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Pricing to market, producer heterogeneity, and geographic barriers

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Abstract

Transport costs are generally attributable to price differentials across geographically separated regions. However, when using price differential data, the identification of distance-elastic transport costs depends on how producers handle transport 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 substitution heterogeneity framework. This also exhibits the property that producers do not fully pass on the increase in transport costs. By not accounting for these features, the distance elasticity of transport costs is underestimated. However, by incorporating these features in our model and using empirical analysis and microlevel data, we reveal that the distance effect is significantly large, suggesting that the price of geographic barriers for regional transportation is high.

Keywords: Law of one price, Transport costs, Geographic barriers, Producer heterogeneity, Pricing to market

JEL classification: F11, F14, F41

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1. Introduction

Geographic separation creates price differentials across regions because of transport costs, even in the absence of institutional differences such as tariffs, taxes, and national borders. Accordingly, if the locations of production and markets are geographically distant, transport 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, 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 transport technology or intense competition in the transport sector, which bring with them a lower cost of transport, 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 burden and set their market prices (pricing-to-market). Because price differentials across regions are often considered to provide evidence of, among other things, spatial market segmentation, it is then an important question how geographic attributes affect transport costs.

This paper addresses the question of how geographic barriers, as measured by distance, contribute to transport costs. In particular, we estimate the elasticity of transport costs with respect to distance. Because we consider this as 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 for 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, which is a situation absent from the constant elasticity of substitution (CES) heterogeneity framework. This also exhibits the property that producers do not fully pass on the increase in transport costs. For instance, only highly productive producers can supply remote markets, absorb a large portion of any increases in transport costs, and not pass these on through price increases. Therefore, the actual geographic burden producers pay for transport costs is larger than the 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 transport costs using price differential data. To measure transport 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, not just market prices, must be used. In addition, because an increase in distance causes not only an increase in the price differential, but also a decrease in the propensity for product delivery, distance promotes selection bias. Thus, delivery choice to other regions 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 relating to the intensive margin resulting from the pricing-to-market mechanism remains. This paper takes into account the biases potentially arising from both margins.

Because the distance elasticity of transport costs is a key parameter when assessing the impact of geographic barriers, there have been attempts by the trade literature, including Hummels (2001, 2007) and Limao and Venables (2001), aimed at its estimation using freight rate data. The empirical findings suggest that the distance elasticity tends to be small, typically less than 0.1.[1] Similarly, LOP studies using price data employ the same iceberg-type specification, estimate the distance elasticity, and report a negligible distance effect. Indeed, the distance elasticity parameter is normally estimated to have a value of less than 0.01 (1 percent). Alternatively, in the trade literature without freight cost data, distance elasticity is obtained by calibrating the elasticity of substitution (for example, Anderson and van Wincoop (2003) and Balistreri et al. (2011)) or estimated using a structural gravity model (Crozet and Koning, 2010). For the most part, the distance elasticity obtained is larger than the estimates using freight cost data and exceeds a value of 0.15. Thus, there is a discrepancy in the magnitude of distance elasticity between these studies. The current analysis attempts to illustrate how to correct the estimation bias of distance elasticity using price data. Moreover, the identification problem resulting from 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 can be a major obstacle to trade in that it significantly increases transport costs.

The study most related to the present analysis is Atkin and Donaldson (2012). Atkin and Donaldson (2012) consider the price differentials between source and destination in

[1] As Grossman (1998) pointed out and Anderson and van Wincoop (2004) and Head and Mayer (2013) subsequently documented, the specification of the trade cost function is crucial when discussing distance elasticity. In a gravity model, such as Helpman et al.'s (2008) iceberg-type trade cost from region j to i, τ_{ij}, is specified as follows: $p_{ij} = \tau_{ij} p_j$ and $\tau_{ij} = D_{ij}^{\delta}$, where p_{ij} is the price in market i from region j, p_j is the price in region j, D_{ij} is the distance between i and j, and δ is the distance elasticity. On the other hand, in Hummels (2001, 2007) and Limao and Venables (2001), the ad valorem trade cost is a function of distance: $\tau_{ij} - 1 = D_{ij}^{\tilde{\delta}}$. The relationship between these elasticities is: $\delta = \tilde{\delta}(\tau_{ij} - 1)/\tau_{ij}$. Because τ_{ij} takes a value greater than one, δ is lower than $\tilde{\delta}$. The distance elasticity we consider here is δ.

Nigeria and Ethiopia by incorporating variable retail markups. Thus, price differentials reflect not only trade costs, but also markups. They first estimate the pass-through rate by regressing the destination price on the source price with fixed effects. They then use the pass-through estimates to construct markup-adjusted prices and regress these on distance, which provides the elasticity of trade costs with respect to distance. While their findings on distance elasticity are similar to those in previous studies, approximately 0.03 to 0.06, this may be because they do not control for the selection problem.

