Price Expectations and Purchase Decisions:

Evidence from an Online Store Experiment

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Abstract

In this research we study (a) the formation of price expectations before consumers are exposed to store prices (PRE) as well as expectations about prices at the next purchase occasion after being exposed to store prices (POST), (b) the effect of PRE and POST on purchases, and (c) consumer heterogeneity in formation and effects of PRE and POST. We conduct an online store experiment to simultaneously study effects of PRE and POST on purchase and examine when one or the other may be dominant. Results reveal the existence of two distinct classes of transactions: a "forward-looking" class (35% of the total) where the effect of POST is stronger than that of PRE on purchase and a "transaction-utility" class (65% of the total) where purchase is influenced more by PRE than by POST. The forward-looking class is more responsive in incorporating store prices in forming price expectations than the transaction-utility class, and purchases for the latter class are significantly affected by price displays (that highlight a price). Further, consumers are more likely to belong to the forward-looking class when purchasing their favorite brands in a category. Finally, we use what-if experiments based on the estimated model to show the differential dynamic impacts of permanent price changes and short-term promotion on future purchases in the two classes.

Key Words: Price expectation, Forward-looking, Transaction-utility, Transaction heterogeneity.

INTRODUCTION

Consumers usually form price expectations to assist their purchase decision for a product. These price expectations are then used as reference points to compare with store prices and make purchase decisions (Monroe 1973). The following example illustrates this process well. Facing the same store price $1.00 for a bag of chips, a consumer who expects the price to be $0.90 is probably less likely to buy the chips than another consumer who expects the price to be $1.10. There are at least two explanations for this prediction. The first is that the transaction utility of the first consumer is reduced as her expectation of the current store price, which we refer to as the *pre-expectation* of price (henceforth, PRE), is lower than the actual price (Thaler 1985). Another explanation is that the consumer is forward-looking as she defers her purchase to later weeks because her expectation of future price, which we refer to as the *post-expectation* of price (henceforth, POST), is lower than the current price. Though the two explanations can equally explain the same phenomenon, their implications on the store promotional policies and predictions on future store sales following promotions can be different. In order to study the effect of both pre- and post-expectations on purchase, we set up an experiment in which consumers make real purchase decisions in an online grocery store. We study how participants form price expectations before and after they are exposed to the prices in the store, and how each of these expectations separately affects their final purchase decisions.

Much previous research has studied how reference price affects purchase decisions (for a detailed review see Mazumdar, Raj, and Sinha 2005). In general researchers postulate an increase in consumers' purchase utility (or a gain) when the current price is lower than the reference price, and a decrease (or a loss) when the current price is higher than the reference price. Gains/losses correspondingly increase/decrease the probability of purchase. Reference prices studied in the literature are postulated to be formed from various sources (Mayhew and Winer 1992). These reference points can be internal that are based on prices paid or observed in the past (memory-based), or external that are based on current price of brands bought in the past (stimulus-based; Mazumdar and Papatla 2000; Rajendran and Tellis 1994). Previous research has used various functional specifications of the gain (prices lower than reference prices) and loss (prices higher than reference prices) and how they affect consumers' utility (Briesch et al. 1997).

Pre-expectations and Transaction Utility

Reference prices are invariably linked to consumers' price expectations. For instance, Thaler (1985) treats the pre-expectation of the current price as a reference point in the prospect theory value function (Kahneman and Tversky 1979). Consequently, a price that is higher than pre-expectations is treated as a loss, whereas a price that is lower than expected is treated as a gain. The transaction utility is a consequence of this loss/gain, and decreases/increases purchase likelihood. In a similar vein, Grewal, Monroe, and Krishnan (1998) discuss the concept of transaction value that the customer derives from the difference between the current price and the pre-expectation (cf. Monroe and Chapman 1987). Some empirical research has tested the predictions of prospect theory by examining how consumers respond to losses and gains (for examples see Krishnamurthi, Mazumdar, and Raj 1992; Mazumdar and Jun 1993; Heath, Chatterjee, and France 1995).

