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**NAKAJIMA Kentaro**  
Tohoku University



Research Institute of Economy, Trade & Industry, IAA

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**Transactions as a Source of Agglomeration Economies:  
Buyer-seller matching in the Japanese manufacturing industry<sup>\*</sup>**

NAKAJIMA Kentaro

Tohoku University

**Abstract**

This paper empirically examines whether the geographical proximity of transaction partners improves firms' profits by using actual microdata on inter-firm transactions. I model the formation of transaction partners between newly entering firms and existing ones as a two-sided, many-to-many matching game with transferable utility and estimate the structural parameters of the model. The results show that the average distance to the transaction partners negatively affects firms' structural revenues. This strongly suggests that the existence of agglomeration economies results from inter-firm transactions that occur between geographically close firms. Furthermore, this effect is larger for entrant firms than for existing ones.

*Keywords:* Buyer-seller network; Matching; Marshallian externality

*JEL classification:* R11, L14

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# 1 Introduction

Economic activities concentrate in narrow areas. It has been pointed that the concentration of economic activities improves the profits and productivities of the firms located there. This is called agglomeration economies. Since Marshall's (1980) pioneering work, many researchers have found the source of agglomeration economies. Transferring knowledge and innovative ideas among densely agglomerated workers and alleviating matching through thick labor markets are the important examples (e.g., Duranton and Puga, 2004)

In addition, reducing transaction costs by transacting with proximate firms has also been pointed as one of the important sources of agglomeration economies. Empirically, this theoretical hypothesis has been confirmed indirectly. For example, Rosenthal and Strange (2001) found that the intense intra-industry transactions positively affect the location concentration of the industry in the U.S. manufacturing industries. Nakajima, Saito, Uesugi (2010) also found the same in Japan, and Ellison, Glaeser, and Kerr (2010) found that the inter-industry transaction ratio of an industry-pair positively affects their location co-agglomeration. These results suggest that intense transactions positively affect location concentrations.

However, what is the exact effect of intensive transactions on firm location choice? Are transaction cost reductions from the proximity of transaction partners actually the source of agglomeration economies? Previous literature has never directly answered above questions. Recently, Nakajima, Saito, Uesugi (2011) investigated the geographical features of inter-firm transactions in Japanese manufacturing firms. They found that the median distance of the inter-firm transactions is 39 km and most of the inter-firm transactions are concentrated around 30 km. The physical distance between the transaction partners is extremely proximate. Furthermore, they also found that the geographical concentration of transactions is positively correlated with the location concentration. Their findings strongly suggest that the geographical proximity of transaction partners would yield agglomeration economies. However, their research did not formally investigate the effect of the geographical proximity of transaction partners on firm location choice.

This paper formally examines whether the geographical proximity of transaction partners improves the firms' profits by using the actual microdata on inter-firm transactions. First, I model the formation of transaction partners between newly entering firms and existing firms as a two-sided many-to-many matching game with transferable utility by introducing the geo-

graphical distance between the transaction partners into the structural revenue function. Then, I estimate the parameters of the firms' structural revenue functions, and investigate the role of the geographical proximity of transaction partners on the firms' profit.

There exist few works that estimate a two-sided many-to-many matching game with the exception of Fox's (2010a, b) pioneering works. He proposed identification strategies for two-sided many-to-many matching games with transferable utility in his series of papers. In this paper, I follow Fox's (2010 b) estimation strategy.

In the result, I found that the average geographical distance between a firm and its transaction partners negatively affects its structural revenue. This strongly suggests that the existence of agglomeration economies results from the inter-firm transactions that occur between geographically close firms. Furthermore, this effect is larger for entrant firms than existing firms.

The rest of the paper is organized as follows. Section 2 describes how to model the formation of transaction partners and the location choice problem. The empirical strategy is described in Section 3. Section 4 provides the basic information about my dataset. Section 5 describes the specific issues on estimation and specifies the structural revenue functions. The results are shown in Section 6. Finally, Section 7 concludes the paper.

## 2 Model

### 2.1 Matching between entrant and existing firms

Before the formal model is presented, I discuss on one important set-up of the model. One difficult problem when building a model of the firms' location and transaction partner choice problem is the timing of location choice and partner choice. That is, when do manufacturing firms choose their transaction partners and locations? Basically, this problem has dynamic features. In terms of location choice, manufacturing production at least requires a factory, and hence, production starts after the decision on the firm's location. Similarly, in terms of transaction partners, if there are no buyers, the manufacturing supplier's production activity does not generate any profit, and hence, it can be considered that manufacturing production starts after some buyers are found. Both deciding a location and deciding the transaction partners are necessary factors for production. Given this, it can be considered that when a manufacturing firm enters a market, it simultaneously chooses its location and transaction partners. However,

a firm's transaction partners tend to change more frequently than its location after starting production. The firms sometimes change their transaction partners after starting operations. To consider the firms' changing of their transaction partners, dynamic features would have to be introduced into the model, which would make it unnecessarily complicated.

