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Milk Demand Heterogeneity and Cost Pass-through in Japan: A Microdata Approach towards Competition Structure

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Research has shown that Japanese retailers have strong buying power when purchasing milk from processors, but not enough is known about differences in market competitiveness at the brand and retailer levels. In order to consider practical knowledges for the Japanese milk market, I used micro-level data to estimate a demand function using a random coefficient logit model that controls for the endogeneity of price due to unobserved heterogeneity. Then, I estimate the demand elasticity for each brand-retail combination in every prefecture each month. The markup was calculated from demand estimates. The results show that, on average, CO-OP milk tended to have a higher markup than NB and PB milk. Using counterfactuals, I find that 13% of milk products had a negative cost pass-through rate, which is concentrated in local NB milk. Finally, I show geographical differences in pass-through rates.

Key words: milk demand, cost pass-through, BLP, scanner data

1. Introduction

There are concerns in the Japanese milk supply chain regarding the low level of pass-through and market malfunctions. The fact that retail and wholesale milk prices did not raise appropriately following shocks to the cost of dairy production has highlighted these concerns (Yasaka, 2008). In general, the pass-through rate is an indicator that shows how producer prices relate to wholesale prices. It is useful to judge whether current market conditions are sound (Nakashima, 2002). If appropriate coordination is not undertaken to transmit cost shocks, it could affect the stability of the food supply system (Hayashida and Suzuki, 2017).

Most studies have attributed the low levels of cost pass-through to the buying power of retailers[1)]. The next step is to establish what sort of policy implementation should be applied in practice. To investigate this point further, one cannot ignore the effect of product differentiation, since there are many milk brands and store channels. By understanding the differences between brands and channels, it is possible to identify which pair plays an important role in cost pass-through and contributes to a sound supply chain structure.

In this paper, I first quantified consumer milk demand preferences to investigate detailed product competition. Second, given the demand side primitives, I derived brand-retail price elasticities, the markup percentage, and the rate of cost pass-through. Furthermore, by clustering those values, I classified each brand in terms of the state of its product market competition, and provided a basis for sound policymaking.

Before moving on to details, I will clarify this paper's importance to the field, since several papers have already estimated milk demand primitives and consumer preferences. The problem in the literature is that it relies on a demand system approach, or classical discrete choice model, without taking into account pos-

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1) Kinoshita *et al*. (2006) developed a bilateral bargaining model and estimated buying power using national aggregated data from 1987 to 2000. They showed that retailers had vertical buying power over the processors. Hayashida (2018) reached a similar conclusion based on an oligopsony model. From a policy perspective, the Ministry of Agriculture, Forestry, and Fishery (MAFF) published guidelines for the fair trade of milk in March 2018 (http://www.maff.go.jp/j/press/shokusan/kikaku/180328.html, accessed 1st May 2018).

sible unobserved heterogeneity. There are roughly four concerns. First, researchers must reduce the number of products in their models, due to the curse of dimensionality. Second, their models make some implicit assumptions about consumers' preferences that may not be true in many cases. Third, there remain uninterpretable results in the demand elasticity and markup, as I will show in the next section. Finally, unobserved factors that affect consumer choice behavior have not been taken into account, which means that the price coefficient, which is vitally important to calculate the markup, might have some biases. To overcome these flaws, I employed a random coefficient logit model, developed by Berry *et al.* (1995), that controls for unobserved heterogeneity.

This paper is organized as follows. Section 2 discusses the literature related to demand estimation for Japanese milk and cost pass-throughs in the food industry. Afterwards, I clarify the distinctive purpose of this paper. Section 3 presents the models for demand estimation with unobserved heterogeneity and for firm competition. The data and estimation methods are discussed in Section 4, and Section 5 provides the results and a discussion on the categorization of milk brands.

2. Literature Review

1) Demand analysis of the milk market

Table 1 summarizes the literature relating to Japanese milk demand[2)]. Traditionally, demand estimations were conducted with narrowly specified functional forms, such as the log-log, with macro data from the Ministry of Internal Affairs and Communications' Retail Price Index Statistical Survey. Since the early 2000s, when the availability of micro-level data surged, fluid milk has been one of the most studied products in consumer demand[3)]. According to a study based on Point-of-Sales (POS) data, the own-price elasticity of milk ranged from −14.9 to −0.59. However, the cross-price elasticity showed positive values, which was hard to interpret when the values were expected to be negative, since milk is a substitutable good among the brands[4)]. Moreover, estimates of the Learner Index (LI), which specifies the relative markup ratio, were even more difficult to interpret, because they had more than one value and so were inconsistent with economic theory. As for the LI, even though Kinoshita *et al.* (2002) expected reconstituted milk to have higher values than fresh milk, since the former had a lower marginal cost and they had similar retail prices, the estimated value results were inverted and hard to reconcile.

Instead of POS data, Ujiie (2002) applied scanner panel data that tracked household consumption and estimated the linear demand system in four selected categories. The results revealed that the own-price elasticities ranged from −1.08 to −0.03. In addition, similar to the previous literature, the values for the cross-price elasticities were not necessarily positive.

There are many studies that estimated the demand for milk at a brand-level, but most of them failed to present fully interpretable results. The reason behind their failures was the models or estimation methods they utilized. First of all, most of them applied a demand system approach that limited the number of products due to the curse of dimensionality, losing much of the information contained in the micro-level data. Secondly, those models had implicitly strong restrictions on substitution patterns such as Independence of Irrelevant Alternatives (IIA) phenomena, resulting in failures to capture consumer preferences. Thirdly, they did not take into account possible endogeneity concerns at all. Even if one had micro-level data, that did not mean that researchers knew everything that consumers observed at the purchasing point. Thus, omitting those unobservables could bias the study estimates.

Contrary to those prior studies, Nakajima (2016) applied Berry, Levinsohn, and Pakes (BLP) approach to Japanese beer industry data, which overcame most of the concerns discussed above. In this study, I employed the BLP approach, highlighting the following key differences from Nakajima (2016). First, although Nakajima did not have information on the stores, the data used in this study included the name of the store where the consumers bought the milk. Therefore, this study did not have to assume homogenous behavior over chains; instead, I set the product as the combination of the brands and the stores, as in Bonnet and

2) There is more research not included in Table 1 that is tangentially related to this study. One is the field of study that investigates the relationship between purchasing decisions and consumer characteristics in detail (Ujiie, 2004, 2005, 2007). However, the studies only focus on a few brands.

3) Kawamura (1999) was the pioneer, estimating demand with brand-level data in the Japanese literature, but he focused on the margarine market in the United States.

4) This point also applies to a study of the linear demand system in beef products, as in Takahashi and Maeda (2016), and is a common problem in that system. In Japanese agricultural products, studies of demand systems have focused on beef products, as in Matsuda (2004, 2006).

Table 1. Literature related to the demand analysis about milk or dairy products

Literature	Product	Model	Data	Aggregation	Endogeneity	PCM	Price elasticity
Kusakari (1982)	Milk	BoxCox	Household survey	Homogeneous	×	△	△
Ito (1989)	Milk / Dairy Products	log-log	Household survey	Homogeneous	×	△	△
Suzuki (1991)	Milk	log-log	Milk dairy statistics	Homogeneous	×	△	△
Ito (1993)	Milk	log-log	Nikkei POS	Homogeneous	×	△	△
Shono *et al*. (2000)	Milk / Dairy Products	log-log	Nikkei POS	18 products	×	△	△
Kinoshita and Suzuki (2002)	Milk / Dairy Products	log-log	Nikkei POS	18 products	×	△	△
Kinoshita *et al*. (2001)	Milk	LA/AIDS	Nikkei POS	6 products	×	△	△
Kinoshita *et al*. (2002)	Milk	linear	Nikkei POS	2 products	×	×	○
Ujiie (2002)	Milk	LA/AIDS	QPR	4 products	×	×	△
Hokazono *et al*. (2009)	Milk	LA/AIDS	Nikkei POS	4 products	×	×	△
Sato and Saito (2016)	Drink	quAIDS	Household survey	Homogeneous	×	×	△

Notes: 1) PCM represents price-cost margin.
2) "Milk" in the table includes "Ingredient adjustment milk" and "processed milk".
3) "○" means that the literature take it into account and the results are interpretable; "△" indicates that the literature take it into account but the results are not interpretable; "×" represents the literature does not take it into account. Whether the results are interpretable or not is determined by the following manner: for endogeneity, it tackles the problem with enough covariates or control method; for PCM, the estimates are within 0-1; for price elasticity, the own-price elasticity is non-positive while the cross-price elasticity is non-negative.

