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Theory and Evidence of Firm-to-firm Transaction Network Dynamics*

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Abstract

How are supply chains formed and restructured over time? This paper investigates firm-to-firm transaction network dynamics from theoretical and empirical perspectives, exploiting large-scale firm-level transaction data from Japan. First, we provide basic facts which show substantial churning in supply chains over time, even after excluding the cases where either supplier or customer firms exit from the market. Second, we empirically find that productivity positive assortative matching between firms exists. Firms are more likely to keep trading with more productive firms and instead stop trading with less productive ones. Alternatively, more productive firms start new transactions with more productive business partners. Lastly, we build a theoretical framework to rationalize these findings. Both supplier and customer firms are heterogeneous and choose their trading partners with a many-to-many matching framework. We derive the implications for supply chain formation and restructuring in response to productivity shocks.

Keywords: Heterogeneous firms; supply chains; productivity; firm dynamics
JEL classification codes: E23, F14, O47, R15

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1 Introduction

Any economy consists of individual firm activities and the interactions between them. Firms are inter-connected with each other to buy inputs from or sell outputs to other firms. It is widely acknowledged that the transaction network propagates the effects of economic shocks and policy changes. There is growing literature with firm-to-firm transaction data. Mostly of which focus on the static aspect, whereas evidence is limited about the dynamic feature of the transaction network. Firms construct their supply chains and reshape them over their growth trajectory. Successful firms could find trading partners while unsuccessful ones struggle to sell their products or purchase key inputs. The matching matters for both sides of the transaction.

This study investigates firm-to-firm transaction network dynamics exploiting Japanese large-scale firm-level transaction data. We first provide basic facts about assortative matching between firms and construct a theoretical framework to rationalize these findings. Each year, we observe churning in transaction network, even after controlling for firm exits. We also find evidence of productivity positive assortative matching between firms. High-productivity firms trade with similarly high-productivity firms while low-productivity firms get matched with low-productivity ones. Across periods, firms are more likely to keep trading with more productive firms and instead separate with less productive ones. Additionally, more productive firms start new transactions with more productive business partners. We provide a theoretical framework, where supplier and customer firms are both heterogeneous in productivity. Supplier firms produce intermediate inputs and customer firms produce final goods. They both compete in monopolistic competition. With the relation-specific costs, we obtain positive assortative matching with a many-to-many matching framework.

Japanese large-scale firm-level transaction data allow us to study how firms select and change their trading partners over time. A private credit reporting company, Tokyo Shoko Research (TSR), collects the information on firm-to-firm transaction on an annual basis. The data span between 2007 and 2018 and identify suppliers and customers, while values and products of transaction are not observable. Our empirical analyses reveal the following three findings. First, we detected substantial churning in supply chains over time. Firms churn about 20% of their transaction partners every year, even after excluding the cases where either supplier or customer firms exit the market. We also estimated the average survival likelihood of a given firm-to-firm transaction and found that 80% of transactions disappear after about ten years.

Second, firm productivity is a key driver in matching between sellers and buyers. When a firm has higher productivity, the transaction is more likely to continue. Similarly, when a firm has lower productivity, the transaction is more likely to disappear. We also find that the productivity of new suppliers is higher than that of disappeared suppliers on average. We empirically find that productivity positive assortative matching exists between firms. The results also show that more productive customers trade with more productive suppliers. As a firm's own productivity increases, both the maximum and minimum productivity among its suppliers tend to increase.

Third, we develop a theoretical framework to rationalize the empirical findings about positive assortative matching in transaction network. We derive the implications for transaction network formation and its churning in response to productivity shocks. Firms choose their trading partners to maximize their profits, and the optimization problem results in sorting functions for both supplier and customer firms. Finally, we derive implications in the case of productivity shocks. The model is novel in that we derive positive assortative matching under many-to-many matching framework.

This study contributes to the literature on firm-to-firm transaction network from both empirical and theoretical perspectives. First, this study adds to the recent literature which exploits firm-to-firm transaction data. Adao et al. (2020), Bernard et al. (2018), Dhyne et al. (2020), and Sugita et al. (2021) among others used the information on international trade to study firm-to-firm transactions. There is also a group of papers which focus on domestic firm-to-firm transactions. Atalay et al. (2011) and Lim (2018) used a propriety dataset, Compustat. Alfaro-Ureña et al. (2022), Bernard et al. (2022), Demir et al. (2021), Gadenne et al. (2020) and Panigrashi (2021) used tax administrative data to observe domestic transaction network.

Also, this study is not the first to use Japanese large-scale firm-level transaction data collected by Tokyo Shoko Research (TSR). This dataset has been explored in Bernard, Moxnes, and Saito (2019), Carvalho et al. (2021), Fujii, Saito, and Senga (2017), and Miyauchi (2021). However, the data used in this paper is a twelve-year panel between 2007 and 2018, which is longer than the data used in the existing papers. Those existing papers did not study endogenous network formation as well. We aim to fill this gap.