In this paper, I focus only on the newly entrant firms' behaviors to avoid including this dynamic issue. Specifically, I consider the situation wherein a manufacturing firm enters the market, simultaneously chooses its location and transaction partners given the existing firms' geographical locations. As such, I ignore the dynamic choice strategy pertaining to the choice of the transaction partners after deciding on the location. Specifically, I focus on the newly *entrant supplier* firms and *existing buyer* firms.

## 2.2 Description of the matching model

I model the entrant firms' and existing firms' transaction partner choice problem as a two-sided many-to-many matching game with transferable utility. Following Fox (2010b), I present the theoretical concept of the matching game.

The two sides in this paper are entrant upstream firms and existent downstream firms. An upstream firm  $u$ 's characteristics can be described as  $x_u^{\text{up}}$ ; a downstream firm  $d$ 's characteristics can be described as  $x_d^{\text{down}}$ . A match between  $u$  and  $d$  can be described as a *full match* given by  $\langle u, d, t_{\langle u, d \rangle} \rangle$ , where  $t_{\langle u, d \rangle}$  denotes the monetary transfer from  $d$  to  $u$ . This monetary transfer is allowed to take negative values. Abbreviating the monetary transfer, we can describe it as a *physical match* given by  $\langle u, d \rangle$ . Note that this paper considers *many-to-many* matching, and as such,  $u$  can match any number of firms up to its *quota* (maximum number of matches)  $q_u$ . Likewise,  $d$  can match up to  $q_d$  firms. Thus, in this many to many matching game, the matching outcome can also be described as a *full partner list* given by  $\langle u, (d_1, t_1), \dots, (d_N, t_N) \rangle$ . This is a list of an upstream firm  $u$ 's matches with downstream firms  $d_1, \dots, d_N$  with each monetary transfers  $t_1, \dots, t_N$ .

A *matching outcome*  $\mu$  can be considered as a set of full matches. That is,  $\{\langle u_1, d_1, t_1 \rangle, \dots, \langle u_N, d_N, t_N \rangle\}$ , where  $N$  denotes the number of matches taking place in the outcome. By abbreviating the monetary transfer, the *assignment*  $A(\mu)$  can be defined. The assignment  $A(\mu)$  is a set of physical matches corresponding to an outcome  $\mu$ .

Each firm's profit is depended on the matching outcome. Suppose that  $u$  matches with a

set  $D$  of downstream firms as a part of a matching outcome  $\mu$ , and let  $M$  be a subset of the corresponding assignment  $A(\mu)$  given by  $M = \bigcup_{d \in D} \{ \langle u, d \rangle \}$ . Under the matching outcome  $\mu$ , the profit of an upstream firm  $u$  is described as  $r^{\text{up}}(M) + \sum_{d \in D} t_{\langle u, d \rangle}$ , where  $r^{\text{up}}(M)$  is the structural revenue function of upstream firms depending on the matching partners' characteristics, and  $t_{\langle u, d \rangle}$  is the monetary transfer between  $u$  and  $d$ . The structural revenue of downstream firms can be described similarly. Suppose that a downstream firm  $d$  matches with a set  $U$  of downstream firms as a part of the assignment  $A(\mu)$ , and let  $M = \bigcup_{u \in U} \{ \langle u, d \rangle \}$ . The profit of a downstream firm  $d$  is described as  $r^{\text{down}}(M) - \sum_{u \in U} t_{\langle u, d \rangle}$ .

Under the above setup, I introduce pairwise stability as a concept of the equilibrium in this buyer-seller matching game. Following Fox (2010b), the definition of the equilibrium can be given as follows.

**Definition** An outcome  $\mu$  will satisfy pairwise stability if and only if the following four conditions hold:

1. Let  $p_1 = \langle u_1, (d_{1,1}, t_{1,1}), \dots, u_1, (d_{1,N_1}, t_{1,N_1}) \rangle$ ,  $p_2 = \langle u_2, (d_{2,1}, t_{2,1}), \dots, u_2, (d_{2,N_2}, t_{2,N_2}) \rangle$ ,  $d_1 \in \{d_{1,1}, \dots, d_{1,N_1}\}$ ,  $d_2 \in \{d_{2,1}, \dots, d_{2,N_2}\}$ ,  $M_{u_1} = \{ \langle u_1, d_{1,1} \rangle, \dots, \langle u_1, d_{1,N_1} \rangle \}$  and  $M_{d_2} = \{ \langle u, d_2 \rangle \in A(\mu) \}$ . The following inequality holds for all full partner lists  $p_1 \in \mu$  and  $p_2 \in \mu$ :

