JOURNAL OF ECONOMIC DEVELOPMENT 69
Volume 34, Number 2, December 2009

AN ANALYSIS OF EQUILIBRIUM RELATIONSHIP BETWEEN PRICE ELASTICITY AND EXPENDITURE LEVEL: A CASE STUDY OF KOREAN MOBILE MARKET DATA

HONGJAI RHEE AND SANGKYU RHEE*

Ajou University and Chung-Ang University

In most developing countries, telecommunications industry has been grown fast and still has more growth potential than in the developed countries. Clearly the telecommunications industry contributes to foster economic developments and also to narrow the communication gaps among countries. Among many components relating to the success of quick developments of telecommunication services, an appropriate and optimal pricing strategies is the most vital element. In this view point, this paper examines the optimal price discrimination strategy for firms in a monopolistically competitive market. The primary interest is the theoretical relationship between price elasticity and the average expenditure level of consumers. Our equilibrium analysis shows that the relationship can go either way (positive or negative) depending on the prevailing price level of the product in concern. As an empirical example, using a hierarchical Bayes model we find that heavy user of mobile service are substantially more elastic to the price of calls in Korea. A discussion of the optimal pricing scheme and market structure is in order.

Keywords: Price Discrimination, Price Elasticity, Price Sensitivity, Mobile Telecommunications, Hierarchical Bayes Model
JEL classification: L10

1. INTRODUCTION

In most developing countries, telecommunications industry has been grown fast and still has more growth potential than in the developed countries. Since the telecommunication services are essential input for all the industries, it is clear that the telecommunications industry contributes to foster economic developments and also to narrow the communication gaps between countries. Among many components relating

* The authors are grateful to the anonymous referee for his/her valuable comments. All remaining errors are ours.

to the success of quick developments of telecommunication services, an appropriate pricing policy is the most vital element. Therefore it will be helpful to learn some lessons from the successful countries in telecommunication sector such as Korea which we explore in this paper. Specifically, we note that price discrimination such as in the form of various tariff options is important to lessen the payment of consumers as well as to increase telecommunication operators' profit margin.

In this view point, this paper examines the optimal price discrimination strategy for firms in a monopolistically competitive market. The primary interest is the theoretical relationship between price elasticity and the average expenditure level of consumers. In theory, monopoly and perfect competition comprise two typical market structures. In reality, however, most markets fall in between the two extremes. Most products in a market have some degree of product differentials in the supply side as well as some degree of consequential switching costs in the demand side. Nevertheless, the existing marketing practices and researches have not fully utilized this structural viewpoint. The existing marketing literature has shown a great interest in the cross-segment difference in *price sensitivity* of customers when choosing a brand or an outlet (e.g., Hoch *et al.* (1995), Bolton (1989), Kumar and Leone (1988), Allenby and Lenk (1995)) while paying much less attention on the fundamental quantity decision of how much to buy at a given price.[1] In contrast, the pricing strategy in economics literatures is mostly about price elasticity in a fairly monopolistic environment. In this environment, economics theory predicts it profitable to have the mark-up (over marginal cost) in a market segment as reverse-proportional to the price elasticity of the consumers in the segment. Thus, from a managerial perspective, it is important to apprehend who is more or less price elastic. In sum, there exists an obvious disparity of concern in economics and marketing literature. For instance, Hoch *et al.* (1995) stated that "a simple strategy for reducing promotion cost would be to have smaller price cuts in the highly sensitive stores coupled with larger cuts in the insensitive stores." On appearance, this suggestion seems contradicting the inverse elasticity rule if we adopt the usual terminological interchange of price 'elasticity' and price 'sensitivity'. As mentioned, while the primary objective in marketing literature is to use the cross-segment heterogeneity in price sensitivity to maximize the choice share of a brand in a highly competitive environment, the economic theory of inverse elasticity rule is mostly relevant for firms with a monopoly power in customers' choice of the quantity of their products.

Having this in mind, one should be careful to apply the findings drawn from a competitive environment to a monopolistic environment, and vice versa. For example, the expenditure level (or 'basket size') and the purchasing frequency of consumers are found the most significant behavioral factors for underlying differences in price sensitivity of customers (e.g., Ainslie and Rossi (1998), Bell and Lattin (1998),

[1] A striking example is Chiang (1991) in which the decisions of whether, what and how much to buy are simultaneously modeled, and applied to coffee purchasing data.