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 that the coefficients of the distance effect range from 0.458 to 0.757. Although these seem large, they are consistent with the existing results for road transport. For example, Duranton et al. (2014) estimate a standard gravity-type model and obtain an elasticity of trade with respect to road distance of –1.41, which is quite a bit higher than the elasticity of trade with respect to rail distance of –0.51. Thus, if we take 5 as the elasticity of substitution, their result implies that the distance elasticity for road trade is 0.35. While this value is small compared with our results, this may be largely the result of sample selection bias. We therefore conclude that there is a substantially large bias when models do not incorporate self-selection, producer heterogeneity, and pricing-to-market behavior. Further, the price of geographic barriers (distance) remains high for regional transport, even in countries with highly developed transport infrastructure, such as Japan.

The remainder of the paper is organized as follows. In Section 2, we briefly review the related literature. In Section 3, we derive the empirical framework by first developing our nonhomothetic preference model with producer heterogeneity, and then constructing a CES model for the purpose of comparison. In Section 4, we introduce our data set, 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. For example, Donaldson (2013) identifies the source region of salt production in India and employs this information to measure transport 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 transport 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 sources of bias, that is, producer heterogeneity and pricing-to-market, have not been examined in detail, with the exception of Atkin and Donaldson (2012). Because producer heterogeneity and pricing-to-market behavior cause different pricing across markets, price differentials may be reflected in more than just transport 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 transport costs characterize price differentials, and different pricing behavior across markets is not considered.

As discussed, the study closest to ours is Atkin and Donaldson (2012). In particular, the identification strategy for trade costs is identical: namely, obtain prices at the source such that only the price differentials between the source and the destination measure trade costs. However, Atkin and Donaldson (2012) consider variable markups using conjectural variations such that the price differentials may reflect both trade costs and markups. Here, we introduce nonhomothetic preferences to take into account variable markups. Both studies identify significant-sized markups (the pass-through rate). A notable difference is that while Atkin and Donaldson (2012) do not consider the selection problem of product delivery due to data limitations, we control for selection and show that the bias introduced by data truncation is large. Another difference is that their focus is broader, including the incidence of source price reduction and welfare implications. In contrast, our focus is rather more narrow, being the measurement of distance elasticity after controlling for variable markups. This allows us to elaborate upon the mechanism accounting for the measurement biases in the distance effect. 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 transport costs, but also include market structure (the number of products) and some productivity threshold value. Because transport costs reduce profitability in remote markets, the productivity threshold level needed to set a positive price depends on transport costs. In particular, as the productivity threshold increases, only highly productive, and thus low-price-setting, firms produce. Hence, ignoring producer heterogeneity creates 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 transport costs. If the focus is instead not on individual price differentials, then important implications are obtained for aggregate (average) 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 transport 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 a simplified version of the Simonovska (2010) framework, and our derivations also rely on Simonovska (2010). However, while the focus there is on trade volumes and price levels, we emphasize individual pricing across markets and sample selection arising from the choice of delivery, as in Helpman et al. (2008).[2]

Consumer nonhomothetic preferences in region i are expressed by:

$$u_i = \int_{\omega \in \Omega_i} \ln(q_i(\omega) + \bar{q}) d\omega, \tag{1}$$

where ω is a variety index, Ω_i is the set of products available in market i, and $q_i(\omega)$ is the consumption of variety ω. 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). There are L_i consumers in region i and each consumer is assumed to supply one unit of labor. Thus, income for the representative consumer is equal to wages, w_i. The budget constraint is:

$$w_i = \int_{\omega \in \Omega_i} p_i(\omega) q_i(\omega) d\omega. \tag{2}$$

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

$$q_i(\omega) = \frac{w_i + \bar{q} P_i}{N_i p_i(\omega)} - \bar{q}, \tag{3}$$

where $P_i = \int_{\omega \in \Omega_i} p_i(\omega)$ is the price index and $N_i = \int_{\omega \in \Omega_i} d\omega$ 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.

[2]Simonovska (2010) demonstrates how the nonhomothetic model works in general equilibrium and compares it with the CES model.

3.2. Producers

Consider a producer located in region j for which we focus on the delivery choice made by producers in region j to market i. Labor is the only factor of production. The number of potential producers is assumed to be fixed, with producers deciding whether to produce and deliver the product or shut down. The timing of the delivery decision is set as follows. Producer productivity, ϕ, 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 to be set when a delivery choice is made. This enables us to establish a similar delivery choice decision problem as in the CES case because the expected profit function in the nonhomothetic case has a multiplicative form.