$$r^{\text{up}}(M_{u_1}) + t_{\langle u_1, d_1 \rangle} \geq r^{\text{up}}((M_{u_1} \setminus \{ \langle u_1, d_1 \rangle \}) \cup \{ \langle u_1, d_2 \rangle \}) + \tilde{t}_{\langle u_1, d_2 \rangle}, \quad (1)$$

where  $\tilde{t}_{\langle u_1, d_2 \rangle} \equiv r^{\text{down}}((M_{d_2} = \{ \langle u_2, d_2 \rangle \}) \cup \{ \langle u_1, d_2 \rangle \}) - (r^{\text{down}}(M_{d_2}) - t_{\langle u_2, d_2 \rangle})$ .

2. The inequality (1) holds if either or both of the existing matches represent a free quota slot, namely  $\langle u_1, d_1 \rangle = \langle u_1, 0 \rangle$  or  $\langle u_2, d_2 \rangle = \langle 0, d_2 \rangle$ . In this case, in (1) we set the transfers corresponding to the free quota slots,  $t_{\langle u_1, d_1 \rangle}$ , or  $t_{\langle u_2, d_2 \rangle}$ , as equal to zero.
3. For all  $\langle u, d, t \rangle \in \mu$  for any  $p$ , where  $M_u = \{ \langle u, d_1 \rangle, \dots, \langle u, d_N \rangle \}$  and  $d \in \{d_1, \dots, d_N\}$ ,

$$r^{\text{up}}(M_u) + t_{\langle u, d \rangle} \geq r^{\text{up}}(M_u \setminus \{ \langle u, d \rangle \}). \quad (2)$$

4. For all  $\langle u, d, t \rangle \in \mu$  for any  $p$ , where  $M_d = \{ \langle u_1, d \rangle, \dots, \langle u_N, d \rangle \}$  and  $u \in \{u_1, \dots, u_N\}$ ,

$$r^{\text{down}}(M_d) + t_{\langle u, d \rangle} \geq r^{\text{down}}(M_d \setminus \{ \langle u, d \rangle \}). \quad (3)$$

Intuitively, condition 1 in the definition implies that  $u_1$  prefers its actual partner  $d_1$  rather than the other partner  $d_2$  (which is not its actual partner) by paying transfer  $\tilde{t}_{\langle u,d \rangle}$ , which results in  $d_2$  switching its partner to  $u_1$  instead of its actual partner  $u_2$ . Fox's (2010b) estimation strategy which I adopt is based on condition 1.

Condition 2 yields that adding a new match or exchanging old matches into the free quota slot cannot improve the firm's profit. Conditions 3 and 4 give that no firm can improve its profit from the equilibrium outcome by dropping its transaction partners. For more details, see Fox (2010b).

### 2.3 Introducing geographical features

This subsection introduces the geographical features into the matching model by assuming the form of structural revenue functions. First, I assume that the structural revenue is linear in parameters. That is,

$$r_{\beta^{\text{up}}}^{\text{up}}(M) = Z^{\text{up}}(M)' \beta^{\text{up}}, \quad (4)$$

and

$$r_{\beta^{\text{down}}}^{\text{down}}(M) = Z^{\text{down}}(M)' \beta^{\text{down}}, \quad (5)$$

where  $Z^{\text{up}}(M)$  and  $Z^{\text{down}}(M)$  are vector-valued functions of  $M$ . Then, I introduce the geographical information on the structural revenue as

$$Z^{\text{up}}(M) = (z_{\text{distance}}^{\text{up}}(M), z_{\text{others}}^{\text{up}}(M)), \quad (6)$$

$$Z^{\text{down}}(M) = (z_{\text{distance}}^{\text{down}}(M), z_{\text{others}}^{\text{down}}(M)), \quad (7)$$

where  $z_{\text{others}}^{\text{up}}(M)$  and  $z_{\text{others}}^{\text{down}}(M)$  are the vector-valued functions of  $M$ . The key terms for introducing the location choice concept into the model are  $z_{\text{distance}}^{\text{up}}(M)$  and  $z_{\text{distance}}^{\text{down}}(M)$ . The variable  $z_{\text{distance}}^{\text{up}}(M)$  is a function of the distance between upstream firm  $u$  and its downstream partners. For example, we can consider the average distance between an upstream firm  $u$  and its downstream partners. Similarly,  $z_{\text{distance}}^{\text{down}}(M)$  is a function of the distance between a downstream firm  $d$  and its upstream partners. The distance terms  $z_{\text{distance}}^{\text{up}}(M)$  and  $z_{\text{distance}}^{\text{down}}(M)$  in the structural revenue function introduce the geographical features into the matching model. That is, I assume that the entrant firm simultaneously chooses its location and transaction partners

given the existent firms' locations. Then, the terms  $z_{\text{distance}}^{\text{up}}(M)$  and  $z_{\text{distance}}^{\text{down}}(M)$  are decided by the entrants' simultaneous choice of location and transaction partners given the existing firms' locations. By this setup, I introduce the geographical features into the matching model.