Manchanda, Ansari and Gupta (1998), Kim and Rossi (1994)). This suggests that some preference parameters are well picked up by those shopping style variables. However, the effect (not only in magnitude but even in direction) of expenditure level or purchasing frequency can be quite different if we rather focus on the quantity decision and so the price elasticity of customers.

This concern in particular as well as the widespread practice of volume-based price discounts drove us to test if there is a systematic relationship between price elasticity and the average expenditure level of consumers. Instead of directly testing it with an empirical data, we first question whether the relationship has a theoretical support. To preview, we verify under some technical conditions that the cross-segment difference in expenditure can explain the difference in price elasticity so that an optimal expenditure-based price discrimination strategy is possible. More importantly to our empirical interest, we find the equilibrium relationship between price elasticity and expenditure level is not deterministic a priori. Rather, the relationship goes either way, positive or negative, depending on the prevailing price level of a focal product and the marginal utility of the outside alternatives. Therefore the relationship can be country- and/or product-specific, and a case-specific empirical investigation is necessary. As an empirical example, we demonstrate that the relationship is strongly positive (i.e., heavy users are *more* price-elastic) for a sample data of Korean mobile telecommunication service market.

The rest of this paper is organized as follows. Chapter 2 derives the demand function for a product. An analysis shows that a theoretical but indeterminate cross-sectional relationship exists between the expenditure and price elasticity. Chapter 3 estimates a case relationship using a panel data for mobile telecommunications service in Korea. Chapter 4 discusses a managerial implication and a possible integration of price sensitivity and elasticity research in the future. Chapter 5 concludes the paper.

2. AN EQUILIBRIUM ANALYSIS

This section introduces a model to analyze the behavior of consumers and a firm. The model is based on Tirole (1988) with a modification to our objective to establish a theoretical link between the price elasticity and the size of demand.

2.1. Model

Let q_i be the individual *i*'s quantity demanded for the product (or service) of concern. Let *p* be the price for unit of consumption, *r* the fixed access charge to the product. Employing the utility function in Tirole (1988), individual *i*'s preference is as follows.

$$W_i(T_i, q_i) = U(M_i - T_i) + V_i(q_i)\ , \tag{1}$$

where M_i denotes individual i's income, and $T_i = r + pq_i$ denotes the expenditure on q_i. It is assumed that

$$U(0) = 0, \quad U' > 0, \quad U'' < 0, \quad V_i(0) = 0, \quad V_i' > 0, \text{ and } V_i'' < 0. \tag{2}$$

If T_i is much smaller than M_i (i.e., the expenditure on this particular good is small relative to income),[2] then the preference on (T_i, q_i) can be approximated as follows:

$$W_i(T_i, q_i) = \theta_i V_i(q_i) - T_i\,, \tag{3}$$

where $\theta_i = \dfrac{1}{U'(M_i)}$ represents inverse of the marginal utility of income.[3] Tirole (1988) attributed the heterogeneity of consumers only to their different income levels (i.e., difference in θ_i) assuming no difference in the functional form of $V_i(q)$ in (3). In fact, this is equivalent to assuming that all individuals have the same preference to the product. More generally in this paper, we extend the model to allow consumers different not only in θ_i but also in their preference to the service such that

$$V_i(q) = \frac{q^{1-\sigma_i} - 1}{1-\sigma_i}. \tag{4}$$

This functional form is very popular in macroeconomic analysis (e.g., Blanchard and Fisher (1989)) and is also adopted by Laffont *et al.* (1998) to discuss the consequence of price discrimination in network industry. For $V_i' > 0$ and $V_i'' < 0$, we should restrict the range of σ_i to (0,1). In sum, consumer i is now represented by the pair of parameters,

[2] In this article, we analyze Korean mobile telecommunication service. Thus T_i represents monthly expenditure on mobile service. In 2007, the ratio of total expenditure on telecom services (fixed line services, broadband internet service, mobile services, value-added services) to household-income is 4.18%. Since the ratio of expenditure on mobile services to household-income is lower than 4.18%, we can say that this condition holds.