Second, this study contributes to the evidence and theory of firm-to-firm transaction network formation. Bernard and Moxnes (2018) provide a nice review of the literature. Among others, Bernard et al. (2018) and Sugita, Teshima, and Seira (2021) are the most relevant papers to our study. Bernard et al. (2018) constructed a model with two-sided heterogeneity and derived sorting functions for trading partner choice. They showed the lower bound of productivity required for the trading partner is decreasing in own productivity. We extended the model to incorporate variable relationship-specific costs and showed that there are both lower and upper bounds of productivity. With relationship specific costs increasing in productivity gap between trading partners, both bounds become increasing in own productivity. Then, we showed that positive assortative matching between firms exists within a many-to-many matching framework. Sugita, Teshima, and Seira (2021) focused on U.S.-Mexican trade and derived positive assortative matching. Our study differs from theirs in that our framework is many-to-many matching while their framework was one-to-one matching.

The rest of the paper is structured as follows. Section 2 explains the data set, and Section 3 explains the basic facts on transaction network dynamics. Section 4 provides the theoretical framework to rationalize these findings. Section 5 concludes the paper.

2 Data

2.1 Data

We exploit large-scale firm-to-firm transaction data from Japan. The data source is annual surveys by a private credit reporting company, Tokyo Shoko Research (TSR), and we refer to the data as the TSR data. The TSR data is not a census but close to comprehensive in that it covers about 70% of all incorporated firms in Japan, including both listed and non-listed ones. From the TSR data, we observe (i) basic firm characteristics including employment, the number of establishments, the number of factories, 4-digit industry, sales, profits, geographical address, (ii) balance sheet information, which allows us to observe firm-level inputs and outputs, and (iii) firm-to-firm transaction relationships.

Firms are asked to report up to 48 partners (24 suppliers and 24 customers). Despite the cutoff, we can back firm-to-firm transaction networks quite well by merging all reports from all firms in the survey. For example, a large firm usually has more than 48 partners, but by using reports from other firms, we can identify the trading partners for that firm. This gives us a comprehensive picture of Japanese firm-to-firm transaction network.

2.2 Summary Statistics

The dataset covers 2007-2018. Table 1 below shows summary statistics. The minimum numbers of suppliers and customers are zero, so the data include firms which exist most upstream and downstream in the supply chains. We restrict our sample to firms for which balance sheet information is available.

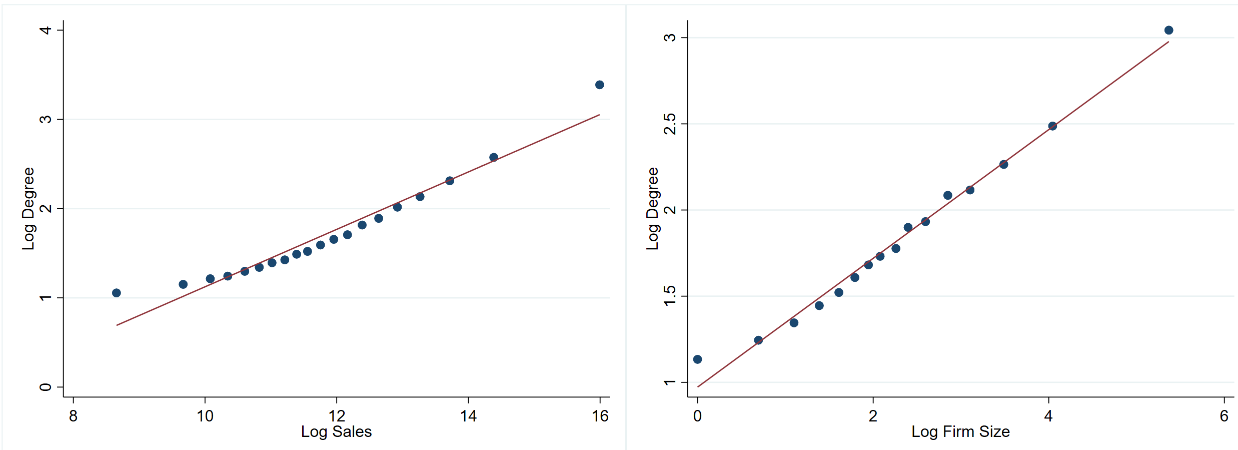
Table 1. Summary Statistics

	# of obs	mean	median	sd	max	min
Firm sales	2,919,435	3,120,987.271	175,095	56,606,696.899	12,291,218,000	11
Firm age	2,855,902	29.319	27	17.144	137	0
Firm size	3,113,190	47.237	8	531.175	200,601	1
Total # of links	3,120,857	14.738	6	74.243	8,647	0
# of suppliers	3,120,857	7.451	3	46.792	6,242	0
# of customers	3,120,857	7.287	2	40.969	6,259	0
Productivity	3,120,857	10.072	9.813	2.406	25.384	-1.700

Notes: Sales unit is 1,000 yen. Firm size is defined as the number of workers. Productivity refers to estimated Total Factor Productivity following Ackerberg, Caves, and Frazer (2015). We restrict our sample to firms for which productivity can be estimated.