Villas-Boas (2016).

2) Cost pass-through literature

There are several strands of research about cost pass-through or price transmission. In this study, I used cost pass-through rather than price transmission. Roughly speaking, cost pass-through specifies the extent to which upstream cost shocks are transmitted to final retail prices. From an interview with processor sales managers, I realized that, in practice, this rate was heavily referenced before and during negotiations between processors and retailers. Given the dominant position of retailers in the food market, it is useful to identify which channels or brands play important roles in cost pass-through, as a thorough investigation by channel may provide some suggestions for alleviating buyer power and increasing the pass-through rate, if necessary.

Note that this definition of cost pass-through is not universal. Therefore, I will briefly review the essence of cost pass-through in order to make my use of it in this study clearer.

In the field of agricultural economics, there is a notion related to cost pass-through called the farm-retail spread. Gardner (1975) performed the seminal work in this field, where he integrated the upstream horizontal competition and downstream horizontal competition models by considering the vertical structures. This model is called the Equilibrium Displacement Model (EDM)[5]. In Japan, Kojima (2007a, b) investigated how shocks to raw agricultural prices of wheat were transmitted to final retail prices utilizing the EDM approach.

Another model is called Asymmetric Price Transmission (APT). The research here stems from the asymmetry of price changes during its rising and declining phases. For instance, it is often difficult to immediately pass-through incremental prices during upward cost shocks, which passed through during the declining price phase. These phenomena are likely to be related to the extent of market competition. There were several empirical studies of APT in various countries, commodities, and models. Meyer and Cramon-Taubadel (2004) and Frey and Manera (2007) comprehensively reviewed this literature. In the Japanese agricultural market, Nakajima (2010) investigated the relationship between the FOB price of corn in the United States and its import price in Japan. APT is based on time series analysis and is less related to economic theory[6]. Also, these studies assumed the homogeneity of their goods[7].

In this study, I assumed the market for the differentiated product and estimated the pass-through rate directly from the economic model[8]. It is similar to the EDM approach, in that this method is based on eco-

5) Wohlgenant (2011) provided a comprehensive review of this model.
6) There are several papers attempting to capture the factors of APT using economic theory, but no general conclusion has been reached yet (Richards *et al*., 2014).
7) There are studies that estimated price relationships in a semi-reduced form approach (Hong and Li, 2017).

nomic theory. However, there is a critical difference, since my model took the increment of the retail price in response to shocks to the marginal cost of production and distribution as the cost pass-through, instead of the price-level relationship between each step in the supply chain as is the case in the EDM studies. I followed the type of cost pass-through estimation made in both Kim and Cotterill (2008) and Bonnet and Requillart (2013). In the next section, I will propose a model for demand estimation at the brand and retail levels, estimating the cost pass-through rate, and a method for recovering the markup.

3. Structural Model

1) Random coefficient logit

Since milk is locally produced and its demand varies by time and place, I defined a market m as a combination of time $t \in \{1, \dots, T\}$ and prefecture $l \in \{1, \dots, 46\}$. In market m, consumer $i \in \{1, \dots, N_m\}$ chooses milk brand $b \in \{1, \dots, B_m\}$ at retailer $r \in \{1, \dots, R_m\}$. I specified the resulting utility U_{ibrm} as follows[9].

$$U_{ibrm} = \alpha_0 + \beta_i p_{brm} + \gamma_1 Ca_b + \gamma_2 FAT_b + \alpha_{b(bc)} + \alpha_{r(rc)} + \xi_{brm} + \epsilon_{ibrm} \qquad (1)$$

where p_{brm} denotes the retail price of brand b at retailer r in market m. I included the amount of calcium Ca_b and fat FAT_b for brand b as representative product characteristics. To control for other unobserved heterogeneity, I included $\alpha_{b(bc)}$, $\alpha_{r(rc)}$, which denoted the brand and retail category fixed effects, respectively. I provide a detailed description of each category in section 4[10].

Moreover, I included the square term of the number of available products, $Variety_{rm}$, at retailer r in market m, in order to consider the relationship between the size of the choice set and the utility[11]. ξ_{brm} is the brand-retailer market-level unobserved shock that consumers observe, and that researchers cannot know. In particular, this potentially correlates with equilibrium retail prices p_{brm}[12]. To take this into account, I applied the estimation method to include explicit care for the endogeneity of equilibrium retail prices p_{brm}. ε_{ibrm} is remaining IID shocks, and follows a probabilistic distribution with a Type I Extreme Distribution (Train, 2009). The parameters to be estimated are β_i, γ_1, γ_2, α_0, α_b, α_r.

I included consumer-specific heterogeneity regarding price sensitivity by including the IID standard normal error in β.

$$\beta_i = \beta + \sigma_p v_i, \ v_i \sim N(0, 1) \qquad (2)$$

Thus, equation (1) can be split into two elements: 1) the mean utility piece, which is invariant among consumers $\delta_{brm} = \beta p_{brm} + \gamma_1 Ca_b + \gamma_2 FAT_b + \alpha_b + \alpha_r + \xi_{brm}$, and 2) the deviation from the mean piece, $\mu_{ibrm} = \sigma_p v_i p_{brm}$. Note that $b = r = 0$ is the outside option in which consumers do not purchase one of the products considered here, and the utility is normalized by $U_{i00m} = \varepsilon_{i00m}$.

According to revealed preference, consumers maximize their utility with $U_{ibrm} > U_{ib'r'm} (\forall b' \neq b, \forall r' \neq r)$, so that the choice probability s_{brt} of consumer i in market m purchasing brand b from retailer r is as follows:

$$s_{brm} = \int \frac{\exp(\delta_{brm} + \mu_{ibrm})}{1 + \Sigma_{k=1}^{B} \Sigma_{s=1}^{R} \exp(\delta_{ksm} + \mu_{iksm})} dF(\mu) \qquad (3)$$

In principle, S_{brm}, the actual share in the data, and the model's predicted share, s_{brm}, are equivalent under the true parameters. Therefore, an appealing approach for estimating the parameters is to maximize the likelihood function. However, due to the existence of the unobserved heterogeneity ξ_{brm}, the construction of the likelihood is not as direct as in the standard logit model. Instead, I used the alternative BLP approach to estimate the model's primitives β_i, γ_1, γ_2, $\alpha_{b(bc)}$, $\alpha_{r(rc)}$, as described in Section 4.

2) Supply side

Given the model's demand-side primitives, I proposed a supply-side model. First, I considered hypothetically coordinated firms f by assuming joint profit maximization for channel profit between milk process-

8) The definition of price transmission in this study corresponds to the definition of cost pass-through in the literature.

9) I did not include an income effect, as milk is only a small portion of household income.

10) It is possible to include a brand-retail fixed effect to control for the unobserved time-invariant effect. In that case, the remaining unobserved heterogeneity is ξ_m instead of ξ_{brm}. The disadvantage of this approach is that the number of parameters to be estimated increases with the number of products. I first estimated the model with the full fixed effect (retail firm name, brand name, and their intersection), but it failed due to the difficulty of inverting the explanatory matrix. Therefore, I only included category-specific fixed effects.

11) Generally, it is difficult to create the complete choice set, as the scanner data only contains information on the products bought. Therefore, the strict method of constructing variety is tricky. In the analysis, I used the number of observed products at the retailer in the market as $Variety_{rm}$, and used this as a proxy variable. The implicit assumption here is that the more of the record the scanner data contains, the larger the true choice set is.