The producer profit-maximization problem is to maximize variable profits, π_{ij}:

$$\max_{p_{ij}} \pi_{ij} = p_{ij} q_{ij} L_i - \frac{\tau_{ij} w_j}{\phi} q_{ij} L_i, \tag{4}$$

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 τ_{ij} is the iceberg-type transport 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 transport costs to deliver its product within the same region. Instead of introducing the transport sector, we adopt the same iceberg-type specification in the literature. Because we assume labor is the only input, the wage rate, w_j, indicates the unit cost and ϕ is a measure of productivity. This productivity parameter differs across producers (producer 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 ω contains information on the producer type (productivity) and the source region j. The optimal price set by a producer with productivity ϕ under the nonhomothetic framework is denoted $p_{ij}^{NHOM}(\phi)$:

$$p_{ij}^{NHOM}(\phi) = \left(\frac{\tau_{ij} w_j (w_i + \bar{q} P_i)}{\phi N_i \bar{q}}\right)^{1/2}. \tag{5}$$

In our model, the optimal price depends on not only transport 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. Thus, we have pricing-to-market behavior. This type of pricing practice is considered to be common in many industries.

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 ϕ^*_{ij}. Then, this threshold value is expressed by:

$$\phi^*_{ij} = \frac{\tau_{ij} w_j N_i \bar{q}}{w_i + \bar{q} P_i}. \tag{6}$$

The threshold value, ϕ^*_{ij}, is increasing in transport costs, τ_{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 ϕ^*_{ij}, which means that the productivity threshold matters for each individual producer's price.[3] In other words, aggregate producer characteristics affect individual pricing behavior in the nonhomothetic case.

From equation (5), the impact of an increase in transport costs on price is lower for highly productive producers ($dp^{NHOM}_{ij}/d\tau_{ij} = (1/2)(w/\phi\phi^*_{ij})^{1/2}$, which is decreasing in ϕ). In addition, the impact is lower for remote markets because of high ϕ^*_{ij}. Thus, in terms of the intensive margin, the effect of distance on market price is mitigated in distant markets. This requires us to account for heterogeneity and pricing-to-market to identify transport 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: $P_i = \sum_\nu \int_{\phi^*_{i\nu}}^{\infty} p_{i\nu}(\phi)\mu(\phi)d\phi$ and $N_i = \sum_\nu N_{i\nu} = \sum_\nu \int_{\phi^*_{i\nu}}^{\infty} \mu(\phi)d\phi$, where μ is the conditional density function of ϕ 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 at the threshold level of productivity and the number of firms is negatively related 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 $\mu = g/(1 - G(\phi^*_{ij})) = {\phi^*_{ij}}^\theta/\phi^{\theta+1}$. This is the conditional density where the productivity

[3] On the other hand, in the CES model, producers charge a constant markup over the marginal cost.

exceeds ϕ^*_{ij}. We then calculate the expected profit as follows:

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

Producers decide whether to deliver their product to region i depending on the above profit measure and the fixed entry costs. If $(1 - G(\phi^*_{ij})) \int \pi_{ij} \mu d\phi / f_{ij} > 1$, then producers in region j will deliver their products to region i. This captures the self-selection problem in delivery patterns. The productivity threshold, ϕ^*_{ij}, affects pricing behavior and delivery choice. The effect of distance on transport costs is underestimated because it is likely that for less productive producers, an increase in transport costs causes their delivery to be unprofitable. Thus, in terms of the extensive margin, only highly productive producers can deliver to 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, ϕ^*_{ij}, 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.

3.3. CES case

We intend to compare our results with those for the CES utility function case. We employ a standard CES model with heterogeneity.

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

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

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

We consider a heterogeneous producer in a monopolistically competitive market. The firm's profits with productivity ϕ are:

$$\pi_{ij} = p_{ij} q_{ij} L_i - \frac{\tau_{ij} w_j q_{ij}}{\phi} L_i - f_{ij}.$$

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

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

Substituting this into the profit function yields:

$$\pi_{ij}(\phi) = (1-\alpha)(\frac{\tau_{ij} w_j}{\alpha P_i \phi})^{1-\epsilon} w_i L_i.$$

A producer's decision to deliver is based on the comparison of profits and the fixed cost of delivery. If $\pi_{ij}/f_{ij} > 1$, then producers in region j will deliver their products to region i. Thus, the delivery data are truncated because of self-selection by the producers. This break-even productivity level ($\phi_{ij} = \{\phi | \pi(\phi_{ij})/f_{ij} = 1\}$) depends on transport costs. If transport costs, τ_{ij}, are high, firms that are sufficiently productive are able to make positive profits: ϕ_{ij} is increasing in τ_{ij}. However, as mentioned, market structure does not affect ϕ_{ij} directly, but only through the price index, P_i.