Figure 1 below shows the relationships between the number of trading partners and firm characteristics. The left panel is for firm sales while the right panel is for firm size measured by the number of employees. Both panels show linear relationships, suggesting that larger firms in terms of higher sales or larger number of employees have more trading partners.

Figure 1. The Relationship Between Log Number of Links and Firm Characteristics



(a) Firm Sales (b) Firm Size

Notes: This figure shows the relationship between the number of links and firm characteristics. The left panel is for firm sales while the right panel is for firm size measured by the number of employees.

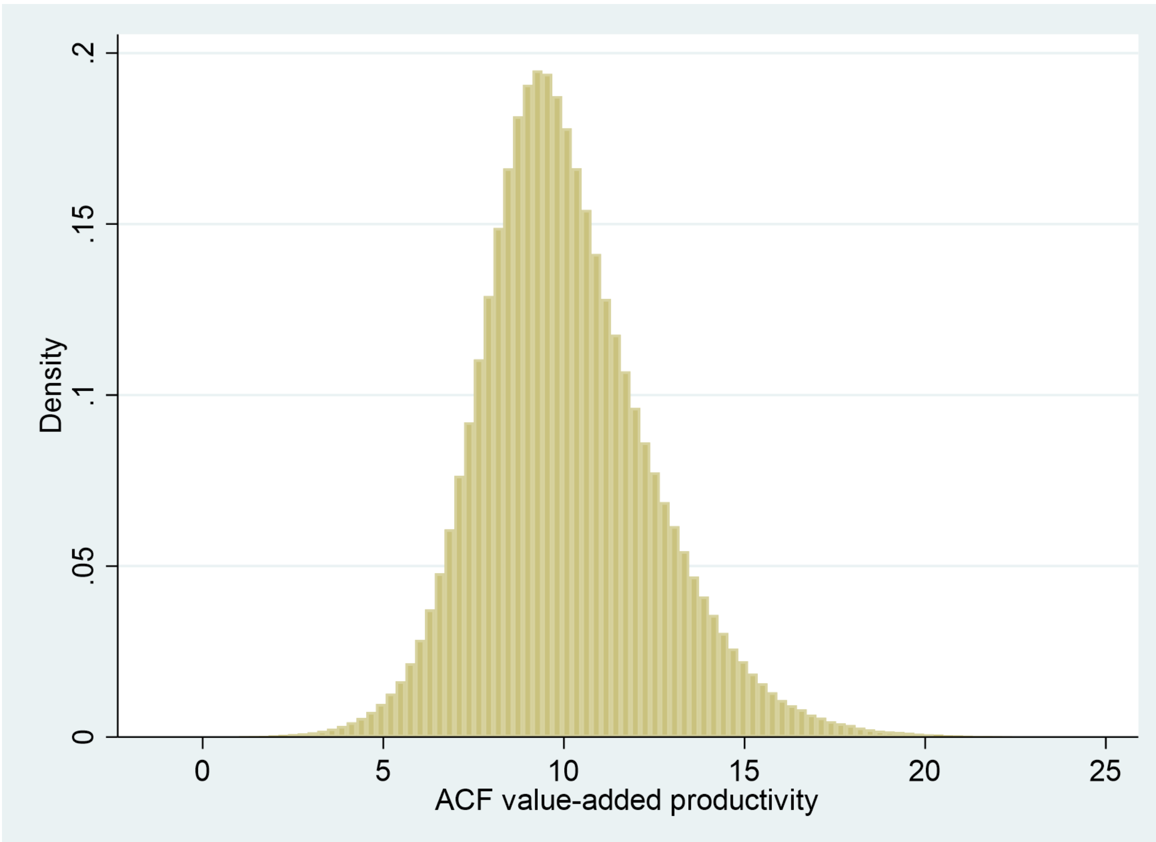
2.3 Estimating Productivity

Using balance sheet information, we estimate firm productivity following Ackerberg, Caves, and Frazer (2015). Figure 2 shows the histogram of estimated productivity. There is a mass of firms but at the same time productivity levels are dispersed across firms. It is also confirmed by the summary statistics for productivity shown in Table 1.

In the following empirical results, we also use two different productivity measures. First, we demean the estimated productivity within three-digit industry code. The purpose is to eliminate the industry-specific components of productivity levels. Second, we use labor productivity, defined as sales divided by the number of employees. As not all firms report variable inputs, this measure gives a larger number of observations. We exploit these two measures as robustness checks for the main findings.

In the analysis below, we restrict the sample to those firms which appear in the data for more than one year to investigate the churning behavior. This restriction is imposed for a conservative purpose, and should not alter the results.

Figure 2. Histogram of Productivity



Notes: This figure shows the histogram of productivity obtained by the ACF value-added productivity estimation method.

