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

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Abstract

This paper proposes a new microfoundation for the agglomeration of economic activity: increasing returns to scale in supplier-to-buyer matching. Using a yearly panel of firm-to-firm trade in Japan, I document that firms gradually match with an alternative supplier after an unanticipated supplier bankruptcy; these rematching rates increase in the geographic density of alternative suppliers, and they do not decrease in the geographic density of other buyers. Motivated by these findings, I develop a quantitative spatial equilibrium model of search and matching frictions in firm-to-firm input trade. By fitting the model to the reduced-form facts, I show that the increasing returns to scale in matching is as important as other agglomeration forces in explaining the geographic concentration of economic activity. In the counterfactuals for a reduction in cross-regional trade cost, misattributing these agglomeration mechanisms substantially biases the estimates of welfare gains.

Keywords: Agglomeration, Production Networks, Economic Geography

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1 Introduction

Firms are more productive in more densely populated areas. There is a broad consensus that a non-trivial fraction of this pattern is driven by agglomeration spillovers.[1] However, there is limited consensus on what precise *mechanisms* of agglomeration spillovers contribute to this phenomena.[2]

One important mechanism originating from Marshall (1890) is that suppliers and buyers in urban areas have more opportunities to meet and initiate transactions. Although intuitive, this agglomeration mechanism has been relatively unexplored both empirically and theoretically. Empirically, evidence of this type of agglomeration force is scarce due to a lack of micro-data on supplier-to-buyer linkages. Theoretically, the complexity of modeling matching frictions in production linkages that connect different regions and industries has been a challenge for building a microfounded model of this type of agglomeration.

In this paper, I study how increasing returns to scale in supplier-to-buyer matching shapes the agglomeration of economic activity. I open this paper by providing a set of reduced-form facts suggestive of this agglomeration mechanism using firm-to-firm trade data in Japan. Based on the reduced-form evidence, I develop a quantitative spatial equilibrium model of search and matching frictions in firm-to-firm input trade. The model accommodates rich heterogeneity in location fundamentals and in trade frictions across regions yet provides tractable aggregate equilibrium conditions for wages, population, bilateral trade flows, and welfare. I estimate the model's key structural parameters in a sequential procedure to fit the reduced-form evidence. Finally, through a sequence of counterfactual simulations, I show that this agglomeration mechanism has a sizable contribution to the spatial distribution of economic activity and to the welfare effects of cross-region trade cost reduction.

I first provide a set of new reduced-form facts suggestive of the matching frictions and increasing returns to scale in supplier-to-buyer matching. Inspired by the labor market literature on firm-to-worker matching, I document how firms respond to unanticipated

[1] See, for example, Ciccone and Hall (1996), Greenstone, Hornbeck, and Moretti (2010), Combes, Duranton, Gobillon, Puga, and Roux (2012), Gaubert (2018) for evidence of agglomeration on firm productivity.

[2] Marshall (1890) identified knowledge spillovers, labor market pooling, and industry linkages as three important agglomeration mechanisms, and Duranton and Puga (2004) classified them into sharing, matching, and learning mechanisms. Empirically, Ellison, Glaeser, and Kerr (2010) studied how various proxies of different agglomeration mechanisms are correlated with observed industry coagglomeration patterns.

supplier bankruptcies by using a panel of firm-to-firm trade data in Japan.[3] After these shocks, firms are in need of alternative suppliers. I document three facts about firms' responses to these shocks. First, firms match with alternative suppliers only gradually and their sales decline. Second, these matching rates increase in the geographic density of alternative suppliers. Third, these matching rates are not correlated with the density of other buyers.

How do these patterns of firm-to-firm trade matter for the spatial distribution of economic activity? To answer this question, I develop a spatial equilibrium model of search and matching frictions in firm-to-firm trade. The model embeds search and matching in input trade (Diamond 1982, Pissarides 1985, Mortensen 1986) in a static framework of firm-to-firm trade in space (Eaton, Kortum, and Kramarz 2016) and in a spatial equilibrium framework with population mobility (Allen and Arkolakis 2014, Redding and Rossi-Hansberg 2017).

The model accommodates two distinct agglomeration spillovers. One type of agglomeration spillover is the increasing returns to scale (IRS) in firm-to-firm matching technology. The other type of agglomeration spillover is the direct effect of local population density on productivity (summarizing all other agglomeration spillovers). I estimate these two agglomeration spillovers using the model's equilibrium conditions and the firm-to-firm trade data. In particular, I estimate the elasticities of firm-to-firm matching technology to fit the reduced-form effects of unanticipated supplier bankruptcies. I also estimate the elasticity of production spillover from local population density by using the spatial productivity distribution revealed from the gravity equations of cross-region trade flows. My estimates suggest that both types of agglomeration spillovers are quantitatively relevant in explaining the spatial productivity distribution.

Equipped with the estimated model, I undertake a sequence of counterfactual simulations to quantify these two agglomeration spillovers in general equilibrium. I show how to use the model structure and the initial values of endogenous variables to undertake these counterfactual simulations, extending the "exact-hat algebra" approach by Dekle, Eaton, and Kortum (2008). In my first counterfactual simulation, I hypothetically shut down each of these two agglomeration spillovers. When I shut down the increasing returns to scale in

[3] See Petrongolo and Pissarides (2001) for a survey of estimating matching frictions in labor market. In particular, Bleakley and Lin (2012) and Jäger and Heining (2019) use exogenous separation between workers and firms (displacement of workers and the death of a worker, respectively) to identify matching frictions, similar in spirit to the use of unanticipated supplier bankruptcy in this paper. Berliant, Reed, and Wang (2006) and Bilal (2020) connect these matching frictions in labor markets to agglomeration.

matching, the population-density premium in wages (regression slope of the logarithms of wages on the logarithm of population density) declines by 41 percent compared to the actual relationship. In comparison, when I further shut down the spillovers from local population density (which summarizes all other agglomeration forces), the population-density premium becomes negative and declines by 117 percent compared to the actual relationship. Therefore, the contribution of the IRS in matching technology on observed population-wage premium is nonnegligible to that of the overall agglomeration spillovers.

In my second counterfactual simulation, I study how a reduction of regional trade cost affects aggregate welfare in the presence of these two types of agglomeration spillovers. Calibrating the reduction of these trade costs from the travel time reduction from Japan's existing highway networks, I find a 6.19 percentage point increase in welfare from this trade cost reduction. When I undertake the same counterfactual simulation by omitting the IRS in matching technology, the predicted welfare gain is 4.53 percentage points, which is 27 percent smaller. On the other hand, omitting the production spillovers from local population density does not meaningfully affect the estimates of welfare gains. This difference arises because of the differences of the margins on which agglomeration spillover arises. The trade cost reduction directly increases the pool of capable suppliers in each location when trade occurs across regions. This effect increases local productivity in the presence of IRS in matching. On the other hand, population spillovers have a limited effect on aggregate welfare because productivity gains in locations with a population increase are largely offset by the productivity losses in locations with a population decrease. This result indicates that misattributing the agglomeration mechanisms substantially biases the estimates of welfare gains of the trade cost reduction.

This paper contributes to different strands of literature. First, this paper contributes to the literature on agglomeration mechanisms through matching frictions and increasing returns to scale in supplier-to-buyer matching. As noted earlier, previous work is limited due to a lack of micro-data on supplier-to-buyer linkages and the complexity of modeling matching frictions in production linkages across regions and industries. The closest empirical evidence is provided by Holmes (1999), who documents that firms in denser areas tend to have higher shares of input purchase from external suppliers. Krugman and Venables (1995) and Venables (1996) propose a theoretical model of agglomeration through the love of varieties in intermediate inputs. This paper instead focuses on matching frictions and IRS in firm-to-firm matching technology.

Second, this paper contributes to the growing literature on the endogenous formation of firm-to-firm production networks, and it is particularly related to general equilibrium models of firm-to-firm trade with stochastic matching between suppliers and buyers.[4] My theoretical model is closest to that of Eaton, Kortum, and Kramarz (2016), who build a static model of firm-to-firm trade across space under search frictions. I extend their model to incorporate dynamic search and matching, which is consistent with the reduced-form evidence from unanticipated supplier bankruptcy.[5] My model is also related to Oberfield (2018), who characterizes general equilibrium of stochastic supplier-to-buyer matching, and Lim (2018) and Huneeus (2018), who model dynamic evolution of firm-to-firm trade in a similar framework. Unlike these papers, I explicitly incorporate geographic structure in which firm-to-firm trade occurs and derive tractable equilibrium conditions for wages, population, aggregate bilateral trade flows, and welfare. This feature of my model allows me to microfound the agglomeration of economic activity through firm-to-firm trade.[6]

Third, this paper contributes to the growing literature on quantitative spatial equilibrium models (Allen and Arkolakis 2014, Redding and Rossi-Hansberg 2017). So far, this literature has been agnostic about the nature of agglomeration mechanisms, and it typically introduces a reduced-form assumption such that the agglomeration spillover is summarized by local population density. In contrast, this paper builds a micro-founded model of agglomeration through supplier-to-buyer matching and shows that the correct specification of agglomeration mechanisms matters for the counterfactuals for trade cost reduction.[7]

Fourth, this paper contributes to the literature highlighting the implication of search and matching frictions in international and domestic trade. This paper is closest to Allen (2014) and Krolikowski and McCallum (2021), who adopt a dynamic search and match-

[4]See Bernard, Moxnes, and Saito (2019) and Dhyne, Kikkawa, Mogstad, and Tintelnot (2020) for the deterministic models of firm-to-firm trade network formation, and Bernard and Moxnes (2018) and Antràs and Chor (2021) for the broader survey of endogenous production network formation.

[5]See Panigrahi (2021) for an extension of Eaton, Kortum, and Kramarz (2016) to incorporate multiple dimensions of firm heterogeneity.

[6]Other papers on endogenous firm-to-firm trade networks focus on the role of domestic and international sourcing decisions (Furusawa, Inui, Ito, and Tang 2017), firm size distribution (Bernard, Dhyne, Magerman, Manova, and Moxnes 2020), misallocation of production resources (Boehm and Oberfield 2020), market power distortions (Kikkawa, Magerman, and Dhyne 2020), effects of supplying to multinational companies (Alfaro-Ureña, Manelici, and Vasquez 2020), and firms' quality choices (Demir, Fieler, Xu, and Yang 2021).

[7]Other recent applications of quantitative spatial models include Diamond (2016), Fajgelbaum and Gaubert (2020), Nagy (2020). Papers using quantitative spatial equilibrium framework to study the effects of transport infrastructure include Donaldson and Hornbeck (2016), Allen and Arkolakis (2019), Fajgelbaum and Schaal (2019), Cosar, Demir, Ghose, and Young (2020), as surveyed by Redding and Turner (2015).

ing framework for the relationship formation between suppliers and buyers in multiple heterogeneous locations.[8] Unlike these papers, I model production networks where firms and industries are interconnected through input-output linkages, and how the increasing returns to scale in matching technology in these production networks connect to the agglomeration phenomena.

The rest of the paper is organized as follows. Section 2 describes the main data set. Section 3 presents reduced-form evidence of firms' responses to unanticipated supplier bankruptcies. Section 4 develops a spatial equilibrium model of firm-to-firm matching. Section 5 estimates the model by combining the model's equilibrium conditions and firm-to-firm trade data. Section 6 presents a sequence of counterfactual simulations. Section 7 concludes.

2 Data

This paper's main data set of firm-to-firm trade comes from Tokyo Shoko Research (TSR), a major credit reporting company in Japan. TSR collects data through face-to-face or phone interviews, and this data is complemented by public resources (financial statements, corporate registrations, and public relations documents). The data is constructed as a yearly panel from 2008 to 2016, covering nearly 70% of all firms in Japan.[9]

Each year, TSR's field surveyors ask each firm to report up to 24 main suppliers and buyers.[10] This paper uses a snapshot of this database at the end of each year. In my analysis, I exclude supplier linkages if there is a major ownership linkage between the firms (corresponding to 1.5% of all supplier linkages). In the baseline analysis, I define the supplier linkages as those reported by the buyer-side firms. I show that my empirical results are robust to including the linkages reported by supplier-side firms.

The data set reports the addressees of each firm's headquarters and all of its establishments. At the same time, supplier-to-buyer linkages are reported at the firm level but

[8] 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 (2016), Startz (2021), Lenoir, Martin, and Mejean (2020).

[9] See Appendix Table A.1. Appendix Figure A.1 shows that the coverage rates of the firms in TSR data set are similar across different municipalities in Japan. Nakajima, Saito, and Uesugi (2013), Bernard, Moxnes, and Saito (2019) and Furusawa, Inui, Ito, and Tang (2017) have previously used this data set to study the spatial extent of firm-to-firm trade, and Carvalho, Nirei, Saito, and Tahbaz-Salehi (2020) used it to study the propagation of shocks from Tohoku Earthquake in Japan through production networks.

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

not at the establishment level. In my main analysis below, I proxy firms' location by the location of their headquarters. I show that the main empirical results are robust to restricting firms whose establishments are concentrated in a single prefecture to deal with the mismeasurement of the location where transactions actually occur.

I merge this firm-to-firm data set with the list of bankruptcies that documents their main reasons. This data is also constructed by TSR through their investigation of the involved parties. About 2 percent of bankruptcies are classified as "unanticipated reasons," which is described as "bankruptcies due to unanticipated accidental problems such as the death of representatives, flood disaster, fire, earthquake, traffic accident, fraud, theft, embezzlement, etc," in a TSR's internal document. In the next section, I use these unanticipated bankruptcies of suppliers as a natural experiment to provide evidence for matching frictions.[11]

Before proceeding to my main empirical results using unanticipated supplier bankruptcy, I first provide suggestive evidence for the agglomeration benefit through supplier-to-buyer matching. First, supplier linkages are geographically concentrated. Panel (A) of Figure 1 shows the cumulative distribution function of the geographic distance between the headquarters of a supplier and a buyer. The median distance between a supplier and a buyer is 37 kilometers, which is substantially smaller than the median distance of all possible pairs in Japan (172 kilometers; Bernard, Moxnes, and Saito 2019). These patterns of results indicate that there is a strong tendency for firms to source from local suppliers, though a nonnegligible fraction of trade occurs across regions.

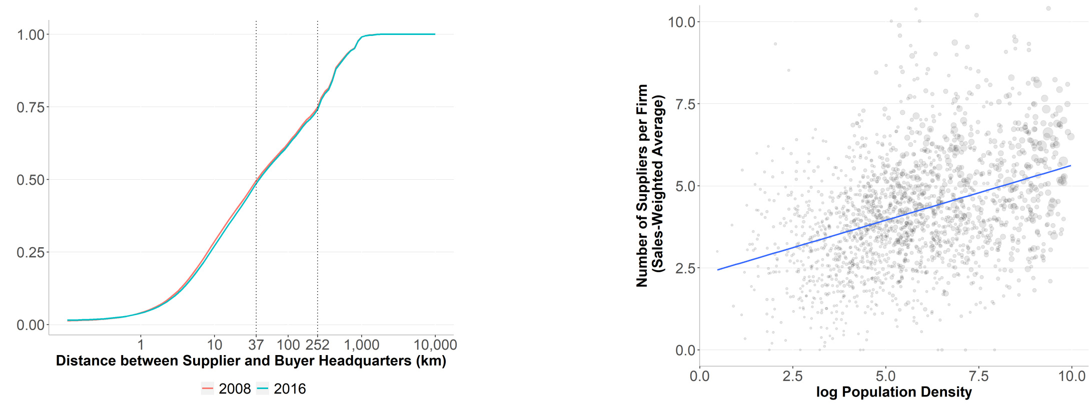
If firms have a tendency to source from local suppliers, do firms in denser areas tend to match with more suppliers? Panel (B) of Figure 1 shows that there is a stark positive correlation between the population density and the number of suppliers per firm at the municipality level. This finding is in line with Holmes (1999), who documents the positive correlation between the fraction of externally purchased inputs per firm and firm density in the United States. These pieces of evidence are suggestive of the link between agglomeration and matching frictions in firm-to-firm trade. However, they are also consistent with an alternative hypothesis that firms in different locations have different demand for external suppliers. In the next section, I provide more direct evidence of matching frictions

[11] Appendix Table A.2 reports the list of all reasons and its share out of all reported bankruptcies. Appendix Figure A.2 shows that these unanticipated bankruptcies occur equally across space and time, suggesting that these bankruptcies are not driven by a single regional shock such as the Great Tohoku Earthquake. I also show that my results are robust to excluding firms in the Tohoku area after 2011, the year of the Great Tohoku Earthquake (Appendix Table B.7).

in firm-to-firm trade using unanticipated supplier bankruptcies as a natural experiment.

Figure 1: Cross-Sectional Evidence of Supplier-to-Buyer Matching and Agglomeration

(A) Distances between Suppliers and Buyers (B) Number of Suppliers and 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. In 2008, median and 75th percentiles of the distributions are 37 and 252 kilometers, respectively. Panel (B) shows the relationship between the population density and the average number of suppliers per firm at the municipality level in 2008, where the latter is weighted by the (buyer-side) firms' sales.

3 Evidence from Unanticipated Supplier Bankruptcies

In this section, I document how firms respond to unanticipated supplier bankruptcies by using a panel of firm-to-firm trade data in Japan. These documented patterns are jointly suggestive of the presence of matching frictions and the increasing returns to scale in matching technology as modelled in Section 4. I also use these reduced-form estimates to estimate the key model parameters in Section 5.

3.1 Average Effects of Unanticipated Supplier Bankruptcies

To understand the nature of matching frictions in firm-to-firm trade, I focus on firms' responses to unanticipated supplier bankruptcies. After these shocks, firms are in need of alternative suppliers. How these firms respond to these supplier bankruptcies is informative about the nature of matching frictions, similar in spirit to the labor search and matching literature that studies the consequences of firm-to-worker separation (Petrongolo 2001, Bleakley and Lin 2012, Jäger and Heining 2019).

In order to identify matching frictions, it is important that these supplier bankruptcies are exogenous to the (buyer-side) firm. For example, if supplier bankruptcy is due to the discontinuation of a product line by the buyer-side firm, the imperfect recovery simply reflects the lack of demand. Therefore, I focus on cases where the reported reason for the bankruptcy is due to "unanticipated reasons" as discussed in Section 2.

To identify the impacts of unanticipated supplier bankruptcies, I implement the difference-in-difference method. For each treatment firm (i.e., firms experiencing unanticipated supplier bankruptcy), I select control firms whose headquarters are in the same municipality and have a supplier in the same four-digit industry as the bankrupt supplier (one year prior to its bankruptcy). Denoting the group of treatment and control firms by g, I estimate the following regression equation:

$$Y_{fgt} = \beta Post_{gt} \times Trt_f + \eta_{gt} + \xi_{fg} + \epsilon_{fgt}, \tag{1}$$

where f is the firm, t is the year, Trt_f denotes the dummy variable that takes one if f is the treatment firm, $Post_{gt}$ is the dummy that takes one if t is after the bankruptcy, and Y_{fgt} is the outcome variable (e.g., number of new suppliers, sales). This regression controls for the group and year fixed effects η_{gt} (so that β is identified off of the within-group comparison) and firm fixed effects ξ_{fg} (so that β does not capture time-invariant firm heterogeneity).[12] Standard errors are clustered at the firm f level. In order to give an equal weight on each group g, each control firm is weighted by the inverse of the number of control firms of group g.[13]

To ensure that control firms are not indirectly affected through supply-chain networks, I exclude control firms that are within second-degree proximity (in firm-to-firm trade network) to firms experiencing unanticipated bankruptcies at some point in the sample period. I further exclude firms whose reported accounting year is not updated for more than one year (at the point of the baseline period). The final sample consists of 421 treatment firms that are connected to 161 bankrupt suppliers, with 10,842 assigned control firms in total.

The identifying assumption of the regression equation (1) is that unobserved trend in outcome variables are uncorrelated with the unanticipated supplier bankruptcy. This assumption is plausibly satisfied if these bankruptcies are indeed unanticipated. In fact, Appendix Table B.1 shows that the characteristics of treatment firms and the control firms

[12] Note that firm f may appear multiple times as control firms in a different group g.

[13] About 80 percent of suppliers immediately exit after their unanticipated bankruptcies. Since these supplier bankruptcies likely disrupt buyers even without a formal exit, I present reduced-form effects of supplier bankruptcies rather than the instrumental variable (IV) effects of supplier exit.

are broadly similar, supporting the interpretation that unanticipated supplier bankruptcies indeed happen orthogonal to observable firm characteristics. Furthermore, in Appendix Table B.2, I show that there are no differential pretrends between treatment firms and control firms in the new supplier matching rates and sales growth.