### 3 Estimation strategy

This section describes how to bridge the theoretical concept and the empirical analysis. Following the estimation strategy proposed by Fox (2010b), I describe a concept, the *sum of revenues inequalities* by modifying a necessary condition of the pairwise stable equilibrium. Then, I show that the sum of revenues inequalities yields the estimators of the structural parameters by using the maximum score function procedure.

#### 3.1 Sum of revenues inequalities

To bridge the theoretical equilibrium concept and the empirical analysis, I describe the concept of the sum of revenues inequalities. In this regard, we revisit condition 1 of the definition of pairwise stability. Substituting  $\tilde{t}_{\langle u_1, d_2 \rangle}$  into (1) yields

$$\begin{aligned} r^{\text{up}}(M_{u_1}) + t_{\langle u_1, d_1 \rangle} + r^{\text{down}}(M_{d_2}) &\geq \\ r^{\text{up}}((M_{u_1} \setminus \{\langle u_1, d_1 \rangle\}) \cup \{\langle u_1, d_2 \rangle\}) + r^{\text{down}}((M_{d_2} \setminus \{\langle u_2, d_2 \rangle\}) \cup \{\langle u_1, d_2 \rangle\}) + t_{\langle u_2, d_2 \rangle}. \end{aligned} \quad (8)$$

Further, the symmetric inequality holds for  $u_2$  as

$$\begin{aligned} r^{\text{up}}(M_{u_2}) + t_{\langle u_2, d_2 \rangle} + r^{\text{down}}(M_{d_1}) &\geq \\ r^{\text{up}}((M_{u_2} \setminus \{\langle u_2, d_2 \rangle\}) \cup \{\langle u_2, d_1 \rangle\}) + r^{\text{down}}((M_{d_1} \setminus \{\langle u_1, d_1 \rangle\}) \cup \{\langle u_2, d_1 \rangle\}) + t_{\langle u_1, d_1 \rangle}. \end{aligned} \quad (9)$$

Summing up those two inequalities, I obtain the sum of revenues inequality as follows:

$$\begin{aligned} r^{\text{up}}(M_{u_1}) + r^{\text{down}}(M_{d_1}) + r^{\text{down}}(M_{d_2}) + r^{\text{up}}(M_{u_2}) &\geq \\ r^{\text{up}}((M_{u_1} \setminus \{\langle u_1, d_1 \rangle\}) \cup \{\langle u_1, d_2 \rangle\}) + r^{\text{down}}((M_{d_2} \setminus \{\langle u_2, d_2 \rangle\}) \cup \{\langle u_1, d_2 \rangle\}) + \\ r^{\text{up}}((M_{u_2} \setminus \{\langle u_2, d_2 \rangle\}) \cup \{\langle u_2, d_1 \rangle\}) + r^{\text{down}}((M_{d_1} \setminus \{\langle u_1, d_1 \rangle\}) \cup \{\langle u_2, d_1 \rangle\}). \end{aligned} \quad (10)$$



which compares the sum of two upstream and two downstream firms' revenues before and after the exchange of one downstream firm each between the two upstream firms.

Then, substituting into the specific form of the structural revenue function which is specified in (4) and (5), I obtain the following inequality:

$$\begin{aligned}
& Z^{\text{up}}(M_{u_1})'\beta^{\text{up}} + Z^{\text{down}}(M_{d_1})'\beta^{\text{down}} + Z^{\text{up}}(M_{u_2})'\beta^{\text{up}} + Z^{\text{down}}(M_{d_2})'\beta^{\text{down}} \geq \\
& Z^{\text{up}}((M_{u_1} \setminus \{\langle u_1, d_1 \rangle\}) \cup \{\langle u_1, d_2 \rangle\})'\beta^{\text{up}} + Z^{\text{down}}((M_{d_2} \setminus \{\langle u_2, d_2 \rangle\}) \cup \{\langle u_1, d_2 \rangle\})'\beta^{\text{down}} + \\
& Z^{\text{up}}((M_{u_2} \setminus \{\langle u_2, d_2 \rangle\}) \cup \{\langle u_2, d_1 \rangle\})'\beta^{\text{up}} + Z^{\text{down}}((M_{d_1} \setminus \{\langle u_1, d_1 \rangle\}) \cup \{\langle u_2, d_1 \rangle\})'\beta^{\text{down}}. \quad (11)
\end{aligned}$$