12) For instance, β_i will be upward biased (approaching zero) if the unobserved quality ξ_{brm} is not included in the model, since ξ_{brm} increases utility and correlates positively with p_{brm}.

ing firms and retailers. Then, I denoted the joint profit function in market m as Π^f_m, which is given as equation (4)[13]. Here, product j is defined as the combination of brands and retail categories, and denoted as $j \in \{1, \ldots, B \times R\}$. The following omitted the subscript for market m.

$$\Pi^f = \Sigma_{j=1}^{J_f}(p_j - mc_j)Ms_j(\boldsymbol{p}) \tag{4}$$

where p_j is the retail price of product j, mc_j is the marginal cost of product j, M is the size of the market, and $s_j(p)$ is product j's market share. Assuming that firm f determines retail prices in order to maximize channel profit under product market competition, the following first-order conditions for all products $j \in \{1, \ldots, J_f\}$ are obtained[14].

$$s_j + \Sigma_{k=1}^{J_f}(p_k - mc_k)\left[\frac{\partial s_k}{\partial p_j} + \Sigma_{l \in J_{-f}}\frac{\partial s_k}{\partial p_l}\frac{\partial p_l}{\partial p_j}\right] = 0 \tag{5}$$

By multiplying p_j/p_j, p_l/p_l, s_k/s_k by the second part of the large parenthesis on the left-hand side, equation (6) can be derived.

$$s_j + \Sigma_{k=1}^{J_f}(p_k - mc_k)\left[\frac{\partial s_k}{\partial p_j} + \Sigma_{l \in J_{-f}}\epsilon_{kl}\eta_{lj*}\frac{s_k}{p_j}\right] = 0 \tag{6}$$

where $\varepsilon_{kl} = \left(\frac{\partial s_k}{\partial p_l}\right)\left(\frac{p_l}{s_k}\right)$ is the price elasticity of product k with respect to product l, $\eta_{lj} = \left(\frac{\partial p_l}{\partial p_j}\right)\left(\frac{p_j}{p_l}\right)$ is the conjectural elasticity, which denotes the degree of inference about a price change in product l in response to a price change in product j.

Equation (6) differs by firm, depending on the number of selling-products. To simplify, I denoted equation (6) using a matrix format. To do so, I first defined the ownership matrix Ω'_{jr}, in which each element is 1 or 0.

$$\Omega'_{jr} = \begin{cases} 1 & (j \text{ and } r \text{ is the same seller} - \text{retailer channel}) \\ 0 & (\text{otherwise}) \end{cases} \tag{7}$$

Moreover, by defining $\Psi_{jr} \equiv \left[\frac{\partial s_k}{\partial p_j} + \Sigma_{l \in J_{-f}}\varepsilon_{kl}\eta_{lj*}\frac{s_k}{p_j}\right]$, $\Omega_{jr} = \Omega_{jr}'\Psi_{jr}$, and stacking equation (6) for every product j and m, equation (8) is derived.

$$s(\boldsymbol{p}) + \Omega(\boldsymbol{p})(\boldsymbol{p} - \boldsymbol{mc}) = 0 \tag{8}$$

where the each element of $\boldsymbol{p} - \boldsymbol{mc}$ is $PCM_j = (p_j - mc_j)$, and PCM_j is the price cost margin.

From equation (8), as long as $\Omega(\boldsymbol{p})$ is invertible, $\boldsymbol{PCM} = \boldsymbol{p} - \boldsymbol{mc} = -\Omega^{-1}\boldsymbol{s}(\boldsymbol{p})$ is true, and one can determine the unobserved PCM from the demand estimates[15].

3) Measuring the competition structure

Using the demand model estimates, I will describe three important indices for studying product market competition: price elasticity, markup ratio, and the degree of cost pass-through.

(1) Price elasticity

From the demand primitives, the own and cross price elasticity for product j in market m can be calculated using equation (9) and (10) (Nevo, 2001). Note that the IIA property, which is the case in the logit model, is alleviated by taking the consumer-level heterogeneity in the utility function.

$$\frac{\partial s_{jt}}{\partial p_{jt}}\frac{p_{jt}}{s_{jt}} = -\frac{p_{jt}}{s_{jt}}\int \beta_i s_{ijt}(1 - s_{ijt})dF(\boldsymbol{v}) \tag{9}$$

$$\frac{\partial s_{jt}}{\partial p_{kt}}\frac{p_{kt}}{s_{jt}} = \frac{p_{kt}}{s_{jt}}\int \beta_i s_{ijt}s_{ikt}dF(\boldsymbol{v}) \tag{10}$$

(2) Derivation of the markup ratio

This section derives the product j-level markup ratio. Following the consensus in the literature, I assumed that the conjectural variation η_{lj} was 0 in every combinations (Berry *et al.*, 1995; Nevo, 2001). This is

13) The hypothetical integrated firms are related to the range of joint profit maximization. These conditions are identical to Nevo (2001) and Kim and Cotterill (2008). As theoretical analysis such as in Baron and Berman (2016) showed, the transaction or contract format is determined in a strategically dependent environment under the vertical relationship between upstream and downstream firms. Here, strategic dependency means that each firm considers other firms' actions. In particular, many theoretical papers investigated cases where the coordination between the vertical channels happens to alleviate the double marginalization problem. Relatedly, the assumption introduced in this paper (joint profit maximization in the channel) is equivalent to the case where retailers have full bargaining power in the linear demand functional form (Baron and Berman, 2016). There are two points worthy of mention. First, the above assumption is not dissimilar to the real market environment, as the dominant position of buyers is clear in Japanese milk transactions. Second, this problem might be trivial in light of the purpose of this study, which is to investigate the effects of cost shocks on final retail prices. According to Rey and Verge (2010), final retail prices were not affected even if upstream firms had full bargaining power or the contract types were nonlinear, as with two-part tariffs. Thus, the amount of bargaining power only affected the distribution of profit among buyers and sellers, and was not related to final retail prices.

14) The following derivation refers to Reimer (2004).

15) The most advantageous feature of this supply model is that it only requires demand primitives to calculate the unknowns *PCM* and *mc*, which are highly difficult to obtain from the detailed transaction-level data.

equivalent to assuming Bertrand type price competition between all firms f. Then, from equation (8), I calculated the size of the margin PCM_{jm} for each product j in each market m. Therefore, the markup ratio can be defined as follows.

$$L_{jm}=\frac{PCM_{jm}}{p_{jm}} \tag{11}$$

This competition mode assumption (that $\eta_{lj}=0$) was reasonable when explaining the competitiveness in the Japanese milk market. As for milk, small and medium-sized local enterprises and retailers had large sales shares, and the number of firms was large. This market structure suggests that it would be hard to infer how a change in the price of an own brand affects other products. Thus, $\eta_{lj}=0$ is not too restrictive, at least in the context of this study[16].

Given the above, conceptually the markup ratio should be equivalent to 0 in the case of homogeneous products and Bertrand type price competition. However, this is not true for differentiated products. That is, it would be possible to discuss the degree of product differentiation through an investigation of the markup ratio as well.

(3) Measurement of the cost pass-through rate

To measure the degree of cost pass-through if the marginal cost has changed after exogenous shocks, one must estimate equilibrium retail prices in counterfactual cases when the marginal cost was changed. Players in the market adjust retail prices at equilibrium to maximize profit, given that consumers demand primitives if the marginal cost has been changed. Thus, the counterfactual retail prices must be equivalent to the post-shock marginal cost plus the counterfactual price-cost margin. I designated the size of the shock on the marginal cost as λ, and the vector of marginal cost as $C_m=(C_{1m}, \ldots, C_{jm}, \ldots, C_{Jm})$. In this analysis, it would be difficult to track the price changing process analytically, so I followed Kim and Cotterill (2008) and Bonnet and Villas-Boas. (2016) and numerically solved the following nonlinear system of equations to find the new equilibrium prices p^*_{jm} in market m.

$$p^*_{jm}-PCM_{jm}(p^*_{jm})-\lambda C_{jm}=0 \tag{12}$$

where $PCM_{jm}(p^*_{jm})$ denotes the vector of the price-cost margin under the counterfactual equilibrium retail prices, p^*_{jm}. In this study, I investigated the case where the marginal cost increased 10 percent ($\lambda=1.10$), as the purpose of this analysis was to find the change in retail prices from a surge in marginal cost due to incremental feed prices[17].