Fact 1. After unanticipated supplier bankruptcies, firms match with alternative suppliers only gradually, and their sales decline. Table 1 presents the impacts of unanticipated supplier bankruptcy on the number of newly matched suppliers and sales using regression specification (1). Column (1) reports the impacts on the number of new suppliers relative to the baseline period (one year before the shock). Treatment firms are significantly more likely to match with new suppliers; they match with 0.17 more suppliers within 1 year, and 0.26 more suppliers within 3 years, compared to control firms. Therefore, treatment firms are indeed in need of an alternative supplier. At the same time, these effects are significantly less than one, yet gradually increasing over time, supporting the evidence for the presence of matching frictions.

Column (2) shows the impacts of supplier bankruptcy on firm sales. To accommodate firm exit during the sample period, I take the inverse hyperbolic sine (IHS) transformation of sales as an outcome variable.[14] I find that the treatment firms' sales significantly decline by 21 percent after 0 or 1 years of the shock, and the magnitude persists (insignificantly) after 2 or 3 years. These patterns of results are consistent with the interpretation that firms face disruption in production until they find a suitable alternative supplier, providing additional support for the presence of matching frictions.[15]

As additional robustness and supportive evidence, Appendix Table B.3 shows that these supplier bankruptcies do not significantly affect the sales of the treatment firms' other existing suppliers, indicating that treatment firms primarily respond by rematching with new suppliers instead of simply substituting from existing suppliers. In Appendix Table B.4, I show that the newly matched suppliers are significantly more likely to belong to the same industry as bankrupt suppliers, consistent with the interpretation that treatment firms are in search of an alternative supplier. Appendix Table B.5 shows that there are no heterogeneous effects by firm size, suggesting that these matching frictions

[14] Inverse hyperbolic sine (IHS) transformation of variable x is defined by $\log(x + (x^2+1)^{(1/2)})$. When x is large, this is approximately $\log(x) + \log(2)$, hence the regression coefficients are interpreted as percentage effect.

[15] These results are also in line with the findings of Carvalho, Nirei, Saito, and Tahbaz-Salehi (2020) and Boehm, Flaaen, and Pandalai-Nayar (2019), who document that the Great Tohoku Earthquake has negatively affected the sales of the domestic and foreign buyers of directly affected firms, respectively.

Table 1: Impacts of Supplier Bankruptcy on Supplier Matching and Sales

	Number of New Suppliers	Sales (IHS)
	(1)	(2)
Trt x 1[t - BankruptYear = 0 or 1]	0.17^{***}	-0.21^{**}
	(0.04)	(0.10)
Trt x 1[t - BankruptYear = 2 or 3]	0.27^{***}	-0.22
	(0.06)	(0.18)
Number of Treatment Firms	421	421
Number of Bankrupt Suppliers	161	161
Number of Control Firms	10,842	10,814
Observations	76,054	74,462

Note: This table reports the result of the difference-in-difference regression (equation 1). The outcome variable of the regression is the number of newly matched suppliers relative to the baseline period (one year before the shock) for Column 1 and the inverse-hyperbolic sine (IHS) transformation of sales for Column 2. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

are relevant for both small and large firms. Appendix Table B.6 presents the effects on other firm-level outcome variables. In particular, I find no effects on profit per sales, indicating that supplier bankruptcy primarily affects firm production through its scale but not through its profitability.

3.2 Heterogeneous Effects of Unanticipated Supplier Bankruptcies

In this section, I document how the matching rates with new suppliers after unanticipated supplier bankruptcies relate to the geographic density of alternative suppliers and other buyers.

First, I examine how these matching rates depend on the geographic density of alternative suppliers. To do so, I estimate the heterogeneous effects of unanticipated supplier bankruptcy using the following regression:

$$\begin{aligned} NewSuppliers_{fgt} = Post_{gt} \times Trt_f \times \left(\beta + \gamma \log SupplierDensity_g + \theta Z_{fg}\right) \\ + \eta_{gt} + \xi_{fg} + \epsilon_{fgt}, \end{aligned} \quad (2)$$

where $SupplierDensity_g$ is the proxy of the geographic density of alternative suppliers. In the baseline specification, I define $SupplierDensity_g$ as the number of firms in the bankrupt suppliers' four-digit industry that have at least one buyer in firm f's headquarter prefecture in 2008 divided by its geographic area. These "alternative suppliers" can be located outside firm f's prefecture, reflecting the fact that supplier linkages happen across regions (Figure 1). I show that my results are robust to alternative measures of supplier density, in particular using the number of firms with headquarters in firm f's location, constructed without using the information of realized supplier-to-buyer linkages (Appendix Table B.8). To control for other dimensions of firm heterogeneity that affect the matching rates with new suppliers, I include location fixed effects, industry fixed effects, and other firm and supplier characteristics as an interaction with treatment and post dummy (Z_{fg} in the above regression) as further discussed below.

Fact 2. The matching rates with suppliers after unanticipated supplier bankruptcies increase in the geographic density of alternative suppliers. Table 2 presents the results of regression (2). Column (1) shows that firms in areas with higher density of suppliers are significantly more likely to match with new suppliers after unanticipated supplier bankruptcies. To facilitate the interpretation of the coefficients, I standardize the log of the supplier density to be mean zero and standard deviation one after residualized by Z_g. The magnitude of this impact heterogeneity is sizable; a one-standard-deviation increase in the seller density proxy increases the effect by 0.13 after 2 or 3 years, relative to the average effects of 0.26. This implies that the treatment effect at the 95th percentile of the supplier density distribution is almost twice the average treatment effect, while it is almost zero at the 5th percentile.

Column (2) shows that these results are robust to controlling for prefecture fixed effects and the bankrupt supplier's two-digit industry (as interaction with treatment dummy and the post dummy). With these sets of fixed effects, this regression effectively compares two treatment firms that are in the same location but faced a supplier bankruptcy in different industries with different (relative) supplier density. The results are further robust to excluding firms that have multiple (non-headquarter) establishments in different prefectures (Column 3). Therefore, although I proxy firms' locations by their headquarter, a mismeasurement of firms' locations unlikely affects these results.

While this evidence is consistent with the interpretation that a higher density of suppliers improves the matching rates, it is also consistent with alternative stories of firm selection. In particular, firms with higher ability in finding an alternative supplier or unobservably higher demand for external suppliers may selectively enter in locations with higher supplier density. To rule out this concern as much as possible, I employ an instrumental variable (IV) approach to exploit an exogenous component of firms' location decision unrelated to supplier matching. To satisfy the exclusion restriction, the IV has

Table 2: Matching Rates and Supplier Density

	Number of New Suppliers					
	OLS	OLS	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Main Regression						
Trt x 1[t - BankruptYear = 0 or 1]	0.16^{***}					
	(0.04)					
Trt x 1[t - BankruptYear = 2 or 3]	0.26^{***}					
	(0.06)					
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density (Std.)	0.10^{**}	0.14^{**}	0.22^{***}	0.09	0.10	0.10
	(0.04)	(0.06)	(0.07)	(0.10)	(0.10)	(0.10)
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density (Std.)	0.13^{*}	0.29^{***}	0.28^{***}	0.39^{***}	0.41^{***}	0.40^{***}
	(0.07)	(0.08)	(0.08)	(0.12)	(0.13)	(0.13)
Panel B: First Stage (Endogenous Variable: log Supplier Density)						
log Supplier Density (At Firms' Ideal Location for Buyer Access)				0.56^{***}	0.55^{***}	0.49^{***}
				(0.04)	(0.05)	(0.05)
Samples	All	All	No Outside-Prefecture Establishments	All	All	All
Trt x Post x Prefecture FE		X	X	X	X	X
Trt x Post x Supplier 2-digit Industry FE		X	X	X	X	X
Trt x Post x log Supplier Density (Ideal Location for Supplier Access)				X	X	X
Trt x Post x log Firm Size, Supplier Size, Number of Existing Suppliers (All, 4-digit)					X	X
Trt x Post x log Distance, Input Share, Relationship Duration to Bankrupt Suppliers						X
First-Stage F-Statistics				1322.9	1412.4	678.7
Number of Treatment Firms	421	421	334	365	365	365
Number of Bankrupt Suppliers	161	161	136	144	144	144
Number of Control Firms	10,842	10,842	7,889	9,475	9,475	9,475
Observations	76,054	76,054	55,612	66,877	66,405	66,405

Note: The regression specification follows equation (2). Seller density is defined as the geographic density of suppliers in the bankrupting suppliers' four-digit industry that have at least one buyer in firm f's prefecture in 2008. The seller density measure is normalized to be mean 0 with standard deviation 1 after residualized by other controls Z_g. Column (1) only controls for log of the geographic area of treatment firm f's prefecture as an interaction with treatment and post dummy. Average effects are omitted from Columns (2) to (6), as they are saturated by the fixed effects. Columns (4)-(6) present results of the IV regressions by instrumenting log supplier density by that evaluated at the firm's ideal location for buyer access (interacted with treatment dummy and post-period dummies), and Panel B shows the first stage of this IV regression. In Column (4)-(6), I omit samples without treatment firms without any buyers throughout the period. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

to be uncorrelated with unobserved supplier matching rates. A candidate for this IV is a factor affecting a firm's location decision other than through access to suppliers. Here, I construct the IV based on the idea that the access to *buyers* is an important determinant for a firm's location choice, on top of the access to *suppliers*.[16]

More concretely, I use the supplier density evaluated at the firm's ideal location *purely from a buyer access perspective* to instrument for the actual supplier density. For each treatment firm f, I collect all buyers of the firm f throughout my sample period. From this list of buyers, I pick the most common four-digit industry ($buyerind_f$). I then identify

[16] In the context of international trade, Redding and Venables (2004) show that firm entry and country welfare is affected by both supplier and buyer access.

the prefecture (n_f^*) where the firm density of industry $buyerind_f$ is the highest. I then construct my IV as the supplier density of the bankrupt supplier industry at this location (n_f^*) instead of the firm's actual location.

Intuitively, this IV captures the following variation. Even if two firms source from the same industry, they produce different products and services and sell to different industries. These two firms tend to enter into different locations depending on the access to their buyer industry. Consequently, they face different supplier densities of alternative suppliers at the point when an unanticipated supplier bankruptcy occurs.[17]

Column (4) presents the results of this IV regression. Panel (B) of the same column shows that there is a strongly significant first stage, confirming that firms' location choice is indeed influenced by buyer access (conditional on supplier access). Using these instruments, I find significantly positive heterogeneous IV effects by supplier density.

These results are further robust to controlling for firms' and bankrupt suppliers' observable characteristics. In Column (5), I additionally control for the employment size of the (buyer-side) firms, the employment size of the bankrupt suppliers, and the number of existing suppliers of the (buyer-side) firms in baseline (interacted with treatment times post dummy). In Column (6), I show robustness to controlling for the proxies for the strength of the relationships to bankrupt suppliers, including the geographic distance to the bankrupt suppliers, the duration of the relationship to the bankrupt supplier, and the input coefficient between buyer and supplier industry (obtained from a separate input-output table).

Appendix Table B.7 shows that these empirical results are further robust to various specification tests, including by omitting exit firms from samples (instead of inserting zero for outcome variables in baseline above), excluding bankrupt suppliers in the Tohoku area after 2011 (the year of the Great Tohoku Earthquake) and those in 2009 (the year followed by the Great Financial Crisis in 2007-08), and by employing another IV strategy using the birthplace of firm CEOs as exogenous variation of firms' location choice. The results are further robust to alternative definitions of supplier density (Appendix Table B.8), splitting samples to manufacturing and non-manufacturing supplier bankruptcies (Appendix Table

[17] One concern for this IV is that firms' main supplier industry correlates with their main buyer industry. To rule out this possibility, in the IV regression, I additionally control for the supplier density at the firm's ideal location purely from a *supplier* access perspective. My strong first stage after this control suggests that there is an independent variation of main supplier and buyer industries that I exploit in the IV strategy. Relatedly, only 7 percent of treatment firms have a main supplier and buyer industries coinciding with each other at the four-digit industry.

B.9), and including supplier-reported supplier-to-buyer-linkages when constructing the outcome variables (Appendix Table B.10).

Lastly, Appendix Table B.11 investigates the heterogeneous effects on sales. I find a significant average increase in sales *per matched supplier* (instrumented by supplier bankruptcy), yet these effects are not significantly different by supplier density. These patterns of the results indicate that, in this context, firms benefit primarily by *faster* supplier matching but not by *better* supplier matching from supplier density.[18]

Fact 3. The matching rates with suppliers after unanticipated supplier bankruptcies are not related to the geographic density of other buyers. I now study how the matching rates are related to the density of other buyers. In urban areas, there are not only many suppliers but also many buyers. If buyers crowd out each other to match with a supplier (for example, due to suppliers' limited production capacity), the presence of more buyers may offset the benefit of the higher supplier density.[19] The regression specification is given by:

$$\begin{aligned} NewSuppliers_{igt} = Post_{gt} \times Trt_f \times (\beta + \gamma \log SupplierDensity_g + \\ \delta \log BuyerDensity_g + \theta Z_{fg}) + \eta_{gt} + \xi_{fg} + \epsilon_{igt}. \end{aligned} \tag{3}$$

Relative to supplier density, it is less straightforward to define the density of relevant buyers, because researchers do not directly observe which firms are looking for a supplier. Here, I take three alternative measures for buyer density. The first measure uses the number of firms in the treatment firm's prefecture that faced an unanticipated supplier bankruptcy in the same four-digit industry in the same year (divided by the geographic area). The second measure uses the number of firms facing any types of supplier separation in the same four-digit supplier industry in the same year. The third measure uses the number of firms that belong to the same two-digit industry and prefecture as the treatment firm.

Table 3 presents the results. The first two rows report the heterogeneous effects by supplier density, and the next two rows report the heterogeneous effects by buyer density

[18] See Helsley and Strange (1990) for a model where the latter force drives the agglomeration benefits and Duranton and Puga (2004) for conceptual distinctions about these two types of channels.

[19] The literature of labor search and matching often find that the presence of more unemployed workers decreases other unemployed workers' reemployment rate (Petrongolo and Pissarides 2001). My finding of no significant association between supplier matching rates and the density of other buyers highlights the differences between labor market and supplier-to-buyer matching markets.

with three different proxies in each column. In all three measures, I find no statistically significant evidence that matching rates relate to buyer density; the estimated coefficients are small in magnitude and close to zero. This lack of statistical significance is not the result of imprecise estimates; the standard errors of these coefficients have similar magnitudes as those for supplier density, which are robustly significant and positive.

To further facilitate the interpretation of these coefficients, in the second to the bottom row of Table 3, I report the P-value of the statistical hypothesis that the coefficients on supplier density and buyer density sum up to zero ($\gamma + \delta = 0$). I find that this null hypothesis is rejected at the 5 percent significance level in all specifications. Therefore, an increase of the density of suppliers and buyers by the same proportion is associated with a higher matching rates. In the next section, I build a model that connects these findings to the scale effects of matching technology.

Table 3: Matching Rates and Other Buyer Density

	Number of New Suppliers		
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density (Std.)	0.11^{**}	0.10^{**}	0.13^{**}
	(0.05)	(0.05)	(0.06)
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density (Std.)	0.24^{***}	0.21^{***}	0.27^{***}
	(0.07)	(0.07)	(0.08)
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Density (Std.)	0.001	−0.01	−0.01
	(0.06)	(0.05)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Density (Std.)	−0.01	−0.03	−0.07
	(0.07)	(0.07)	(0.06)
Trt x Post x Prefecture FE	X	X	X
Trt x Post x Supplier 2-digit Industry FE	X	X	X
Definition of Buyers	Buyers facing Unanticipated Supplier Bankruptcies	Buyers facing Supplier Separation	Buyers in Same Two-Digit Industry
P-Value (Null: Sum of Coeffcieints on Supplier Density + Buyer Density = 0)	0.002	0.001	0.028
Observations	76,054	76,054	76,054

Note: The regression specification follows equation (3) with three alternative definitions of buyer density. Buyer density is defined using the number of firms in the treatment firm's prefecture that faced an unanticipated bankruptcy of suppliers in the same four-digit industry in the same year divided by the geographic area (in Column 1); those facing any types of supplier separation in the same four-digit supplier industry in the same year (in Column 2); and those that belong to the same two-digit industry and prefecture as the treatment firm (in Column 3). Both supplier density and buyer density are normalized to be mean zero and standard deviation one after residualized by prefecture fixed effects and supplier industry fixed effects. The second to bottom row reports the P-value of the statistical hypothesis that the coefficients on supplier density and buyer density sum up to zero ($\gamma + \delta = 0$). Standard errors are clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

4 Model

In this section, I develop a model of spatial firm-to-firm trade under search and matching frictions. I model dynamic firm-to-firm matching following a canonical search and matching framework popularized to study labor market frictions (Diamond 1982, Pissarides 1985, Mortensen 1986). A firm can source intermediate inputs either from a long-term supplier or by producing in-house. When firms do not have an ongoing supplier for a particular input, they meet with a potential supplier and decide to form a long-term relationship. I embed this firm-to-firm matching in the static firm-to-firm trade framework of Eaton, Kortum, and Kramarz (2016) and in a spatial equilibrium framework with population mobility (Allen and Arkolakis 2014, Redding and Rossi-Hansberg 2017). I also incorporate multiple heterogeneous industries connected through input-output linkages following Johnson and Noguera (2012) and Caliendo and Parro (2014).

4.1 Basic Set-up

Space is partitioned into a discrete number of locations, denoted by $i, j \in N$. A unit mass of the population decides their residential locations. I denote L_i as the population size in location i. I later describe how L_i is determined by the free population mobility.

Time is continuous and denoted by t. In this paper, I mainly 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.

In each location, there is a continuum of potential producers in each sector. Sectors are denoted by $k, m \in K$. All firms produce both final goods, consumed by final goods consumers, and intermediate inputs, used for production by other firms. In this sense, each firm can be simultaneously a buyer and a supplier in intermediate input trade. Each of these firms is owned by foreigners, and hence all firm profit goes outside the economy.

Each firm produces a differentiated final good. Intermediate inputs are homogeneous within each input sector. Intermediate input trade is possible only when two firms form a long-term relationship as a supplier and a buyer. I assume that each buyer-side firm can form a relationship with at most one supplier in each input sector at a time. On the other hand, suppliers can form a relationship with multiple buyers simultaneously.

4.2 Technology

Each firm produces both final goods and intermediate inputs with the same Cobb-Douglas production technology. The unit cost by firm ω in location i in sector m is

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

where w_i is the wage in ω's production location i, $p_{\omega t,k}$ is the unit cost of intermediate inputs that firm ω has access to in period t in input sector k, φ_ω is the exogenous productivity of firm ω, $\gamma_{L,m}$ is the labor share in production for sector m, and γ_{km} is the sector-k intermediate inputs share for sector m's production. I assume that production function exhibits constant returns to scale, i.e., $\gamma_{L,m} + \sum_k \gamma_{km} = 1$ for all $m \in K$.[20]

Both final goods and intermediate goods are tradable across locations and subject to iceberg cost. For firms in location i to sell one unit of final goods to location j, it has to ship $\tau_{ij,k} (> 1)$ unit of goods.

The measure of firms whose productivity is above φ is given by:

$$\mu_{i,m}(\varphi) = \left(\frac{\varphi}{A_{i,m}} \right)^{-\theta}. \tag{5}$$

Here, $A_{i,m}$ governs the productivity of the location and sector. Following the tradition of spatial equilibrium models, I assume that this productivity is affected both by exogenous location fundamentals and agglomeration spillovers, depending on the local population density, such that:

$$A_{i,m} = A^*_{i,m} \left(\frac{L_i}{Z_i} \right)^{\iota} \tag{6}$$

where $A^*_{i,m}$ is the exogenous productivity, Z_i is the geographic area, L_i/Z_i is the population density in location i, and ι is the elasticity of productivity with respect to local population density. The second term captures agglomeration spillovers arising from higher population density. In my model, this term captures all other agglomeration spillovers other than the increasing returns to scale in firm-to-firm matching modeled below, such as knowledge spillover or labor market pooling.

[20] For simplicity, I assume that each firm produces at a single location. When I take the model to data, I assume that all production occurs in the prefecture of the firms' headquarters. My estimates of the agglomeration spillovers are robust to excluding firms that have establishments outside their headquarter prefecture in Section 5 (Appendix Table D.1).

