Daily Gravity

Kazutaka Takechi
Faculty of Economics
Hosei University
4342 Aihara-machi
Machida, Tokyo, 194-0298, Japan
Email: ktakechi@hosei.ac.jp
& Sauder School of Business
University of British Columbia
2053 Main Mall
Vancouver BC V6T 1Z2, Canada
Email: kazu.takechi@sauder.ubc.ca

Abstract

We estimate trade costs under large zero trade by using daily data on agricultural goods trade within a country. Because of the nature of daily data, there is a prominent zero daily trade between regions and daily delivery is subject to noisy demand and supply shocks, which tends to create heteroskedasticity of the data. Hence, we use Poisson Pseudo Maximum Likelihood (PPML) to estimate gravity model and investigate non-linear nature of trade costs. Empirical analysis shows a statistically significant, but economically subtle nonlinearity in trade costs. We also aggregate daily data to monthly level to examine whether shocks are smoothed and thus those impacts are dampened. Our estimation shows that the difference is minor. Comparison of the results with other estimation methods such as the least squares of linear-in-log model and various Tobit procedures is also conducted. There is a large difference in the results between simple least squares and PPML, suggesting the significant heteroskedasticity. We also calculate outward and inward multilateral resistance terms to derive the incidence of trade costs and find that a large portion of trade costs is the buyers' burden.

Key Words : *Trade costs; Zero Trade; Daily Data*
JEL Classification Number : F11, F14, F41

This study is conducted as a part of the Project "Analyses of Trade Costs" undertaken at Research Institute of Economy, Trade and Industry(RIETI). We also gratefully acknowledge the financial support of the Ministry of Science, Technology, and Education (No. 15K03647).

1. Introduction

Treating heteroskedasticity and zero trade has become a central issue in the gravity model estimation since Santos Silva and Tenreyro (2006). The main concern about heteroskedasticity in the data is that when errors exhibit heteroskedasticity, taking log of these may make regressors dependent on errors. This leads to an inconsistent estimation. Furthermore, when dependent variable has a large fraction of zeros, taking log faces numerical difficulty. The seminal work by Santos Silva and Tenreyro (2006) proposes Poisson Pseudo Maximum Likelihood (PPML) method to take into account heteroskedasticity and zero trade.

Heteroskedasticity is caused by many reasons. In this study, we consider that the data with significant noises and shocks are subject to the problem of heteroskedasticity. Unobservable shocks are different in different times and affect the transaction behavior when economic agents make their decisions on that time horizon. The noise is partly caused by measurement error but also demand and supply shocks to the agents. If these shock are prominent, then the agent's economic behavior, for example delivery decision, is affected. These properties are prevalent for daily data set because we observe that dailiy delivery pattern is quite discrete. For example, today producer located in region j ships the product to region n. However, yesterday it shipped to region n', not n, and it may plan to deliver to region n'' tomorrow. Why on this particular day, does it supply the good to region n? The reason can be: 1) demand shock that increase the price in region n, 2) supply shock that the producer in region j can supply their goods, or 3) trade cost shocks that make cheaper to deliver from a particular source region j to a particular market n. Because every day has different shocks, daily data is likely to exhibit heteroskedasticity. Daily data has not been often used to examine bilateral transactions to our knowledge. While the success of gravity model is well documented, it is important to investigate whether gravity model performs well for daily data and thus the contribution of this study is to show how good gravity model works for daily data.

Moreover, the nature of trade costs may cause zero trade. If there is a substantial scale economy in transport, producers may not deliver their goods to different markets, but concentrate on shipping to one market. This may save transport costs. Thus, the presence of fixed cost or the lumpiness of trade costs causing scale economy creates discreteness of quantity supplied. While our estimation procedure does not incorporate fixed costs, our specification can examine whether a fixed cost element exist. We consider this lumpiness in a context of, in particular, scale economy in distance shipped. When shipping products, initial loading costs may be large compared to the costs of moving goods for example from 100 kilometers to 110 kilometers. The relationship between trade costs and distance caused by the combination of loading fixed costs and constant unit cost of transport implies that trade costs function may have a nonlinear property and thus it is important to examine how severe the nonlinearly in trade cost function is. Thus, we also contribute to the literature by demonstrating the impact and property of trade costs using daily traded data that contains substantial shocks.