Lastly, Equation (13) represents the degree of cost pass-through ρ_{jm} (percent). This is the ratio of the change in retail prices divided by the change in the marginal cost.

$$\rho_{jm}=\frac{\Delta p_{jm}}{\Delta mc_{jm}}=\frac{p^*_{jm}-p_{jm}}{\lambda C_{jm}-C_{jm}}\times 100 \tag{13}$$

4. Data and Estimation

1) Data

The primary data used in this study was the Japanese consumer scanner panel data (QPR) collected by Macromill Ltd.[18] The data was collected from June 2012 to December 2014, with around 60,000 monitors over that period. The data concerned 1-liter packages of white drinkable milk[19]. The QPR data monitor corresponded to population demographic information, so that the data was representative. I aggregated the original diary-level data into monthly-level data. The regional market was defined as the prefecture, which was the narrowest choice in the data. The market m was defined as the combination of the month and the prefecture.

For brevity, I selected the top 34 brands with viewpoint shares of sales, while the remaining products were aggregated into three categories: 1) national brands (NB), 2) private label brands (PB), and

16) It is impossible to estimate the degree of conduct and the demand primitives simultaneously, unless one includes more restrictions in the model. I believe that it is acceptable under a case such as that described in the passage, even though it lacks the model's generality. Recent studies that estimated the markup ratio under product differentiation (Nevo, 2001; Bonnet and Requillart, 2013) could be inconsistent with previous studies in the NEIO with homogenous products, which had sought to estimate the degree of competition (Suzuki *et al*., 1993).

17) As an illustration, the major input ingredient, the feed price, increased 17.1% from June 2012 to December 2014 according to the "Trend of the Feed Price (for dairy cattle breeding), Agriculture Price Statistics" by the MAFF. Bonnet and Villas-Boas (2016) conducted similar studies, but allowed asymmetric shocks in order to investigate whether asymmetric price responses by consumers during the increasing and decreasing stages existed. This related to the APT literature based on a time series analysis with a structural model.

18) QPR covers all prefectures except for Okinawa. The monitor is the representative of the household who scanned the product barcode to record the brand name, chain, purchase price, and quantity information. This was classified as home-scan panel data in the scanner data. Ujiie (2007) used the same dataset.

19) Due to a lack of data, this study captured the substitution pattern in drinkable white milk only.

Table 2. Descriptive table

ID	Firm	Brand	Type	Price	SD	Ca	Fat	Share（%）
1	CO-OP	CO-OP Milk	CO-OP	174.967	21.151	2.30	8.30	1.997
2	Other	Other	CO-OP	182.333	18.826	2.20	8.10	2.116
3	Griko	Calcium-To-Iron-No-Oi-Milk	NB	168.940	27.641	3.59	3.40	0.362
4	Other	Other	NB	146.162	27.310	2.27	7.80	31.811
5	Takanashi	Hokkaido-Sawayaka-Kazoku	NB	147.657	15.083	2.08	3.60	0.592
6	Takanashi	Seinyu-Zitate	NB	163.993	18.346	2.06	4.80	0.110
7	Takanashi	Teion-Sakkin-Milk	NB	224.265	41.422	2.00	2.80	0.207
8	Meito	Rakuno-3.6 Milk	NB	150.802	15.008	2.60	7.80	1.039
9	Meito	Shikkari-Noko-4.4	NB	164.462	25.424	1.98	9.30	0.526
10	Yotsuba	Hokkaido-Tokachi-Karoyaka-Shibori	NB	155.957	17.828	2.46	5.20	0.642
11	Yotsuba	Tokusen-Hokkaido-Tokachi Milk	NB	209.538	34.690	2.27	8.10	0.180
12	Morinaga	Ajiwai-Dayori	NB	135.243	14.041	2.10	3.80	0.743
13	Morinaga	Makiba-No-Daichi	NB	139.765	12.227	2.06	4.10	1.075
14	Morinaga	Calcium-No-Tatsujin	NB	148.905	21.024	3.52	0.80	0.218
15	Morinaga	Makiba-No-Sora	NB	151.948	12.601	2.27	3.30	2.164
16	Morinaga	Morinaga Milk	NB	162.280	17.059	2.27	7.60	0.295
17	Morinaga	Morinaga-No-Oishi-Teishibo Milk	NB	167.777	19.625	2.29	2.40	0.266
18	Morinaga	Morinaga-No-Oishi Milk	NB	187.433	16.446	2.27	7.60	0.883
19	YukiMegu	Sukkiri-Nomeru-Ca + Iron	NB	139.194	18.518	3.40	1.20	0.825
20	YukiMegu	Mainichi-Honebuto	NB	150.527	16.628	3.40	1.90	0.741
21	YukiMegu	Nokyo Milk	NB	168.729	20.495	2.20	7.40	0.280
22	YukiMegu	MegMilk Milk	NB	182.559	25.677	2.27	7.60	1.006
23	YukiMegu	Tokuno	NB	183.533	21.756	2.27	9.10	0.642
24	Meiji	Makiba-Gokoro	NB	139.599	11.102	1.82	2.20	0.694
25	Meiji	Rabu	NB	152.786	18.646	3.50	2.40	0.992
26	Meiji	Meiji Milk	NB	163.228	20.257	2.27	7.80	0.384
27	Meiji	Oishi-Teishibo Milk	NB	182.945	20.736	2.68	2.40	0.350
28	Meiji	Irodoru-Kisetsu	NB	191.538	28.286	2.27	7.80	0.247
29	Meiji	Oishi Milk	NB	209.422	23.748	2.27	7.80	1.411
30	CGC	3.6 Milk	PB	161.446	13.948	2.27	7.80	1.074
31	Loson	Value Line	PB	100.452	14.747	2.27	7.80	0.438
32	AEON	Top-Value	PB	134.039	27.70	2.32	7.80	4.711
33	SEVEN	Magokoro-Rakuno-3.6 Milk	PB	169.761	12.093	2.27	7.80	0.397
34	SEVEN	Karoyaka-Zitate	PB	159.477	10.854	2.07	5.40	0.317
35	SEVEN	Mainichi-No-Shokutaku	PB	188.877	11.680	2.27	7.80	0.381
36	Other	Other	PB	151.452	28.860	2.32	7.80	3.058
37	Seiyu	Minasama-No-Osumitsuki	PB	157.313	11.176	2.28	7.80	0.265

Notes: 1) The average retail prices and market shares are calculated to take the weighted mean over all markets (month-prefecture) for each product.
2) ID is ordered by type, firm, and retail prices.
3) Ca and Fat denote the content of Calcium and FAT respectively. The source of these information are obtained from the website of each manufacturer or the telephone interview.

3）cooperative brands（CO-OP）. In total, the study considered 37 brands. Table 2 gives the descriptive summary after these aggregations. The most popular brand is ID 4, which is the aggregated category for “Other NB.” This category contains milk products made at local plants.

I aggregated the retail chains in the following way. First, I removed observations from the kiosk and vending machine channels, as most markets lacked those channels, at least in this scanner data. Second, I picked the top three retail chains（AEON, CO-OP delivery, Seven & i）, and aggregated the remaining channels into four different categories: 1）Home center or Discount store, 2）Drugstore, 3）Convenience Store（CVS）, and 4）Other local supermarkets. In total, there were seven retail chain categories considered in the analysis. There are many small stores in the data that lacked store-level master information, such as the chain's name. Thus, I used these for the potential market or outside option[20]. The observations used in the analysis, excluding the outside options, covered 76.3% of the total market.

2) BLP estimation

This section explains the BLP estimation method from Berry *et al.* (1995). This method can recover the unobserved heterogeneity, $\xi_{j,m}$, given parameters, and construct the moment using the recovered $\xi_{j,m}$ and instruments $h(z_{j,m}, x_{j,m})$, which do not correlate with $\xi_{j,m}$ but relate to the price. Thus, the moment equation is:

$$E(\xi_{j,m} h(z_{j,m}, x_{j,m})) = 0 \tag{14}$$

where $h(.)$ is the arbitrary function by instrument $z_{j,t}$ and exogenous variables $x_{j,m}$. Using this equation, one can estimate parameters through GMM (generalized method of moments).