There are two possible ways to source input goods: forming a long-term relationship with a supplier or producing them in-house using local labor. This process defines the stochastic process of $p_{\omega t,k}$. As I describe in detail below, the steady-state distribution of the unit cost follows power-law distribution given the power-law distribution of productivity φ_ω stated above. I denote the measure of firms in location i and sector m whose unit cost is below c by:

$$H_{i,m}(c) = \Gamma_{i,m} c^{\theta}, \tag{7}$$

where $\Gamma_{i,m}$ is the "supply capacity" term, which depends on wages and the scope of supplier matching as analytically characterized below.

4.3 Final Goods Market

The final goods market follows the same structure as Melitz (2003). In each period, all firms produce and sell a differentiated variety of final goods. To sell in location j, each firm has to pay a fixed cost $f_{j,k}$ in each period by local labor. I assume that workers do not have access to saving technology and therefore use all of their labor income for consumption in each period. The representative final goods consumer (workers) has a CES utility function:

$$U = \prod_{k \in K} \left(\int_{\omega \in \Omega_{j,k}} q_k(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}\alpha_k}, \tag{8}$$

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

Because of the power law distribution of the unit cost, the model predicts a gravity equations of trade flows (Melitz 2003 and Chaney 2008). More specifically, the measure of firms that produce in location i whose unit cost net of trade cost is below c in location j is given by $H_{i,m}(c/\tau_{ij,m}) = \Gamma_{i,m} \left(\tau_{ij,m}\right)^{-\theta} (c)^{\theta}$. Hence, the share of final goods consumed in location j that are produced in location i is given by:

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

where $\Omega_{j,m}c^{\theta} = \sum_{i' \in N} \Gamma_{i,m} \left(\tau_{ij,m}\right)^{-\theta} c^{\theta}$ is the measure of firms whose unit cost net of trade cost is below c in sales location i. Furthermore, Appendix C.1 shows that the consumer price index is given by:

$$P_j = \varsigma \left(L_j\right)^{-\frac{\theta-\sigma+1}{\theta(\sigma-1)}} \prod_k \left(f_{j,k}\right)^{\frac{\theta-\sigma+1}{\theta(\sigma-1)}\alpha_k} \left(\Omega_{j,k}\right)^{-\frac{\alpha_k}{\theta}}, \tag{10}$$

where $\varsigma = \left(\frac{\theta-\sigma+1}{\theta\sigma}\right)^{\frac{1}{\theta}} \sigma^{\frac{1}{\sigma-1}} \prod_k \left(\alpha_k\right)^{\alpha_k \frac{\theta-\sigma+1}{\theta(\sigma-1)}}$.

4.4 Search and Matching in Intermediate Goods Market

As mentioned above, there are two possible ways to source input goods: producing them in-house using local labor or forming a direct relationship with a supplier. For the first option, I assume that all firms can produce one unit of sector-k intermediate goods using ζ_k unit of local labor. Furthermore, in order to produce in-house intermediate goods, firms have to pay $\chi - 1 (\geq 0)$ additional unit of transaction cost per unit of output.

Below, I first discuss the matching process and its technology. I then derive and solve for Bellman equations for the decision of forming a relationship conditional on a match. Lastly, I derive the steady-state match probabilities.

Matching Technology. I first assume that $0 \leq \delta \leq 1$ fraction of firms ever matches with a supplier. When I fit the model to data, this parameter rationalizes the relative magnitudes of the matching rates, separation rates, and the probability of matching in a steady-state.

If a potential input buyer (i.e., δ fraction of firms producing in location j) does not currently have a supplier, it stochastically draws a potential supplier. Following the approach of labor search and matching literature (Diamond 1982, Pissarides 1985, Mortensen 1986), I assume that the matching between suppliers and buyers occurs through matching technology summarized by a matching function. The total matches created in one unit of geographic area by buyers producing in location j with suppliers (that can be producing anywhere) is given by

$$M\left(S_{j,k}, B_{j,km}\right) = \eta \left(S_{j,k}\right)^{\lambda} \left(B_{j,km}\right)^{\nu} \tag{11}$$

where $S_{j,k}$ is the density of suppliers in location j whose unit cost (net of iceberg trade cost) is below $\zeta_k w_j$, and $B_{j,km}$ is the density of buyers in location i whose unit cost is below some sufficiently large threshold ϑ and who is not currently matched with a supplier in sector k. This matching function implies that the Poisson rate for buyers to match with a supplier is $M\left(S_{j,k}, B_{j,km}\right)/B_{j,km}$. Similarly, the Poisson rate for suppliers to match with a buyer is $M\left(S_{j,k}, B_{j,km}\right)/S_{j,k}$. I allow the matching technology to have a scale effect; i.e., $\lambda+\nu$ can be different from one. If $\lambda+\nu=1$, the matching function exhibits constant returns to scale. If $\lambda+\nu>1$, the matching function exhibits increasing returns to scale.

The measure of suppliers with unit cost below $\zeta_k w_j$ (net of trade cost) in location j is given by $\Omega_{j,k}\left(\zeta_k w_j\right)^{\theta}=\sum_{i'\in N}\Gamma_{i',k}\left(\tau_{i'j,k}\right)^{-\theta}\left(\zeta_k w_j\right)^{\theta}$. The measure of buyers whose unit cost for production is below ϑ and who is looking for a supplier is $\Phi_{j,km}\Gamma_{j,m}\vartheta^{\theta}$, where $\Phi_{j,km}$ is the steady-state probability that a firm in location j and sector m has a supplier in sector k.[21] Together, the Poisson rate of matching with a supplier $v_{j,km}$ is given by:

$$v_{j,km}=\frac{1}{B_{j,km}}M\left(S_{j,k}, B_{j,km}\right)=\eta\left(\frac{\Omega_{j,k}\left(\zeta_k w_j\right)^{\theta}}{Z_j}\right)^{\lambda}\left(\frac{\Phi_{j,km}\Gamma_{j,m}\vartheta^{\theta}}{Z_j}\right)^{\nu-1}, \tag{12}$$

where Z_j is again the geographic area of location j.

Conditional on a match, the two firms jointly determine if they form a long-term relationship. The buyer cannot match with another supplier until the relationship is exogenously destroyed at the Poisson rate ρ_{km}. This creates an option value for buyers to forego the supplier that they draw and wait for a better supplier. On the other hand, suppliers can match with other buyers simultaneously. Therefore, suppliers do not have an option value for waiting, and they always form a relationship whenever the profit is positive.

Nash Bargaining and Bellman Equations for Firm-to-Firm Matching. Following the standard search and matching framework, the joint surplus of a match is split between buyers and suppliers according to Nash bargaining. Since Nash bargaining is efficient, intermediate goods are traded at supplier's unit cost to avoid double marginalization. In addition, there is a lump-sum transfer from the buyer to the supplier in each period based on Nash bargaining.

To avoid that this bargaining involves infinitely many third firms indirectly connected through the dynamic firm-to-firm trade network, I assume that the two firms bargain

[21] In Appendix C.3, I analytically derive that $\Phi_{j,km}=\left(\delta-\Lambda_{j,km}\right)/\left(1+\Lambda_{j,km}(\phi_{j,km}-1)\right)$, where $\Lambda_{j,km}$ and $\phi_{j,km}$ are given by equations (21) and (22) below.

only over the profit from the buyer's final goods sales. Furthermore, I assume that the relationship-specific unit cost of the supplier is fixed at the beginning of the relationship (by assuming that the supplier can keep receiving the intermediate goods for this specific relationship from its own suppliers until the relationship ends). Under these two assumptions, the bargaining problem can be solved for each pair of suppliers and buyers, independent of the actions of other firms in the economy.

I now define the Bellman equations. I first consider the value functions of the buyer. Denote the value of the buyer ω that has an ongoing relationship with a supplier in sector k at unit cost c (net of iceberg cost) by $V^B_{\omega t,k}(c)$, and the value of the firm that does not have an ongoing supplier relationship in sector k by $U^B_{\omega t,k}$. The Bellman equation for the buyers when the firm is matched with a supplier is given by

$$\xi V^B_{\omega t,k}(c) = \Pi^F_{\omega t,k}(c) - \delta_{\omega t,k}(c) - \rho_{km}\left(V^B_{\omega t,k}(c) - U^B_{\omega t,k}\right) + \dot{V}^B_{\omega t,k}(c), \tag{13}$$

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; $\delta_{\omega t,k}(c)$ is the lump-sum transfer to the supplier in sector k; ρ_{km} is again 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 $V^B_{\omega t,k}(c)$. As discussed above, Nash bargaining involves only the buyer's final goods profit ($\Pi^F_{\omega t,k}(c)$), and hence I omit the profit from intermediate goods sales from the value function.[22]

The Bellman equation for the buyers in location i when they are not matched with a supplier in sector k is given by

$$\xi U^B_{\omega t,k} = \chi^{1-\sigma}\Pi^F_{\omega t,k}(\zeta_k w_i) + v_{i,km} a_{\omega,k}\int_0^{\bar{c}_{\omega,k}}\left(V^B_{\omega t,k}(c) - U^B_{\omega t,k}\right) dG_{\omega,k}(c) + \dot{U}^B_{\omega t,k}, \tag{14}$$

where χ is the iceberg cost of producing intermediate goods in-house; $\Pi^F_{\omega t,k}(\zeta_k w_i)$ is the profit from final goods sales when the unit cost of intermediate goods in sector k is $\zeta_k w_i$; $v_{i,km}$ is the Poisson rate of matching with a supplier; $a_{\omega,k}$ is the probability that the match is accepted (derived below); $\bar{c}_{\omega,k}$ 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

[22] I normalize $V^B_{\omega t,k}(c)$ and $U^B_{\omega t,k}$ by omitting the payment to suppliers in other sectors ($\delta_{\omega t,\tilde{k}}(c)$ for $\tilde{k} \neq k$), which equally affects both $V^B_{\omega t,k}(c)$ and $U^B_{\omega t,k}$.

$G_{\omega,k}(\bar{c}_{\omega,k}) = 1$); and $\dot{U}^B_{\omega t,k}$ indicates time derivatives of $U^B_{\omega t,k}$.[23]

Turning to the supplier's side, the value of the supplier with unit cost c from the relationship with buyer ω is given by

$$\xi V^S_{\omega t,k}(c) = \delta_{\omega t,k}(c) - \rho_{km}\left(V^S_{\omega t,k}(c) - U^S_{\omega t,k}\right) + \dot{V}^S_{\omega t,k}(c), \tag{15}$$

where $\delta_{\omega t,k}(c)$ is again the lump-sum transfer from the buyer to the supplier, and ρ_{km} is the Poisson rate at which the relationship is destroyed. Since the supplier does not have an option value of waiting (because it can simultaneously form a relationship with other buyers), I normalize the value of the supplier when it is not matched with ω by zero, i.e.,[24]

$$U^S_{\omega t,k} = 0. \tag{16}$$

Because of the Nash bargaining, the joint surplus $J_{\omega t,k}(c) = \left(V^S_{\omega t,k}(c) - U^S_{\omega t,k}\right) + \left(V^B_{\omega t,k}(c) - U^B_{\omega t,k}\right)$ is split between the supplier and buyer with a weight of $1-\beta$ and β, where β denotes the bargaining power of the buyer. Therefore:

$$\begin{aligned} V^S_{\omega t,k}(c) - U^S_{\omega t,k} &= (1-\beta)J_{\omega t,k}(c), \\ V^B_{\omega t,k}(c) - U^B_{\omega t,k} &= \beta J_{\omega t,k}(c). \end{aligned} \tag{17}$$

I now solve these Bellman equations to derive the decision of whether to form a relationship conditional on a match. Because suppliers have no option value, this problem comes down to the buyer's decision of accepting the match. Buyers decide to form a relationship if the supplier's unit cost is sufficiently low. I assume that buyers set $\bar{c}_{\omega,k}$ to maximize the expected value of unmatched state. This implies that $\bar{c}_{\omega,k}$ is determined so that firms are in expectation indifferent between accepting or rejecting a match when the supplier's unit cost is $\bar{c}_{\omega,k}$:

$$E[V^B_{\omega t,k}(\bar{c}_{\omega,k})] = E[U^B_{\omega t,k}], \tag{18}$$

where the expectation is taken with respect to intermediate goods cost other than input

[23]It is straightforward to show that there exists such a threshold. The per-period profit of the buyer is strictly decreasing in c. Therefore, the joint surplus is also strictly decreasing in c, which guarantees the existence of $\bar{c}_{\omega,k}$.

[24]Similarly to the normalization of the buyer's value functions, I normalize $V^S_{\omega t,k}(c)$ and $U^S_{\omega t,k}$ by omitting the profits from other buyers and final consumers, which equally affects $V^S_{\omega t,k}(c)$ and $U^S_{\omega t,k}$.

sector k. In Appendix C.2, I show that $\bar{c}_{\omega,k}$ and $a_{\omega,k}$ depend only on firms' location i, sector m, and the supplier sector k, such that $\bar{c}_{\omega,k} = \bar{c}_{i,km}$ and $a_{\omega,k} = a_{i,km}$ when fixed cost for final goods sales is negligible ($f_{j,k} \to 0$), and they are analytically solved to give the following expressions:

$$a_{i,km} = \min \left\{ 1, \quad \chi^{\frac{\theta}{\gamma_{km}}} \left[1 - \beta \frac{v_{i,km} a_{i,km}}{\xi + \rho_{km}} \frac{(\sigma - 1)\,\gamma_{km}}{\theta - (\sigma - 1)\,\gamma_{km}} \right]^{\frac{\theta}{(\sigma-1)\gamma_{km}}} \right\}, \tag{19}$$

and

$$\bar{c}_{i,km} = \zeta_k w_i a_{i,km}^{\frac{1}{\theta}}. \tag{20}$$

Note that the expression of $a_{i,km}$ in equation (19) is implicit because $a_{i,km}$ also appears in both sides of the equations. Because the right-hand side is decreasing in $a_{i,km}$, equation (19) uniquely determines $a_{i,km}$.

These equations are intuitive. In equation (19), $a_{i,km}$ is increasing in $v_{i,km}$ because faster matching rates imply that the option value of waiting is higher. $a_{i,km}$ is decreasing in ρ_{km} and ξ because an anticipation of faster separation ρ_{km} and a higher discount rate ξ discourage firms to wait longer. $a_{i,km}$ is decreasing in β because a higher value of β implies a greater option value of buyers to wait for a better supplier. Lastly, $a_{i,km}$ is decreasing in χ because a higher transaction cost for in-house production increases the opportunity cost of waiting. In equation (20), $\bar{c}_{i,km}$ is increasing in $a_{i,km}$ because accepting at higher probability (higher $a_{i,km}$) means that firms accept more costly suppliers (higher $\bar{c}_{i,km}$). When $a_{i,km} = 1$ (always accept the supplier), $\bar{c}_{i,km} = \zeta_k w_i$, i.e., buyers accept suppliers as long as the supplier's unit cost is equal to or less than the in-house production of intermediate goods.

Value of a Match and Steady-State Match Probability. Given the solution to the Bellman equations, I now define several key moments that are useful to characterize the aggregate steady-state equilibrium. I first derive the ratio of the expected firm sales $r_{j,m}$ of firms in location j and industry m conditional on having a supplier $d_{j,k} = 1$ in sector k relative to being without a supplier $d_{j,k} = 0$, i.e., $\phi_{j,km} \equiv \frac{E[r_{j,m} | d_{j,k}=1]}{E[r_{j,m} | d_{j,k}=0]}$. (The expectation is taken with respect to productivity φ and the unit cost of intermediate goods other than in sector k.) In Appendix C.3, I show that $\phi_{j,km}$ is explicitly solved as:

$$\phi_{j,km} = \frac{\chi^{\theta}}{1 - \gamma_{km}} \left(a_{j,km} \right)^{-\gamma_{km}}. \tag{21}$$

Intuitively, when $a_{j,km}$ is high, firms are more selective about the supplier's productivity. Therefore, each firm faces a greater increase in sales when they decide to form a relationship with a supplier. Similarly, a higher in-house production iceberg cost (χ) leads to higher sales by firms when they are matched with a supplier.

Given $a_{j,km}$, the steady-state probability that a firm in location j and sector m is forming a relationship with a supplier in sector k is given by:

$$\Lambda_{j,km} = \delta \frac{v_{j,km} a_{j,km}}{v_{j,km} a_{j,km} + \rho_{km}}, \tag{22}$$

where δ is again the fraction of firms that can match with an external supplier, $v_{j,k}$ is the matching rate with a new supplier, and ρ_{km} is the exogenous separation rate.

4.5 Gravity Equations of Intermediate Goods Flows

Now I derive the spatial structure of the intermediate goods trade. Since buyers' match and accept probabilities are independent of the suppliers' production location conditional on the unit cost (net of trade cost), the probability that firms in location j to source from a supplier in location i is given by:

$$\pi_{ij,m} = \frac{\Gamma_{i,m} \left(\tau_{ij,m}\right)^{-\theta}}{\sum_{i' \in N} \Gamma_{i',m} \left(\tau_{i'j,m}\right)^{-\theta}}, \tag{23}$$

which is same gravity equation for final goods trade flows (9). Furthermore, from the same logic as in Melitz (2003) and Chaney (2008), $\pi_{ij,m}$ also coincides with the expenditure share of intermediate goods consumed in location j that are produced in location i.

The characterization so far allows me to derive an analytical expression for the supply capacity $\Gamma_{i,m}$. In Appendix C.4, I show that:

$$\Gamma_{i,m} = \varrho A_{i,m}^{\theta} w_i^{-\theta} \prod_{k \in K} \left(1 + \Lambda_{i,km} \left(\phi_{i,km} - 1\right)\right), \tag{24}$$

where $\varrho \equiv \prod_{k \in K} \left(\zeta_k\right)^{-\theta \gamma_{km}}$, $A_{i,m}$ is again the measure of the productivity of the location and sector given by equation (6), and w_i are the local wages. Intuitively, the supplier capacity ($\Gamma_{i,m}$) is higher if productivity ($A_{i,m}$) is higher, labor cost (w_i) is lower, the probability of matching with a supplier ($\Lambda_{i,km}$) is higher, and the benefit of a supplier match ($\phi_{i,km}$) is higher.

4.6 Total Expenditure and Trade Balance

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

$$X^I_{i,k} = \sum_{j \in N} \sum_{m \in K} Y^I_{j,km} \pi_{ij,k}, \tag{25}$$

where $Y^I_{j,km}$ is the aggregate input goods expenditure by firms in sector m and location j for input sector k. Aggregate final goods sales by firms producing in location i and sector k ($X^F_{i,k}$) is given by:

$$X^F_{i,k} = \sum_{j \in N} Y^F_{j,k} \pi_{ij,k} \tag{26}$$

where $Y^F_{i,k}$ is the final goods demand.

From the Cobb-Douglas utility function (equation 8), the final goods demand in sector k is given by:

$$Y^F_{i,k} = \alpha_k w_i L_i. \tag{27}$$

Furthermore, from the Cobb-Douglas production function assumption, the intermediate input demand by firms in location i and sector m toward input sector k is given by

$$Y^I_{i,km} = \gamma_{km} \Psi_{i,km} \left\{ X^I_{i,m} + X^F_{i,m} \right\}. \tag{28}$$

where $\Psi_{i,km} = \phi_{i,km} \Lambda_{i,km} / \left(1 - \Lambda_{i,km} + \phi_{i,km} \Lambda_{i,km}\right)$ is the sales-weighted fraction of firms in location i and sector m that has an ongoing supplier relationship in sector k.

Lastly, denoting the trade deficit of location i by D_i, the aggregate intermediate goods sales from location i has to balance the aggregate intermediate input purchase up to the trade deficit, i.e.,

$$\sum_{k \in K} \left(X^I_{i,k} + X^F_{i,k} \right) = \sum_{k,m \in K} Y^I_{i,km} + \sum_{k \in K} Y^F_{i,k} - D_i. \tag{29}$$

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

4.7 Free Population Mobility

I assume that the utility of workers who reside in location i is given by:

$$U_j = K_j \left(\frac{w_j}{P_j} \right) L_j^{-1/v},$$

where K_j is the exogenous residential amenity, w_j is the nominal wage, P_j is the consumer price index, and L_j is the population size j. Parameter v governs the dispersion force, which includes housing costs, negative residential spillovers, and idiosyncratic preference heterogeneity.

Workers are freely mobile across locations. This implies that the utility is equalized across locations, i.e., $U_j = U$ for all locations j. Therefore, the population size of location j is given by:

$$L_j = \frac{K_j^v \left(\frac{w_j}{P_j} \right)^v}{\sum_\ell K_\ell^v \left(\frac{w_\ell}{P_\ell} \right)^v}, \tag{30}$$

and the utility of workers in the economy is given by:

$$\mathcal{U} = \left(\sum_\ell K_\ell^v \left(\frac{w_\ell}{P_\ell} \right)^v \right)^{1/v}. \tag{31}$$

4.8 Steady-State Equilibrium

The aggregate steady-state equilibrium is characterized by the following three sets of equilibrium conditions.