2.4 Network Dynamics

Table 2 below shows the summary of the firm-to-firm transaction network. Panel A shows the static patterns of the network. The average number of suppliers for firms is 7.451, and that of customers is 7.287. Panel B shows the dynamic patterns of the network. The average probability of continuing transactions between two consecutive years is 0.800 in the next year; conversely, the probability that it terminates from a year to the next is 0.200. The average probability of starting a new transaction with a new trading partner is 0.126. This implies that firms churn 20% of their transaction partners every year. The probability of separation and that of creation do not sum up to be one because the denominators are different.

In Figure 3, we plot the survival functions of firm-to-firm transactions by using the Kaplan-Meier estimator. The horizontal axis represents the time variable expressed in years. All transactions existing in 2007 start at the top of the vertical axis, which indicates the proportion that has not experienced a separating event. The horizontal axis represents the survival time (in years) of each interval, and the vertical distance between the lines corresponds to the change in cumulative probabilities. Thus, a decline in the plot is associated with a separating event. Note that the separation is the largest in the first year and gets smaller over time. We can see that 80% of total transactions disappear in about 10 years.

Table 2. Network Dynamics

Panel A: Static Patterns	
Average number of suppliers	7.451
Average number of customers	7.287
Panel B: Dynamic Patterns	
Average probability of continuing links	0.800
Average probability of separating links	0.200
Average probability of creating new links	0.126

Notes: Panel A shows the static patterns of firm-to-firm transactions. Panel B shows the dynamic patterns. "Average probability of continuing links" indicates the percentage of transactions existing in period t that remain in period $t+1$. "Average probability of separating links" indicates the percentage of transactions existing in period t that are disappeared at $t+1$. "Average probability of creating new links" represents the percentage of transactions that did not exist in period t among those that existed in period $t+1$.

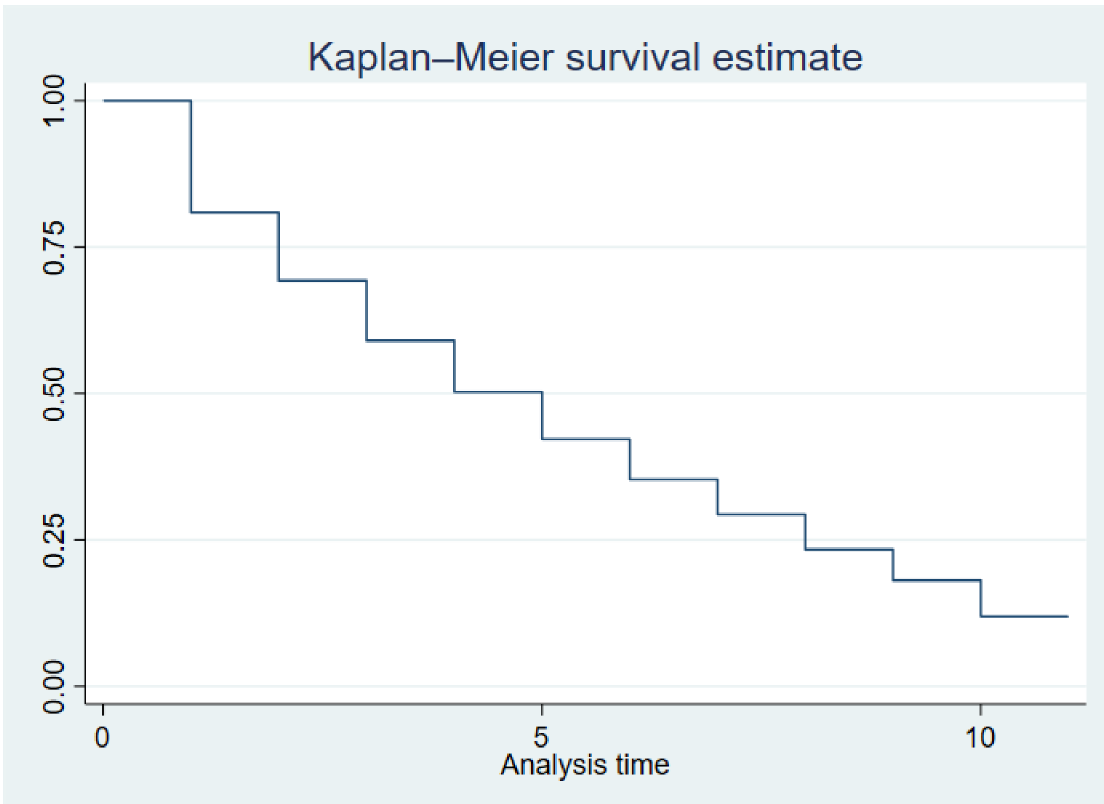
3 Empirical Results

3.1 Graphical Evidence

Here, we examine the feature of endogenous network formation. In particular, we look for empirical evidence for the presence of positive assortative matching or negative assortative matching between firms.

