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Investigating Behavioral Explanations for Asymmetric Price Competition

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ABSTRACT

Asymmetric price competition in consumer packaged goods is a well-known phenomenon. Researchers have proposed three behavioral explanations: (1) heterogeneity in consumer preference, (2) the income effect, and (3) the reference and loss-aversion effects. These explanations have been offered independently by different researchers using different types of data with different methodology. Despite the interest in asymmetric price competition by the marketing community, no attempt has been made to compare across the three explanations and draw an inference on which one is most likely.

The objectives of this paper are three-folds. Firstly, important factors when studying asymmetric price competition are discussed. These include, (1) confounding of the supply-side and demand-side factors when analyzing aggregate data, such as market share, and (2) an appropriate measure for asymmetric price competition as the change in market share of a brand for a unit price change of a competing brand. Second, based on these considerations, theoretical arguments against previous explanations are provided.

(1) The Heterogeneity Effect: Aggregate data is analyzed and cross-price elasticity is used. The explanation is inferred indirectly.

(2) Income effect: Infinite divisibility of goods is assumed.

(3) Loss-aversion effect: Household heterogeneity is not well accounted for.

These claims are then supported empirically using scanner-panel data from four categories. Third, an alternative explanation is proposed to show that a basic assumption of consumer utility in Microeconomic theory, the diminishing-marginal-return effect in price, results in asymmetric competition. It was shown that the concavity (i.e., the diminishing-marginal-return effect) in price was stronger than that of logarithm in all four product categories.

Keywords: Price competition, Buyer behavior, Choice models, Heterogeneity

1. INTRODUCTION

For many consumer packaged goods, researchers have shown that competition among products of different quality within a category is asymmetric: price promotion by a higher quality brand draws significant share from lower quality brands, whereas price promotion by a lower quality brand has much less effect on higher quality brands (Sivakumer and Raj 1996). Carpenter et al. (1988) and Russell and Bolton (1988) demonstrated asymmetric competition empirically by using aggregate share and sales models. The DEFENDER model by Hauser and Shugan (1983) infers an asymmetric competitive pattern by assuming a Lancaster-type tradeoff among product attributes that are uniformly distributed across consumers. However, competition is limited to adjacent products in the attribute-per-dollar perceptual map (Shugan 1987; Waarts, Carree, and Wierenga 1991). Kamakura and Russell (1989) observed an asymmetric pattern between national brands and private-label brands of detergent. Blattberg and Wisniewski (1989) showed asymmetric competition between different price-tier brands with an econometric model using store-level sales data.

Though such asymmetric patterns might be a result of several forces at work simultaneously, they can be classified into two groups, supply-side and demand-side factors. The supply-side factors are associated with asymmetry in the efficacy of marketing activities by sellers. For example, many high-quality high-priced brands (e.g., Coke, Tide, Tropicana, etc.) are sold by leading national manufacturers that have more market power, money, and resources than their competitors. The fact that such firms can obtain better information about the market, provide better control over channels and retailers, and conduct more effective promotion and advertising leads to asymmetric competition. The demand-side factors are associated with buyer behavior, and several alternative explanations were proposed by past researchers as will be described shortly.

Because many factors from both supply and demand sides are confound with each other, the aggregate analysis may not always exhibit the pattern of asymmetric price competition. Existing empirical studies based on aggregate data, such as estimating cross price elasticity, produced mixed results, failing to converge on empirical generalization, while some even question asymmetric price effect (Blattberg and Wisniewski 1989, Bronnenberg and Wathieu 1996, Sethraman, Srinivasan and Kim 1999, Sethraman and Srinivasan 2000).

To disentangle these confounding factors, we concentrate on demand-side behavioral factors that might affect asymmetric price competition. Because competition --- a macro-level phenomenon caused by purchasing pattern of individual consumers --- is contaminated by supply-side factors, descriptive study using aggregate sales data offers little insight for our purpose. Micro-level analysis of consumers' brand choice behavior, either with household-level disaggregate data or by laboratory experiment, is warranted to understand the underlying buyer behavior that is responsible for asymmetric competition. We will pursue the former approach by analyzing scanner panel data that contain household-level brand switching information in a field setting.

Previous study suggested that strength of the asymmetric phenomenon is greatly affected by the precise definition of "price competition" whether it refers to the effect of either absolute or relative price change on either absolute or relative sales or share change. For example, Sethraman, Srinivasan, and Kim (1999) found that asymmetry tends to disappear when cross-price elasticity is replaced by absolute cross effect. Because the formula for elasticity involves share and price in the denominator, its magnitude is confounded by the absolute size of brands' market share and price level. Following other researchers, when assessing asymmetry, we assert that focusing on elasticity is not appropriate and define cross-price effect as change in market share of a brand for a unit price change of a competing brand (Mela, Gupta and Lehmann 1997, Sethraman, Srinivasan, and Kim 1999, Sivakumar and Raj 1997).

The corresponding definition at the household level is change in the choice probability of a brand for a unit price change of a competing brand.

Three behavioral explanations have been have been offered independently by different researchers using different types of data with different methodology.

1. *Heterogeneity in consumer preference:* Blattberg and Wisniewski (1989) postulated a utility-based model of individual consumer choice with heterogeneous preference, whereby an asymmetric pattern of competition could arise when choices of individuals are aggregated. From the asymmetric pattern of competition observed with an aggregate sales model, they conjectured the shape of the preference distribution across consumers.

2. *Income effect:* On the basis of microeconomic theory, Allenby and Rossi (1991) proposed that consumers' preference shifts toward higher quality brands when their purchasing power is increased due to temporary price reduction (i.e., the income effect). Such a shift results in asymmetric switching whereby switching up to high quality brands is more likely than switching down. The researchers formulated a choice model using a rotating indifference curve to capture the brand-specific income effect, and validated the model with scanner-panel data.

3. *Loss-aversion effect:* Prospect theory (Kahneman and Tversky 1979) postulates that consumers perceive losses from a reference point to be larger than gains of the same amount. Hardie, Johnson, and Fader (1993) suggested that, under loss-aversion for price and quality, the slope of an indifference curve (for price and quality) depends on whether it is evaluated in the region of a gain or loss in price and quality relative to the consumer's reference point. In particular, the amount of quality traded for a given level of price reduction is larger for superior brands (located in the quality-gain and price-loss region relative to a reference brand) than for inferior brands (located in the quality-loss price-gain region relative to a reference

brand). Its implication is that the same price cut is perceived to be more favorable for high quality brands than for low quality brands, offering a psychological explanation for asymmetric switching. Using scanner-panel data, they calibrated a choice model that demonstrated loss-aversion effect on price and quality attributes.

Despite the interest in asymmetric price competition by the marketing community, no attempt has been made to compare across the three explanations. In this study, I will investigate the above three explanations on the common ground and propose an alternative explanation --- the decreasing-marginal-return effect in price.

4. *Decreasing marginal return effect:* Many consumer utility models assume decreasing marginal return, whereby incremental utility for a unit increase in the attribute quantity decreases as the absolute level of that attribute increases. This translates to a concave diminishing-return utility function of the attribute, and it is sometimes referred to as a risk averse utility function. It is a common and weak assumption that most researchers posit it in their utility models without even questioning.

The paper is organized as follows. First, a brief literature review is presented in Section 2. Then, the following three sections investigate the existing explanations, the heterogeneity, income, and loss-aversion effects, respectively. In each section, the rationale for the original explanation is reviewed, its limitation is described, then the effect is re-examined with actual scanner-panel data. The study concludes that all three existing explanations have difficulty explaining asymmetric pattern of price competition. In Section 6, an alternative decreasing-marginal-return effect is proposed and its role in asymmetric price competition is explained, followed by its empirical support. The final section summarizes the conclusions and discusses the managerial implications.

2. PREVIOUS FINDINGS

Study in psychology, which started the stream of reference price research in marketing, demonstrated the reference and loss-aversion effects repeatedly for single and multiple attributes through experimentation (Kahneman and Tversky 1979, Tversky and Kahneman 1991). In marketing, loss-aversion effect for price and quality as well as the asymmetric switching phenomenon were supported by both laboratory experiments (O'Curry and Lovallo 1996) and field study using scanner panel data (Bronnenberg and Wathieu 1996). The latter researchers not only reconfirmed the existence of the reference and loss-aversion effects in the framework of Hardie, Johnson, and Fader, but also investigated additional conditions which competing brands must satisfy in order to exhibit the asymmetric pattern that favors higher quality brands. Other field studies using scanner-panel data also confirmed the reference and loss-aversion effects for a single attribute of price (Kalyanaram and Little 1994; Kalwani, Yim, Rinne, and Sugita 1990; Lattin and Bucklin 1989; Mayhew and Winer 1992, Winer 1986). Recently, however, Bell and Lattin (2000) showed that the previously observed loss-aversion effect in scanner panel data is an artifact arising from not accounting for consumer heterogeneity in price responsiveness. Based on analysis of scanner panel data from eight categories in consumer-package goods, they found that the loss-aversion effect tends to disappear when price heterogeneity is accommodated by a latent segment model. This is a big news invalidating all of the aforementioned scanner panel studies that found the loss-aversion effect because none of them captured heterogeneity in price sensitivity across households. Suddenly, the explanation by the loss-aversion effect became doubtful.

What about the heterogeneity and income explanations? Apparently, no studies either supporting or rejecting those explanations have been reported. Therefore, current research was undertaken to re-examine whether the heterogeneity and income effects can be reasons for asymmetric competition.

The heterogeneity explanation is supported by the fact that price elasticity predicted by heterogeneous choice models, such as latent segment and random coefficient logit models whose choice elasticity within a homogeneous segment is symmetric, is no longer symmetric when segments are aggregated.[1] Blattberg and Wisniewski conjectured that heterogeneity in consumer preferences must have a bimodal shape for the asymmetric pattern to be consistent with price-tier competition, whereby high priced brands have stronger influence on lower priced brands than vice visa. In the current research, the shape of a preference distribution is obtained directly from the estimate of household-specific preferences using household-level choice data. The results from four product categories suggest that it is single modal, and thus the heterogeneity effect cannot explain asymmetric competition. The methodology to estimate the shape of a preference distribution by itself is of interest to academic researchers. Many choice models make use of consumer heterogeneity on the basis of a certain distributional assumption (typically a uniform distribution), which drives the result and hence its marketing implication of these studies (Hauser and Shugan 1983; Raj, Srinivasan, and Lal 1990; Rao 1991; Sethuraman 1996).

A motivation to re-evaluate the income explanation comes from an innocuous question: will a price cut of 20 to 30 cents change consumers' preference? In Marketing, "preference" is one measure of buyer attitude, which is considered to be enduring and persistent over time --- something that does not change readily by temporary price promotion (Churchill 1995, p.454; Kotler 1988, p.190; Lilien, Kotler and Moorthy 1992, p.27). In Economics, the income effect is often applied in the context of consumption shift from one product category to another, such as from bread/potato to meat as income goes up. Can we apply the standard income effect formulation of microeconomic theory to consumer packaged goods? The nonhomothetic

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[1] Researchers of latent segment and random coefficient logit models are well aware that when segments are aggregated, the share is no longer restricted to IIA even though choices within a homogeneous segment are constrained by IIA.

model of Allenby and Rossi assumes that goods are infinitely divisible, whereas packaged goods are actually purchased in discrete units. Because utility (which is inferred from an observed choice) is specified as a product of the marginal utility and quantity in their model, an infinitely divisible formulation of quantity may adversely affect the estimate of the marginal utility for a brand. This could in turn lead to an incorrect prediction of the income effect characterized by the marginal utility. A modified model based on a discrete quantity formulation fails to detect an appreciable presence of the income effect when calibrated with scanner-panel data from four categories.

3. THE HETEROGENEITY EXPLANATION

3.1. Heterogeneity Effect on Asymmetric Pattern of Competition

Blattberg and Wisniewski (1989) explained how heterogeneity in price-quality tradeoff across consumers produces an asymmetric pattern of competition. In their notation, utility of brand i for consumer c, $U^c{}_i$, is

$$U^c{}_i = \theta^c q^c{}_i - p_i \tag{1}$$

where $q^c{}_i$ is consumer c's perceived quality of brand i, p_i is the actual price, and $\theta^c > 0$ is consumer c's willingness to pay for quality. θ^c can be interpreted as the importance weight on overall quality relative to an importance weight of 1 on price. The model is widely adopted in utility theory and economics, and it is a basic formulation of a utility function in a multinomial logit model of discrete choice.

In comparing two brands i and k, consumer c chooses brand i if $U^c{}_i > U^c{}_k$ and chooses brand k if $U^c{}_k > U^c{}_i$. Define $R^c \equiv \theta^c (q^c{}_i - q^c{}_k)$ as consumer c's relative preference for brand i over brand k. Then consumer c chooses brand i if $R^c > (p_i - p_k)$ and brand k if $R^c < (p_i - p_k)$. The consumer is indifferent between brands i and k if $R^c = (p_i - p_k) \equiv I_{ik}$, which is called the point of indifference. Because R^c is consumer specific, depending on the consumers' tradeoff between quality and price, consumers whose relative preference is larger than $(p_i - p_k)$ would choose brand i whereas consumers whose relative preference is smaller than $(p_i - p_k)$ would choose brand k. If the distribution of relative preference R^c for the population is known, the shares of brands i and k can be obtained for given prices of brands i and k, as illustrated in Figure 1. Change in share due to brands' price promotion can be inferred readily from the figure because price cut by brand i (k) would shift the point of indifference, I_{ik}, to the left (right), as in Figure 2. Therefore, shape of the distribution will determine the pattern of price competition by the two brands.

