The Price of Distance: 
Producer Heterogeneity, Pricing to Market, and Geographic Barriers

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Current Draft: July 26, 2013

Abstract
Transportation costs are generally attributable to price differentials across geographically separated regions. However, when using price differential data, the identification of distance-elastic transportation costs depends on how producers handle transportation costs and set prices in remote markets. To address this problem, we adopt a nonhomothetic preference framework with heterogeneous producers. We show that the presence of nonhomothetic preferences is important in causing producer heterogeneity to alter individual pricing behavior depending on market conditions, a property absent in the constant elasticity of a substitution heterogeneity framework. This also exhibits the property that producers do not fully pass on the increase in transportation costs. By not accounting for these features, the distance elasticity of transportation costs is underestimated. However, by incorporating these features in our model, we reveal, using empirical analysis and microlevel data, that the distance effect is significantly large, suggesting that the price of geographic barriers for regional transportation is high.

Key Words: Law of one price; Transportation costs; Geographic barriers; Producer heterogeneity; Pricing to market

JEL Classification Number: F11, F14, F41

We thank Andrew Bernard for insightful discussions and suggesting the title of this paper, and Volodymyr Lugovskyy and Alexandre Skiba for helpful advice. We gratefully acknowledge the comments of Masahisa Fujita, Russell Hillberry, Yuji Honjo, James Markusen, Toshiyuki Matsuura, Daisuke Miyakawa, Kiyoyasu Tanaka, and Dao-Zhi Zeng. We would also like to thank seminar participants at Chuo University, the Development Bank of Japan, Hosei University, Keio University, the Research Institute of Economy, Trade and Industry, the Asia Pacific Trade Seminars at Singapore Management University, the Japanese Economic Association Meeting at Kyushu Sangyo University, the Japan Society of International Economics Meeting at Nanzan University, and the Western Economic Association International Meeting at Keio University for their useful comments and suggestions. Financial support for this research was provided by Grants-in-Aid for Scientific Research (No. 23330087, No. 25285085, No. 25301027, and No. 24530270) and the Seimeikai Foundation.

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1. Introduction

Geographic separation creates price differentials across regions because of transportation costs, even in the absence of institutional differences such as tariffs, taxes, and national borders. Accordingly, if the locations of production and their markets are geographically distant, transportation costs will be high and hence there will be large price differentials across regions. In this regard, the existing law-of-one-price (LOP) literature (Engel and Rogers, 1996; Parsley and Wei, 1996; Parsley and Wei, 2001; Crucini et al., 2010) generally identifies the positive effect of distance on price dispersion, although the magnitude of the distance effect is minute. We can consider that this negligible distance effect is the result of innovations in transportation technology or intense competition in the transportation sector, which bring with them a lower cost of transportation, and thus distance has only a minor effect on price differentials. However, the identification of the distance effect is subject to how producers deal with their geographic burdens and set their market prices (pricing-to-market). Because price differentials across regions are often considered to provide evidence, among other things, of spatial market segmentation, it is then an important question how geographic attributes affect transportation costs.

This paper addresses the question of how geographic barriers, as measured by distance, contribute to transportation costs. In particular, we estimate the elasticity of transportation costs with respect to distance. Because this is considered the price that producers must pay to deliver their goods over distance, we can refer to it as “the price of distance,” such that the price differential is then generated by either the price of distance or pricing behavior across markets or both. We then investigate how serious the biases are in inferences of the price of distance caused by producer pricing behavior.

We adopt a nonhomothetic preference framework with producer heterogeneity and pricing-to-market. We show that the presence of nonhomothetic preferences is important in causing producer heterogeneity to alter individual pricing behavior depending on market conditions, a situation absent in the constant elasticity of substitution (CES) heterogeneity framework. This also exhibits the property that producers do not fully pass on the increase in transportation costs. For instance, only highly productive producers can supply remote markets, absorb a large portion of any increases in transportation costs, and not pass these on through prices. Therefore, the actual geographic burden producers pay for transportation costs is larger than price differentials across regions. This provides a source of under-bias in the estimation of the distance effect. Thus, we contribute to the literature by estimating the distance effect while controlling for heterogeneity and pricing-to-market.

This study measures the impact of transportation costs using price differential data.
To measure transportation costs correctly using price data, as Anderson and van Wincoop (2004) argue, the difference between market prices and the prices at the point of production must be used, not just market prices. In addition, because an increase in distance causes not only increases in price differentials, but also a decrease in the propensity for product delivery, distance promotes selection bias. Thus, delivery choice to other regions (such as the export decision) should be accounted for to control for sample selection biases, as in Helpman et al. (2008) and adopted in Kano et al. (2013). While Kano et al. (2013) reveal that sample selection (the extensive margin) causes under-bias in the estimation of the distance effect, the bias related to the intensive margin as caused by the pricing-to-market remains. This paper takes into account the biases potentially arising from both margins.

We employ the same agricultural price data for Japan as in Kano et al. (2013), which enables us to obtain price information about both the market and source regions. By estimating the price differential equation and taking into account sample selection, producer heterogeneity, and pricing-to-market behavior, we find evidence of a large distance effect. In the extant literature, Donaldson (2013) and Kano et al. (2013) both use information on prices in the production regions and find significant and moderate distance elasticity estimates of 0.24 and 0.21 to 0.325, respectively. In this study, we find the coefficients of the distance effect range from 0.458 to 0.757. Although these seem large, they are consistent with the results in the economic geography literature. In particular, large distance effects are found when investigating truck transportation. Because truck transportation is also a major type of transportation in our analysis, our results are then close to those of Combes and Lafourcade (2005), who use data on trade shipped by truck and estimate the distance elasticity to be 0.8. We therefore conclude that there is a substantially large bias when models do not incorporate producer heterogeneity and pricing-to-market behavior. Further, the price of geographic barriers (distance) remains high for regional transportation, even in countries with highly developed transportation infrastructure, such as Japan.

Because the distance elasticity of transportation costs is a key parameter when assessing the impact of geographic barriers, the trade literature, including Hummels (2007), Helpman et al. (2008), Crozet and Koenig (2010), and Balistreri et al. (2011), has attempted to identify and correctly estimate it. The empirical findings therein indicate that the distance elasticity tends to be larger than that in the prevailing LOP literature, such that it typically exceeds 15 percent (0.15). Conversely, LOP studies also use the same iceberg-type specification, estimate the distance elasticity, and report a negligible distance effect. Indeed, the distance elasticity parameter is normally estimated to be less than 1 percent (0.01). However, the identification problem caused by pricing-to-market for the price differential effect of geographic barriers (distance) has not been examined extensively. This study proposes
an identification strategy for the distance effect and demonstrates that geography is in fact a major obstacle that raises transportation costs.

