correlated with other dimensions of treatment effect heterogeneity. For instance, it is possible that firms with a higher ability to find an alternative supplier tend to enter regions where the geographic density of alternative suppliers is higher. Similarly, firms that heavily rely on a particular input may preemptively enter those regions. In both scenarios, the heterogeneous effects with respect to supplier and buyer densities are confounded by the unobserved differences in firms' characteristics.

[12] In Appendix Table B.3, I provide further robustness checks by excluding all supplier bankruptcies in 2009 (the year subsequent to the Great Financial Crisis) and excluding firms headquartered in Tokyo prefecture, the most densely populated prefecture in Japan.

To address these concerns, I first demonstrate the robustness of my results by controlling for observed dimensions of treatment heterogeneity through a series of location fixed effects and firm-level controls (X_{fjkmg} in regression equation 3). In particular, my results are robust to controlling for prefecture fixed effects in X_{fjkmg}. This specification ensures that the heterogeneous effects with supplier densities are identified as a comparison of treatment effects between firms within the same prefecture but facing supplier bankruptcies in different input sectors. I also show that controlling for firm sizes and relationships with bankrupt suppliers (e.g., relationship duration, geographic distance) does not affect my results.

However, these fixed effects and firm controls do not completely eliminate the identification concern. In particular, location fixed effects do not rule out the possibility that firms that are more reliant on a particular input (and therefore more responsive to supplier bankruptcies in those inputs) may proactively locate in regions where the *relative* density of suppliers for those inputs is higher. To address this concern, I implement two additional empirical specifications.

First, I demonstrate that my results remain robust when using the supplier and buyer density *evaluated at the birth prefecture of CEOs* as an instrumental variable (IV) for the supplier and buyer density evaluated at the firms' actual prefecture. The idea is that firms' location choices are influenced not only by supplier access but also by CEOs' preferences to be close to their birthplaces. Therefore, the birthplaces of CEOs serve as a plausibly exogenous variation for the firms' exposure to supplier density. To ensure that this IV does not capture systematic differences in the CEOs' ability that depend on their birthplaces (e.g., schooling, probability of entrepreneurship), I further control for the fixed effects of the CEOs' birth prefectures and the CEOs' observed characteristics (education level, age, and gender) interacted with treatment dummies.[13]

Second, I demonstrate the robustness of my results by focusing solely on cases where bankruptcy occurs for treatment firms' non-primary suppliers. While the availability of alternative suppliers in the event of supplier disturbance may influence firms' location choices, this consideration is arguably less significant for non-primary suppliers. Therefore, if the results remain robust when solely focusing on non-primary supplier bankruptcy, the evidence supports the interpretation that the heterogeneous effects are not substantially driven by selection. To implement this idea, I use the reported ranking

[13]Following a similar idea, Bleakley and Lin (2012) use a worker's birth location as an exogenous variation to study thick market externality in the labor market.

of suppliers and exclude the supplier bankruptcy events that occur for the top 1 and 2 suppliers.

3.2 Empirical Results

3.2.1 Samples

After excluding firms whose accounting years are outdated for more than a year, the final sample consists of 433 treatment firms connected to 181 bankrupt suppliers, with 11,889 assigned control firms in total.[14]

Table 1 presents the characteristics of both treatment and control firms prior to the supplier bankruptcy events. For each statistic in the first column, the table reports the mean and the standard error within the treatment group (second column) and the control group (third column). The last column reports the p-value of the null hypothesis that the means of each statistic is identical between the treatment and control groups. No statistically significant differences are observed in the number of suppliers, sales, employment, and their growth prior to the supplier bankruptcy event. In particular, the average number of suppliers is 5.09 for treatment firms and 5.18 for control firms, with no statistically significant difference between the two. These findings support the assertion that unanticipated bankruptcies occur independently of the characteristics of the buyers.

Table 1: Baseline Characteristics of Treatment and Control Firms

Variable	Treatment	Control	P-value (Treatment = Control)
Number of Suppliers (Baseline)	5.09 (3.51)	5.18 (3.62)	0.65
Number of Suppliers (Pre-Period Yearly Growth)	0.24 (1.09)	0.23 (1.12)	0.77
log Sales (Baseline)	5.44 (0.69)	5.48 (0.77)	0.29
log Sales (Pre-Period Yearly Growth)	-0.00 (0.14)	-0.01 (0.13)	0.95
log Employment (Baseline)	1.05 (0.57)	1.08 (0.61)	0.35
log Employment (Pre-Period Yearly Growth)	-1.38 (0.76)	-1.42 (0.80)	0.34
Sample Size	433	11,889	

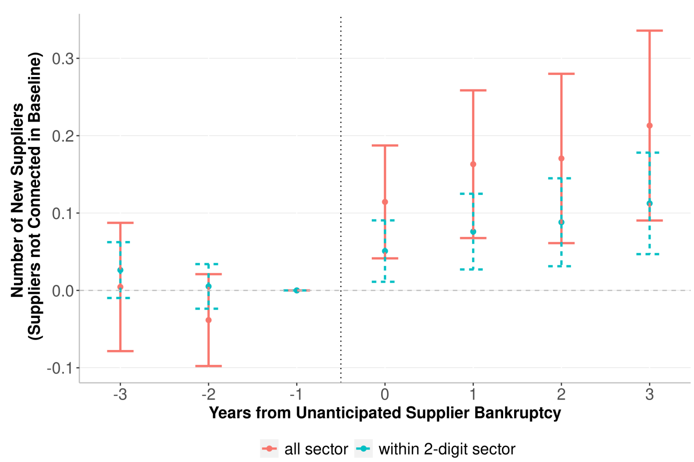
Note: This table shows the characteristics of treatment and control firms prior to the supplier bankruptcy events. "Baseline" indicates one year prior to the supplier bankruptcy events and "Pre-Period Yearly Growth" indicates the growth rates from two to one year prior to supplier bankruptcy events. The parentheses in Columns "Treatment" and "Control" indicate the standard error of each variable. The unit of sales is 1000 Japanese Yen, and the bases of the logs for sales and employment are 10.

[14] This number of bankrupt suppliers (181) is smaller than the total number of suppliers with unanticipated bankruptcies (269; Table A.2) after removing cases where there are no control firms satisfying the criteria outlined in Section 3.1.2.

3.2.2 Average Effect of Unanticipated Supplier Bankruptcies

I start by documenting the average effects of unanticipated supplier bankruptcy on new supplier matching rates. Figure 2 displays the regression coefficients $\tilde{\eta}_\Delta$ from regression specification (3), excluding the terms that capture treatment heterogeneity ($\log S_{j,k}, \log B_{j,m}, X_{fjkmg}$). "All sector" indicates the impacts on the number of new suppliers across all input sectors (i.e., the number of connected suppliers in each period that are not connected prior to supplier bankruptcy events). "Within 2-digit sector" indicates the impacts on the number of new suppliers belonging to the same 2-digit industry as the bankrupt suppliers. I present the results for both total suppliers and suppliers within the two-digit sector of bankrupt suppliers, considering the potential mismeasurement of the set of alternative suppliers using reported two-digit sector classification. In cases where a firm exits during the sample period, the last observed value of the outcome variable is used as a substitute.

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



Note: This figure plots the regression coefficients $\tilde{\eta}_\Delta$ and their 95 percent confidence intervals following specification (3) against the years Δ since the supplier bankruptcy event, where the regression omits the terms corresponding to treatment heterogeneity ($\log S_{j,k}, \log B_{j,m}, X_{fjkmg}$). "All sector" indicates the impacts on the number of new suppliers across all input sectors (i.e., the number of connected suppliers in each period that are not connected prior to supplier bankruptcy events). "Within 2-digit sector" indicates the impacts on the number of new suppliers that belong to the same 2-digit industry as the bankrupt suppliers. In cases where a firm exits during the sample period, the last observed value of the outcome variable is used as a substitute.

The figure shows that firms gradually match with a new supplier after an unanticipated supplier bankruptcy. The impacts on the number of new suppliers are approximately 0.1 in the year of the supplier bankruptcy and approximately 0.2 after 3 years from the supplier bankruptcy event. These impacts are statistically significant and above zero, indicating that firms are indeed in need of an alternative supplier. At the same time, the impacts are significantly below one and gradually increasing, indicating that the process of matching with new suppliers is imperfect and takes time. Furthermore, the impact on the number of new suppliers within the same two-digit industry as the bankrupt suppliers ("within 2-digit sector") is almost half of the impact on suppliers across all sectors ("all sector"), even though there are a total of 98 distinct two-digit sectors. This finding indicates that the newly matched suppliers are predominantly likely to belong to the same industry as bankrupt suppliers, likely substituting bankrupt suppliers.

Table 2 demonstrate the robustness of these findings to alternative specifications. Column (1) reports the results of the same baseline specification. Column (2) confirms the robustness of the results when excluding firms that exit during the sample period (instead of using the last observed value prior to the firm's exit).

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

	Dependent Variable: Number of New Suppliers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trt x 1[t - BankruptYear = -2 or -3]	-0.02	-0.01	-0.06	-0.02	0.04	-0.01	-0.06	0.02	-0.01
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.03)	(0.02)
Trt x 1[t - BankruptYear = -1]									
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Trt x 1[t - BankruptYear = 0 or 1]	0.14^{***}	0.15^{***}	0.09^{**}	0.15^{***}	0.23^{***}	0.12^{**}	0.15^{**}	0.18^{***}	0.13^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.04)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3]	0.19^{***}	0.21^{***}	0.19^{***}	0.20^{***}	0.37^{***}	0.18^{***}	0.21^{**}	0.25^{***}	0.18^{***}
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.09)	(0.06)	(0.05)
Specification	Baseline	Exclude Exit Firms	Exclude Tohoku & Hokkaido	Exclude Same-Industry Control Firms	Exclude Indirect Connection to Bankrupt Firms	Exclude Top 1 Supplier	Exclude Top 2 Suppliers	Exclude Ever-Treated Control Firms	Impute Pre-Period Fixed Effects
Number of Treatment Firms	433	433	342	433	433	348	261	433	433
Number of Bankrupt Suppliers	181	181	142	181	181	163	136	181	181
Number of Control Firms	11,889	11,889	9,277	11,177	7,880	9,012	6,669	10,889	11,889
Observations	85,951	83,548	67,542	80,934	55,441	64,909	47,837	79,052	83,944

Note: Results of the stacked-by-event difference-in-difference regression specification (3), omitting the terms corresponding to treatment heterogeneity ($\log S_{j,k}, \log B_{j,m}, X_{fjkmg}$). The outcome variable of the regression is the number of newly matched suppliers relative to the baseline period (one year before the shock). Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01. See the main text for additional details on each specification.

Columns (3)-(7) address endogeneity concerns of supplier bankruptcy as discussed in Section 3.1.3. Column (3) presents the robustness results by excluding firms headquartered in the Tohoku and Hokkaido regions and firms that had direct trading relationships with these regions before 2011. Column (4) addresses concerns about direct competition by excluding control firms located in the same prefecture and belonging to the same two-digit industry as the treatment firms.[15] Column (5) demonstrates the robustness of the results by excluding control firms that are within second-degree proximity in the firm-to-firm trade network to firms experiencing unanticipated bankruptcies. The somewhat larger treatment effects observed in this specification may be attributed to the omission of larger firms from the sample, which may have the capacity to switch to in-house production.

Columns (6) and (7) show the robustness of the results when excluding supplier bankruptcies that occur to a firm's top 1 and top 2 suppliers, respectively. Columns (8) and (9) present additional specification tests for the difference-in-difference framework. Recall that my baseline specification adopts the stacked-by-event difference-in-difference design, which circumvents the potential bias in the two-way fixed-effects specification as discussed in Section 3.1.2. On top of this treatment, Column (7) shows the robustness by explicitly excluding control firms if they receive supplier bankruptcy shocks (regardless of the reasons) in the post periods, as suggested by Sun and Abraham (2021). In Column (8), I show robustness using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2023), which involves estimating the firm-and-event fixed effects solely using data before supplier bankruptcy events and then plugging these fixed effects into the regression equation.

I now turn to the impacts on firm sales and exit. In Column (1) of Table 3, I report the impacts on firm sales growth defined by arc-elasticity as $\left(\text{Sales}_{f\Delta} - \text{Sales}_{f0}\right) / \left(\frac{1}{2}\left(\text{Sales}_{f\Delta} + \text{Sales}_{f0}\right)\right)$ following Davis and Haltiwanger (1992), where I define $\text{Sales}_{f\Delta} = 0$ if firm f exits the market. This measure ranges between -2 and 2 and approximates log sales growth when the sales growth is infinitesimally small. In Column (1), I find that supplier bankruptcy leads to a decrease in this measure of sales growth by 0.042 (after 2 or 3 years from supplier bankruptcy). This finding supports the interpretation that firms experience disruptions in production until they find a suitable alternative supplier, providing further evidence of the presence of matching frictions. Column (2) shows that there is a positive effect on the exit probability of 0.025 (after 2 or 3 years from supplier bankruptcy). This is a large effect compared to the control mean of 0.044. Column (3) shows that the effects on sales growth are not statistically significant if I exclude firms that exit the markets. Therefore, the reduction in sales observed in Column (1) is primarily driven by the exit of firms.

[15] Columns (5) and (6) of Appendix Table B.1 further alleviates the concerns about direct competition by demonstrating that supplier bankruptcy has no statistically significant effects on the new supplier matching rates and sales growth of other firms within the same prefecture and industry.

Table 3: Average Impacts of Unanticipated Supplier Bankruptcy on Sales and Exit

	Dependent Variable:		
	Sales Growth (Arc-Elasticity)	Exit	Sales Growth (Arc-Elasticity)
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = -2 or -3]	-0.014		-0.005
	(0.013)		(0.011)
Trt x 1[t - BankruptYear = -1]			
	(0.000)	(0.000)	(0.000)
Trt x 1[t - BankruptYear = 0 or 1]	-0.034^{**}	0.010^{*}	-0.005
	(0.015)	(0.006)	(0.010)
Trt x 1[t - BankruptYear = 2 or 3]	-0.042^{*}	0.025^{***}	0.020
	(0.023)	(0.009)	(0.013)
Samples	All	All	Cond. on Survival
Control Mean	-0.145	0.044	-0.059
Number of Treatment Firms	433	433	433
Number of Bankrupt Suppliers	181	181	181
Number of Control Firms	11,889	11,889	11,889
Observations	84,113	85,951	81,989

Note: Results of the stacked-by-event difference-in-difference regression specification (3) by omitting the terms corresponding to treatment heterogeneity ($\log S_{j,k}$, $\log B_{j,m}$, X_{fjkmg}) with alternate outcome variables. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01. For Column (2), the interaction term of the pre-period dummy and the treatment dummy is omitted because the outcome variables in the pre-period are all zero.

In Appendix Table B.1, I examine the impacts of supplier bankruptcy on other firm-level outcomes. I find that there are no statistically significant effects on firms' employment growth or profit-to-sales ratio. I also find a positive effect on the probability of retaining existing suppliers. Although the magnitude is smaller than the response of new supplier matching, this evidence suggests that retaining a supplier is an additional mechanism through which firms cope with supplier bankruptcy shocks.

In Appendix Table B.2, I explore the heterogeneous effects of new supplier matching rates and sales growth with respect to reported supplier ranking, firm size, and supplier size. When supplier bankruptcy occurs for a primary (top 1) supplier, the effects on new supplier matching rates tend to be higher (although statistically insignificant), and the negative effects on sales growth are significantly larger, suggesting that bankruptcies of primary suppliers may have a more significant impact compared to those of secondary suppliers. I also find that the effects on new supplier matching rates are significantly lower for larger treatment firms (in terms of employment size), suggesting that larger firms may have the capacity to substitute bankrupt suppliers by relying on in-house production capabilities. Lastly, I do not find statistically significant heterogeneous effects with respect to the size of the bankrupt suppliers.

3.2.3 Heterogeneous Effects with respect to Supplier and Buyer Density

In this section, I explore the heterogeneous effects of supplier bankruptcies with respect to supplier and buyer density, thereby investigating the evidence for thick market and congestion externality.

Table 4 presents the results of regression specification (3). Each column in the table corresponds to a separate regression, with Panel A and B displaying the regression coefficients for the pre-period and post-period, respectively. In all the specifications, I include prefecture fixed effects in X_{fjkmg} (interacted with treatment dummies). This specification ensures that the heterogeneous effects with respect to supplier densities are identified by comparing the treatment effects among firms located in the same prefecture but facing supplier bankruptcies in different input sectors. Since these fixed effects saturate the coefficients of treatment status dummies ($Trt_f \times 1[t - \text{BankruptYear}_g = \Delta]$), I omit the average effects and solely report the heterogeneous effects.

Column (1) reveals statistically significant and positive heterogeneous effects in relation to supplier density. In particular, a one log point increase in supplier density is associated with an increase in the treatment effects by 0.13 in 0-1 years (first row in Panel B) and 0.17 in 2-3 years (second row in Panel B). These effects are sizable relative to the average treatment effects (0.14 and 0.19 in Table 2). These findings support the existence of thick market externality in firm-to-firm trade. On the other hand, there are no statistically significant heterogeneous effects observed for buyer density; the estimated coefficients are small in magnitude and close to zero (third and fourth rows in Panel B). It should be noted that the lack of statistical significance is not due to imprecise estimates, as the standard errors of these coefficients are similar in magnitude to those for supplier density. Overall, these results suggest limited evidence for congestion externality.

While these patterns of heterogeneous effects suggest the presence of thick market externality and the absence of congestion externality, there is a concern that they may capture other dimensions of treatment heterogeneity through the selective firm entry. To address this concern, I provide additional robustness tests as discussed in Section 3.1.3. In Column (2), I demonstrate the robustness of the results by including additional controls for heterogeneous effects related to the employment size of the firm and the bankrupt supplier, as well as the strength of the relationship with the bankrupt suppliers (reported supplier rankings, geographic distance, and relationship duration). In Column (3), I demonstrate the robustness of the results by using the supplier and buyer density evaluated at the birth prefecture of a CEO as an IV for the supplier and buyer density evaluated at the

Table 4: Heterogeneous Impacts of Unanticipated Supplier Bankruptcies

	Dependent Variable: Number of New Suppliers							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Pre-period								
Trt x 1[t - BankruptYear = -3 or -2] x log Supplier Density	0.04	0.03	−0.03	0.01	0.01	0.004	0.03	0.03
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)
Trt x 1[t - BankruptYear = -3 or -2] x log Buyer Density	0.02	0.05	0.09*	0.06	0.08	0.02	0.05	0.03
	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)	(0.04)	(0.04)	(0.04)
Panel B: Post-period								
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density	0.13***	0.14***	0.16***	0.11**	0.08*	0.10***	0.11***	0.11***
	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density	0.17***	0.16***	0.17**	0.17***	0.23***	0.10*	0.13**	0.09
	(0.06)	(0.06)	(0.08)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Density	−0.01	−0.03	−0.01	−0.03	−0.07	−0.06	−0.003	−0.03
	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)	(0.04)	(0.04)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Density	−0.07	−0.08	0.02	−0.09	−0.05	−0.06	−0.06	−0.09
	(0.06)	(0.06)	(0.08)	(0.08)	(0.10)	(0.07)	(0.06)	(0.06)
Specification			IV: Firm Density in CEO's Birth Prefecture	Exclude Top 1 Supplier	Exclude Top 2 Suppliers	Exclude Tohoku & Hokkaido	Exclude Same-Industry Control Firms	Exclude Indirect Connection to Bankrupt Firms
Trt FE x Year FE x Prefecture FE	X	X	X	X	X	X	X	X
Trt FE x Year FE x Buyer and Supplier Size		X	X	X	X	X	X	X
Trt FE x Year FE x Firm-Relationship Controls		X	X	X	X	X	X	X
Trt FE x Year FE x CEO Birth Prefecture FE and CEO Characteristics			X					
Number of Treatment Firms	433	433	405	348	261	342	433	433
Number of Bankrupt Suppliers	181	181	174	163	136	142	181	181
Number of Control Firms	11,889	11,889	10,933	9,012	6,669	9,277	11,177	7,880
Observations	85,939	85,395	60,767	64,522	47,516	67,079	80,440	56,783

Note: Results of the stacked-by-event difference-in-difference regression specification (3). Each column corresponds to a separate regression, and Panel A and B report the regression coefficients for the pre-period and post-period, respectively. Supplier density is defined as the number of firms in the bankrupt suppliers' four-digit industry and that have at least one buyer in firm f's headquarter prefecture j in 2008 (beginning of the sample) divided by j's geographic area. Buyer density is defined by the geographic density of firms that belong to the same two-digit industry to firm f and whose headquarters are located in prefecture j. The standard deviation of log supplier and buyer densities among treatment firms is 1.73 and 1.78, respectively. Column (2) controls for the employment size of the firm and the bankrupt supplier, the reported supplier rankings, geographic distance to the bankrupt suppliers, and the relationship duration to the bankrupt supplier in X_{fjkmg}. Column (3) controls for the prefecture FE for the CEO's birthplaces and the CEO's age, gender, and education levels. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01. See the main text for additional details on each specification.

firm's actual prefecture. In Columns (4) and (5), I show robustness to my results by excluding supplier bankruptcies that occur to a firm's top 1 and top 2 suppliers, respectively.