(i) trade linkages. Given population $\{L_i\}$ and the steady-state matching variables $\{\Lambda_{i,km}, \phi_{i,km}\}$, aggregate intermediate and final goods sales $\{X_{i,k}^I, X_{i,k}^F\}$, aggregate intermediate and final goods demand $\{Y_{i,km}^I, Y_{i,k}^F\}$, trade flow shares $\{\pi_{ij,k}\}$, location and sector productivity $\{A_{i,m}\}$, supply capacity $\{\Gamma_{i,m}\}$, wages $\{w_i\}$, and consumer price index $\{P_j\}$ are given by equations (6), (9), (10), (24), (25), (26), (27), (28), (29).

(ii) population mobility. Given $\{w_i\}$ and $\{P_i\}$, population size $\{L_i\}$ and worker utility U are given by (30) and (31).

(iii) matching in intermediate goods market (for each location i and sector pairs k, m). Given $\{\Gamma_{i,m}\}$ and $\{w_i\}$, steady-state probability of having an ongoing relationship with a supplier $\{\Lambda_{i,km}\}$, Poisson matching and acceptance rates $\{a_{i,km}, v_{i,km}\}$, acceptance threshold of unit cost to form a supplier relationship $\{\bar{c}_{i,km}\}$, and sales increase form a supplier match $\{\phi_{i,km}\}$ are determined by equations (12), (19), (20), (21), and (22).[25]

In the above equilibrium conditions, the trade and population mobility conditions are standard components of a canonical quantitative spatial model (Allen and Arkolakis 2014, Redding and Rossi-Hansberg 2017). Therefore, this model extends these classes of models to incorporate the endogenous matching outcomes given by the third set of the equilibrium conditions. Despite this extension, this model remains tractable because the matching market outcomes are solved independently for each sector pairs k, m and location i. This property is useful for the sequential estimation procedure in Section 5 and for the counterfactual simulations in Section 6.

There are two agglomeration forces in the model. The first channel is the increasing returns to scale in matching technology ($\lambda + \nu > 1$). In particular, in a special case of the model where $\lambda = \nu - 1 = 0$ (which implies $\lambda + \nu = 1$), matching outcomes $\{\Lambda_{i,km}, a_{i,km}, v_{i,km}\}$ become independent of location (i) given sectors (k, m). The second channel of agglomeration force is the production spillover from local population density ($\iota > 0$). As discussed above, this channel summarizes all other types of agglomeration production spillovers (e.g., labor market pooling, knowledge spillovers). In a typical quantitative spatial model, the second term is the only channel of production agglomeration spillover, assuming that all production spillovers are summarized by this term. Below, I argue that both of these agglomeration spillovers significantly contribute to the observed spatial economic activity and that misattributing these two agglomeration forces biases for counterfactual allocations for the reduction of trade cost.

5 Structural Estimation

In this section, I estimate the parameters of the model developed in Section 4 using firm-to-firm trade data. The estimation proceeds in four steps, each of which uses different components of equilibrium conditions. In the first step, I start by calibrating a subset of parameters directly from the data or from central estimates in the literature. Second, I esti-

[25] Appendix C.5 shows that an equilibrium always exists. The same appendix further shows that the equilibrium is unique when agglomeration spillovers are sufficiently small, succeeding the property of Allen and Arkolakis (2014).

mate the gravity equations of cross-regional trade flows. Third, I estimate matching technology using the impulse responses of unanticipated supplier bankruptcy documented in Section 3 as moment conditions. Fourth, I estimate the productivity of each location and the elasticity of productivity spillovers from local population density.

In order to execute the estimation procedure, I need to take a stand on how I map the model's location and sectors to data. Locations in the model correspond to the 47 prefectures in Japan. Sectors in the model correspond to 33 two-digit sectors in manufacturing, commerce (wholesale and retail), and construction/equipment services. These 33 two-digit sectors together represent over 80% of firms in Japan (Appendix Table B.1).

5.1 Calibrating Subset of Parameters (Step 1)

First, I calibrate a subset of parameters directly from the data or using central values from the existing empirical literature.

I calibrate the intermediate input share $\{\gamma_{L,m}\}$, labor share of production $\{\gamma_{km}\}$, and the final goods consumption share $\{\alpha_m\}$, directly from the input-output table in 2011 created by Japan's Ministry of International Affairs and Communications in Japan. I set the productivity dispersion parameter θ as 4.3 from Gaubert and Itskhoki (2021), the elasticity of substitution parameter σ as 5 from Broda and Weinstein (2006), and the elasticity of migration with respect to real wage v as 2 from Kondo and Okubo (2015). I provide a sensitivity analysis of these values in the estimation and counterfactual simulations below.

5.2 Estimating Gravity Equations of Trade Flows (Step 2)

Next, I estimate the gravity equations of trade flows (equation 9). I parameterize the iceberg trade cost $\tau_{ij,m}$ as a power function of travel time $\tau_{ij,k} = \left(T_{ij}\right)^{\tilde{\kappa}_m}$, where T_{ij} is the travel time from location i to location j and $\tilde{\kappa}_m$ is a parameter governing the elasticity of trade cost with travel time. The gravity equation is rewritten as

$$\pi_{ij,m} = \frac{\Gamma_{i,m}\left(T_{ij}\right)^{\kappa_m}}{\Omega_{i,m}}, \tag{32}$$

where $\kappa_m = \theta\tilde{\kappa}_m$.

I estimate this equation separately for each sector using the Poisson Pseudo-Maximum Likelihood (PPML) method (Santos Silva and Tenreyro 2006). I use PPML instead of OLS on the log-linear relationship to deal with the presence of zero bilatral cross-region trade flows in the data. I construct the fraction of supplier linkages ($\pi_{ij,m}$) from TSR data in 2008, and I obtain the bilateral travel time T_{ij} from the Google Maps API. I use the estimated $\Gamma_{i,m}$, $\Omega_{i,m}$, and κ_m in the subsequent estimation procedure.

5.3 Estimating Matching Technology Parameters (Step 3)

Third, I estimate the matching technology parameters.

I first directly obtain the separation rates ρ_{km} from the TSR firm-to-firm trade data, using the separation rate of a firm and sector m with a supplier in sector k in my sample period (between 2008 and 2016).

I next calibrate a subset of parameters. I set the discount rate (ξ) such that $\xi = 0.05$, and the bargaining weight (β) is set such that $\beta = 0.5$. In Appendix Table D.1, I show that the subsequent estimation results are not sensitive to the choice of these values.[26]

The remaining parameters, $\Theta = \{\lambda,\ \nu,\ \eta,\ \chi,\ \delta,\ \{\zeta_k\}\}$, are estimated in the indirect estimation procedure. The basic idea is to find parameter Θ that closely replicates the reduced-form estimates of the impacts of unanticipated supplier bankruptcies as documented in Section 3.[27] More specifically, given parameter values Θ and already estimated $\Gamma_{i,k}$ and $\Omega_{i,m}$ from the gravity equations above, I compute the endogenous matching outcomes $\{v_{i,km}(\Theta), a_{i,km}(\Theta), \bar{c}_{i,km}(\Theta), \phi_{i,km}(\Theta), \Lambda_{i,km}(\Theta), \Psi_{i,km}(\Theta)\}$ by solving equations (12), (19), (20), (21), and (22) for each location i and sector pair k, m. Using these objects, I construct the model's prediction of the impulse responses of the unanticipated supplier bankruptcy (interpreted as exogenous separation in the model) on the new supplier matching and sales growth and obtain the average responses and the heterogeneous responses with respect to supplier and buyer density. (See Appendix D.1 for further details of this estimation procedure.) Denoting the collection of these model-predicted average and heterogeneous impulse responses by $\boldsymbol{\beta}(\Theta)$, the indirect inference estimator $\hat{\Theta}$ is defined by the value of Θ that minimizes the Euclidean distance between $\boldsymbol{\beta}(\Theta)$ and the

[26] Intuitively, ξ and β affect the equilibrium matching outcomes only through the acceptance rates ($a_{j,km}$ in equation 19). At the same time, $a_{j,km}$ tends to be close to one in most sectors and locations within a reasonable range of these parameters. Hence, ξ and β have limited effects on other parameter estimates. Recall also that firms are owned by foreigners outside of the economy, hence the bargaining share β does not affect the spatial income distribution.

[27] I normalize ϑ and ζ_k for the first sector to one. Because these parameters enter multiplicatively with η in equation (12), these normalizations do not affect any of our counterfactual simulation results.

difference-in-difference effects $\boldsymbol{\beta}$ using the actual data reported in Section 3. Formally,

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \|\boldsymbol{\beta}(\Theta) - \boldsymbol{\beta}\|^2 + \frac{1}{|N||K|} \sum_{i \in N;\ k,m \in K} \left(\Psi_{i,km}(\Theta) - \Psi_{i,km}\right)^2, \tag{33}$$

where $\|\|$ indicates the Euclidean norm. On top of the Euclidean distance of the impulse responses as discussed above, I also include the Euclidean distance in sales-weighted steady-state matching probability ($\Psi_{i,km}$) between the model-prediction and the data in the second term.

Intuitively, this indirect inference identifies each of the structural parameters $\Theta = \{\lambda, \nu, \eta, \chi, \delta, \{\zeta_k\}\}$ from the following moment conditions. The efficiency of the matching technology (η) is identified from the average impacts of supplier bankruptcy on the number of new suppliers. The elasticities of matching function with supplier density (λ) and buyer density (ν) are identified by this impact heterogeneity. The iceberg cost of in-house intermediate goods production (χ) is identified from the average impacts on sales growth. The fraction of firms that can match with a supplier (δ) and the efficiency of in-house intermediate goods production ($\{\zeta_k\}$) are identified by the steady-state match probability for each sector ($\Psi_{i,km}$).

Table 4 presents the estimation results and the model fit. Panel (A) presents the point estimates and their bootstrapped confidence intervals. I start by discussing the elasticity of matching functions with respect to supplier density (λ) and buyer density (ν). As defined in equation (12), $\lambda > 0$ implies that the matching rates with suppliers increase in supplier density, $\nu < 1$ implies that the matching rates with suppliers decrease in buyer density, and $\lambda + \nu > 1$ implies that the matching function exhibits increasing returns to scale (IRS). My estimate of $\lambda = 0.622$ (with a bootstrap confidence interval of $[0.497, 0.738]$, significantly above 0) indicates that supplier matching rates are significantly increasing in supplier density. My estimate of $\nu = 0.974$ (with a confidence interval of $[0.852, 1.076]$, not significantly different from 1) indicates the lack of evidence for the crowding-out effects by other buyers. Lastly, I find the point estimate of $\lambda + \nu = 1.596$, which is significantly greater than one, indicating that the matching technology exhibits increasing returns to scale (IRS).

My estimate of matching efficiency parameter $\eta = 0.045$ (with a confidence interval of $[0.044, 0.047]$) supports the evidence that firms indeed match with an alternative supplier after separation of the supplier relationships. My estimate of the iceberg cost of in-house intermediate goods production $\chi = 1.070$ (with a confidence interval of $[1.067, 1.071]$)

indicates that matching with external suppliers indeed benefits firms by significantly reducing the marginal cost. Finally, my estimate of the fraction of firms that can match with a supplier $\delta = 0.147$ indicates that a substantial fraction of firms do not ever match with external suppliers.

In Panel (B) of Table 4, I present how closely the estimated model replicates the impulse responses of supplier bankruptcy on new supplier matching and sales decline. Across the board, the model successfully captures the pattern of the actual impacts of unanticipated supplier bankruptcies. In particular, the point estimates of the regression on model-predicted outcomes (Column 2, 4, 6) are within the confidence intervals of the regression coefficients on actual outcomes in the data (Column 1, 3, 5). Importantly, in Columns 3 and 4, the model successfully replicates the positive heterogeneous impacts with the number of new suppliers by supplier density (row 3 and 4) and the lack of heterogeneous impacts with buyer density (row 5 and 6).

Table 4: Estimation Results and Model Fit of Matching Technology Parameters

(A) Key Parameter Estimates

Parameters	Description	Point Estimate	Confidence Interval
ξ	discount rate (calibrated)	0.050	
β	bargaining share to buyers (calibrated)	0.500	
λ	elasticity of matching function with supplier density	0.622	[0.497, 0.738]
ν	elasticity of matching function with buyer density	0.974	[0.852, 1.076]
η	efficiency of matching function	0.045	[0.044, 0.047]
χ	iceberg cost for in-house intermediate goods production	1.070	[1.067, 1.071]
δ	fraction of firms that can match with external suppliers	0.147	[0.130, 0.153]

(B) Model Fit

	Dependent variable:					
	Number of New Suppliers				Sales (IHT)	
	Data	Model	Data	Model	Data	Model
	(1)	(2)	(3)	(4)	(5)	(6)
Trt x 1[t - BankruptYear = 0 or 1]	0.16 (0.04)	0.11			−0.21 (0.10)	−0.31
Trt x 1[t - BankruptYear = 0 or 1]	0.26 (0.06)	0.28			−0.22 (0.18)	−0.25
Trt x 1[t - BankruptYear = 0 or 1] x log Supplier Density (Std.)			0.12 (0.06)	0.14		
Trt x 1[t - BankruptYear = 2 or 3] x log Supplier Density (Std.)			0.27 (0.08)	0.27		
Trt x 1[t - BankruptYear = 0 or 1] x log Buyer Density (Std.)			−0.01 (0.04)	−0.02		
Trt x 1[t - BankruptYear = 2 or 3] x log Buyer Density (Std.)			−0.07 (0.06)	−0.03		
Observations	76,054		76,054		74,462	
Adjusted R^2	0.60		0.62		0.73	

Note: Estimation results and model fit of the matching parameters through indirect inference procedure. Panel (A) reports the point estimates of the indirect inference estimator defined by equation (33). To construct the bootstrapped confidence interval, I resample treatment firms at equal probability (with replacement) to construct 100 sets of bootstrapped samples, and obtain the 5th and 95th percentiles of the estimates of the structural parameters across these bootstrapped samples. Panel (B) reports the estimated effects of unanticipated supplier bankruptcies using actual data (Column 1, 3, 5) and using the model's prediction (Column 2, 4, 6). Column 1 corresponds to Column 1 of Table 1, Column 3 corresponds to Column 3 of Table 3, and Column 5 corresponds to Column 2 of Table 1, respectively.

Appendix Table D.1 shows that these estimation results are not sensitive to calibrated parameters (ξ, β, σ, θ) and by using treatment firms that have no establishments outside the headquarter locations.

5.4 Estimating Productivity Spillovers (Step 4)

In the fourth step, I estimate the productivity of each location $A_{i,m}$ and the productivity spillover elasticity from the local population density (ι).

I first estimate $A_{i,m}$ using the expression for the supply capacity (equation 24). By inverting this equation, I have

$$A_{i,m} = \Gamma_{i,m}^{\frac{1}{\theta}} \left[\varrho w_i^{-\theta} \prod_{k \in K} \left(1 + \Lambda_{i,km} \left(\phi_{i,km} - 1\right)\right) \right]^{-\frac{1}{\theta}}. \tag{34}$$

I estimate $A_{i,m}$ using this equation with already estimated $\Gamma_{i,m}$ from the gravity equation of trade flows (Step 2), directly observed wages w_i from official statistics, and model-predicted $\Lambda_{i,km}$ and $\phi_{i,km}$ using the estimated matching parameters (Step 3).

I next estimate the elasticity of productivity spillovers from local population density (ι) using the estimates of $A_{i,m}$. By taking the logarithms of the definition of $A_{i,m}$ in equation (5), I have:

$$\log A_{i,m} = \iota \log\left(\frac{L_i}{Z_i}\right) + \varphi_m + \epsilon_{i,m}, \tag{35}$$

where $\varphi_m \equiv \mathbb{E}[\log A^*_{i,m}]$ is the industry fixed effects and $\epsilon_{i,m} \equiv \log A^*_{i,m} - \mathbb{E}[\log A^*_{i,m}]$ is the residual exogenous productivity. Estimating this regression by OLS yields a biased estimate of spillover elasticity (ι) because the population density (L_i/Z_i) is plausibly correlated with the residual exogenous productivity ($\epsilon_{i,m}$) through endogenous population mobility. An ideal theory-consistent instrument for the population density in this equation is the component of residential amenities (K_i) that is unrelated to productivity ($A^*_{i,m}$). Here, following the approach of Glaeser and Gottlieb (2008) and Allen and Donaldson (2020), I use mean temperature and average rainfall as instruments for the population density. For the sectors considered in this section (manufacturing, commerce, and construction/equipment services), these climate characteristics are unlikely to affect the productivity ($A^*_{i,m}$), and hence they arguably satisfy the exclusion restriction.

Table 5 presents the estimation results. Column (1) presents the first stage regression. Higher temperatures and fewer rainy days are significantly associated with population density, consistent with the interpretation that a warmer and more sunny climate is associated with higher residential amenity. Column (2) reports the IV regression results of my estimation equation (35) using the average temperature and the number of rainy days as an instrument for the population density ($\log\left(\frac{L_i}{Z_i}\right)$). I obtain the point estimate of $\iota = 0.11$, which is within the range of parameter values of the productivity spillover estimates in the literature (Melo, Graham, and Noland 2009).

To benchmark this result, in Column (3), I estimate regression equation (35) by (falsely) assuming that there were no increasing returns to scale (IRS) in matching function, such that $\lambda = \nu - 1 = 0$ (unlike the estimated value of 0.622 and 0.974 above). Under these assumptions, the matching probability $\Lambda_{i,km}$ and the match benefit $\phi_{i,km}$ are constant across locations (i), and hence the term $\prod_{k \in K} \left(1 + \Lambda_{i,km} \left(\phi_{i,km} - 1\right)\right)$ in the estimation equation of $A_{i,m}$ (equation 34) drops out as constant (up to sector m). In Column (3), I show that the elasticity of productivity spillover (ι) is substantially overestimated using this falsely-estimated $A_{i,m}$ as a dependent variable ($\iota = 0.18$ instead of 0.11). Intuitively, the contribution of IRS in matching technology to location productivity ($\prod_{k \in K} \left(1 + \Lambda_{i,km} \left(\phi_{i,km} - 1\right)\right)$) in equation (34) is positively correlated with observed population density, and hence the omission of this term creates an upward omitted variable bias (OVB). In the next section, I show that misattributing these two channels substantially biases the welfare gains from trade cost reduction.

6 Counterfactual Simulations

In this section, I use the estimated model to undertake a sequence of counterfactual simulations to highlight how the increasing returns to scale (IRS) in firm-to-firm matching affects the spatial distribution of economic activity. In Section 6.1, I hypothetically shut down the model's two agglomeration forces (IRS in matching technology and productivity spillovers from local population density) and study how the equilibrium changes under these counterfactuals. In Section 6.2, I simulate the hypothetical reduction of cross-regional trade cost and study how the predicted welfare gains change by omitting each of these two agglomeration forces.

To conduct these counterfactual simulations, I follow the exact-hat algebra approach of Dekle, Eaton, and Kortum (2008) and rewrite the counterfactual equilibrium conditions in terms of the unobserved changes in the endogenous variables between the counterfactual and initial equilibria (see Appendix E.1 for the formal system of equilibrium condi-

Table 5: Estimation Results of Production Spillover Elasticity

	$\log(L_i/Z_i)$ First Stage	$\log A_{i,m}$ IV	$\log A_{i,m}$ IV
	(1)	(2)	(3)
Average Annual Temperature	0.16^{***}		
	(0.01)		
Number of Rainy Days	-0.01^{***}		
	(0.0002)		
$\log(L_i/Z_i)$		0.11^{***}	0.18^{***}
		(0.02)	(0.02)
Specification			No IRS in Matching Function ($\lambda = \nu - 1 = 0$)
Observations	1,449	1,449	1,449
Adjusted R^2	0.21	0.87	0.88

Note: Estimation results of the instrumental variable (IV) regression of equation (35). Column (1) presents the results of the first stage regression. Column (2) reports the IV estimates of productivity spillover (ι). Column (3) reports the same IV estimates by (falsely) assuming that there were no increasing returns to scale (IRS) in matching function (such that $\lambda = \nu - 1 = 0$) when constructing the outcome variable $A_{i,m}$ in equation (34). *p<0.1; **p<0.05; ***p<0.01.

tions). Compared to a canonical trade and spatial equilibrium model, there are additional equilibrium conditions due to endogenous matching (equilibrium condition (iii) in Section 4.8). Since these additional components of equilibrium conditions can be independently solved for each sector and location, this exact-hat algebra approach remains computationally tractable.