To recover $\xi_{j,m}$, BLP uses the inner loop approach with contraction mapping. The steps are as follows: 1) give an arbitrary starting value for θ_2, 2) calculate the predicted share $s(x_m, p_m, \delta_m^h; \theta_2)$, 3) search mean utility which satisfies equation (3); that is, calculate $\delta_m^{h+1} = \delta_m^h + \log(S_m) - \log(s(x_m, p_m, \delta_m^h; \theta_2))$ and update $\delta_{j,m}$, and stop if $\delta_{j,m}^{h+1} - \delta_{j,m}^h$ is small enough. This inner loop approach provides $\delta_{j,m}$ as fixed points. This process is itself contraction mapping, so that a convergence to the fixed points is guaranteed under the general conditions (Berry *et al.*, 1995).

Once $\delta_{j,m}$ is calculated, it is easy to obtain $\xi_{j,m}$ by $\xi_{j,m} = \delta_{j,m} - (\beta p_{brm} + \gamma_1 Ca_b + \gamma_2 FAT_b + \alpha_b + \alpha_r)$. Therefore, using the appropriate instrument $z_{j,m}$ and moment (14), one can estimate the remaining parameters θ_1 via GMM as follows:

$$\min_{\theta_1} \xi(\theta_1)' Z W^{-1} Z' \xi(\theta_1) \tag{15}$$

where $\xi(\theta_1)$ and Z are vectors and each element is $z_{j,m}$. For the weighting matrix W, I used the two-step approach from Nevo (2001). First, I used $W = Z'Z$ as the weighting matrix for the first stage of the GMM, and then estimated the parameters θ_0. Next, using those estimates, I constructed the new weighting matrix, defined as $W = \left(\frac{1}{n}\right) \Sigma_{i=1}^n \xi(\theta_0) \xi(\theta_0)^2 Z'Z$, and used this for the second stage of the GMM. The sample size of the data was n.

3) Instrumental variables

I employed three types of instrumental variables, $z_{j,m}$, which have been widely accepted in the literature[21]. First, I utilized the average retail prices in other regional markets and for the rival's products during the same period, which are known as Hausman type instruments (Hausman, 1996). For these instruments to identify the demand primitives, the shock on the demand side must be market independent, while the supply side shock must be correlated across markets. Second, I employed the summation of the characteristics of rival products in the same market, as used in Berry *et al.* (1995) and Reynaert and Verboven (2014). It relates to the degree of price competition in each market, so it satisfies the requirement for an effective instrument. Third, I introduced supply shifters, as is typical in demand estimation.

For the supply (cost) shifters, I used gasoline prices obtained from the "*Monthly Price and Annual Average Price of the Survey Item (1L Automobile Gasoline), Retail Price Index Survey*" from the Ministry of Internal Affairs and Communications. Retail wages were calculated by dividing average retail salaries by the average hours worked. Average retail salaries and average hours worked were obtained from "*Salary to Be Paid on an Average Monthly Per Person (Wholesale and Retail Sector With More Than 29 Workers), Monthly Labor Statistics Survey*," by the Ministry of Health, Labor and Welfare. The wholesale price index for fluid milk came from the "*Corporate Price Index (Fluid Milk)*" by Japan Bank, and the raw milk price from the "*Weighted Average Over Any Usage (Yen/L), Agricultural Price Statistics Survey*" by the MAFF. As an informal check for instrument validity, I regressed the endogenous retail prices on the instruments. The F statistic was 3,934 (p-value 0.000) and the adjusted R-

20) To calculate the actual share S_{brm}, I set the market size equal to the observed total quantity in each market. Then, I derived S_{brm} by dividing the observed quantity of each product in market m by the market size. As Nevo (2001) pointed out, a model based on a BLP-type specification usually assumes that consumers purchased nothing or only one unit of the product, whereas the actual data shows multiple unit purchasing during a single shopping trip. In that case, this method of modeling becomes an approximation.

21) The strict argument about instrumental variables in BLP estimation is in Nevo (2001). Usually, researchers assume that product characteristics are exogenous, which cannot always be the case. As mentioned in Berry *et al.* (1995), that assumption is problematic, since firms adjust their product lines and characteristics in response to consumer behavior. To overcome this, we need a dynamic decision model that incorporates product line decisions into the firms' model and estimates the supply and demand sides simultaneously. The data used in this study only covered around three years, so the adjustment of product characteristics was slight and not meaningful.

squared was 0.587, so the instruments performed well.

5. Results

1) Demand estimation

Table 3 reveals that consumers hated price increases, while their degree of sensitivity to price changes varied by 0.004 standard deviations. These results suggest that there existed a statistically significant heterogeneous response to retail milk prices. Moreover, in terms of product characteristics, consumers valued the amount of fat and calcium content. From the estimates of milk brand fixed effects, consumers tended to value NB more than CO-OP, and CO-OP more than PB.

As for retail category fixed effects, every category showed statistically significant negative values compared to the base, which was other supermarket categories. This base category contained local small and medium-sized retail stores. Thus, these estimates indicated that consumers were willing to pay higher prices in local stores than in large retailers and CO-OP. Moreover, consumers had relatively smaller average utilities when they purchased milk at stores in the Home Center or Discounter categories. This means that retail price reduction can be an effective strategy for attracting customers, by compensating for their low evaluations of the stores.

Furthermore, proxies for the product range in each retail type had first order negative values and positive values in the squared term, signifying that a convex relationship existed between the level of indirect utility and the number of available products. Therefore, there were an optimal number of products available, and too much variety might have reduced consumer utility[22].

Table 3. The estimates of the BLP type demand model

	Coefficient	S.E.
Retail price		
Mean (β)	−0.037***	(0.001)
SD (σ_p)	0.004*	(0.002)
Product characteristics		
Ca (γ_1)	0.129***	(0.015)
Fat (γ_2)	0.272***	(0.004)
Brand category fixed ($\alpha_{b(bc)}$)		
NB	0.197***	(0.030)
PB	−0.490***	(0.035)
Retail category fixed ($\alpha_{r(rc)}$)		
Variety	−0.110***	(0.004)
Variety squared	0.001***	(0.001)
AEON	−1.018***	(0.021)
CO-OP (delivery)	−1.027***	(0.039)
SEVEN	−1.763***	(0.026)
Home center and discount	−2.701***	(0.028)
Drugstore	−2.068***	(0.028)
CVS	−1.548***	(0.037)
Constant (a_0)	2.437***	(0.208)
Observation	69,079	

Notes: 1) The base category of Brand Category Fixed is CO-OP, and the base category of Retail Category Fixed is Other supermarkets.
2) Standard Error (S.E.) is calculated to allow for the product and period level heteroskedasticy as in Berry *et al.* (1995) and Nevo (2001).
3) *, **, *** represent the statistical significance level for 5%, 1%, and 0.1%, respectively.

2) Own price elasticity

From the demand estimates, I calculated the price elasticity matrix for each market in order to identify the product substitution pattern. Figure 1 displays the box plot of the own-price elasticity. The range of the own-price elasticity (25% and 75% quantiles) in this study was almost equivalent to those in prior studies[23]. In addition, there was leeway even within the same brands, and the minimum value of the own-price elasticity was similar to that found in the previous literature. Besides, there was heterogeneous price sensitivity even within the brands of the same firm, suggesting that each firm promoted different price strategies by creating separate roles for each product, and composing its product portfolio to maximize its profit.

Next, I highlighted a few points for an individual brand to demonstrate how estimates could be interpreted reasonably. First, ID 29, “Meiji, Oishi Milk,” which was sold nationwide and had the one of the highest prices, had a lower own price elasticity than other

22) Generally speaking, consumer attention to food purchases is not fully rational, and the effect of product quantity on their utility is unclear. The estimates in this study suggested that an excessive number of products reduced consumer utility. This was consistent with several theoretical papers, such as Branco *et al.* (2016) and Kuksov and Villas-Boas (2009), and empirical papers, such as Sato and Niiyama (2008) and Richards *et al.* (2014).