First, we divide the transaction into three types: (i) continued transaction, (ii) separated transaction, and (iii) newly created transaction between years t to $t+1$. With revealed preference, continued transactions as well as newly created transactions should be more preferable to separated ones. Figure 4 plots three productivity distributions for different groups. Con-

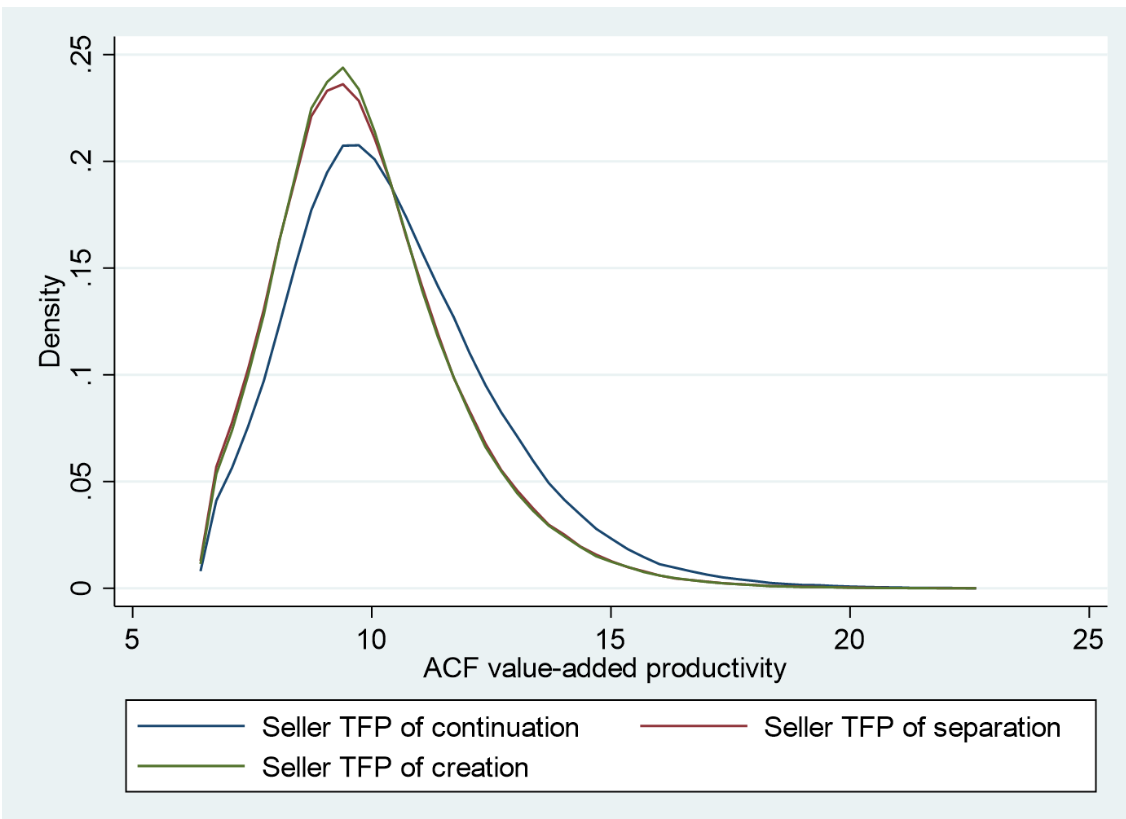
Figure 3. Survival Share of Transactions



Notes: This figure plots the Kaplan-Meier survival estimates of firm-to-firm transactions that existed in 2007. The length of the horizontal line represents the survival time (in years) of each interval, and the vertical distance between the horizontal lines corresponds to the change in cumulative probability as the curve moves to the right.

tinuation corresponds to the group of supplier firms with which customer firms continued to trade. Separation corresponds to the group of supplier firms with which customer firms stopped trading. Lastly, creation corresponds to the group of supplier firms with which customer firms newly started trading. It shows that the productivity distribution for continued transactions is the most to the right as expected, but that for newly created transactions differs little from that for separated transactions. This observation can be explained as follows. Created transactions do not necessarily occur when a firm's own productivity increases and is matched with a more productive counterpart. Matching can also happen when a firm's own productivity is lowered and is matched with a less productive counterpart. A similar argument can be made for separated transactions. We interpret that the productivity distributions is closer for the created and separated transactions because of the mixture of these downward and upward matching patterns.

Figure 4. Distributions of Productivity



Notes: This figure plots the distribution of supplier productivity for each of continued, separated and created transactions by customer firms.