3.4. Price differentials

Our approach of taking the difference between the prices in markets and those in source regions allows us to accurately measure transport 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 transport costs. However, if the source price and the wholesale market price with information about the source are available, the difference between these prices captures the costs of transport. We can highlight this idea in a CES utility framework. The price differential is:

$$p_{ij}^{CES}/p_{jj}^{CES} = \tau_{ij}. \tag{9}$$

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, ϕ_{ij}, 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 characteristics and the productivity parameters cancel each other out.

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

$$p_{ij}^{NHOM}/p_{jj}^{NHOM} = \tau_{ij} {\phi_{jj}^*}^{1/2} / {\phi_{ij}^*}^{1/2}. \tag{10}$$

Because the threshold value, ϕ^*_{ij}, depends on transport costs, ignoring producer heterogeneity causes biases in identifying the relationship between the price differential and transport costs. If τ_{ij} increases, ϕ^*_{ij} will increase. Because ϕ^*_{jj} does not depend on τ_{ij}, a larger ϕ^*_{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 transport costs. In addition, ϕ^*_{ij} depends on the number of firms, N_i. This is a function of the threshold value itself and thus is affected by transport costs. Hence, changes in τ_{ij} are associated with 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 transport costs will be biased.

As mentioned previously, one of the objectives of this paper is to highlight the changes arising from incorporating pricing-to-market. In the CES framework, optimal pricing does not depend on the threshold value of productivity, which is a key factor in heterogeneity. Besides, each producer's productivity is cancelled out when considering the price differentials. Hence, producer heterogeneity does not play an important role in the link between price differentials and transport costs in the CES model. However, producer heterogeneity matters for the link between price differentials and distance when they are nonhomothetic. If we introduce nonhomothetic preferences, producers 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, ϕ^*_{ij}, we are able to express the price differential as follows:

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

The heterogeneity effect reduces the direct impact of transport costs from τ_{ij} to $\tau^{1/2}_{ij}$ in our nonhomothetic specification. In general, the effect of transport costs will also be weakened in a nonhomothetic specification because the effect of a transport cost increase on price differentials is mitigated by the producer selection. In the presence of high transport 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 transport costs, omitted variable biases occur. Taking the log of the above equation yields:

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

As we can see, the price differential depends on not only transport costs, but also market characteristics, such as the number of products and price indices. This property directly reflects the pricing-to-market behavior. 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 transport 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, transport costs also increase. The constant term μ corresponds to the uniform transport costs component and u_{ij} denotes unobservable transport 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, γ, is our main parameter. Identifying this parameter is important if delivery choice, producer heterogeneity, and pricing-to-market are to be accounted for.

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}:

$$Z_{ij}^{NHOM} = \frac{\frac{b^{\theta}\tau_{ij}w_j\bar{q}L_i}{(2\theta+1)(\theta+1){\phi_{ij}^{*}}^{\theta+1}}}{f_{ij}}.$$

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:

$$\begin{aligned}
\ln Z_{ij}^{NHOM} &= z_{ij}^{NHOM} \\
&= \theta \ln b + \ln \tau_{ij} + \ln w_j + \ln \bar{q} + \ln L_i - \ln(2\theta+1)(\theta+1) - (\theta+1)\ln {\phi^{*}}_{ij} - \ln f_{ij} \\
&= \theta \ln b - \theta \ln \tau_{ij} - \theta \ln w_j - \theta \ln \bar{q} - \ln(2\theta+1)(\theta+1) \\
&- (\theta+1)\ln N_i + (\theta+1)\ln(w_i + \bar{q}P_i) - \ln f_{ij}.
\end{aligned}$$

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}:

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

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

$$\begin{aligned}
\ln Z_{ij}^{CES} = z_{ij}^{CES} &= \ln(1-\alpha) + (1-\epsilon)\ln \tau_{ij} + (1-\epsilon)\ln w_j \\
&- (1-\epsilon)\ln \alpha - (1-\epsilon)\ln P_i - (1-\epsilon)\ln \phi + \ln w_i + \ln L_i - \ln f_{ij}.
\end{aligned}$$