[3] A first-order Taylor expansion of Equation (1) with respect to variable T_i around M_i yields Equation (3): $W_i(T_i, q_i) = U(M_i) + U'(M_i)[(M-T)-M] + V_i(q_i) = U'(M_i)\left\{\dfrac{U(M)}{U'(M_i)} - T + \dfrac{1}{U'(M_i)}V_i(q_i)\right\}$. Therefore we get $W_i(T_i, q_i) = U'(M_i)\{v_0 + \theta_i V_i(q_i) - T\}$, where $v_0 = \dfrac{U(M)}{U'(M_i)}, \theta_i = \dfrac{1}{U'(M_i)}$.

(θ_i, σ_i). For brevity of exposition, we further employ a discrete type of customers in each parameter such that

$$\theta_i \in \{\theta_L, \theta_H\}, \quad \sigma_i \in \{\sigma_L, \sigma_H\} \quad \text{for} \quad i = 1, 2, \ldots, I, \tag{5}$$

where $0 < \theta_L < \theta_H$ and $0 < \sigma_L < \sigma_H < 1$. Then the consumers are classified into four distinct types (or segments): $i \in \{I, II, III, IV\}$, where $I = (\theta_H, \sigma_L)$, $II = (\theta_L, \sigma_L)$, $III = (\theta_H, \sigma_H)$ and $IV = (\theta_L, \sigma_H)$.

One advantage of the above specification is that the parameter σ is related to the price elasticity as one-to-one basis. To see this, we derive the optimal level of consumption q_i^* for the given price of (r, p) as

$$q_i^*(p) = \arg \ \max_q \ \theta_i \frac{q^{1-\sigma_i} - 1}{1 - \sigma_i} - r - pq. \tag{6}$$

And solving (6) results in the following demand function

$$q_i^*(p) = \left(\frac{\theta_i}{p}\right)^{\frac{1}{\sigma_i}}. \tag{7}$$

So, $1/\sigma_i$ amounts to the constant price elasticity so that the consumer with higher σ_i turns out *less* price elastic.

2.2. Price Discrimination Strategy

As mentioned before, our main question is whether there exists a systematic cross-segment link between the price elasticity ($1/\sigma_i$) and the quantity demanded (q_i^*). Obviously, Equation (7) tells that the relationship hinges on the marginal utility of income (θ_i) and the prevailing price (p).

Figure 1 displays typical demand schedule of each consumer segment according to Equation (7). In order to price discriminate, a firm should be able to separate consumer segments with different price elasticities on the observable ground. The following proposition makes it possible to use the average size of the demand (or expenditure level) as a proxy for the price elasticity but only in some circumstances:

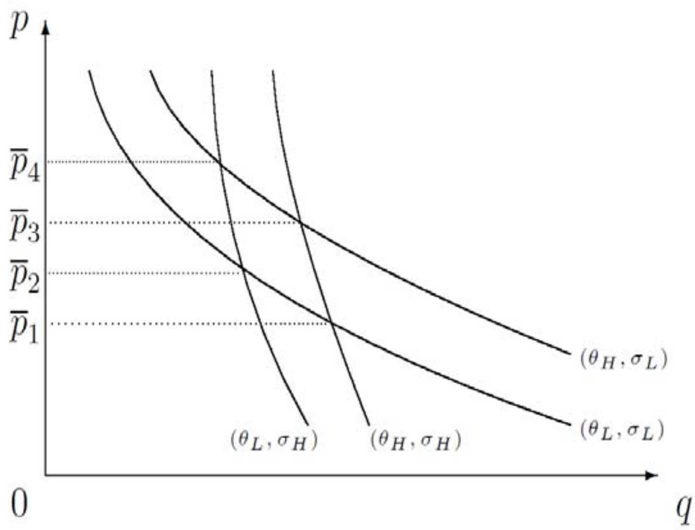

Figure 1. Illustration of Demand Functions for Each Segment

Proposition 1. Regardless of θ_i, the high-demand segments are more price elastic if the price level is below $\overline{p}_1 = \theta_L \left(\frac{\theta_L}{\theta_H}\right)^{\frac{\sigma_L}{\sigma_H - \sigma_L}}$, or less price elastic if the price above $\overline{p}_4 = \theta_H \left(\frac{\theta_H}{\theta_L}\right)^{\frac{\sigma_L}{\sigma_H - \sigma_L}}$. No systematic relationship holds otherwise.