3.2 Reduced-form Evidence

Next, we run the following regression to further examine the assortativity of the firm-to-firm transaction network. In order to study how the set of trading partners changes depending on firm i's productivity, we run the following regression:

$$Y_{it} = \beta \text{Productivity}_{it} + X_{it}\gamma + \eta_i + \tau_{jkt} + \epsilon_{it} \tag{1}$$

where Productivity_i is firm i's productivity level and X_{it} refers to firm covariates. We also include firm fixed effects, η_i, and industry-prefecture-year fixed effects, τ_{jkt}. For outcome, Y_{it}, we use the maximum and minimum productivity among firm i's suppliers. The moments should rise as firm i's productivity increases when there exists positive assortative matching. The opposite should be the case for negative assortative matching.

Table 3. Productivity Positive Assortative Matching: Maximum and Minimum

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.0152***	0.0148***	0.00383*	0.00689***
	(0.00107)	(0.00110)	(0.00216)	(0.00227)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	1,220,811	1,172,061	1,177,903	1,220,811
R-squared	0.969	0.967	0.791	0.788
Mean of Dep.Var.	16.61	16.77	10.15	10.12

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log firm age and the log the number of workers as the covariates.

Table 3 shows the regression results with maximum and minimum productivities as the outcomes. Columns (1) and (2) use the maximum productivity as the outcome, and columns (3) and (4) use the minimum productivity. All columns show the results with firm fixed effects. Columns (2) and (4) add firm covariates as independent variables. The results show that maximum and minimum productivities among suppliers are increasing in firm's own productivity, even after controlling for firm characteristics and including fixed effects. This implies that there exists positive assortative matching.[1] The positive assortativity is

[1] The results of positive assortative matching are related to many theoretical studies on labor and marriage

confirmed in the same way in Table 4 when we use the mean and the standard deviation of the suppliers' productivity as the outcome.

Table 4 shows the regression results as mean and standard deviation of the productivity as the outcomes. Columns (1) and (2) use the mean productivity as the outcome, and columns (3) and (4) use the standard deviation of the productivity among suppliers. The results confirm the finding shown above. The mean productivity is increasing in own productivity. Notably, the standard deviation is decreasing in own productivity. This reveals the selection mechanism of trading partners.

Table 4. Productivity Positive Assortative Matching: Mean and Standard Deviation

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00455***	0.00596***	-0.00341***	-0.00330***
	(0.00114)	(0.00119)	(0.000986)	(0.00106)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	1,220,811	1,172,061	1,029,885	964,976
R-squared	0.927	0.926	0.810	0.811
Mean of Dep.Var.	13.17	13.24	2.891	2.898

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log firm age and the log the number of workers as the covariates.

4 Theoretical Framework

We provide a theoretical framework to rationalize the findings of positive assortative matching. As in Bernard et al. (2018), both supplier and customer firms are heterogeneous in productivity and compete in monopolistic competition. Supplier firms provide differentiated intermediate inputs, and customer firms produce differentiated final goods. We denote the elasticity of substitution as $\sigma > 1$; it is identical for both intermediates and final goods.

A supplier has productivity z, which follows the Pareto distribution: $z \sim F(z) = 1 - z^{-\gamma}$. A customer has productivity Z, which also follows the Pareto distribution: $Z \sim G(Z) = 1 - Z^{-\Gamma}$. We impose $\Gamma > \gamma > \sigma - 1$ so that the price index for final goods is finite.

markets (e.g., Becker 1973; Shimer, and Smith 2000). For theoretical surveys, see, for example, Petrongolo, and Pissarides (2001) and Chade, Eeckhout, and Smith (2017).

We incorporate the variable relationship-specific cost $f(z, Z)$, which is dependent on productivity levels of both supplier and customer as follows:

$$\begin{aligned} \frac{\partial f}{\partial z} &> 0 \quad \text{if } z > Z \\ \frac{\partial f}{\partial Z} &> 0 \quad \text{if } Z > z \\ \frac{\partial^2 f}{\partial z \partial Z} &< 0 \quad \forall z \; \forall Z \end{aligned}$$

We assume that the relationship-specific cost is increasing in productivity gap between supplier and customer, and decreases when both firms simultaneously get more productive. This is intuitive as a more productive firm would search for better partners if the existing partners are not well matched in that the productivity levels are far from each other.

Both intermediates and final goods markets are characterized by monopolistic competition. Intermediates producers (suppliers) have the pricing rule

$$p(z) = \frac{\sigma}{\sigma - 1} \frac{w}{z} \tag{2}$$

Similarly, final goods producers (customers) have the pricing rule

$$P(Z) = \frac{\sigma}{\sigma - 1} \frac{q(Z)}{Z}, \tag{3}$$

where $q(Z)$ is the ideal price index for intermediate inputs. A customer firm with Z trade with sellers with $z \in [\underline{z}, \bar{z}]$ so that

$$q(Z)^{1-\sigma} = \int_{\underline{z}}^{\bar{z}} p(z)^{1-\sigma} dF(z)$$

The sales of intermediates by an intermediates producer (seller) z to a final goods producer (buyer) Z becomes

$$r(z, Z) = \left(\frac{p(z)}{q(Z)} \right)^{1-\sigma} E(z) \tag{4}$$

where $E(Z)$ is total spending on intermediates by a final goods producer Z. Then, an intermediate firm's net profits from a (z, Z) match is

$$\Pi(z, Z) = \frac{r(z, Z)}{\sigma} - wf(z, Z) \tag{5}$$

The upper and lower bounds are derived from zero cutoff profit conditions. Zero cutoff profit condition for seller with the lower bound of productivity for buyers $\underline{Z}$: $\Pi(z, \underline{Z}) = 0$

$$q(\underline{Z})^{\sigma-1}E(\underline{Z}) = \sigma w f(z, \underline{Z}) \left(\frac{\sigma}{\sigma-1}w\right)^{\sigma-1} z^{1-\sigma} \tag{6}$$