The remainder of the paper is organized as follows. In Section 2, we briefly review the related literature. In Section 3, we develop our nonhomothetic preference model with producer heterogeneity. For comparison, we also develop a CES model. In Section 4, we derive the empirical framework, and report the estimation results in Section 5. The final section concludes.

2. Related Literature

Most recent studies, particularly those of Donaldson (2013) and Kano et al. (2013), follow Anderson and van Wincoop’s (2004) suggestion of using the price in the source region of production. Donaldson (2013), for example, identifies the source region of salt production in India and employs this information to measure transportation costs using market prices, while Kano et al. (2013) use agricultural wholesale price data in Japan, where both source and market prices are available. They also propose an estimation procedure to take into account selection bias following Helpman et al. (2008). Because high transportation costs are likely to deter firms from shipping their products to more distant markets, shipment data will be truncated for these markets. This accounts for an under-bias in estimates of the distance elasticity. In evidence, Kano et al. (2013) demonstrate that if not controlled for, the distance effect found is quite weak given these biases. However, when controlled for, distance actually has quite a significant impact on geographic price differentials.

Although these studies both identify the biases involved in the estimation of the distance effect, two possible remaining causes of bias, that is, producer heterogeneity and pricing-to-market, have not been examined in detail. Because producer heterogeneity and pricing-to-market behavior cause different pricing across markets, price differentials may be reflected in more than just transportation costs. For example, in Kano et al. (2013), markets are monopolistically competitive, producers set invariant markups and there is no producer heterogeneity. By way of contrast, Donaldson (2013) applies the Eaton and Kortum (2002) model in which there is dispersion in producer productivity and the market is perfectly competitive. Therefore, in both these studies, only transportation costs characterize price differentials, and different pricing behavior across markets is not considered.

In a nonhomothetic preference framework, because an individual firm’s pricing depends on local market characteristics (as shown by, for example, Melitz and Ottaviano, 2008), price differentials do not simply reflect transportation costs, but also include market structure (the number of products) and some productivity threshold value. Because transportation
costs reduce profitability in a remote market, the productivity threshold level needed to set a positive price depends on transportation costs. In particular, as the productivity threshold increases, only highly productive, and thus low-price-setting firms, produce. Hence, ignoring producer heterogeneity creates an omitted variable bias, which in turn promotes the underestimation of the distance effect.

The introduction of nonhomothetic preferences is essential for investigating the distance effect on individual producers’ price differentials with producer heterogeneity. If a CES utility function is used, and thus monopolistically competitive firms set constant markup prices, the heterogeneity term will be cancelled out in the price differential equation and the price differential will then depend only on transportation costs. If the focus is instead not on individual price differentials, then important implications are obtained for aggregate price levels under firm heterogeneity using CES because, as Ghironi and Melitz (2005) and Bergin et al. (2006) show, Balassa–Samuelson effects emerge. Here, because we study individual price differentials, there is no room for producer heterogeneity in a standard CES framework. Nonhomothetic preferences instead lead firms to set different prices across markets, and these prices depend on a heterogeneous threshold. Therefore, heterogeneity plays an important role in our analysis.

With regard to heterogeneity and pricing-to-market, Berman et al. (2012) report that the pass-through rate depends on firm productivity such that the pass-through rate is high for highly productive firms. Thus, producer heterogeneity and pricing-to-market behavior are important factors in understanding international prices. We show that in a remote market, only highly productive producers can supply goods. We refer to price differentials caused by selection as the extensive margin. This extensive margin accounts for the under-bias in the distance effect. In addition, under incomplete pass-through, the increase in costs does not simply lead to a price increase by the same amount. We refer to price differentials caused by pricing behavior as the intensive margin. The intensive margin also causes under-bias in the estimation of distance-related transportation costs. Thus, our study identifies the biases caused by both types of margins (extensive and intensive) and thus demonstrates the importance of heterogeneity and pricing-to-market behavior in studies of this type.

3. Model

In this section, we develop a model of pricing and delivery patterns. Consumers purchase a variety of products delivered from their own and other regions, with each product being produced by a single producer. These producers are heterogeneous in terms of productivity and engage in monopolistic competition. Because one of the main purposes of this paper
is to demonstrate the differences between the cases of nonhomothetic and CES preferences, we first introduce a nonhomothetic model. We then consider a CES utility model for the purposes of comparison.

3.1. Consumers

Consumer preferences are expressed by a nonhomothetic utility function. Nonhomothetic preferences have already been introduced to account for pricing-to-market (Melitz and Ottaviano, 2008; Simonovska, 2010). We employ the Simonovska (2010) framework and our derivations also rely on Simonovska (2010), although while she focuses on trade volumes and price levels, the focus here is on individual pricing across markets.1

Consumer nonhomothetic preferences in region $i$ are expressed by:

$$u_i = \int_{\omega \in \Omega} \ln(q_i(\omega) + \bar{q}) d\omega,$$

where $\omega$ is a variety index, $\Omega$ is the set of products available in market $i$, and $q_i(\omega)$ is the consumption of variety $\omega$. The presence of $\bar{q}$ makes these preferences nonhomothetic. This represents an endowment good, which consumers cannot buy or sell (Markusen, 2013). If $\bar{q} = 0$, the utility function is a typical homothetic function. The size of $\bar{q}$ can be changed, so this can be normalized to one as in Young (1991). Each consumer is assumed to supply one unit of labor. Thus, income is equal to wages, $w_i$. The budget constraint is:

$$w_i = \int_{\omega \in \Omega} p_i(\omega) q_i(\omega) d\omega.$$

Then, from utility maximization, the demand function is obtained by:

$$q_i(\omega) = \frac{w_i + \bar{q} P_i}{N_i p_i(\omega)} - \bar{q},$$

where $P_i = \int_{\omega \in \Omega} p_i(\omega)$ is the price index and $N_i = \int_{\omega \in \Omega} d\omega$ is the number of products in market $i$. This demand function has regular characteristics such that demand is decreasing in prices and increasing in income (wages). Consequently, given monopolistic competition, if the number of products supplied to the market increases, the demand for each product will fall. This in turn will affect the pricing behavior of producers.

3.2. Producers

1Simonovska (2010) demonstrates how the nonhomothetic model works in general equilibrium and compares it with the CES model.
Consider a producer located in region \( j \). The number of potential producers is assumed fixed. Firms decide whether to produce and deliver the product or to shut down. The timing of the delivery decision is set as follows. Producer productivity, \( \phi \), is assumed to follow a random distribution, \( G(\phi) \). Producers have to incur a fixed cost to draw their productivity. Based on the distribution of productivity, they calculate the expected profits and decide whether to deliver. Their optimal prices are assumed set when a delivery choice is made. This enables us to establish a similar delivery choice decision problem as in the CES case.