6.1 Shut Down Agglomeration Forces

In my first set of counterfactual simulations, I assess the contribution of the two agglomeration forces to the observed spatial differences in wages through three sets of counterfactual simulations. In my first counterfactual, I hypothetically shut down increasing returns to scale (IRS) in matching technology such that $\lambda = \nu - 1 = 0$. In my second counterfactual, I shut down productivity spillovers from local population density, such that $\iota = 0$. In my third counterfactual, I shut down both types of agglomeration forces, such that $\lambda = \nu - 1 = 0$ and $\iota = 0$.

Table 6 presents the results of these counterfactual simulations. For the observed equilibrium (in Column 1) and for the counterfactual equilibrium (in Columns 2-4), the table shows the regression coefficients of the logarithm of wages on the local population density.

Column (1) reports the population-density wage premium observed in the data. The point estimate of 0.076 indicates that a 100 percentage point increase in population density is associated with a 7.6 percentage point increase in observed wages, which is within the range of previous estimates of this relationship (Melo, Graham, and Noland 2009).

In Column (2), I report the counterfactual population-density wage premium under my first counterfactual to shut down the IRS in matching technology ($\lambda = \nu - 1 = 0$). The predicted premium decreases to 0.045, which is a 41 percent reduction from the observed premium ($= (0.076 - 0.045)/0.076$). In other words, 41 percent of observed wage inequality is explained by IRS in matching technology.

To benchmark this result, in Column (3), I report the predicted population-density wage premium under my second counterfactual simulation to shut down the local production spillovers (summarizes all other agglomeration forces) such that $\iota = 0$. The predicted premium decreases to 0.011, or a 86 percent reduction from the observed premium ($= (0.076 - 0.011)/0.076$). In Column (4), I further shut down both types of agglomeration spillovers (such that $\lambda = \nu - 1 = 0$ and $\iota = 0$). The predicted premium becomes negative and decreases to -0.013, or a 117 percent reduction from the observed premium ($= (0.076 - (-0.013))/0.076$). Therefore, the contribution of the IRS in matching technology on observed population-wage premium is nonnegligible to that of the overall agglomeration spillovers.

In Appendix Table E.1, I find a similar patterns for the counterfactual changes in population density (in terms of the relative contribution of IRS in matching technology out of overall agglomeration spillovers). Appendix Table E.2 reports that these conclusions are robust to the value of calibrated parameters in Section 5.

6.2 Cross-Regional Trade Cost

In my second counterfactual simulation, I study how the welfare gains of the reduction of cross-regional trade costs are affected by these two types of agglomeration spillovers.

To consider a realistic spatial pattern of trade cost reduction, I analyze the trade cost reduction that is proportional to travel time reduction from existing highway networks in Japan. In particular, I calibrate the model using the observed travel time with existing highway networks, and I simulate the counterfactual equilibrium in the absence of

Table 6: Agglomeration Forces and Population-Density Wage Premium

	Dependent Variable: log Wages			
	Baseline	Shut Down IRS in Matching Function ($\lambda = \nu - 1 = 0$)	Shut Down Population Productivity Spillovers ($\iota = 0$)	Shut Down Both Agglomeration Spillovers ($\lambda = \nu - 1 = 0$ and $\iota = 0$)
	(1)	(2)	(3)	(4)
log Population Density	0.076***	0.045***	0.011	−0.013
	(0.010)	(0.009)	(0.012)	(0.010)
C.I. from Bootstrap Parameter Estimates		[0.039, 0.055]	[0.0096, 0.013]	[-0.018, -0.0043]
Percentage Difference from Baseline (%)	0	-41	-86	-117
Observations	47	47	47	47
Adjusted R^2	0.547	0.323	−0.002	0.011

Note: Results of the counterfactual simulations to shut down agglomeration forces. Each column reports the regression coefficients of the logarithm of wages on the local population density. Column (1) reports this relationship in the observed data, and columns (2)-(4) report these premiums under the three counterfactuals described in Section 6.1. In the fourth to bottom row, I report the confidence intervals using bootstrapped estimates of matching parameters (Table 4). *p<0.1; **p<0.05; ***p<0.01.

highway networks. The increase of trade cost is specified as $\hat{\tau}_{ij,k} = \left(T_{ij}^{\text{nohighway}} / T_{ij}\right)^{\tilde{\kappa}_m}$, where $T_{ij}^{\text{nohighway}}$ is the travel cost without using highway networks obtained from Google Maps API, and $\tilde{\kappa}_m = \theta \kappa_m$ is the estimated elasticity of trade volume with respect to travel time (estimated in Section 5.2).

I undertake this counterfactual simulation under four different scenarios. In my first scenario, I incorporate both types of agglomeration spillovers (IRS in matching technology and the local population spillovers). In my second scenario, I (falsely) omit the IRS in matching technology, such that $\lambda = \nu - 1 = 0$. In my third counterfactual scenario, I (falsely) omit the local population spillover, such that $\iota = 0$. In my fourth counterfactual scenario, I (falsely) omit both types of agglomeration spillovers, such that $\lambda = \nu - 1 = 0$ and $\iota = 0$.

The goal of this counterfactual simulation is not to provide an accurate welfare evaluation of the highway networks in Japan. The model abstracts important realistic features relevant to this question, such as the reduction of migration frictions by highway networks. Instead, the goal of this counterfactual is to highlight how different agglomeration mechanisms lead to different predictions about the welfare gains of cross-regional trade cost reduction, and how the incorrect specifications of agglomeration mechanisms biases the predicted welfare gains.

Table 7 presents estimates of the welfare gains under these four counterfactual simulations. The second column reports the percentage point increases in the expected utility. The third column reports their confidence intervals, based on the bootstrapped confidence sets of parameter estimates of matching technology parameters (Table 4). The fourth column reports the estimates of the welfare gains as a percentage of the same estimates under the first scenario of including both types of agglomeration forces.

When both types of agglomeration spillovers is present (first row), this trade cost reduction leads to a 6.19 percentage points increase in expected utility. When I (falsely) abstract the IRS in matching technology ($\lambda = \nu - 1 = 0$, second row), the welfare gains is underestimated as 4.53 percentage points, which is 27 percent smaller ($= (6.19 - 4.53)/6.19$) than baseline. In other words, about 27 percent of the welfare gains of trade cost reduction is attributed to the IRS in matching technology. Intuitively, these trade cost reductions lead to an increase of the pool of potential suppliers in the affected regions. In the presence of IRS in matching, increasing the supplier pool increases the productivity of firms in these regions.

On the other hand, when I (falsely) abstract the production spillovers from population density ($\iota = 0$, third row), the estimated welfare gains are 6.17 percentage points, which is virtually identical to the estimates when I include this type of agglomeration effect (first row). Similarly, the predicted welfare gain when abstracting both types of agglomeration forces (4.53 percentage point, fourth row) is virtually identical to the scenario where I only abstract the IRS in matching technology (second row). Therefore, while the IRS in matching technology significantly contributes to the welfare gains of trade cost reduction, production spillovers from local population density have negligible contributions to the welfare gains in this context. Intuitively, population spillovers only affect productivity through population mobility. Because aggregate population size is fixed, productivity gains in locations with a population increase are largely offset by the productivity losses in locations with a population decrease.

Table 7: Welfare Gains of Trade Cost Reduction

Specification	Welfare Gains (p.p.)	Confidence Interval	Relative to Baseline (%)
Baseline	6.19	[5.87, 6.33]	100
Shut Down IRS in Matching Function ($\lambda = \nu - 1 = 0$)	4.53	[4.48, 4.63]	73.2
Shut Down Population Productivity Spillovers ($\iota = 0$)	6.17	[5.87, 6.31]	99.7
Shut Down Both Agglomeration Spillovers ($\lambda = \nu - 1 = 0$ and $\iota = 0$)	4.53	[4.48, 4.63]	73.2

Note: Results of the counterfactual simulations to reduce cross-region trade cost described in Section 6.2.. For each assumption of the agglomeration forces, the table reports the percentage point increase in the expected utility (in the second column), its confidence interval using bootstrapped matching parameter estimates from Table 4 (in the third column), and its ratio to the baseline (assuming both types of agglomeration spillovers).

These results indicate that misattributing the agglomeration mechanisms substantially biases the estimates of welfare gains of the trade cost reduction.[28]

7 Conclusion

This paper provides new theory and evidence of how firm-to-firm matching in input trade shapes the agglomeration of economic activity. Using a yearly panel of firm-to-firm trade in Japan, I document that firms gradually match with an alternative supplier after an unanticipated supplier bankruptcy; these rematching rates increase in the geographic density of alternative suppliers, and they do not decrease in the geographic density of other buyers. Motivated by these findings, I develop a quantitative spatial equilibrium model of search and matching frictions in firm-to-firm trade. I structurally estimate the key model parameters and show that the increasing returns to scale (IRS) in matching technology is equally important as other channels of agglomeration spillovers in explaining the spatial productivity spillovers. Undertaking counterfactuals for changes in trade cost, I show that misattributing these agglomeration mechanisms substantially biases the estimates of welfare gains.

This paper highlights a particular agglomeration mechanism: IRS of firm-to-firm matching technology in input trade. This is, of course, not the only relevant agglomeration mechanism. Other agglomeration mechanisms, such as labor market pooling or knowledge spillover, are equally 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 its equilibrium implications.

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[28] Appendix Table E.3 reports that these conclusions are robust to the value of calibrated parameters in Section 5. Appendix Section E.3 discusses the transition dynamics and shows that it takes time for the welfare gains to fully materialize due to a gradual adjustment of supplier matching.

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

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A Additional Information of TSR (Tokyo Shoko Research) Firm-to-Firm Trade Data

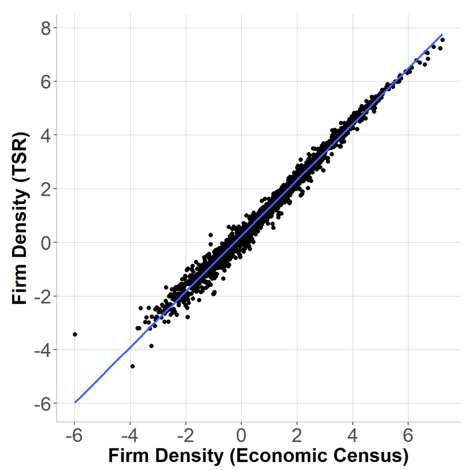
In this section of the online appendix, I provide additional information about the firm-to-firm trade data from Tokyo Shoko Research (TSR). Table A.1 and Figure A.1 show the coverage rates of TSR data and show that the TSR data is broadly representative across geography. Table A.2 presents the list of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

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

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

Note: By year (2009 or 2016) and Sample size (first column) and firm size (over or under 5 employees), this table reports the sample size of the TSR data set (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 data sets relative to Economic Census



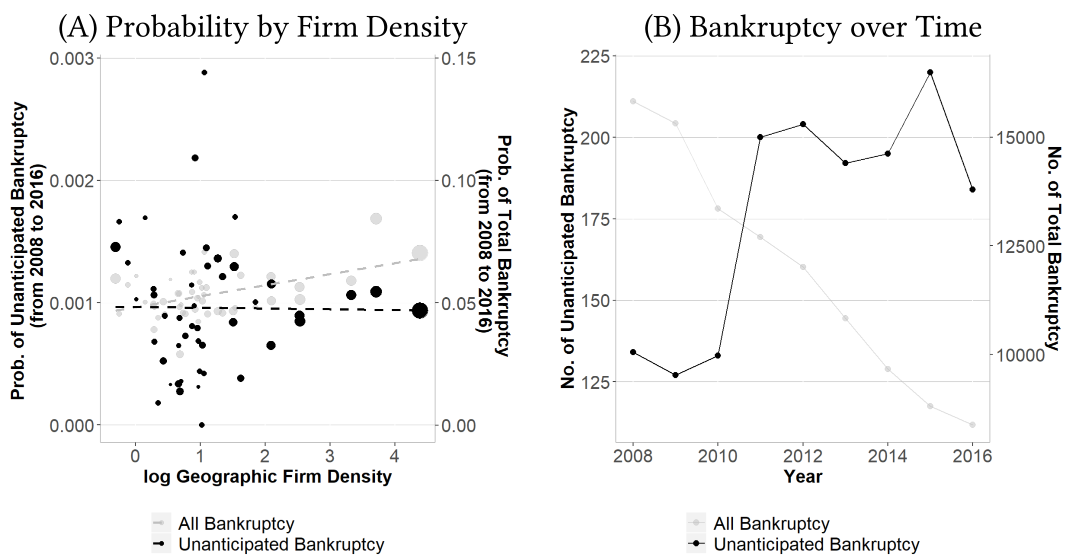
Note: This figure plots the density of firms using two data sources: The economic census on the horizontal access and TSR data on the vertical access. Each dot represents a municipality in Japan. All data is from 2009. The straight line in the graph is the linear regression fit between the two variables. The slope of the regression line is 1.04 (with an intercept of 0.25) and the R-squared is 0.98. The tight log-linear relationship with a coefficient close to one suggests that the TSR data set is representative across different municipalities in Japan.

Table A.2: List of Reasons of Bankruptcies

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

Note: 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 size of the dot represents the 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 Additional Empirical Results for Reduced-Form Evidence

In this section of the online appendix, I present additional results for the reduced-form evidence of matching frictions and increasing returns to scale (IRS) in firm-to-firm matching presented in Section 3 of the paper.

Table B.1 shows that the characteristics of treatment firms and the control firms are broadly similar. Table B.2 shows that there are no differential pretrends between treatment firms and control firms in the new supplier matching rates and sales growth.

Table B.1: Characteristics of Treatment Firms

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

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

Table B.2: Pretrends on New Supplier Matching Rates and Sales

	Number of New Suppliers	Sales (IHS)
	(1)	(2)
Trt x 1[t - BankruptYear = -3 or -2]	0.04	−0.01
	(0.03)	(0.01)
Observations	31,861	31,221

Note: This table assesses the pretrends for the difference-in-difference regression (equation 1) by running this regression using only pre-period data and replacing the post dummy with the dummy for 2 or 3 years before the bankruptcy (omitted category is 1 year before the bankruptcy). The outcome variable of the regression is the number of newly matched suppliers relative to the baseline period (one year before the shock) for Column 1 and the inverse-hyperbolic sine (IHS) transformation of sales for Column 2. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Tables B.3-B.6 reports additional robustness results for the average effects of the supplier bankruptcy presented in Section 3.1. Table B.3 shows that these supplier bankruptcies do not significantly affect the sales of the treatment firms' other existing suppliers, indicating that treatment firms primarily respond by rematching with new suppliers instead of simply substituting from existing suppliers. In Table B.4, I show that the newly matched suppliers are significantly more likely to belong to the same industry as bankrupt suppliers, consistent with the interpretation that treatment firms are in search of an alternative supplier. Table B.5 shows that there are no heterogeneous effects by firm size, suggesting that these matching frictions are relevant for both small and large firms. Table B.6 presents the effects on other firm-level outcome variables.

Table B.3: Average Impacts of Supplier Bankruptcy on Other Existing Suppliers

	Continued Relationships with Other Suppliers	log Sales of Other Surviving Suppliers
	(1)	(2)
Trt x 1[t - BankruptYear = -2 or -3]	0.02	0.01
	(0.03)	(0.01)
Trt x 1[t - BankruptYear = -1]	−0.06	0.03
	(0.04)	(0.02)
Observations	76,054	66,784

Note: This table reports the result of the difference-in-difference regression (equation 1). Column (1) reports the effects on the number of continuing relationships with other existing suppliers (suppliers that are connected one year before the bankruptcy). Column (2) reports the effects on the mean of the log sales of the firm's other existing suppliers. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.4: Decomposition of Impacts of Supplier Bankruptcy on Newly Matched Suppliers

	Dependent Variable: Number of New Suppliers within Specified Subset				
	All	Within 4-digit Industry	Within 2-digit Industry	Headquarter in Same Prefecture	Has Buyer in Same Prefecture
	(1)	(2)	(3)	(4)	(5)
Trt x 1[t - BankruptYear = 0 or 1]	0.17^{***}	0.04^{***}	0.05^{***}	0.08^{***}	0.08^{***}
	(0.04)	(0.01)	(0.02)	(0.03)	(0.03)
Trt x 1[t - BankruptYear = 2 or 3]	0.27^{***}	0.07^{***}	0.10^{***}	0.16^{***}	0.16^{***}
	(0.06)	(0.02)	(0.03)	(0.04)	(0.05)
Random Matching Benchmark (Impacts after 2-3 Years)	0.27	0.001	0.007	0.012	0.004
Actual Impacts / Random Matching Benchmark	1	56	15	14	40

Note: This table reports the result of the difference-in-difference regression (equation 1). The outcome variables are the number of newly matched suppliers (i.e., number of suppliers which are not connected in the baseline period) within a specified subset of potential suppliers in each column. Column (1) reproduces the impacts on the number of all new suppliers (Column 1 of Table 1). Columns (2) and (3) report the impacts on the number of newly matched suppliers within the same four-digit and two-digit industry as the bankrupt suppliers, respectively. Column (4) reports the impacts on the number of newly matched suppliers whose headquarters are located in the same prefecture as the treatment firms. Column (5) reports the impacts on the number of newly matched suppliers that already have existing buyers in the treatment firm's prefecture (at the point of 2008). The second to bottom row (labelled "Random Matching Benchmark") indicates the hypothetical impacts if supplier matching happens randomly independent of the supplier's industry or location. The bottom row (labelled "Actual Impacts/Random Matching Benchmark") indicates the ratio of the estimated coefficients and the hypothetical impacts under this random matching benchmark. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.5: Heterogeneous Impacts of Supplier Bankruptcy by Firm Size

	Number of New Suppliers		Sales (IHS)	
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1]	0.17^{***}	0.24^{***}	-0.21^{**}	-0.22
	(0.04)	(0.09)	(0.10)	(0.18)
Trt x 1[t - BankruptYear = 2 or 3]	0.27^{***}	0.21^{**}	-0.22	-0.25
	(0.06)	(0.09)	(0.18)	(0.40)
Trt x 1[t - BankruptYear = 0 or 1] x Employment (Medium Tercile)		-0.07		-0.06
		(0.14)		(0.24)
Trt x 1[t - BankruptYear = 2 or 3] x Employment (Medium Tercile)		0.07		0.004
		(0.16)		(0.54)
Trt x 1[t - BankruptYear = 0 or 1] x Employment (Top Tercile)		-0.19		0.04
		(0.13)		(0.25)
Trt x 1[t - BankruptYear = 2 or 3] x Employment (Top Tercile)		0.04		-0.04
		(0.17)		(0.53)
Number of Treatment Firms	421	421	421	421
Number of Bankrupt Suppliers	161	161	161	161
Number of Control Firms	10,842	10,842	10,814	10,814
Observations	76,054	75,749	74,462	74,300

Note: The results of the difference-in-difference regression (equation 1 in the main paper). The outcome variable of the regression is the number of newly matched suppliers relative to the baseline period (one year before the shock) for Column 1 and 2, and the inverse-hyperbolic sine (IHS) transformation of sales for Column 3 and 4. "Employment (Medium Tercile)" and "Employment (Top Tercile)" indicate the dummy variables that takes one if the firm's employment size in baseline period is in the medium tercile and top tercile of the treatment firms. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.6: Impacts of Supplier Bankruptcy on Additional Firm Outcomes

	Number of New Suppliers		Exit	Profit / Sales	Employment (IHS)
	(1)	(2)	(3)	(4)	(5)
Trt x 1[t - BankruptYear = 0 or 1]	0.170^{***}	0.184^{***}	0.009	0.005	0.006
	(0.041)	(0.043)	(0.007)	(0.007)	(0.013)
Trt x 1[t - BankruptYear = 2 or 3]	0.267^{***}	0.288^{***}	0.010	0.016	0.021
	(0.063)	(0.066)	(0.012)	(0.014)	(0.015)
Specification	All Firms	Excluding Exit Firms			
Observations	76,054	73,422	76,021	59,167	75,749

Note: This table reports the result of the difference-in-difference regression (equation 1). The outcome variables are the number of newly matched suppliers in Column (1) and (2); the dummy variable that takes one if the firm exits in Column (3); accounting profit divided by sales in Column (4); and the inverse hyperbolic sine (IHS) transformation of employment in Column (5). Column (2) excludes observations if firms drops out from the sample. *p<0.1; **p<0.05; ***p<0.01.