Zero cutoff profit condition for seller with the upper bound of productivity for buyers $\bar{Z}$: $\Pi(z, \bar{Z}) = 0$

$$q(\bar{Z})^{\sigma-1}E(\bar{Z}) = \sigma w f(z, \bar{Z}) \left(\frac{\sigma}{\sigma-1}w\right)^{\sigma-1} z^{1-\sigma} \tag{7}$$

Combining these, we obtain solutions for the sorting functions, $\underline{z}(Z)$ and $\bar{z}(Z)$. It can be shown that both are increasing in Z. Both lower and upper bounds of the matched supplier is increasing in customer firm's own productivity. This implies that productivity positive assortative matching exists.

Proposition 1. *Suppose there are two buyer firms with different productivity levels ($Z_1 < Z_2$), respectively. Then, the matched set of seller firms is $[\underline{z}(Z_1),\ \bar{z}(Z_1)]$ for Z_1 buyer and is $[\underline{z}(Z_2),\ \bar{z}(Z_2)]$ for Z_2 buyer. Then, since we have $\partial\underline{z}(Z)/\partial Z > 0$ and $\partial\bar{z}(Z)/\partial Z > 0$, we get*

$$\underline{z}(Z_1) < \underline{z}(Z_2)$$
$$\bar{z}(Z_1) < \bar{z}(Z_2)$$

i.e., productivity positive assortative matching property between buyer and seller firms.

This framework brings transaction network churning when there comes productivity shocks. The original set of matches divides into continuation and separation, and new matches are created. Proposition 2 looks at productivity shock on the seller side while Proposition 3 focuses on the buyer side.

Proposition 2. *Fix seller productivity at z. Suppose that there is positive productivity shock on the buyer such that productivity improves from Z to $Z + \Delta$, with Δ>0. Then, the match continues if seller productivity $z \sim [\underline{z}(Z+\Delta),\ \bar{z}(Z)]$ while it separates if seller productivity $z \sim [\underline{z}(Z),\ \underline{z}(Z+\Delta)]$. Additionally, the new match is created if seller productivity $z \sim [\bar{z}(Z),\ \bar{z}(Z+\Delta)]$.*

Proposition 3. *Fix buyer productivity at Z. Suppose that there is positive productivity* *shock on the seller such that productivity improves from z to $z + \delta$, with δ>0. Then, the match continues if seller productivity $\underline{z}(Z) < z < z + \delta < \bar{z}(Z)$ while it separates if seller productivity $z < \bar{z}(Z) < z + \delta$. Additionally, the new match is created if seller productivity $z < \underline{z}(Z) < z + \delta$.*

These theoretical implications allow us to study how firms would churn their transaction network due to productivity shocks. This work contributes to the existing literature in that we incorporated many-to-many matching framework and that we derived the upper and lower bounds of the matched set between firms.

5 Conclusion

This study contributes to the vibrant discussion of firm-to-firm transaction network by exploiting Japanese large-scale firm-level transaction data. Adding to the existing literature, we focus on the dynamic aspect of the network. We exploit a large-scale firm-level transaction data between 2007 and 2018 that allow us to observe firm-to-firm transactions and firm characteristics. First, we provided basic facts about positive assortative matching between firms. We found that more productive firms are more likely to trade with similarly more productive firms. This occurs not just in each time period but also across times in that more productive firms are more likely to keep trading with more productive ones while they are more likely to stop trading with less productive ones. Second, we built a theoretical framework to rationalize these findings with many-to-many matching setting. The model allows us to derive separate implications in the case of productivity shocks coming from supplier or customer. A promising area of future research is to study the relationship between firm-to-firm matching and aggregate economic growth and what policies could promote growth exploiting transaction network.

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A Tables and Figures

A.1 Reduced-form Evidence

Tables A1 and A2 show the estimation results when we use demeaned ACF productivity within three-digit industry code for the outcomes and own productivity. Tables A3 and A4 show the estimation results when we use labor productivity defined as sales per employee for the outcomes and own productivity.

Although the baseline estimation uses data from 2007-2018, the supply chain shocks caused by the 2011 Great East Japan Earthquake may have affected firms' choice of trading partners. Therefore, as a robustness check, we estimated using data from 2007-2010, and the results are shown in Tables A5 through A10. Tables A5 and A6 show the estimation results when we use ACF productivity, Tables A7 and A8 show the results when we use industry-demeaned productivity, and Tables A9 and A10 show the results when we use labor productivity.