The producer profit maximization problem is to maximize variable profits, \( \pi_{ij} \):

\[
\max_{p_{ij}} \pi_{ij} = p_{ij}q_{ij} - \frac{\tau_{ij}w_{j}}{\phi}q_{ij},
\]

where \( p_{ij} \) is the price in region \( i \) for products from region \( j \), \( q_{ij} \) is the quantity of products from region \( j \) sold in region \( i \), and \( \tau_{ij} \) is the iceberg-type transportation cost, \( \tau_{ij} > 1 \) for \( i \neq j \) and \( \tau_{ij} = 1 \) for \( i = j \). Thus, we assume that a producer does not have to pay transportation costs to deliver its product within the same region. Because we assume labor is the only input, the wage rate, \( w_{j} \), indicates the unit cost and \( \phi \) is a measure of productivity. This productivity parameter differs across producers (firm heterogeneity). Because each product is produced by a single producer, the number of varieties is equal to the number of producers. We can denote each variety using producer productivity and thus \( \omega \) contains information on the producer type (productivity) and the source region \( j \). The optimal price set by a producer with productivity \( \phi \) under the nonhomothetic framework is denoted \( p^{NHOM}_{ij}(\phi) \):

\[
p^{NHOM}_{ij}(\phi) = \left( \frac{\tau_{ij}w_{j}(w_{i} + \bar{q}P_{i})}{\phi N_{i}\bar{q}} \right)^{1/2}.
\]

In our model, the optimal price depends on not only transportation costs, but also local market characteristics. If income in markets \( (w_{i}) \) is high, producers can charge high prices. The existence of a large number of competitors implies a large \( N_{i} \), which induces low prices because of severe competition.

In contrast to the CES preference case, if the price is sufficiently high, demand will be zero. Then, the profit for the firm in region \( j \) derived from supplying this product to region \( i \) will also be zero. We denote the productivity of this firm as \( \phi_{ij}^{*} \). Then, this threshold value is expressed by:

\[
\phi_{ij}^{*} = \frac{\tau_{ij}w_{j}N_{i}\bar{q}}{w_{i} + \bar{q}P_{i}}.
\]

The threshold value, \( \phi_{ij}^{*} \), is increasing in transportation costs, \( \tau_{ij} \): that is, only high-productivity firms can overcome any trade barriers. In addition, market structure, as measured by the number of firms, \( N_{i} \), influences the threshold value, whereas it has no effect in
the CES case. This is because of variable markups in the nonhomothetic model. Thus, the
optimal price in the nonhomothetic case depends on market structure through \( \phi_{ij}^* \), which
means that the productivity threshold matters for each individual producer’s price.\(^2\) In other
words, aggregate producer characteristics affect individual pricing behavior in the nonhomo-
thetic case.

From equation (5), the impact of an increase in transportation costs on price is lower
for highly productive producers (\( \frac{dp_{ij}^{NHOM}}{d\tau_{ij}} = (1/2)(w/\phi_{ij}^*)^{1/2} \)). Also, the impact is lower
for remote markets because of high \( \phi_{ij}^* \). Thus, in terms of the intensive margin, the effect of
distance on transportation costs is mitigated in distant markets. This requires us to account
for heterogeneity and pricing-to-market to identify transportation costs using regional price
differential data. Because of the assumption of monopolistic competition, the price index
can be expressed by a producer’s productivity measure: \( P_i = \sum_\nu \int_{\phi_{ij}^*}^\infty p_\nu(\phi)\mu(\phi)d\phi \) and
\( N_i = \sum_\nu N_\nu = \sum_\nu \int_{\phi_{ij}^*}^\infty \mu(\phi)d\phi \), where \( \mu \) is the conditional density function of \( \phi \) conditional
on delivery.

The relationship between the optimal price and the threshold value in this case is
similar to that in the Melitz and Ottaviano (2008) case. Melitz and Ottaviano (2008) specify
a quadratic utility function and show how market size affects the key features in a model with
firm heterogeneity. The optimal price is increasing in the threshold level of productivity and
the number of firms is related negatively to the threshold value. Thus, many of the properties
derived here are common to nonhomothetic models.

Assuming that productivity follows a Pareto distribution (\( G(\phi) = 1 - b^\theta / \phi^\theta, \theta > 0 \)),
the expected profit will be:

\[
E\pi_{ij} = (1 - G(\phi_{ij}^*)) \int \pi_{ij} \mu d\phi, \tag{7}
\]

where \( \mu = g/(1 - G(\phi^*)) = \phi^\theta / \phi^{\theta+1} \). This is the conditional density where the productivity
exceeds \( \phi_{ij}^* \). We then calculate the expected profit as follows:

\[
(1 - G(\phi_{ij}^*)) \int \pi_{ij} \mu d\phi = \frac{b^\theta \tau_{ij} w_j \bar{q}}{(2\theta + 1)(\theta + 1)\phi^{\theta+1}}. \tag{8}
\]

Producers decide whether to deliver their product to region \( i \) depending on the above profit
measure and the fixed entry costs. This captures the self-selection problem in delivery
patterns. The productivity threshold, \( \phi_{ij}^* \), affects pricing behavior and delivery choice. The
effect of distance on transportation costs is underestimated because it is likely that for
less productive producers an increase in transportation costs causes their delivery to be

\(^2\)On the other hand, in the CES model, firms charge a constant markup over the marginal cost.
unprofitable. Thus, in terms of the extensive margin, only highly productive producers can deliver in remote markets. This creates biases in the inference of the distance elasticity because the observed price data are subject to sample selection bias.

In our setting, even though productivity is higher than the threshold level, $\phi^*$, such firms may still choose not to deliver their products because of negative expected profits. We assume that delivery decisions are based on expected profits and that firms set their pricing formula when the delivery choice is made. Thus, the selection is determined by comparing the expected profits and fixed costs. Importantly, the threshold parameter does not directly separate producers into those that deliver and those that do not. Rather, the threshold directly influences prices across markets.

3.3. CES case

We intend to compare our results with those for the CES utility function case. As we will show, the same implications for price differentials are derived with or without producer heterogeneity. Thus, we employ the CES model without heterogeneity to compare our results with those in Kano et al. (2013).

We briefly specify a consumer’s preferences using a simple CES model as follows:

$$u_i = \left[ \int_{\omega \in \Omega} x_i(\omega)^\alpha \, d\omega \right]^{1/\alpha}.$$  

Then, maximizing utility subject to the budget constraint ($w_i = \int p_i(\omega)q_i(\omega) \, d\omega$) yields the following demand function:

$$x_i = \frac{p_i(\omega)^{-\epsilon}}{P_i^{1-\epsilon}} w_i,$$

where $\epsilon$ is the elasticity of substitution, $\epsilon = 1/(1 - \alpha)$, and $P_i = \left[ \int_{\omega \in \Omega} p_i(\omega)^{1-\epsilon} \, d\omega \right]^{1/(1-\epsilon)}$.