< Figures 1 and 2 here >

Blattberg and Wisniewski conjectured the shape of the relative preference distribution to be bimodal and the point of indifference to be located toward the lower-quality end of the distribution on the basis of an aggregate sales pattern of asymmetric price-tier competition. However, they did not estimate the distribution explicitly.

Though their important work demonstrated asymmetric competition and provided valuable insights about the phenomenon, the drawbacks to their approach are threefold. First, the utility theory for asymmetric competition was developed at the individual level but tested at the aggregate level. Furthermore, the aggregate model provided sales elasticity rather than share elasticity, which is more compatible within the context of brand switching by individual consumers.[2] Second, the observed pattern of competition depended on the classification of products into different price-tier groups. In many categories, the price range of products is continuous. Hence, the number and boundaries of the classifications (e.g., premium, moderate, and generic) are often difficult to define. Third, it is a conjecture as Blattberg and Wisniewski stated, "Little is known empirically about the shape of this relative preference distribution or its underlying components, the distributions of θ^c and $(q^c_i - q^c_k)$." Without actually estimating the utility-based model, validity of their conjecture on the preference distribution is difficult to assess. Indeed, probability theory alone suggests that a bimodal shape for the distribution of relative preference, $R^c = \theta^c (q^c_i - q^c_k)$, is unlikely. The reason is that the probability distribution of a sum (difference) of two random variables with any distributions tends to be concentrated in the middle --- a key phenomenon used to derive the central limit theory. For example, the difference of two uniform i.i.d. variables is distributed as a symmetric triangular shape.

3.2. Estimation Method for Heterogeneity Distribution

Estimating the relative preference distribution directly from scanner-panel data on household brand choice provides insight into Blattberg and Wisniewski's conjecture. The distribution is estimated nonparametrically in order to capture the shape to the smallest detail by avoiding influence from the underlying parametric assumption. A basic idea behind the nonparametric approach is to regard the distribution as a histogram of relative preferences of individual households. As the number of households in the sample increases, the empirical distribution of household-specific relative preferences approaches the population distribution.

While the theoretical model of Blattberg and Wisniewski considers deterministic utility, for robust parameter estimation we adopt a stochastic utility model to account for various uncertainties inherent in empirical applications, such as unobserved attributes, measurement errors and imperfect information. The relative preference of a single household can be

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[2] For example, unlike panel data, store data reflect the effect of store switching: the set of consumers is not fixed.

obtained from parameter estimates of its constituents, θ^c, q^c_i and q^c_k, using only that household's purchases. In scanner-panel data covering a period of one year, a typical household makes at most 25 to 30 purchases in a category. It is not unusual to observe households with fewer than five purchases, depending on the product category. For this reason, household-specific parameters may not be estimable due to insufficient variability in observed data. Even if the estimate is obtained, the value tends to be unstable and only its asymptotic standard error, which is meaningless for such a small sample size, can be computed.

To overcome this problem, a Bayesian approach to estimating household parameters is pursued. An increasing popular method in marketing for capturing heterogeneity by estimating individual-level parameters is through Hierarchical Bayesian (HB) modeling (Lenk and Rao 1990, McCulloch and Rossi 1994). A household-level parameter represents a posterior distribution, whereby a population-level prior is updated by that household's choice data. In HB, parameters of the prior distribution themselves are regarded as random variables, whose distribution is updated by data (likelihood) from its hyper-prior distribution as below.

$\beta_h \sim f(\beta_h \mid X_h, N(\theta))$ where β_h is parameter of household h
$f(.)$ is a posterior for β_h
X_h is data from household h
$N(\theta)$ is a 1st-stage prior for β_h which is specified by θ

$\theta \sim g(\theta \mid X, M(\varphi))$ where θ is parameter of 1st-stage prior
$g(.)$ is a posterior for θ
X is data from all households
$M(\varphi)$ is a 2st-stage prior for θ which is specified by φ

Var[f(β_h|X_h,$N(\theta)$)] represents uncertainty in estimation for household-specific parameter, Var[$N(\theta)$] represents heterogeneity of parameters across households, and Var[$M(\varphi)$] can be interpreted as uncertainty of parameters for the 1st-stage prior distribution. A researcher specifies only the 2ndstage-prior $M(\varphi)$, which is then combined with data X to construct the 1ststage-prior itself. Subjective influence of the researcher's (2nd-stage) prior selection on the final parameter estimation is attenuated through the data-driven 1st stage prior.

For our objective of investigating the shape of a household-specific parameter distribution, however, we must pay special attention to the limitation of a hierarchical Bayes model in capturing heterogeneity. While it is true in HB that the *parameters* of the 1st-stage prior is automatically updated by data from the 2nd-stage prior, the *functional form* (such as normal and gamma) of the 1st-stage prior must be still specified by a researcher. In other words, only after a researcher chooses a distributional form for the 1st-stage prior, say, normal, then its mean and variance can be computed from the data and the 2nd-stage prior. This choice of a normal prior shape, however, could adversely drive the resulting shape of the parameters' distribution in such way that it is more likely to resemble a single-modal normal distribution even if that may not be the case. Allenby and Rossi (1999) proposed a diagnostic checking on the distributional form of the 1st-stage prior and demonstrated that, for coefficients in multinomial probit models, a normal prior can be justified.

In this research, we pursue an alternative approach with empirical Bayes estimation, in which the mean of the prior is obtained from the pooled data by MLE. It has an advantage in that the prior strength (i.e., variance) can be controlled subjectively while the location (e.g., mean and mode) of the prior is determined objectively by data. The approach is perhaps more suited to our study because the impact of prior on the resultant histogram of household-specific parameters can be evaluated. Another advantage is its computational efficiency. Estimation of 200 sets of household-specific parameters can be estimated in a few seconds on PC.

The underlying choice model of individual households is based on ubiquitous multinomial logit (MNL), which is a natural stochastic extension of the deterministic formulation of Blattberg and Wisniewski exhibiting symmetric switching (IIA) at the household-level whereas aggregation over heterogeneous households leads to the asymmetry.[3] The Bayesian estimation combines the likelihood function and a prior, which is based on the standard MNL estimate of the pooled sample across households, to avoid the sample size problem that can arise in classical estimation methods such as maximum likelihood. The prior is assumed to be normally distributed and the strength of the prior information can be controlled by a parameter that represents the equivalent sample size of the prior. With the normal prior, the posterior distribution of household h's parameters for the Bayesian estimation, $L(\beta_h|data_h)$, is expressed as

$$L(\beta_h|data_h) = L(\beta_h) - 1/2\,(\beta_h - b)'\,\Sigma^{-1}\,(\beta_h - b), \tag{2}$$

where β_h is a vector of the household parameters, $L(\beta_h)$ is a loglikelihood function of the standard multinomial logit model, and b and Σ are the prior mean vector and the variance-covariance matrix, respectively. The mode of the posterior distribution, $L(\beta_h|data_h)$, can be searched easily by the fact that $L(\beta_h|data_h)$ is concave possessing a unique global maximum because both $L(\beta_h)$ and the second quadratic term are concave. The variance of the posterior is calculated from the hessian of (2) as the asymptotic approximation (Rossi and Allenby 1993).

One issue that requires careful attention in Bayesian approaches is the choice and strength of the prior. As the preceding statistical argument suggests, relative preference $R^c \equiv \theta^c\,(q^c{}_i - q^c{}_k)$ tends to be concentrated in the middle regardless of the shape of the distribution of brand

[3] A probit model does not serve our purpose here because it produces an asymmetric switching pattern at the household level. A crucial point of the heterogeneity explanation, as shown in the preceding table, is that aggregation itself is the main cause of the asymmetric pattern. This argument is motivated by the fact that heterogeneity of parameters for MNL serves to introduce a correlated random term across alternatives (Ben-Akiva and Lerman 1985, p. 129). Household parameter estimation of a probit model, even for an independent

constant q^c_i. Hence, obtaining the exact distribution may not be critical for the purpose of estimating the distribution of R^c. Nevertheless, we want to ensure that the assumed prior can still reproduce the underlying shape of the parameter distribution correctly. We chose the normal prior and its strength on the basis of the following considerations. First, previous studies of household parameter estimation showed close resemblance to a normal distribution (Rossi and Allenby 1993, Rossi, McCllloch, and Allenby 1996, Allenby and Rossi 1999), providing our ex-ante expectation -- a definition of prior. Second, to minimize the influence from a prior, we selected a highly diffused prior. In particular, the variance of the prior was made as large as possible as long as the posterior mode of the price parameter has a correct negative sign for each household. Third, a simulation study, presented in the appendix, verified that a bimodal distribution of model parameters can be recovered, if that was indeed the case, with the shape (normal) and strength (equivalent sample size of 10) of the prior chosen for the study.

Now, a multinomial logit model of brand choice is expressed as

$$P_{iht} = \frac{\exp(V_{iht})}{\sum_j \exp(V_{jht})}$$

where P_{iht} is the choice probability and V_{iht} is the systematic utility of brand i for household h at the t-th purchase. Following the formulation of (1), utility V_{iht} is specified as

$$V_{iht} = q_{hi} - \alpha_h \, PRICE_{iht} + \textstyle\sum_m \beta_{mh} X_{ihtm}, \tag{3}$$

where: q_{hi} is a brand constant of brand i for household h,
$PRICE_{iht}$ is a price of brand i faced by household h at the t-th purchase occasion,
α_h (>0) is a price parameter for household h,
X_{ihtm} is the m-th covariate of brand i faced by household h at the t-th purchase, and
β_{mh} is a parameter of the m-th covariate for household h.

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probit model with a diagonal covariance structure, requires the use of computationally intensive Bayesian techniques such as Gibbs sampling (Rossi, McCulloch, and Allenby 1996).

Note that all parameters are household specific and thus have subscript h.

In the model of Blattberg and Wisniewski, for two alternative brands i and k, household h chooses brand i at the t-th purchase if $V_{iht} > V_{kht}$ and chooses brand k otherwise. This condition can be rewritten in terms of the relative preference for household h, R^h, and the point of indifference, I_{ikht}, as choosing brand i if

$$R^h > I_{ikht}, \tag{4}$$

where:

$$R^h = (q_{hi} - q_{hk}) / \alpha_h \text{ , and} \tag{5}$$

$$I_{ikht} = (PRICE_{iht} - PRICE_{kht}) - \Sigma_m \beta_{mh} / \alpha_h \cdot (X_{ihtm} - X_{khtm}) \text{ .} \tag{6}$$

In the current formulation, the additional covariates X are nonprice promotion variables whose role is to reduce the adverse impact of nonprice promotions on estimation of other parameters. Because we are interested in the effect of price cut from regular price, the point of indifference must be evaluated at the regular prices without nonprice promotions (X = 0). Thus, I_{ik} = ($REGPRICE_i$ - $REGPRICE_k$) by dropping subscripts h and t.

The *posterior* distribution for the relative preference of each household, R^h, can be computed by repeated draws of q_{hi}, q_{hk}, and α_h from the joint posterior distribution to account for their correlation. Households with short purchase strings tend to have a diffuse posterior whereas those with long purchase strings tend to have a concentrated posterior, thereby providing the accuracy measure for the Bayesian estimate. Finally, the *empirical* distribution of the relative preferences for the sample households is obtained by summing the posterior distributions across households and normalizing it. The variance of the posterior distribution for each household, while offering the estimation accuracy, operates like a kernel under the aggregation to produce a smooth empirical distribution even if the number of households are small.

3.3. Description of Scanner Panel Data

The estimation was conducted with households' brand choice data for two product categories. One category was refrigerated orange juice (64-oz size) consisting of six brands: regional brand, Citrus Hill, Minute Maid, private label, Tropicana Regular, and Tropicana Premium. These brands accounted for more than 80% of the category share at the time. The scanner panel data contained 2307 purchases made by 200 households at five stores in a small Midwestern city over a period of 78 weeks from mid-1983. The number of purchases per panelist ranged from two to 73. The average number of purchases for each quartile group of panelists was 2.4, 3.9, 10.3, and 30.5, respectively. Thus, the data represented panelists with diverse length of a purchase string.

The second category was regular ground coffee in six *brandsizes*: three brands, Butternut, Folgers, and Maxwell House, each with two sizes, 1 pound and 3 pounds. Again, these brands accounted for more than 80% of the category share. The scanner panel data contained 3776 purchases made by 167 households at four stores in a small Midwestern city over a period of 65 weeks in early 1980s. The number of purchases per panelist ranged from 10 to 70, representing diverse purchase frequency.