In addition to the estimation of trade costs, estimating gravity model with PPML gives us an important measure of trade costs. When estimating gravity equation, since Anderson and van Wincoop (2003) pointed out that there are omitted variable biases without general equilibrium effects, we have to estimate structural gravity or include importer and exporter fixed effects (Harrigan (1996) and Redding and Venables(2004)). An important contribution by Fally (2015) is that the estimated importer and exporter fixed effects by using PPML are used to calculate the multilateral resistance terms exactly as in structural gravity model in Anderson and van Wincoop (2003). Thus, we can get true general equilibrium effects when we use an importer-exporter fixed effects PPML. The multilateral resistance term is not merely price index, but economically important meanings are given by Anderson and Yotov (2010). Outward MRT is the average costs of seller and inward MRT exhibits the buyer's average costs. These shows the incidence of trade costs, so by comparing outward and inward MRTs, we can show whether seller or buyer incurs the large portion of trade costs.

In this study, we find that there is a substantial trade costs for regional transactions. The presence of heteroskedasticity and nonlinearity in trade cost function is also confirmed.

We then calculate outward and inward MRTs for daily data and find that inward MRTs are larger than outward MRTs on average. By comparing these MRTs provides us an important policy implication: which side of trading party should operate more efficiently. When inward MRT is large, wholesalers incur a large part of trade costs. Thus, improving efficiency of wholesale markets may create a large welfare gains, which provides justifications for government policy on wholesale market evolution. A column on the Japanese newspaper, Nikkei (March 23rd, 2015), argued that more liberalization is required to reduce transaction costs in agricultural wholesale markets. Our results support the idea that there is a still room for improvement in wholesale market efficiency.

This paper is organized as follows. In the next section, we briefly outline our data set and show how volatile the daily delivery decision is. Then, in section 3, the standard gravity model is derived from a constant elasticity of substitution (CES) preference framework. Section 4 shows our estimation procedures and reports our empirical results. Final section concludes.

2. Data

We use a wholesale price data of agricultural products in Japan. The data set is called "Daily Wholesale Market Information on Fresh Fruits and Vegetables" (Seikabutsu Hinmokubetsu Shikyo Joho in Japanese). While the data set contains price and shipment data and product characteristic information more than 100 vegetables, we simply use the data of one vegetable, carrot in 2007. While carrot may not be a representative vegetable in our data, the same analysis can be conducted for other vegetables.

This data set reports the price, quantity and product characteristics in 55 wholesale markets daily. There are 47 prefectures in Japan. Each prefecture has at least one wholesale market, so data variation is nationwide. The market opening days in 2007 is 274 days. The example of the data set is shown in Table 1. Table 1 shows daily data pattern from the source prefecture, Hokkaido, on October 11, 12, and 13, 2007 to various markets. On October 11, the carrot from Hokkaido is traded in Morioka and Maebashi markets at average prices 136.5

and 155.8 yen, respectively. Then, next day, on October 12, there is no trade of carrot from Hokkaido in these markets, instead, in Yamagata and Kumamoto markets, it is traded at 98 and 134.8 yen, respectively. Then, the day after October 12, carrots from Hokkaido are again traded in Morioka, Maebashi, and again Kumamoto, but not in Yamagata. Thus, there are large variations over the supply pattern and the price traded each day. This may be due to demand and supply shocks that alter delivery decisions by producers on daily basis.

Because delivery decision is made on daily basis, it is important to use daily trade data to investigate the effects of trade costs. The use of daily data enables us to have the same dimension between the timing that economic agents act and the unit of data recorded. Thus, it is accurate to measure trade costs rather than using aggregated level data, while we aggregate daily data to monthly level simply to see whether the shocks are smoothed out.

The descriptive statistics are shown in Table 2. The average price per kilogram is approximately 100 yen (1 US dollar) and the average quantity supplied is approximately 16 kirogram. The data set provides us detailed product characteristics; sizes, grades, and varieties. Because each prefecture use different categories, for example, the number of size categories is 62. The size categorizes are not just small, medium, and large: there are numeric ones, 1,2,3, and other categorical names, such as LL. Thus, because we consider that if at least one characteristic is different, then we treat these goods are different goods, the total number of product is 1186. This seems too large for the number of differentiated carrot, however this is caused by partly because these goods are differentiated based on the place of origin. In fact, the wholesale prices are different when the source prefectures are different. Therefore, we adopt this level of detailed categorization to represent the characteristics of a particular product.

The price data is always reported, however there are missing values for quantity. While we calculate the regional trade volume by the price multiplied by the quantity, when quantity data is missing, we cannot derive the value of trade. As we can see from third row in Table 1, for example, the quantity data is missing for Yamagata market. The same missing value problem occurs when we calculate the total value of expenditure and output. In particular, all data on quantity supplied is missing for one prefecture, Toyama, we cannot calculate these variables for this prefecture.