We consider a homogeneous firm in a monopolistically competitive market. The firm’s profits are:

$$\pi_{ij} = p_j(\omega)x_j(\omega) - \frac{\tau_{ij} w_j x_j(\omega)}{\phi} - f_{ij}.$$  

Then, by profit maximization, the optimal price is obtained using constant markup pricing as follows:

$$p_{ij}^{CES}(\phi) = \frac{\tau_{ij} w_j}{\phi^{1-\epsilon}}.$$  

Substituting this into the profit function yields:

$$\pi_{ij}(\phi) = (1 - \alpha)\left( \frac{\tau_{ij} w_j}{\alpha P_i \phi} \right)^{1-\epsilon} w_i.$$
Because firms are assumed homogeneous, their decision to deliver does not depend on a randomly selected level of productivity. Instead, the choice is based on the comparison of profits and the fixed cost of delivery. If $\pi_{ij}/f_{ij} > 1$, then firms in region $j$ will deliver their products to region $i$. Thus, similarly to the heterogeneous firm case, the delivery data are truncated because of self-selection by the producers.

This breakeven productivity level ($\phi_{ij} = \{\phi|\pi(\phi_{ij})/f_{ij} = 1\}$) depends on transportation costs. If transportation costs, $\tau_{ij}$, are high, firms that are sufficiently productive are able to make positive profits: $\phi_{ij}$ is increasing in $\tau_{ij}$. However, as mentioned, market structure does not affect $\phi_{ij}$ directly, but only through the price index, $P_i$.

3.4. Price differentials

Our approach of taking the difference between the price in markets and that in source regions allows us to accurately measure transportation costs. Because retail prices do not consider information about the source, taking the difference between two market prices does not necessarily enable the measurement of transportation costs. However, if the source price and the market price with information about the source are available, the difference between these prices captures the costs of transportation. We can highlight this idea in a CES utility framework. The price differential is:

$$\frac{p_{ij}^{CES}}{p_{jj}^{CES}} = \tau_{ij}. \quad (9)$$

In contrast to the nonhomothetic case, as we will show, price differentials in the CES case are independent of market characteristics. This is because the productivity threshold level does not affect individual pricing. The thresholds are derived from the zero-profit conditions and determine not prices but the selection of producers that deliver. As a result, when obtaining price differentials, the market characteristic variables cancel out.

In the nonhomothetic model, using the optimal prices set by firms, the price differential between the market and the source is:

$$\frac{p_{ij}^{NHOM}}{p_{jj}^{NHOM}} = \tau_{ij}\phi_{jj}^{1/2}/\phi_{ij}^{1/2}. \quad (10)$$

Because the threshold value, $\phi_{ij}^{*}$, depends on transportation costs, ignoring producer heterogeneity causes biases in identifying the relationship between the price differential and transportation costs. If $\tau_{ij}$ increases, $\phi_{ij}^{*}$ will increase. Because $\phi_{jj}^{*}$ does not depend on $\tau_{ij}$, a larger $\phi_{ij}^{*}$ induces a smaller price differential. Thus, heterogeneity reduces the price differential. This omitted variable bias may account for the underestimation of the effect of transportation costs.
In addition, $\phi_{ij}$ depends on the number of firms, $N_i$. This is a function of the threshold value itself and thus is affected by transportation costs. Hence, the changes in $\tau_{ij}$ are associated with the changes in market structure. This implies that market prices are set depending on market structure, and therefore the number of firms across markets is a determinant of price differentials. If we do not control for this type of pricing-to-market behavior, the estimates of transportation costs will be biased.

As mentioned, one of our objectives in this paper is to highlight the changes arising from incorporating firm heterogeneity. In fact, equation (9) holds with and without producer heterogeneity. This is because even if firm productivity is heterogeneous, optimal pricing does not depend on the threshold value of productivity, which is a key factor of heterogeneity. Besides, each firm’s productivity is cancelled out when considering price differentials. Hence, producer heterogeneity does not play an important role in the link between price differentials and transportation costs in the CES model. However, producer heterogeneity matters for the link between price differentials and distance, not when preferences are CES, but when they are nonhomothetic. If we introduce nonhomothetic preferences, firms set variable markups across markets in the setting of optimal prices and thus we deal with pricing-to-market behavior. Therefore, the bias caused by producer heterogeneity is indispensable for pricing-to-market.

By using the formula for the threshold value in the nonhomothetic model, $\phi_{ij}^*$, we are able to express the price differential as follows:

$$\frac{p^{NHOM}_{ij}}{p^{NHOM}_{jj}} = \tau_{ij}^{1/2} \frac{(w_i + \bar{q}P_i)^{1/2}}{(w_j + \bar{q}P_j)^{1/2}} \frac{N_j}{N_i}^{1/2}. \quad (11)$$

The heterogeneity effect reduces the direct impact of transportation costs from $\tau_{ij}$ to $\tau_{ij}^{1/2}$ in our nonhomothetic specification. In general, the effect of transportation costs will also be weakened in a nonhomothetic specification because the effect of a transportation cost increase on price differentials is mitigated by the producer selection. In the presence of high transportation costs, only high-productivity firms are able to ship their products. Such firms set their prices at a low level. Thus, the greater the distance between markets, the lower the magnitude of the increase in prices. This mechanism creates under-bias in the distance elasticity when only price differential data are used.

This selection mechanism operates at the individual pricing level. This mechanism also influences the average price changes associated with general productivity shocks, as shown by Ghironi and Melitz (2005) and Atkeson and Burstein (2008). If only high-productivity firms can export because of negative shocks, then because they set the price at a low level, the average price will also be low. However, if free entry is assumed, firm exit
because of negative shocks will cause labor demand to decrease and thus labor costs will decrease. This enables low-productivity firms to export, implying an increase in the average export price. Thus, depending on the entry condition assumptions, the average price either increases or decreases. Similarly, in our study, because we do not consider free entry, negative shocks will decrease individual prices set in the market.