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 in the CES framework. We estimate the price differential and delivery choice equations using maximum likelihood. We specify regional dummies to control for market-specific effects, as suggested in the literature (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: $f_{ij} = \exp(\lambda_i + \lambda_j - \nu_{ij})$, where λ_i captures the market-specific effects, λ_j the source-specific effects, and ν_{ij} the dyadic-specific effects. The estimating self-selection equation is expressed as follows:

$$\begin{aligned} z_{ij}^{NHOM} =& - \ln f_{ij} + \theta(\ln b - \bar{q}) + \ln L_i - \theta\mu - \theta u_{ij} - \ln(2\theta+1)(\theta+1) \\ & - \theta\gamma \ln D_{ij} - \theta \ln w_j - (\theta+1)\ln N_i + (\theta+1)\ln(w_i + \bar{q}P_i) \\ =& c_0 + c_1 - \theta\gamma \ln D_{ij} - \theta \ln w_j - (\theta+1)\ln N_i + (\theta+1+c_2) dum_i + c_3 dum_j + \eta_{ij}, \end{aligned} \tag{13}$$

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. Because our focus is on the estimation of distance elasticity, we do not examine each regional specific factors in detail, but use regional dummies to control for these. The variables N_i and N_j are the number of products traded each trading day in the markets of regions i and j, respectively. The wages in regions i and j, w_i and w_j, are monthly wages. While these data involve variation over time, we omit the time subscript for simplicity. As we treat our sample as pooled cross-sectional data, we estimate the regional fixed effects with these variables. Given that the number of products may be a noisy variable or the method by which the number of products is introduced may be misspecified, we use $\chi \ln N_i$ instead of $\ln N_i$ in the estimations, where χ is a free parameter. This allows us some flexibility in estimation of the market structure effects. 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:

$$\begin{aligned} q_{ij}^{NHOM} &= \ln p_{ij}^{NHOM} - \ln p_{jj}^{NHOM} \\ &= (1/2)\mu + (1/2)\gamma \ln D_{ij} + (1/2)\ln N_j - (1/2)\ln N_i + c_4 dum_j - c_5 dum_i + (1/2)u_{ij}, \end{aligned} \tag{14}$$

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, γ, the price differential and product delivery equations reveal an important result. Simply estimating the price differential equation only may lead to underestimation of γ. This is because the errors in these equations are correlated, and this is because $\eta_{ij} = -\theta u_{ij} +$

ν_{ij}, and the error terms η_{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 $E[u_{ij}|X] = \rho \frac{\sigma_u}{\sigma_\eta} E[\eta_{ij}|X]$, if we ignore this correlation, there will be bias in the estimate of the distance effect.[4] 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, ρ.

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:

$$
\begin{aligned}
L = &\sum_{i,j}(1-T_{ij})\ln[\Phi(-W_{1ij})] + \sum_{i,j} T_{ij} \ln\left[\Phi\left(\frac{W_{1ij} + 2\rho\sigma_u^{-1}(W_{2ij})}{(1-\rho^2)^{1/2}}\right)\right] \\
&+ \sum_{i,j} T_{ij}\ln\phi\left(\frac{W_{2ij}}{(\sigma_u/2)}\right) - \sum_{i,j} T_{ij}\ln(\sigma_u/2),
\end{aligned}
$$

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 explicitly. However, our approach has the disadvantage of possible misspecification; we address this misspecification issue by undertaking diagnostic checks.

In the case of CES utility, the self-selection equation is:

$$
z_{ij}^{CES} = \beta_0 - (\epsilon-1)\gamma d_{ji} + (\epsilon-1)\ln P_i + (1-\epsilon)\ln w_j + \ln w_i + \zeta_\omega + \xi_j + \lambda_i + \eta_{ij},
$$

where $\beta_0 = -\epsilon\ln\epsilon - (1-\epsilon)\ln(\epsilon-1) + (1-\epsilon)\mu$, $\zeta_\omega = (1-\epsilon)\phi$, 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:

$$
\begin{aligned}
L = &\sum_{i,j}(1-T_{ij})\ln[\Phi(-W_{3ij})] + \sum_{i,j} T_{ij} \ln\left[\Phi\left(\frac{W_{3ij} + \rho\sigma_u^{-1}(W_{4ij})}{(1-\rho^2)^{1/2}}\right)\right] \\
&+ \sum_{i,j} T_{ij}\ln\phi\left(\frac{W_{4ij}}{\sigma_u}\right) - \sum_{i,j} T_{ij}\ln\sigma_u,
\end{aligned}
$$

[4]Because u and ν are orthogonal, $E[\eta u] = E[(-\theta u + \nu)u] = -\theta\sigma_u^2$. The correlation ρ is defined by $\rho = \sigma_{\eta u}/\sigma_u$. Thus, $\sigma_{\eta u} = \rho\sigma_u = -\theta\sigma_u^2$. Then, $\sigma_u = -\rho/\theta$.

where $W_{3ij} = \beta_0 - (\epsilon - 1)\gamma d_{ji} + (\epsilon - 1)\ln P_i + (1 - \epsilon)\ln w_j + \ln w_i + \zeta_\omega + \xi_j + \lambda_i$ and $W_{4ij} = q_{ij} - \mu - \gamma d_{ij} - c_6 dum_i - c_7 dum_j$. We use the monthly consumer price index as the price index, while the use of region-specific effects controls for the other region-specific factors.