Proof. The threshold price level ($\overline{p}_k$) in Figure 1 can be obtained by the pair-wise equality of the type-specific demands such that

$$\overline{p}_1 = \theta_L \left(\frac{\theta_L}{\theta_H}\right)^{\frac{\sigma_L}{\sigma_H - \sigma_L}},\ \overline{p}_2 = \theta_L,\ \overline{p}_3 = \theta_H,\ \overline{p}_4 = \theta_H \left(\frac{\theta_H}{\theta_L}\right)^{\frac{\sigma_L}{\sigma_H - \sigma_L}}.$$

The claimed relationship between price elasticity $\left(\frac{1}{\sigma_i}\right)$ and the size of demand is evident from Figure 1. ■

If this is the case, what will be the best price discrimination strategy from firm's perspective? Clearly, it will depend on the current price level utilizing Proposition 1 such as follows.

Corollary 1. It pays to increase firms' profit to discriminate price in favor of high-demand segments (i.e., heavy users) if the current price level is below $\overline{p}_1$, or in favor of low-demand segments if the current price is above $\overline{p}_4$.

Proof. To maximize profit, the firm must apply the inverse elasticity rule such that the price is set reverse-proportional to the price elasticity of each segment. More formally, the first-order condition for profit maximization ends up with $p_I^* = p_{II}^* = \dfrac{c}{1-\sigma_L}$, $p_{III}^* = p_{IV}^* = \dfrac{c}{1-\sigma_H}$ where p_j^* denote the optimal price for segment $j \in \{I, II, III, IV\}$ and c the marginal cost.[4] Due to the relationship between price elasticity and the size of demand as in Proposition 1, the corollary holds. ■

Summing up, the bottom line prediction is that the quantity-oriented price discrimination is relevant only in certain circumstance, and the direction of profitable discrimination can go either way depending on the prevailing price level of the focal product. In fact, the empirical relationship can vary depending on the competitive market environment, product lifecycle[5], and many others that affect the price levels. And this calls for a careful investigation before employing an expenditure-based price discrimination strategy in practice.

3. EMPIRICAL FINDINGS

We now proceed to an empirical model to explore a case relationship between price elasticity and the average expenditure of consumers. We select the mobile telecommunications services in Korea because of data availability and also with a concern that the mobile operators in particular require a smart pricing strategy against the trend of market saturation and continual pressure on regulatory or competitive tariff reduction. In addition, the Korean mobile market makes a good case of the monopolistic industry structure at least for the sample period in our dataset. While three firms compete with differentiated service and marketing activities, consumers bear a substantial churning cost arising from the absence of handset and number portability[6] as well as the loss of loyalty benefits such as accumulated mileages.

It is interesting to note that this empirical relationship in mobile industry was

[4] It is note worthy that the type-difference in θ (i.e., marginal utility of income) does not matter in the optimal price discrimination strategy. It simply drops out of the first-order condition.

[5] If the price level tends to decline over the life cycle of a product, one can also argue that the relationship is likely to be positive in the long run.

[6] The mobile number portability has begun only in 2004 after the end of the sample period, and switchers are still subject to the handset incompatibility among operators.

exploited in Jain, Muller and Vilcassim (1999). To explain why the mobile tariff level in U.S. is stable in contrast to the rapid downturn of the handset price in the late nineties, they postulated that mobile consumers consist of high- and low-usage segments in which the higher-use segment is more sensitive to the price of phone calls. This assumption was backed up by a conjoint analysis to a focused group of consumers. Obviously, we do not attempt to challenge or validate this finding. Nonetheless, we believe that our empirical study using an actual panel consumption data could provide a better support to their proposition too if found consistent.