Actual delivery decision is made by not individual farmers, but local agricultural cooperative. Agricultural cooperative have collection facilities and farmers carry their products to these facilities. Then based on the market conditions and the amount of vegetable brought to the facilities, local cooperative makes a delivery decision. The main transport mode is truck, while ferries can be used when they have to move across islands. According to the document by the Ministry of Agriculture, Forestry and Fisheries, there are more than 4000 facilities across the country. The entity of decision markers' locations are dispersed across the country and thus, the geographical trade costs they face are quite variable. We attempt to measure distance-related trade costs and the major part of such trade costs is associated with transport. Thus, while agricultural cooperatives may engage in information acquisition activities, our focus is on distance-related transport costs.

The distance used here is the distance between prefecture head offices at the prefecture capital cities, because wholesale markets are located in prefecture capital cities. Figure 1 depict the relationship between distance to market and trade volume measured by the value of goods traded in markets. The pattern does not exhibit simple negative relationship. It rather shows that there are negative relationship in two parts: short distance area and long distance area as the fourth-order polynomial fitted curve shows. This is because the short distance delivery occurs in local area and major agricultural prefectures ships their products to remote markets, in particular, large markets.

The horizontal axis in Figure 1 measures log of distance to market. We can see a large number of delivery occurs in 3 to 5 log distance markets. If log of distance is 3 to 5, it is the distance from approximately 20 km to 50 km. which means local or neighboring prefecture delivery. On the other hand, there is another large shipment in around 7 log of distance area: the distance is approximately 1100 km. This is the distance between the major agricultural prefecture, Hokkaido, and the major markets, Tokyo and Osaka: 1156 to Tokyo and 1458 to Osaka. We can divide the delivery pattern into two cases: one is local and the other is nationwide. For local delivery (for log distance between 3 and 5), there seems negative relationship between trade volume and distance to market. Similarly, for nationwide delivery (for log distance from 6.5 and 8), trade decreases as distance gets longer. Hence, we have to control for the market and source specific effects to sort out the impact of distance on trade costs.

We aggregate daily data to create monthly data. We sum up total volume of trade in each month from source j to market n. When we aggregate the daily data, if in a given month there is no supply in the source region, these observations are eliminated.

As mentioned, daily data is subject to many shocks and therefore contains many zero trade observations. The percentage of actual delivery occurred to total delivery possibility is 4%. In other words, 96% of the dependent variable of our sample is zero. On the other hand, when we aggregate daily data on monthly basis, then the delivery percentage rises up to approximately 1.5 times higher, 6%. The share of delivery cases is still small when the data is monthly aggregated. This is because many goods supply is made locally and only a few prefectures deliver their goods nationwide as we have seen in Figure 1. Thus, the monthly shocks they face may not be different from the daily shocks largely. We conduct our estimations to daily and monthly data to see whether aggregation at monthly level causes any differences.

3. Model

We adopt a standard CES model to derive a gravity equation (Anderson and van Wincoop 2003). Consumer's preference in region n is expressed as follows:

$$U_n = (\sum_j c_{nj}^{(\sigma-1)/\sigma})^{\sigma/(\sigma-1)}$$

where c_{nj} is consumption by region n consumer of goods from region js. σ is the elasticity of substitution and greater than 1. We impose the Armington assumption: goods are differentiated by place of origin. Because we focus on an agricultural sector, this utility can be considered as sub-utility and at the upper level, the utility consists of this sub-utility function and other utility from composite goods consumption. We assume that these satisfies trade separability conditions (Anderson and van Wincoop (2003)).

By maximizing the utility with budget constraint, $y_n = \sum p_{nj} c_{nj}$, the demand function is expressed by:

$$c_{nj} = \frac{y_n p_{nj}^{-\sigma}}{\sum_j p_{nj}^{1-\sigma}}$$

Then, we can express the value of shipment:

$$x_{nj} (= p_{nj} c_{nj}) = \frac{y_n p_{nj}^{1-\sigma}}{P_n^{1-\sigma}} = y_n [p_{nj}/P_n]^{1-\sigma} = y_n [\tau_{nj} p_j / P_n]^{1-\sigma},$$

where p_j is the price at the place of origin and $P_n^{1-\sigma} = \sum_j p_{nj}^{1-\sigma}$. P_n is the price index and it is called inward multilateral resistance term.

With regard to supply side, we also adopt a simple endowment economy model as in Anderson and van Wincoop (2003). Because we use agricultural product (carrot), the fixed output assumption here is more appropriate than the case of manufacturing goods. Natural environmental conditions make carrots produced in different prefecture distinct as we discussed in the data section. We also assume that the products are sold in a competitive market.