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 that 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 transport 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 transport 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": 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 transport 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 the source–market price differential 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 11 US dollars) per kilogram, while the cheapest product is c-cabbages, at 61.628 yen (approximately 0.6 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 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 ω, we count the number of deliveries as $T_{ij}(\omega) = 1$ and nondeliveries as $T_{ij}(\omega) = 0$ only for the dates on which the product is traded in the wholesale market in producing prefecture j. We identify product delivery $T_{ij}(\omega) = 1$ if the data report that the source prefecture of product entry ω 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 Web site.[5] We use daily temperature for identification purposes to control for supply and demand shocks in the selection equation. We download the daily temperature data compiled by the Japan Meteorological Agency.[6] For the CES estimations, we include the monthly consumer price index from the Retail Price Survey of the Ministry of Internal Affairs and Communications. 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.[7]

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 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 distance elasticity are larger than those in previous studies, which implies the presence of an under-bias in distance elasticity in previous studies.

As in previous studies, if instead we use two observed market prices to construct price differentials and simply regress these on distance, then the distance effect coefficient is at

[5] www.gsi.go.jp/kokujyoho/kenchokan.html.

[6] www.data.jma.go.jp/obd/stats/etrn/index.php.

[7] The data are available at www.mhlw.go.jp/toukei/list/30-1.html.

most 0.05. That is, even if the transport distance doubles, the price differential increases by only 5 percent. Thus, even using our data, regressing only the price differential 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 price and the price in the producing prefecture, and delivery choice is explicitly modeled to control for sample selection. 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 when compared with the results from both simple regression analysis and the CES framework. 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 transport 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 transport costs. Thus, the presence of large distance effects after accounting for producer heterogeneity suggests that the price of geographic barriers remains high for regional transport.

Another important parameter in our estimations is the heterogeneity parameter, θ. Our estimates range from 1.155 to 2.313. A small θ 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.[8] 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 θ may reflect this dispersion across farms. In fact, as shown in Table 2, the estimates obtained using carrots and potatoes have small θ values. 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, θ, has been investigated extensively in the trade literature. In the Eaton and Kortum (2002) framework, this is the elasticity of the trade

[8] www.maff.go.jp/j/tokei/sihyo/index.html.

parameter, which is a crucial parameter in the analysis of the welfare gain from trade (Arkolakis 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 (2014) 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, γ and θ, 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 θ.

The correlation parameter ρ 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 transport costs (for example, a fuel price increase) will also decrease the probability of delivery. Without controlling for negative correlations 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 models is the elasticity of the substitution parameter, ϵ. 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 θ and large estimates of γ. 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 transport, 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 transport 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 access to markets and thus inhibit efficient resource allocation.

Although incorporating producer heterogeneity and pricing-to-market corrects the biases in distance elasticity, there are other concerns regarding pricing behavior. For example, as Hummels and Skiba (2004) have shown, there may be specific transport 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 transport costs are assumed and the Alchian–Allen effect is not taken into account. Investigating these effects is a topic for further research.

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Table 1: Summary Statistics

	Cabbages	Carrots	C-cabbages	Lettuce	Potatoes	S-mushrooms	Spinach	Welsh onions
Average price (yen per kg)	77.833	101.25	61.628	183.909	79.565	1113.627	496.372	382.099
Product entry								
No. of varieties	3	10	4	7	10	1	4	11
No. of size categories	63	62	50	71	50	74	17	103
No. of grade categories	34	66	50	46	93	55	85	58
No. of producing prefectures	47	46	46	43	47	44	47	46
No. of wholesale markets	47	47	47	47	47	47	47	47
No. of distinct product entries	1,207	1,186	1,001	903	1,423	909	551	1,115
Data truncation								
No. of $T_{ij}(\omega) = 0$ or 1	369,343	198,129	241,871	239,703	264,280	476,919	466,337	547,272
No. of $T_{ij}(\omega) = 1$	15,841	8,395	10,803	11,565	10,921	11,845	15,977	14,874