Descriptive statistics (share, average price, and promotion frequency) for the two categories are reported in Table 1. The only nonprice promotion covariate available in both databases was the presence of advertising feature. Therefore, parameters of the MNL model included five alternative-specific constants (one of the six was set to zero as a reference alternative), price, and feature. Because the study was descriptive, all data points were used to estimate the parameters for maximum degrees of freedom. The Bayesian estimation produced 200 and 167 sets of parameter estimates for orange juice and ground coffee, respectively, each corresponding to a single household. The equivalent prior sample sizes are 10 and five for the orange juice and ground coffee databases, respectively (see Appendix).

< Table 1 here >

3.4. Estimation Results of the Heterogeneity Distribution

Figure 3 shows the estimated relative preference distributions for the orange juice data. For six brands, there are 15 possible pairs of brands for the relative preferences. None of the distributions have the bimodal shape hypothesized by Blattberg and Wisniewski. All are single modal with close resemblance to a normal distribution. The vertical line in each plot indicates the location of the point of indifference --- a regular price difference between the two brands (p_1 - p_2). Households to the right of the point choose the first brand over the second, whereas households to the left choose the second brand.

< Figure 3 here >

Figure 4 shows the estimated relative preference distributions for the coffee data. Again, there are 15 pairs of brandsizes. Though the shapes are more detailed, perhaps because of the longer purchase strings of the sample panelists, all of the distributions still have a single major mode. Similar results were obtained from two additional categories, detergent and ketchup, but are not reported here for brevity. Therefore, at least in these categories, it seems reasonable to conclude that relative preference distributions have a single mode and strongly resemble a normal distribution. This observation is consistent with the previous argument based on probability theory that the distribution of a difference of two random variables tends to be concentrated in the middle regardless of the variables' distributions.

< Figure 4 here >

The implication of the single-modal distribution of relative preference is that, for the same price cut, a smaller share brand is more effective than a larger share brand is in stealing share away from the other brand. This can be illustrated in Figure 2. If brand i has a smaller share than brand k, the point of indifference is located to the right of the single mode. Price cut by brands i and k would shift the indifference point to the left and right, respectively, and changes in the areas would result. Comparison of the two areas indicates that promotion of brand i is more effective than promotion of brand k. The reverse situation arises if brand i has a larger share than brand k, in which case the point of indifference is located to the left of the single mode. Though the plot depicts a two-brand case, the result can be generalized to a case of more than two brands. Intuitively, promotion of a smaller brand draws more share than similar promotion of a larger brand, simply because the smaller brand has a larger pool of potential customers and is less prone to the saturation effect (Sethuraman and Srinivasan 2000). Therefore, while the preference heterogeneity might contribute to the saturation effect of brand competition, it cannot explain price-tier asymmetric competition.

4. THE INCOME EXPLANATION

4.1. Income Effect on Asymmetric Pattern of Competition

Microeconomic theory posits that when the price of a good falls, the change in its demand is affected in two ways characterized by the Slutsky equation: the substitution effect and the income effect. The substitution effect refers to the fact that a good is now relatively cheaper than substitute goods, so consumers demand more of it by replacing the substitutes. This effect is always negative, that is, opposite to the direction of the price change. The income effect refers to the change in demand for a good due to the fact that the consumers' purchasing power has been increased by a decrease in the good's price. When the demand for a good goes up by a greater proportion than income (utility), the good is referred to as a luxury good, whereas if the demand goes up by a lesser proportion than income, it is referred to as a necessary good. Thus consumers' preference shifts from necessary to luxury goods as their income increases even if the relative prices of the goods remain the same. This phenomenon, which is often applied to reallocation of product categories consumed (e.g., from bread/potato to meat), is referred to as nonhomothetic preference and characterized by the nonlinear income offer curve (Varian 1993, p. 100).

Allenby and Rossi (1991) proposed that the brand-specific income effect could explain asymmetric brand switching by consumers in favor of higher quality brands. They introduced brand-specific marginal utility that depended on the total utility level to capture the shift in brand preference as income changes. Their choice model implied that a consumer chooses a brand with the highest utility expressed as

$$\text{Utility of brand i (i=1,..,J):} \quad u_i = MU_i \times x_i \tag{7}$$

where:

$$MU_i = \exp(\alpha_i - k_i\, u_i), \text{ is marginal utility of brand i,} \tag{8}$$

$$x_i = v / p_i, \text{ is the quantity of brand i purchased,} \tag{9}$$

v is a category budget, p_i is the price of brand i, and α_i and k_i are parameters.

The marginal utility depends on the level of utility u_i, and parameter k_i ($k_i>0$) specifies how preference changes with utility. Consistent with the diminishing return predicted by economic theory, the marginal utility decreases at the higher level of utility for all brands but with a brand-specific rate. Allenby and Rossi postulated that the rate of the decrease is slower for high quality than for low quality brands, thereby causing asymmetry in brand switching. The quantity was a category budget, v, divided by the price. When calibrated on scanner panel data, the model was shown to perform better than benchmark logit models. With the assumption that the higher the quality, the slower the rate of decrease in marginal utility, estimated parameter k_i provided the objective measure of brand quality.

Though Allenby and Rossi's ingenious approach resulted in a model that is consistent with microeconomic theory, it has one disadvantage. The quantity term, x_i, is continuous (infinitely divisible), whereas most consumer packaged goods are purchased in discrete quantities. Equation 9 implies that a price cut of 20% leads to 25% increase in the quantity purchased at a particular occasion. In reality, price promotion induces consumers to change package sizes or switch brands (Gupta 1988).[4] If consumers were stockpiling, quantity should increase by the unit of package size (e.g., 1 pound for margarine) rather than by a fractional amount, so that the increase would be 100%, 200%, and so on. Kalyanam and Putler (1997) point out general problems associated with the use of infinitely divisible choice models in packaged goods, and introduce an alternate approach called the indivisible alternatives formulation.

Because utility in equation 7 is estimated from actual consumer brand choices, an infinitely divisible quantity formulation may adversely affect the estimation result of the other term, the marginal utility, and thus the value of k_i in particular. That is, the marginal utility may be overestimated (underestimated) for a higher (lower) priced brand to compensate for the divisible formulation whereby the quantity becomes smaller (larger), despite in reality the quantity remains the same regardless of the price. As a result, the estimate of k_i tends to be confounded with the price of brand i.

4.2. Modified Nonhomothetic Choice Model

[4] Gupta (1988) found that 84%, 14%, and 2% of the sales increase due to price promotion are attributable to brand switching, purchase acceleration, and stock piling, respectively, for the ground coffee category he studied.

We propose to make a minor modification to their nonhomothetic choice model so that the quantity purchased is always one if the brand is chosen, while retaining the spirit of their income effect formulation intact as much as possible.[5] The utility for a product is derived from the sum of two sources: utility derived from consumption of a unit quantity of the product and the monetary saving arising from the purchase (i.e., $v - p_i$). A consumer chooses a brand that provides the highest combined utility where

$$\text{Utility of brand i (i=1,..,J):} \qquad u_i = MU_i + f(v - p_i) \tag{10}$$

and:

$$MU_i = \exp(\alpha_i - k_i u_i), \text{ is utility from consuming brand i, as before, and} \tag{11}$$

$$f(\cdot) = \text{utility arising from the monetary saving } (f' > 0 \text{ and } f'' < 0) \tag{12}$$

As in Allenby and Rossi (1991), brand-specific rate k_i captures preference shift from necessary to luxury brands as the level of the combined utility (income) increases. Nonhomothetic preference implies that k_i, which is greater than 0, is smaller for luxury brands than necessary brands. The second term $f(v - p_i)$ represents a composite good --- utility from other goods --- with usual diminishing return. Kalyanam and Putler (1997), in their indivisible alternatives framework, also adopt this formulation, which is fairly standard in microeconomics.[6] Now, it is insightful to interpret the linear approximation of equation 10 as:

$$u_i \cong 1 + \alpha_i - k_i u_i - f'(v) p_i + f(v). \tag{13}$$

Solving for u_i results in

[5] Multiple-unit purchases were rare, and over 95% of the purchases were for a single unit in the data analyzed. The observation is consistent with the product categories studied by Kalyanam and Putler (1997). However, that may not apply to certain product categories such as yogurt.

[6] Although Kalyanam and Putler do not explicitly model diminishing marginal utility, it is implied by the formulation of the holding cost.

$$u_i = \frac{1 + a_i + \mathrm{f(v)}}{1 + k_i} - \frac{\mathrm{f'(v)}}{1 + k_i} p_i \qquad (14)$$

Notice the usual linear-in-parameters utility function of a logit model --- the sum of a brand dummy and a price term --- but the price coefficient, f '(v)/(1+k_i), is brand specific. k_i would be different from brand to brand if and only if the estimate of these price coefficients differ by brands. Brand specific k_i implies nonhomothetic preference, resulting in asymmetric switching.

We now calibrate the modified nonhomothetic model of equation 14 with real data to examine the presence of the brand-specific income effect. We test the null hypothesis of equal price coefficients across brands by two nested specifications of a multinomial logit model: one with a single price coefficient common across brands and the other with brand-specific price coefficients. Rejection of the null hypothesis by the likelihood ratio test would indicate that k_i is brand specific, thereby implying nonhomothetic preference.

Table 2 reports the estimation results from the databases for orange juice and ground coffee. For generalization, two different operationalizations of a loyalty variable, those of Guadagni and Little (1983) and Allenby and Rossi (1991), were used. The results from the first one are given here because of its superior fit. Estimates of the price coefficients are similar across brands in both data sets. Indeed, the null hypothesis of equal magnitudes could not be rejected at α=0.10 for either the orange juice or coffee data. The models also failed to reject the null hypothesis using the other operationalization of a loyalty variable. Furthermore, brand-specific income effect was not observed with the additional two categories, detergent and ketchup. In sum, at least for these databases, the income effect cannot explain price-tier asymmetric competition because k_i was not brand specific.[7]

< Table 2 here >

5. LOSS-AVERSION EXPLANATION

5.1. Model without Loss-Aversion Effect

To clarify the exposition, let us first describe a model that does not accommodate the loss-aversion effect. Consider an additive utility function of two attributes, x and y, as follows.

$$v = v_x + v_y = a\,x + b\,y$$

For example, $x \equiv$ value = (constant – price) and $y \equiv$ quality. Figure 5 plots v_x and v_y as well as the indifference curve, which is linear.

< Figure 5 >

The marginal rate of substitution becomes constant as in $MRS = -\frac{\partial v/\partial x}{\partial v/\partial y} = \frac{a}{b}$. Substitution of this utility function into the deterministic component of the multinomial logit model of brand choice results in the well-know proportional draw (IIA) property. Change in the choice probability of brand i for a unit price change of brand j becomes

$$\frac{dP_i}{dx_j} = -P_i P_j a \qquad (i \neq j).$$

Note that the expression is symmetric with respect to i and j, that is $dP_i / dx_j = dP_j / dx_i$.

5.2. Model with Loss-Aversion Effect

[7] Allenby and Rossi (1991), in the margarine category, found brand-specific price coefficients to be statistically

Loss-aversion implies the existence of a reference point that separates loss from gain and a steeper slope in the region of loss than gain, as in Figure 6. Consider the same additive utility function of the two attributes, x and y. Now, the indifference curve becomes kinked line segments with a different slope at each quadrant depending on whether it corresponds to loss or gain for attributes x and y. The origin of asymmetric price switching proposed by Hardie, Johnson and Fader (1993) stems from this difference in slopes, which they found in orange juice scanner panel data.

< Figure 6 >

Bell and Lattin (2000), however, showed that the observed loss-aversion effect could merely be an artifact if the underlying consumer heterogeneity in price responsiveness is not accounted for. Using a latent segment model --- a more sophisticated method to capture heterogeneity than inclusion of a loyalty variable pursued by Hardie, Johnson, and Fader[8] --- Bell and Lattin observed that the loss-aversion effect disappeared or weakened substantially in multiple datasets. Considering that latent segment still approximates the underlying continuous distribution of heterogeneity by assuming *homogeneity within* segments, use of a more thorough method for capturing heterogeneity might vanish the loss-aversion effect all together even in datasets where the weak effect was left off by the latent segment model. Without the loss-aversion effect, asymmetric switching cannot be supported as illustrated in Section 5.1. To capture underlying heterogeneity without making the discrete approximation, we adopt an alternative formulation of estimating household-specific parameters using a Bayesian method in Section 5.3. We will reconfirm the study of Bell and Lattin in that loss-aversion in price is not found in scanner panel data.

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significant. Therefore, presence of nonhomothetic preference could be a category specific phenomenon.

8 The model of Hardie, Johnson and Fader accounts for heterogeneity in intercept only, whereas that of Bell and Lattin accounts for heterogeneity in slopes as well.

The model of loss-aversion poses other difficulties. First, the model assumes the existence of a reference point to which loss and gain are judged. However, there is no consensus among researchers as to what the appropriate measure of this reference point should be (Briesch, Krishnamurthi, Mazumdar and Raj 1997). Some researchers even advocate that the reference point is brand specific --- often referred to as a sticker-shock model. For example, Bell and Lattin (2000), Briesch, Krishnamurthi, Mazumdar and Raj (1997), and Hardie, Johnson and Fader (1993) conduct their analyses using 3, 5, and 5 alternative reference formulations, respectively, to guard against such criticism. Second difficulty is that switching is still symmetric among brands within each quadrant where the indifference curve is linear.