Post-expectations and Forward Looking

In contrast to the research on pre-expectations affecting offer evaluations and purchase, Jacobson and Obermiller (1990) argue that past prices should be immaterial for a forward-looking consumer. Several research studies find support for the argument that consumers are, indeed, forward-looking in making their purchase decisions. They form post-expectation for the price in future purchase occasion, based on their prior expectation and observed price, in a way consistent with Bayesian learning. If post-expectation price is lower than actual price, consumers may defer their purchases instead of buying it now. For example, Narasimhan (1989) included future price expectations into the Bass model in predicting a product diffusion process. Bridges, Yim, and Briesch (1995) used a similar model for high-tech products. A more structural approach involving dynamic choice models was formulated and empirically applied in various works such as Erdem and Keane (2003), Hendel and Nevo (2006) and Sun, Neslin and Srinivasan (2003). Using a similar approach, researchers have tried to decompose the effects of temporary price promotions, especially those that lead to inventory-holding among forward-looking consumers. For examples see Ailawadi and Neslin (1998), Ailawadi, Gedenk, Lutzky, and Neslin (2005), Chan, Narasimhan and Zhang (2006).

Simultaneous Consideration of Pre- and Post-expectations

The large amount of research on price expectations notwithstanding, to the best of our knowledge no previous study has identified *whether* and *when* the effect of pre-expectations would dominate the effect of post-expectations on purchase decision or vice versa. The major reason is identification – in a typical consumer panel data price expectations are unobservable. Instead, they have to be inferred from past store prices. Since consumers may update their post-expectations based on their pre-expectations and current prices, it is difficult to separately identify the impacts of pre- and post-expectations if we only observe prices and purchases. Suppose we find from data that, conditional on the current price, a lower level of past prices correlates with fewer purchases in the current period. Such observation can be explained either by low past prices leading to lower pre-expectation of current price and a perceived loss in consumers' transaction utility, or by low past prices leading to lower post-expectation of future price which causes consumers to defer purchases. To illustrate this argument, let's consider the example discussed above: suppose we observe a consumer who previously purchased a bag of chips at $0.90, compared with another who previously purchased a bag of chips at $1.1, is less likely to purchase the chips again at current store price $1.0. This could be primarily driven by her expectation of paying $0.90 before exposed to the actual price (PRE), or by her expectation of paying a lower price in the next store trip (POST). As different explanations lead to same observable outcomes, typical consumer panel data do not allow us to infer the separate impacts of pre-expectation and post-expectation on purchases.

We, therefore, designed an experiment that involved shopping at an online store. One of the major advantages of setting up this experiment is that we were able to collect information at a much greater level of detail, including participants' pre- and post-expectations, than is possible to extract from scanner data. Specifically, participants in the study reported how much they expected to pay for a specific product before they knew the actual price in the store, as well as how much they expected to pay for the product when they would purchase it next. If a consumer's decisions are driven by transaction utility, their pre-expectation will determine the final purchase decision; however, if the consumer is forward-looking, their post-expectation (which may be affected by the pre-expectation) will play a more important role in the decision. Furthermore, the simulated online store was superior to intercepting consumers in real stores as the former allowed us to study the changes in participants' purchasing behavior and price expectations over several periods with controlled price changes. A more detailed discussion of the study design and data is provided in a later section.

PRE formulation. Previous research has tried to study the formation of pre-expectation and post-expectation of price among consumers. A few studies assume that consumers have rational expectation and their information set is the same as that of managers who set the prices. Muth (1961) was one of the earliest researchers to make the rational expectation assumption. In this case, the true values will be the price expectations plus a random noise. Winer (1986) highlighted the importance of reference price in brand choice and purchase quantity decisions, empirically testing two different reference price formation processes. Later studies (Krishnamurthi, Mazumdar, and Raj 1992; Raman and Bass 2002) found evidence that price in the previous store visit was an adequate measure of pre-expectation. Briesch et al. (1997) evaluated various alternative model specifications and found the best fit for exponential smoothing using brand-specific past price paid. For consumer *i* in period *t*, her pre-expectation of price (PRE) is the following:

(1) $$PRE_{it} = \alpha.PRE_{i(t-1)} + (1-\alpha).PRICE_{ib(t-1)}$$

where *b(t-1)* is the brand purchased in the previous visit, and the range of α is between 0 and 1. Such an exponential smoothing process is based on the adaptation-level theory (Helson 1964) which draws its inspiration from the study of elasticity of expectation (Hicks 1939). It has found wide acceptance among researchers applying to many of the empirical studies (Erdem, Mayhew, and Sun 2001; Fibich, Gavious, and Lowengart 2005). A similar approach can be applied to the formation of the post-expectation of price.