3.1. Specification

We begin with the demand function derived in Equation (7):

$$\log q_{it} = \alpha_i + \beta_i \log p_{it} + \varepsilon_{it}, \quad i = 1,\ldots,I; \quad t = 1,\ldots,T. \tag{8}$$

Using the logarithm in Equation (7) and comparing with Equation (8), α_i denotes individual difference in preference (or in income), and β_i denotes the negative price elasticity such that

$$\alpha_i = \frac{\log \theta_i}{\sigma_i}, \quad \beta_i = -\frac{1}{\sigma_i}, \quad i = 1,\cdots,I. \tag{9}$$

The error term ε_{it} is assumed to follow an independent normal distribution N($0,\chi^2$). To allow consumer heterogeneity in elasticity in most flexible way (e.g., Allenby and Rossi (1999)), we use a hierarchical random effect Bayes model which is popularly utilized in recent marketing literature such as in Rossi, MuCulloch and Allenby (1996) among many others. That is, we assume

$$[\alpha_i, \beta_i] \sim N(X_i'\delta, \Sigma), \quad i = 1,\cdots,I, \tag{10}$$

where X_i denotes $1\times K$ vector of K demographic covariates of consumer i including intercept, δ $K\times 2$ parameter matrix of the marginal impact of demographics in X_i to the mean of heterogeneity in either in α (the 1st row) or in β (the 2nd row), and Σ denotes 2×2 variance-covariance matrix of (α_i, β_i), respectively.

3.2. Data

We use a monthly panel data of 2298 sample customers of a mobile operator in Korea. The Korean mobile telecommunication service market has rapidly grown to about 47 million subscribers as of June 2009 comprising almost 95% of total population. The panel data records the amount of voice calls (in billing unit of 10 seconds) for 21 months from August 2000 to April 2002, and demographic information on sex and age of the panelists. It is important to note that each panelist in the data uses the same tariff plan (namely the standard tariff). Therefore, we worry little about a possible self-selection of consumers regarding to their preference to particular tariff plans.

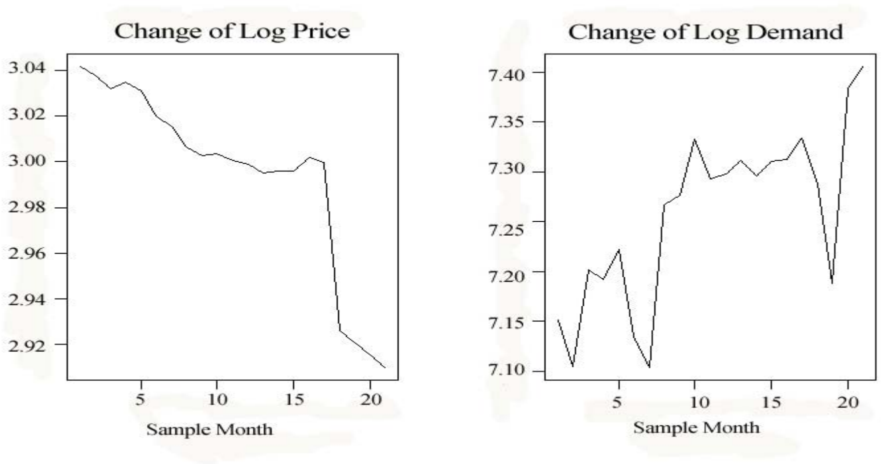

Figure 2. The Average Change of Mobile Price and Demand (in log scale)

To construct a price measure (per 10 second voice calls), we computed a real price index for each month using the available nominal prices[7] and the consumer price index (CPI). Figure 2 displays the month-to-month variation of the real price index (in log scale). In short, we note that the price gradually decreases over the sample period except a prominent break in the month #18 (Jan 2000). Because every consumers use the same standard tariff plan during the entire sample period, it should be noted that the individual price measure (p_{it}) in Equation (8) becomes identical across every sample consumer in our data such as $p_{it} = p_t$.

For the demand variable (q_{it}), we take the log units of voice calls (in 10 seconds) made by each panelist for each month. Meanwhile, as clear in the average demand profile in Figure 2, an apparent seasonal variation was noticed in the data particularly in

[7] In fact, the operator provides different rates for day time, night time, and weekends. With a known distribution of calls, we computed a weighted average of the rates.