Other factors that affect the price differentials are the source, market characteristics, and market structure. Because these factors are correlated with transportation costs, omitted variable biases occur. Taking the log of the above equation yields:

\[
\ln \frac{p_{ij}^{NHOM}}{p_{jj}^{NHOM}} = (1/2) \ln \tau_{ij} + (1/2) \ln N_j - (1/2) \ln N_i \\
+ (1/2) \ln (w_i + \bar{q}P_i) - (1/2) \ln (w_j + \bar{q}P_j). \tag{12}
\]

The price differential depends not only on transportation costs, but also on market characteristics, such as the number of products and price indices. This property directly reflects the pricing-to-market behavior. Because the optimal price depends on local market characteristics, the price differentials reflect market structure. The ability to capture this element is an advantage of the nonhomothetic model over the CES framework. So far, we have not imposed any functional form on transportation costs. We adopt the following conventional specification:

\[
\tau_{ij} = D_{ij}^\gamma e^{\mu + u_{ij}},
\]

where \(D_{ij}\) is the distance between two regions. That is, if \(\gamma > 0\), then as distance increases, transportation costs also increase. The constant term \(\mu\) corresponds to the uniform transportation costs component and \(u_{ij}\) denotes unobservable transportation costs, \(u_{ij} \sim N(0, \sigma_u)\). The log form is:

\[
\ln \tau_{ij} = \gamma \ln D_{ij} + \mu + u_{ij}.
\]

The distance elasticity, \(\gamma\), is our main parameter. Identifying this parameter is important if delivery choice, producer heterogeneity, and pricing-to-market are to be accounted for.

Regarding the threshold value (\(\phi_{ij}^*\)), even if \(\phi_{ij}^* < \phi\), the producer with productivity \(\phi\) may not deliver its product because demand is too low to cover the fixed costs. Thus, producer heterogeneity (threshold value \(\phi^*\)) matters mainly for the individual pricing decision, and not for the delivery decision. We take the delivery decision into account by considering the sample selection problem caused by the positive profit condition.

3.5. Delivery choice
The price differential is observed only when there is an actual delivery. Thus, there will be a data truncation problem. As the delivery choice is made based on profitability, we consider the producer’s delivery decision. Because producers pay $f_{ij}$, the delivery decision is summarized by the variable $Z_{ij}$:

$$Z_{ij}^{NHOM} = \frac{b^\theta \tau_{ij} w_j \bar{q} \prod_{k} (\theta + 1)^{\phi_{ij}^{\theta+k}}}{f_{ij}}.$$ 

Thus, if $Z_{ij}^{NHOM}$ is greater than one, firms in region $j$ choose to deliver the product to region $i$. Taking logs, we have the following delivery choice equation:

$$\ln Z_{ij}^{NHOM} = z_{ij}^{NHOM} = \theta \ln b + \ln \tau_{ij} + \ln w_j + \ln \bar{q} - \ln (2\theta + 1)(\theta + 1) - (\theta + 1) \ln \phi_{ij} - \ln f_{ij}$$

$= \theta \ln b - \theta \ln \tau_{ij} - \theta \ln w_j - \theta \ln \bar{q} - \ln (2\theta + 1)(\theta + 1)$

$- (\theta + 1) \ln N_i + (\theta + 1) \ln (w_i + \bar{q}P_i) - \ln f_{ij}.$

If $z_{ij}^{NHOM} > 0$, then delivery from region $j$ to region $i$ will take place. Because the price differential is observed only when $z_{ij}^{NHOM} > 0$, we take this selection bias into account when estimating the price differential equation. We do this by jointly estimating the price differential and delivery choice equations.

Similarly, in the CES framework, the delivery choice is expressed by $Z_{ij}$:

$$Z_{ij}^{CES} = \frac{(1 - \alpha) [\tau_{ij} w_j]^{1-\epsilon} w_i}{f_{ij}}.$$ 

Thus, taking logs yields a similar expression for delivery choice:

$$\ln Z_{ij}^{CES} = z_{ij}^{CES} = \ln (1 - \alpha) + (1 - \epsilon) \ln \tau_{ij} + (1 - \epsilon) \ln w_j$$

$- (1 - \epsilon) \ln \alpha - (1 - \epsilon) \ln P_i - (1 - \epsilon) \ln \phi + \ln w_i - \ln f_{ij}.$

Our focus is on the individual firm’s choice of prices, rather than on trade volume, as in Helpman et al. (2008). Thus, it is not necessary to control for the effect of heterogeneity on aggregate variables. Rather, we need to account for the impact of heterogeneity on the individual firm’s pricing across markets and its delivery choice according to this selection mechanism.

Similarly to the nonhomothetic preference case, we estimate the price differential equation taking selection bias into account. However, whereas the Kano et al. (2013) model is estimated using an instrumental variable approach, our control for selection bias is based on this delivery choice equation. Thus, in this paper, we simply estimate the price differential and delivery choice equations using maximum likelihood. We specify regional dummies to
control for market-specific effects, such as price indices (Anderson and van Wincoop, 2003; Helpman et al., 2008).

3.6. Empirical specification

For the estimation, we need to parameterize the price differential and delivery choice equations. As in Helpman et al. (2008), fixed costs have the following specification: $f_{ij} = \exp(\lambda_i + \lambda_j - \nu_{ij})$. The estimating equations are expressed as follows:

$$z_{ij}^{NHOM} = -\ln f_{ij} + \theta (\ln b - \bar{q}) - \theta \mu - \theta u_{ij} - \ln(2\theta + 1)(\theta + 1)$$
$$- \theta \gamma \ln D_{ij} - \theta \ln w_j - (\theta + 1) \ln N_i + (\theta + 1) \ln(w_i + \bar{q}P_i)$$
$$= c_0 + c_1 - \theta \gamma \ln D_{ij} - \theta \ln w_j - (\theta + 1) \ln N_i + (\theta + 1 + c_2)dum_i + c_3 dum_j + \eta_{ij},$$

(13)

where $c_0 = -\theta \mu - \ln(2\theta + 1)(\theta + 1)$, $c_1 = \theta (\ln b - \bar{q})$, $\ln(w_i + \bar{q}P_i) - \lambda_i$ is captured by region i’s specific effect; therefore, $(\theta + 1) \ln(w_i + \bar{q}P_i) - \lambda_i = (\theta + 1 + c_2)dum_i$, and $dum_i$ is region i’s specific effect. The number of products may be a noisy variable or the method by which the number of products is introduced may be misspecified; therefore, we use $\chi \ln N_i$ instead of $\ln N_i$ in the estimations, where $\chi$ is a free parameter. The error term is $\eta_{ij} = -\theta u_{ij} + \nu_{ij} \sim N(0, \theta^2 \sigma_u^2 + \sigma_\nu^2)$.

Similarly, the price differential equation is:

$$q_{ij}^{NHOM} = \ln p_{ij}^{NHOM} - \ln p_{jj}^{NHOM}$$
$$= (1/2)\mu + (1/2)\gamma \ln D_{ij} + (1/2) \ln N_j - (1/2) \ln N_i + c_4 dum_j - c_5 dum_i + (1/2)u_{ij},$$

(14)

where $dum_j$ controls for region-specific effects, including wages and price indices, as in the delivery choice equation. Because of the pricing-to-market, the disturbance term is modified to $u_{ij}/2$. Thus, not only do the covariates differ from the CES case, but the shape of the price differential distribution also differs.