Then, by considering market clearing condition in nationwide carrot market ($y_j = \sum_n p_{nj} c_{nj}$), we have the following gravity equation as in Anderson and van Wincoop (2003):

$$x_{nj} = y_n y_j (\frac{\tau_{nj}}{P_n \Pi_j})^{1-\sigma}, \tag{1}$$

where $\Pi_j^{1-\sigma} = \sum_n y_n (\tau_{nj}/P_n)^{1-\sigma}$ and this is called outward multilateral resistance term. We use the value of trade per tons as the dependent variable and calculate the total expenditure and output by summing the all shipment data for consuming prefecture and source prefecture, respectively. The importer and exporter characteristics (for example, y_n and y_j) are captured by fixed effects. The inward and outward MRTs are derived by the estimation using importer and exporter fixed effects. Using PPML gives us a precise MRTs as shown in Fally (2015).

Trade cost is a function of distance and unobservable component:

$$\tau_{nj} = D_{nj}^{\gamma} \exp(u_{nj}),$$

where D_{nj} is the distance between source j and market n and γ is the elasticity of trade costs with respect to distance. Because trade costs may exhibit nonlinearity in distance, in addition to this simple formula, we consider the following specifications:

Combes, et al (2010) specification: $\tau = D^{\gamma_1} \exp(D^{\gamma_2})^2$

Novy (2013) specification: $\ln \tau = \gamma_1 \ln D + \gamma_2 (\ln D)^2$

Eaton and Kortum (2002) specification: $\ln \tau = \gamma_1 \ln ShortD + \gamma_2 \ln LongD$

The first two specifications incorporate a quadratic term. There are two ways of introducing the quadratic term: quadratic distance term (for example, Combes et al (2010) and quadratic log distance term (for example, Novy (2013)). The third specification allows different distance effect for short and long distance. We divide the distance to markets into short and long by using the median value of distance, which is 511.3 kilometer. While nonlinearity is a result of the presence of fixed costs, it is difficult to identify unit trade costs and fixed costs separately. Here, we can interpret the significant nonlinear term as the evidence of fixed costs.

Because we estimate the single gravity equation (**??**), we cannot estimate the elasticity of substitution, σ, and the distance elasticity parameter, γ, separately. Estimating these parameters requires to use trade cost information or impose additional structure on the model. Because our focus here is on the overall trade cost effects, we simply report the coefficients of distance in this paper.

4. Estimation Results

In this section, we introduce our estimation procedures and report the results. We also show the inward and outward MRTs calculated by using the importer and exporter fixed effects in PPML.

4.1. Estimation Procedures

While our main estimation results are those by PPML, we conduct other methods dealing with zero trade. As explained by Head and Mayer (2014) and Feenstra (2015), these are several procedures that take into account zero dependent variable observations. Here, we use 1) simple linear-in-log OLS, 2) linear-in-log Tobit 3) Eaton-Tamura (1995) Tobit, 4) Eaton-Kortum (2001) Tobit, 5) Eaton-Kortum-Sotelo (2015) multinomial, and 6) PPML.

The simple log linear OLS model estimate the following equation:

$$\ln(1 + x_{nj}) = \beta \ln(dist_{nj}) + \alpha_n + \alpha_j + \xi + \epsilon_{nj}, \tag{2}$$

where α_n is importer specific effects, α_j is exporter specific effects, ξ is constant term, and ϵ_{nj} is the error term. Because log of zero is not defined, we add one to all observations. Thus, these zero observations are not omitted in estimation, but treated as zero. The linear-in-log Tobit uses the same equation above. However, log of 1 plus zero observations are considered as truncated, thus we assign zero trade probability to these observations.

The Eaton-Tamura Tobit is the first gravity estimation procedure to account for zero trade, where the threshold value is not zero, but some constant. Thus, as Head and Mayer (2014) describe it, it is the Tobit with the dependent variable $\ln(a + x_{nj})$, where a is the parameter estimated. The Eaton-Kortum Tobit also treats zero trade, where the threshold value is not zero but replaced by the minimum value of trade: $\min(x_n)$.

The next estimation procedure we consider here is Eaton-Kortum-Sotelo multinomial method. While as we will see, the Poisson model considers that each observation in each market is treated as a realization of Poisson random variable, the multinomial model takes the all import share in a consuming region as a realization of multinomial distribution. The probability of supply from source j to market n is given by: $\pi_{nj} = \psi_{nj}/\sum_k \psi_{nk}$, where $\psi_{nj} = \alpha_j exp(\alpha_n + z_{nj}b)$, z_{nj} is a vector of explanatory variables, and b is a vector of parameter. If the model is not misspecified, then $E[s_{nj}] = \pi_{nj}$, where s_{nj} is import share of goods j in market n. The probability of $\{s_{nj}\}_j$ is given by $\Pi_j(\pi_{nj})^{s_{nj}}$. As Sotelo (2014) demonstrates, the difference between PPML and multinomial PML estimators is in the first order condition of maximum likelihood and it is the weight on each contribution to the likelihood when importer fixed effects are included. Thus, we can estimate multinomial PML model by using Poisson regression procedure: in PPML, the dependent variable is trade volume and in multinomial model, it is import share.