POST formulation. If consumers have some prior expectation of price (*PRE*) and then are exposed to the actual price once they are in the store, both PRE and the actual price will be used to form their post-expectations. One of the specifications, for consumer *i* in period *t*, is the following:

$$POST_{it} = \gamma.PRE_{it} + (1-\gamma).PRICE_t \tag{2}$$

where $POST_{it}$ is the post-expectation of price, and the range of γ is again between 0 and 1. Such a specification is consistent with the information integration (Anderson 1981) and Bayesian updating (Degroot 1970) framework. Another major research objective in this paper is to study the process of formation of both pre-expectation and post-expectation of prices among consumers using participants' reported expectations data.

Preview of Method and Results

In summary, this paper studies the formation of pre-expectation and post-expectation of price and how these expectations impact consumers' final purchase decisions. We develop an econometric model to jointly estimate the formations of pre-expectation and post-expectation as well as the purchase probabilities. Further, we use a latent class approach in the estimation model to allow for potential heterogeneity among consumers. For example, while some consumers are more forward-looking the others may rely more on the perceived transaction utility in their decision-making. Also, previous research has found large variation in the range of the parameters in Equation 1. Kalyanaram and Little (1994) found α in Equation 1 to be 0.82. On the other hand, Erdem, Mayhew and Sun (2001) found this parameter to be between 0.39 and 0.71 for different product categories. We will try to understand the reasons and implications of these heterogeneities among our consumers.

From our estimation we find that there exist two distinct classes among our participants. The smaller (35% of the total) class is forward-looking and POST affects its purchase decisions relatively more strongly than PRE. This class is also more responsive in incorporating store prices in forming price expectations. On the other hand, the larger (65% of the total) class is transaction-utility driven and is influenced more by PRE than by POST. This class is less affected by current prices in updating the price expectations. Moreover, this class is significantly affected by price displays (sign highlighting a price).

We believe that the results of our research have significant implications. To understand the role of forward-looking vs. transaction utility in purchasing behavior and the formation of price expectations helps us to better understand consumers' decision process. This understanding can inform promotion strategies. For example, under a price promotion the response of the transaction-utility driven consumers can be different from that of forward-looking consumers depending on how the promotion leads to the formation of PRE and POST. The impact on future purchases can also be very different since the updating processes of PRE and POST are different between transaction-utility driven and forward-looking consumers. With such knowledge, managers may be able to use proper promotion policies to stimulate beneficial outcomes from different price expectations. We will provide detailed discussion later in the result section.

The rest of the paper is organized as follows. In section 2 we explain the online store shopping experiment and how the data is collected. In section 3 we provide a detailed description of our model and estimation approach. Section 4 provides a discussion of the estimation results and some “what-if” pricing experiments. An extension of the current model, which incorporates zones of insensitivity, will be discussed. Finally section 5 concludes and acknowledges some limitations of this study.

AN ONLINE STORE EXPERIMENT

We designed an online grocery store to study household shopping behavior for a period of five weeks between September 11 and October 13, 2006. We created a shopping environment as close as possible to any functioning store in which shoppers made real purchases by spending real money. We also collected detailed information of the participants’ browsing and purchasing behaviors and their price expectations before and after they were in the store. This section provides a detailed discussion of our experiment set-up.

Data Collection Process

Subjects and procedure. 59 adults were invited to participate in this study after prescreening responses (Median age = 40; Median household income = $50,000; 95% women). Participants were primary grocery shoppers for their family and visited a grocery store at least once in two weeks. One of these 59 participants dropped out after the first week, and another joined in the second week. The rest visited the laboratory once a week for five weeks to take part in the experiment.

The online store was situated in an experimental laboratory inside the university. Each participant was provided with a dedicated computer terminal to shop during their visit. The online store stocked 89 products in nine product categories (the product list is provided in Appendix A) which remained unchanged throughout the experiment. Detailed pricing data was collected for several months preceding the study from a local grocery chain. We used these data to calculate the average price, price range and normal price changes for each of the 89 SKUs.