February (with fewer days) and the months with big holidays (January and August by lunar calendar). Therefore, we adjusted the quantity variables by the exact number of working days in a month (with 30-day standard).[8] The other key variable is the average quantity demanded (denoted as $\bar{y}_i$) of each panelist during the sample period. We constructed this variable by taking the sample average of the number of voice calls for the entire sample period. Figure 3 displays the histogram of the average quantity across panelists.

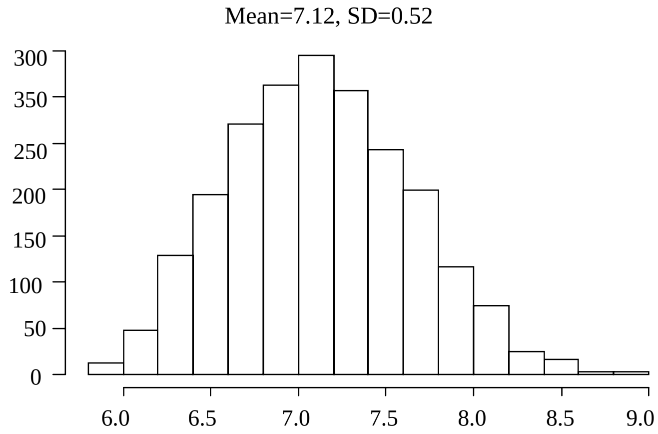

Figure 3. The Histogram of Average Log Demand per Month Across Panelists

In sum, the demographic covariates X_i in Equation (10) includes four variables including intercept, $\log(\bar{y}_i)$, $sex_i = 1$ if male, and $\log(age_i)$ in turn. Of course, the other covariates such as individual income level may play a key role in determining price sensitivity of mobile consumers. Due to data limitation, we could not sufficiently control for possible omitted variable biases. Technically, we subtracted the means from each non-intercept variables to have the intercept parameter interpreted as (α_i, β_i) of the average panelist in the sample.[9] Of primary concern is the regression coefficient between the average expenditure ($\log(\bar{y}_i)$) and the price elasticity (β_i).

[8] This adjustment turned out to increase the magnitude of price elasticity a little bit. However, we verified that our main finding is qualitatively intact.

[9] The mean subtraction procedure was suggested in Rossi, Allenby and MuCulloch (2005).

3.3. Estimation

The likelihood function for Equation (8) contains many individual parameters (α_i, β_i). Furthermore, the individual parameters are possibly correlated with each other by the random effect specification in Equation (10). Our objective is to estimate the predictive distributions of the hyper parameters in Equation (10), δ and Σ, as well as the individual parameters of 2,298 sample consumers in our data. Therefore, the joint likelihood seems hard to evaluate analytically. To sidestep this difficulty, we use a Markov Chain Monte Carlo (MCMC) method which becomes popular in the recent marketing literature (e.g., Rossi, Allenby and McCulloch (2005)).

To implement a Bayesian hierarchical model, it is necessary to specify a prior distribution of the hyper parameters in the bottom of the hierarchy, i.e., χ^2, δ and Σ. As usual, we employ quite diffuse but proper priors for the hyper parameters to make the impact of prior as small as possible. Specifically, we used R program language, and worked with the 'hierarchical Bayes model' included in the 'bayesm' package developed by Rossi, Allenby and McCulloch (2005). In what follows, all results summarize 1000 posterior draws of each parameter with 1000 burn-ins and 5 thinning interval of sequences. To diagnose the convergence of the sampler, we verified the posterior descriptive statistics vary little with the number of sequences after the initial burn-in period.

3.4. Result

Table 1 summarizes the estimated posterior distribution of parameters (means and standard deviations in parenthesis). The average of constant elasticity demand function was estimated to have the intercept of 10.91 and the slope (price elasticity) of -1.20 with strong significance. For demographic effects, the sex and age do not give significant effects on the demand parameters. In contrast, the average log expenditure of panelists turned out to increase the demand intercept (3.36) and to make the price elasticity even more negative (-0.792). The latter finding *per se* clearly tells about our primary concern such that the heavy mobile users are more likely to have high price elasticity. The unobserved heterogeneity in individual demand parameters is profound as can be seen from the estimates of Σ, and this is probably due to poor performance of the demographic covariates except the log expenditure.