23) Several studies have indicated that estimates of own-price elasticity (in the absolute sense) tend to be larger when they use micro instead of macro household survey data (Shono *et al*., 2000). This highlights the difference between the inter-category and intra-category substitution patterns. As for cross-price elasticity, the model used in this study did not produce negative values, in contrast to previous studies. Thus, this model reasonably explained the inter-brand substitution pattern within the milk category.

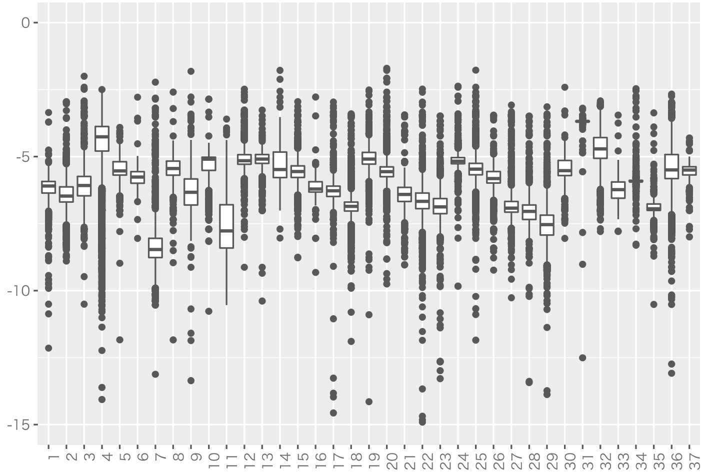

Figure 1. Box plot of the own price elasticity by brand ID

Notes: 1) The head of each box represents 25 percent quantile while the lower part of the box indicates the 75 percent quantile. The horizontal bar within each box is showing the mode.
2) Brand ID corresponds to that in Table 1.

products in its mode. One reason was that it already had such a high price that consumers tended to hate further incremental price increases. The same interpretation applied to ID 7, "Takanashi, Teion-Sakkin-Milk," which had an even higher price than ID 29. Thus, the estimates indicated that higher retail prices were not maintained because of the higher value of the brand.

ID 4, "Other NB," and ID 32, "AEON, Top-Value," had the highest degrees of own-price elasticities. In particular, the latter brand had a lower average retail price, and thus consumers had a smaller price sensitivity. In contrast, the former brand had the highest own price elasticity in the mode among the brands, and there were many observations which were below the 75% quantile. This brand was a local plant brand, and had 31% of the market share. This suggested that local small and medium-sized plants had a dominated position, with higher brand characteristics on average, although there were broad variations among them. However, this also implied that the existence of these popular local brands in every county increased the market competition among brands.

Table 4 provides the difference in own-price elasticity by milk brand type and retail category. From the brand type point of view, CO-OP had a lower own price elasticity, while PB had a higher one. From the retail category point of view, NB milk in CO-OP and CVS shops had a lower own price elasticity than CO-OP milk. Moreover, for all types of brands, CO-OP, Seven, and CVS had lower own price elasticities than average. In particular, CO-OP was a distinct channel, in that consumers decided whether they purchased the product at home through a flyer, so it may have been more price-sensitive than other channels.

Table 5 shows the trend of the own-price elasticities by channel, suggesting that they were stable over time within channels, and that consumers' price sensitivities did not vary significantly.

3) Markup

Table 6 presents a summary of estimated LI by brand level in two realistic cases: under Bertrand price competition, and under collusion[24]. The size of the markup was larger in the collusion case than in the Bertrand competition case. Numerically, the CO-OP type brands had 109%, the NB type brands had 67%, and the PB type brands had 108% greater markup under collusion than under Bertrand competition.

In terms of rankings, on average, NBs had higher markups than PBs, and PBs had higher markups than CO-OPs. This was highlighted by the fact that consumers were more price sensitive in relation to CO-OP type

24) Markup under collusion can be determined by setting each element in the ownership matrix Ω'_{jr}, as proposed in the supply model of Section 3, equal to 1.

Table 4. The own price elasticities by retail categories and brand type

Retail channel	COOP	NB	PB
AEON	NA	−5.617	−4.695
CO-OP (delivery)	−6.456	−7.063	NA
SEVEN	NA	−5.797	−5.901
Home center and discount	NA	−5.173	−3.996
Drugstore	NA	−4.587	−4.709
CVS	NA	−7.25	−5.727
Other	−5.951	−4.692	−5.394
Weighted mean	−6.297	−5.74	−5.304

Note: The first row of each cell indicates the corresponding own price elasticities, and the second row of each cell shows the corresponding market share on average.

Table 5. The trend of own price elasticities by retail channels

Retail channel	2012	2013	2014
AEON	−5.305	−5.312	−5.329
CO-OP (delivery)	−6.561	−6.53	−6.626
SEVEN	−5.872	−5.772	−5.877
Home center and discount	−4.847	−4.91	−5.152
Drugstore	−4.594	−4.58	−4.597
CVS	−6.039	−5.988	−6.047
Other	−4.768	−4.805	−4.927
Weighted mean	−5.427	−5.414	−5.508

Note: The first row of each cell indicates the corresponding own price elasticities, and the second row of each cell shows the corresponding market share on average.

Table 6. Markup ration by retail categories and brand type under different competition mode

	Bertrand price competition			Collusion		
Retail channel	COOP	NB	PB	COOP	NB	PB
AEON	NA	0.225	0.220	NA	0.395	0.470
CO-OP (delivery)	0.160	0.204	NA	0.329	0.320	NA
SEVEN	NA	0.212	0.173	NA	0.370	0.345
Home center and discount	NA	0.264	0.254	NA	0.433	0.534
Drugstore	NA	0.314	0.229	NA	0.495	0.486
CVS	NA	0.185	0.196	NA	0.329	0.417
Other	0.173	0.307	0.194	0.367	0.507	0.408
Weighted mean	0.168	0.244	0.204	0.351	0.407	0.425

Note: The corresponding share for each retail channel-brand type is in the Table 4.

brands, as I discussed above, so they tended to have lower markups. Moreover, there were similarities in several channels with respect to the size of the markups for CO-OP and PB type milk. Considering that the former had a higher retail price range than the latter, the similarity indicated that CO-OP type brands were differentiated products with higher marginal costs, while PB type brands were lower priced products with lower marginal costs.

Under collusive pricing, however, every brand can increase its markup. In particular, the rankings of the average markup changed: PB type brands had the highest average markup, instead of the NB type brands who had it under the Bertrand case. The reason behind this can be inferred from the fact that, under collusion, firms could increase retail prices even with low levels of product differentiation. Note that the estimated markup size in this study was 40% even under collusion, while U.S. breakfast cereal had markups ranging from 24.4% to 46.4%, according to Nevo (2001), and U.S. cheese had markups ranging from 10.58% to 42.6%, according to Kim and Cotterill (2008). Thus, the markup in Japanese milk from product differentiation was modest or lower[25].

Next, from the retail channel point of view in the Bertrand case, CO-OP type brands had relatively stable markups across the channel, while NB and PB type brands had varying markups across their channels. In particular, the aggregated retail category "*other supermarket*" had a high markup in NB type brands (30.7% on average). In contrast, under collusion, even CO-OP type brands had heterogeneous markup values the channel. Even so, the average markup was still higher in the traditional store formats compared to the CO-OP delivery channel, reflecting the higher price sensitivity in that channel, as mentioned above.

4) The degree of cost pass-through

In this subsection, I discuss how much of the mar-

25) I left the analysis about the apportionment of the markup throughout the supply chain, and its impact on industry structure and welfare, for future research.

ginal cost shock is passed through to the retail prices of the corresponding products. Beforehand, I conducted a few surveys with the Japanese Dairy Council based on a semi-structured interview method. From those surveys, I developed four hypotheses: ID 7, "Takanashi, Teion-Sakkin-Milk," had a higher cost pass-through than other brands (Hypothesis 1); ID 29, "Meiji, Oishi Milk," (the leading brand) had a higher cost pass-through (Hypothesis 2); CO-OP type brands, such as ID 1 "CO-OP, CO-OP Milk," ID 2 "CO-OP, Other," and the CO-OP delivery channel had higher cost pass-through (Hypothesis 3); and the Discounter and Drugstore channels had lower cost pass-through (Hypothesis 4).