5.3. Household Model to Investigate the Loss-Aversion Effect

We now pursue an alternative formulation of heterogeneity to Bell and Lattin by estimating household-specific gain and loss parameters, and show the absence of loss-aversion in price from scanner data using an. An utility function for the MNL model of household-specific parameters in Section 3 becomes

$$V_{iht} = q_{hi} + \alpha_h \, GAIN_{iht} - \beta_h \, LOSS_{iht} + \gamma_h \, FEATURE_{iht}$$

$$\text{where} \qquad GAIN_{iht} = \max(\, PRICE_{rht} - PRICE_{iht}, 0)$$

$$LOSS_{iht} = \max(\, PRICE_{iht} - PRICE_{iht}, 0) \; .$$

Following Bell and Lattin, the reference price, $PRICE_{rht}$, is defined as the price paid by that household at the last purchase --- a memory-based operationalization.

< Figures 7 and 8 >

Figure 7 plots a histogram of the difference between the absolute magnitudes of gain and loss coefficients within each household, $(\alpha_h - \beta_h)$, for the orange juice and coffee databases. Figure 8 is a histogram of t-statistics for the differences using their asymptotic standard errors.[9] Under a small sample of the household-specific estimation, the actual standard errors would be much larger, and these t-values are grossly overestimated. Even with the asymptotic standard t-values, only 4.1% and 4.8 % of the households in orange juice and coffee, respectively, exhibit the significant loss-aversion effect (i.e., $\alpha_h < \beta_h$) at the 5% significant level. The corresponding small-sample t-values would be even less significant, implying that the difference in slopes between gain and loss --- i.e., loss-aversion in price --- was not observed from the household-specific model. Analysis on additional two categories of scanner panel data also failed to detect loss-aversion either, thereby supporting the claim made by Bell and Lattin.

6. THE DECREASING MARGINAL RETURN EXPLANATION

In the previous three sections, we examined each of the three past explanations for asymmetric price competition. Based on the analysis of scanner panel data from four categories, we showed that none of them can be supported. We now propose an alternative yet a simple explanation based on the decreasing marginal return effect in price.

6.1. Rationale

Consider the sum of two decreasing-marginal-return utility functions of attributes x and y, as shown in Figure 9. The corresponding indifference curve is also shown.

< Figure 9 >

For expositional purposes, let us chose a logarithmic function to represent this decreasing-marginal-return utility function. Utility then becomes a well-know Cob-Douglas function.

$$v = v_x + v_y = a \log x + b \log y$$

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[9] Note that if d=a-b, cov(d) = cov(a)+cov(b)-2cov(a,b)

The marginal rate of substitution is $MRS = -\frac{\partial v / \partial x}{\partial v / \partial y} = \frac{a\, y}{b\, x}$, implying that MRS differs depending on the relative amount of x and y. Note that the indifference curve resembles some similarity to that of Figure 6, but it is smooth rather than kinked. When this utility function is substituted into MNL, change in the choice probability of brand i for a unit price change of brand j becomes

$$\frac{dP_i}{dx_j} = -P_i P_j \frac{a}{x_j} \quad (i \neq j)$$

The expression is no longer symmetric with respect to i and j. If $x \equiv$ value = (constant – price) as in Section 5.1, higher-priced brand j means smaller x_j, which in turn implies larger dP_i/dx_j in absolute magnitude. This suggests that the higher the price of brand j, the larger the impact of its price change on competing brand i. Hence, asymmetric switching occurs under a very weak assumption of the diminishing marginal return in price.

6.2. Empirical Support

To show the diminishing-marginal-return effect, we investigate the concavity of the utility function with respect to price. A nonparametric utility function of a brand choice model (Abe 1999) would have been an ideal approach, if we wanted to study the average effect of consumers. Without properly accounting for heterogeneity, however, we might expose ourselves to the danger of the artifact that was explained in Bell and Lattin (2000). Therefore, to quantify the concavity, we estimate a Box-Cox transformation of price in the household-specific utility function of an MNL model as

$$V_{iht} = q_{hi} + \alpha_h f(\text{PRICE}_{iht}, \lambda) + \beta_h \text{ FEATURE}_{iht} \tag{15}$$

$$\text{where} \quad f(\text{PRICE}_{iht}, \lambda) = (\text{ PRICE}_{iht}^{\lambda} - 1\ ) / \lambda$$

To account for heterogeneity, parameters q_{hi}, α_h, β_h, are household-specific. $f(\text{PRICE}_{iht}, \lambda)$ is a Box-Cox transformation with parameter λ, which specifies the concavity of the price function, or equivalently, the strength of the diminishing-marginal-return effect. When $\lambda = 1$, the utility is linear in price. If $\lambda > 1$, the utility is convex in price, whereas if $\lambda < 1$ it is concave in price. The concavity in price strengthens as λ decreases from 1. When $\lambda = 0$, the transformation is equivalent to logarithm.

< Figure 10 >

We fit the household-specific utility function of (15) for different values of λ by adopting a glid-search like procedure. Figure 10 shows the loglikelihood for different values of λ in the two categories. The loglikelihood was maximized when λ was -1.7 for orange juice and -2.3 for coffee. These results imply that, even after accounting for household heterogeneity, there remains the diminishing-marginal-return effect in price, whose concavity is stronger than that of logarithm (i.e., $\lambda = 0$). We also observed the same pattern in the two additional categories studied, detergent and ketchup. We, therefore confirmed empirically that, the strong diminishing marginal return effect in price is indeed present in at least the four datasets we investigated.

7. CONCLUSIONS

Let us summarize the key issues and findings in asymmetric price competition.

(1) Confounding of the supply-side and demand-side factors in asymmetric price competition when analyzing aggregate data such as market share.

When analyzing aggregate data, therefore, asymmetric competition may not always be observed due to influence from supply-side factors. To isolate the supply-side factors, it is crucial to study disaggregate panel data.

(2) Measure of asymmetric price competition.

Due to confounding of the cross-price effect with the share effect, cross price elasticity is not suitable. A better measure is a change in market share of a brand for a unit price change of a competing brand.

(3) Investigation of the past three behavioral explanations for asymmetric competition.

Theoretical arguments against previous explanations --- the heterogeneity effect, the income effect, and the loss-aversion effect --- are provided, which are then supported empirically using scanner-panel data from four categories.

(3.1) Heterogeneity effect: Aggregate data is used (confounding) and cross-price elasticity (inappropriate measure) is analyzed. The explanation is inferred indirectly.

Blattberg and Wisniewski suggested that an asymmetric pattern could arise from consumer heterogeneity in tradeoff between price and quality. They conjectured that the shape of the distribution must be bimodal to be consistent with the pattern of competition observed in their econometric study using aggregate sales data. However, estimating the distribution directly from household-level disaggregate data by a nonparametric method suggested that the shape was single modal for all four categories studied. Probability theory and the simulation study also supported this result. Implication of the single-modal distribution is that heterogeneity in consumer preference, while influencing brand competition through the saturation effect of share, does not appear to produce the asymmetric pattern observed in price-tier competition.

(3.2) Income effect: Infinite divisibility is assumed.

Allenby and Rossi postulated the income effect, suggesting that consumers' preference shifts from low to high quality brands when their purchasing power is increased by price promotion. The effect was captured by a choice model that supported such a preference shift through brand-specific income effect. However, the infinite divisibility assumption of the model, in which quantity purchased was specified as a category budget divided by the price, poses difficulty modeling the discrete purchase unit for consumer packaged goods. A minor modification provided a model that accommodated a discrete quantity formulation while accounting for the income effect. When the proposed model was calibrated with households' choice data from four product categories, the statistical test showed that the income effect was not brand specific. The result suggested the absence of the preference shift, and therefore the income effect could not explain asymmetric competition, either.

(3.3) Loss-aversion effect: Household heterogeneity is not well accounted for.

Consistent with the prospect theory, Hardie, Johnson, and Fader suggested that, under loss-aversion for price and quality, the slope of an indifference curve (for price and quality) depends on whether it is evaluated in the region of a gain or loss in price and quality relative to the consumer's reference point. The implication is that the same price cut is perceived to be more favorable for brands that provide gain in quality than those that provide loss, offering a psychological explanation for asymmetric switching. Using scanner-panel data, they calibrated a choice model with a loyalty variable to capture household heterogeneity and demonstrated the loss-aversion effect on price and quality attributes. Bell and Lattin, however, showed that the observed loss-aversion effect could merely be an artifact if the underlying consumer heterogeneity in price responsiveness is not accounted for. They observed that much of the loss-aversion effect disappeared when the household heterogeneity was captured with a more sophisticated latent segment model. Utilizing even more elaborate methodology to capture heterogeneity by estimating a household-specific model (i.e., segment of size one), we did not find evidence for the loss-aversion effect from four categories studied.

(4) Proposition of a simple alternative explanation.

It was shown that a basic assumption of consumer utility in Microeconomic theory, the diminishing-marginal-return effect in price, resulted in asymmetric competition. With a household-specific model that accounted for heterogeneity, it was shown that the concavity (i.e., the diminishing-marginal-return effect) was stronger than that of logarithm in all datasets. Under such a circumstance, the same amount of price cut acts in favor of high priced-brands than low-priced brands, thereby causing the asymmetric pattern of price competition.

The main conclusion of the research is that the demand factor for asymmetric price competition appears to be the diminishing-marginal-return effect of price on utility. Though the empirical analysis is limited to four categories studied here, theoretical and logical rationale also supported the conclusion. Future research could strengthen our results through cross-category analysis. Another direction is to investigate the diminishing-marginal-return in other attributes, say, quality. If that was the case, then those brands lacking quality such as generic and private labels and low-priced brands are better of resorting to quality improvement while price reduction is a viable tactic for higher-priced brands.

Finally, let us note that the current research reiterates the importance of accounting for household heterogeneity when analyzing disaggregate data in substantive behavioral research, or else one might draw a misleading conclusion. A classic case, for example, is illustrated in the explanation for the drop of an after-promotion repeat rate by Neslin and Shoemaker (1989).

APPENDIX

Recovering a Bimodal Parameter Distribution with Bayesian Estimation

A simulation study was conducted to demonstrate that the Bayesian estimation with the database and the strength of prior used for the study could recover a bimodal parameter distribution if it indeed existed. The equivalent prior sample sizes for the orange juice and ground coffee databases were 10 and five, respectively, following the criterion of the maximum diffused prior that produces a correct sign for the posterior mode of the price parameter. If a bimodal shape can be recovered for the orange juice database that has a stronger prior influence, the recovery would automatically follow for the ground coffee database that has a weaker prior. Hence, the simulation study was conducted on the orange juice data.

Brand choice data were generated from a multinomial logit model by using the actual covariates in the orange juice database. The values of nonprice parameters in the utility function (brand constants and feature) were set to those of the pooled estimate, whereas the value of the price parameter was set to -3.6 for one half of the randomly chosen households and -1.2 for the other half. This choice of a price parameter coincides with the mean (-2.4) and standard deviation (1.2) of the sample distribution of the household-specific price parameters obtained in Section 3.4.

Now, the Bayesian estimation was applied to the simulated choice data to recover the distribution of the price parameter, which has support points at -3.6 and -1.2, each with a probability of 0.5. Figure 11 is the estimated distribution based on the equivalent prior sample size of 10 as in the current study. The bimodal shape is clearly recovered, though some shift in the locations of the two modes --- shrinkage toward the prior mean --- can be observed.

< Figure 11 here >

The study was repeated for the Citrus Hill brand constant with support points at 1.4 and 0.0, each with a probability of 0.5. Again, these locations were chosen so that the mean (0.7) and the standard deviation (0.7) coincided with those of the Bayesian estimation of the household-specific Citrus Hill brand constant. Figure 12 is the estimated distribution based on the same prior strength as in the study. The bimodal shape is clearly recovered, though some shift in the locations of the two modes can be seen.