Focusing on the key parameters of interest, Figure 4 displays the posterior kernel densities of the average price elasticity (left panel), and of the effect of log expenditure on the price elasticity (right panel). Because the priors are selected as conditional conjugate to the likelihood, both posterior densities look very similar to the normal curvature.

Table 1. Mean and Standard Deviation of Posterior Distribution of Parameters

Parameters	Covariates effect on the demand parameters (δ)			
	Constant	Log(expenditure)*	Male=1*	Log(age)*
Demand Intercept (α_i)	10.908** (0.25)	3.367** (0.47)	0.271 (0.58)	-0.345 (1.46)
Demand Slope (β_i)	-1.198** (0.08)	$\boxed{-0.792^{**}\ (0.16)}$	-0.089 (0.19)	0.125 (0.49)
SD(α_i) $= \sqrt{\Sigma_{1,1}}$	10.060** (0.22)			
SD(β_i) $= \sqrt{\Sigma_{2,2}}$	3.362** (0.07)			
Cov(α_i , β_i) $= \Sigma_{1,2}$	-33.83** (1.50)			
SD(ε_i) $= \sqrt{\chi^2}$	0.091** (0.03)			

Notes: * These variables were subtracted from their means. ** The 95% posterior interval does not include zero.

Finally, it is noteworthy that our empirical finding is in line with the conjoint analysis of Jain, Muller and Vilcassim (1999) for U.S. mobile services. However, as our model predicts that the relationship can go either way depending on the prevailing price of the product in a country, this analogy may be a coincidence.

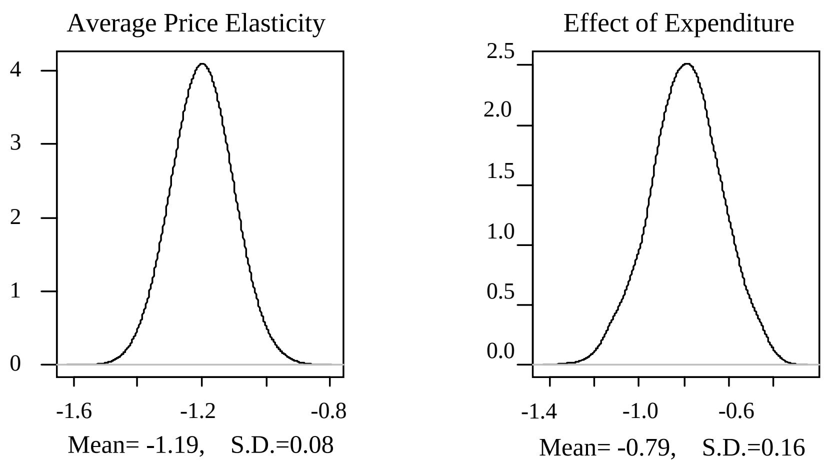

Figure 4. The Posterior Kernel Density of Key Parameters

4. DISCUSSION

So far, we proposed that the theoretical relationship between price elasticity and expenditure level can go positive, neutral or negative depending on the characteristics of the focal product, and then demonstrated a positive case with an example data for Korean mobile telecommunication service market. Let alone our two way theoretical predictions, the empirical finding can help to boost the profit of mobile operators in devising a consistent price differentiation or segmentation strategy. However, it is also noteworthy that the empirical finding seems in contrast to those in the previous shopping behavior literature in marketing. For example, Bell and Lattin (1998) showed that large-basket shoppers tend to be less ‘sensitive’ to a category-level price promotion when choosing retailers. However, one should remind the disparity of concerns in price *elasticity* and *sensitivity* literature as was highlighted before. While the marketing literature focuses mostly on the choice of a supplier in highly competitive environment, our elasticity study in this paper is more valid for the choice of quantity for a given supplier in a monopolistic environment with substantial product differentiation and switching cost.

One may argue that the inverse elasticity rule we explored in this paper only works for a pure monopoly case. On the other hand, we contend that the empirical scope of monopolistic price strategy goes beyond it. In reality, there is no distinctive borderline between monopoly and competition. To avoid unsustainable price competition, most products in a market are differentiated in a variety of dimensions such as brand, quality, distribution channel and many others. In addition, consumers bear a substantial switching cost (both in economic and psychological sense) which hinders them from churning for a small price gap among alternatives. Therefore, we believe our analysis in this paper can be applied to a broad range of monopolistically competitive markets in the field. More generally, though it seems quite interesting to extend our analysis to more competitive environment through a simultaneous parameterization of the switching cost and price elasticity, this is left a fruitful research track to proceed.