For the simplified notations, I define a vector  $X_{u_1, u_2, d_1, d_2} = (X_{u_1, u_2, d_1, d_2}^{\text{up}}, X_{u_1, u_2, d_1, d_2}^{\text{down}})$ , where

$$\begin{aligned}
X_{u_1, u_2, d_1, d_2}^{\text{up}} = & Z^{\text{up}}(M_{u_1}) + Z^{\text{up}}(M_{u_2}) - \\
& Z^{\text{up}}((M_{u_1} \setminus \{\langle u_1, d_1 \rangle\}) \cup \{\langle u_1, d_2 \rangle\}) - Z^{\text{up}}((M_{u_2} \setminus \{\langle u_2, d_2 \rangle\}) \cup \{\langle u_2, d_1 \rangle\}), \quad (12)
\end{aligned}$$

and

$$\begin{aligned}
X_{u_1, u_2, d_1, d_2}^{\text{down}} = & Z^{\text{down}}(M_{d_1}) + Z^{\text{down}}(M_{d_2}) - \\
& Z^{\text{down}}((M_{d_2} \setminus \{\langle u_2, d_2 \rangle\}) \cup \{\langle u_1, d_2 \rangle\}) - Z^{\text{down}}((M_{d_1} \setminus \{\langle u_1, d_1 \rangle\}) \cup \{\langle u_2, d_1 \rangle\}). \quad (13)
\end{aligned}$$

I also define the vector of all structural revenue parameters  $\beta = (\beta^{\text{up}}, \beta^{\text{down}})$ . Then, I simplify the notation of inequality (11) to

$$X_{u_1, u_2, d_1, d_2}'\beta \geq 0. \quad (14)$$

This is the specified sum of revenues inequality, and the next subsection shows how to estimate the structural parameters  $\beta$ .

### 3.2 Maximum score estimator

Fox (2010b), proposed using the maximum score functions to estimate the structural parameters  $\beta$ , and I follow his procedure. Let  $h = 1, \dots, H$  be a matching market<sup>1</sup>,  $A_h$  be an assignment in market  $h$ , and  $I_h$  be the set of inequalities in market  $h$ . Thus, an element of  $I_h$  is indexed by

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<sup>1</sup>The definition of the matching market in this paper will be explained in Section 5.1.

the matches  $\{\langle u_1, d_1 \rangle, \langle u_2, d_2 \rangle\} \subseteq A_h$ . Then, the maximum score function is defined as follows:

$$Q_H(\beta) = \frac{1}{H} \sum_{h \in H} \sum_{\{\langle u_1, d_1 \rangle, \langle u_2, d_2 \rangle\} \in I_h} 1[X_{u_1, u_2, d_1, d_2}'\beta \geq 0] \quad (15)$$

where,  $1[\cdot]$  is an indicator function that takes the value of one if the inequality condition in the bracket is satisfied, and the value zero if the inequality is not satisfied. By numerically maximizing this maximum score objective function, I obtain the point estimators of the structural parameters.

## 4 Data

We employ a unique and massive dataset of Japanese firms compiled by Tokyo Shoko Research (TSR). The TSR dataset covers 826,169 firms, which is equivalent to over half of all incorporated firms in Japan, and provides information on the firms' location and four-digit industry classification code. We geocode the firm location data using the CSV Address Matching Service provided by the Center for Spatial Information Science, University of Tokyo. Furthermore, this dataset provides information on each firm's transaction partners. Specifically, this dataset provides the information on the main suppliers and customers in each firm. In this paper, I focus only on the manufacturing sector, which reduces the sample used for our analysis to 142,282 firms. The dataset was purchased from TSR only once, at the end of March 2006, so that we only have a cross-sectional observations and no longitudinal observations.

On the definitions of the entrant and existing firms, the TSR dataset provides information on the foundation year of each firm. I set the firms younger than 10 years as entrants, and the others as existing firms.

## 5 Estimation issues

### 5.1 Definition of the market

I define each market as a pair of three-digit industries to which the firms belong based on the Japanese Standard Industry Classifications (JSIC). Ideally, the matching market should be defined by goods that actually transact from upstream firms to downstream firms (e.g., engines for automobile, microprocessors for personal computers, and so on). Unfortunately, I cannot

identify specific goods that actually transact between the firms in my dataset. Instead, I define each market as a pair of three-digit industries to which the firms belong. For example, if we observe several buyer-seller transactions from the Glass and its Products industry (JSIC221) to the Alcoholic Beverages industry (JSIC102), I define that there exists a matching market that some goods transact from Glass and its Products industry to the Alcoholic Beverages industry. In this example, we can easily guess that in this market, “glass bottles” are purchased for alcoholic beverages. In the JSIC, there are 150 three-digit manufacturing industries, and thus, potentially, there are  $150^2$  markets. From this potential market, I choose the pairs of industries with several transactions. Specifically, I restrict only to the markets that have 100 or more matches to ensure enough number of observations.