Tables B.7-B.10 report the robustness to the heterogeneous effects with supplier density reported in Section 3.2. Table B.7 shows that these empirical results are further robust to various restrictions on samples and adjustment. The results are further robust to alternative definitions of supplier density (Table B.8), splitting samples to manufacturing and non-manufacturing supplier bankruptcies (Table B.9), and including supplier-reported supplier-to-buyer-linkages when constructing the outcome variables (Table B.10).

Table B.7: Average Impact Heterogeneity by Supplier Density: Robustness

	Dependent Variable: Number of New Suppliers						
	Exclude Exiting Firms	Exclude Tohoku After 2011	Exclude Bankruptcy in 2009	Exclude Tokyo	Exclude No Update in Accounting Year	Adjust Sampling Rate	IV: Seller Density in Birth Prefecture
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline							
Trt x 1[t - BankruptYear = 0 or 1]	0.15^{***}	0.15^{***}	0.16^{***}	0.15^{***}	0.15^{***}	0.27^{***}	0.15^{***}
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.07)	(0.05)
Trt x 1[t - BankruptYear = 2 or 3]	0.26^{***}	0.22^{***}	0.30^{***}	0.25^{***}	0.26^{***}	0.39^{***}	0.25^{***}
	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.10)	(0.07)
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.10^{**}	0.10^{**}	0.10^{**}	0.10^{**}	0.10^{**}	0.16^{**}	0.10^{**}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.05)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.16^{**}	0.16^{**}	0.12^{*}	0.11	0.11	0.18^{*}	0.13^{*}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)	(0.07)
Panel B: Control for Prefecture Fixed Effects and Supplier Industry Fixed Effects							
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.12^{**}	0.14^{**}	0.12^{**}	0.16^{***}	0.16^{**}	0.22^{**}	0.15^{*}
	(0.06)	(0.06)	(0.06)	(0.05)	(0.07)	(0.09)	(0.08)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.23^{***}	0.27^{***}	0.18^{**}	0.30^{***}	0.30^{***}	0.43^{***}	0.30^{**}
	(0.09)	(0.08)	(0.09)	(0.08)	(0.08)	(0.12)	(0.13)
First Stage F-Statistics							16301.4
Number of Treatment Firms	421	400	368	374	421	421	386
Number of Bankrupting Suppliers	161	154	138	145	161	161	154
Number of Control Firms	10,842	10,613	9,137	6,625	10,842	10,842	9,820
Observations	73,422	74,245	66,578	47,208	70,831	76,054	68,497

Note: This table reports the robustness of the regression (2) of the main paper. Panel A controls for the log of the geographic area interacted with treatment and post dummy (corresponding to Column 1 of Table 1), and Panel B controls for prefecture fixed effects and the supplier two-digit industry fixed effects interacted with treatment and post dummy (corresponding to Column 2 of Table 1). In Column (1), I exclude firms that drop out during the sample period (instead of including them as zero in baseline). Column (2) excludes the bankruptcies of suppliers in the Tohoku area after 2011 (the year of the Great Tohoku Earthquake). Column (3) eliminates all supplier bankruptcies in 2009 (the year subsequent to the Financial Crisis). Column (4) excludes firms with headquarters in Tokyo prefecture. Column (5) excludes samples whose accounting information is not available after supplier bankruptcy. Column (6) adjusts the number of reported suppliers by the coverage rates of TSR data set at the suppliers' headquarter location. Column (7) instruments the supplier density proxy by that evaluated at the birth prefecture of the firm CEO. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.8: Impact Heterogeneity by Supplier Density: Alternative Definitions of Supplier Density

	Number of New Suppliers		
	(1)	(2)	(3)
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)	0.14^{**}	0.13^{**}	0.07
	(0.06)	(0.06)	(0.04)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)	0.28^{***}	0.23^{***}	0.22^{***}
	(0.08)	(0.08)	(0.06)
Trt x Post x Prefecture FE	X	X	X
Trt x Post x Supplier 2-digit Industry FE	X	X	X
Definition of Seller Density	Evaluated Right Before Bankrutpcy	Count Locally-Headquarterd Suppliers	Defined by Two-Digit Supplier Industry
Observations	76,054	76,054	76,054

Note: The regression specification follows equation (2) of the main paper with alternative definitions of supplier density. Recall that the baseline definition of the supplier density (in Table 2) is defined as the geographic density of suppliers in the bankrupting suppliers' four-digit industry that have at least one buyer in firm *i*'s prefecture in 2008. In Column (1), instead of evaluating the supplier density in 2008, I evaluate the supplier density one year before each supplier bankruptcy. In Column (2), I count the number of suppliers whose headquarters are established in the treatment firms' prefecture, instead of counting the number of suppliers *selling* to the treatment firms' prefecture. Column (3) 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.9: Impact Heterogeneity by Supplier Density: By Bankrupt Supplier Industry

	Dependent Variable: Number of New Suppliers			
	Manufacturing Bankruptcy		Non-manufacturing Bankruptcy	
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1]	0.11		0.23^{***}	
	(0.08)		(0.07)	
Trt x 1[t - BankruptYear = 2 or 3]	0.20		0.33^{***}	
	(0.12)		(0.12)	
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)		0.15^{***}		0.16^{*}
		(0.04)		(0.08)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)		0.17^{**}		0.27^{***}
		(0.08)		(0.10)
Trt x Post x Prefecture FE		X		X
Trt x Post x Supplier 2-digit Industry FE		X		X
Number of Treatment Firms	159	159	185	185
Number of Bankrupting Suppliers	50	50	83	83
Number of Control Firms	1,043	1,043	1,451	1,451
Observations	7,552	7,552	65,870	65,870

Note: The regression specification follows equation (2) of the main paper by dividing samples by bankrupt suppliers' industries. Column (1) and (2) use subsamples where bankrupt suppliers belong to manufacturing sector, and Column (3) and (4) use subsamples where bankrupts suppliers belong to non-manufacturing sector. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.10: Impact Heterogeneity by Supplier Density: Include Reverse Reporting

	Number of New Suppliers (IHS)			
	Baseline		Include Reverse Reporting	
	(1)	(2)	(3)	(4)
Trt x 1[t - BankruptYear = 0 or 1]	0.15***		0.10***	
	(0.03)		(0.03)	
Trt x 1[t - BankruptYear = 2 or 3]	0.18***		0.14***	
	(0.04)		(0.04)	
Trt x 1[t - BankruptYear = 0 or 1] x log Seller Density (Std.)		0.05**		0.03
		(0.03)		(0.03)
Trt x 1[t - BankruptYear = 2 or 3] x log Seller Density (Std.)		0.13***		0.09***
		(0.04)		(0.03)
Trt x Post x Prefecture FE		X		X
Trt x Post x Supplier Industry FE		X		X
Observations	76,054	76,054	76,064	76,064

Note: This table reports the robustness of the results in Table 2 by including the supplier linkages reported by the supplier-side firms, in addition to the buyer-reported suppliers as in baseline, to construct the outcome variable of the number of newly matched suppliers. I apply the inverse hyperbolic transformation (IHT) of this outcome variables to deal with the fat tailed distribution of this outcome variable. Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table B.11 shows the heterogeneous effects of supplier matching on sales by the following regression:

$$Y_{ft} = \beta \text{NumberSuppliers}_{ft} + \gamma \text{NumberSuppliers}_{ft} \times \log SupplierDensity_g + \eta_{gt} + \xi_{fg} + \epsilon_{ft}, \tag{B.1}$$

where $\text{NumberSuppliers}_{ft}$ is the number of suppliers of firm i in period t, and Y_{ft} is the inverse hyperbolic sine (IHS) transformation of sales, and $\text{NumberSuppliers}_{ft}$ (and its interaction term) is instrumented by the unanticipated supplier bankruptcies. I find a significant IV effects of the number of matched suppliers on sales (Column 1), yet these effects are not significantly different by supplier density (Column 2), consistent with the interpretation that firms in a location with denser suppliers may benefit primarily by *faster* supplier matching but not by *better* supplier matching.

Table B.11: IV Impacts of the Number of Matched Suppliers on Firm Sales

	Sales (IHS)	
	(1)	(2)
Number of Suppliers	0.29*	0.28*
	(0.18)	(0.17)
Number of Suppliers x log Supplier Density (Std.)		−0.01
		(0.16)
First Stage F-Statistics	48.8	38.1
Observations	44,870	44,870

Note: The results of the IV regression specified in equation (B.1). Standard errors are clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

C Model Appendix

In this section of the Online Appendix, I discuss additional details of the model developed in Section 4. Section C.1-C.4 discuss the mathematical derivations. Section C.5 discusses the existence and uniqueness property of the steady-state equilibrium.

C.1 Consumer Price Index

To derive the consumer price index, I first derive the cutoff of entry as a final good seller in location i. The final goods sales of firms in location i with unit cost c (net of trade cost) when they enter in location i is given by

$$r^F_{i,k}(c) = \varrho_{i,k} c^{-\sigma+1}$$

where $\varrho_{i,k}$ is a demand shifter that depends on aggregate equilibrium conditions. Denoting the unit cost threshold of entry as $\bar{c}^F_{j,k}$, the goods market clearing condition is given by:

$$\alpha_k w_j L_j = \int_0^{\bar{c}^F_{j,k}} \varrho_{j,k} c^{-\sigma+1} \Omega_{j,k} \theta c^{\theta-1} dc = \frac{\theta\sigma}{\theta-\sigma+1} f_{j,k} w_j \Omega_{j,k} \left(\bar{c}^F_{i,k}\right)^{\theta}$$

where I used the zero-profit condition for a marginal seller $f_{j,k} w_j = \frac{1}{\sigma} \varrho_{j,k} \left(\bar{c}^F_{i,k}\right)^{-\sigma+1}$. From this equation, the entry cut-off is solved as:

$$\left(\bar{c}^F_{j,k}\right)^{\theta} = \frac{\theta-\sigma+1}{\theta\sigma} \frac{\alpha_k L_j}{f_{j,k}\Omega_{j,k}}$$

Using this expression, consumer price index of location i for goods in sector k is given by:

$$\begin{aligned} P_{j,k}^{1-\sigma} &= \int_0^{\bar{c}^F_{j,k}} c^{1-\sigma} \Omega_{j,k} \theta c^{\theta-1} dc \\ &= \frac{\theta}{\theta-\sigma+1} \Omega_{j,k} \left(\bar{c}^F_{j,k}\right)^{\theta-\sigma+1} \\ &= \frac{1}{\sigma} \left(\frac{\theta-\sigma+1}{\theta\sigma}\right)^{\frac{-\sigma+1}{\theta}} \left(\frac{\alpha_k}{f_{j,k}}\right)^{\frac{\theta-\sigma+1}{\theta}} \left(\Omega_{j,k}\right)^{\frac{\sigma-1}{\theta}} \left(L_j\right)^{\frac{\theta-\sigma+1}{\theta}} \end{aligned}$$

and the consumer price index aggregated across all sector is given by

$$P_j = \prod_k \left(P_{j,k}\right)^{\alpha_k} = \varsigma \left(L_j\right)^{-\frac{\theta-\sigma+1}{\theta(\sigma-1)}} \prod_k \left(f_{j,k}\right)^{\frac{\theta-\sigma+1}{\theta(\sigma-1)}\alpha_k} \left(\Omega_{j,k}\right)^{-\frac{\alpha_k}{\theta}} \tag{C.1}$$

where $\varsigma = \left(\frac{\theta-\sigma+1}{\theta\sigma}\right)^{\frac{1}{\theta}} \sigma^{\frac{1}{\sigma-1}} \prod_k (\alpha_k)^{\alpha_k \frac{\theta-\sigma+1}{\theta(\sigma-1)}}$.

C.2 Solving for Bellman Equations

In this section, I solve the Bellman equations of suppliers and buyers to form a relationship. Reproducing the Bellman equations in Section 4.4,

$$\xi V^B_{\omega t,k}(c) = \Pi^F_{\omega t,k}(c) - \delta_{\omega t,k}(c) - \rho_{km}\left(V^B_{\omega t,k}(c) - U^B_{\omega t,k}\right) + \dot{V}^B_{\omega t,k}(c), \tag{C.2}$$

$$\xi U^B_{\omega t,k} = \chi^{1-\sigma}\Pi^F_{\omega t,k}(\zeta_k w_i) + v_{i,km} a_{\omega,k}\int_0^{\bar{c}_{\omega,k}}\left(V^B_{\omega t,k}(c) - U^B_{\omega t,k}\right) dG_i(c) + \dot{U}^B_{\omega t,k}, \tag{C.3}$$

$$\xi V^S_{\omega t,k}(c) = \delta_{\omega t,k}(c) - \rho_{km}\left(V^S_{\omega t,k}(c) - U^S_{\omega t,k}\right) + \dot{V}^S_{\omega t,k}(c), \tag{C.4}$$

$$U^S_{\omega t,k} = 0, \tag{C.5}$$

$$\begin{aligned} V^S_{\omega t,k}(c) - U^S_{\omega t,k} &= (1-\beta) J_{\omega t,k}(c), \\ V^B_{\omega t,k}(c) - U^B_{\omega t,k} &= \beta J_{\omega t,k}(c). \end{aligned} \tag{C.6}$$

where $\Pi^F_{\omega t,k}(c) = K_{i,m}(p_{\omega t,-k}c^{\gamma_{km}})^{1-\sigma}$ is the instantaneous final goods profit by buyer ω when the supplier's unit cost is c when fixed cost for final goods sales is negligible ($f_{j,k} \to 0$); and $p_{\omega t,-k}$ indicates the component of marginal cost of firm ω other than the component from input sector k; and $K_{i,m}$ is the aggregate final goods demand shifter exogenous to the firm.

I now solve these set of equations. Using equation (C.6),

$$\begin{aligned} \xi J_{\omega t,k}(c) =& \xi\left(V^S_{\omega t,k}(c) - U^S_{\omega t,k}\right) + \xi\left(V^B_{\omega t,k}(c) - U^B_{\omega t,k}\right) \\ =& \left(\Pi^F_{\omega t,k}(c) - \chi^{1-\sigma}\Pi^F_{\omega t,k}(\zeta_k w_i)\right) - \rho_{km}\left(V^B_{\omega t,k}(c) - U^B_{\omega t,k} + V^S_{\omega t,k}(c) - U^S_{\omega t,k}\right) \\ & - v_{i,km} a_{\omega,k}\int_0^{\bar{c}_{\omega,k}}\left(V^B_{\omega t,k}(c) - U^B_{\omega t,k}\right) dG_{\omega,k}(c) + \dot{J}_{\omega t,k}(c) \iff \\ (\xi+\rho_{km}) J_{\omega t,k}(c) =& \left(\Pi^F_{\omega t,k}(c) - \chi^{1-\sigma}\Pi^F_{\omega t,k}(\zeta_k w_i)\right) \\ & - v_{i,km} a_{\omega,k}\int_0^{\bar{c}_{\omega,k}}\left(V^B_{\omega t,k}(c) - U^B_{\omega t,k}\right) dG_{\omega,k}(c) + \dot{J}_{\omega t,k}(c). \end{aligned}$$

By taking the derivative of this with respect to c, I have:

$$
\begin{aligned}
(\xi + \rho_{km})\frac{\partial}{\partial c}J_{\omega t,k}(c) &= \frac{\partial}{\partial c}\Pi^F_{\omega t,k}(c) + \dot{J}_{\omega t,k}(c) \\
&= \gamma_{km}(\sigma - 1)K_{i,m}\left(p_{\omega t,-k}\right)^{1-\sigma} c^{(1-\sigma)\gamma_{km}-1} + \frac{\partial}{\partial c}\dot{J}_{\omega t,k}(c)
\end{aligned}
$$

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

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

Using this equation, equation (C.3) is rewritten as:

$$
\begin{aligned}
\xi U^B_{\omega t,k} &= \chi^{1-\sigma}\Pi_{\omega t,k}(\zeta_k w_i) + v_{i,km}a_{\omega,k}\int_0^{\overline{c}_{\omega,k}} \beta J_{\omega t,k}(c)dG_{\omega,k}(c) + \dot{U}_{\omega t,k} \\
&= \chi^{1-\sigma}\Pi_{\omega t,k}(\zeta_k w_i) + v_{i,km}a_{\omega,k}\beta\frac{K_{i,m}\left(p_{\omega t,-k}\right)^{1-\sigma}}{\xi + \rho_{km}}\int_0^{\overline{c}_{\omega,k}}\left(\overline{c}_{\omega,k}^{(1-\sigma)\gamma_{km}} - c^{(1-\sigma)\gamma_{km}}\right)dG_{\omega,k}(c) \\
&\quad + \int_0^{\overline{c}_{\omega,k}}\left[\dot{J}_{\omega t,k}(c) - \dot{J}_{\omega t,k}(\overline{c}_{\omega,k})\right]dG_{\omega,k}(c) + \dot{U}^B_{\omega t,k} \\
&= \chi^{1-\sigma}K_{i,m}\left((\zeta_k w_i)^{\gamma_{km}} p_{\omega t,-k}\right)^{1-\sigma} - v_{i,km}a_{\omega,k}\beta\frac{K_{i,m}\left(p_{\omega t,-k}\right)^{1-\sigma}}{\xi + \rho_{km}}\overline{c}^{(1-\sigma)\gamma_{km}}\frac{(1-\sigma)\gamma_{km}}{(1-\sigma)\gamma_{km} + \theta} \\
&\quad + \int_0^{\overline{c}_{\omega,k}}\left[\dot{J}_{\omega t,k}(c) - \dot{J}_{\omega t,k}(\overline{c}_{\omega,k})\right]dG_{\omega,k}(c) + \dot{U}^B_{\omega t,k} \qquad \text{(C.7)}
\end{aligned}
$$

where the last transformation uses the fact that $G_{\omega,k}(\cdot)$ is the inverse of the Pareto distribution with upper bound $\overline{c}_{\omega,k}$ ($G_{\omega,k}(c) = c^{\theta}/(\overline{c}_{\omega,k})^{\theta}$ for $c < \overline{c}_{\omega,k}$)).

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

$$
E[V^B_{\omega t,k}(\overline{c}_{\omega,k})] = E[U^B_{\omega t,k}], \qquad \text{(C.8)}
$$

where the expectation is taken with respect to intermediate goods cost other than input sector k.