< Figure 12 here >

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Table 1. Descriptive Statistics for the Two Databases

Orange Juice Database

Brand	Share (% of purchases)	Average Price ($)	Feature (% of purchases)
Regional	15.4	1.82	45.8
Citrus Hill	32.9	1.86	17.8
Minute Maid	22.5	2.03	37.6
Private Label	11.7	1.47	7.0
Tropicana Regular	13.7	1.81	49.0
Tropicana Premium	3.9	2.38	2.4

Ground Coffee Database

Brandsize	Share (% of purchases)	Average Price ($/lb)	Feature (% of purchases)
Butternut 1 lb	18.8	2.98	34.6
Butternut 3 lb	4.1	2.95	62.5
Folgers 1 lb	41.8	3.11	44.3
Folgers 3 lb	10.1	3.15	44.9
Maxwell 1 lb	18.6	3.01	36.1
Maxwell 3 lb	6.5	3.03	39.7

Table 2. Estimation Results of the MNL Logit Models

(The t-values are in parentheses)

Orange Juice Data

Variable	Single price	Brand-specific price
Price	-2.69 (-11.1)	------
Price1	------	-3.22 (-7.2)
Price2	------	-2.01 (-2.7)
Price3	------	-2.36 (-6.2)
Price4	------	-4.50 (-4.6)
Price5	------	-2.23 (-4.1)
Price6	------	-2.49 (-3.1)
Loyalty	3.70 (26.2)	3.70 (25.9)
Feature	0.58 (4.6)	0.65 (5.0)
Loglikelihood: L(β)	**-875.61**	**-871.92**
ρ^2	**0.552**	**0.554**
Adjusted-ρ^2	**0.548**	**0.547**
BIC	**-903.59**	**-917.39**

Coffee Data

Variable	Single price	Brand-specific price
Price	-1.45 (-8.83)	------
Price1	------	-1.37 (-3.84)
Price2	------	-1.68 (-2.77)
Price3	------	-1.80 (-5.85)
Price4	------	-1.39 (-2.75)
Price5	------	-1.29 (-4.82)
Price6	------	-1.23 (-3.23)
Loyalty	3.84 (33.3)	3.85 (33.3)
Feature	1.86 (21.3)	1.87 (21.2)
Loglikelihood: L(β)	**-1822.88**	**-1821.58**
ρ^2	**0.479**	**0.479**
Adjusted-ρ^2	**0.476**	**0.475**
BIC	**-1853.18**	**-1870.83**

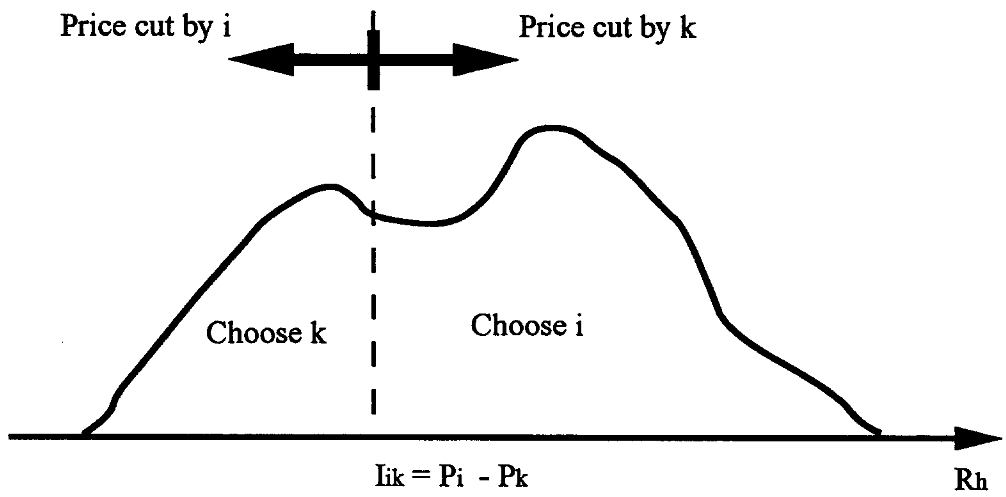


Figure 1. Relative Preference Distribution and Point of Indifference

The area to the right (left) of the point of indifference, I_{ik}, corresponds to the share of brand i (brand k). Price cut by brand i (brand k) would shift I_{ik} to the left (right).

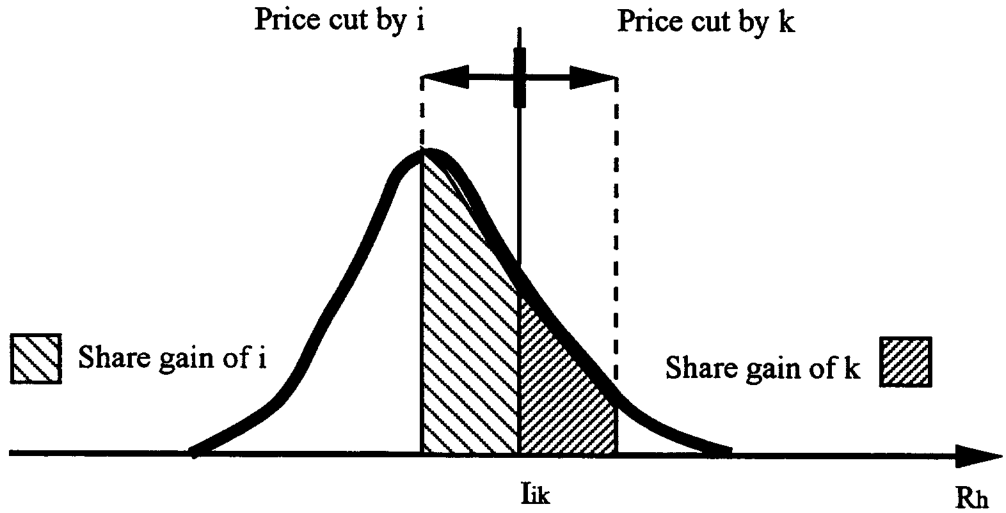


Figure 2. Implication of the Relative Preference Distribution to Asymmetric Price Competition

The region bounded between regular-price and promotional-price indifference points indicates the share gain due to the price promotion. If there is a large difference in the areas of the two regions identified by the different shades, competition is asymmetric. A small difference between the areas implies symmetric competition.

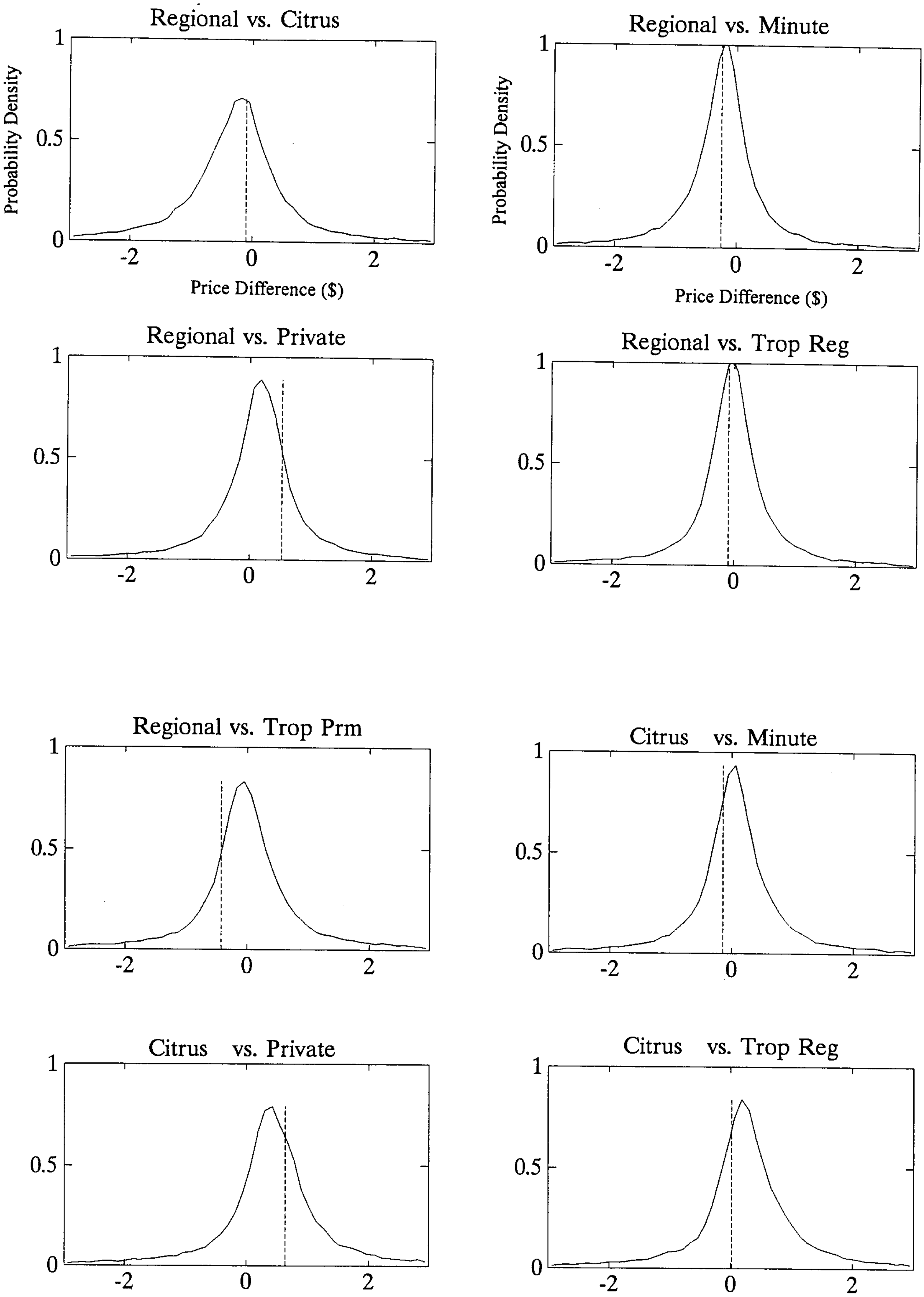
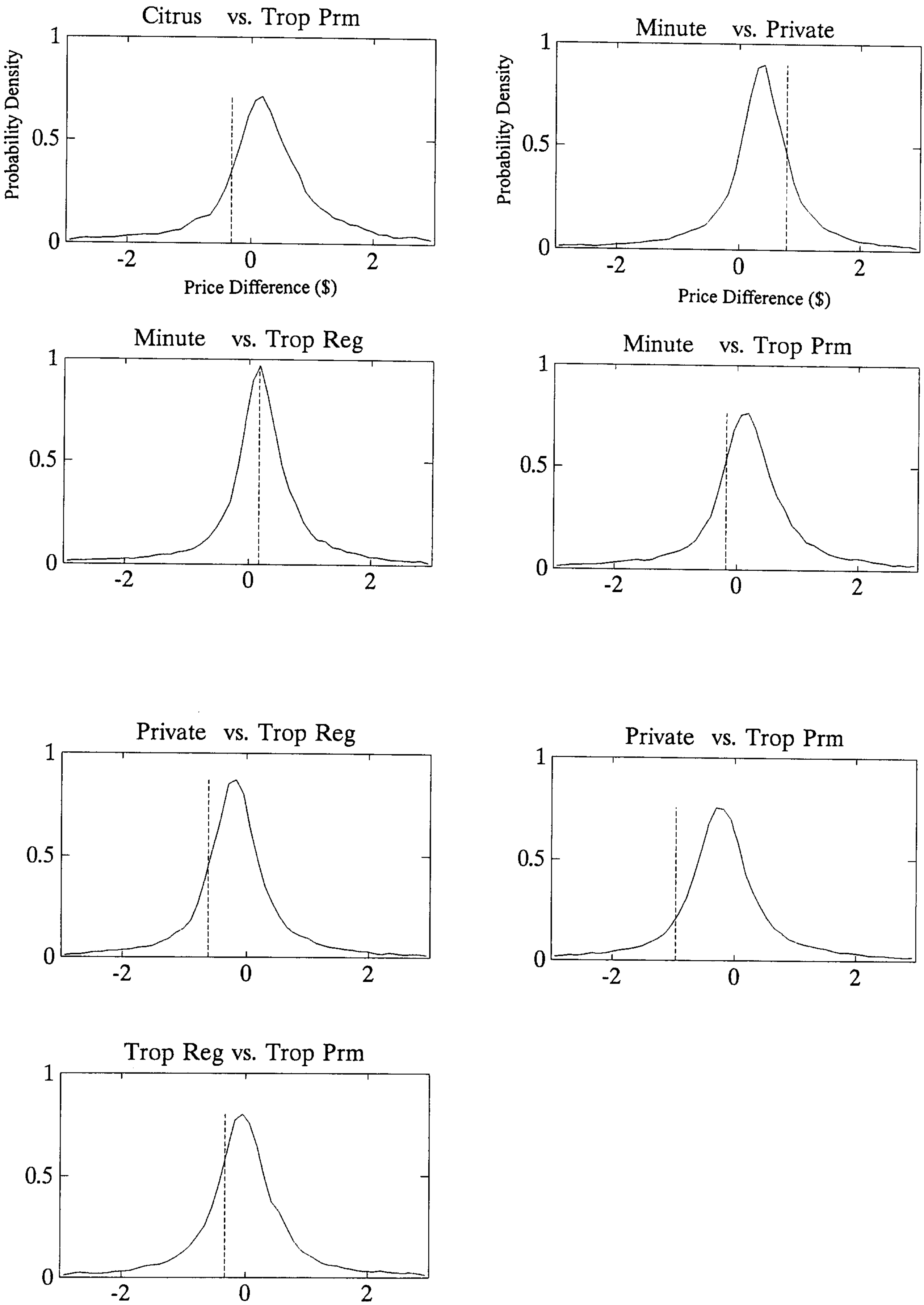


Figure 3. Relative Preference Distributions for Orange Juice

The vertical line indicates the point of indifference, I_{ik}.