Table 2: Estimation Results

	Cabbages	Carrots	C-cabbages	Lettuce	Potatoes	S-mushrooms	Spinach	Welsh onions
Nonhomothetic								
γ	0.458	0.628	0.646	0.687	0.615	0.757	0.668	0.563
	(0.003)	(0.006)	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)	(0.004)
θ	1.981	1.155	1.573	1.181	1.264	2.313	1.638	1.939
	(0.011)	(0.008)	(0.009)	(0.008)	(0.007)	(0.018)	(0.009)	(0.011)
ρ	-0.836	-0.873	-0.818	-0.857	-0.786	-0.62	-0.844	-0.833
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
log-likelihood	-20911.389	-17596.548	-14370.527	-21931.139	-25077.556	-23951.703	-19860.187	-15543.191
CES								
γ	0.287	0.345	0.382	0.402	0.335	0.49	0.402	0.354
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)
ϵ	3.326	2.123	2.78	2.126	2.381	3.688	2.83	3.292
	(0.019)	(0.014)	(0.017)	(0.014)	(0.012)	(0.028)	(0.013)	(0.018)
ρ	-0.86	-0.884	-0.83	-0.874	-0.793	-0.546	-0.848	-0.848
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.003)
log-likelihood	-24137.852	-18563.794	-15956.433	-23317.952	-26013.89	-4383.126	-22797.953	-18319.21
OLS								
γ	0.033	0.051	0.042	0.022	0.037	0.007	0.044	0.033
N	369,343	198,129	241,871	239,703	264,280	476,919	466,337	547,272
PCP for T_{ij}	0.966	0.964	0.961	0.961	0.966	0.994	0.979	0.988

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.