Now, equations (C.6) and (C.8) together imply that $E[J_{\omega t,k}(\overline{c}_{\omega,k})] = 0$ and $E[V^S_{\omega t,k}(\overline{c}_{\omega,k})] = E[U^S_{\omega t,k}] = 0$. Furthermore, $E[\dot{U^B}_{\omega t,k}] = E[\dot{V}^B_{\omega t,k}(c)] = E[\dot{J}^B_{\omega t,k}(c)] = 0$ in the steady-state so that firms' values do not diverge to infinity. Given these observations, evaluating equation (C.2) at $c = \overline{c}_{\omega,k}$ and taking expectation yields:

$$
\xi E[V^B_{\omega t,k}(\overline{c}_{\omega,k})] = \xi E[V^B_{\omega t,k}(\overline{c}_{\omega,k}) + V^S_{\omega t,k}(\overline{c}_{\omega,k})] = E[\Pi^F_{\omega t,k}(\overline{c}_{\omega,k})] = K_{i,m}\overline{c}_{\omega,k}^{(1-\sigma)\gamma_{km}}E[(p_{\omega t,-k})^{1-\sigma}], \qquad \text{(C.9)}
$$

which coincides with $E[U^B_{\omega t,k}]$ from equation (C.8). Plugging this expression in the left hand side of equation (C.7),

$$
\begin{aligned}
\xi E[U^B_{\omega t,k}] &= \xi E[V^B_{\omega t,k}(\bar{c}_{\omega,k})] = K_{i,m}\bar{c}_{\omega,k}^{(1-\sigma)\gamma_{km}} E[(p_{\omega t,-k})^{1-\sigma}] \\
&= K_{i,m}\chi^{1-\sigma}\left(\zeta_k w_i\right)^{(1-\sigma)\gamma_{km}} E[(p_{\omega t,-k})^{1-\sigma}] \\
&\quad - v_{i,km}a_{\omega,k}\beta\frac{K_{i,m}E[(p_{\omega t,-k})^{1-\sigma}]}{\xi+\rho_{km}}\bar{c}_{\omega,k}^{(1-\sigma)\gamma_{km}}\frac{(1-\sigma)\gamma_{km}}{(1-\sigma)\gamma_{km}+\theta} \\
\iff \bar{c}_{\omega,k}^{(1-\sigma)\gamma_{km}} &= \chi^{1-\sigma}\left(\zeta_k w_i\right)^{(1-\sigma)\gamma_{km}} - v_{i,km}a_{\omega,k}\beta\frac{1}{\xi+\rho_{km}}\bar{c}_{\omega,k}^{(1-\sigma)\gamma_{km}}\frac{(1-\sigma)\gamma_{km}}{(1-\sigma)\gamma_{km}+\theta} \\
\iff \bar{c}_{\omega,k}^{(1-\sigma)\gamma_{km}}&\left[1-\beta\frac{v_{i,km}a_{\omega,k}}{\xi+\rho_{km}}\frac{(\sigma-1)\gamma_{km}}{\theta-(\sigma-1)\gamma_{km}}\right] = \chi^{1-\sigma}\left(\zeta_k w_i\right)^{(1-\sigma)\gamma_{km}} \\
\iff \left(\frac{\bar{c}_{\omega,k}}{\zeta_k w_i}\right)^{\theta} &= \chi^{\frac{\theta}{\gamma_{km}}}\left[1-\beta\frac{v_{i,km}a_{\omega,k}}{\xi+\rho_{km}}\frac{(\sigma-1)\gamma_{km}}{\theta-(\sigma-1)\gamma_{km}}\right]^{\frac{\theta}{(\sigma-1)\gamma_{km}}} \qquad \text{(C.10)}
\end{aligned}
$$

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

$$
a_{\omega,k} = \min\left\{1,\quad \chi^{\frac{\theta}{\gamma_{km}}}\left[1-\beta\frac{v_{i,km}a_{\omega,k}}{\xi+\rho_{km}}\frac{(\sigma-1)\gamma_{km}}{\theta-(\sigma-1)\gamma_{km}}\right]^{\frac{\theta}{(\sigma-1)\gamma_{km}}}\right\}, \qquad \text{(C.11)}
$$

and

$$
\bar{c}_{\omega,k} = \zeta w_i a_{\omega,k}^{\frac{1}{\theta}}. \qquad \text{(C.12)}
$$

These expressions imply that $\bar{c}_{\omega,k}$ and $a_{\omega,k}$ depend only on firms' location i, sector m, and the supplier sector k such that $\bar{c}_{\omega,k} = \bar{c}_{i,km}$ and $a_{\omega,k} = a_{i,km}$, and they correspond to equations (C.11) and (C.12) of the main paper.

C.3 Match Benefit $\phi_{j,km}$ and Fraction of Unmatched Buyers $\Phi_{j,km}$

Given the solution to the Bellman equations, I now define several key moments that are useful to characterize the steady-state equilibrium. I first derive the ratio of the expected firm sales $r_{j,m}$ of firms in location j and industry m conditional on having a supplier $d_{j,k} = 1$ in sector k relative to being without a supplier $d_{j,k} = 0$, i.e., $\phi_{j,km} \equiv \frac{E[r_{j,m}|d_{j,k}=1]}{E[r_{j,m}|d_{j,k}=0]}$. (The expectation is taken with respect to productivity φ and the unit cost of intermediate goods other than in sector k.) Under the assumption of power law distribution of the unit cost, these sales ratio is entirely driven by the differences in extensive margin (number of matched buyers for intermediate goods sales, entry to sales location for final goods sales), similarly as in Melitz (2003), Chaney (2008). Since this extensive margin responds to the marginal cost shifter with a factor of θ (for both intermediate goods and final goods sales),

$\phi_{j,km}$ is given by

$$\phi_{j,km} = \frac{\int_0^{\bar{c}_{j,km}} c^{-\gamma_{km}\theta} dG_{j,km}(c)}{\chi^{-\theta} \left(\zeta_k w_j\right)^{-\gamma_{km}\theta}},$$

where $G_{j,km}(c)$ is the cumulative distribution function for the inverse of the Pareto distribution with upper-bound $\bar{c}_{j,km}$. The denominator of this equation is given by:

$$\int_0^{\bar{c}_{j,km}} c^{-\gamma_{km}\theta} dG_{j,km}(c) = \frac{1}{1-\gamma_{km}} \left(\bar{c}_{j,km}\right)^{-\theta\gamma_{km}}$$

Together with expression (C.12),

$$\phi_{j,km} = \frac{\chi^{\theta}}{1-\gamma_{km}} \left(a_{j,km}\right)^{-\gamma_{km}}, \tag{C.13}$$

which corresponds to equation (21) of the main paper.

I next derive the steady-state probability that a firm in location j and sector m does not have a supplier in sector k and it is among the δ fraction of firms that can match with a supplier, $\Phi_{j,km}$ (which enters in supplier matching rates through the density of buyers (12)). From its definition,

$$\Phi_{j,km} = Pr[d_{j,k} = 0, \mathbb{T}_{\omega,k} | c < \vartheta] = Pr[d_{j,k} = 0 | c < \vartheta, \mathbb{T}_{\omega,k}] Pr[\mathbb{T}_{\omega,k} | c < \vartheta]$$

where $\mathbb{T}_{\omega,k}$ indicates the event that firm ω is the δ fraction of firms that can match with a supplier, and $d_{j,k}$ is the probability that the firm has a supplier in sector k.

The first term of $\Phi_{j,km}$ is given by:

$$\begin{aligned}
&Pr[d_{j,k} = 0 | c < \vartheta, \mathbb{T}_{\omega,k}] \\
&= \frac{Pr[c < \vartheta | d_{j,k} = 0, \mathbb{T}_{\omega,k}] Pr[d_{j,k} = 0 | \mathbb{T}_{\omega,k}]}{Pr[c < \vartheta | d_{j,k} = 0, \mathbb{T}_{\omega,k}] Pr[d_{j,k} = 0 | \mathbb{T}_{\omega,k}] + Pr[c < \vartheta | d_{j,k} = 1, \mathbb{T}_{\omega,k}] Pr[d_{j,k} = 1 | \mathbb{T}_{\omega,k}]} \\
&= \frac{\delta - \Lambda_{j,km}}{\phi_{j,km}\Lambda_{j,km} + \left(\delta - \Lambda_{j,km}\right)}
\end{aligned}$$

where the last transformation used the following fact:

$$\frac{Pr[c < \vartheta | d_{j,k} = 1, \mathbb{T}_{\omega,k}]}{Pr[c < \vartheta | d_{j,k} = 0, \mathbb{T}_{\omega,k}]} = \int_0^{\bar{c}_{j,km}} \left(\frac{c}{\zeta_k w_j}\right)^{-\gamma_{km}\theta} dG_{j,k}(c) = \phi_{j,km},$$

and $Pr[d_{j,k} = 1 | \mathbb{T}_{\omega,k}] = \Lambda_{j,km}/\delta$.

The second term of $\Phi_{j,km}$ is given by:

$$Pr[\mathbb{T}_{\omega,k}|c<\vartheta]=\frac{Pr[c<\vartheta|\mathbb{T}_{\omega,k}]}{Pr[c<\vartheta]}Pr[\mathbb{T}_{\omega,k}]=\frac{1+\Lambda_{j,km}/\delta(\phi_{j,km}-1)}{1+\Lambda_{j,km}(\phi_{j,km}-1)}\delta,$$

by noting that $Pr[c<\vartheta]=Pr[c<\vartheta|d_{j,k}=1]Pr[d_{j,k}=1]+Pr[c<\vartheta|d_{j,k}=0]Pr[d_{j,k}=0]$ and similarly for $Pr[c<\vartheta|\mathbb{T}_{\omega,k}]$.

Together,

$$\Phi_{j,km}=\frac{\delta-\Lambda_{j,km}}{1+\Lambda_{j,km}(\phi_{j,km}-1)} \tag{C.14}$$

which corresponds to the expression in footnote 21 in the main paper.

C.4 Solving for Supply Capacity $\Gamma_{i,m}$

I now derive the expression for the supply capacity $\Gamma_{i,m}$. From equation (7),

$$\begin{aligned} H_{i,m}(c)=\Gamma_{i,m}c^{-\theta} &= \int_{p_{1,\dots,p_K}}\mu_{i,m}\left(\frac{c}{w_i^{\gamma_{L,m}}\prod_{k\in K}p_k{}^{\gamma_{km}}}\right)\prod_{k\in K}dG^I_{i,km}(p_k) \\ &= \left(A^{\theta}_{i,m}w_i^{-\theta\gamma_{L,m}}\prod_{k\in K}\int_{p_k}p_k{}^{-\theta\gamma_{km}}dG^I_{i,km}(p_k)\right)c^{-\theta}. \end{aligned} \tag{C.15}$$

where $G^I_{i,km}(\cdot)$ is the steady-state distribution of input goods prices in sector k that firms in location i and sector m face. Given the above matching process, I have

$$\begin{aligned} \int_{p_k}p_k{}^{-\theta\gamma_{km}}dG^I_{i,km}(p_k) &= \Lambda_{i,km}\int_0^{\bar{c}_{i,km}}c^{-\gamma_{km}\theta}dG_{i,km}(c)+(1-\Lambda_{i,km})\left(\zeta_k w_i\right)^{-\theta\gamma_{km}} \\ &= \Lambda_{i,km}\frac{1}{1-\gamma_{km}}\left(\zeta_k w_i\right)^{-\theta\gamma_{km}}\left(a_{i,km}\right)^{-\gamma_{km}}+(1-\Lambda_{i,km})\left(\zeta_k w_i\right)^{-\theta\gamma_{km}} \\ &= \Lambda_{i,km}\left(\zeta_k w_i\right)^{-\theta\gamma_{km}}\phi_{i,km}+(1-\Lambda_{i,km})\left(\zeta_k w_i\right)^{-\theta\gamma_{km}} \\ &= \left(\zeta_k w_i\right)^{-\theta\gamma_{km}}\left\{1+\Lambda_{i,km}\left(\phi_{i,km}-1\right)\right\} \end{aligned}$$

Together,

$$\Gamma_{i,m}=\varrho A^{\theta}_{i,m}w_i^{-\theta}\prod_{k\in K}\left\{1+\Lambda_{i,km}\left(\phi_{i,km}-1\right)\right\} \tag{C.16}$$

where $\varrho\equiv\prod_{k\in K}\left(\zeta_k\right)^{-\theta\gamma_{km}}$. This equation coresponds to (24) of the main paper.

C.5 Existence and Uniqueness of Equilibrium

In this online appendix, I discuss the existence and uniqueness properties of the steady-state equilibrium of the model developed in the main paper.

Existence. I first prove the existence of the steady-state equilibrium by applying Brouwer's fixed point theorem. To apply the Brouwer's fixed point theorem. I define a mapping in the space of ($\{w_i\}$, $\{L_i\}$, $\{\Lambda_{i,km}\}$, $\{1/\phi_{i,km}\}$) as follows:

1. Obtain $\{A_{i,m}\}$ using equation (6)
2. Obtain $\{\Gamma_{i,m}\}$ using equation (24)
3. Obtain $\{\pi_{ij,m}\}$ and $\{\Omega_{i,m}\}$ using equation (9)
4. Obtain $\{v_{i,km}\}$ using equation (12)
5. Obtain $\{a_{i,km}\}$ using equation (19)
6. Obtain $\{\Lambda_{i,km}\}$ using equation (22)
7. Obtain $\{\phi_{i,km}\}$ using equation (21)
8. Obtain $\{P_i\}$ using equation (10)
9. Obtain $\{L_i\}$ using equation (30)
10. Solve for $\{X^I_{i,m}, X^F_{i,m}, Y^I_{i,km}, Y^F_{i,m}, w_i\}$ using equation (25), (26), (27), (28), (29) under $\sum_i D_i = 0$. Note that one equation is redundant, so these variables can be only solved up to scale. Therefore, I normalize $\{w_i\}$ such that $\sum_i w_i = 1$.

From the definition of the steady-state equilibrium, it is clear that the fixed point of this mapping is an equilibrium. Furthermore, this mapping is continuous (because each step of this mapping is a continuous function) in a compact space. Therefore, an equilibrium exists by Brouwer's fixed point theorem.

Uniqueness. Providing a sufficient condition for the uniqueness of the equilibrium in a general model is difficult because the system of equations are highly nonlinear and does not follow the type of equilibrium systems with known sufficient conditions for uniqueness. However, in a special case with a single sector ($|K| = 1$), no trade deficits ($D_i = 0$ for all i), and if the matching rates are constant within sector pairs ($\lambda = 0$ and $\nu = 1$), the system of equations falls into the class of models analyzed by Allen, Arkolakis, and Li (2020). First, combining gravity equations (9), trade balancing conditions (29), and the fact that utility is equalized across locations at $\mathcal{U}$, I have

$$w_i^{-\theta} L_i^{1-\upsilon\tilde{\sigma}} = \mathcal{U}^{-\theta} \sum_{j \in N} K_{1,ij} w_j^{-\theta} L_j^{\iota\theta}, \tag{C.17}$$

where $\tilde{\sigma} = \frac{\theta-(\sigma-1)}{\theta(\sigma-1)}$, and $K_{2,ij}$ is some constant. Second, by using the free mobility condition (30), I have

$$w_i^{1+\theta} L_i^{1-\theta\iota} = \mathcal{U}^{-\theta} \sum_{j \in N} K_{2,ij} w_j^{1+\theta} L_j^{1-(1-\upsilon\tilde{\sigma})\frac{\theta}{\upsilon}}. \tag{C.18}$$

These two conditions constitute the system of equations of w_j and L_j. By applying the theorem of Allen, Arkolakis, and Li (2020), one can show that the equilibrium is guaranteed to be unique (up to scale) when $\upsilon\tilde{\sigma} < 1$ and $\upsilon\iota < 1 - \upsilon\tilde{\sigma}$. Intuitively, these conditions are likely to be satisfied when the dispersion force (commensurate with $1/\upsilon$) is sufficiently strong compared to the agglomeration productivity spillovers (ι) and the love-of-variety effects ($\tilde{\sigma}$).

When these conditions are not satisfied, in particular when matching rates are endogenous and exhibits increasing returns to scale ($\lambda + \nu > 1$), it is possible that there are multiple equilibria. However, the multiple equilibria is not an issue for the estimation in Section 5 because the equilibrium conditions used for the estimation hold for any equilibria. Furthermore, I find that the counterfactual simulation results in Section 6 are not sensitive to the initial values of the iteratition algorithm, suggesting that the presence of multiple equilibria is unlikely to be driving my counterfactual results.

D Structural Estimation Appendix

In this section of the online appendix, I discuss additional details of the estimation procedure and the estimation results. Section D.1 discusses further details about the estimation of matching parameters in Section 5.3. Section D.2 provides additional results and sensitivity analysis.

D.1 Additional Details of the Estimation of Matching Parameters

As discussed in Section 5.3, I estimate $\Theta = \{\lambda, \nu, \eta, \chi, \delta, \{\zeta_k\}\}$ in the following indirect estimation procedure. Given parameter values Θ and already estimated $\Gamma_{i,k}$ and $\Omega_{i,m}$ from the gravity equations above, I compute the endogenous matching outcomes $\{v_{i,km}(\Theta)$, $a_{i,km}(\Theta)$, $\bar{c}_{i,km}(\Theta)$, $\phi_{i,km}(\Theta)$, $\Lambda_{i,km}(\Theta)$, $\Psi_{i,km}(\Theta)\}$ by solving equations (12), (19), (20), (21), and (22) for each location i and sector pair k, m. Using these objects, I construct the model's prediction of the impulse responses of the unanticipated supplier bankruptcy (interpreted as exogenous separation in the model) on the new supplier matching and sales growth and obtain the average responses and the heterogeneous responses with respect to supplier and buyer density. I then estimate model parameters that minimize the Euclidean distance between these model-predicted impulse responses and the reduced-form estimates with actual data in Section 3, as defined in estimating equation (33).

Below, I discuss further details of the construction of the impulse responses of unanticipated supplier bankruptcy on the number of newly matched suppliers and on sales growth.

I first construct the impulse responses on the number of new suppliers. Following the standard property of the Poisson process, the expected probability that a firm is matched with a new supplier is approximated by[1]

$$NewSuppliers_{i,km,\Delta}(\Theta) \equiv 1 - \exp\left(-v_{i,km}(\Theta)a_{i,km}(\Theta)\Delta\right), \tag{D.1}$$

where $v_{i,km}(\Theta)$ is the matching rate and $a_{i,km}(\Theta)$ is the acceptance probability, and Δ is the year since the shock. Evaluating this expression for each treatment firm f, I obtain the model-predicted number of new suppliers matched in Δ years since supplier bankruptcy ($NewSuppliers_{f,\Delta}(\Theta)$). I then take the average value for each time interval (Δ) to obtain the average responses of new supplier matching after Δ years.

I next obtain the heterogeneous impulse responses by supplier and buyer density by estimating the following regression equation:

$$\begin{aligned} NewSuppliers_{f,\Delta}(\Theta) = \beta_\Delta(\Theta) + \gamma_\Delta(\Theta) \log SupplierDensity_f \\ + \delta_\Delta(\Theta) \log BuyerDensity_f + \epsilon_{f,\Delta}, \end{aligned} \tag{D.2}$$

where $\log SupplierDensity_f$ and $\log BuyerDensity_f$ are the empirical proxies for supplier and buyer density as defined in Section 3. This regression corresponds to the difference-in-difference regression with actual data (3).

Lastly, I construct the impulse response of supplier separation on firm's sales in model. In the model, when a firm forms a new supplier relationship, the firms' sales increases by a factor $\phi_{i,km}(\Theta)$ (equation 21). Since the probability that treatment firms have a supplier in sector k after Δ periods is approximately $1 - NewSuppliers_{i,km,\Delta}(\Theta)$ less than that of the control firms, the change of sales after supplier bankruptcy is given by

$$\Delta \log Sales_{i,km,\Delta} = \phi_{i,km}(\Theta) \times \left(NewSuppliers_{i,km,\Delta}(\Theta) - 1\right), \tag{D.3}$$

where $\left(NewSuppliers_{i,km,\Delta}(\Theta) - 1\right)$ is the model-predicted differences in probability that treatment firms have a supplier in sector k compared to the control group. Evaluating this expression for each treatment firm f, I obtain the model-predicted sales reduction in Δ years since supplier bankruptcy.

D.2 Sensitivity Analysis

Table D.1 presents the matching technology parameter estimates in Section 5.3 under different values for calibrated parameters.

Column (1) reports the baseline point estimates as presented in Table 4. Column (2) increases discount rate ξ to 0.5 instead of 0.05 in the baseline. Column (3) and (4) set

[1]This is an approximation because it does not take into account of the possibility that a firm forms a new supplier relationship, becomes separated again, and then rematches one more time. However, for a sufficiently short interval of Δ, the probability of such an event is small.

bargaining share β as 0 and 1 instead of 0.5. The estimated parameters are not sensitive to the parameter values of ξ and β. This is because these parameters affect the equilibrium matching outcomes only through the acceptance rates (equation 19), yet in my setting acceptance rates ($a_{j,km}$) are close to one in most sectors and locations.[2] (Under my estimated parameters, less than one percent of sector-location pairs have acceptance rates $a_{i,km}$ strictly less than one, due to relatively small input coefficient γ_{km} and relatively large iceberg cost of in-house production for intermediate goods $\chi > 1$.) Column (5) sets elasticity of substitution σ as 3 instead of 5, and estimation results are stable.

Column (6) sets shape parameter for productivity distribution θ as 6 instead of 4.3. The estimation results are stable except for χ, which is estimated slightly smaller. This is because the sales decrease of supplier separation depends on χ^{θ} as evident from equation (21), hence a higher value of θ implies a smaller value of χ.

Lastly, Column (7) estimates matching parameters using restricted set of treatment firms whose establishments are located within the same prefecture. The estimates are robust, consistent with the fact that the reduced-form difference-in-difference regressions are robust to this treatment in Column 3 of Table 2.

Table D.1: Sensitivity of Matching Technology Estimation to Calibrated Parameters

Parameter	(1) Baseline	(2) $\xi = 0.5$	(3) $\beta = 0$	(4) $\beta = 1$	(5) $\sigma = 3$	(6) $\theta = 6$	(7) Only firms with local establishments
λ	0.622	0.624	0.623	0.624	0.623	0.605	0.624
ν	0.974	0.973	0.972	0.986	0.974	0.994	0.962
η	0.045	0.045	0.045	0.045	0.045	0.045	0.045
χ	1.07	1.07	1.07	1.071	1.07	1.05	1.07
δ	0.147	0.145	0.145	0.143	0.144	0.143	0.147

Note: Sensitivity of the matching technology parameter estimates in Section 5.3 under different values for calibrated parameters. Columns (1) reports the baseline estimates reported in Table 4. Column (2) sets discount rate ξ as 0.5 instead of 0.05. Column (3) and (4) set bargaining share β as 0 and 1 instead of 0.5. Column (5) sets elasticity of substitution σ as 3 instead of 5. Column (6) sets shape parameter for productivity distribution θ as 6 instead of 4.3. Column (7) estimates matching parameters using restricted set of treatment treatment firms whose establishments are located within the same prefecture.