On their first visit, participants provided some background and demographic details (see Appendix B for details). Each participant was given a budget of $15 for each visit. She could choose to spend any (including none at all) amount within that budget, and actual delivery of purchased groceries was managed through a local grocery chain that provided this service for a fee.[1] Any amount that remained unspent from the budget was refunded to them as cash. Hence, during shopping our participants faced a choice between buying from the store or taking the cash and spending for any outside option.

Design. Participants were randomly assigned to one of eight pricing environments. These pricing environments differed in the rate of change (gradual vs. sudden), direction of change for a particular SKU (increase vs. decrease) and degree of balance (balanced number of SKUs seeing a price increase and decrease vs. an unbalanced number). As normally seen in the stores, prices of SKUs under the same brand name (within a category) moved in tandem. Actual price changes varied from category to category and were based on previously collected price data.

For a selected set of SKUs, price reduction (from the previous week) was accompanied by an on-screen banner stating that the price of the selected SKU was $X this week (note that the banner did not provide a reference to the original price). We call this banner a "price display".[2] About 29% of SKUs that saw a price reduction had a price display. The price display was SKU-specific, i.e. only select SKUs were accompanied by a sign highlighting the price when their price went down. The remaining price reductions were not highlighted by a display. Such a set-up helps us differentiate the effect of a price reduction from that of a price display. Furthermore, it allows us to study the effect of price reduction features on purchase (cf. Inman, McAlister, and Hoyer 1990), and explore possible individual differences in sensitivity to this manipulation (e.g., Inman, Peter, and Raghubir 1997).

Our online store mimicked a local online grocery store (including the price display) to create a realistic shopping environment. For each product category a webpage was designed with the following information for all SKUs within the category: (i) picture of the product (barring a few SKUs) (ii) detailed product description including the brand name; (iii) package size of the product; (iv) price information possibly with a price display; and (v) a space for participants to type in the quantity they would purchase (the default was 0). Participants had to browse through all nine category pages in a fixed sequence to finish their shopping experience. They could choose to re-visit any of the previously visited category pages if they wanted to make changes from previous purchasing decisions.

Data collected. In each of the five visits, participants had to go through an interaction cycle. They had to complete a pre-purchase questionnaire and a post-purchase questionnaire during each cycle. The pre-purchase questionnaire collected the following information from each of the participants *before* they observed current product prices:

- the SKUs that the participant intended to purchase during the present visit;
- the participant's expected store price for each of the selected SKUs (PRE);
- response on a scale reflecting confidence in the reported PRE (1= not at all confident, 10= absolutely confident)

Participants were allowed to change their purchase plan at any point in time before final check out. If a participant decided to buy an SKU without indicating her intention at the pre-questionnaire phase we could not capture their PRE for that SKU. During shopping, the following information was collected:

- how much time participants spent on the browsing of each of the category pages
- detailed price and price display information for all products
- the quantity of all products that participants have purchased.

After shopping a post-purchase questionnaire asked participants about

- when they planned to make the next purchase for the products that they had planned to buy and those SKUs that they had not planned but ended up buying during the current visit
- their expected price of those SKUs when they made the next purchase (POST)
- response on a scale reflecting confidence in the reported POST (1 = not at all confident, 10 = very confident)

- In the fifth (last) week, participants responded to a debriefing questionnaire where we asked them about their most preferred brands for each of the nine categories. In addition, they also gave us their opinion about the price level in the online grocery store.

Some Summary Statistics

As discussed before, we pre-screened participants to select only those who were primary shoppers for their family and made at least one shopping trip in every two weeks. Their shopping and household characteristics were as follows:

(Insert Table 1 about here)

Participants in the eight different pricing environments found changing price levels similar to those seen in grocery stores that follow HILO pricing format. Therefore, for the same SKU it was possible that while one set of participants saw the price to be high and coming down (gradually or suddenly), another set of participants saw the price movement in opposite direction. Over the five weeks' period, participants saw 3560 different prices (8 pricing environments, each with 89 SKUs, and over 5 weeks). The price trends are summarized in table 2.