As in Kano et al. (2013), with regard to the identification of the distance elasticity, $\gamma$, the price differential and product delivery equations reveal an important result. Simply estimating the price differential equation only may lead to underestimation of $\gamma$. This is because the errors in these equations are correlated and this is because $\eta_{ij} = -\theta u_{ij} + \nu_{ij}$, and the error terms $\eta_{ij}$ and $u_{ij}$ are correlated. As shown by Helpman et al. (2008), taking the conditional expectation of $q_{ij}^{NHOM}$ yields: $E[q_{ij}^{NHOM}|X] = (1/2)\mu + (1/2)\gamma \ln D_{ij} + (1/2) \ln(1 + N_i) - (1/2) \ln(1 + N_j) + c_4 dum_j - c_5 dum_i + (1/2)E[u_{ij}|X]$, where $X$ is a vector of observables. Because $E[u_{ij}|X] = \rho_{\eta u} E[\eta_{ij}|X]$, if we ignore this correlation, there will be bias.
in the estimate of the distance effect. This bias term is expressed as an inverse Mills ratio: 
\[ E[\eta_{ij}|X] = \phi(\hat{z}_{ij})/\Phi(\hat{z}_{ij}) \]
Hence, to obtain consistent estimates, we need to account for the correlation between the price differential and delivery choice equations; the significance of sample selection relies on this correlation parameter, \( \rho \).

To take into consideration this selection effect, we employ a full information maximum likelihood (FIML) approach. We assume that the distribution of the errors is joint normal. The log-likelihood function is:
\[
L = \sum_{i,j} (1 - T_{ij}) \ln[\Phi(-W_{1ij})] + \sum_{i,j} T_{ij} \ln \left[ \Phi \left( \frac{W_{1ij} + 2\rho \sigma_u^{-1}(W_{2ij})}{(1 - \rho^2)^{1/2}} \right) \right] \\
+ \sum_{i,j} T_{ij} \ln \phi \left( \frac{W_{2ij}}{(\sigma_u/2)} \right) - \sum_{i,j} T_{ij} \ln(\sigma_u/2),
\]
where 
\[ W_{1ij} = c_0 + c_1 + \theta \gamma \ln D_{ij} + \theta \ln w_j + (\theta + 1)\chi_1 \ln N_i + (\theta + 1 + c_2)dum_i + c_3 dum_j \]
and 
\[ W_{2ij} = q_{ij} - (1/2)\mu - (1/2)\gamma \ln D_{ij} - (1/2)\chi_2 \ln N_j + (1/2)\chi_3 \ln N_i - c_4 dum_j - c_5 dum_i. \]
The use of FIML has several advantages: namely, it is efficient, it allows us to examine delivery choice, and it can detect unobservable factors driving self-selection bias in an explicit way. However, our approach has the disadvantage of possible misspecification; we address this misspecification issue by undertaking diagnostic checks.

In the case of CES utility without producer heterogeneity, the estimating equation is:
\[
\tilde{z}_{ij}^{CES} = \beta - (\epsilon - 1)\gamma d_{ji} + (\epsilon - 1) \ln P_i + (1 - \epsilon) \ln w_j + \ln w_i + \xi_j + \omega_l + \lambda_i + \eta_{ij},
\]
where 
\[ \beta = -\epsilon \ln \epsilon - (1 - \epsilon) \ln(\epsilon - 1) + (1 - \epsilon)\mu, \omega_l = (1 - \epsilon)\phi, \text{ and } \eta_{ij} = (1 - \epsilon)u_{ij} + \nu_{ij}. \]
The price differential equation is:
\[
q_{ij}^{CES} = \mu + \gamma d_{ij} + c_6 dum_i + c_7 dum_j + u_{ij}.
\]
Then, the log-likelihood function is as follows:
\[
L = \sum_{i,j} (1 - T_{ij}) \ln[\Phi(-W_{3ij})] + \sum_{i,j} T_{ij} \ln \left[ \Phi \left( \frac{W_{3ij} + \rho \sigma_u^{-1}(W_{4ij})}{(1 - \rho^2)^{1/2}} \right) \right] \\
+ \sum_{i,j} T_{ij} \ln \phi \left( \frac{W_{4ij}}{\sigma_u} \right) - \sum_{i,j} T_{ij} \ln \sigma_u,
\]
where 
\[ W_{3ij} = \beta - (\epsilon - 1)\gamma d_{ji} + (\epsilon - 1) \ln P_i + (1 - \epsilon) \ln w_j + \ln w_i + \xi_j + \omega_l + \lambda_i \]
and 
\[ W_{4ij} = q_{ij} - \mu - \gamma d_{ij}. \]
We use the consumer price index as the price index, while the use of region-specific effects controls for the other region-specific factors.

3Because \( u \) and \( \nu \) are orthogonal, \( E[\nu u] = E[(-\theta u + \nu)u] = -\theta \sigma_u^2 \). The correlation \( \rho \) is defined by 
\[ \rho = \sigma_{nu}/\sigma_u. \]
Thus, \( \sigma_{nu} = \rho \sigma_u = -\theta \sigma_u^2 \). Then, \( \sigma_u = -\rho/\theta \).
These two empirical models, namely the nonhomothetic model and the CES model, account for the data truncation problem caused by the self-selection of producers. The main difference between these approaches is in the price differential equation. In the CES case, it is simply a function of distance. In the nonhomothetic case, the effect of distance is different, and there are local market characteristics and these reflect producer heterogeneity and pricing-to-market behavior. We apply our model to the price and delivery data to find the distance elasticity.

4. Data

We apply our approach to data on the wholesale prices of individual goods and delivery patterns across regions. Using wholesale prices enables us to focus on transportation costs because retail prices include local distribution costs. The individual goods are agricultural products in Japan. As the wholesale prices of the agricultural products in both the source regions and markets are available, the price differential between the market and source prices can be used to properly measure transportation costs.

The data source for wholesale prices is the Daily Wholesale Market Information on Fresh Fruit and Vegetables ("Seikabutsu Hinmokubetsu Shikyo Joho" in Japanese). The data set is collected by the Center for Fresh Food Market Information Services ("Zenkoku Seisen Syokuryohin Ryutsu Joho Senta"; URL: www2s.biglobe.ne.jp/fains/index.html), which provides data on nearly all transactions at the 55 wholesale markets operating daily across Japan’s 47 prefectures. Each prefecture has at least one wholesale market, so the data variation is nationwide. This daily market survey covers the wholesale prices of 120 different fruits and vegetables.