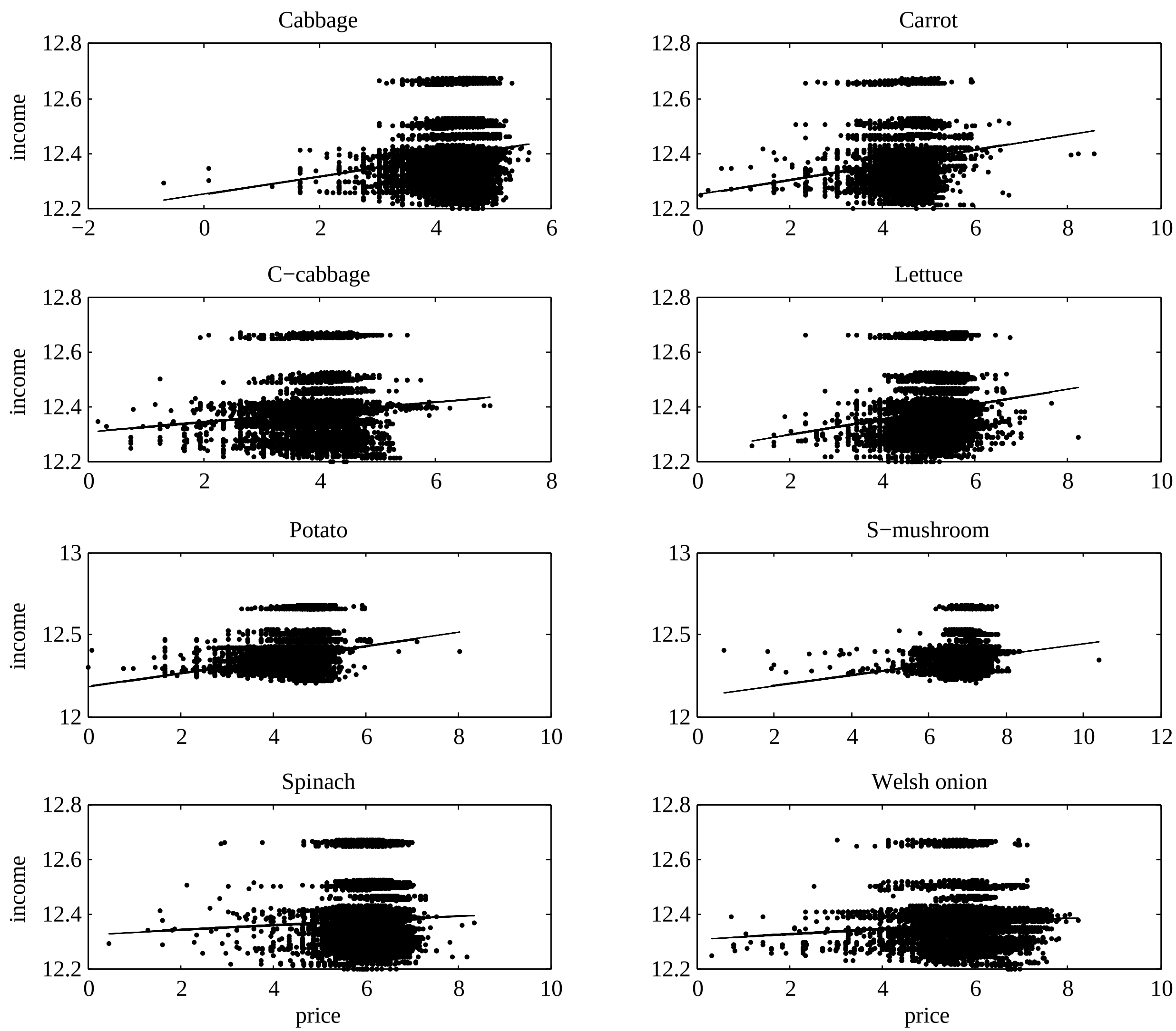

Figure 1: Log of price and log of per capita income relationship

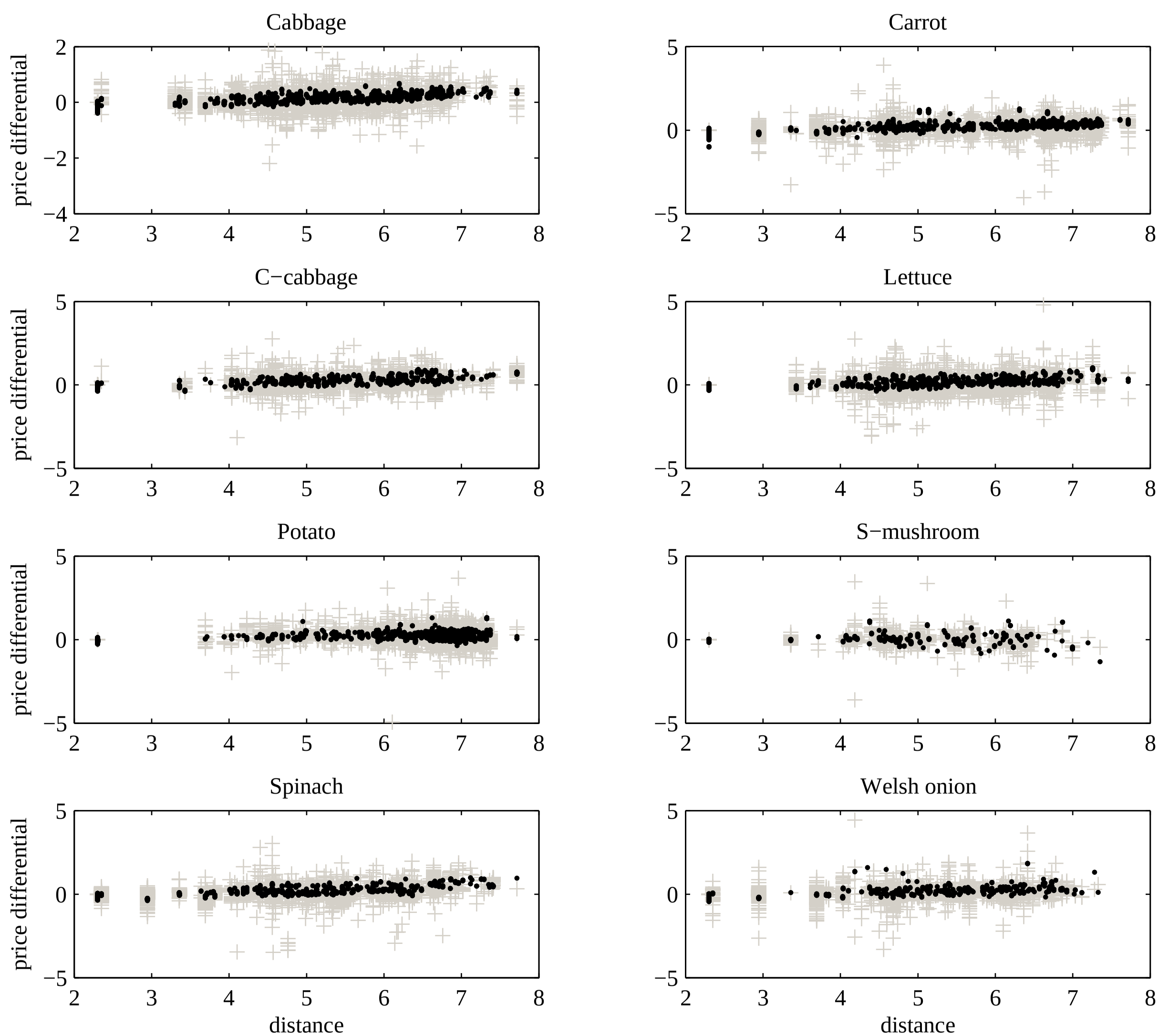

Figure 2: Actual (+) and predicted (.) values