Columns (6), (7), and (8) repeat the same robustness tests in Columns (3), (4), and (5) of Table 2 to excluding firms in and connected with Tohoku and Hokkaido regions, excluding firms within second-degree proximity to firms experiencing unanticipated bankruptcies, and excluding control firms in the same prefecture and industry of the treatment firms.

Appendix Table B.3 shows that these empirical results are further robust to various alternative specifications, including by omitting exited firms from samples, excluding bankruptcies in 2009 (the year of the Great Financial Crisis) and firms in Tokyo prefecture (the densest prefecture in Japan), excluding firms that have establishments outside their headquarter locations, and excluding firms with potentially outdated accounting information. The results are further robust to alternative definitions of supplier density, such as counting only local suppliers or taking the distance-weighted sum of the number of suppliers (Appendix Table B.4). The results are also robust to an alternative definition of buyer density, such as using firms that faced supplier bankruptcy or separation during the same periods (Appendix Table B.5). I also find a similar (but noisier) pattern of results by including supplier-reported supplier-to-buyer-linkages when constructing the outcome variables (Appendix Table B.6).

An additional concern for the above analysis is the external validity, given its focus on a limited number of supplier bankruptcies that occur due to unanticipated reasons. To address this concern, I provide additional analyses in Appendix Tables B.7, B.8 and B.9, where I examined the impacts of supplier bankruptcies resulting from "management failures" among the list of bankruptcy reasons in Appendix Table A.2. Compared to supplier bankruptcy that occurs for "unanticipated reasons", this type of supplier bankruptcy has a potential endogeneity concern. For example, firms that source from suppliers with problematic management practices may preemptively switch suppliers in advance. Despite this concern, I find a similar pattern of the average and heterogeneous effects on the number of new suppliers, except that there are significant pretrends in the outcome variables. These results suggest that the analysis presented above has wider applicability beyond a narrow focus on unanticipated supplier bankruptcies.

4 Theoretical Framework

In this section, I develop a general equilibrium model of matching frictions in firm-to-firm trade across space. In Section 4.1, I show how firm-to-firm matching shapes aggregate productivity across regions. In Section 4.2, I embed this model into a general equilibrium with endogenous wages and population mobility. In Section 4.3, I examine how the thick market externality gives rise to agglomeration externalities in regional production and welfare.

4.1 Production and Firm-to-Firm Matching

Space is partitioned into discrete locations, denoted by $i, j \in \mathcal{N}$. A unit mass of the population decides their residential locations. I denote L_i as the population size in location i. Time is continuous and denoted by t. I focus on a steady-state equilibrium in which aggregate variables are constant (e.g., wages, output). Only firm-level variables, such as supplier matching status, vary by t. Without risk of confusion, the subscript t is therefore omitted from the aggregate variables.

4.1.1 Technology and Preferences

There is a continuum of firms in each location. Each firm belongs to a sector $k, m \in K$ and has different productivity φ. All firms produce a product that can be used for final consumption or intermediate input for other firms. The unit cost of production for a firm ω in location i and sector m is given by

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

where φ_ω is the productivity of firm ω; $A_{i,m}$ is the productivity of location i and sector m; w_i is the wage in firm ω's production location i; $p_{\omega t,k}$ is the unit cost of intermediate inputs that firm ω has access to in period t in input sector k; $\gamma_{L,m}$ is the labor share in production for sector m; and γ_{km} is the share of sector-k intermediate inputs for sector m's production. I assume that the production function exhibits constant returns to scale such that $\gamma_{L,m} + \sum_k \gamma_{km} = 1$ for all $m \in K$. The dynamic matching with suppliers determines the stochastic process of $p_{\omega t,k}$, as further described below.

There are measure $N_{i,k}$ of entrepreneurs who jointly own firms in location i and sector k. Each entrepreneur owns $\varphi^{-\theta}$ measure of firms with productivity above φ (for any value of φ). Therefore, in location i and sector k, there exists a measure $\mu_{i,k}(\varphi) = N_{i,k}\varphi^{-\theta}$ of firms with productivity above φ. Following Eaton et al. (2022), this assumption implies that the distribution of firms' unit costs also follows a power-law distribution. In particular, I conjecture that the measure of firms in location i and sector k with unit cost below c is given by $\Gamma_{i,k}c^\theta$, where $\Gamma_{i,k}$ represents the endogenously determined inverse cost shifter in the equilibrium. I verify this conjecture by explicitly deriving $\Gamma_{i,k}$ in Section 4.1.4.

Final goods are consumed by workers. Workers' utility in location j from goods consumption is defined by:

$$U_j = \prod_{k \in K} \left(\int_{\omega \in \Psi_{j,k}} q_k(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}\alpha_k}, \tag{5}$$

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

4.1.2 Cross-Location Trade

Both final goods and intermediate goods can be tradable across locations. When firms want to sell their final or intermediate goods in location j, they must incur a fixed cost $f_{j,k}$ in each period, regardless of the firms' production location. Once this fixed cost is paid, firms can deliver their products to location j subject to an iceberg trade cost $\tau_{ij,k}(> 1)$, which represents the amount of goods required to deliver one unit of goods from location i to j.

After entering location j, firms determine prices for both their final and intermediate goods. For final goods, the combination of CES utility and monopolistic competition implies that firms charge a constant markup of $\sigma/(\sigma - 1)$ over their marginal cost, net of the iceberg trade costs. Regarding intermediate goods, I assume that all bargaining power is held by the buying-side firms, resulting in prices equal to their marginal costs.[16]

By following the framework of Melitz (2003) and Chaney (2008), it can be shown that there exists a cutoff value for the marginal cost (inclusive of iceberg trade costs) that determines firms' entry into each location. Employing standard algebra (see Appendix C.1), the threshold marginal cost for entering location j and sector k, denoted as $\bar{c}_{j,k}$, and the measure of suppliers selling in location j, denoted as $S_{j,k}$, are given by:

$$\bar{c}_{j,k} = \left[\frac{\theta - \sigma + 1}{\theta\sigma} \frac{Y^F_{j,k}}{w_j f_{j,k} \Omega_{j,k}} \right]^{1/\theta}, \quad S_{j,k} = \Omega_{j,k} \bar{c}^{\theta}_{j,k}, \tag{6}$$

where $Y^F_{j,k}$ represents the demand for final goods in location j and sector k, and $\Omega_{j,k} \equiv \sum_i \Gamma_{i,k} \tau^{-\theta}_{ij,k}$ captures the shifter for the marginal cost distribution of suppliers entering location j (inclusive of iceberg trade costs).

4.1.3 Matching between Suppliers and Buyers

Conditional on entering location j as a seller, firms match with input buyers producing in the location. To model this matching process, I adopt the framework outlined in Section 3.1.1. More specifically, the Poisson rate at which connections are formed between suppliers in sector k and buyers in sector m per unit of geographic area in location j is

[16] In Appendix E.1, I examine an alternative setup in which firms apply the same markup ratio for intermediate input buyers as they do for final consumers.

represented by $M\left(S^*_{j,k}, B^*_{j,m}\right) = \eta \left(S^*_{j,k}\right)^{\lambda^S} \left(B^*_{j,m}\right)^{\lambda^B}$. Here, $S^*_{j,k} = S_{j,k}/Z_j$ is the density of suppliers, where Z_j is the geographic area of location j. I proxy the buyer density by the geographic density of entrepreneurs, given by $B_{j,m} = B_{j,m}/Z_j = N_{j,m}/Z_j$.[17]

Once a match occurs, two firms establish a long-term relationship if and only if the buyer does not already have a supplier in sector k.[18] Once formed, the relationship persists until it is exogenously terminated at the Poisson rate $\rho_{j,km}$. During the duration of the relationship, the buyer is unable to form new matches with other suppliers.

In cases where a firm lacks an existing supplier relationship in input sector k, it can source inputs through intermediaries. Intermediaries, in turn, randomly acquire intermediate goods from a pool of suppliers who have entered the market to sell in location j. However, this indirect sourcing comes with costs, as intermediaries face an additional iceberg cost denoted by $\chi > 1$. This cost reflects the drawbacks associated with indirect procurement, such as transaction costs with intermediaries or a lack of customization.

The steady-state probability that a firm in location j and sector m has a direct relationship with a supplier in sector k is given by:

$$\Lambda_{j,km} = \frac{v_{j,km}}{v_{j,km} + \rho_{j,km}}, \tag{7}$$

where $v_{j,km} = \eta \left(S^*_{j,k}\right)^{\lambda^S} \left(B^*_{j,m}\right)^{\lambda^B - 1}$ is the Poisson rate at which a buyer in location j and sector m matches with a supplier in sector k.

4.1.4 Aggregate Production and Gravity Equations

Recall my earlier conjecture that the measure of firms producing in location i and sector m with unit costs below c is given by $\Gamma_{i,m} c^{\theta}$. Given the process of matching with suppliers, I can now explicitly derive the inverse cost shifter, denoted as $\Gamma_{i,m}$, as follows:

$$\Gamma_{i,m} = \varrho_m N_{i,m} A^{\theta}_{i,m} w_i^{-\theta\gamma_{L,m}} \prod_{k \in K} \bar{c}_{i,k}^{-\theta\gamma_{km}} \left(1 + \Lambda_{i,km}\left(\chi^{\theta\gamma_{km}} - 1\right)\right), \tag{8}$$

[17] Alternatively, one can define the relevant set of buyers as those with a productivity level above $\underline{\varphi}$. My baseline specification is isomorphic to this specification by multiplying η by $\underline{\varphi}^{-\theta\lambda^B}$.

[18] In Appendix E.2, I explore an extension where buyer-side firms make forward-looking decisions regarding accepting matches.

where ϱ_m is a constant that solely depends on exogenous parameters (refer to Appendix C.2 for the derivation).

This equation summarizes the main channels in which firm-to-firm matching affects aggregate regional productivity. Similarly to standard trade models with sectoral input-output linkages (e.g., Caliendo and Parro 2014), $\Gamma_{i,m}$ depends on the measure of entrepreneurs ($N_{i,m}$), location and sector productivity ($A_{i,m}$), wages (w_i), and the cost threshold of suppliers to enter market i ($\bar{c}_{i,k}$). In addition to these conventional factors, if the location and sector has a high steady-state probability of matching with a supplier (a higher $\Lambda_{i,km}$), firms can produce at a lower cost on average (a higher $\Gamma_{i,m}$). This effect is more pronounced if the indirect sourcing is more costly (a higher χ).

Following Melitz (2003) and Chaney (2008), it is also straightforward to show that aggregate bilateral trade flows follow gravity equations. In particular, the share of expenditure in location j for sector m goods that are produced in location i, both for intermediate goods and final goods, can be expressed as follows:

$$\pi_{ij,m} = \frac{\Gamma_{i,m}\left(\tau_{ij,m}\right)^{-\theta}}{\sum_{i'\in\mathcal{N}}\Gamma_{i',m}\left(\tau_{i'j,m}\right)^{-\theta}}. \tag{9}$$

Furthermore, following the usual property in this class of model with power law distribution of production cost, conditional on a firm in location j sourcing from a supplier in location i, the expected transaction volume does not depend on the origin i. Therefore, this expenditure share coincides with the probability that firms in location j source from a supplier in location i for sector m input.

4.2 General Equilibrium

I now embed the production and firm-to-firm trade in a general equilibrium framework, which incorporates the entry of entrepreneurs into production in each location and the mobility of workers across locations.

Free Entry of Entrepreneurs. In each location and sector, there are a continuum of potential entrepreneurs. For entrepreneurs to initiate firm operations, they are required to make a fixed cost payment denoted as $F_{j,m}$ in the unit of local labor (separately from the fixed cost associated with making sales as described in Section 4.1.2). Under free entry of entrepreneurs, the fixed cost payment prcisely offset the post-entry profit. Therefore,

$$N_{j,m} = \frac{\sigma - 1}{\sigma\theta} \frac{X^F_{j,m}}{w_j F_{j,m}}, \tag{10}$$

where $X^F_{j,m} \equiv \sum_n \pi_{jn,m} Y^F_{n,m}$ is the aggregate final sales generated by firms in location j and sector m. The term $\frac{\sigma-1}{\sigma\theta}$ corresponds to the share of post-entry profit (excluding sales fixed cost) as a fraction of aggregate final sales (see Appendix C.1 for details).

Productivity Spillovers. The productivity of location i and sector m, $A_{i,m}$, is given by:

$$A_{i,m} = \tilde{A}_{i,m} \left(\frac{L_i}{Z_i} \right)^{\varepsilon} \tag{11}$$

where $\tilde{A}_{i,m}$ is the exogenous productivity of the location and sector, and ε is the elasticity of total factor productivity (TFP) with respect to local population density. This term summarizes all other types of agglomeration spillovers that operate through TFP (e.g., knowledge spillovers, labor market pooling).

Market Clearing. The final goods market, intermediate goods market, and labor market clear in equilibrium. Final goods market clearing in location i and sector k is given by:

$$Y^F_{i,k} = \alpha_k w_i L_i \psi_i, \tag{12}$$

where ψ_i is the (exogenous) efficiency unit of labor input per population, and α_k is the expenditure share for final goods in sector k.

Intermediate goods market clearing condition in location i for sales from sector k to sector m is given by:

$$Y^I_{i,km} = \gamma_{km} \tilde{X}_{i,m}, \quad \tilde{X}_{i,m} = \sum_{j \in \mathcal{N}} \left(\sum_{m' \in K} Y^I_{j,mm'} + \frac{\sigma - 1}{\sigma} Y^F_{j,m'} \right) \pi_{ij,m'}, \tag{13}$$

where $\tilde{X}_{i,m}$ denotes the total expenditure on inputs (including both labor and intermediate inputs) required by firms in location i and sector m to meet demand from all downstream sectors m'.[19]

[19] In the expression for $\tilde{X}_{i,m}$, recall that $1/\sigma$ fraction of final goods sales goes to firm profit, and remaining revenue (including those from intermediate goods sales) are compensated for input expenditure.

Finally, labor market clearing condition in location i is given by:

$$w_i L_i \psi_i = \sum_k \left(\gamma_{L,k} \tilde{X}_{i,k} + \frac{\sigma - 1}{\sigma\theta} \sum_{j \in \mathcal{N}} Y^F_{j,k} \pi_{ij,k} + \frac{\theta - \sigma + 1}{\sigma\theta} Y^F_{i,k} \right). \tag{14}$$

In this expression, the right-hand side shows the labor demand. The first term stems from variable labor cost, the second term stems from the fixed labor cost for the entrepreneurs' entry, and the third term stems from sales fixed cost payment (see Appendix C.1 for the derivation of each term).

Steady-State Equilibrium with Exogenous Population. I first define the equilibrium without population mobility. Given population size $\{L_i\}$, the steady-state equilibrium is given by the steady-state matching probability $\{\Lambda_{i,km}\}$, inverse cost shifter $\{\Gamma_{i,k}\}$, entry cut-off $\{\bar{c}_{i,k}\}$ sourcing share $\{\pi_{ij,k}\}$, wage $\{w_i\}$, measure of entrepreneurs $\{N_i\}$, and location and sector productivity $\{A_{i,k}\}$ that satisfy equations (6), (7), (8), (9), (10), (11), and market clearing conditions as stated above.

Steady-State Equilibrium with Population Mobility. I next define the equilibrium with population mobility. Workers are freely mobile across locations. The utility of workers who reside in location j is given by $\mathcal{U}_j = K_j U_j L_j^{-1/v}$, where K_j is the exogenous residential amenity, L_j is the population size j, U_j is the utility from goods consumption as defined by equation (5). The parameter v governs the dispersion force, which includes housing costs, negative residential spillovers, and idiosyncratic preference heterogeneity (Allen and Arkolakis 2014). Note that, with a CES utility function given by equation (5), the welfare of residents in location j is given by the real wage such that $U_j = w_j / P_j$, where $P_j = \prod_k P_{j,k}^{\alpha_k}$ is the ideal price index for final goods given by:

$$P_{j,k}^{1-\sigma} = \int_0^{\bar{c}_{j,k}} c^{1-\sigma} \Omega_{j,k} \theta c^{\theta-1} dc = \frac{\theta}{\theta - \sigma + 1} \Omega_{j,k} \left(\bar{c}_{j,k}\right)^{\theta-\sigma+1}. \tag{15}$$

Free mobility implies that utility is equalized across locations, i.e., $\mathcal{U}_j = \mathcal{U}$ for all locations j. Therefore, the population size of location j is given by:

$$L_j = \frac{K_j^v (w_j / P_j)^v}{\sum_\ell K_\ell^v (w_\ell / P_\ell)^v}, \tag{16}$$

and the aggregate welfare is given by $\mathcal{U} = \left(\sum_{\ell} K_{\ell}^{v}(w_{\ell}/P_{\ell})^{v}\right)^{1/v}$.

The steady-state equilibrium is defined by the steady-state matching probability $\{\Lambda_{i,km}\}$, inverse cost shifter $\{\Gamma_{i,k}\}$, entry cut-off $\{\bar{c}_{i,k}\}$, sourcing share $\{\pi_{ij,k}\}$, wage $\{w_i\}$, measure of entrepreneurs $\{N_i\}$, location and sector productivity $\{A_{i,k}\}$, and population size $\{L_i\}$ that satisfy equations (6), (7), (8), (9), (10), (11), (16) and market clearing conditions as stated above.

Appendix D.2 shows that an equilibrium always exists. The same appendix further shows that, in the single sector special case, equilibrium without population mobility is unique (up to scale) regardless of the values of λ^S and λ^B, and provides sufficient conditions for equilibrium uniqueness with population mobility.