(Insert Table 2 about here)

On average, over the period of five weeks each participant spent \$12.27 (minimum \$0 and maximum \$15) every week and bought 5.58 (minimum 0 and maximum 11) unique SKUs. We chose to use the observations of last three weeks for model estimation to accommodate the learning phase of the participants. As discussed above, we do not record the PRE for the SKUs that consumers do not plan to purchase.[3] For the purpose of model estimation (full discussion will be provided in the next section), we only choose those (participant, week, SKU) combinations with reported PRE as data points for our analysis. Overall, we have 1,183 complete data-points that include price expectations of PRE and POST and the quantity purchased (including no purchase). Column 2 of table 3 gives the number of SKUs in each category in our online store, and column 3 reports the number of intended purchasing instances in these categories. The last two columns of the table report the purchase details. Overall, about 40% of purchase intentions translate into purchases (see last column).

(Insert Table 3 about here)

Table 4 summarizes the price dispersion within each category and the average price expectation reported by participants. These summary statistics are only for the last three periods' data (the data used for analysis). The price variation within and across the categories is substantial. However, at the aggregate level it appears that participants' expectations are quite close and realistic when compared to our store prices.

(Insert Table 4 about here)

Altogether 145 SKUs were on price display in the last three weeks. This constituted about 29% of all the SKUs whose price decreased and about 7% of all the SKUs that were available for purchase during that period. A detailed category-wise breakup is presented in table 5. Distribution across categories is in line with similar promotion activities undertaken by grocery stores.

(Insert Table 5 about here)

MODEL

We model the formations of PRE and POST as well as how both these expectations impact the purchase decisions. We postulate that before walking into a store, consumers have a list of products that they intend to purchase and form a PRE for each of these SKUs. Our analysis is conditional on this shopping list. Consumers' PREs are updated based on their previously observed store prices. Based on such PREs and the observed prices in the store during this visit, consumers will form POST for each product representing the expected future purchasing price.[4] We assume that the consumer's final decision of whether or not to buy each of the products in their list depends on the actual prices in the store as well as their PRE and POST. While the difference between a store price and corresponding PRE may lead to a psychological gain or loss in the purchasing decision, the difference between a store price and corresponding POST implies the cost of buying today relative to buying later either in our online store or outside stores. If a transaction belongs to the transaction-utility class, the consumer's PRE will determine the final purchase decision; however, if the transaction belongs to the forward-looking class, the consumer's POST will play a more important role in decision-making. The relationships between PRE, POST, actual price and purchase decision are depicted graphically in figure 1.

(Insert Figure 1 about here)

We model the three phases of the process – PRE formation, POST formation and purchase decision – and jointly estimate them using the maximum likelihood approach. We also allow for the heterogeneity in consumer behavior by using a latent class approach and enrich it with personal and demographic characteristics that help to distinguish members of each class.

PRE Formation

Our estimation model is similar to the exponential smoothing process in Equation 1 with log transformation. For consumer *i* in week *t* who belongs to a latent class *s*, her PRE formation for product *j* is as follows:

$$\ln(PRE_{ijt}) = \theta_0^s + \theta_1^s \ln(PRE_{ij(t-1)}) + \theta_2^s \ln(PRICE_{j(t-1)}) + \varepsilon_{ijt} ,$$

$$\varepsilon_{ijt} \sim N(0, \sigma_1^2) \tag{3}$$

where the superscript "*s*" implies that the (*i*, *j*, *t*) tuple belongs to a latent class *s*. We estimate the intercept term θ_0^s as a free parameter instead of restricting it as zero here to capture a potential time trend in participants' PRE formation. We also do not impose the restriction that $\theta_1^s = (1-\theta_2^s)$. To avoid the over-parameterization problem in model estimation, we restrict θ's to be the same across all of the 89 SKUs in our data. This is the major reason why we choose to use the log specification in our PRE formation as well as the POST formation and purchase decision discussed below – under log specification the coefficients represent elasticities that are invariant to changes in measurement scale. This is particularly useful for our model since prices of different categories and within the same category prices of different products may vary a lot. For example, the most expensive item in our store is paper towel at $ 7.59 per unit and the least expensive item is yogurt at $0.50 per unit. A price change of 10 cents is a large percent change for the latter but may be negligible for the former as perceived by consumers. A linear specification as in Equation 1 cannot be applied in our model.[5]