The following were the results from a counterfactual simulation based on Equation (12). First of all, according to Table 7, on average, most products had a 90% cost pass-through, which was slightly below 100% and indicated not only that Hypothesis 1 and 2 were true, but also that it applied to many others[26). Moreover, the first part of Hypothesis 3 was true, since ID 1 and ID 2 also had relatively higher cost pass-throughs: 92.5% and 92.9% on average, respectively. On the other hand, ID 4, the "Other NB" category, had a far lower cost pass-through, and 11.4% of the products in that category had a less than −50% cost pass-through rate. Overall, these results revealed that the factor driving the lower cost pass-through in the milk market as a whole was caused by something within the "Other NB"[27) category.

According to Table 8, CO-OP brands sold through the CO-OP delivery channel were around the overall average, 92.82%, though they were slightly below the average. On the other hand, NB type brands, which had more market share, had a 73.70% cost pass-through rate, which was above the 68.93% average. Thus, the latter part of Hypothesis 3 was consistent with these findings.

As for Hypothesis 4, from Table 8 it is clear that the Discounters and Drugstore channels had cost pass-through rates around the overall average. The former channel was well above the overall average, 68.93%, while the latter was slightly below that of the NB type brands. Therefore, Hypothesis 4 was not suite much during the sample period, and I concluded that the degree of cost pass-through was different among those channels.

Table 9 presents the trends in the cost pass-through rates by channel. The AEON, CO-OP delivery, Seven, and CVS channels had higher cost pass-throughs than average, regardless of the timeframe. On the other hand, the other local supermarkets channel, which was the most popular channel, had a lower cost pass-through, suggesting that this channel was the potential cause of the lower rate of cost pass-through. Lastly, Figures 2 through 4 display geographical plots of the cost pass-throughs. They reveal that the average rate of cost pass-through decreases in the following order in most prefectures: CO-OP, PB, and NB type brands[28). Hokkaido, which is the largest supplier of raw milk, had a higher cost pass-through in every type. It can be inferred that neighborhood prefectures had similar rates of cost pass-through. In metropolitan areas such as Osaka and Tokyo, the cost pass-throughs tended to be lower than in the surrounding prefectures. The heterogeneity of cost pass-throughs among prefectures was largest among NB type brands.

5) Classification of the brand-retail category and the structure of cost pass-through

Here, I classify brands based on the actual or estimated competitive characteristics of each product, such as market share, own-price elasticity, LI, the level of cost pass-through, and retail price. For analysis, I used Ward's method for clustering to detect clusters of milk brands and investigate the relationship between cost pass-through rates and clusters[29).

Table 10 provides the result of the cluster analysis. There were five clusters, with the following characteristics. Cluster 1 (the Low Price with Balanced Features cluster) was composed of many reconstituted NB and PB milk brands, which had relatively large LI and pass-through rates.

Cluster 2 (the High Price with Low Markup cluster) was composed of high-priced brands such as ID 29, "Meiji, Oishi Milk." However, this cluster had lower own price elasticity, with lower LI than in other cate-

26) The interpretation of the amount of cost pass-through, around 90%, is not clear. In terms of the supply chain as a whole, below 100% pass-through could be inappropriate since it meant that the incremental cost was not fully transmitted. In this study, I only referred to the size of the cost pass-throughs in terms of the comparison among the costs themselves.

27) It would be meaningful to study these local categories more, to understand why there was such a heterogeneous degree of cost pass-through among them.

28) Matsubara (2016), through a case study on two CO-OP firms, Kyoto Seikyo and Seikatsu Club, pointed out that contracting policies varied by player, which affected the cost pass-through structure. In light of those findings, the estimates in this study implied that the differences in the cost pass-through rates were higher in milk brand types or retail firms/chains.

29) The number of clusters was fixed at five, considering the dendrogram.

Table 7. Frequency distribution of the degree of cost pass-through by brand

ID	<−50	−50−0	0−50	50−70	70−90	90−110	< 110	Total (%)	Mean (%)
1	0.000	0.000	0.000	0.000	0.501	2.306	0.000	2.808	92.493
2	0.000	0.000	0.000	0.000	0.663	3.694	0.000	4.357	92.909
3	0.000	0.000	0.000	0.000	0.122	0.310	0.000	0.433	91.201
4	11.400	1.530	0.400	0.088	0.125	36.594	0.114	50.265	12.370
5	0.000	0.000	0.000	0.000	0.070	0.396	0.000	0.465	93.894
6	0.000	0.000	0.000	0.000	0.019	0.021	0.000	0.040	88.168
7	0.000	0.000	0.000	0.000	0.065	0.224	0.000	0.289	89.726
8	0.000	0.000	0.000	0.001	0.476	0.494	0.000	0.971	87.342
9	0.000	0.000	0.000	0.000	0.159	0.343	0.000	0.502	90.056
10	0.000	0.000	0.000	0.000	0.011	0.766	0.000	0.777	97.536
11	0.000	0.000	0.000	0.000	0.018	0.112	0.000	0.130	92.062
12	0.000	0.000	0.000	0.001	0.246	0.723	0.000	0.970	92.420
13	0.000	0.000	0.000	0.000	0.190	0.999	0.000	1.189	94.201
14	0.000	0.000	0.000	0.000	0.016	0.065	0.000	0.081	93.111
15	0.000	0.000	0.000	0.000	0.662	2.567	0.000	3.229	92.917
16	0.000	0.000	0.000	0.000	0.007	0.019	0.000	0.026	91.756
17	0.000	0.000	0.000	0.000	0.132	0.256	0.000	0.389	89.605
18	0.000	0.000	0.000	0.000	0.511	1.213	0.000	1.724	90.114
19	0.000	0.000	0.000	0.004	0.310	1.564	0.000	1.878	94.049
20	0.000	0.000	0.000	0.001	0.349	1.047	0.000	1.397	92.176
21	0.000	0.000	0.000	0.000	0.066	0.182	0.000	0.249	90.430
22	0.000	0.000	0.000	0.002	0.428	1.631	0.000	2.061	91.879
23	0.000	0.000	0.000	0.000	0.175	0.596	0.000	0.770	91.396
24	0.000	0.000	0.000	0.005	0.215	0.782	0.000	1.002	92.816
25	0.000	0.000	0.000	0.000	0.513	1.529	0.000	2.043	92.125
26	0.000	0.000	0.000	0.001	0.022	0.302	0.000	0.325	95.727
27	0.000	0.000	0.000	0.000	0.142	0.401	0.000	0.543	90.695
28	0.000	0.000	0.000	0.000	0.053	0.139	0.000	0.192	90.061
29	0.000	0.000	0.000	0.001	0.651	2.020	0.000	2.671	90.343
30	0.000	0.000	0.000	0.000	0.122	0.568	0.000	0.690	93.912
31	0.000	0.000	0.000	0.053	0.084	0.308	0.000	0.446	91.447
32	0.000	0.000	0.000	0.031	1.120	4.455	0.000	5.606	93.795
33	0.000	0.000	0.000	0.000	0.075	0.341	0.000	0.416	92.081
34	0.000	0.000	0.000	0.000	0.058	0.206	0.000	0.264	91.933
35	0.000	0.000	0.000	0.000	0.093	0.336	0.000	0.430	91.133
36	0.000	0.000	0.000	0.001	1.573	6.742	0.000	8.315	93.460
37	0.000	0.000	0.000	0.000	0.435	1.621	0.000	2.055	92.706
Total (%)	11.4	1.53	0.4	0.191	10.481	75.869	0.115	100.000	−

Note: The summation of share by brand in column (9) does not match with that in the Table 2 as a few markets are excluded in the simulation analysis due to the lack of the convergence of the optimization algorithm.

gories. Therefore, this cluster was likely to have a higher marginal cost to produce and distribute milk.

Cluster 3 (the Middle Price Balanced cluster) was composed of many CO-OP brands, and had higher retail prices. This cluster showed the highest percentage of cost pass-through.