Table A1. Demeaned Productivity Positive Assortative Matching: Maximum and Minimum

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00640***	0.00504***	0.00358*	0.00630***
	(0.00106)	(0.00109)	(0.00190)	(0.00199)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	1,220,811	1,172,061	1,220,811	1,172,061
R-squared	0.958	0.957	0.757	0.755
Mean of Dep.Var.	5.282	5.414	-0.401	-0.421

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table A2. Demeaned Productivity Positive Assortative Matching: Mean and Standard Deviation

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00361***	0.00449***	-0.00618***	-0.00590***
	(0.00100)	(0.00105)	(0.000893)	(0.000956)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	1,220,811	1,172,061	1,029,885	964,976
R-squared	0.907	0.905	0.802	0.803
Mean of Dep.Var.	2.271	2.321	2.499	2.506

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table A3. Labor Productivity Positive Assortative Matching: Maximum and Minimum

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00588	0.00581	0.000980*	0.000977*
	(0.00376)	(0.00373)	(0.00190)	(0.00199)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	6,100,451	5,608,656	6,100,451	5,608,656
R-squared	0.859	0.861	0.809	0.812
Mean of Dep.Var.	308,756	323,511	40,751	39,444

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age as the covariate.

Table A4. Labor Productivity Positive Assortative Matching: Mean and Standard Deviation

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00143**	0.00141**	0.00143**	0.00141**
	(0.000712)	(0.000704)	(0.000712)	(0.000704)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	6,100,451	5,608,656	6,100,451	5,608,656
R-squared	0.866	0.870	0.866	0.870
Mean of Dep.Var.	109,227	111,025	109,227	111,025

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age as the covariate.

Table A5. Productivity Positive Assortative Matching: Maximum and Minimum, 2007-2010

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00963***	0.00955***	0.00864*	0.0108**
	(0.00187)	(0.00192)	(0.00511)	(0.00529)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	254,839	247,540	254,839	247,540
R-squared	0.981	0.981	0.822	0.821
Mean of Dep.Var.	17.33	17.46	10.09	10.07

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table A6. Productivity Positive Assortative Matching: Mean and Standard Deviation, 2007-2010

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00542**	0.00600**	-0.00628***	-0.00685***
	(0.00251)	(0.00259)	(0.00207)	(0.00212)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	254,839	247,540	228,562	224,584
R-squared	0.942	0.942	0.850	0.849
Mean of Dep.Var.	13.51	13.56	2.999	3.009

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table A7. Demeaned Productivity Positive Assortative Matching: Maximum and Minimum, 2007-2010

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00930***	0.00939***	0.00791*	0.0103**
	(0.00193)	(0.00198)	(0.00446)	(0.00461)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	254,839	247,540	254,839	247,540
R-squared	0.973	0.972	0.793	0.791
Mean of Dep.Var.	5.800	5.900	-0.596	-0.617

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table A8. Demeaned Productivity Positive Assortative Matching: Mean and Standard Deviation, 2007-2010

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00821***	0.00907***	-0.00466**	-0.00518***
	(0.00219)	(0.00225)	(0.00185)	(0.00189)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	254,839	247,540	228,562	224,584
R-squared	0.924	0.923	0.846	0.845
Mean of Dep.Var.	2.423	2.458	2.617	2.626

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table A9. Labor Productivity Positive Assortative Matching: Maximum and Minimum, 2007-2010

	Maximum		**Minimum**	
	(1)	(2)	(3)	(4)
Own Productivity	0.0260*	0.0257*	0.00145*	0.00145*
	(0.0153)	(0.0152)	(0.000743)	(0.000744)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	2,039,208	1,880,467	2,039,208	1,880,467
R-squared	0.935	0.935	0.864	0.863
Mean of Dep.Var.	331,272	346,955	40,068	38,982

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.

Table A10. Labor Productivity Positive Assortative Matching: Mean and Standard Deviation, 2007-2010

	Mean		**Standard Deviation**	
	(1)	(2)	(3)	(4)
Own Productivity	0.00457**	0.00451**	0.00808**	0.00793**
	(0.00192)	(0.00190)	(0.00356)	(0.00355)
Covariates		x		x
Firm FE	x	x	x	x
Other FEs	x	x	x	x
Observations	2,039,208	1,880,467	1,695,767	1,589,930
R-squared	0.935	0.935	0.945	0.945
Mean of Dep.Var.	113,761	115,875	135,860	140,227

Notes: Robust standard errors clustered at the level of the firm in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) show the results when we take the maximum supplier productivity as the outcome, and columns (3) and (4) show the results when we take the minimum supplier productivity as the outcome. Columns (2) and (4) control for the log of firm age and the log of the number of workers as the covariates.