4.3 Discussion: Agglomeration Forces

I now analyze the agglomeration effects from thick market externality. To do so, I consider the impacts of an increase in the population size L_j in the steady-state equilibrium (with exogenous population). I adopt the conventional notation to denote the marginal percentage change of equilibrium variable x by $d\log x \approx x'/x - 1$. Take location j's wage as a numeraire such that $w_j = 1$. Using equations (6), (12), and (15), the change in the real wage in location j, $d\log U_j = d\log\left(w_j/P_j\right) = -d\log P_j$ is expressed as:

$$d\log U_j = \sum_m \alpha_m \left[\frac{\theta - \sigma + 1}{\theta(\sigma - 1)} d\log L_j + \frac{1}{\theta}\sum_i \pi_{ij,m} d\log \Gamma_{i,m}\right]. \tag{17}$$

The first term of this expression captures the love-of-variety effects for final consumption from market size, i.e., a larger market attracts a greater number of sellers, leading to a greater variety of available goods. The second term represents the cumulative effect of changes in the inverse cost shifter weighted by the expenditure share $\pi_{ij,m}$. To further decompose the second term, I specifically focus on the change in the inverse cost shifter within location j, which usually occupies the largest expenditure share in location j:

$$d\log\Gamma_{j,m} = \underbrace{d\log N_{j,m}}_{\text{firm entry effect}} + \underbrace{\theta\varepsilon d\log L_j}_{\text{productivity spillover effect}} + \sum_{k\in K}\left[\underbrace{d\log\left(1+\Lambda_{j,km}\left(\chi^{\theta\gamma_{km}}-1\right)\right)}_{\text{thick market and congestion effect}} - \underbrace{\theta\gamma_{km} d\log\bar{c}_{j,k}}_{\text{input cost effect}}\right]. \tag{18}$$

The first term of this expression, referred to as "firm entry effect," captures the cost reduction benefit that arises from a larger number of entrepreneurs entering the market. This term represents a standard market size effect observed in models with firm entry and productivity heterogeneity (Melitz 2003, Chaney 2008). The second term, referred to as "productivity spillover effect," represents the agglomeration productivity spillovers as introduced by equation (11).

The third term is the new agglomeration channel in this model through thick market externality in firm-to-firm matching. This term can be further rewritten as (see Appendix C.3 for derivation):

$$d\log\left(1+\Lambda_{j,km}\left(\chi^{\theta\gamma_{km}}-1\right)\right) = \frac{\Lambda_{j,km}\left(\chi^{\theta\gamma_{km}}-1\right)\left(1-\Lambda_{j,km}\right)}{1+\Lambda_{j,km}\left(\chi^{\theta\gamma_{km}}-1\right)} \times \left(\lambda^S d\log S_{j,k} + (\lambda^B-1)d\log B_{j,m}\right), \tag{19}$$

$$d\log S_{j,k} = d\log L_j, \quad d\log B_{j,m} = d\log N_{j,m}. \tag{20}$$

Equation (19) summarizes how thick market externality and congestion externality shape the agglomeration externality. The presence of thick market externality ($\lambda^S > 0$) implies that an increase in the measure of suppliers ($d\log S_{j,k} > 0$) raises the steady-state supplier matching probability. This, in turn, leads to a decrease in aggregate production costs depending on the cost of indirect sourcing (χ). At the same time, in the presence of congestion externality ($\lambda^B - 1 < 0$), an increase in the measure of buyers ($d\log B_{j,m} > 0$) reduces the probability of matching with suppliers and consequently increases production costs. The agglomeration effect is determined by the balance between these two externalities.[20]

The fourth term of equation (19), refered to as "input cost effect," captures the changes in intermediate goods costs. Similar to standard models of sectoral input-output linkages (e.g., Caliendo and Parro 2014), $d\log \bar{c}_{j,k}$ is influenced by $\Gamma_{n,k}$ in all other locations n, creating a positive feedback loop of input costs that spans across locations and sectors. At the same time, $d\log \bar{c}_{j,k}$ can also respond positively to a population shock $d\log L_j$. This occurs because a larger market has the capacity to accommodate suppliers with higher costs, as indicated by equation (6). This force is analogous to the pooling externality analyzed in the labor search and matching context (e.g., Acemoglu 2001, Bilal 2023), and it operates as negative externality.[21]

The presence of agglomeration externality also influences the effects of exogenous productivity shocks on the economy. Consider an increase in the exogenous component of total factor productivity (TFP) in location i and sector k, $d\log \tilde{A}_{i,k} > 0$. Regardless of the presence of thick market or congestion externalities, this shock increases real wages in location i as a direct shock to the location and sector, and through the cost propagation as captured by the "input cost effect" in equation (18). Furthermore, if workers are mobile, the increased real wage attracts more workers to location i. If there are agglomeration externalities, this population movement amplifies the impact of the productivity shock on local welfare.

5 Quantitative Analysis

In this section, I combine the reduced-form results in Section 3 and the model in Section 4 to quantitatively assess the magnitude of the agglomeration benefit arising from thick market externality in firm-to-firm trade. Section 5.1 calibrates the model and the key structural parameters. Section 5.2 quantifies the importance of agglomeration externality through a set of counterfactual simulations.

[20]In a special case of a single sector, population size L_j and entrepreneurs entry $N_{j,m}$ are proportional to each other (Appendix D.1). In this case, equation (19) is zero under any specification of constant returns to scale (CRS) matching technology ($\lambda^S + \lambda^B = 1$).

[21]In Appendix D.3, I discuss how the externalities discussed above lead to inefficiency in equilibrium entry by analyzing a planning problem in a special case of a single location and sector.

5.1 Calibration

To take the model to data, I first characterize the minimal set of sufficient statistics needed for conducting counterfactual simulations. Following the exact-hat algebra approach proposed by Dekle et al. (2008), I reformulate the counterfactual equilibrium conditions in terms of the changes in the endogenous variables between the initial and counterfactual equilibria as fully described in Appendix F. Denoting the relative change in equilibrium x by $\hat{x} = x'/x$ (with a hat), I show that, given the values of the production and preference parameters $\{\alpha_k, \gamma_{L,m}, \gamma_{km}, \theta, \sigma, \varepsilon\}$, parameters for the matching process $\{\lambda^S, \lambda^B, \chi\}$, and a subset of baseline equilibrium variables $\{L_i, \pi_{ij,k}, Y^F_{i,k}, \Lambda_{i,km}\}$, counterfactual equilibrium can be computed in terms of the changes in the endogenous variables $\{\hat{\Lambda}_{i,km}, \hat{\Gamma}_{i,k}, \hat{\tilde{c}}_{i,k}, \hat{w}_j, \hat{N}_{j,m}, \hat{L}_j, \hat{A}_{j,m}\}$.

I map the locations in the model to the 47 prefectures in Japan. Sectors in the model correspond to 98 two-digit sectors. Table 5 summarizes the calibrated parameters and observed equilibrium variables necessary for the counterfactuals. I describe the details of these calibrated parameters in turn.

Table 5: Baseline Calibration

Parameters	Description	Values
(1) Parameters for Production and Preference		
γ_{km}	intermediate goods share for production	input-output table (2011)
$\gamma_{L,m}$	labor share for production	input-output table (2011)
α_m	final goods consumption share	input-output table (2011)
σ	elasticity of substitution of final goods	3
θ	dispersion of productivity distribution	5
υ	elasticity of migration with respect to real wage	3
ε	elasticity of productivity spillover with population density	0.05
(2) Parameters for Firm-to-Firm Matching		
λ^S	elasticity of matching function with supplier density	0.9
λ^B	elasticity of matching function with buyer density	1.0
χ	iceberg cost for sourcing from intermediaries	1.37
(3) Baseline Variables		
L_i	population size	Population census (2010)
$\pi_{ij,k}$	sourcing share	TSR firm-to-firm trade data (2008)
$\Lambda_{i,km}$	steady-state probability of matching with suppliers	TSR firm-to-firm trade data (2008)
$Y^F_{i,k}$	aggregate final goods consumption	market clearing condition

5.1.1 Production and Preference Parameters

I start by calibrating a subset of production and preference parameters $\{\alpha_k, \gamma_{L,m}, \gamma_{L,m}, \theta, \sigma, \upsilon, \varepsilon\}$. Given that these parameters commonly appear in many trade and spatial equilibrium models (e.g., Caliendo and Parro 2014, Redding and Rossi-Hansberg 2017), I calibrate these parameters following the standard procedure or using central values from the existing empirical literature.

Following Caliendo and Parro (2014), I calibrate the intermediate input share $\{\gamma_{L,m}\}$, labor share of production $\{\gamma_{km}\}$, and the final goods consumption share $\{\alpha_m\}$ from the input-output table of overall Japan in 2011. I set the elasticity of substitution σ to 3 and productivity dispersion parameter θ to 5, as estimated by Eaton, Kortum, and Kramarz (2011) based on firm-level export data in France. The elasticity of migration with respect to real wage υ is set to 3 from Allen and Arkolakis (2014). Lastly, I set the productivity spillovers from population density at $\varepsilon = 0.05$, which is the mean value of the meta-analysis conducted by Melo et al. (2009). In the subsequent quantitative analysis, I explore different values of ε to provide a benchmark for the strength of agglomeration externality arising from thick market externality.

5.1.2 Matching Parameters

The key parameters that capture the thick market externality are the matching function elasticities, $\{\lambda^S, \lambda^B\}$, and the iceberg cost for indirect sourcing, χ. As discussed in Section 4, these parameters play a pivotal role in determining the agglomeration externality resulting from thick market and congestion externalities in firm-to-firm trade. To calibrate these parameters, I utilize the impacts of unanticipated supplier bankruptcies as documented in Section 3 of this paper.

I begin by calibrating the elasticities of the matching function, λ^S and λ^B, based on the effects of unanticipated supplier bankruptcies on new supplier matching rates. By employing a first-order approximation of the model's implied matching rates as discussed in Section 3.1.2, the average effects on new supplier matching rates after Δ years from an unanticipated supplier bankruptcy can be approximated as $\tilde{\eta}_\Delta \approx \eta\Delta$. Similarly, the heterogeneous effects with respect to the log of supplier and buyer density can be approximated as $\tilde{\lambda}^S_\Delta \approx \eta\Delta\lambda^S$ and $\tilde{\lambda}^B_\Delta \approx \eta\Delta(\lambda^B - 1)$. Using these relationships, I can calibrate the magnitude of thick market externality as $\lambda^S \approx \tilde{\lambda}^S_\Delta / \tilde{\eta}_\Delta$ and that of congestion externality as $\lambda^B \approx \tilde{\lambda}^B_\Delta / \tilde{\eta}_\Delta + 1$. Using the estimates from Section 3 for the average effect on new supplier matching within 0 to 1 years as $\tilde{\eta}_\Delta = 0.14$ (Column (1) of Table 2) and the heterogeneous effects with respect to supplier density as $\tilde{\lambda}^S_\Delta = 0.13$ (Column (1) of Table 4), I calibrate the elasticity of the matching function with respect to supplier density as $\lambda^S = 0.9 \approx 0.13/0.14$. On the other hand, the heterogeneous effect with respect to buyer density is $\tilde{\lambda}^B_\Delta = -0.01$, which is statistically insignificant (Column (1) of Table 4). Therefore, I calibrate $\lambda^B = 1$, indicating no congestion externality.

I calibrate the iceberg cost for indirect sourcing, χ, using the average impact of unanticipated supplier bankruptcy on firm sales. From equation (4), the marginal production cost of a firm in sector m increases by a factor of $\chi^{\gamma_{km}}$ if it loses a supplier in sector k. Given the power law distribution of firm productivity with dispersion parameter θ, it then translates to a decrease in expected sales by a factor of $\chi^{\theta\gamma_{km}}$.[22] Therefore, the log changes in the expected sales after supplier bankruptcy are given by $\Delta \log \mathbb{E}[\text{Sales}_{fjkm\Delta}] = -(1 - \text{NewSuppliers}_{fjkm\Delta}) \times \log \chi^{\theta\gamma_{km}}$, where $(1 - \text{NewSuppliers}_{fjkm\Delta})$ represents the probability that the treatment firm has not yet recovered a supplier and remains unmatched with a supplier in sector k. Using the reduced-form estimates of the average impacts on the arc-elasticity of sales growth after 0-1 years since supplier bankruptcy at -0.034 (Table 3), the impacts on the number of new suppliers at $\text{NewSuppliers}_{fjkm\Delta} = 0.14$ (Table 2), the average value of γ_{km} at 0.025 among my treatment firms, and a baseline calibration of $\theta = 5$, I calibrate $\chi = 1.37$. This implies that the cost of sourcing inputs through intermediaries is, on average, 37 percent higher than sourcing from a directly matched supplier.

In Table 6, I show that the calibrated values of λ^S, λ^B, and χ indeed closely replicate the reduced-form results in Section 3. In Columns (1), (3), and (5), I reproduce the reduced-form estimates of the average and heterogeneous effects of unanticipated supplier bankruptcies from Section 3. In Columns (2), (4), and (6), I present the model-predicted coefficients based on responses to exogenous separation from a supplier. To obtain these coefficients, I additionally need to calibrate η, which is not required for counterfactual simulation. I do so by minimizing the sum of squared differences between the two coefficients in Columns (1) and (2).

I find that the calibrated parameters closely replicate the reduced-form estimates in the remaining columns. Columns (3) and (4) show that, given my choice of λ^S and

[22] Because of the power law distribution of marginal cost, the drop of sales is driven entirely by decreasing the entry probability to make sales in each destination market, and not by the decrease of sales conditional on this entry decision, following the same logic as Melitz (2003) and Chaney (2008). Therefore, the elasticity of substitution σ does not play a role for this value.

λ^B, the model replicates the patterns of heterogeneous effects on new supplier matching rates with supplier and buyer densities. The model-predicted regression coefficients for the supplier density are somewhat smaller than those using actual data, arising from the first-order approximation error. Nonetheless, the model-predicted regression coefficients remain within the 95% confidence intervals of data regression. Finally, Columns (5) and (6) demonstrate that my chosen χ closely reproduces the negative effects of supplier bankruptcy on sales growth.

Although my baseline selection of λ^S, λ^B, and χ reproduces the point estimates of the reduced-form regressions, it is important to consider the associated statistical uncertainties. In Section 5.2, I address this point by conducting a sensitivity analysis using alternative values for λ^S, λ^B, and χ, taking into account the statistical uncertainty in these parameter estimates.[23]

Table 6: Model Fit of Matching Parameters to Targeted Regression Coefficients

	Dependent variable:					
	Number of New Suppliers				Sales Growth (Arc-Elasticity)	
	Data	Model	Data	Model	Data	Model
	(1)	(2)	(3)	(4)	(5)	(6)
Trt x 1[t - BankruptYear = 0 or 1]	0.139 (0.040)	0.110			−0.034 (0.015)	−0.038
Trt x 1[t - BankruptYear = 2 or 3]	0.191 (0.057)	0.227			−0.042 (0.023)	−0.036
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density			0.134 (0.041)	0.078		
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density			0.168 (0.056)	0.130		
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Density			−0.008 (0.042)	−0.007		
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Density			−0.071 (0.059)	−0.007		
Observations	85,951		85,939		84,113	
Adjusted R^2	0.604		0.617		0.530	

Note: Columns (1) and (3) reproduce the reduced-form estimates of the average and heterogeneous effects of unanticipated supplier bankruptcies on new supplier matching rates (Column 1 of Table 2 and 4, respectively), and Column (5) reproduces the average effects on sales growth (Column 1 of Table 3). Columns (2), (4), and (6) are the same regression coefficients using the model-predicted responses to exogenous supplier separation. To construct the model prediction, for each treatment and control firm in my sample, I simulate the probability that firms are matched with a new supplier after Δ years since the supplier bankruptcy using the Poisson match rate $v_{j,km} = \eta(S^*_{j,k})^{\lambda^S}(B^*_{j,m})^{\lambda^B-1}$ and separation rates $\rho_{j,km}$, where I choose the value of η to minimize the sum of squared differences between the two coefficients in Columns (1) and (2), and I obtain $\rho_{j,km}$ from TSR data. I also compute the expected sales changes using the expression $\Delta \log \mathbb{E}[\text{Sales}_{fjkm\Delta}] = -(1 - \text{NewSuppliers}_{fjkm\Delta}) \times \log \chi^{\theta\gamma_{km}}$ for Column (6).

5.1.3 Baseline Variables

I calibrate population share, L_i, using data from the Population Census in 2010. For the construction of the input sourcing share, $\pi_{ij,k}$, I rely on the cross-sectional patterns observed in the TSR firm-to-firm trade data from 2008. Specifically, I count the number of

[23] In Appendix G, I provide additional evidence of model fit using untargeted moments, including the supplier matching rates unconditional on supplier bankruptcy and aggregate firm sales by sector and location.

supplier-buyer linkages from suppliers located in prefecture i and sector k to buyers located in prefecture j, and normalize this count by the total number of supplier linkages in prefecture j for input sector k. Note that, as discussed in Section 4.1.4, my model predicts that the sourcing share probability coincides with the expenditure share for intermediate and final goods. I also calibrate the steady-state probability of matching with a supplier for buyers in location j and sector m for input sector k, $\Lambda_{j,km}$, using the TSR firm-to-firm trade data in 2008. Finally, I calibrate the final goods consumption, $Y^F_{j,k}$, by solving for the market clearing conditions (12), (13), and (14) given parameter values of $\{\alpha_k, \gamma_{L,m}, \gamma_{km}, \theta, \sigma\}$ and observed trade shares, $\{\pi_{ij,k}\}$.[24]

5.2 Counterfactual Simulations

In this section, I use the calibrated model to quantify the agglomeration externality resulting from thick market externality through two counterfactual simulations: increasing local population size and increasing local productivity.

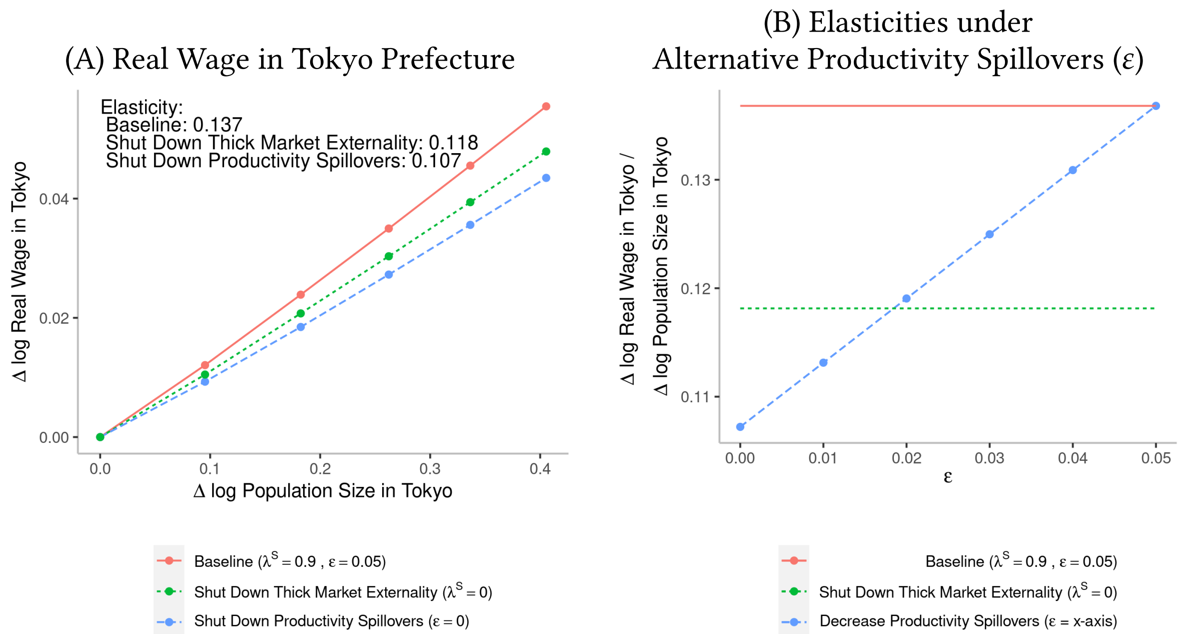
5.2.1 Impacts of Population Size

In my first counterfactual simulation, I examine the effects of increasing local population size on local production and welfare. In particular, I conduct this counterfactual simulation for Tokyo prefecture, which is the most densely populated prefecture in Japan with more than 10 percent of the overall population. To highlight the significance of thick market externality, I compare the results of this counterfactual simulation with two alternative scenarios: one without thick market externality ($\lambda^S = 0$ instead of $\lambda^S = 0.9$) and one with lower levels of productivity spillovers ($\varepsilon \in [0, 0.05)$ instead of $\varepsilon = 0.05$).