Cluster 4 (the Low Price PB cluster) was composed of only the PB brand, and had the lowest retail prices. This was mainly comprised of reconstituted milk. Other characteristics of this cluster were a higher cost pass-through rate, and LI, than in other clusters.

Cluster 5 (the Low-Cost Pass-through NB cluster) was composed of only NB brands, with a high LI, although the average pass-through rate was negative only among clusters. Therefore, in terms of the percentage of cost pass-through, this cluster was not favorable[30).

Thus, one approach to achieving both channel profit maximization and a high cost pass-through rate was to avoid enhancing the brands in Clusters 2 and 5, and to

Table 8. The degree of cost pass-through by retail categories and brand type

Retail channel	CO-OP	NB	PB
AEON	NA	80.548	93.753
CO-OP (delivery)	91.903	73.700	NA
SEVEN	NA	90.069	93.664
Home center and discount	NA	73.408	91.574
Drugstore	NA	68.262	92.183
CVS	NA	83.239	94.211
Other	94.691	13.292	92.923
Weighted mean	92.806	68.931	92.21

Note: The corresponding share for each retail channel-brand type is in the Table 4.

Table 9. The trend of the cost pass-through by retail categories

Retail channel	2012	2013	2014
AEON	82.101	85.690	85.574
CO-OP (delivery)	85.823	91.041	87.220
SEVEN	90.780	92.787	90.335
Home center and discount	74.985	81.884	71.741
Drugstore	69.614	81.073	59.257
CVS	89.934	93.272	92.151
Other	10.519	39.059	28.211
Weighted mean	71.965	80.687	73.498

Note: The corresponding share for each retail channel-year is in the Table 5.

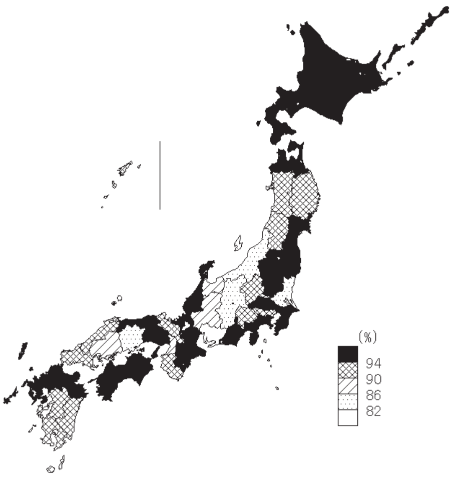

Figure 2. The degree of cost pass-through by brand type (CO-OP) in each prefecture

Note : The values are weighted mean.

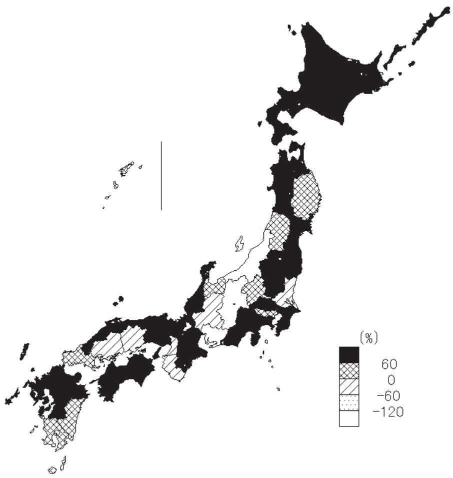

Figure 3. The degree of cost pass-through by brand type (NB) in each prefecture

Note : The values are weighted mean.

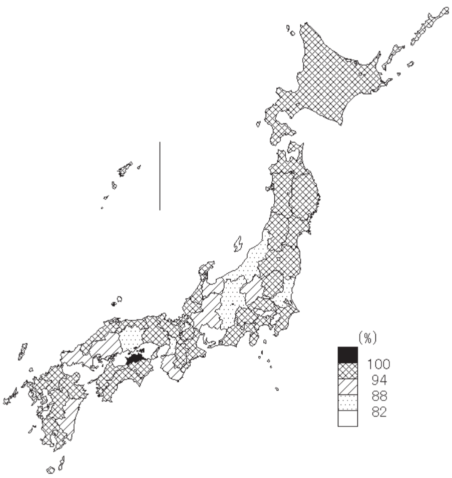

Figure 4. The degree of cost pass-through by brand type (PB) in each prefecture

Note : The values are weighted mean.

pursue milk brands in Cluster 3 and Cluster 1, which seemed to be balanced in reconstituted milk. Moreover, further detailed and individualized analysis of Cluster 5, which had an extremely low cost pass-through rate, would be required to understand its exact cause.

6. Conclusion

This paper examined market competition in the Jap-

Table 10. Summary results of clustering in terms of market competition proxies

Cluster	Type	Own-price elasticity	LI	Cost pass-through	Retail price	Share (%)
1	CO-OP	−5.785	0.178	92.425	155.968	0.001
1	NB	−5.037	0.258	77.984	144.251	33.009
1	PB	−5.106	0.205	93.133	145.116	12.804
2	CO-OP	−6.956	0.150	91.374	187.471	0.002
2	NB	−7.262	0.154	87.619	198.039	7.315
2	PB	−6.976	0.145	91.126	188.952	0.422
3	CO-OP	−6.304	0.164	92.744	175.126	7.135
3	NB	−6.392	0.161	91.838	174.176	4.354
3	PB	−5.623	0.193	94.298	160.125	4.156
4	PB	−3.972	0.254	92.788	107.849	0.801
5	NB	−4.023	0.373	−25.310	146.733	30.000

Note: The values are weighted average.

anese milk market, exploring several concerns regarding price transmission by using brand- and retail-level demand elasticity, markup ratios, and the extent of cost pass-through. I applied BLP estimation to estimate a demand function that included many products, caring for the price endogeneity originating from unobserved heterogeneity. This method provided less biased and more interpretable price elasticities. Given those demand-side primitives, this study derived the product-level markup and degree of cost pass-through for each market. This allowed the investigation of market competition indexes at the brand and retail category levels, and provided more detailed conclusions than in prior studies. Utilizing those product and market-level indexes to classify products can help managers when they consider their strategies.

The results showed that the own-price elasticities were heterogeneous by brand, even within the same firm, suggesting that each firm determined its product portfolio strategically, such as the product line and the price level. As for own-price elasticities, private label brands with lower prices had lower price sensitivities, while CO-OP brands with higher prices had higher price sensitivities. Overall, the degree of LI was not large, and the level of product differentiation was minor. As for cost pass-throughs, the simulation results revealed that most of the popular brands had higher pass-through rates, around 90%. However, there were local brands and retail chains that had negative rates of pass-through, implying that these categories were the driving force for the low degree of price transmission in the result. Applying clustering analysis based on market competition characteristics, 30% of milk products had a lower degree of cost pass-through with a higher markup ratio, due to product differentiation. In that sense, these clusters will remain. Therefore, this cluster can be potential candidates for policy targeting, in terms of the higher pass-through rate in the whole channel.

Challenges remain, however. First, the model used in this study left out profit distribution between buyers and sellers. It would be interesting to include bargaining or vertical structures in the model explicitly, as that has been one of the industry's arguments. Second, a disaggregated level demand analysis that includes demographic variables and their heterogeneity might be informative, as this study ignored those aspects. One candidate to elaborate on this demand analysis with more realistic assumptions is the multiple discrete-continuous type demand analysis in Dube (2005). By combining that method with demographic information, as in Ujiie (2005), it would be possible to identify the consumer segment that is driving such a low level of cost pass-through. Finally, considering local product preferences for milk, an extension of the demand model using spatial econometrics would be interesting. Including spatial correlation in both the demand and supply sides will be a further challenge.

30) Note that I did not insist that the low cost pass-through rate was always harmful to society, as I did not compare it to an "optimal" level of cost pass-through. For instance, if the cost pass-through rate was lower, consumers would benefit from lower prices. Therefore, an "optimal" cost pass-through rate would exist that balanced the gains and losses for both producers and consumers. However, as I pointed out in the introduction, there was a shortage of raw milk due to the low level of cost pass-through, and it caused market failures, such as butter shortage shocks. Keeping those aspects in mind, I mentioned that the estimated cost pass-through rates were lower than they should have been.

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