## 5.2 Structural revenue function

Now, I describe the full specification of the structural revenue functions. First, I assume the structural revenue function of the upstream entrant firms as follows:

$$Z^{\text{up}}(M)' \beta^{\text{up}} = \left( z_{\text{distance}}^{\text{up}}(M), z_{\text{worker}}^{\text{up}}(M), z_{\text{degree}}^{\text{up}}(M), z_{\text{credit}}^{\text{up}}(M) \right) \beta^{\text{up}}, \quad (16)$$

where  $\beta^{\text{up}} = \left( \beta_{\text{distance}}^{\text{up}}, \beta_{\text{worker}}^{\text{up}}, \beta_{\text{degree}}^{\text{up}}, \beta_{\text{credit}}^{\text{up}} \right)'$  is a vector of estimable parameters.

Again, my primary interest variable is  $z_{\text{distance}}^{\text{up}}(M)$ . This is the natural logarithm of average great-circle distance between an upstream firm  $u$  and its downstream partners. If the geographical proximity of the transaction partners actually improves the firm profits, the estimate of the structural parameter  $\beta_{\text{distance}}^{\text{up}}$  is expected to have a negative sign (a higher average distance reduces the firm profits). If so, the entrant firms tend to locate the nearby existent transaction partners. The descriptive statistics are shown in Table 1.

Table 1

The median distance between the transaction partners is 87 km, and the 25 percentile value is 16 km. This suggests that most of the transactions between newly entrant supplier firms and existing buyer firms are bounded in shorter distances. However, as compared to the result of Nakajima, Saito, Uesugi (2011) that the median bilateral transaction distance among whole Japanese manufacturing firms is 39 km and its 25 percentile is 8 km, the transaction distances between newly entrant suppliers and existing buyers seems longer. This would suggest that after

entering the market and starting operations, the transaction partners are switched to the firms that are more closely located. If so, focusing on the transactions between whole manufacturing firms requires introducing dynamic features pertaining to the transaction partners into the theoretical model. Thus, focusing only on the transactions between entrant and existing firms and avoiding this dynamic transaction problem seems appropriate.

The structural revenue of an upstream firm is expected to be dependent on the performances of the downstream firms (e.g., productivity and creditability). The variable  $z_{\text{worker}}^{\text{up}}(M)$  gives the natural logarithm of average number of workers of downstream transaction partners as a proxy for their performance.

Moreover, an upstream firm's revenue is also dependent on the downstream firms' creditability. I introduce the number of transaction partners of the downstream firm as a proxy for the downstream firms' creditability. The term  $z_{\text{degree}}^{\text{up}}(M)$  denotes the natural logarithm of average number of transaction partners of the upstream firm  $u$ 's transaction partners. The descriptive statistics of the number of transaction partners is shown in Table 1. When I count the number of transaction partners, I restrict transactions only to the existing firms, and exclude transactions with other entrants. The average number of transaction partners of existing buyer firms is 46. This large average number of transaction partners is induced by the heavily skewed distribution of the number of transaction partners. The maximum number of transaction partners is 2000; on the other hand, the 75 percentile value is only 31. The transactions concentrate in a few of the largest buyers (the so called assembler firms like Toyota). The minimum value of zero would imply that the firm transacts only with the non-manufacturing firms.

Finally, there exist other firms' performance factors that affects the structural revenue, but cannot be captured by the number of workers and degrees. The TSR dataset fortunately provides the information on each firm's total credit score. The score is constructed on the basis of the TSR researchers' periodic interviews for each firm and its observable performance. The most creditable and high performing firm is marked 100, and the absolutely non-creditable firm is marked 0. The descriptive statistics are shown in Table 1. Conceptually, this variable can mark from 0 to 100, but the observed value of this variable varied from 35 to 91. I introduce this firm credit score into the structural revenue function as the proxy for the firm's total performance as  $z_{\text{credit}}^{\text{up}}(M)$ , the natural logarithm of average credit score of the downstream partners.

I also assume the structural revenue function of the downstream existing firms as follows:

$$Z^{\text{down}}(M) = \left( z_{\text{distance}}^{\text{down}}(M), z_{\text{worker}}^{\text{down}}(M) \right) \quad (17)$$

Similar to the entrant firms, the average distance to the transaction partners also affects the downstream firms' profits. The firm size of the entrant firm also affects the downstream firms.