Figure 3 reports the results. In Panel (A), I plot the log changes in real wages in Tokyo prefecture ($w_{\text{Tokyo}}/P_{\text{Tokyo}}$) against the log change in Tokyo prefecture's population size. Each line indicates alternate model specifications: The red solid line ("Baseline") reports the results under my baseline calibration of thick market externality and productivity spillovers ($\lambda^S = 0.9, \varepsilon = 0.05$); the green dotted line ("Shut Down Thick Market Externality") indicates the specification where I shut down thick market externality ($\lambda^S = 0$); the blue dashed line ("Shut Down Productivity Spillovers") indicates the specification where I completely shut down productivity spillovers ($\varepsilon = 0$).

[24] The baseline values of wages, w_i, and the efficiency unit of labor, ψ_i, are not required for the counterfactual simulation.

Figure 3: Effects of Increasing Population Size in Tokyo



Note: Results of the counterfactual simulation to increase population size in Tokyo prefecture. Panel (A) plots the log changes in real wages in Tokyo prefecture ($w_{\text{Tokyo}}/P_{\text{Tokyo}}$) against the log change in Tokyo prefecture's population size. Panel (B) plots the elasticity of log wage with respect to population size in Tokyo (evaluated at its 50 percent increase) against alternative value for ε.

Panel (A) reveals that, across all specifications, an increase in population size in Tokyo prefecture has a positive impact on real wages in Tokyo. The relationship between population size and real wages appears to be approximately log-linear. In my baseline specification, I find that the elasticity of Tokyo's real wage with respect to population size is 0.137. When I exclude thick market externality in firm-to-firm trade, this elasticity decreases to 0.118. Thus, the elasticity of regional welfare with respect to population density resulting from thick market externality is approximately 0.02 ($\approx 0.137 - 0.118$). When I instead shut down productivity spillovers, this elasticity decreases to 0.107. Therefore, the elasticity of regional welfare with population density resulting from local productivity spillovers (with $\varepsilon = 0.05$) is approximately 0.03 ($\approx 0.137 - 0.107$).[25] The remaining margin of agglomeration benefit mainly comes from the increased firm entry (i.e., Section 4.3).

[25]Note that the effect of population size on the real wage is smaller than the assumed value of elasticity on local productivity ($\varepsilon = 0.05$). This is due to the decline in the ratio of producer price to consumption price (terms of trade) as population size increases. For related discussions, refer to Ramondo, Rodríguez-Clare, and Saborío-Rodríguez (2016).

In Panel (B), I further examine this elasticity under different levels of productivity spillovers $\varepsilon \in [0, 0.05]$ indicated in the horizontal axis. The results show that excluding thick market externality has a similar magnitude of effects compared to reducing the elasticity of local productivity spillovers by 0.03 ($= 0.05 - 0.02$). Although on the lower end, this value is within the range of existing estimates for agglomeration productivity spillovers (from 0.02 to 0.1; i.e., Melo et al. 2009). This evidence suggests that agglomeration benefit from thick market externality is sizable relative to overall agglomeration productivity spillovers.

Table 7 presents the results of the same counterfactual simulation with additional model specifications. For each model specification indicated in Column (1), I report the elasticity of real wages in Tokyo with respect to its population size (in Column 2) and the elasticity of average real wages across all prefectures in Japan with respect to Tokyo's population size (in Column 3). Rows (a) to (c) in Column (2) present the same results explained in Figure 3. In Column (3) of these rows, I find that the average real wage across all of Japan increases at a faster rate compared to that in Tokyo prefecture in response to the population increase in Tokyo. This result arises because other regions benefit from increased productivity in Tokyo through trade linkages, while they do not directly suffer from pooling externality resulting from the increased entry cost threshold $\bar{c}_{j,k}$ in Tokyo prefecture.[26]

Table 7: Effects of Increasing Population Size in Tokyo

1) Specification	2) Elasticity of Real Wage in Tokyo (Diff. from Baseline in Parenthesis)	3) Elasticity of Average Real Wage (Diff. from Baseline in Parenthesis)
(a) Baseline ($\lambda^S = 0.9$, $\lambda^B = 1$, $\varepsilon = 0.05$)	0.137 (0.000)	0.170 (0.000)
(b) No Thick Market Externality ($\lambda^S = 0$, $\lambda^B = 1$)	0.118 (-0.019)	0.162 (-0.007)
(c) No Productivity Spillover ($\varepsilon = 0$)	0.107 (-0.030)	0.162 (-0.008)
(d) Alternative CRS Matching Technology ($\lambda^S = 0.5$, $\lambda^B = 0.5$)	0.119 (-0.018)	0.161 (-0.009)
(e) Alternative CRS Matching Technology ($\lambda^S = 1$, $\lambda^B = 0$)	0.120 (-0.016)	0.160 (-0.010)

Note: Results of the counterfactual simulation to increase population size in Tokyo prefecture under alternative model specifications. The figures presented are the elasticities of the effects of the counterfactual simulation on the corresponding variable with respect to population size in Tokyo, evaluated at its 50 percent increase.

In Rows (d) and (e), I report the results under alternative configurations of the thick market and congestion externality that satisfy constant returns to scale (CRS) matching technology ($\lambda^S = 0.5$ and $\lambda^S = 0.5$ in Row d and $\lambda^S = 1$ and $\lambda^B = 0$ in Row e), instead of simply eliminating thick market externality ($\lambda^S = 0$ and $\lambda^B = 1$ in Row b). The

[26] In Appendix Figure H.1, I show that the increase in real wages is positively correlated with the strength of trade linkages with Tokyo prefecture.

results across these three specifications are broadly similar, indicating that thick market externality generates agglomeration benefits primarily through increasing returns to scale (IRS) in matching technology.

In Appendix Table H.1, I provide a sensitivity analysis of the results under alternative calibrations and model specifications. As expected, the extent to which thick market externality contributes to agglomeration benefit varies significantly depending on the values of λ^S, λ^B, and χ. The parameters σ and θ have an impact on the overall agglomeration benefit, although the contribution of thick market externality remains relatively stable. Furthermore, I explore alternative model specifications, such as incorporating forward-looking acceptance decisions and accounting for firm profits from intermediate goods sales. I find that they yield similar conclusions regarding the contribution of thick market externality to agglomeration benefit.

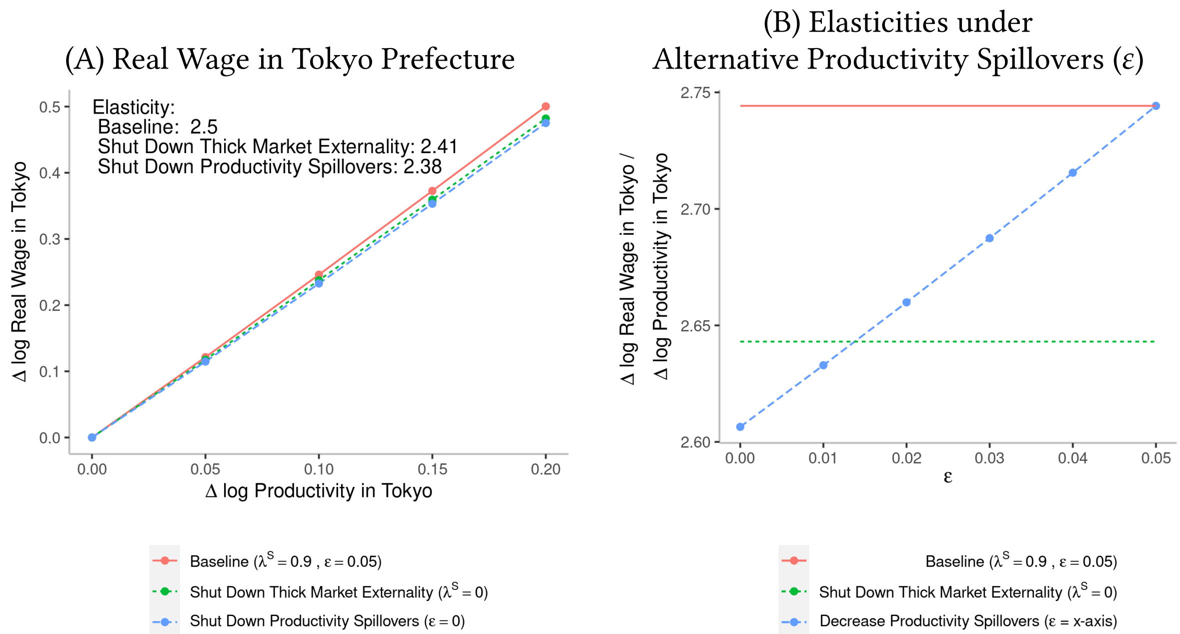
5.2.2 Impacts of Local Productivity

I next investigate how these agglomeration externalities amplify the impacts of an exogenous increase in local productivity. In particular, I conduct a counterfactual simulation using the calibrated model by raising the total factor productivity (TFP) in Tokyo prefecture ($\tilde{A}_{\text{Tokyo},k}$ for all $k \in K$) while allowing for population mobility.

Figure 4 reports my results. In Panel (A), I plot the log changes in real wages in Tokyo prefecture against the log change in Tokyo prefecture's TFP. Similar to Figure 3, each line represents different model specifications: baseline specification ($\lambda^S = 0.9, \varepsilon = 0.05$), shutting down thick market externality ($\lambda^S = 0$), and shutting down productivity spillovers ($\varepsilon = 0$).

Panel (A) reveals that in all specifications, a productivity shock generates an increase in the local real wage with approximate log-linear relationships. In the baseline model, the elasticity of local real wage with respect to the productivity increase is estimated to be 2.5. This high elasticity (which is above one) is primarily driven by the input cost propagation effects through input-output linkages, as discussed in Section 4.3. When I abstract thick market externality in firm-to-firm trade, this elasticity decreases to 2.41. Therefore, the thick market externality in firm-to-firm trade amplifies the productivity shock. Hence, the presence of thick market externality amplifies the impact of the productivity shock that operates through increased population size in Tokyo prefecture. When I abstract productivity spillovers by decreasing ε from 0.05 to 0, the elasticity decreases to 2.38. Consequently, the contribution of thick market externality to amplifying productiv-

Figure 4: Effects of Increasing Productivity in Tokyo



Note: Results of the counterfactual simulation to increase total factor productivity (TFP) in Tokyo prefecture ($A^*_{\text{Tokyo},k}$ for all $k \in K$). Panel (A) plots the log changes in real wages in Tokyo prefecture ($w_{\text{Tokyo}}/P_{\text{Tokyo}}$) against the log change in Tokyo prefecture's TFP. Panel (B) plots the elasticity of log wage with respect to the TFP in Tokyo (evaluated at its 20 percent increase) against the alternative value for ε.

ity shocks is smaller but still comparable to the effect of local productivity spillovers with $\varepsilon = 0.05$. It is important to note that while these agglomeration effects result in significant amplification, the direct and cost propagation effects through input-output linkages play a quantitatively dominant role.

In Panel (B), I present the same elasticity under alternative values for productivity spillovers $\varepsilon \in [0, 0.05]$ indicated in the horizontal axis. I find that abstracting thick market externality has a similar magnitude of effects as reducing the elasticity of local productivity spillovers by 0.03-0.04. As emphasized in Figure 3, this value is smaller but comparable in magnitude to the range of existing estimates of agglomeration productivity spillovers found in the previous literature.

Table 8 provides the results of the same counterfactual simulation, including additional model specifications. Similar to Table 7, each model specification is listed in Column (1), followed by the elasticity of real wages in Tokyo (Column 2) and the impact on aggregate welfare ($\mathcal{U}$) across all prefectures in Japan (Column 3). Column (2) of Rows (a) to (c) report the same results explained in Figure 4. In Column (3) of these rows, I observe a substantial increase in aggregate welfare in this counterfactual, consistent with the interpretation that other regions also benefit from the increased productivity in Tokyo through trade linkages.[27] In Rows (d) and (e), I report the results under alternative configurations of the thick market and congestion externality that satisfy constant returns to scale (CRS) matching technology. Similar to the previous counterfactual, the results across these three specifications are broadly similar, indicating that thick market externality generates agglomeration benefits primarily through increasing returns to scale (IRS) in matching technology.[28]

Table 8: Effects of Increasing Productivity in Tokyo

1) Specification	2) Elasticity of log Real Wage in Tokyo (Diff. from Baseline in Parenthesis)	3) Elasticity of log Aggregate Welfare (Diff. from Baseline in Parenthesis)
(a) Baseline ($\lambda^S = 0.9$, $\lambda^B = 1$, $\varepsilon = 0.05$)	2.50 (0.00)	1.31 (0.00)
(b) No Thick-Market Externality ($\lambda^S = 0$, $\lambda^B = 1$)	2.41 (-0.09)	1.25 (-0.05)
(c) No Productivity Spillover ($\varepsilon = 0$)	2.38 (-0.13)	1.24 (-0.06)
(d) Alternative CRS Matching Technology ($\lambda^S = 0.5$, $\lambda^B = 0.5$)	2.42 (-0.08)	1.25 (-0.05)
(e) Alternative CRS Matching Technology ($\lambda^S = 1$, $\lambda^B = 0$)	2.44 (-0.06)	1.26 (-0.05)

Note: Results of the counterfactual simulation to increase total factor productivity (TFP) in Tokyo prefecture under alternative model specifications. The figures presented are the elasticities of the effects of the counterfactual simulation on the corresponding variable with respect to TFP increase in Tokyo, evaluated at its 20 percent increase.

6 Conclusion

This paper shows that matching frictions and thick market externality in firm-to-firm trade shape the agglomeration of economic activity. Using yearly panel data of firm-to-firm trade in Japan, I document that firms gradually match with an alternative supplier after an unanticipated supplier bankruptcy, and that these rematching rates increase in the geographic density of alternative suppliers. I develop a general equilibrium model of firm-to-firm matching in input trade across space and show that the thick market externality leads to agglomeration externality for regional production and welfare. By fitting the model to the reduced-form patterns of firm-to-firm matching, I show that the substantial impact of thick market externality on the overall agglomeration benefit.

[27] From equation (16), the change in aggregate welfare is given by $\hat{\mathcal{U}} = (\sum_i \frac{L_i}{\sum_\ell L_\ell}(\hat{w}_i/\hat{P}_i)^{v})^{1/v}$, which is the geometric average of the changes in real wages across locations. In Appendix Figure H.2, I show that the increase in real wages is positively correlated with the strength of trade linkages with Tokyo prefecture.

[28] In Appendix Table H.2, I present the sensitivity analysis of calibrated parameters. The patterns of the results are broadly similar to the observations discussed in the sensitivity analysis in Section 5.2.1 (Appendix Table H.1). In addition, a larger value of v leads to a greater contribution of thick market externality, which is driven by a greater population movement in the counterfactual simulation.

This paper highlights a particular agglomeration mechanism: matching friction and thick market externality of firm-to-firm trade. This is, of course, not the only relevant agglomeration mechanism. Other agglomeration mechanisms, such as labor market pooling or knowledge spillover, are also important and provide different policy implications. Therefore, an important direction of future work is to explore various agglomeration mechanisms using spatially-granular microdata and study their equilibrium implications.

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Online Appendix for "Matching and Agglomeration: Theory and Evidence from Japanese Firm-to-Firm Trade" (Not for Publication)

Yuhei Miyauchi

May 2023

A Data Appendix

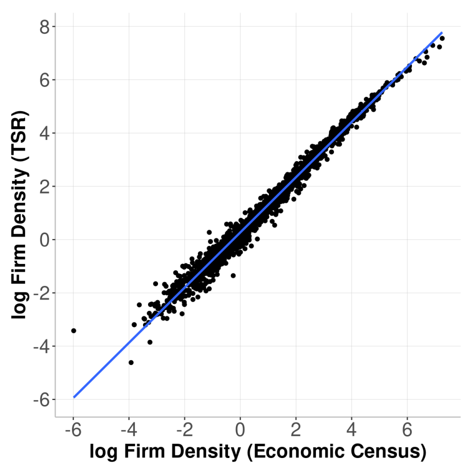
In this section of the online appendix, I provide additional information about the firm-to-firm trade data from Tokyo Shoko Research (TSR). Table A.1 and Figure A.1 show the coverage rates of TSR data and show that the TSR data is broadly representative across geography. Table A.2 presents the list of reported reasons for bankruptcies from which I identify unanticipated bankruptcies. Figure A.2 presents the frequency of unanticipated bankruptcies across space and time.

Table A.1: Sample Size and Coverage of TSR Datasets

		TSR	Economic Census	TSR / Economic Census
2009	All	1,241,490	1,805,545	0.68
	Employment <= 4	587,611	1,067,825	0.55
	Employment >= 5	653,879	737,720	0.88
2016	All	1,473,991	1,877,438	0.78
	Employment <= 4	793,967	1,047,189	0.75
	Employment >= 5	680,024	830,249	0.81

Note: This table reports, for year (2009 or 2016) and firm size (over or under 5 employees), the sample size of the TSR dataset (third column), the number of firms in Japan based on economic censuses (fourth column), and the ratio of the third and fourth columns (fifth column).