The PPML procedure does not take log of the original gravity equation. It estimates the original gravity, $x_{nj} = \exp(\ln dist_{nj}^{\beta} + \alpha_n + \alpha_j + \xi)$, while ξ is the error term. As shown in Gourieroux, et al (1984), if the trade volume in market n from source j, x_{nj}, is assumed to be drawn from a Poisson distribution with parameter λ_{nj} conditional on the covariates, the density function is $\exp(-\lambda_{nj})\lambda_{nj}^{x_{nj}}/x_{nj}!$, where $\lambda_{nj} = exp(\ln dist_{nj}^{\beta} + \alpha_n + \alpha_j)$. Thus, the log likelihood is:

$$L = -\sum^{n,j} \lambda_{nj} + \sum^{n,j} x_{nj} \ln \lambda_{nj} - \sum^{n,j} \ln(x_{nj}!). \tag{3}$$

As Gourieroux, et al (1984) and Santos Silva and Treneyo (2006) show, even if the data does not follow Poisson distribution, because from the first order condition, consistency is achieved when the conditional expectation is an exponential function. Our main results are obtained by using PPML.

As Fally (2015) shows, using the importer and exporter fixed effects, the inward and outward MRTs are expressed by $P_n^{-\theta} = \exp(-\hat{\alpha_n})E_0^{-1}E_n$ and $\Pi_j^{-\theta} = \exp(-\hat{\alpha_j})E_0 Y_j$, where E_n is expenditure and Y_j is output. Thus, we can derive MRTs from the estimated fixed effects and the total value of shipment in a market (because we do not have expenditure data). As Anderson and van Wincoop (2003) show, MRTs are unique up to some constant. Hence, we take Okinawa prefecture as a normalized prefecture, so inward MRT is one.

4.2. Results

Estimation results are reported in Table 3. While we include all importer and exporter fixed effects, only the main distance coefficients are reported. While the small distance effects are obtained in OLS and large effects in simple Tobit, these may be biased as documented in Santos Silva and Treneyo (2004) and Head and Mayer (2014). Eaton-Tamura Tobit results show that distance effect is -1.141. Eaton-Kortum Tobit and Eaton-Kortum-Sotelo multinomial model show a similar results: -1.701 and -1.501, respectively. Our main estimation results from PPML also provide a similar estimates, -1.225. As argued by Head and Mayer (2014), the fact that the results of simple OLS or tobit and those of pseudo maximum likelihood are different implies that there may be a substantial heteroskedasticity in our data. While more structured Tobits demonstrate similar results, we mainly discuss the results obtained by PPML because of the property for calculating MRTs,

To investigate the characteristics of trade costs, we use quadratic trade costs specifications and also consider different coefficient depending on the length of distance to market, short or long. When incorporating nonlinear term, these quadratic terms are statistically significant in both specifications. The magnitude of these estimates of nonlinear term are large, for example the log of distance coefficient is -4.277 and the quadratic log distance term is 0.345. This implies that trade costs are increasing only at least up to the median distance (511.3km). Thus these impacts are considered as economically large. Decreasing trade costs with respect to distance is not realistic, hence we have to interpret our estimation results in terms of short and long distance cases as shown in Figure 1. That is, the seemingly increasing trade volume with respect to distance captures the transition from trade in local area to that in long distance area. This may be caused by the heterogeneity in trade costs. Trade costs per kilometer may be smaller for the producers who deliver nationwide than for those shipping locally. Hence, it is important to examine distance effect in short and long distance cases separately.

Using short or long distance coefficients, we find the larger distance effects for short distance than the effects of long distance. This is consistent with the results of quadratic specifications, which confirms the nonlinearity in trade costs function. It also suggests that unit trade costs are different for producers shipping locally and those shipping nationwide who normally deliver a large volume, hence they may enjoy volume discount from transporters. These results suggest that there is a fixed cost of trade (or transport) to every destination, hence the unit costs for short distance is relatively larger than those for long distance. Hence, if it is not enough profitable to cover delivery fixed costs, there may be no delivery. Profitability may depend on demand and supply shocks and/or simply enough quantity to raise certain amount of revenue. Our results imply the presence of scale economy in shipment.