Each agricultural product is further categorized by variety, size, and grade, as well as by the producing prefecture. Hence, for example, the data set reports the wholesale prices of potatoes in six wholesale markets for the “Dansyaku (Irish Cobbler equivalent)” variety, size “L”, with grade “Syu (excellent)” produced in “Hokkaido” Prefecture on September 7, 2007. Because prices depend on characteristics, each combination of characteristics is identified as the same product. Thus, the goods sharing the same brand name, size and grade of product, production prefecture, and trading date are considered identical products. This high degree of categorization is important because the LOP requires a comparison of the prices of identical goods to precisely infer transportation costs. We focus on eight vegetables: cabbages, carrots, Chinese cabbages (c-cabbages, hereafter), lettuce, shiitake mushrooms (s-mushrooms, hereafter), spinach, potatoes, and Welsh onions. In this paper, we examine the 2007 survey that reports the market transactions for a period of 274 days. Thus, the unit of
measurement for the sample is source–market price differential given in yen/kg for the same product on a given trading day.

The price reported in each market has three forms: the highest price, the modal price, and the lowest price. Most markets record all three prices, but several markets report only the highest and the lowest prices or only the modal price. Thus, we construct our price variable by averaging these price variables. We use the modal price when this is the only price available. The transaction unit of measurement for each product is also reported. To obtain the same unit of measurement for each product, we divide the price by the number of transaction units (kilograms). Table 1 provides several descriptive statistics for these products. The first row reports the average price per kilogram (1 kilogram = approximately 2.2 pounds). As shown, s-mushrooms are the most expensive product, at 1113.627 yen (approximately 13 US dollars) per kilogram, while the cheapest product is c-cabbages, at 61.628 yen (approximately 0.9 US dollars) per kilogram.

Table 1 also shows that each product is highly categorized by product variety, size, and grade. The numbers of distinct products are also large: 1,207 for cabbages; 1,186 for carrots; 1,001 for c-cabbages; 903 for lettuce; 1,423 for potatoes; 909 for s-mushrooms; 551 for spinach; and 1,115 for Welsh onions. For each product entry l, we count the number of deliveries as \( T_{ij}(l) = 1 \) and nondeliveries as \( T_{ij}(l) = 0 \) only for the dates on which the product is traded in the wholesale market in producing prefecture \( j \). We identify product delivery \( T_{ij}(l) = 1 \) if the data report that the source prefecture of product entry l sold in consuming region \( i \) is region \( j \). We construct the price differential by subtracting the wholesale price in producing prefecture \( j \), \( p_j(\omega) \), from that in the consuming prefecture \( i \), \( p_i(\omega) \). If the sample of \( q_{ij}(\omega) \) is available, this means that \( T_{ij}(\omega) = 1 \) for pair \( (i, j) \).

The bottom part of Table 1 reports that the total number of both delivery and nondelivery observations across all products is greater than 190,000 for each vegetable. We use this as the number of observations in our FIML estimation. Of the total number of delivery and nondelivery cases, the number of delivery cases is relatively small, at approximately 10,000 cases for each vegetable. Our data set, therefore, indicates that product delivery is quite limited. In justification, for many products there is only local delivery. For example, carrots are produced in every prefecture and mostly shipped to own-prefecture markets. In contrast, only agriculturally intensive prefectures such as Hokkaido generally ship to remote markets. Thus, the data truncation issue is quite important in this sample.

We obtain the other data we use in this paper as follows. The geographic distance between prefectural pair \( (i, j) \) is approximated by the distance between the prefectural head offices located in the prefectural capital cities. The distance data are provided by the Geospatial Information Authority of Japan (GSI) and are publicly available on the GSI.
We use daily temperature to control for supply and demand shocks. We download the daily temperature data compiled by the Japan Meteorological Agency. Finally, we use monthly data on scheduled cash earnings for wages, as reported in the Monthly Labour Survey ("Maitsuki Kinrou Tokei Chosa") conducted by the Japanese Ministry of Health, Labour, and Welfare.

One verification strategy when introducing a nonhomothetic preference is to check whether high-quality (and therefore high-price) goods are sold in high-income markets. This positive relationship is one of the main focuses in the recent literature (Simonovska, 2010; Waugh, 2010). We use the data on wholesale market prices and scheduled cash earnings to check for a positive correlation between these variables. Figure 1 places each prefecture’s wages on the vertical axis and vegetable prices on the horizontal axis. All data variations reveal a positive relationship between incomes and prices, as shown by the solid line with positive slope. This indicates that high-income regions tend to consume high-quality (high-price) goods, suggesting that our nonhomothetic preference specification is consistent with a certain characteristic in our data.

### 5. Estimation Results

Table 2 reports the estimation results, with the main results reported in the top half of the same table. For comparison, the results using the CES utility function and the simple regression results are reported in the bottom half of the table. The distance elasticity in the nonhomothetic framework ranges from 0.458 (cabbages) to 0.757 (s-mushrooms). This indicates that when the shipment distance from origin to destination increases by 1 percent, the price differential increases by about 0.5 percent. These values for the distance elasticity are larger than those in previous studies, which implies the presence of an under-bias of the distance elasticity in previous studies. As in previous studies, if we instead use two market prices to construct price differentials and regress these on distance, then the distance effect coefficient is at most 0.05. That is, even if the transportation distance doubles, the price differential increases by only 5 percent. Thus, even using our data, regressing only the price differential (i.e., not identifying the source region) on distance, which is the conventional method in the literature, yields similar results. The results of the CES utility function are similar to those in Kano et al. (2013). As in Kano et al. (2013), and following Anderson and van Wincoop (2004), the price differential measure is the difference between the market

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6. The data are available at [www.mhlw.go.jp/toukei/list/30-1.html](http://www.mhlw.go.jp/toukei/list/30-1.html).
price and the price in the producing prefecture, and delivery choice is explicitly modeled
to control for sample selection. However, one difference between the estimations in this
study and Kano et al. (2013) is that they propose an instrumental variable approach for the
structural estimation. Although the results of the CES framework indicate significantly large
distance effects of 0.287 to 0.49, these are all smaller than those from the nonhomothetic model.

When incorporating producer heterogeneity and pricing-to-market, the results under
nonhomothetic preferences indicate a much larger distance effect compared with both simple
regression analysis and the CES framework. In turn, the CES results are larger than the
conventional OLS results. The results under nonhomothetic preferences are found to be
even larger than in the CES case. This is consistent with our argument that producer
heterogeneity affects the pricing decision in each market and thus causes under-bias in the
distance elasticity estimates. This is because transportation costs induce only productive
firms to deliver products, and these firms can charge a low price. Large distance elasticity
estimates also imply that geographic barriers influence delivery choice. Consequently, the
probability of delivery will be reduced by an increase in transportation costs. Thus, the
presence of large distance effects after accounting for producer heterogeneity suggests that
the price of geographic barriers remains high for regional transportation.