Under these structural revenue functions, I consider the situation that entrant upstream and existing downstream firms choose transaction partners and furthermore, upstream firms simultaneously choose their locations.

### 5.3 Issues related to maximizing the score function and to statistical inference

Before presenting the estimation results, this subsection mentions some issues related to estimating the structural revenue functions. Following Fox (2010a), I numerically maximize the score function using the differential optimization routine that is well suited to the global optimization (Stone and Price, 1997).<sup>2</sup> For the differential evolution, I use a population of 200 points and a scaling factor of 0.5. I run the numerical optimization 10 times with different initial populations of 200 points, and then, choose the maximum value of the objective functions over the 10 runs for the point estimates.

For the statistical inference, I adopt the subsampling set inference proposed by Chernozhukov, Hong, and Tamer (2007) and Romano and Shaikh (2010). I subsample 1/4th of the matching markets, and replicate 150 times. In the subsampling estimations, I also run 10 numerical optimizations and choose the best estimates in each artificial subsampled dataset.

## 6 Results

The estimation results are shown in Table 2. First, this estimation uses 16,489 inequalities, of which, 74.1% are satisfied at the reported pointed estimates. This suggests a good fit of the estimation. The parameter for the average number of workers  $\beta_{\text{worker}}^{\text{down}}$  is normalized to be 1. The other parameters are interpreted relative to the parameter for the partners' average number of workers.

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<sup>2</sup>I use the DEoptim package for R written by David Ardia, Katharine Mullen, Brian Peterson, and Joshua Ulrich.

Table 2

Our main parameter of interest is  $\beta_{\text{distance}}^{\text{up}}$ , the parameter for the average distance to the transaction partners. The point estimate is  $-30.17$ . This implies that a longer average distance to the transaction partners reduces the upstream firm's structural revenue, and its effect is much larger than  $\beta_{\text{worker}}^{\text{down}}$ . For the upstream entrant firms, the one percent decrease of the average distance to the transaction partners improve the structural profit 30 times larger than the improvement by the one percent increase of average size of workers of the partners for the downstream existing firms. Furthermore, its 95% confidence interval is entirely in the negative region. These imply that a shorter average distance largely improves firm's structural profit. This is very indicative of the existence of agglomeration economies that results from the inter-firm transactions occurring between geographically close firms.

Second, the point estimate of the coefficient of the partners' average worker size is 20.52, and its 95% confidence interval is entirely located in the positive region. This suggests that transacting to larger buyers improves firm's profit.

Interestingly, the point estimate of the coefficient of the partners' average number of transaction partners is  $-14.29$  and its 95% confidence interval is entirely located in the negative region. This suggests that transacting to buyer firms that have a large number of transaction partners reduces the firm's profit. This would imply that an existing buyer firm with a large number of transaction partners has a stronger bargaining power because it has many other suppliers as outside options. Thus, the profit of a new supplier firm that transacts with such a firm would be compressed by the latter's strong bargaining power.

Finally, the point estimate of the coefficient of the partners' average credit score is 5.80, and its 95% confidence interval is entirely located in the positive region. This suggests that transacting with firms who have higher credit scores improves firm's profit.

As for the revenue function of the downstream firms, as with the upstream firms, the point estimate of the parameter for the average distance to the transaction partners is negative, and its 95% confidence intervals are entirely located in the negative region. This implies that a shorter average distance to the transaction partners improves downstream firms' profits. This is similar to the upstream firms. But, very interestingly, the absolute value of the point estimate is quite smaller than that of the upstream firm's revenue function. This suggests that a shorter distance to the transaction partners improves the newly entrant supplier firm's profit considerably more

than the existing buyer firms' profit.

In sum, I confirm that a shorter distance to the transaction partners improves the profit of both an entrant supplier and the existing buyer firms. This is very indicative of the existence of the existence of agglomeration economies through the geographically proximate transactions. Furthermore, the effect of the agglomeration economies is larger for newly entrant suppliers than for existing buyers.

## 6.1 More on distance

In the previous section, I found the importance of the distance to the transaction partners on the decision of choosing transaction partners by focusing on the average distance. On the other hand, other features of the distance to the transaction partners would have important roles on the decision of choosing partners. In this section, I investigate the role of the distance more in detail by focusing on the maximum distance.