Citrus vs. Trop Prm
Minute vs. Private
Minute vs. Trop Reg
Minute vs. Trop Prm
Private vs. Trop Reg
Private vs. Trop Prm
Trop Reg vs. Trop Prm
Probability Density
Price Difference ($)
1
0.5
0
-2
0
2

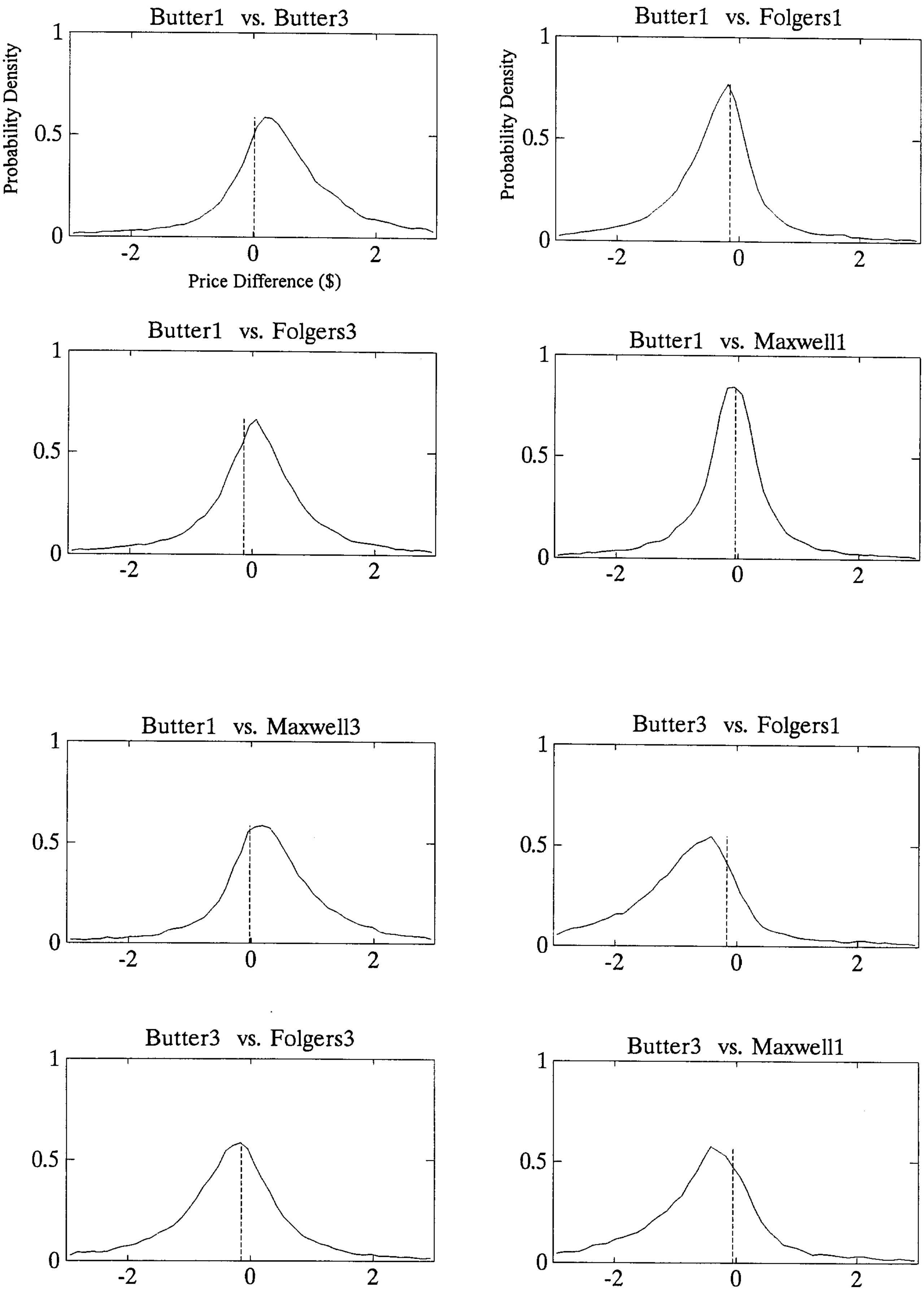


Figure 4. Relative Preference Distributions for Ground Coffee

The vertical line indicates the point of indifference, I_{ik}.

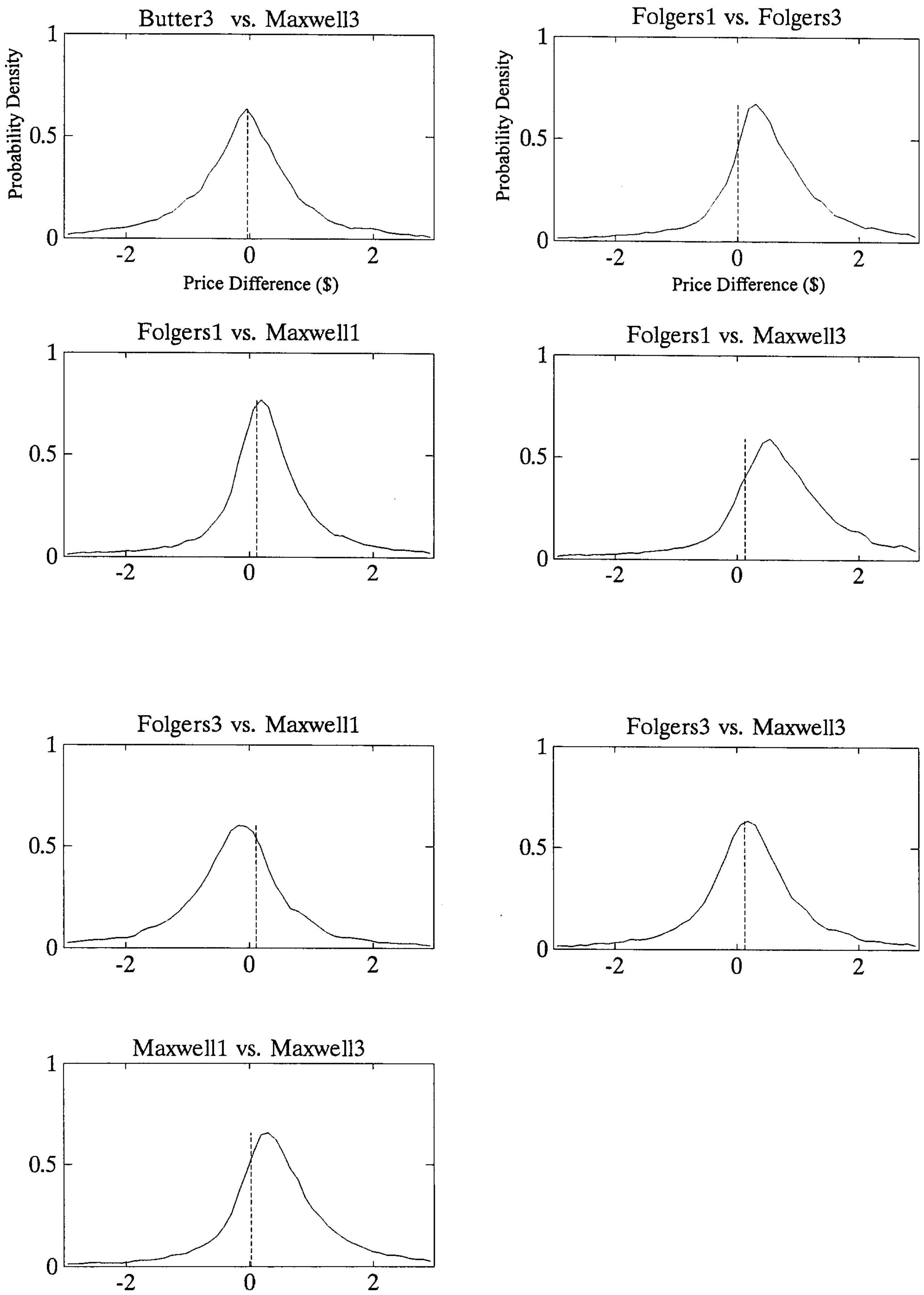

Butter3 vs. Maxwell3
Probability Density
Price Difference ($)
Folgers1 vs. Folgers3
Probability Density
Price Difference ($)
Folgers1 vs. Maxwell1
Folgers1 vs. Maxwell3
Folgers3 vs. Maxwell1
Folgers3 vs. Maxwell3
Maxwell1 vs. Maxwell3

Figure 5. Utility Function and Indifference Curve without Loss Aversion

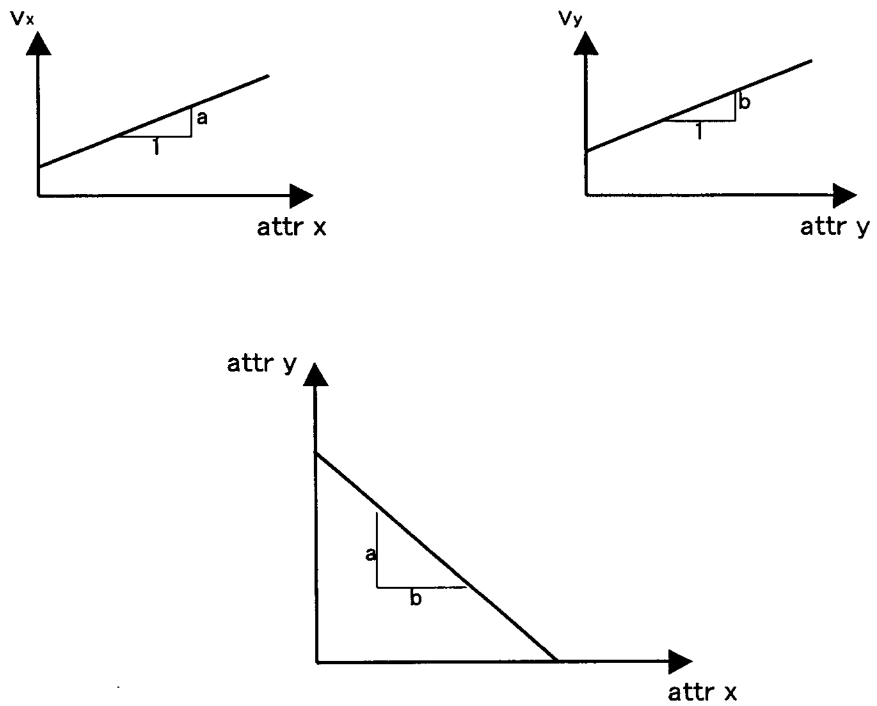
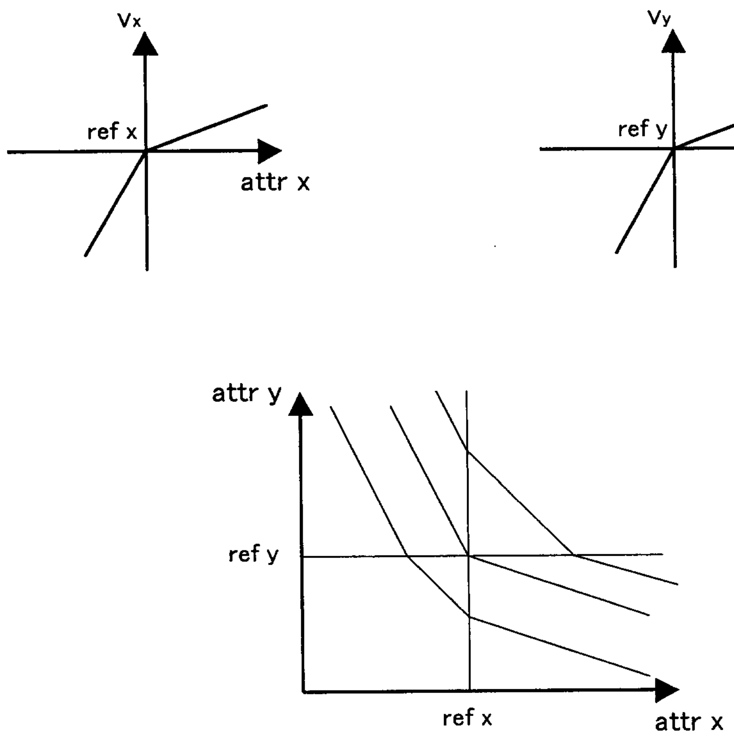
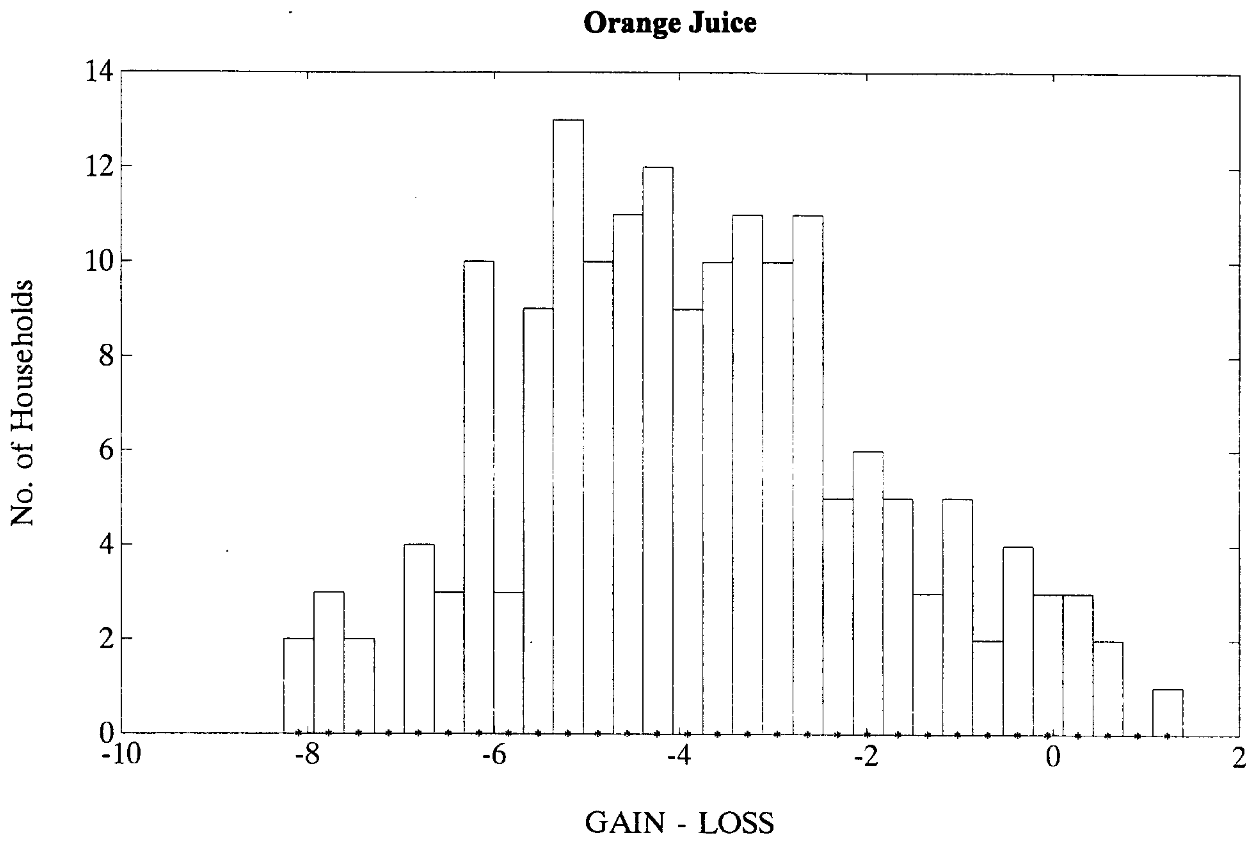