5. CONCLUSION

Knowing the cross-segment heterogeneity in price elasticity of consumers makes it profitable to devise a relevant price discrimination strategy for a firm in a monopolistic market. The bottom line suggestion is to give relatively deeper discounts to the consumers of higher price elasticity. Despite the simplicity of this guideline, the price elasticity of demand has not been fully utilized in the previous marketing literature as compared to substantial emphases on the price sensitivity in choosing a brand or a store. Probably, this is mostly because the literature has postulated substantially competitive business environment. In this paper, we alternatively contended that the empirical relevance of the inverse elasticity rule goes beyond the pure monopoly case. If with substantial product differentiation and/or switching costs in the market, firms would price discriminate across segments based on a reliable proxy of the price elasticity. Unlike the conventional pricing practice in favor of heavy users, our theoretical model predicts that expenditure and price elasticity can be correlated to either direction depending on the prevailing price level of the focal product. Therefore, a careful case-by-case investigation is necessary.

REFERENCES

Ainslie, A., and P.E. Rossi (1998), "Similarities in Choice Behavior across Product Categories," *Marketing Science*, 17, 92-106.

Allenby, G.M., and P.J. Lenk (1995), "Reassessing Brand Loyalty, Price Sensitivity, and Merchandising Effects on Consumer Brand Choice," *Journal of Business and Economic Statistics*, 13, 281-289.

Allenby, G.M., and P.E. Rossi (1999), "Marketing Models of Consumer Heterogeneity," *Journal of Econometrics*, 89, 57-78.

Bell, D., and J. Lattin (1998), "Shopping Behavior and Consumer Preference for Store Price Format: Why Large Basket Shoppers Prefer EDLP," *Marketing Science*, 17, 66-88.

Blanchard, O.J., and S. Fisher (1989), *Lectures on Macroeconomics*, The MIT Press.

Bolton, R. (1989), "The Relationship between Market Characteristics and Promotional Price Elasticities," *Marketing Science*, 8, 153-169.

Chiang, Jeongwen (1991), "A Simultaneous Approach to Whether, What and How Much to Buy Questions," *Marketing Science*, 10, 297-315.

Hoch, S., B-D. Kim, A. Montgomery, and P. Rossi (1995), "Determinants of Store-Level Price Elasticity," *Journal of Marketing Research*, 32, 17-29.

Jain, D., E. Muller, and N.J. Vilcassim (1999), "Pricing Patterns of Cellular Phones and Phones and Phone Calls: A Segment-level Analysis," *Management Science*, 45(2), 131-141.

Kim, B-D., and P. Rossi (1994), "Purchase Frequency, Sample Selection, and Price Sensitivity: The Heavy User Bias," *Marketing Letters*, 5, 57-68.

Kumar, V., and R. Leone (1988), "Measuring the Effect of Retail Store Promotions on Brand and Store Substitution," *Journal of Marketing Research*, 25, 178-186.

Laffont, J-J., P. Rey, and J. Tirole (1998), "Network Competition II: Price Discrimination," *Rand Journal of Economics*, 29, 38-56.

Manchanda, P., A. Ansari, and S. Gupta (1998), "The Shopping Basket: A Model for Multicategory Purchase Incidence Decisions," *Marketing Science*, 18, 95-115.

Rossi, P., R.E. McCulloch, and G. Allenby (1996), "The Value of Purchase History Data in Target Marketing," *Marketing Science*, 15, 321-340.

_____ (2005), *Bayesian Statistics and Marketing*, NJ: Wilie.
Tirole, J. (1988), *The Theory of Industrial Organization*, MIT press.

Mailing Address: Sangkyu Rhee; Department of Economics, Chung-Ang University, 221 Heuksuk-Dong, Dongjak-Gu, Seoul, Korea. Tel: 82-2-820-5519. E-mail: skrhee@cau.ac.kr

Received August 24, 2009, Revised November 5, 2009, Accepted November 23, 2009.