Figure A.1: Coverage of TSR Datasets relative to Economic Census



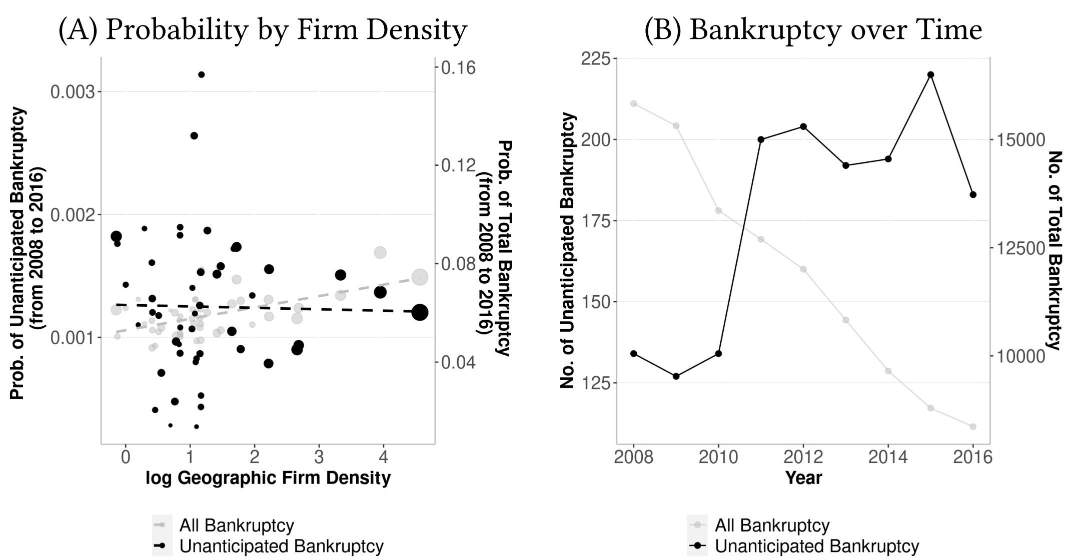
Note: This figure plots the density of firms using two data sources: The economic census on the horizontal axis and TSR data on the vertical axis. Each dot represents a municipality in Japan. All data is from 2009. The straight line in the graph is the linear regression fit between the two variables. The slope of the regression line is 1.04 (with an intercept of 0.27) and the R-squared is 0.98.

Table A.2: List of Reasons for Bankruptcies

Reason of Bankurptcy	Freq.	Freq. (At Least One Buyer)
Unanticipated Reasons	1588	269
Sales Decline	72437	9460
Accumulation of Debt	10700	2267
Spillovers from Other Bankruptcy	6222	938
Shortage of Capital	5577	1021
Management Failure	4843	601
Unknown	3585	458
Over-Investment in Capital	802	211
Deterioration of Credit Conditions	547	161
Difficulty in Collecting Account Receivables	454	126
Over-Accumulation of Inventory	73	29
Total	106828	15541

Note: This table reports the number of bankruptcies in each category of reported reasons. The second column ("Freq") reports the number of firms experiencing bankruptcies from 2008 to 2016 for each reason, and the third column ("Freq. (At Least One Buyer)") reports the number of bankrupt firms with at least one buyer (reported as a supplier by at least one firm). In an internal document by TSR, "unanticipated reasons" is described as "unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc."

Figure A.2: Spatial and Temporal Patterns of Unanticipated Bankruptcies



Note: Panel (A) plots the probability of unanticipated bankruptcies (colored in black; on the left vertical axis) and that of all bankruptcies (colored in gray; on the right vertical axis) against firm density (on the horizontal axis) during the sample period. Each dot represents a prefecture, and the area of the dot represents the log number of firms in the prefecture. Panel (B) plots the frequency of unanticipated bankruptcies (colored in black; on the left vertical axis) and that of all bankruptcies (colored in gray; on the right vertical axis) against year.

B Reduced-Form Results Appendix

In this section of the online appendix, I present additional results and robustness of the impacts of unanticipated supplier bankrupcies reported in Section 3 of the main paper.

Table B.1: Impacts of Supplier Bankruptcy on Additional Firm Outcomes

	Employment Growth (Arc-Elasticity)	Profit / Sales	Prob. Continuing Relationship with Existing Suppliers in Baseline Period	Sales Growth (Arc-Elasticity) of Existing Suppliers in Baseline Period	Number of New Suppliers of Firms in Same Industry and Prefecture	Sales Growth (Arc-Elasticity) of Firms in Same Industry and Prefecture
	(1)	(2)	(3)	(4)	(5)	(6)
Trt x 1[t - BankruptYear = -2 or -3]	-0.007	-0.006	-0.031	-0.007	0.003	-0.002
	(0.010)	(0.008)	(0.048)	(0.005)	(0.016)	(0.005)
Trt x 1[t - BankruptYear = -1]						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trt x 1[t - BankruptYear = 0 or 1]	-0.017	-0.012	0.069^{**}	-0.004	0.003	0.002
	(0.014)	(0.008)	(0.034)	(0.008)	(0.017)	(0.007)
Trt x 1[t - BankruptYear = 2 or 3]	-0.025	0.006	0.080^{*}	0.002	0.001	0.002
	(0.022)	(0.013)	(0.044)	(0.011)	(0.027)	(0.009)
Observations	85,439	67,756	85,951	76,737	80,838	79,141

Note: Results of the stacked-by-event difference-in-difference regression specification (3) by omitting the terms corresponding to treatment heterogeneity ($\log S_{j,k}$, $\log B_{j,m}$, X_{fjkmg}). In Columns (3) and (4), "existing suppliers in baseline period" indicates the set of suppliers (excluding bankrupt ones) that firms are connected to one year prior to the supplier bankruptcy. In Columns (5) and (6), I take the number of new suppliers and sales growth of firms in the same two-digit industry and prefecture as treatment and control firms as outcome variables. The lack of statistically significant results in Columns (5) and (6) provide additional robustness of Column (4) of Table 2 to address the concern that treatment firms' supplier bankruptcy may have a direct effect on other firms in the same prefecture and industry. See footnote of Table 2 for further details about the specification.

Table B.2: Heterogeneous Impacts of Supplier Bankruptcy by Reported Ranking and Firm Size

	Number of New Suppliers				Sales Growth (Arc-Elasticity)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trt x 1[t - BankruptYear = 0 or 1]	0.14^{***}	0.11^{**}	0.13^{***}	0.12^{*}	-0.03^{**}	-0.01	-0.03^{**}	-0.05^{**}
	(0.04)	(0.05)	(0.04)	(0.06)	(0.02)	(0.02)	(0.01)	(0.02)
Trt x 1[t - BankruptYear = 2 or 3]	0.19^{***}	0.17^{**}	0.19^{***}	0.29^{***}	-0.04^{*}	-0.02	-0.04^{*}	-0.05
	(0.06)	(0.07)	(0.06)	(0.09)	(0.02)	(0.03)	(0.02)	(0.03)
Trt x 1[t - BankruptYear = 0 or 1] x X		0.11	-0.11^{**}	-0.05		-0.11^{**}	0.01	-0.01
		(0.10)	(0.04)	(0.04)		(0.05)	(0.01)	(0.01)
Trt x 1[t - BankruptYear = 2 or 3] x X		0.07	-0.10^{*}	0.02		-0.12^{*}	-0.01	-0.02
		(0.15)	(0.05)	(0.05)		(0.06)	(0.02)	(0.02)
X		Top 1 Supplier	Firm Size (Buyer)	Firm Size (Supplier)		Top 1 Supplier	Firm Size (Buyer)	Firm Size (Supplier)
Observations	85,951	85,951	85,596	85,762	84,113	84,113	83,897	83,939

Note: Results of the stacked-by-event difference-in-difference regression specification (3) without supplier and buyer density ($\log S_{j,k}$, $\log B_{j,m}$) but with treatment heterogeneity (X_{fjkmg}) as specified in the bottom row. Columns (2) and (6) include the dummy variable that takes one if the bankrupt supplier is top 1 supplier. Columns (3) and (7) include the log of employment size of firm f (normalized to mean zero), and Columns (4) and (8) include that of bankrupt suppliers. See footnote of Table 2 for further details about the specification.

Table B.3: Heterogeneous Impacts of Unanticipated Supplier Bankruptcy: Robustness

	Number of New Suppliers				
	(1)	(2)	(3)	(4)	(5)
Panel A: Average Effects					
Trt x 1[t - BankruptYear = 0 or 1]	0.15^{***}	0.15^{***}	0.16^{***}	0.14^{***}	0.17^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Trt x 1[t - BankruptYear = 2 or 3]	0.21^{***}	0.22^{***}	0.22^{***}	0.19^{***}	0.25^{***}
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Panel B: Heterogeneous Effects					
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density	0.15^{***}	0.14^{***}	0.12^{***}	0.15^{***}	0.15^{***}
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density	0.17^{***}	0.14^{**}	0.10	0.15^{**}	0.15^{**}
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Density	−0.04	−0.03	0.02	−0.01	0.01
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Density	−0.09	-0.11^{*}	−0.05	−0.08	−0.04
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
Specification	Exclude Exit Firms	Exclude Bankruptcy in 2009	Exclude Tokyo	Exclude Outdated Accounting Year	Exclude Firms with Outside-Prefecture Establishments
Trt FE x Year FE x Prefecture FE	X	X	X	X	X
Trt FE x Year FE x Buyer and Supplier Size	X	X	X	X	X
Trt FE x Year FE x Firm-Relationship Controls	X	X	X	X	X
Number of Treatment Firms	433	380	374	433	334
Number of Bankrupting Suppliers	181	159	155	181	144
Number of Control Firms	11,889	10,094	7,358	11,889	8,311
Observations	83,548	75,758	54,442	81,582	60,554

Note: Results of the stacked-by-event difference-in-difference regression specification (3). Panel A corresponds to the specification without treatment heterogeneity as in Table 2, and Panel B corresponds to the specification (2) of Table 4. Column (1) excludes firms that drop out during the sample period. Column (2) excludes all supplier bankruptcies in 2009 (the year subsequent to the Great Financial Crisis). Column (3) excludes firms with headquarters in Tokyo prefecture. Column (4) excludes firms whose accounting information is not available after supplier bankruptcy event. Column (5) excludes firms that have establishments outside the headquarter prefecture. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.4: Heterogeneous Impacts: Alternative Supplier Density

	Dependent Variable: Number of New Suppliers					
	(1)	(2)	(3)	(4)	(5)	(6)
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density	0.11^{***}	0.12^{***}	0.13^{***}	0.14^{***}	0.07^{**}	0.14^{***}
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density	0.15^{***}	0.13^{**}	0.14^{**}	0.15^{***}	0.08^{**}	0.16^{***}
	(0.05)	(0.05)	(0.06)	(0.06)	(0.03)	(0.06)
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Density	−0.04	−0.02	−0.03	−0.03	−0.03	−0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Density	−0.10	−0.08	−0.08	−0.08	−0.08	−0.08
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Trt FE x Year FE x Prefecture FE	X	X	X	X	X	X
Trt FE x Year FE x Buyer and Supplier Size	X	X	X	X	X	X
Trt FE x Year FE x Firm-Relationship Controls	X	X	X	X	X	X
Definition of Seller Density	Count Local Suppliers	Sum of Suppliers × Travel Time $^{-0.5}$	Sum of Suppliers × Travel Time $^{-1}$	Sum of Suppliers × Travel Time $^{-2}$	Evaluated Right Before Bankrutpcy	Two-Digit Supplier Industry
Observations	85,395	85,395	85,395	85,395	85,395	85,395

Note: Results of the stacked-by-event difference-in-difference regression specification (3) with alternative definitions for supplier density. Column (1) defines the supplier density by the number of suppliers whose headquarters are established in the treatment firms' prefecture divided by the geographic area. Column (2) to (4) defines it as the sum of the number of suppliers in each prefecture times the power function of travel time between the prefecture and firm f's prefecture divided by the geographic area of firm f's prefecture. Column (5) evaluates the supplier density one year before each supplier bankruptcy, instead of the value in 2008 in my baseline specification. Column (6) defines the industry of suppliers at the two-digit level, instead of four-digit level in baseline. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.5: Heterogeneous Impacts: Alternative Buyer Density

	Dependent Variable: Number of New Suppliers		
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density	0.13^{***}	0.14^{***}	0.13^{***}
	(0.04)	(0.04)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density	0.17^{***}	0.15^{**}	0.11^{**}
	(0.06)	(0.06)	(0.06)
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Density	−0.01	−0.01	0.01
	(0.04)	(0.03)	(0.02)
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Density	−0.07	0.02	0.07^{**}
	(0.06)	(0.05)	(0.03)
Definition of Buyers	Buyers in Same Two-Digit Industry	Buyers facing Supplier Separation	Buyers facing Unanticipated Supplier Bankruptcies
Trt FE x Year FE x Prefecture FE	X	X	X
Trt FE x Year FE x Buyer and Supplier Size	X	X	X
Trt FE x Year FE x Firm-Relationship Controls	X	X	X
Observations	85,939	85,951	85,951

Note: Results of the stacked-by-event difference-in-difference regression specification (3) with alternative definitions for buyer density. Column (1) defines buyer density as the density of firms in the same 2-digit industry and prefecture. Column (2) defines it using the number of firms in the treatment firm's prefecture that faced an unanticipated supplier bankruptcy in the same two-digit industry up to 3 years prior to the event. Column (3) defines buyer density using the number of firms in the treatment firm's prefecture that faced separation of supplier linkages in the same two-digit industry up to 3 years prior to the event. Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

Table B.6: Heterogeneous Impacts: Inverse Hyperbolic Sine (IHS) Transformation and Reverse Reporting

	Dependent variable:			
	Number of New Suppliers (IHS)			
	Baseline		Include Reverse Reporting	
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1]	0.12^{***}		0.06^{**}	
	(0.02)		(0.03)	
Trt x 1[t - BankruptYear = 2 or 3]	0.15^{***}		0.09^{***}	
	(0.03)		(0.03)	
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density		0.07^{***}		0.06^{***}
		(0.02)		(0.02)
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density		0.05^{*}		0.02
		(0.03)		(0.03)
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Density		−0.02		0.01
		(0.02)		(0.03)
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Density		-0.05^{*}		0.002
		(0.03)		(0.03)
Trt FE x Year FE x Prefecture FE		X		X
Trt FE x Year FE x Buyer and Supplier Size		X		X
Trt FE x Year FE x Firm-Relationship Controls		X		X
Observations	85,951	85,395	85,965	85,409

Note: This table reports the robustness of the results in Table 4 using different transformations of outcome variables and by including the supplier linkages reported by the supplier-side firms to define the number of new suppliers. Columns (1) and (2) apply the inverse hyperbolic sine (IHS) transformation to the number of new suppliers. Columns (3) and (4) define the number of new suppliers by including the supplier linkages reported by the supplier-side firms, in addition to the buyer-reported suppliers, as in the baseline specification. For the latter, I apply the inverse hyperbolic sine (IHS) transformation because of the fat-tailed distribution of the outcome variable, unlike the buyer-reported suppliers which is bounded at 24 (Section 2). Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.7: Average Impacts of Supplier Bankruptcy due to Management Failure

	Dependent Variable: Number of New Suppliers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trt x 1[t - BankruptYear = -2 or -3]	0.05^{**}	0.06^{***}	0.01	0.05^{**}	0.13^{***}	0.05	0.05	0.08^{***}	0.001
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)
Trt x 1[t - BankruptYear = -1]									
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Trt x 1[t - BankruptYear = 0 or 1]	0.24^{***}	0.25^{***}	0.24^{***}	0.23^{***}	0.35^{***}	0.21^{***}	0.23^{***}	0.27^{***}	0.18^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)
Trt x 1[t - BankruptYear = 2 or 3]	0.36^{***}	0.38^{***}	0.34^{***}	0.34^{***}	0.61^{***}	0.32^{***}	0.38^{***}	0.41^{***}	0.30^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)
Specification	Baseline	Exclude Exit Firms	Exclude Tohoku & Hokkaido	Exclude Same-Industry Control Firms	Exclude Indirect Connection to Bankrupt Firms	Exclude Top 1 Supplier	Exclude Top 2 Suppliers	Exclude Ever-Treated Control Firms	Impute Pre-Period Fixed Effects
Number of Treatment Firms	1688	1688	1221	1688	1688	1316	1035	1688	1688
Number of Bankrupt Suppliers	337	337	258	337	337	301	275	337	337
Number of Control Firms	32,840	32,840	25,428	31,060	18,797	25,062	18,558	29,933	32,840
Observations	239,292	231,385	182,213	226,239	131,127	182,517	135,297	218,433	231,805

Note: A version of Table 2 where I instead use supplier bankruptcy due to “Management Failure” in Table A.2.

Table B.8: Average Impacts of Supplier Bankruptcy due to Management Failure

	Dependent Variable:		
	Sales Growth (Arc-Elasticity)	Exit	Sales Growth (Arc-Elasticity)
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = -2 or -3]	−0.001		0.009
	(0.008)		(0.007)
Trt x 1[t - BankruptYear = -1]			
	(0.000)	(0.000)	(0.000)
Trt x 1[t - BankruptYear = 0 or 1]	-0.020^{**}	0.005	−0.003
	(0.009)	(0.004)	(0.006)
Trt x 1[t - BankruptYear = 2 or 3]	-0.057^{***}	0.017^{***}	-0.019^{**}
	(0.014)	(0.006)	(0.009)
Samples	All	All	Cond. on Survival
Control Mean	-0.185	0.052	-0.086
Number of Treatment Firms	1688	1688	1688
Number of Bankrupt Suppliers	337	337	337
Number of Control Firms	32,840	32,840	32,840
Observations	234,302	239,292	227,326

Note: A version of Table 3 where I instead use supplier bankruptcy due to "Management Failure" in Table A.2.

Table B.9: Heterogeneous Impacts of Supplier Bankruptcy due to Management Failure

	Dependent Variable: Number of New Suppliers							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Pre-period								
Trt x 1[t - BankruptYear = -3 or -2] x log Supplier Density	0.03	0.005	−0.02	−0.03	0.01	−0.01	0.01	0.02
	(0.02)	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)
Trt x 1[t - BankruptYear = -3 or -2] x log Buyer Density	0.05^{**}	0.03	0.04	0.02	0.03	0.01	0.03	0.03
	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
Panel B: Post-period								
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density	0.06^{***}	0.05^{**}	0.07^{**}	0.05^{**}	0.08^{***}	0.08^{***}	0.05^{**}	0.07^{***}
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density	0.10^{***}	0.09^{***}	0.15^{***}	0.11^{***}	0.12^{***}	0.13^{***}	0.08^{**}	0.11^{***}
	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Density	0.03	−0.01	−0.02	−0.02	−0.02	−0.01	−0.02	0.01
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Density	0.07^{*}	0.01	0.07	−0.02	0.03	0.01	−0.01	0.05
	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Specification			IV: Firm Density in CEO's Birth Prefecture	Exclude Top 1 Supplier	Exclude Top 2 Suppliers	Exclude Tohoku & Hokkaido	Exclude Same-Industry Control Firms	Exclude Indirect Connection to Bankrupt Firms
Trt FE x Year FE x Prefecture FE	X	X	X	X	X	X	X	X
Trt FE x Year FE x Buyer and Supplier Size		X	X	X	X	X	X	X
Trt FE x Year FE x Firm-Relationship Controls		X	X	X	X	X	X	X
Trt FE x Year FE x CEO Birth Prefecture FE			X					
Number of Treatment Firms	1688	1688	1565	1316	1035	1221	1688	1688
Number of Bankrupt Suppliers	337	337	325	301	275	258	337	337
Number of Control Firms	32,840	32,840	30,006	25,062	18,558	25,428	31,060	18,797
Observations	239,282	237,106	167,314	180,800	133,956	180,347	224,159	134,727

Note: A version of Table 4 where I instead use supplier bankruptcy arising due to "Management Failure" in Table A.2.

C Model Derivations

This appendix discusses additional details of the model developed in Section 4.