Figure 6. Utility Function and Indifference Curve with Loss Aversion





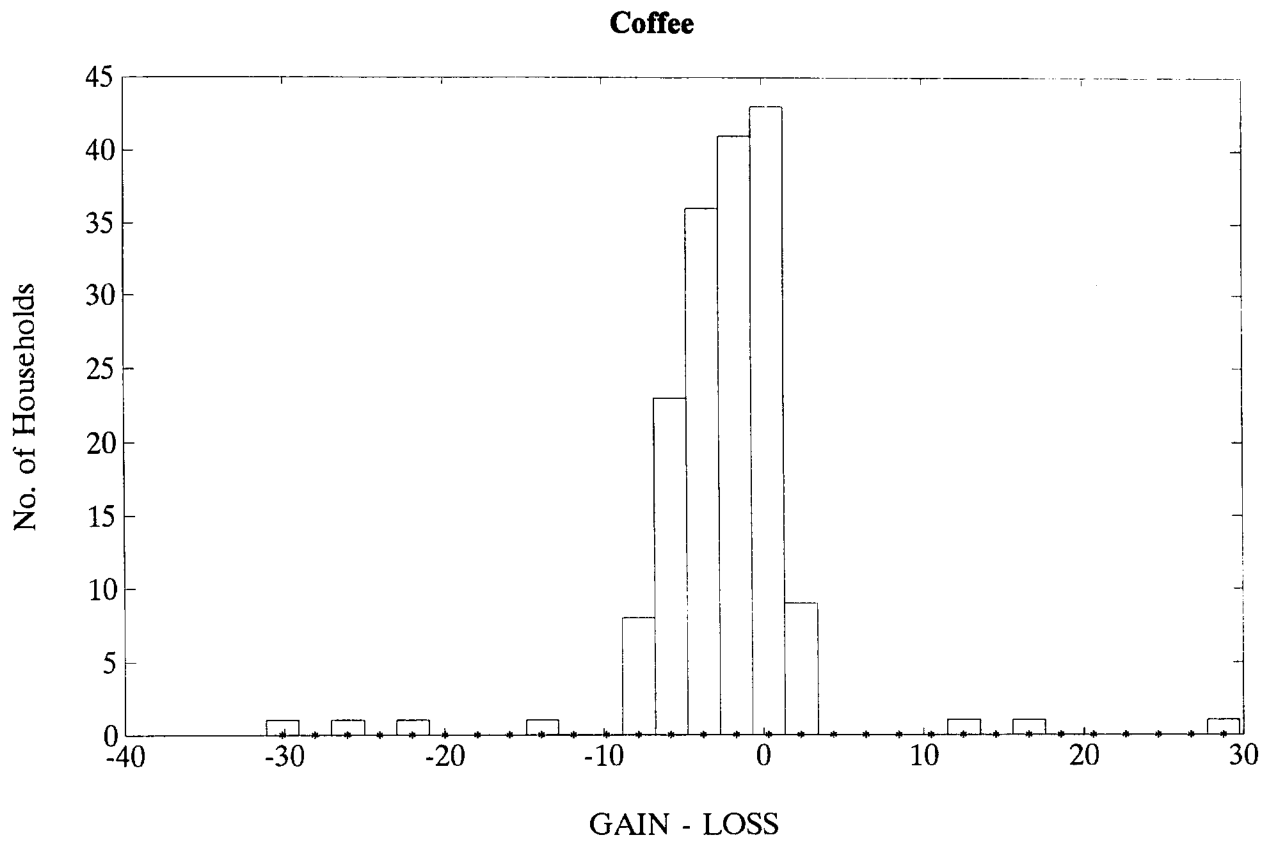
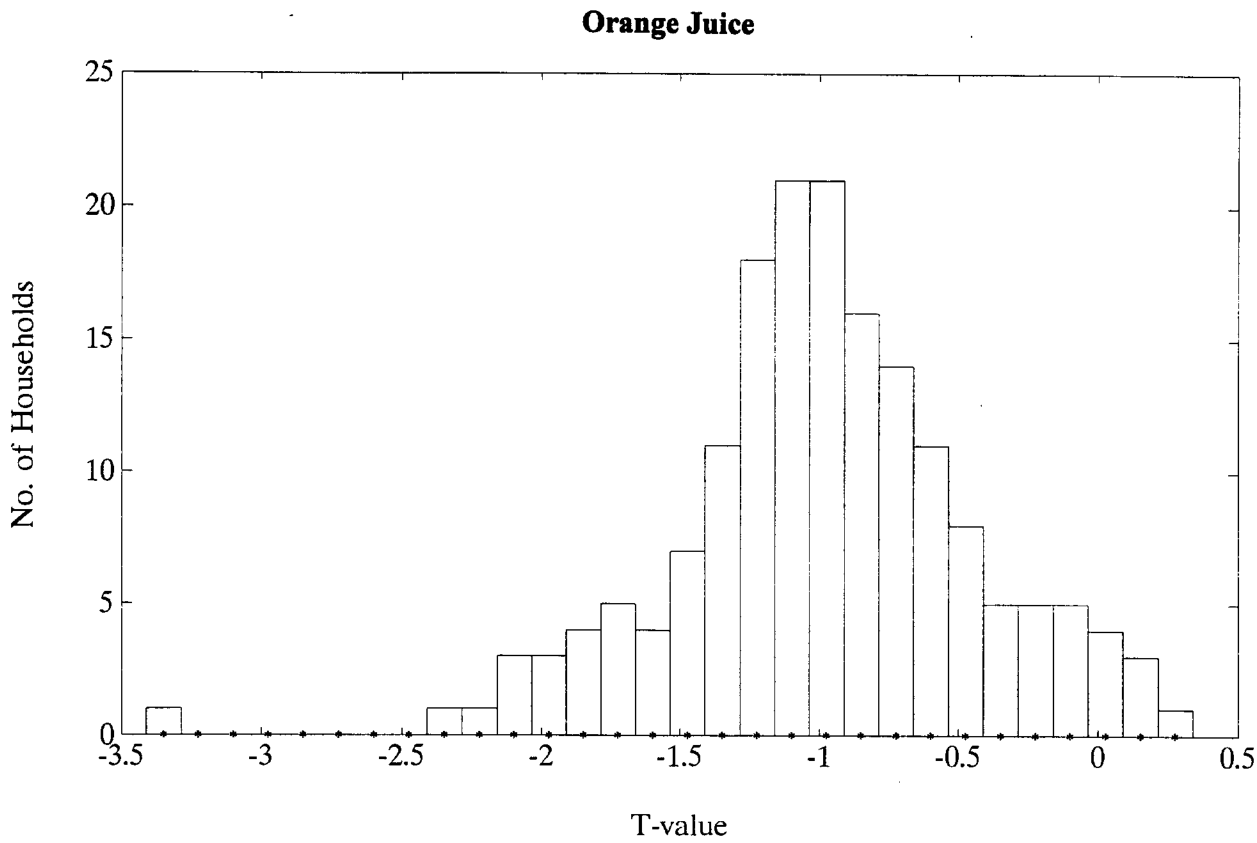


Figure 7. Histogram of the Difference between Absolute Magnitudes of Gain and Loss Coefficients.



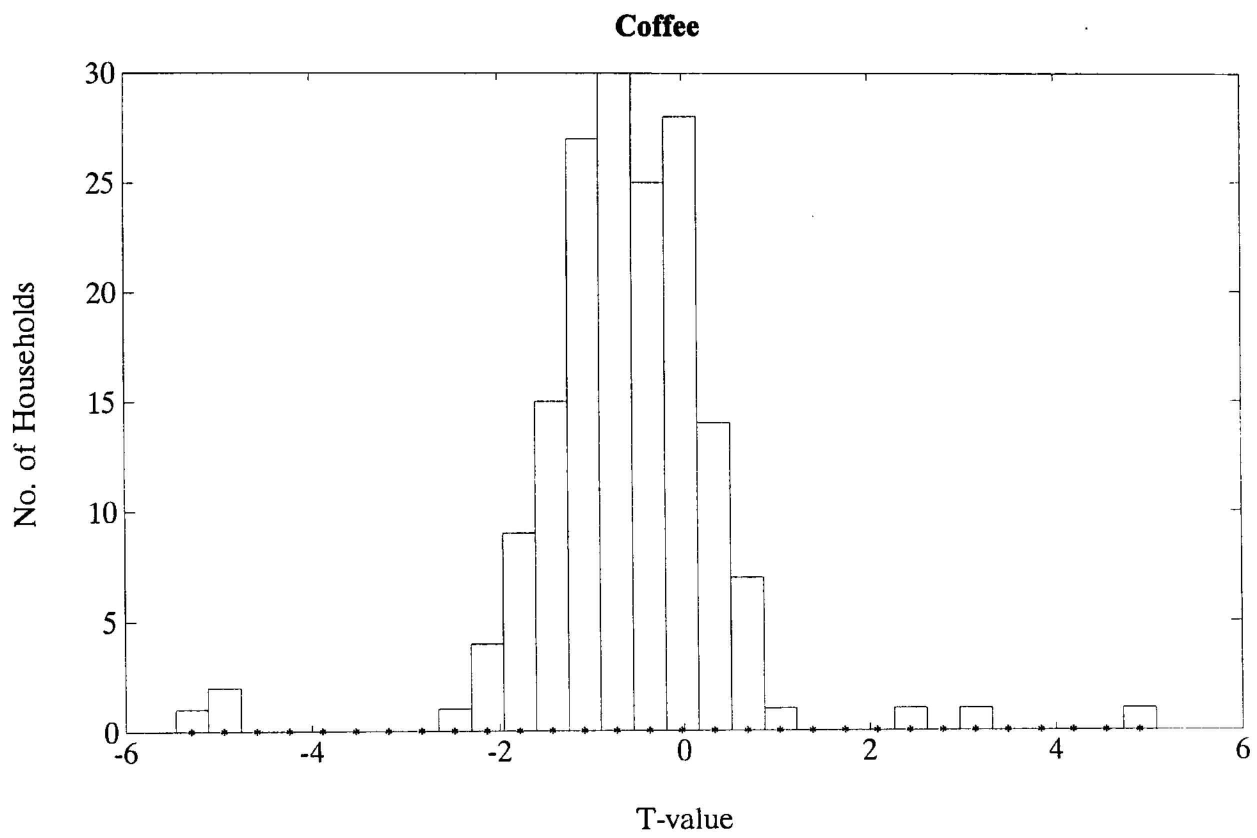


Figure 8. Histogram of t-statistics for the Differences Using Their Asymptotic Standard Errors.