POST Formation

Our estimation model is similar to the specification in Equation 2 but with a difference. Current price does not enter directly into the equation. Instead, following Nerlove's (1958) "adaptive expectation" model, we look at the impact of difference between PRE and price on POST (in logarithmic scale, as before). This allows us to see how much of the disconfirmation (difference between PRE and price) is incorporated by consumers in forming their future expectation. In addition, the latent class analysis allows us to differentiate between different updating behaviors of classes. The updating process of latent class *s* for POST is as follows:

$$\ln(POST_{ijt}) = \beta_0^s + \beta_1^s \ln(PRE_{ijt}) + \beta_2^s (DIFF_{ijt}) + \eta_{ijt}$$

(4) $$\eta_{ijt} \sim N(0, \sigma_2^2)$$

where,

$$DIFF_{ijt} = \ln\left(\frac{PRICE_{jt}}{PRE_{ijt}}\right);$$

As discussed before we do not assume that $POST_{ijt}$ to be equivalent to $PRE_{ij,t+1}$ since for most of our participants the POST is the expected price at outside stores but PRE measures the expected price inside our store. The intercept β_0^s helps to capture the perceived difference in average prices between our store and outside stores. To avoid the over-parameterization problem we also restrict all β's to be homogeneous across product categories within the same latent class.

Purchase Decision

A consumer's utility of purchase is captured by a reduced-form specification as a function of current price, its (log) differences between price and PRE and POST, and price display (*Display*). For a latent class *s*, we specify the consumer utility as the following:

(5) $$u_{ijt} = \delta_0^s + \delta_1^s \ln(PRICE_{jt}) + \delta_2^s \ln\left(\frac{PRICE_{jt}}{PRE_{ijt}}\right) + \delta_3^s \ln\left(\frac{PRICE_{jt}}{POST_{ijt}}\right) + \delta_4^s Display_{jt} + \upsilon_{ijt}$$

The parameter δ_1^s on the right hand side of the equation measures the direct price effect. The parameter δ_2^s measures the effect of gain or loss when current price is different from PRE on the transaction utility. The (log) difference between current price and POST measures the future purchasing cost or opportunity as perceived by our participants. Given that we only have five weeks of experiment and do not have data on our participants' purchases in outside stores within and after the experiment period, it is difficult for us to structurally model the dynamic choice of consumers as in Erdem, Imai and Keane (2003), Sun, Neslin and Srinivasan (2003) and others. Instead, we choose to model the effect of POST on consumers' utility in a reduced-form which is captured by the parameter δ_3^s. The parameter δ_4^s measures the effect of price display on the utility of purchase. The effect may be important for those consumers who are not aware of the difference between current promotion price and the regular price. Again to avoid the over-parameterization problem in model estimation we restrict the δ's to be the same across product categories.

Since our participants make purchase decisions with multiple alternatives in each product category, ideally we would like to estimate a multinomial choice model to capture the competitive effect from other products within or outside the category. However, as we discussed in the previous section, it is unrealistic and potentially misleading if we ask participants to report their price expectations (PRE and POST) for all of the 89 SKUs in the experiment. Therefore, in the pre-questionnaire and post-questionnaire we only asked participants to report the PREs of those products that they intended to buy before they knew the actual prices and their POSTs afterward.[6] This brings us a missing data problem if we want to estimate a multinomial choice model – we do not have the data of PRE and POST for those products that participants did not intend to buy *a priori*. Therefore, we choose to estimate a binary choice model instead, i.e., the buy vs. not-buy decisions for those products our participants intended to purchase before knowing the actual prices. Further, the binary choice model also ignores multiple unit purchase decisions. This is partly justified by the fact that more than two-thirds of purchases are in single unit. We assume that the stochastic variable υ_{ijt} in (5) belongs to Type 1 extreme value distribution. Let “1” denotes the buy decision, and let

$$\hat{u}_{ijt}^{s} = \delta_0^s + \delta_1^s \ln(PRICE_{jt}) + \delta_2^s \ln\left(\frac{PRICE_{jt}}{PRE_{ijt}}\right) + \delta_3^s \ln\left(\frac{PRICE_{jt}}{POST_{ijt}}\right) + \delta_4^s Display_{jt}$$

The probability that *j* will be finally purchased has the following binary logit specification:

(6) $$\mathrm{P}_{ijt}^{s} = \Pr^{s}(y_{ijt} = 1) = \frac{\exp(\hat{u}_{ijt}^{s})}{1 + \exp(\hat{u}_{ijt}^{s})}$$