Now, we discuss the estimation results using monthly aggregated data. The results are similar to those in daily data. The estimate of simple OLS is small, while other estimates exhibit similar results. The distance coefficients are -1.508, 1.225, -1.956, -1.503, and -1.241

for Tobit, Eaton-Tamura, Eaton-Kortum, Eaton-Kortum-Sotelo, and PPML, respectively. The trade cost coefficients are not largely different from the results in daily data. There are possibly two reasons. One is that the distance effect is in fact different because delivery decision is smoothed out in monthly data, however, the elasticity of substitution also change. The distance coefficient is the composite of distance effect and the elasticity of substitution. If the substitution parameter is different between daily and monthly data, the distance coefficients remain the same when distance effects are different. This is possible because as in Broda and Weinstein (2010) the elasticity of substitution are different at the aggregation level.

Based on the results of the parsimonious specification of PPML, we calculate inward and outward MRTs to address the incidence of trade costs as shown by Anderson and Yotov (2010). The computation of MRTs are conducted by the results by Fally (2015) using importer and exporter fixed effects. We set the Okinawa prefecture's inward MRT to be normalized to one. Our result is shown in Table 5. The left column reports inward MRTs and the right one is for outward MRTs. While there are 47 prefectures and price data is reported in any observations, unfortunately because no quantity data is reported for Toyama market and no quantity shipment data are reported for Yamagata, Yamagnashi, and Yamaguchi prefectures, these are omitted. The supply share of these prefectures is only 0.81 percent, thus the omission does not cause serious bias in our results.

As shown at the bottom of the table, average inward MRT is larger than average outward MRT. The inward MRT of Hokkaido prefecture is substantially larger than other prefectures, because the estimated importer fixed effects are largest may be due to geographic location and the net import (total expenditure minus total supply) on carrot is low. Thus, the fact that it has to incur high cost to get goods delivered and the imbalance in supply and consumption for that product exists implies the high value of inward MRT. However, even if we omit the inward MRT value of Hokkaido, the average inward MRT is still larger than the average outward MRT. This suggests that the large part of trade costs are buyer's burden. As mentioned, in our case, buyers are wholesalers, so it provides justifications for government policy on wholesale market evolution. While the share of agricultural transactions not through wholesale market is growing, wholesale markets still play an important role of agricultural product distribution. Our results support the policy making wholesale market more efficient.

5. Concluding Remarks

The gravity models have been used to detect the determinants of trade and explain the trade patterns. Because there are many trading partners who do not trade, zero trade observations are prominent. We consider that if there are severe demand and supply shocks and scale economies in shipments, these trade patterns are observed. When suppliers and consumers decide their decision daily, even tiny demand or supply shocks alter their behavior. Hence, we estimate the gravity equation by using daily data set and see how severe these shocks and nonlinearities in trade costs. Substantial shocks may also create heteroskedasticity, hence our main results are obtained by PPML.

Estimation results suggests that there is a heteroskedasticity in our data and the trade costs function is nonlinear. Hence, the presence of substantial shocks and the fixed cost of transport may be prominent. These mainly causes many zero delivery patterns daily. While the estimation results do not differ between daily and monthly aggregated data, this is because the delivery patterns do not change at the monthly level: many local or neighborhood prefecture delivery and only a few prefecture supplying nationwide. We also calculate inward and outward MRTs to infer the incidence of trade costs. We find that the trade cost incidence is larger for buyers, thus the policies taken to improve wholesale market efficiency are required.

While our focus is on controlling for zero trade and heteroskedasticity, serial correlation may have a sizable impact on transaction pattern. Because regional transmission of shocks and its persistence (Crucini et al 2015) are important issues, it requires future research.

References

[1] Anderson, J., van Wincoop, E., 2003 Gravity with gravitas: a solution to the border puzzle, American Economic Review 93, 170–192.

[2] Anderson, J., van Wincoop, E., 2004. Trade costs, Journal of Economic Literature 42, 691–751.

[3] Anderson, J., Yotov, Y. V., 2010. The changing incidence of geography, American Economic Review 100, 2157-86.

[4] Atkin, D., Donaldson, D., 2014. Who's getting globalized? The size and implications of intra-national trade costs, mimeo.

[5] Bastos, P., Silva, J., 2010. The quality of a firm's exports: where you export to matters. Journal of International Economics 82 (2), 99–111.

[6] Broda, C., Weinstein, D., 2006. Globalization and gains from variety, Quarterly Journal of Economics 121, 541–585.

[7] Combes,P-P., Lafourcade, M., Mayer, T., The trade-creating effects of business and social networks: evidence from France, Journal of International Economics 66, 1-29.

[8] Crucini, M. J., Shintani, M., Tsuruga, T., 2015 Noisy information,distance and law of one price dynamics across US cities, Journal of Monetary Economics 74, 52–66.