I assume the structural profit function as follows,

$$Z^{\text{up}}(M)' \beta^{\text{up}} = \left( z_{\text{average distance}}^{\text{up}}(M), z_{\text{maximum distance}}^{\text{up}}(M), z_{\text{credit}}^{\text{up}}(M) \right) \beta^{\text{up}}, \quad (18)$$

$$Z^{\text{down}}(M)' \beta^{\text{down}} = \left( z_{\text{average distance}}^{\text{down}}(M), z_{\text{maximum distance}}^{\text{down}}(M), z_{\text{worker}}^{\text{down}}(M) \right) \beta^{\text{down}}, \quad (19)$$

where  $z_{\text{maximum distance}}^{\text{up}}(M)$  is the maximum distance to the transaction partners in  $M$ . By using this structural revenue function, I try to distinguish the effect of average and maximum distances to the transaction partners.

The estimation results are shown in Table 3. The point estimate of the parameter for the average distance to the transaction partners  $\beta_{\text{average distance}}^{\text{up}}$  is  $-6.13$  and still negative. But its 95% confidence interval includes zero. On the other hand, the parameter for the maximum distance  $\beta_{\text{maximum distance}}^{\text{up}}$  is negative and its 95% confidence interval is entirely locates negative region. This suggests that the shorter maximum distance rather than the average is significantly important for the choice of the transaction partners for upstream entrant firms.

Table 3

On the other hand, for downstream existing firms, parameters for both of average and maximum distances are negative and their confidence intervals locate negative region. Thus, for the existing down stream firms both of the average and maximum distance is important for the choice of the transaction partners for upstream entrant firms.

## 7 Concluding remarks

This paper empirically examined whether the geographical proximity of transaction partners improved the firms' profits by using the actual microdata on inter-firm transactions. I modeled the formation of transaction partners between newly entering firms and existing firms as a two-sided many-to-many matching game with transferable utility and estimated the structural parameters of the model.

In the results, I found that the average distance to the transaction partners negatively affected the firms' structural profit. This is very indicative of the existence of agglomeration economies that results from the inter-firm transactions occurring between geographically close firms. Furthermore, the effect of the agglomeration economies is larger for newly entrant suppliers than for existing buyers.

This paper first empirically found that the agglomeration economies resulting from the inter-firm transactions occurring between geographically close firms using actual microdata on the inter-firm transaction relationships. However, to avoid the dynamic feature pertaining to the choice of the transaction partners, I only focused on the transactions between newly entrant firms and existing firms. In the future, I plan to analyze the geographic features over the transaction relationships of every firm by introducing dynamic features pertaining to the transactions.

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Table 1: Descriptive statistics

No. of suppliers (entrants) : 679								
No. of buyers (existing firms) : 1112								
No. of matches: 1389								
	Observations	Mean	SD	Min	25p	Median	75p	Max
Transaction distance (km)	1389	197	238	0	16	87	307	1140
No. of workers (Suppliers)	679	94	364	1	7	18	55	4950
No. of workers (Buyers)	1112	1030	4144	1	29	110	469	66000
Credits (Buyers)	1112	58.83	8.64	35.00	52.00	58.00	65.00	91.00
No. of transaction partners (Buyers)	1112	46	150	0	4	10	31	2000

Table 2: Results of the structural revenue function estimates

Variables	Parameters	Point Estimate	95% CI
Upstream firms			
Average distance	$\beta_{\text{distance}}^{\text{up}}$	-30.17	(-32.0, -27.9)
Average no. of workers	$\beta_{\text{worker}}^{\text{up}}$	20.52	(11.92, 21.42)
Average no. of transaction partners	$\beta_{\text{degree}}^{\text{up}}$	-14.29	(-14.69, -13.69)
Average credit scores	$\beta_{\text{credit}}^{\text{up}}$	5.80	(1.01, 8.50)
Downstream firms			
Average distance	$\beta_{\text{distance}}^{\text{down}}$	-1.03	(-1.83, -0.63)
Average no. of workers	$\beta_{\text{worker}}^{\text{down}}$	1	Superconsistent
# of inequalities			16489
% satisfied			74.1

Table 3: Results of the structural revenue function estimates

Variables	Parameters	Point Estimate	95% CI
Upstream firms			
Average distance	$\beta_{\text{average distance}}^{\text{up}}$	-6.13	(-11.61, 13.87)
Maximum distance	$\beta_{\text{maximum distance}}^{\text{up}}$	-16.97	(-33.11, -10.32)
Average credit scores	$\beta_{\text{credit}}^{\text{up}}$	15.35	(13.70, 15.58)
Downstream firms			
Average distance	$\beta_{\text{average distance}}^{\text{down}}$	-1.69	(-2.60, -1.16)
Maximum distance	$\beta_{\text{maximum distance}}^{\text{up}}$	-1.04	(-1.23, -0.98)
Average no. of workers	$\beta_{\text{worker}}^{\text{down}}$	1	Superconsistent
# of inequalities			16489
% satisfied			66.2