Another important parameter in our estimations is the heterogeneity parameter, \(\theta\). Our estimates range from 1.155 to 2.313. A small \(\theta\) means that there is a large dispersion
in productivity. These estimates can be considered to be small (producer heterogeneity is
highly dispersed). This may be because farmers in Japan are quite heterogeneous. For
example, in Japan, small farms operated by elderly people in suburban areas often produce
agricultural products, whereas agriculturally intensive prefectures, such as Hokkaido, are
often home to large-scale farms. In 2009, the average area under cultivation for each farm
in Hokkaido prefecture was 20.50 hectares (approximately 50.66 acres), compared with an
average area of 1.41 hectares (approximately 3.48 acres) in the other prefectures. These
farms may deliver their products to the same markets. In our framework, all prefectures
have the same productivity distribution, so the low value of \(\theta\) may reflect this dispersion
across farms. In fact, as shown in Table 2, the estimates obtained using carrots and potatoes
have small values of \(\theta\). Because Hokkaido is known to be a high-productivity region for these
products, the presence of heterogeneous suppliers yields large dispersion results.

The heterogeneity parameter, \(\theta\), has been investigated extensively in the trade lit-
erature. In the Eaton and Kortum (2002) framework, this is the elasticity of the trade
parameter, which is a crucial parameter in the analysis of the welfare gain from trade (Arko-

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lakis et al., 2012). For example, Eaton and Kortum (2002) estimate this parameter to be 8.28, Bernard et al. (2003) estimate it to be 3.6, Crozet and Koenig (2010) estimate it to be from 1.65 to 7.31, Simonovska and Waugh (2010) use the simulated method of moments to obtain estimates from 3.57 to 4.46, and Balistreri et al. (2011) estimate it to be from 3.924 to 5.171. Donaldson (2013) also uses the Eaton and Kortum (2002) model to estimate the productivity variability parameter, and estimates an average value of 3.8. As in Donaldson (2013), we use price data to estimate two crucial parameters in the producer heterogeneity model. In general, the magnitudes of our estimates are lower than those of these other studies, possibly because the more disaggregated the product level, the greater the dispersion of heterogeneity. Our sample also contains disaggregated product-level data and has quite a fine categorization; as a result, our estimates report a small \( \theta \).

The correlation parameter \( \rho \) is also important for the significance of these sample selections. These estimates range from \(-0.62\) to \(-0.873\). All results are negative and statistically significant. Hence, to identify the true parameter, controlling for selectivity bias is crucial. A positive shock that increases the price differentials caused by transportation costs (for example, a fuel price increase) will also decrease the probability of delivery. Without controlling for this negative correlation caused by unobservable shocks, as we have seen, the distance effects are found to be small. We detect the existence of such a negative effect.

The relevance of the estimates depends on the empirical validity of our model. For model validation purposes, we conduct diagnostic checks of our model with respect to two important aspects of the actual data: the pattern of product delivery and the association of price differentials with delivery distances. First, we calculate the percentage of correctly predicted measures (PCPs) for \( T_{ij}(l) = 0 \) or 1. To construct the PCPs, we calculate the predicted conditional probabilities and the predicted delivery index where the predicted probabilities are greater than 0.5. We report the results in the bottom row of Table 2. As shown, the PCPs are all greater than 0.96, which suggests that our model successfully predicts the actual delivery patterns.

The second diagnosis concerns price differentials with respect to delivery distances. The question is whether our sample-selection model predicts the actual price differentials. To conduct this diagnosis check, we derive the prediction of the model for price differentials after controlling for selection bias. Each panel in Figure 2 plots the resulting predicted price differentials (dots), as well as the data counterparts (crosses), against the corresponding log distances for each vegetable. As shown, the distribution of the dots is within the cloud formed by the crosses in all panels. This means that our model successfully predicts the relationship between the price differentials and distances overall.

One issue remaining when comparing the results of the nonhomothetic and CES mod-
els is the elasticity of the substitution parameter, $\epsilon$. In the nonhomothetic preference model, the utility function is in log form to obtain an explicit solution for the optimal price. Because the coefficient of distance in the selection equation is $\theta \gamma$ in the nonhomothetic case and $(\epsilon - 1)\gamma$ in the CES model, ignoring the elasticity of substitution may cause small estimates of $\theta$ and large estimates of $\gamma$. If this composite remains constant, a small elasticity of substitution may imply a large distance effect. The identification of these parameters separately requires a model that incorporates both the dispersion and elasticity of substitution components. This is a limitation of our study and an important issue for future research.

6. Concluding Remarks

In this paper, we investigated the impact of producer heterogeneity and pricing-to-market behavior on the distance elasticity in regional price differentials. Because producer heterogeneity is not treated as crucial in the identification of the distance effect in a conventional CES utility framework, we developed a nonhomothetic preference model, thus incorporating pricing-to-market behavior.

Our empirical analysis showed that ignoring these factors causes underestimation in the CES utility framework. We find that the distance effect is significantly large for regional price differentials. These results suggest that the price of geographic barriers remains high for regional transportation, even in Japan. Even though Japan is considered to have well-established infrastructure and a sophisticated logistics system, the geographic barriers are large enough to create substantial price differentials. Thus, in a country with poor transportation facilities and services, regional differences may be very large and markets geographically segmented. In such a country, even if some regions are productive and have a potential for growth, the geographic burden may hamper the access to markets and thus inhibit efficient resource allocation.

Although incorporating producer heterogeneity and pricing-to-market corrects the biases in the distance elasticity, there are yet other concerns regarding pricing behavior. For example, as Hummels and Skiba (2004) have shown, there may be specific transportation costs, the presence of which leads firms to ship high-quality goods to more remote markets (the so-called Alchian–Allen effect). Although our study extends existing work to account for variable markups, iceberg-type transportation costs are assumed and the Alchian–Allen effect is not taken into account. Investigating these effects is a topic for further research.
References


[22] Parsley, D. C., S.-J. Wei, 1996 Convergence to the law of one price without trade barriers or currency fluctuation, Quarterly Journal of Economics 111, 1211–1236.


## Table 1: Summary Statistics

<table>
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<tr>
<th></th>
<th>Cabbages</th>
<th>Carrots</th>
<th>C-cabbages</th>
<th>Lettuce</th>
<th>Potatoes</th>
<th>S-mushrooms</th>
<th>Spinach</th>
<th>Welsh onions</th>
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<tr>
<td>Average price (yen per kg)</td>
<td>77.833</td>
<td>101.25</td>
<td>61.628</td>
<td>183.909</td>
<td>79.565</td>
<td>1113.627</td>
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### Table 2: Estimation Results

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<td>Spinach</td>
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<td>0.757</td>
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<td>(0.007)</td>
<td>(0.005)</td>
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Note: The numbers in parentheses are standard errors. All estimations include origin and destination dummies, origin and destination daily temperatures, the number of products in both equations, and wages for the selection equation.
Figure 1: Log of price and log of per capita income relationship
Figure 2: Actual (+) and predicted (.) values