C.1 Cutoff for Entry for Sales

Let denote the final goods sales of firms in location j with unit cost c (net of trade cost) when they enter location j as $r^F_{j,k}(c) = \varrho_{j,k}c^{-\sigma+1}$, where $\varrho_{j,k}$ is a demand shifter that depends on aggregate equilibrium conditions. Denoting the unit cost threshold of entry as $\bar{c}_{j,k}$, the goods market clearing condition is given by:

$$Y^F_{j,k} = \int_0^{\bar{c}_{j,k}} \varrho_{j,k}c^{-\sigma+1}\Omega_{j,k}\theta c^{\theta-1}\bar{c}^{-\theta}_{j,k}dc = \frac{\theta}{\theta-\sigma+1}\varrho_{j,k}\Omega_{j,k}\left(\bar{c}_{j,k}\right)^{-\sigma+1}.$$

Now, combining with the zero-profit condition for a marginal seller $f_{j,k}w_j = \frac{1}{\sigma}\varrho_{j,k}\left(\bar{c}_{j,k}\right)^{-\sigma+1}$, the entry cutoff $\bar{c}_{j,k}$ is solved as:

$$\bar{c}_{j,k} = \left[\frac{\theta-\sigma+1}{\theta\sigma}\frac{Y^F_{j,k}}{w_j f_{j,k}\Omega_{j,k}}\right]^{1/\theta}, \tag{C.1}$$

and I also have $S_{j,k} = \Omega_{j,k}\bar{c}^{\theta}_{j,k}$.

Furthermore, the aggregate sales fixed cost payment by firms that sell in location j, $\mathcal{F}_{j,k}$, is given by

$$\mathcal{F}_{j,k} = f_{j,k}w_j S_{j,k} = \frac{\theta-\sigma+1}{\sigma\theta}Y^F_{j,k}. \tag{C.2}$$

Therefore, $\frac{\theta-\sigma+1}{\sigma\theta}$ fraction of aggregate final goods sales are required as sales fixed cost payment. Therefore, the share of profit (subtracting sales fixed cost) to aggregate final sales is given by $\frac{1}{\sigma} - \frac{\theta-\sigma+1}{\sigma\theta} = \frac{\sigma-1}{\sigma\theta}$.

C.2 Inverse Cost Shifter $\Gamma_{i,m}$

From the assumption of the measure of firms such that $\mu_{i,m}(\varphi) = N_{i,m}\varphi^{-\theta}$, the measure of firms below unit cost c is given by

$$\begin{aligned} H_{i,m}(c) = \Gamma_{i,m}c^{\theta} &= \int_{p_1,\ldots,p_K} \mu_{i,m}\left(\frac{w_i^{\gamma_{L,m}}\prod_{k\in K} p_k{}^{\gamma_{km}}}{cA_{i,m}}\right)\prod_{k\in K} dG^I_{i,k}(p_k) \\ &= \left(N_{i,m}A^{\theta}_{i,m}w_i^{-\theta\gamma_{L,m}}\prod_{k\in K}\int_{p_k} p_k{}^{-\theta\gamma_{km}}dG^I_{i,k}(p_k)\right)c^{\theta}, \end{aligned} \tag{C.3}$$

where $G^I_{i,k}(\cdot)$ is the steady-state distribution of potential suppliers in location i and sector k, which follows the inverse of the Pareto distribution with an upper bound $\bar{c}_{i,k}$. Given the steady-state match probability $\Lambda_{i,km}$, I have:

$$\begin{aligned}\int p_k{}^{-\theta\gamma_{km}} dG^I_{i,k}(p_k) &= \Lambda_{i,km}\int_0^{\bar{c}_{i,k}} c^{-\gamma_{km}\theta} dG_{i,k}(c) + (1-\Lambda_{i,km})\int_0^{\bar{c}_{i,k}} (\chi c)^{-\gamma_{km}\theta}\, dG_{i,k}(c)\\ &= \Lambda_{i,km}\frac{1}{1-\gamma_{km}}\left(\bar{c}_{i,k}\right)^{-\theta\gamma_{km}} + (1-\Lambda_{i,km})\,\frac{\chi^{-\theta\gamma_{km}}}{1-\gamma_{km}}\left(\bar{c}_{i,k}\right)^{-\theta\gamma_{km}}\\ &= \frac{\chi^{-\theta\gamma_{km}}}{1-\gamma_{km}}\left(\bar{c}_{i,k}\right)^{-\theta\gamma_{km}}\left\{1+\Lambda_{i,km}\left(\chi^{\theta\gamma_{km}}-1\right)\right\},\end{aligned} \tag{C.4}$$

where $G_{i,k}(\cdot)$ the CDF of inverse Pareto distribution with upper bound $\bar{c}_{i,k}$, i.e., $G_{i,k}(c) = c^\theta/\bar{c}^\theta_{i,k}$. (Note that $\{\Gamma_{n,m}\}$ affect the supplier cost distribution only through $\bar{c}_{i,k}$ because production costs follow a power law distribution.) Combining equations (C.3) and (C.4) leads to equation (8) of the main paper with $\varrho_m \equiv \prod_k \frac{\chi^{-\theta\gamma_{km}}}{1-\gamma_{km}}$.

C.3 Derivation for Equation (19)

$$d\log\left(1+\Lambda_{j,km}\left(\chi^{\theta\gamma_{km}}-1\right)\right) = \frac{d\log\left(1+\Lambda_{j,km}\left(\chi^{\theta\gamma_{km}}-1\right)\right)}{d\log\Lambda_{j,km}}\frac{d\log\Lambda_{j,km}}{d\log v_{j,km}}d\log v_{j,km},$$

where

$$\frac{d\log\left(1+\Lambda_{j,km}\left(\chi^{\theta\gamma_{km}}-1\right)\right)}{d\log\Lambda_{j,km}} = \frac{\Lambda_{j,km}\left(\chi^{\theta\gamma_{km}}-1\right)}{1+\Lambda_{j,km}\left(\chi^{\theta\gamma_{km}}-1\right)},$$

and

$$\frac{d\log\Lambda_{j,km}}{d\log v_{j,km}} = \frac{\rho_{j,km}}{\left(v_{j,km}+\rho_{j,km}\right)^2}\frac{v_{j,km}}{\Lambda_{j,km}} = \frac{\rho_{j,km}}{v_{j,km}+\rho_{j,km}} = 1-\Lambda_{j,km},$$

and

$$d\log v_{j,km} = \lambda^S d\log S_{j,k} + \left(\lambda^B-1\right)d\log B_{j,m}.$$

Furthermore, from equation (6) and (12), $d\log S_{j,k} = d\log Y^F_{j,k} = d\log L_j$.

D Additional Theoretical Results

This appendix provides additional theoretical results. Section D.1 derives the equilibrium in a special case of my model with a single sector. Section D.2 provides sufficient conditions for equilibrium existence and uniqueness. Section D.3 analyzes the planner's problem and highlights the sources of misallocation in the equilibrium.

D.1 Single Sector Model

In this section, I derive the system of equations for a special case of my model with a single sector (i.e., $|K| = 1$). Note that in the single sector model final consumption is proportional to intermediate goods absorption ($Y_i^F \propto Y_i^I$) and entry is proportional to population size ($N_i \propto L_i$).[1] Moreover, from equation (6), $\bar{c}_i \propto (L_i/\Omega_i)^{1/\theta}$. The equilibrium is then summarized by two sets of equilibrium conditions, "buyer access" and "supplier access" equations, analogous to Arkolakis et al. (2023).

First, it can be shown that the labor market clearing condition (equation 14) becomes

$$w_i L_i \psi_i = \sum_{j \in \mathcal{N}} w_j L_j \psi_j \pi_{ij}.$$

This equation corresponds to "buyer-access" equation. Together with the gravity equation of $\pi_{ij} = \Gamma_i \tau_{ij} / \Omega_j$ (equation 9) and the expression for Γ_i (equation 8), I have:

$$\frac{w_i^{1+\theta\gamma} L_i^{-\theta\epsilon+(1-\gamma)} \Omega_i^{-(1-\gamma)}}{1 + \Lambda_i(\chi^{\theta(1-\gamma)} - 1)} = \sum_{j \in \mathcal{N}} K_{ij}^B w_j L_j \Omega_j^{-1}, \tag{D.1}$$

where K_{ij}^B is a constant that only depends on the exogenous variables and parameters. Using the expression of the steady-state match probability (equation 7)

$$\Lambda_i = \left[1 + K_i^\Lambda L_i^{1-\lambda^S-\lambda^B}\right]^{-1}, \tag{D.2}$$

where K_i^Λ is a constant, and I used the fact that $S_i \propto L_i$ and $B_i \propto N_i \propto L_i$ for single-sector model.

Second, from the definition of $\Omega_j = \sum_i \Gamma_i \tau_{ij}^\theta$ (equation 6), I have

$$\Omega_j = \sum_{i \in \mathcal{N}} K_{ij}^S w_i^{-\theta\gamma} L_i^{1+\theta\varepsilon-(1-\gamma)} \Omega_i^{1-\gamma} \left(1 + \Lambda_i(\chi^{\theta(1-\gamma)} - 1)\right), \tag{D.3}$$

where K_{ij}^S is a constant. This equation corresponds to "supplier-access" equation.

Lastly, population mobility equation (16) is given by

$$w_i^v L_i^{-1+v\frac{\theta-\sigma+1}{\theta(\sigma-1)}} \Omega_i^{\frac{v}{\theta}} = \sum_{j \in \mathcal{N}} K_j^L w_j^v L_j^{v\frac{\theta-\sigma+1}{\theta(\sigma-1)}} \Omega_j^{\frac{v}{\theta}}, \tag{D.4}$$

where K_j^L is a constant.

Together, the single-sector model with exogenous population is characterized by $\{w_i, \Omega_i\}$ that satisfy equations (D.1), (D.2), (D.3). The equilibrium with endogenous pop-

[1] See Arkolakis, Huneeus, and Miyauchi (2023) for a related derivation.

ulation mobility is characterized by $\{w_i, \Omega_i, L_i\}$ that satisfy equations (D.1), (D.2), (D.3), and (D.4).

D.2 Equilibrium Existence and Uniqueness

In this appendix, I discuss conditions for equilibrium existence and uniqueness.

Equilibrium Existence. The equilibrium existence of my multi-sector and location model is immediate from Brower's fixed point theorem. To see this, equilibrium variables $\{w_i, L_i, \Lambda_{i,km}, \pi_{ij,k}\}$ are bounded under normalization $\sum_i w_i = 1$, and all the mappings are continuous and differentiable.

Equilibrium Uniqueness without Population Mobility. Deriving clear analytical results for the equilibrium uniqueness is challenging using my model with multiple sectors. However, one can show that equilibrium is unique (up to scale) without population mobility with a single sector (Appendix D.1). To see this, from Allen, Arkolakis, and Li (2022), equilibrium is unique if the matrix $|B\Gamma^{-1}|$ has a spectral radius equal to or less than one, where

$$\Gamma = \begin{bmatrix} 1+\theta\gamma & -(1-\gamma) \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & -1 \\ -\theta\gamma & 1-\gamma \end{bmatrix}.$$

By invoking the Collatz–Wielandt Formula (see Remark 5 in Allen et al. (2022)), one can show that the largest eigenvalue of $|B\Gamma^{-1}|$ is one regardless of the parameter values.

Sufficient Conditions for Equilibrium Uniqueness with Population Mobility. I next provide sufficient conditions for uniqueness with population mobility in a single-sector model. Notice that the equilibrium system is not constant elasticity so I apply the results of Allen et al. (2022) that allow for the variable elasticity system. It can be show that equilibrium is unique if the spectral radius of $\max_{\overline{\Lambda}_i \in [0,1]} |B\Gamma^{-1}|$ is equal to or less than one, where $\max_{\overline{\Lambda}_i \in [0,1]}$ is the element-by-element maximum and

$$\Gamma = \begin{bmatrix} 0 & 0 & 1 \\ v & -1+\tilde{\sigma}\theta & -\frac{v}{1-\sigma} - \tilde{\sigma}\theta \\ 1+\theta\gamma & -\theta\epsilon + (1-\gamma) - \overline{\Lambda}_i(\lambda^S + \lambda^B - 1) & -(1-\gamma) \end{bmatrix},$$

$$B = \begin{bmatrix} -\theta\gamma & 1+\theta\epsilon - (1-\gamma) + \overline{\Lambda}_j(\lambda^S + \lambda^B - 1) & 1-\gamma \\ v & \tilde{\sigma}\theta & -\frac{v}{1-\sigma} - \tilde{\sigma}\theta \\ 1 & 1 & -1 \end{bmatrix},$$

where $\tilde{\sigma} = \frac{\theta-\sigma+1}{\theta(\sigma-1)}$ and $\overline{\Lambda}_j = \frac{\Lambda_j\left(\chi^{\theta(1-\gamma)}-1\right)\left(1-\Lambda_j\right)}{1+\Lambda_j\left(\chi^{\theta(1-\gamma)}-1\right)}$.

Note that while this condition is sufficient, it is not necessary. As discussed in Allen et al. (2022), in the context of a variable elasticity system (as in this case), the sufficient condition may be significantly more conservative compared to the necessary and sufficient condition. In fact, although my baseline parametrization in Section 5 does not satisfy the aforementioned condition, I have confirmed that the choice of initial values does not affect my counterfactual simulation results. This indicates that the existence of multiple equilibria is unlikely to pose an issue under my baseline calibration.

D.3 Planning Problem and Sources of Misallocation

In this appendix, I discuss how thick market and congestion externalities lead to inefficiency in equilibrium entry in a special case of a single location and sector by analyzing an optimal planning problem. I focus on the case with single location and sector to provide a clear and straightforward explanation.

Laissez-Faire Equilibrium with a Single Sector and Location. Given that there is single sector, I normalize the wage $w = 1$.

The inverse cost shifter, Γ, is simplified from equation (18) as

$$\Gamma = N\bar{c}^{-\theta\gamma}\left(1 + \Lambda\left(\chi^{\theta\gamma} - 1\right)\right), \tag{D.5}$$

where I normalized $\varrho A^{\theta} = 1$.[2]

The cut-off of marginal cost below which firms enter a location as a seller, $\bar{c}$, and the measure of sellers, S, is simplified from equation (6) as

$$\bar{c} = \Gamma^{-1/\theta}, \quad S = \Gamma\bar{c}^{\theta}, \tag{D.6}$$

where I normalized $\frac{\theta-\sigma+1}{\theta\sigma}\frac{L}{f} = 1$.[3]

The measure of entrepreneurs, N, is simplified from equation (10) as

$$N = 1, \tag{D.7}$$

where I normalized $\frac{\sigma-1}{\sigma\theta}\frac{L}{F} = 1$.

Together, the laissez-faire equilibrium is characterized by $\{\Gamma, \bar{c}, N\}$ that satisfy equations (D.5), (D.6), (D.7) above.

Planning Problem. I consider an optimal taxation problem where the planner has access to taxes for entrepreneurs' entry, sellers' entry, and income tax. First, I assume that the planner imposes labor income tax, τ^W, as a fraction of labor income. Keeping the

[2]This normalization, and subsequent normalization in this section, has no effect on any of the results presented in this section. Note also that L, and hence A, is exogenous in the single-location model.

[3]To derive this equation, note that $Y^F = wL = L$ and $\Omega = \Gamma$ in a single location case.

same normalization that wage $w = 1$, individual post-tax income is given by

$$w^* = 1 - \tau^W. \tag{D.8}$$

Second, I assume that the planner imposes taxes for sales entry, τ^S, as a fraction of fixed cost payment f. Noting that the aggregate sales are also affected by the income tax above, the seller entry cutoff is modified from equation (D.6) as

$$\bar{c} = \left(\Gamma^{-1}\left(1-\tau^W\right)\left(1-\tau^S\right)\right)^{1/\theta}, \quad S = \Gamma \bar{c}^{\theta}. \tag{D.9}$$

Third, I assume that the planner imposes taxes for entrepreneurs' entry, τ^N, as a fraction of fixed cost payment F. The entrepreneur entry condition is modified from equation (D.7) as

$$N = \left(1-\tau^W\right)\left(1-\tau^N\right). \tag{D.10}$$

The planner chooses τ^W, τ^S, τ^N subject to the government's budget constraint

$$\tau^W L + \frac{\tau^S}{1-\tau^S} Sf + \frac{\tau^N}{1-\tau^N} NF = 0,$$

where $\frac{1}{1-\tau^S} Sf$ and $\frac{1}{1-\tau^N} NF$ are the aggregate fixed cost payment for entrepreneurs' entry inclusive of taxes and that for sellers' entry inclusive of taxes, respectively. From the discussions in Appendix C.1, these two objects are $\frac{\theta-\sigma+1}{\theta\sigma}$ and $\frac{\sigma-1}{\sigma\theta}$ fraction of aggregate final goods sales $\left(1-\tau^W\right)L$, respectively. Together, the government budget constraint is rewritten as

$$\frac{\tau^W}{1-\tau^W} = \tau^N \frac{\sigma-1}{\theta\sigma} + \tau^S \frac{\theta-\sigma+1}{\theta\sigma}. \tag{D.11}$$

The welfare in this economy is given by

$$\log U = \log \frac{w^*}{P} = \log\left(1-\tau^W\right) - \frac{1}{1-\sigma}\log\Gamma - \frac{\theta-\sigma+1}{1-\sigma}\log\bar{c}, \tag{D.12}$$

where the expression for the price index P followed from equation (15). Together, the planner's problem is given by maximizing equation (D.12) with respect to τ^W, τ^S, τ^N subject to equations (D.8), (D.9), (D.10) and (D.11).

Reformulating the first-order conditions, I can show that the optimal tax system satisfies the following two sets of conditions:

$$\left(1-\tau^S\right)\left(1-\tau^W\right) - 1 = \underbrace{-\frac{(\sigma-1)\gamma}{(\theta-\sigma+1)(1-\gamma)}}_{\text{pooling externality},\leq 0} + \underbrace{\frac{1}{1-\gamma}\frac{\Lambda\left(\chi^{\theta\gamma}-1\right)(1-\Lambda)}{1+\Lambda\left(\chi^{\theta\gamma}-1\right)}\lambda^S}_{\text{thick-market externality},\geq 0}. \tag{D.13}$$

$$\left(1-\tau^{N}\right)\left(1-\tau^{W}\right)-1=\underbrace{\frac{\gamma}{1-\gamma}}_{\text{input-output externality,}\geq 0}+\underbrace{\frac{1}{1-\gamma}\frac{\Lambda\left(\chi^{\theta\gamma}-1\right)\left(1-\Lambda\right)}{1+\Lambda\left(\chi^{\theta\gamma}-1\right)}\left(\lambda^{B}-1\right)}_{\text{congestion externality,}\leq 0}. \tag{D.14}$$

These two equations succinctly summarize the sources of misallocation present in the laissez-faire equilibrium, which the planner aims to correct. Equation (D.13) summarizes the inefficiency in sellers' entry. The first term, labeled "pooling externality," arises from the fact that increased seller entry raises the average cost of suppliers in the matching market. The second term, labeled "thick market externality," is positive if $\gamma > 0$ and $\lambda^S > 0$. Both of these effects disappear when $\gamma = 0$ (i.e., no intermediate inputs), which is consistent with the assumption that there are no matching frictions in the final goods market.

Equation (D.14) summarizes the inefficiency in entrepreneur's entry. The first term, labeled "input-output externality," arises from firms not internalizing the impact of their entry on reducing intermediate goods costs and generating social surplus. This effect is commonly observed in models with firm entry and input-output linkages (e.g., Krugman and Venables 1995 and Antràs, Fort, Gutiérrez, and Tintelnot 2022). The second term, labeled "congestion externality," is positive if $\gamma > 0$ and $\lambda^B < 1$.

E Model Extensions

This appendix provides several extensions of my theoretical framework. I explore these alternative specifications as a part of sensitivity analysis in Appendix H.