[9] Eaton, J., Kortum, S., 2001. Technology, trade, and grow th: a unified framework. European Economic Review 45, 742-755

[10] Eaton, J., Kortum, S., 2002. Technology, geography, and trade, Econometrica, 1741–1779.

[11] Eaton, J., Kortum, S., Sotelo, S., 2013. International trade: linking micro and macro, in Advances in Economics and Econometrics, Chapter 8, 329-370, Cambridge University Press

[12] Fally, T., 2015. Structural gravity and fixed effects, Journal of International Economics 97, 76-85.

[13] Gourieroux, C., Monfort, A., Trognon, A., 1984, Pseudo maximum likelihood methods: applications to Poisson models, Econometrica, 701–720.

[14] Harrigan, J., 1996. Openness to trade in manufacturing in the OECD, Journal of International Economics 40, 23-39.

[15] Head, K., Mayer, T., 2014. Gravity Equations: workhorse, toolkit, and cookbook, in Handbook of International Economics, edited by Gopinath, G., Helpman, E., and K. Rogoff. North Holland.

[16] Helpman, E., Melitz, M., Rubinstein, Y. 2008. Estimating trade flows: trading partners and trading volumes, Quarterly Journal of Economics, 441–487.

[17] Hummels, D. 2001. Toward a geography of trade costs. Working Paper, Purdue University.

[18] Irarrazabal, A., Moxnes, A., Opromolla, L.D., 2013. The tip of the iceberg: a quantitative framework for estimating trade costs, NBER Working Paper 19236.

[19] Kano, K., Kano, T., Takechi, K., 2013 Exaggerated death of distance: revisiting distance effects on regional price dispersions, Journal of International Economics 90, 403–413.

[20] Kano, K., Kano, T., Takechi, K., 2014 The price of distance: pricing to market, producer heterogeneity, and geographic barriers, mimeo.

[21] Melitz, M., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity, Econometrica 71, 1695–1725.

[22] Novy, D., 2013. International trade without CES: Estimating translog gravity, Journal of International Economics 89, 271-282.

[23] Redding, S., Venables, A. J., 2004. Economic geography and international inequality, Journal of International Economics 62, 53-82.

[24] Sotelo, S., 2014. Essays in trade theory and applications, Ph.D. Dissertation, University of Chicago.

	Carrots
Average price (yen per kg)	101.25
Average shipment (kg)	16.275
Product entry	
No. of varieties	10
No. of size categories	62
No. of grade categories	66
No. of producing prefectures	46
No. of wholesale markets	47
No. of distinct product entries	1,186
Data truncation (daily)	
No. of $T_{ij}(\omega) = 0$ or 1	198,129
No. of $T_{ij}(\omega) = 1$	8,395
Delivery ratio	4.237 %
Data truncation (monthly)	
No. of $T_{ij}(\omega) = 0$ or 1	15,652
No. of $T_{ij}(\omega) = 1$	1,017
Delivery ratio	6.498%

Table 1: Summary statistics

Date	Source	Market	Price	Quantity	Grade	Size
2007/10/11	Hokkaido	Morioka	136.5	6	Syu(Excellent)	M
2007/10/11	Hokkaido	Maebashi	155.8	5.5	Syu(Excellent)	L
2007/10/12	Hokkaido	Yamagata	98	n.a.		LL
2007/10/12	Hokkaido	Kumamoto	134.8	46.3		L
2007/10/13	Hokkaido	Morioka	136.5	17.1		M
2007/10/13	Hokkaido	Maebashi	143.5	10.7	Syu(Excellent)	L
2007/10/13	Hokkaido	Kumamoto	126.4	18.7		L

Table 2: Example of Data Entry

	OLS	Tobit	EatonTamura	EatonKortum	EKS	PPML	PPML	PPML	PPML
dep var	$\ln(1+x)$	$\ln(1+x)$	$\ln(a+x)$	$\ln(x)$	share	x	x	x	x
$\ln distance$	-0.622	-5.896	-1.141	-1.701	-1.501	-1.225	-1.299	-4.277	
	0.003	0.067	0.002	0.02	0.006	0.02	0.021	0.115	
$distance^2$							4.65E-07		
							3.43E-08		
$(\ln dist)^2$								0.345	
								0.013	
short dist									-0.929
									0.012
long dist									-0.749
									0.011
log-likelihood/R^2	0.24	-38118.1	-152533.772	-28557.083	-119185.5	-26763.36	-26677.273	-25899.321	-25659.2
number of obs	198129	198129	198129	198129	198129	198129	198129	198129	198129

Table 3: Estimation Results (Daily)