E Counterfactual Simulation Appendix

In this section of the online appendix, I provide additional details of the counterfactual simulation in Section 6 of the main paper. Section E.1 details the counterfactual simulation procedure. Section E.2 provides the sensitivity analysis of the estimation results. Section E.3 discusses the transition dynamics of trade cost reduction.

E.1 Additional Details of Counterfactual Simulation Procedure

To conduct these counterfactual simulations, I follow the exact-hat algebra approach of Dekle, Eaton, and Kortum (2008) and rewrite the counterfactual equilibrium conditions in

[2] Recall also that firms are owned by foreigners outside of the economy, hence the bargaining share β does not affect the spatial income distribution.

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). Given the values of the endogenous variables in the initial equilibrium ($\{\pi_{ij,k}, \Gamma_{i,k}, \Omega_{i,k}, L_i, D_i\}$), the counterfactual equilibrium is determined by the following system of equations in terms of the changes in the endogenous variables ($\{\hat{\pi}_{ij,k}, \hat{\Gamma}_{i,k}, \hat{\Omega}_{i,k}, \hat{w}_j, \hat{L}_j, \hat{P}_j\}$) and the values in the new equilibrium ($\{Y^{I'}_{i,km}, Y^{F'}_{i,k}, X^{I'}_{i,k}, X^{F'}_{i,k}, v^{'}_{i,km}, a^{'}_{i,km}, \phi^{'}_{j,km}\}$):

(i) trade linkages.

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

$$\hat{\Gamma}_{i,m} = \left(\hat{L}_i\right)^{\iota\theta}\hat{w}_i^{-\theta}\prod_{k\in K}\frac{\left(1+\Lambda^{'}_{i,km}\left(\phi^{'}_{i,km}-1\right)\right)}{\left(1+\Lambda_{i,km}\left(\phi^{I}_{i,km}-1\right)\right)} \tag{E.2}$$

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

$$Y^{I'}_{i,km} = \gamma_{km}\Psi^{'}_{i,km}\left\{\sum_{m\in K}Y^{'I}_{j,km}\pi^{'}_{ij,k} + \sum_{j\in N}w^{'}_iL^{'}_i\pi^{'}_{ij,k}\right\} \tag{E.4}$$

$$Y^{F'}_{i,k} = \alpha_k w^{'}_i L^{'}_i \tag{E.5}$$

$$X^{I'}_{i,k} = \sum_{j\in N}\sum_{m\in K}Y^{I'}_{j,km}\pi^{'}_{ij,k}$$

$$X^{F'}_{i,k} = \sum_{j\in N}Y^{F'}_{j,k}\pi^{'}_{ij,k} \tag{E.7}$$

$$\sum_{k\in K}\left(X^{'I}_{i,k} + X^{'F}_{i,k}\right) = \sum_{k,m\in K}Y^{'I}_{i,km} + w^{'}_iL^{'}_i - D_i \tag{E.8}$$

(ii) population mobility.

$$\hat{L}_j = \frac{\left(\hat{w}_j/\hat{P}_j\right)^{v}}{\sum_{\ell}\left(\hat{w}_{\ell}/\hat{P}_{\ell}\right)^{v}L_{\ell}} \tag{E.9}$$

$$\hat{P}_j = \hat{L}_j^{\frac{\theta-\sigma+1}{\theta(\sigma-1)}}\prod_{k\in K}\left(\hat{\Omega}_{j,k}\right)^{-\frac{\alpha_k}{\theta}} \tag{E.10}$$

(iii) matching in intermediate goods market (for each location i and sector pairs k, m).

$$v_{i,km}^{'} = \eta \left(\frac{\Omega_{i,k}^{'} \left(\zeta_k w_i^{'} \right)^{\theta}}{Z_i} \right)^{\lambda} \left(\frac{\Phi_{i,km}^{'} \Gamma_{i,m}^{'} \vartheta^{\theta}}{Z_i} \right)^{\nu-1} \tag{E.11}$$

$$a_{i,km}^{'} = \max \left\{ 1, \quad \chi^{\frac{\theta}{\gamma_{km}(\sigma-1)}} \left[1 - \beta \frac{v_{i,km}^{'} a_{i,km}^{'}}{\xi + \rho_{km}} \frac{(\sigma-1)\gamma_{km}}{\theta - (\sigma-1)\gamma_{km}} \right]^{\frac{\theta}{(\sigma-1)\gamma_{km}}} \right\} \tag{E.12}$$

$$\phi_{j,km}^{'} = \frac{\chi^{\theta}}{1-\gamma_{km}} \left(a_{j,km}^{'} \right)^{-\gamma_{km}} \tag{E.13}$$

$$\Psi_{j,km}^{'} = \frac{\phi_{j,km}^{'} \Lambda_{j,km}^{'}}{1 - \Lambda_{j,km}^{'} + \phi_{j,km}^{'} \Lambda_{j,km}^{'}} \tag{E.14}$$

$$\Lambda_{j,km}^{'} = \delta \frac{v_{j,km}^{'} a_{j,km}^{'}}{v_{j,km}^{'} a_{j,km}^{'} + \rho_{km}} \tag{E.15}$$

$$\Phi_{j,km}^{'} = \frac{\delta - \Lambda_{j,km}^{'}}{1 + \Lambda_{j,km}^{'} (\phi_{j,km}^{'} - 1)} \tag{E.16}$$

Calibration of initial equilibrium. In addition to the estimated parameters, I need to construct the proxies for the initial equilibrium for $\{\pi_{ij,k}, \Gamma_{i,k}, \Omega_{i,k}, L_i, D_i\}$. To construct $\{\pi_{ij,k}, \Gamma_{i,k}, \Omega_{i,k}\}$, I use the estimated gravity equations of trade flows in Section 5.2 of the main paper. Using the estimated $\Gamma_{i,m}$ and $\Omega_{i,m}$ and κ_m, I construct $\pi_{ij,k}$ using the same gravity equations. I use this predicted $\pi_{ij,k}$ as the initial equilibrium, instead of the observed $\pi_{ij,k}$, to deal with the presence of zero trade flows due to the sparsity of firm-to-firm trade data (Dingel and Tintelnot 2020). I obtain L_i from the population distribution in each prefecture using the official statistics in Japan. Lastly, I construct D_i using the trade (in)balance condition (equation 29). Rewriting this equation, I have

$$D_i = \sum_{k,m \in K} Y_{i,km}^{I} + \sum_{k \in K} Y_{i,k}^{F} - \sum_{k \in K} \left(X_{i,k}^{I} + X_{i,k}^{F} \right) \tag{E.17}$$

where I obtain $\{Y_{i,km}^{I}, Y_{i,k}^{F}, X_{i,k}^{I}, X_{i,k}^{F}\}$ by solving the set of equations (25), (26), (27), and (28), given the observed data of w_i and L_i (from official statistics) and the predicted trade shares $\pi_{ij,m}$.

E.2 Additional Results and Sensitivity Analysis

Table E.1 presents the changes of population density in the counterfactual simulations to shut down agglomeration spillovers (Section 6.1). The table shows the regression coefficients of the counterfactual log population density on the log of observed population density from three counterfactual simulations discussed in Section 6.1 in Columns (2)-(4).

Shutting down IRS in matching reduces the concentration of population by 7 percent (Column 2). Shutting down the population-productivity spillovers reduces the concentration of population by 14 percent (Column 3). Lastly, omitting both types of agglomeration spillovers decrease the concentration of population by 19 percent (Column 4). These changes are smaller in absolute terms compared to the counterfactual changes in wages (Table 6). However, the relative magnitudes of Column (2) to Column (3) and (4) remain similar to Table 6. Therefore, IRS in matching is a quantitatively relevant component of overall agglomeration spillovers in terms of its contribution to the observed population density, similarly to the contribution to the observed wages as discussed in Table 6.

Table E.1: Agglomeration Forces and Population Density

	Dependent Variable: log Counterfactual Population Density			
	Baseline	Shut Down IRS in Matching Function ($\lambda = \nu - 1 = 0$)	Shut Down Population Productivity Spillovers ($\iota = 0$)	Shut Down Both Agglomeration Spillovers ($\lambda = \nu - 1 = 0$ and $\iota = 0$)
	(1)	(2)	(3)	(4)
log Observed Population Density	1.00***	0.93***	0.87***	0.81***
	(0.00)	(0.01)	(0.01)	(0.01)
C.I. from Bootstrap Parameter Estimates		[0.92, 0.95]	[0.87, 0.87]	[0.8, 0.83]
Percentage Difference from Baseline (%)	0	-7	-14	-19
Observations	47	47	47	47
Adjusted R^2	1.00	0.99	0.99	0.99

Note: Results of the counterfactual simulations to shut down agglomeration forces. Each column reports the regression coefficient of the logarithm of the counterfactual population density on those of the observed data. Columns (1) takes the observed population density as the dependent variable, hence mechanically the regression coefficient is one and R^2 is one. and Columns (2)-(4) correspond to the counterfactual simulations of shutting down the increasing returns to scale (IRC) in matching technology such that $\lambda = \nu - 1 = 0$ (Column 2), shutting down productivity spillovers from local population density such that $\iota = 0$ (Column 3), and shutting down both types of agglomeration forces, such that $\lambda = \nu - 1 = 0$ and $\iota = 0$ (Column 4). *p<0.1; **p<0.05; ***p<0.01.

Table E.2 shows the sensitivity of the results of the counterfactual simulations to shut down the agglomeration spillovers to the value of calibrated parameters. Panel (A) shows the regression coefficients of the log of counterfactual wages on the log of counterfactual population density (corresponding to Table 6), and Panel (B) shows the regression coefficients of the log of counterfactual population density on the log of observed population density (Table E.1).

Column (1) is my baseline results. The empirical results are virtually identical for the values of discount rate (ξ, Column 2) and bargaining share (β, Columns 3 and 4), consistent with the findings that these parameter values do not affect the estimation results of matching parameters (Table D.1).

When elasticity of substitution (σ) is smaller (in Column 5) or the elasticity of migration (υ) is higher (in Column 7), wages respond less (in Panel A) and population responds more (in Panel B). This is because population movement is more elastic to real wage change under these alternative parameterization.

Lastly, the counterfactual responses of wages and population are both greater if the shape parameter for productivity (θ) is greater (Column 6). This is because the supplier capacity term ($\Gamma_{i,m}$) is more elastic to the changes in productivity (equation 24).

Despite these differences in Column (5)-(7) in absolute values, the relative magnitudes of the three counterfactuals of shutting down agglomeration forces (across different rows) remain stable in Column (5)-(7).

Table E.2: Sensitivity Analysis of Counterfactual Simulations to Shut Down Agglomeration Spillovers

(A) Wages

Specification	(1) Baseline	(2) $\xi = 0.5$	(3) $\beta = 0$	(4) $\beta = 1$	(5) $\sigma = 3$	(6) $\theta = 6$	(7) $\upsilon = 4$
Baseline	0.076	0.076	0.076	0.076	0.076	0.076	0.076
($\lambda = \nu - 1 = 0$)	0.045	0.045	0.045	0.045	0.05	0.036	0.05
($\iota = 0$)	0.011	0.011	0.011	0.011	0.025	0.001	0.025
($\lambda = \nu - 1 = 0$ and $\iota = 0$)	-0.013	-0.013	-0.013	-0.013	0.008	-0.025	0.008

(B) log Population Density

Specification	(1) Baseline	(2) $\xi = 0.5$	(3) $\beta = 0$	(4) $\beta = 1$	(5) $\sigma = 3$	(6) $\theta = 6$	(7) $\upsilon = 4$
Baseline	1	1	1	1	1	1	1
($\lambda = \nu - 1 = 0$)	0.932	0.933	0.933	0.932	0.879	0.899	0.878
($\iota = 0$)	0.869	0.868	0.868	0.869	0.787	0.826	0.786
($\lambda = \nu - 1 = 0$ and $\iota = 0$)	0.815	0.815	0.815	0.815	0.7	0.756	0.699

Note: Results of the counterfactual simulations for trade cost reduction presented in Section 6.2. For each type of sensitivity analysis in each column, each entry reports the regression coefficients of the counterfactual wages on the counterfactual population density (Panel A) and the log of counterfactual population density on the observed population density (Panel B), for each type of counterfactual indicated in the first column. Columns (1) reports the baseline estimates reported in Table 4 for Panel (A) and Table E.1 for Panel (B). Column (2) sets discount rate ξ as 0.5 instead of 0.05. Column (3) and (4) set bargaining share β as 0 and 1 instead of 0.5. Column (5) sets elasticity of substitution σ as 3 instead of 5. Column (6) sets shape parameter for productivity distribution θ as 6 instead of 4.3. Column (7) sets the elasticity of migration with respect to real wages υ as 4 instead of 2.

Table E.3 shows the same set of sensitivity analyses for the counterfactuals of reducing trade cost. Column (1) is my baseline results from Table 7, and Column (2)-(7) is the same set of sensitivity analysis as above. The predicted welfare gains are stable for the value of discount rate (ξ, Column 2), bargaining share (β, Column 3 and 4), elasticity of substitution (σ, Column 5), and the elasticity of migration (υ, Column 7). The estimates of welfare gains are somewhat smaller with a greater productivity dispersion parameter (θ, Column 6) because of a greater responses in supplier capacity $\Gamma_{i,k}$ (equation 24). Despite these differences, the relative magnitudes of the three counterfactuals (Rows 2-4) remain stable across the board.

Table E.3: Sensitivity Analysis of Welfare Gains from Trade Cost Reduction

Specification	(1) Baseline	(2) $\xi = 0.5$	(3) $\beta = 0$	(4) $\beta = 1$	(5) $\sigma = 3$	(6) $\theta = 6$	(7) $v = 4$
Baseline	6.19	6.19	6.18	6.2	6.36	4.72	6.34
($\lambda = \nu - 1 = 0$)	4.53	4.55	4.55	4.56	4.68	2.8	4.66
($\iota = 0$)	6.17	6.17	6.17	6.18	6.33	4.72	6.31
($\lambda = \nu - 1 = 0$ and $\iota = 0$)	4.53	4.55	4.55	4.56	4.67	2.81	4.64

Note: Results of the counterfactual simulations for trade cost reduction presented in Section 6.2. For each type of sensitivity analysis in each column, each entry reports the percentage point increase in expected utility from the trade cost reduction under four different assumptions about the agglomeration spillovers indicated in the first column. Columns (1) reports the baseline estimates reported in Table 4. Column (2) sets discount rate ξ as 0.5 instead of 0.05. Column (3) and (4) set bargaining share β as 0 and 1 instead of 0.5. Column (5) sets elasticity of substitution σ as 3 instead of 5. Column (6) sets shape parameter for productivity distribution θ as 6 instead of 4.3. Column (7) sets the elasticity of migration with respect to real wages v as 4 instead of 2.

E.3 Transition Dynamics of Trade Cost Change

In this section of the appendix, I discuss the transition dynamics of the model discussed in Section 4.

To do so, I focus on a special case of the model where the discount rate $\xi \to \infty$. This corresponds to a special case of the model such that firms always accept a match ($a_{i,km} = 1$). This special case closely approximates my estimates of baseline model, because my baseline estimates imply that $a_{i,km}$ are close to one for most sector and locations.[3] Under this assumption, one can simply simulate the transition dynamics by forward simulation without having to solve for the dynamic changes in option values.

More specifically, the law of motion of $\Lambda_{j,km}$ for a small time interval Δ is given by

$$\Lambda_{i,km}\left(t+\Delta\right) = \left(1-\exp\left(-\Delta v_{i,km}\right)\right)\left(\delta - \Lambda_{i,km}(t)\right) + \exp\left(-\Delta\rho_{km}\right)\Lambda_{i,km}(t). \quad \text{(E.18)}$$

I assume that all other equilibrium variables flexibly adjust in each period given $\Lambda_{i,km}\left(t\right)$. Therefore, the equilibrium allocation is given by the set of equations (E.1)-(E.16) for each period, except that equation (E.15) is replaced by equation (E.18).

As an application, I undertake the same counterfactual simulation of cross-regional trade cost change as in Section 6.2 of the main paper. More specifically, I calibrate the baseline model in period $t = 0$ using the observed equilibrium assuming that it is in the steady state. I then assume that there is a sudden increase of the trade cost that is proportional to $\hat{\tau}_{ij,k} = \left(T_{ij}^{\text{nohighway}}/T_{ij}\right)^{\tilde{\kappa}_m}$, where $T_{ij}^{\text{nohighway}}$ is the travel cost without using highway networks.

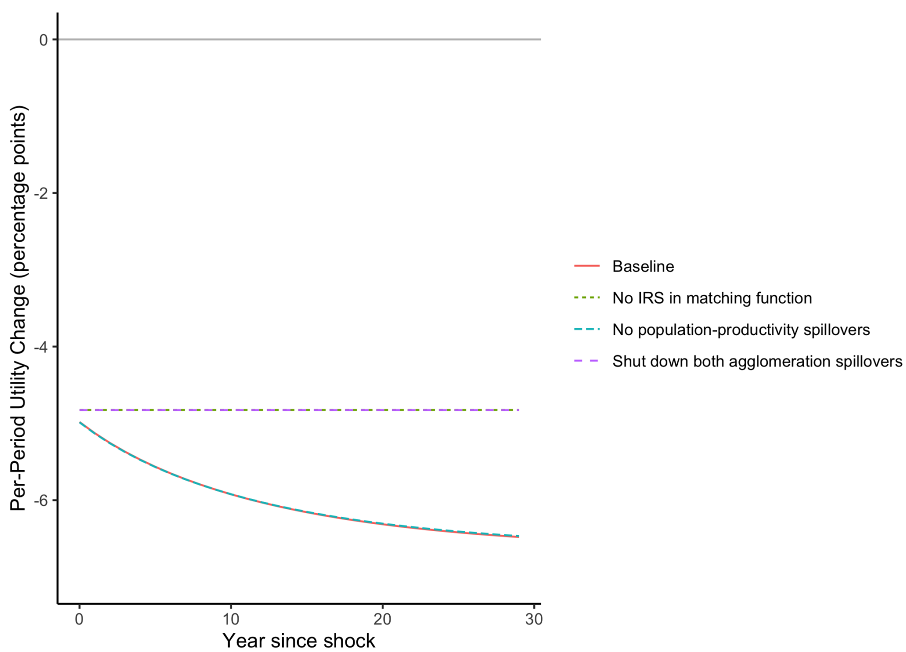
Figure E.1 plots the transition dynamics of the expected per-period utility under the same four scenarios discussed in Section 6.2 (incorporate both types of agglomeration spillovers, omit IRS in matching function, omit population-productivity spillovers, omit both types of agglomeration spillovers).

[3] As noted in Section D.1, less than one percent of sector-location pairs acceptance rates $a_{i,km}$ strictly less than one. Relatedly, the value of ξ has virtually no effects on my counterfactual simulations in Table E.2 and E.3.

Consistent with the findings in Table 7, whether to incorporate population-productivity spillovers or not has a negligible effect. ("Baseline" is on top of "No population-productivity spillovers", and "No IRS in matching function" is on top of "Shut down both agglomeration spillovers".) By comparing "Baseline" and "No IRS in matching function," several things stand out. Right after the shock ($t = 1$), per-period utilities are relatively similar in both scenarios. When IRS in matching function is incorporated ("Baseline"), per-period utility gradually decreases to the level of steady state. This is because supplier matching ($\Lambda_{j,km}(t)$) slowly adjust to the new steady state level. While most of the welfare gains materialize within 10 years, there is still an adjustment in longer time interval. On the other hand, when IRS in matching function is omitted ($\lambda = \nu - 1 = 0$), per-period utility remains unchanged over time. In this case, matching rates $\Lambda_{j,km}(t)$ are exogenous and hence does not depend on time t.

The analysis of this section suggests that it takes time for the welfare gains from trade cost changes to fully materialize due to a gradual adjustment of supplier matching.

Figure E.1: Transition Dynamics of Per-period Utility after Trade Cost Increase



Note: This figure plots the percentage point change of per-period utility (relative to the baseline period) due to a sudden increase in trade cost in period. See Appendix Section E.3 for the counterfactual simulation procedure.