E.1 Markups in Intermediate Input Sales

In this appendix, I consider an alternative setting of the model where firms charge markups for intermediate input sales instead of marginal cost pricing in the main paper. More specifically, I assume that firms apply the same markup ratio $\sigma/(\sigma-1)$ as final goods consumers. This modification changes the condition for the threshold of marginal cost to enter location j and sector k, $\bar{c}_{j,k}$, and the measure of suppliers selling in location j, $S_{j,k}$, as

$$\bar{c}_{j,k}=\left[\frac{\theta-\sigma+1}{\theta\sigma}\frac{Y^{F}_{j,k}+\sum_{m}Y^{I}_{j,km}}{w_{j}f_{j,k}\Omega_{j,k}}\right]^{1/\theta},\quad S_{j,k}=\Omega_{j,k}\bar{c}^{\theta}_{j,k}, \tag{E.1}$$

where the difference from equation (6) is the addition of input demand $\sum_m Y^I_{j,km}$. Similarly, the condition for the free entry of entrepreneurs is replaced from equation (10) as

$$N_{j,m}=\frac{\sigma-1}{\sigma\theta}\frac{X^{F}_{j,m}+X^{I}_{j,m}}{w_{j}F_{j,m}}, \tag{E.2}$$

where $X^I_{j,m} \equiv \sum_n \pi_{jn,m} \sum_{m'} Y^I_{n,mm'}$. Market clearing conditions are also replaced from equations (13) and (14) as

$$\tilde{X}_{i,m} = \sum_{j \in \mathcal{N}} \left(\sum_{m' \in K} \frac{\sigma - 1}{\sigma} Y^I_{j,mm'} + \frac{\sigma - 1}{\sigma} Y^F_{j,m'} \right) \pi_{ij,m'}, \tag{E.3}$$

$$w_i L_i \psi_i = \sum_k \left(\gamma_{L,k} \tilde{X}_{i,k} + \frac{\sigma - 1}{\sigma\theta} \sum_{j \in \mathcal{N}} (Y^F_{j,k} + \sum_m Y^I_{j,km}) \pi_{ij,k} + \frac{\theta - \sigma + 1}{\sigma\theta} (Y^F_{i,k} + \sum_m Y^I_{j,km}) \right). \tag{E.4}$$

All other equilibrium conditions remain the same.

E.2 Forward-Looking Acceptance Decision

In this appendix, I extend the model by incorporating a forward-looking acceptance decision regarding matching with a supplier. In particular, I assume that buyer-side firms now have the choice to accept or reject a match, leading to the formation of a long-term relationship. This is in contrast to the baseline model discussed in the main text, where firms always form a relationship conditional on a match. I maintain the assumption that suppliers set prices at their marginal cost, meaning that buyers have all the bargaining power. Consequently, suppliers make no profit from the relationships, and the suppliers' forward-looking decision becomes irrelevant in this context.

Let $V^B_{\omega t,k}(c)$ denote the continuation value of a buyer ω engaged in an ongoing relationship with a supplier in sector k with a unit cost of c (net of iceberg cost). Additionally, let $U^B_{\omega t,k}$ represent the value of a firm without an ongoing supplier relationship in sector k. The Bellman equation for the matched buyer can be expressed as follows:

$$\xi V^B_{\omega t,k}(c) = \Pi^F_{\omega t,k}(c) - \rho_{km} \left(V^B_{\omega t,k}(c) - U^B_{\omega t,k} \right) + \dot{V}^B_{\omega t,k}(c), \tag{E.5}$$

where ξ is the discount rate of the firm; $\Pi^F_{\omega t,k}(c)$ is ω's final goods profit when the unit cost of intermediate goods in sector k is c; ρ_{km} is the Poisson rate at which the relationship is destroyed; and $\dot{V}^B_{\omega t,k}(c)$ indicates the time derivative of the value function $V^B_{\omega t,k}(c)$.

The Bellman equation for the unmatched buyer is given by

$$\xi U^B_{\omega t,k} = \Pi^{F,U}_{\omega t,k} + v_{i,km} a_{\omega,k} \int_0^{c^*_{\omega,k}} \left(V^B_{\omega t,k}(c) - U^B_{\omega t,k} \right) dG_{\omega,k}(c) + \dot{U}^B_{\omega t,k}, \tag{E.6}$$

where $\Pi^{F,U}_{\omega t,k}$ is the profit from final goods when the firm does not have a directly matched supplier in sector k; $v_{i,km}$ is the Poisson rate of matching with a supplier; $a_{\omega,k}$ is the unconditional probability that the buyer accepts a match; $c^*_{\omega,k}$ is the threshold of the supplier's unit cost below which the buyer decides to form a relationship; $G_{\omega,k}(\cdot)$ is the cumulative distribution function of the suppliers' unit cost conditional on match acceptance (such that $G_{\omega,k}(0) = 0$ and $G_{\omega,k}(c^*_{\omega,k}) = 1$); and $\dot{U}^B_{\omega t,k}$ indicates time derivatives of $U^B_{\omega t,k}$.

To solve these Bellman equations analytically, I take a limit of sales fixed cost to zero ($f_{j,k} \to 0$). This assumption implies that the instantaneous profit $\Pi^F_{\omega t,k}(c)$ and $\Pi^{F,U}_{\omega t,k}$ are isoelastic in costs and allows me to derive an analytical solution. Under this assumption, I have

$$\Pi^F_{\omega t,k}(c) = K_{i,m}(p_{\omega t,-k}c^{\gamma_{km}})^{1-\sigma}, \tag{E.7}$$

$$\begin{aligned}\Pi^{F,U}_{\omega t,k} &= \int_0^{\bar{c}_{i,k}} K_{i,m}(p_{\omega t,-k}\,(\chi c)^{\gamma_{km}})^{1-\sigma} dG^I_{i,k}(c) \\ &= K_{i,m}(p_{\omega t,-k}\chi^{\gamma_{km}})^{1-\sigma}\frac{\theta}{\theta + \gamma_{km}\,(1-\sigma)}(\bar{c}_{i,k})^{\gamma_{km}(1-\sigma)},\end{aligned} \tag{E.8}$$

where $\bar{c}_{i,k}$ is the entry cutoff of suppliers in market i as defined by equation (6), $G^I_{i,k}(\cdot)$ denotes the cost distribution of suppliers in market i (which follows the inverse of Pareto distribution with upperbound $\bar{c}_{i,k}$, and $p_{\omega t,-k}$ indicates the component of marginal cost of firm ω other than the component from input sector k.

I assume that buyers set $c^*_{\omega,k}$ to maximize the expected value of the unmatched state.[4] This implies that $c^*_{\omega,k}$ is determined so that firms are in expectation indifferent between accepting or rejecting a match:

$$E[V^B_{\omega t,k}(c^*_{\omega,k})] = E[U^B_{\omega t,k}], \tag{E.9}$$

where the expectation is taken with respect to intermediate input cost other than input sector k. Evaluating equation (E.5) at $c = c^*_{\omega,k}$ and taking expectation in the steady state (i.e. $E[\dot{V}^B_{\omega t,k}] = 0$) yields:

$$\xi E[V^B_{\omega t,k}(c^*_{\omega,k})] = E[\Pi^F_{\omega t,k}(c^*_{\omega,k})] = K_{i,m}{c^*_{\omega,k}}^{(1-\sigma)\gamma_{km}}E[(p_{\omega t,-k})^{1-\sigma}], \tag{E.10}$$

Furthermore, by defining $J_{\omega t,k}(c) = V^B_{\omega t,k}(c) - U^B_{\omega t,k}$, equations (E.5) and (E.6) yield:

$$(\xi + \rho_{km})J_{\omega t,k}(c) = \left(\Pi^F_{\omega t,k}(c) - \Pi^{F,U}_{\omega t,k}\right) - v_{i,km}a_{\omega,k}\int_0^{c^*_{\omega,k}} J_{\omega t,k}(c)dG_{\omega,k}(c) + \dot{J}_{\omega t,k}(c).$$

Taking the derivative of this equation with respect to c yields:

$$(\xi + \rho_{km})\frac{\partial}{\partial c}J_{\omega t,k}(c) = \gamma_{km}(\sigma - 1)K_{i,m}\,(p_{\omega t,-k})^{1-\sigma}\,c^{(1-\sigma)\gamma_{km}-1} + \frac{\partial}{\partial c}\dot{J}_{\omega t,k}(c)$$

[4] I assume that the cut-off value $c^*_{\omega,k}$ is determined ex-ante. If the cut-off were dependent on input prices in other sectors at each time point, obtaining a closed-form solution would be infeasible.

By integrating this expression from c to $c^*_{\omega,k}$, I have:

$$J_{\omega t,k}(c) - J_{\omega t,k}(c^*_{\omega,k}) = \frac{K_{i,m}\left(p_{\omega t,-k}\right)^{1-\sigma}}{\xi + \rho_{km}}\left[\left(c^*_{\omega,k}\right)^{(1-\sigma)\gamma_{km}} - c^{(1-\sigma)\gamma_{km}}\right] + \left[\dot{J}_{\omega t,k}(c) - \dot{J}_{\omega t,k}(c^*_{\omega,k})\right]$$

Using this equation, equation (E.6) is rewritten as:

$$\begin{aligned}\xi U^B_{\omega t,k} &= \Pi^{F,U}_{\omega t,k} + v_{i,km}a_{\omega,k}\int_0^{c^*_{\omega,k}} J_{\omega t,k}(c)dG_{\omega,k}(c) + \dot{U}_{\omega t,k} \\ &= \Pi^{F,U}_{\omega t,k} - v_{i,km}a_{\omega,k}\frac{K_{i,m}\left(p_{\omega t,-k}\right)^{1-\sigma}}{\xi + \rho_{km}}\left(c^*_{\omega,k}\right)^{(1-\sigma)\gamma_{km}}\frac{(1-\sigma)\gamma_{km}}{(1-\sigma)\gamma_{km}+\theta} \\ &\quad + v_{i,km}a_{\omega,k}J_{\omega t,k}(c^*_{\omega,k}) + \int_0^{c^*_{\omega,k}}\left[\dot{J}_{\omega t,k}(c) - \dot{J}_{\omega t,k}(c^*_{\omega,k})\right]dG_{\omega,k}(c) + \dot{U}^B_{\omega t,k}\end{aligned} \tag{E.11}$$

where the last transformation uses the fact that $G_{\omega,k}(\cdot)$ is the inverse of the Pareto distribution with dispersion parameter θ and upper bound $c^*_{\omega,k}$. By taking the expectation of this equation,

$$\xi E[U^B_{\omega t,k}] = E[\Pi^{F,U}_{\omega t,k}] - v_{i,km}a_{\omega,k}\frac{K_{i,m}E[\left(p_{\omega t,-k}\right)^{1-\sigma}]}{\xi + \rho_{km}}\left(c^*_{\omega,k}\right)^{(1-\sigma)\gamma_{km}}\frac{(1-\sigma)\gamma_{km}}{(1-\sigma)\gamma_{km}+\theta}. \tag{E.12}$$

Together with equations (E.9) and (E.10), and by solving for $E[\Pi^{F,U}_{\omega t,k}]$ using the Pareto distribution of input cost,

$$\begin{aligned}K_{i,m}{c^*_{\omega,k}}^{(1-\sigma)\gamma_{km}}E[\left(p_{\omega t,-k}\right)^{1-\sigma}] =& K_{i,m}E[\left(p_{\omega t,-k}\right)^{1-\sigma}](\chi^{\gamma_{km}})^{1-\sigma}\frac{\theta}{\theta+\gamma_{km}(1-\sigma)}\left(\bar{c}_{i,k}\right)^{\gamma_{km}(1-\sigma)} \\ & - v_{i,km}a_{\omega,k}\frac{K_{i,m}E[\left(p_{\omega t,-k}\right)^{1-\sigma}]}{\xi + \rho_{km}}\left(c^*_{\omega,k}\right)^{(1-\sigma)\gamma_{km}}\frac{(1-\sigma)\gamma_{km}}{(1-\sigma)\gamma_{km}+\theta}\end{aligned}$$

$$\begin{aligned}&\iff {c^*_{\omega,k}}^{(1-\sigma)\gamma_{km}}\left[1 - \frac{v_{i,km}a_{\omega,k}}{\xi+\rho_{km}}\frac{(\sigma-1)\gamma_{km}}{\theta-(\sigma-1)\gamma_{km}}\right] = \chi^{\gamma_{km}(1-\sigma)}\left(\bar{c}_{i,k}\right)^{(1-\sigma)\gamma_{km}}\frac{\theta}{\theta+\gamma_{km}(1-\sigma)} \\ &\iff \left(\frac{c^*_{\omega,k}}{\bar{c}_{i,k}}\right)^{\theta} = \chi^{\theta}\left(\frac{\theta+\gamma_{km}(1-\sigma)}{\theta}\right)^{\frac{\theta}{\gamma_{km}(\sigma-1)}}\left[1 - \frac{v_{i,km}a_{\omega,k}}{\xi+\rho_{km}}\frac{(\sigma-1)\gamma_{km}}{\theta-(\sigma-1)\gamma_{km}}\right]^{\frac{\theta}{(\sigma-1)\gamma_{km}}}\end{aligned} \tag{E.13}$$

Now, noting that $a_{\omega,k} = \left(\frac{c^*_{\omega,k}}{\bar{c}_{i,k}}\right)^{\theta}$ and $a_{\omega,k} \leq 1$,

$$a_{\omega,k} = \min\left\{1,\ \ \chi^{\theta}\left(\frac{\theta+\gamma_{km}(1-\sigma)}{\theta}\right)^{\frac{\theta}{\gamma_{km}(\sigma-1)}}\left[1-\frac{v_{i,km}a_{\omega,k}}{\xi+\rho_{km}}\frac{(\sigma-1)\gamma_{km}}{\theta-(\sigma-1)\gamma_{km}}\right]^{\frac{\theta}{(\sigma-1)\gamma_{km}}}\right\}, \tag{E.14}$$

and

$$c^*_{\omega,k} = \bar{c}_{i,k}a_{\omega,k}^{\frac{1}{\theta}}. \tag{E.15}$$

Furthermore, these expressions imply that $c^*_{\omega,k}$ and $a_{\omega,k}$ depend only on firms' location i and the supplier sector k such that $c^*_{\omega,k} = c^*_{i,km}$ and $a_{\omega,k} = a_{i,km}$.

E.3 Firm Heterogeneity for Supplier Demand

In this appendix, I extend the model to incorporate the feature that not all firms possess demand to match with external suppliers. In particular, I assume that only a fraction $\delta_{j,km}$ of firms in location j and sector m have the demand to match with a supplier in sector k. These exogenous parameters, $\delta_{j,km}$, can vary based on j, k, and m. By introducing these additional parameters, I can rationalize the differential patterns of supplier matching between conditional and unconditional on supplier bankruptcy as observed and documented in Appendix G and Table G.1.

The model remains largely unchanged, with the only modification being the replacement of the steady-state probability that a firm in location j and sector m has a direct relationship with a supplier in sector k, denoted as $\Lambda_{j,km}$ in equation (7), with the following expression:

$$\Lambda_{j,km} = \delta_{j,km}\frac{v_{j,km}}{v_{j,km}+\rho_{j,km}}. \tag{E.16}$$

Similarly, the counterfactual equilibrium remains the same as in Appendix F except that equation (F.7) is replaced with:

$$\hat{\Lambda}_{j,km} = \frac{(\Lambda_{j,km}/\delta_{j,km})\left(\hat{S}_{i,k}\right)^{\lambda^S}\left(\hat{B}_{i,m}\right)^{\lambda^B-1}}{(\Lambda_{j,km}/\delta_{j,km})\left(\hat{S}_{i,k}\right)^{\lambda^S}\left(\hat{B}_{i,m}\right)^{\lambda^B-1}+\left(1-\Lambda_{j,km}/\delta_{j,km}\right)}. \tag{E.17}$$

To undertake counterfactual simulation using this extended model in my sensitivity analysis (Appendix H), I additionally need to know the values of $\delta_{j,km}$. I calibrate $\delta_{j,km}$ using equation (E.16) with the observed steady-state match probability ($\Lambda_{j,km}$), model-predicted matching rates ($v_{j,km}$), and the observed link separation rates ($\rho_{j,km}$).

F System of Equations for Counterfactual Equilibrium

To conduct these counterfactual simulations, I follow the exact-hat algebra approach of Dekle et al. (2008) and rewrite the counterfactual equilibrium conditions in terms of the unobserved changes in the endogenous variables between the counterfactual and initial equilibria. I denote the value of a variable in the initial equilibrium by x, the value of this variable in the counterfactual equilibrium by x' (with a prime), and the relative change in this variable by $\hat{x} = x'/x$ (with a hat). Consider a counterfactual to change exogenous productivity $\hat{A}_{j,m}$ and iceberg trade costs $\hat{\tau}_{ij,m}$.[5] Given the values of the production and preference parameters $\{\alpha_k, \gamma_{L,m}, \gamma_{km}, \theta, \sigma, \varepsilon\}$, baseline population size and trade flows $\{L_i, \pi_{ij,k}, Y^F_{i,k}\}$, parameters and baseline variables for firm-to-firm matching $\{\lambda^S, \lambda^B, \chi\}$ and $\{\Lambda_{i,km}\}$, counterfactual equilibrium is computed in terms of the changes in the endogenous variables $\{\hat{\Lambda}_{i,km}, \hat{\Gamma}_{i,k}, \hat{\tilde{c}}_{i,k}, \hat{w}_j, \hat{N}_{j,m}, \hat{L}_j, \hat{A}_{j,m}\}$:

(i) Production and Trade Linkages:

$$\hat{\pi}_{ij,m} = \frac{\hat{\Gamma}_{i,m} \left(\hat{\tau}_{ij,m}\right)^{\theta}}{\sum_{\ell \in \mathcal{N}} \hat{\Gamma}_{\ell,m} \left(\hat{\tau}_{\ell j,m}\right)^{\theta} \pi_{\ell j,m}} \tag{F.1}$$

$$\hat{\Gamma}_{i,m} = \hat{N}_{i,m} \hat{A}^{\theta}_{i,m} \hat{w}_i^{-\theta\gamma_{L,m}} \prod_{k \in K} \hat{\tilde{c}}_{i,k}^{-\theta\gamma_{km}} \frac{1 + \Lambda'_{i,km} \left(\chi^{\theta\gamma_{km}} - 1\right)}{1 + \Lambda_{i,km} \left(\chi^{\theta\gamma_{km}} - 1\right)} \tag{F.2}$$

$$\hat{\Omega}_{j,m} = \sum_{\ell \in \mathcal{N}} \hat{\Gamma}_{\ell,m} \left(\hat{\tau}_{\ell j,m}\right)^{\theta} \pi_{\ell j,m} \tag{F.3}$$

$$\hat{\tilde{c}}_{j,k} = \left[\frac{\hat{L}_j}{\hat{\Omega}_{j,k}}\right]^{1/\theta} \tag{F.4}$$

(ii) Matching:

$$\hat{S}_{j,k} = \hat{\Omega}_{j,k} \left(\hat{\tilde{c}}_{j,k}\right)^{\theta} \tag{F.5}$$

$$\hat{B}_{j,m} = \hat{N}_{j,m} \tag{F.6}$$

$$\hat{\Lambda}_{j,km} = \Lambda_{j,km} \left(\hat{S}_{j,k}\right)^{\lambda^S} \left(\hat{B}_{j,m}\right)^{\lambda^B - 1} + \left(1 - \Lambda_{j,km}\right) \tag{F.7}$$

(ii) General Equilibrium:

$$\hat{N}_{j,m} = \frac{1}{\hat{w}_j} \frac{\sum_i \pi'_{ji,m} Y^{F\prime}_{i,m}}{\sum_i \pi_{ji,m} Y^F_{i,m}} \tag{F.8}$$

[5]The counterfactual to change population size $\hat{L}_j$ follows the same procedure, except that equation (F.14) is replaced by the assumed exogenous values.

$$\hat{A}_{i,m} = \hat{\bar{A}}_{i,m} \hat{L}_i^{\varepsilon} \tag{F.9}$$

$$\hat{Y}^F_{i,k} = \hat{w}_i \hat{L}_i \tag{F.10}$$

$$Y^{I'}_{i,km} = \gamma_{km} \tilde{X}'_{i,m} \tag{F.11}$$

$$\tilde{X}'_{i,m} = \sum_{j \in \mathcal{N}} \left(\sum_{m' \in K} Y^{I'}_{j,mm'} + \frac{\sigma - 1}{\sigma} Y^{F'}_{j,m'} \right) \pi'_{ij,m'} \tag{F.12}$$

$$\hat{w}_i = \frac{1}{\hat{L}_i} \frac{\sum_k \left(\gamma_{L,k} \tilde{X}'_{i,k} + \frac{\sigma-1}{\sigma\theta} \sum_{j \in \mathcal{N}} Y^{F'}_{j,k} \pi'_{ij,k} + \frac{\theta-\sigma+1}{\sigma\theta} Y^{F'}_{i,k} \right)}{\sum_k \left(\gamma_{L,k} \tilde{X}_{i,k} + \frac{\sigma-1}{\sigma\theta} \sum_{j \in \mathcal{N}} Y^{F}_{j,k} \pi_{ij,k} + \frac{\theta-\sigma+1}{\sigma\theta} Y^{F}_{i,k} \right)} \tag{F.13}$$

$$\hat{L}_j = \frac{\left(\hat{w}_j / \hat{P}_j \right)^{\upsilon}}{\sum_{\ell} \left(\hat{w}_{\ell} / \hat{P}_{\ell} \right)^{\upsilon} L_{\ell}} \tag{F.14}$$

G Model Fit to Untargeted Moments

In this appendix, I discuss additional evidence of model fit.