Figure 9. Utility Function and Indifference Curve with Decreasing Marginal Return

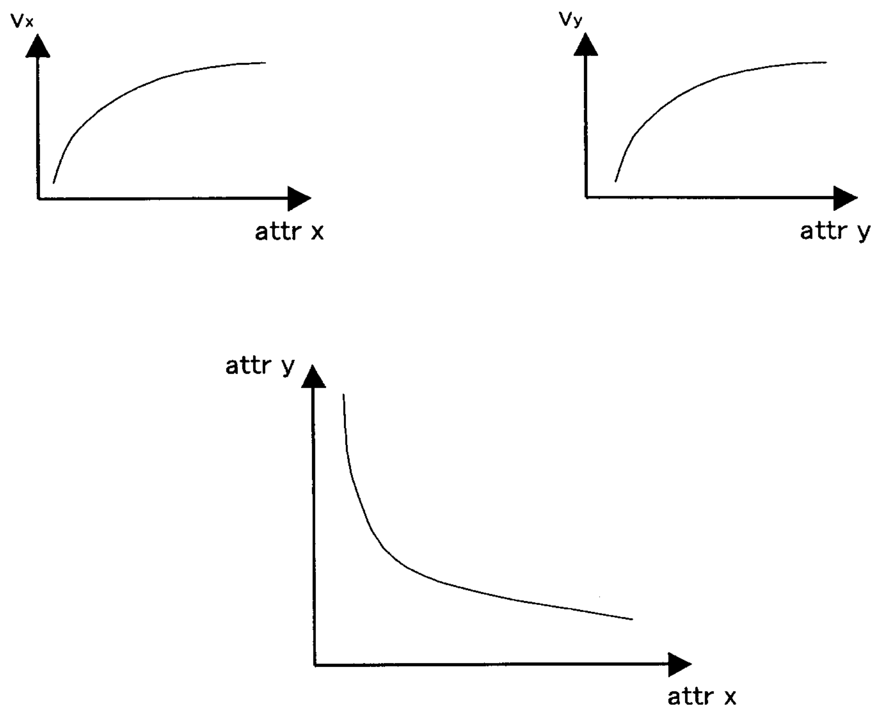
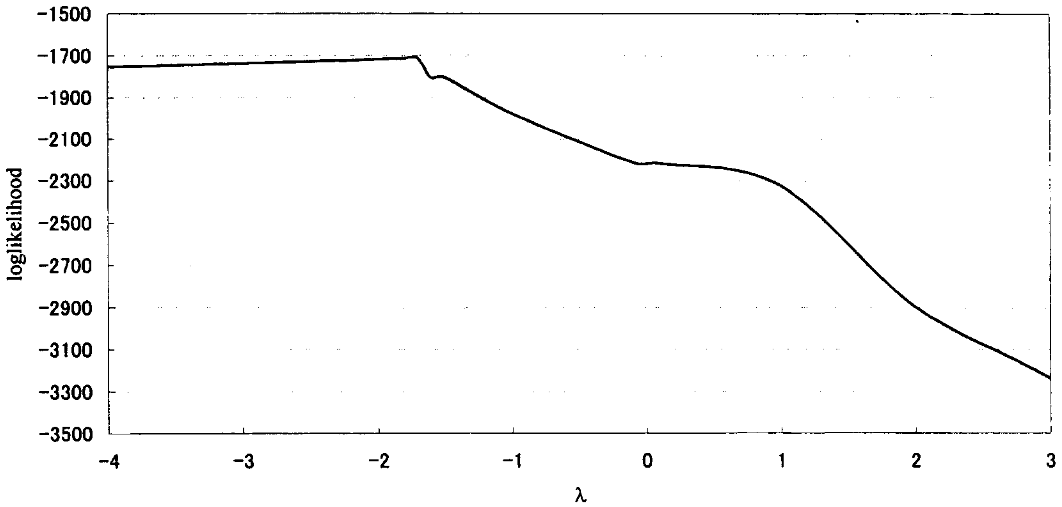


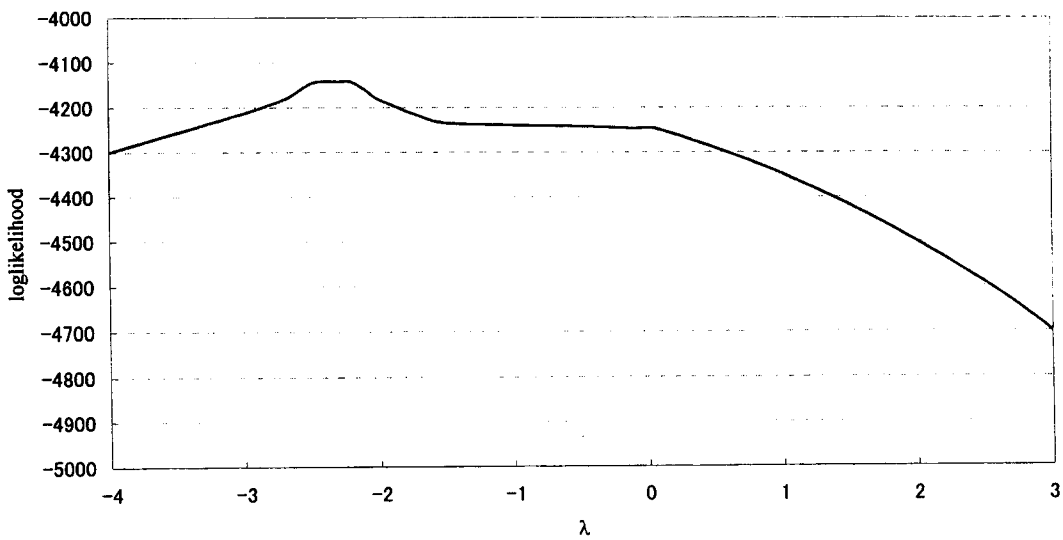
Figure 10. Loglikelihood for Different Concavity λ

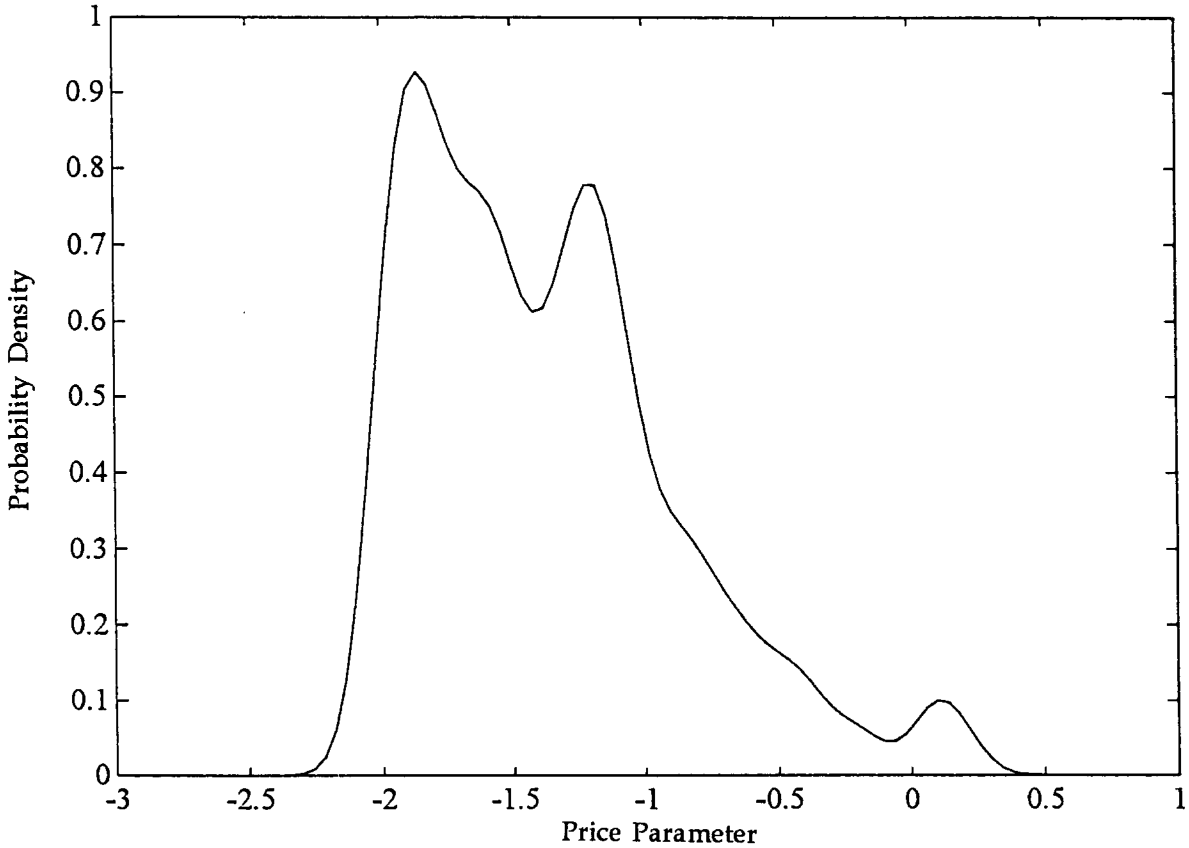
The smaller the value of λ is, the stronger the concavity is (λ=1 and 0 correspond to linear and logarithm, respectively)

Loglikelihood for Different Concavity λ in Orange Juice Data



Loglikelihood for Different Concavity λ in Coffee Data





prior sample size = 10

Figure 11. Recovered Bimodal Distribution of Price Parameter for Simulation Study

Bimodality at -3.6 and -1.2 is recovered although some shrinkage toward the prior mode can be observed.

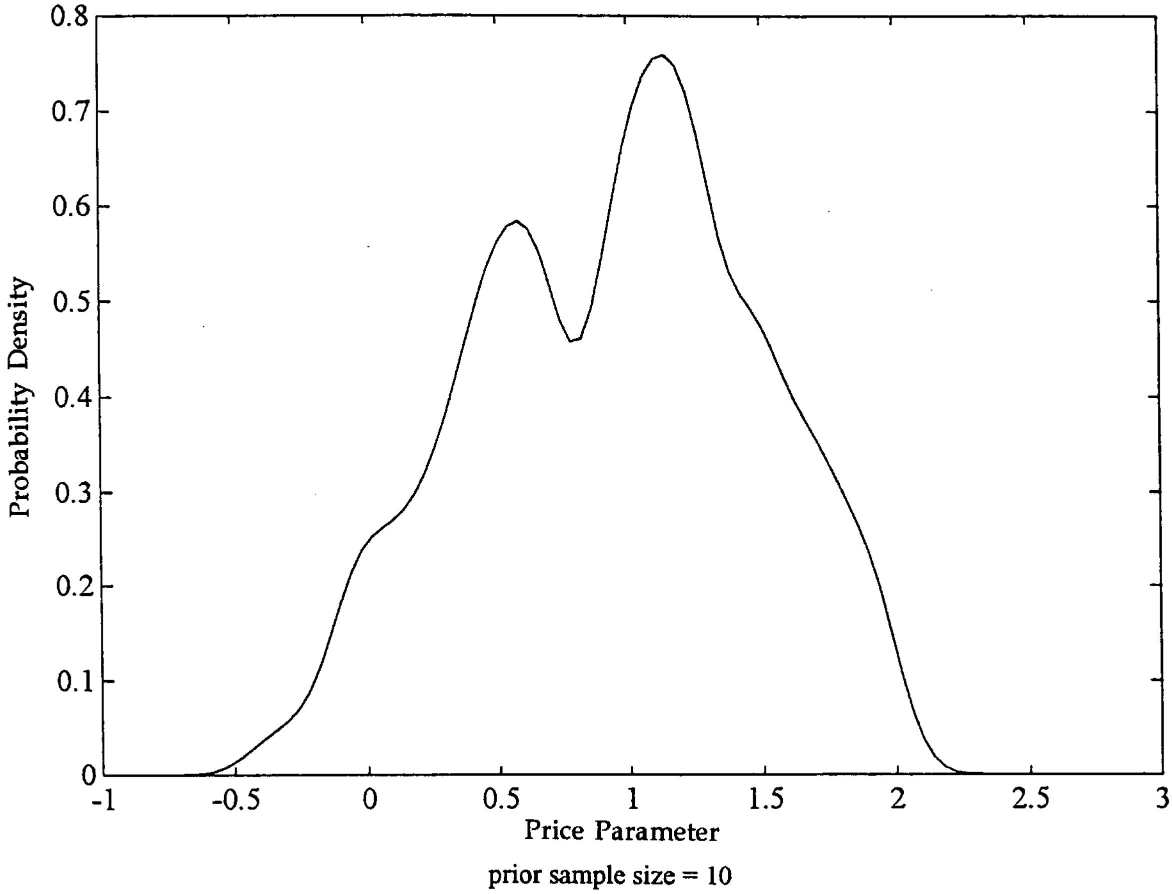


Figure 12. Recovered Bimodal Distribution of Citrus Hill Brand Constant for Simulation Study

Bimodality at 1.4 and 0 is recovered although some shrinkage toward the prior mode can be observed.