	OLS	Tobit	EatonTamura	EatonKortum	EKS	PPML	PPML	PPML	PPML
dep var	$\ln(1+x)$	$\ln(1+x)$	$\ln(a+x)$	$\ln(x)$	share	x	x	x	x
$\ln distance$	-0.185	-1.508	-1.225	-1.956	-1.503	-1.241	-1.382	-4.273	
	0.004	0.047	0.075	0.064	0.191	0.073	0.067	0.342	
$distance^2$							4.80e-7		
							1.13e-07		
$(\ln dist)^2$								0.342	
								0.035	
short dist									-1.525
									0.066
long dist									-1.223
									0.056
log-likelihood/R^2	0.232	-3104.05	-8778.030528	-3348.166	-199.398	-15524.4	-160.6	-14678.3	-14988.5
number of obs	15651	15651	15651	15651	15651	15651	15651	15651	15651

Table 4: Estimation Results (Monthly)

Prefecture	$P_n^{-\theta}$	$\Pi_j^{-\theta}$
Hokkaido	202.6144	0.604986
Aomori	18.82951	0.475483
Iwate	3.380054	0.315124
Miyagi	2.101507	0.28079
Akita	3.112611	0.121933
Fukushima	1.94144	0.309256
Ibaraki	3.46377	4.199817
Tochigi	1.989586	0.384973
Gunma	1.718214	0.240976
Saitama	2.676233	4.489544
Chiba	8.50434	2.920965
Tokyo	3.69506	0.857701
Kanagawa	2.350941	2.352009
Niigata	2.285334	0.455086
Ishikawa	1.521982	0.301489
Fukui	1.505134	0.475572
Nagano	1.539149	1.433066
Gifu	2.767059	1.863051
Shizuoka	1.61429	0.500894
Aichi	2.949429	7.435119
Mie	1.360881	0.329916
Shiga	1.331935	0.06719
Kyoto	1.320764	0.479155
Osaka	1.350206	0.925766
Hyogo	1.406145	0.498046
Nara	1.279404	0.16573
Wakayama	1.651792	0.910192
Tottori	1.430832	0.765287
Shimane	1.016128	0.119606
Okayama	1.602365	0.591083
Hiroshima	0.951877	0.047753
Tokushima	3.966562	1.157329
Kagawa	1.60503	0.620669
Ehime	1.078279	0.176888
Kochi	1.333981	0.563945
Fukuoka	0.988027	0.474846
Saga	1.065176	0.06837
Nagasaki	3.024791	1.772697
Kumamoto	2.380004	4.346832
Oita	1.06643	0.795358
Miyazaki	1.963513	2.288372
Kagoshima	2.585901	1.435446
Okinawa	1	1.116582
Average	7.146979	1.156625
Average without Hokkaido	2.492992	

Table 5: Inward and outward MRTs

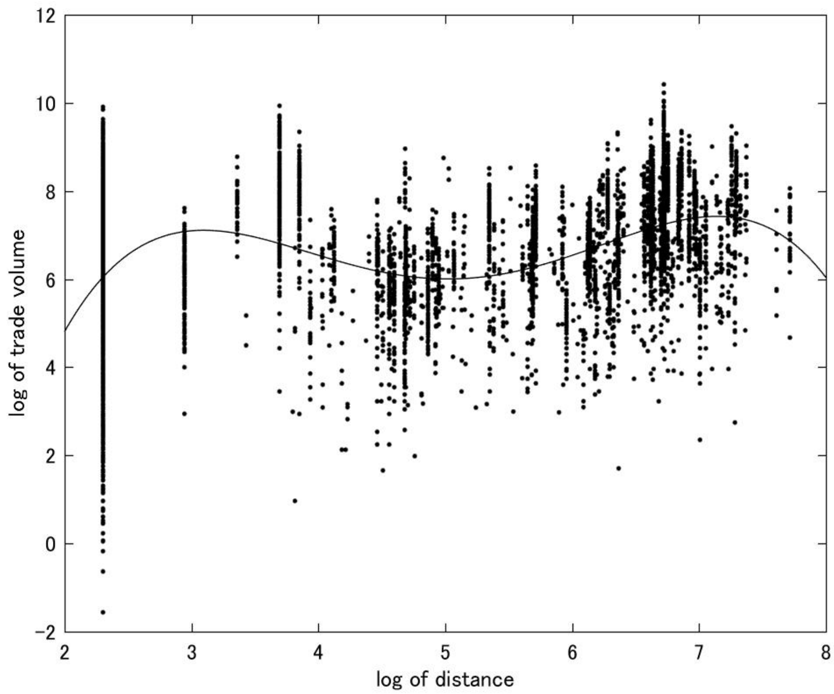

Figure 1: Log of Distance and Trade Volume