New Supplier Link Creation Rates Unconditional on Supplier Bankruptcy. In Section 5, I calibrate the matching function elasticities targeting the spatial heterogeneity of new supplier matching rates *conditional on* supplier bankruptcy. In this calibration process, I do not specifically target the spatial heterogeneity of supplier matching rates *unconditional on* supplier bankruptcy. To assess how these untargeted statistics align between the data and model predictions, in Table G.1, I report the regression coefficients of the log of new supplier link creation rates *unconditional on supplier loss* on the log of supplier density ($S^*_{j,k}$, as defined in Section 3) for each sector pairs and (buyer) location. For the model predictions (Columns 1 and 3), I calculate the independent variable using the expression $(1 - \exp(\eta S^{*\lambda^S}_{j,k} B^{\lambda^B}_{j,m})) \times (1 - \Lambda_{j,km})$, where the multiplication by $1 - \Lambda_{j,km}$ reflects the fact that firms with ongoing supplier relationships do not match with new suppliers. For the data (Columns 2 and 4), I calculate the independent variable as the average number of new linkages generated per year and buyer.

Both the model prediction and the data reveal a significant positive relationship between new supplier link creation rates and supplier density. However, it is worth noting that the coefficient on the log supplier density is larger in the model prediction (0.52, Column 1) compared to the data (0.20, Column 2). Additionally, the intercepts are larger in the model (-3.07) than in the data (-4.35). This evidence indicates that the model tends to overpredict the new supplier creation rates, particularly for locations and sectors with high supplier density.

One potential explanation for this discrepancy lies in the existence of unmodeled het-

Table G.1: Supplier Link Creation Rates: Model vs Data

	log New Supplier Link Creation Rates (Unconditional on Supplier Loss)			
	Model	Data	Model	Data
	(1)	(2)	(3)	(4)
log Supplier Density	0.52^{***}	0.20^{***}	0.66^{***}	0.34^{***}
	(0.06)	(0.03)	(0.06)	(0.03)
Constant	-3.07^{***}	-4.35^{***}		
	(0.13)	(0.14)		
Prefecture FE			X	X
Supplier Sector FE			X	X
Observations	1,547,590	1,547,590	1,547,590	1,547,590
Adjusted R^2	0.81	0.15	0.86	0.42

Note: Standard errors are clustered at the supplier sector and prefecture level. *p<0.1; **p<0.05; ***p<0.01.

erogeneity in the demand for matching with suppliers. To grasp the intuition, consider a scenario where a subset of firms in the economy has no demand for external suppliers. As a result, these firms never encounter supplier bankruptcies, and thus they are excluded from the samples in Section 3 and do not influence the calibrated matching function elasticities (λ^S and λ^B). However, their presence does impact the heterogeneity of supplier matching rates *unconditional on* supplier bankruptcy.

To address this potential model misspecification, I introduce an extension to the model in Appendix E.3, which incorporates firm heterogeneity regarding the demand for external suppliers across different sectors and locations. In my sensitivity analysis for counterfactual simulations (Appendix H), I demonstrate the robustness of my findings when considering this alternative specification.

Aggregate Sales by Location and Sector. Another untargeted moment in my calibration procedure is the aggregate firm sales by sector and location. Unlike the approach taken by Caliendo and Parro (2014), where they precisely match the world input-output tables at a detailed sector and location level, my calibration only targets the aggregate input-output table (aggregated across locations) and the cross-regional trade patterns.

Table G.2 presents the regression coefficients for the log aggregate sales, both predicted by the model and observed in the data, against a measure of supplier access ($\prod_{k\in K}\left(1+\Lambda_{i,km}\left(\chi^{\theta\gamma_{km}}-1\right)\right)$ that appears in equation (8). Both the model prediction and the data exhibit a positive relationship between aggregate sales and the supplier access measure. The regression coefficients are similar, with the model prediction at 0.89 (Column 1) and the data at 0.99 (Column 2). These findings hold even when controlling for prefecture and sector fixed effects (Columns 3 and 4). These results provide further support for the adequacy of my model, particularly the market clearing assumptions used in calibrating the input and final goods demand, $Y^I_{j,km}$ and $Y^F_{j,k}$.

Table G.2: Aggregate Sales: Model vs Data

	log Sales (Normalized)			
	Model	Data	Model	Data
	(1)	(2)	(3)	(4)
log Supplier Access	0.89^{**}	0.99^{**}	0.52^{**}	0.51^{*}
	(0.40)	(0.44)	(0.24)	(0.26)
Prefecture FE			X	X
Sector FE			X	X
Observations	3,700	3,700	3,700	3,700
Adjusted R^2	0.42	0.64	0.78	0.89

Note: Standard errors are clustered at the prefecture level. log supplier access is defined by $\prod_{k \in K} \left(1 + \Lambda_{i,km} \left(\chi^{\theta \gamma_{km}} - 1\right)\right)$. *p<0.1; **p<0.05; ***p<0.01.

H Additional Results and Sensitivity Analysis for Counterfactual Simulations

In this appendix, I provide additional results and sensitivity analysis of the counterfactual simulation in Section 5.2.

Increasing Population Size in Tokyo. Figure H.1 presents the results of a counterfactual simulation of increasing Tokyo's population size on average real wages in Japan and in various prefectures within Japan.

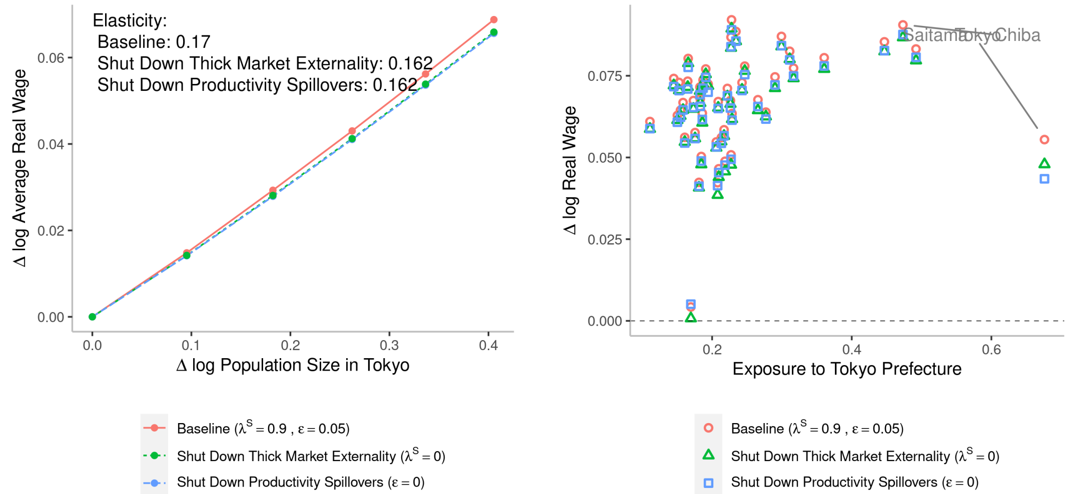
Table H.1 presents a sensitivity analysis of the same counterfactual simulation regarding the increase in Tokyo's population size. For each model specification, Column (a) presents the elasticity of Tokyo's real wage with population size in baseline specification, Column (b) presents the same elasticity by shutting down thick market externality, and Column (c) presents the same elasticity by shutting down productivity spillovers. Row (1) represents the baseline specification from Table H.1, which serves as the reference point for further analysis. In the subsequent analysis, I specifically focus on the contribution of thick market externality to this elasticity (Column b; "Diff. from Baseline").

Rows (2) to (7) provide a sensitivity analysis of the matching function elasticities (λ^S and λ^B) and the iceberg cost of indirect sourcing (χ). These alternative parameter values are calibrated based on the same methodology as outlined in Section 5.1.2, targeting plus and minus 1.64 times the standard errors of the point estimates from the reduced-form regression coefficients in Columns (3) and (5) of Table 6. As anticipated, the contribution of thick market externality varies significantly across different parameter values, although it consistently has a negative sign, indicating a positive influence of thick market externality on agglomeration benefits.

Rows (8) and (9) consider alternative values for σ and θ, which impact the overall

Figure H.1: Effects of Increasing Population Size in Tokyo

(A) Average Real Wage in Overall Japan (B) Real Wage in Other Prefectures



Note: Results of the counterfactual simulation to increase population size in Tokyo prefecture. Panel (A) plots the log changes in average real wages across Japan against the log change in Tokyo prefecture's population size. Panel (B) shows the log changes in real wages in each prefecture for a 50 percent increase in Tokyo's population size against the prefecture's exposure to Tokyo prefecture, defined as the share of supplier linkages from Tokyo prefecture.

agglomeration benefit (Column a) through the love-of-variety externality from firm entry and pooling externality discussed in Section 4.3. Notably, with $\sigma = 5$ and $\theta = 5$, the agglomeration benefit becomes negative due to the dominance of pooling externality over other positive agglomeration externalities. However, the contribution of thick market externality remains stable in this scenario.

Rows (10) and (11) consider different values of agglomeration productivity spillovers ε. The contribution of thick market externality remains stable.

In Row (12), I consider an alternative model specification to incorporate profits from intermediate input sales as discussed in Appendix E.1. In Row (13), I consider an alternative model specification to accommodate forward-looking match acceptance decisions by input buyers as discussed in Appendix E.2.[6] In both specifications, the contribution of thick market externality remains similar.

In Row (14), I consider an alternative model specification discussed in Appendix E.3, where only a fraction $\delta_{j,km}$ of firms in location j and sector m have demand to match with a supplier in sector k. Interestingly, I observe a somewhat larger contribution of thick market externality in this specification. This can be attributed to the fact that the changes in matching rates ($v_{j,km}$) triggered by an increase in population size have a more pronounced impact on the steady-state match probability ($\Lambda_{j,km}$) in this model specification (as seen in equation E.17). Consequently, the contribution of thick market externality becomes more significant in this alternative model specification.

[6]For this simulation, I set the discount rate ζ to 0.03.

Table H.1: Sensitivity Analysis: Effects of Increasing Population Size in Tokyo

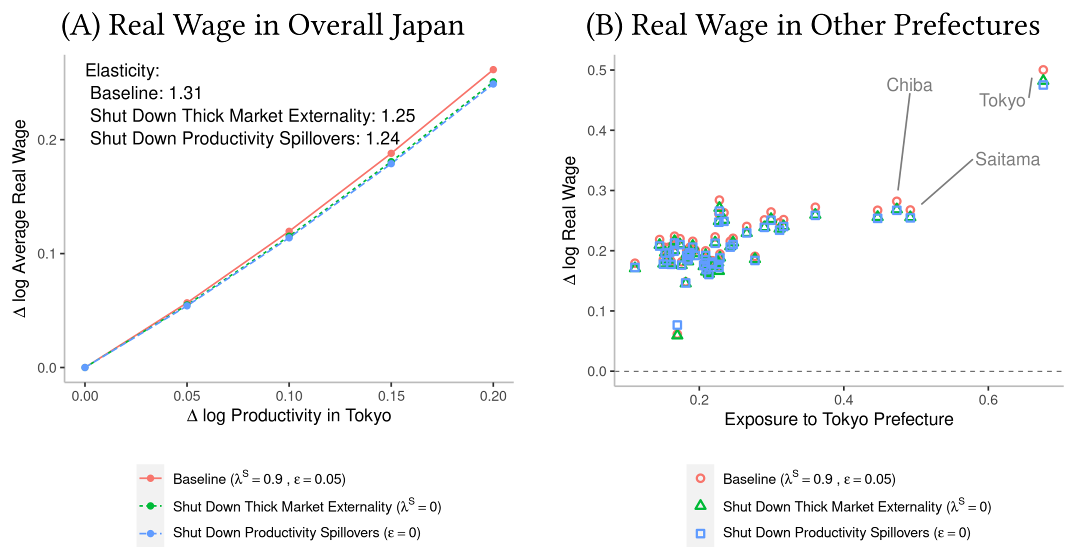
Specification	(a) Baseline	(b) $\lambda^S = 0$	Diff. from Baseline	(c) $\varepsilon = 0$	Diff. from Baseline
(1) baseline	0.137	0.118	-0.019	0.107	-0.030
(2) $\lambda^S = 1.39$	0.157	0.118	-0.039	0.127	-0.030
(3) $\lambda^S = 0.46$	0.125	0.118	-0.006	0.095	-0.030
(4) $\lambda^B = 1.29$	0.146	0.121	-0.025	0.117	-0.030
(5) $\lambda^B = 0.60$	0.128	0.116	-0.012	0.098	-0.030
(6) $\chi = 2.48$	0.178	0.118	-0.060	0.149	-0.030
(7) $\chi = 1.15$	0.126	0.118	-0.008	0.096	-0.030
(8) $\sigma = 5$ and $\theta = 5$	-0.092	-0.111	-0.019	-0.122	-0.030
(9) $\sigma = 5$ and $\theta = 10$	0.045	0.021	-0.024	0.010	-0.036
(10) $\varepsilon = 0.1$	0.167	0.148	-0.019	0.107	-0.059
(11) $\varepsilon = 0.03$	0.125	0.106	-0.019	0.107	-0.018
(12) Incorporate Profit for Intermediate Goods Sales	0.136	0.121	-0.016	0.107	-0.030
(13) Introduce Firms without Demand for Suppliers	0.136	0.118	-0.017	0.106	-0.030
(14) Introduce Forward-Looking Match Acceptance	0.149	0.118	-0.031	0.119	-0.030

Note: Results of the counterfactual simulation to increase population size in Tokyo prefecture under alternative specifications indicated by the first column. Column (a) shows the elasticity of Tokyo's real wages with Tokyo's population (following the same definition as Table 7) under baseline specification; Column (b) shows the results under no thick market externality ($\lambda^S = 0$); Column (c) shows the results under no agglomeration productivity spillover ($\varepsilon = 0$). See the main text for further details about each specification.

Increasing Productivity in Tokyo. Figure H.2 presents the results of a counterfactual simulation to increase Tokyo's productivity on aggregate welfare in Japan and real wages in different prefectures in Japan.

In Table H.2, I provide a sensitivity analysis for the same counterfactual simulation. The patterns observed in the sensitivity analysis closely mirror those observed in Table H.1. Rows (15) and (16) introduce an alternative calibration for the migration elasticity υ. As anticipated, a larger value of υ leads to a greater contribution of thick market externality. This occurs because a higher migration elasticity induces more significant population responses to the productivity shock, thereby amplifying the effects of thick market externality.

Figure H.2: Effects of Increasing Productivity in Tokyo



Note: Results of the counterfactual simulation to increase productivity in Tokyo prefecture. Panel (A) plots the log changes in aggregate welfare in Japan ($\mathcal{U}$) against the log change in Tokyo prefecture's population size. Panel (B) shows the log changes in real wages in each prefecture for a 20 percent increase in Tokyo's productivity against the prefecture's exposure to Tokyo prefecture, defined as the share of supplier linkages from Tokyo prefecture.

Table H.2: Sensitivity Analysis: Effects of Increasing Productivity in Tokyo

Specification	(a) Baseline	(b) $\lambda^S = 0$	Diff. from Baseline	(c) $\varepsilon = 0$	Diff. from Baseline
(1) baseline	0.252	0.238	-0.014	0.238	-0.014
(2) $\lambda^S = 1.39$	0.251	0.238	-0.014	0.238	-0.014
(3) $\lambda^S = 0.46$	0.248	0.238	-0.010	0.234	-0.014
(4) $\lambda^B = 1.29$	0.252	0.242	-0.010	0.238	-0.014
(5) $\lambda^B = 0.60$	0.249	0.233	-0.017	0.236	-0.014
(6) $\chi = 2.48$	0.279	0.238	-0.042	0.262	-0.017
(7) $\chi = 1.15$	0.244	0.238	-0.006	0.231	-0.013
(8) $\sigma = 5$ and $\theta = 5$	0.181	0.175	-0.007	0.175	-0.006
(9) $\sigma = 5$ and $\theta = 10$	0.269	0.251	-0.018	0.251	-0.018
(10) $\varepsilon = 0.1$	0.268	0.252	-0.016	0.238	-0.030
(11) $\varepsilon = 0.03$	0.246	0.232	-0.014	0.238	-0.008
(12) Incorporate Profit for Intermediate Goods Sales	0.251	0.240	-0.011	0.238	-0.013
(13) Introduce Firms without Demand for Suppliers	0.253	0.238	-0.015	0.239	-0.014
(14) Introduce Forward-Looking Match Acceptance	0.246	0.238	-0.009	0.233	-0.013
(15) $\upsilon = 4$	0.255	0.223	-0.031	0.232	-0.022
(16) $\upsilon = 1$	0.223	0.220	-0.003	0.218	-0.004

Note: Results of the counterfactual simulation to increase productivity in Tokyo prefecture under alternative specifications indicated by the first column. Column (a) shows the elasticity of Tokyo's real wages with Tokyo's productivity (following the same definition as Table 8) under baseline specification; Column (b) shows the results under no thick market externality ($\lambda^S = 0$); Column (c) shows the results under no agglomeration productivity spillover ($\varepsilon = 0$). See the main text for further details about each specification.