Latent Classes

To allow for consumer heterogeneity we use a finite latent class approach (Kamakura and Russell 1989) in model estimation. Let f_s be the size of class s with the standard restriction $\sum_s f_s = 1$. We incorporate transaction-level characteristics in the probability function for f_s to allow us to make predictions about the propensity of an individual that belongs to a particular class. The probability is specified in the following logit form:

(7) $$f_{ijt}^{s} = \frac{\exp(Z_{ijt} \cdot \theta^{s})}{\sum_{s'} \exp(Z_{ijt} \cdot \theta^{s'})}$$

where Z_{ijt} is a vector of the covariates – a constant term, some time-variant (transaction-specific) measures and the others are time-invariant (mostly demographic) measures. The time-variant covariates are "Fav_Brand_{ij}", which is an indicator variable that takes the value 1 if product *j* is participant *i*'s favorite brand; "$PreConfidence_{ijt}$", which is the participant's confidence level when she estimates PRE for the product; and "$Display_{jt}$", which is an indicator variable that takes value 1 if product *j* is displayed in that week. The time-invariant covariates are "$Freq\_Shop_i$", which equals 1 if participant *i* visits a grocery store more than five times in a month and 0 otherwise; and "$ln(Inc_i)$", which is the log of the household income of the participant. Our hypothesis is that these variables may determine why for a particular transaction a consumer is more or less sensitive to PRE vs. POST as well as the updating of PRE and POST. For example, if a participant who shops frequently or with lower income is more sensitive to store prices and more knowledgeable in predicting future prices, POST may have a larger role in determining her purchase decision.

Model Estimation

Conditional on belonging to the latent class *s*, let $l_{ijt}^1 \mid s$ be the conditional probability density function of $\ln(PRE_{ijt})$ in (3), $l_{ijt}^2 \mid s$ be the conditional probability density function of $\ln(POST_{ijt})$ in (4), and $l_{ijt}^3 \mid s = [\mathrm{P}_{ijt}^s]^{y_{ijt}}[1-\mathrm{P}_{ijt}^s]^{(1-y_{ijt})}$, where y_{ijt} is the indicator function for purchase incidence which equals to 1 if *j* is purchased, be the conditional purchase probability in Equation 6. We simultaneously estimate the composite model of PRE and POST formation and purchase probability using the following log-likelihood function:

(8) $$\ell = \sum_i \sum_t \sum_j [\ln(\sum_s f_{ijt}^s \times (l_{ijt}^1 \mid s \times l_{ijt}^2 \mid s \times l_{ijt}^3 \mid s))]$$

To allow for the possible heteroskadisticity of ε and η across product categories, we estimate category-specific σ_1 and σ_2 (see Equations 3 and 4). However, we impose the independent restriction of ε and η across SKUs.

One of the known estimation difficulties for latent class model is that multiple local optima may exist in the estimation algorithm. To overcome such problem, we preceded the standard gradient parameter searching method with a simplex method Nelder-Mead algorithm. We also tried multiple different starting points to make sure that our estimates generate the highest likelihood function value in Equation 8.

Limitations

The binary choice model in Equation 6 ignores the competitive effects from other products within or outside the category; hence, our estimated price coefficient can be biased if the competition effects are significant, especially for those price-sensitive consumers who do not have strong brand preference. In the experiment we have tried to balance the competitive effects across participants and across product categories (e.g., the same participant would face some products in a category with higher prices and some other products with lower prices, and for any particular product some participants would face a lower price while the others face a higher price, in each week); hence, we believe that the relative magnitudes of our estimated coefficients at the aggregate level should not be too biased.

We acknowledge two other limitations in this model: First, as noted above our analysis is conditional on the list of products that our participants intend to purchase. However, we do not model how this list is generated. It is possible that such list is created based on the current price expectations and previous purchasing decisions. Though it may be important to understand how consumers plan their purchases before visiting stores, to model all possible combinations of the available 89 SKUs in our store that form the shopping list is very complicated. This is beyond the scope of our research.

Second, by focusing solely on the purchasing decisions of products in the shopping list we ignore the purchasing decisions for other products that are not in the list. Buying these products can be due to the decision of substituting for products in the list or simply due to impulse buying. One more reason is that during each visit our participants may simply want to spend their remaining budget after buying what they intended to buy. This study does not model these decisions because of the restriction of the PRE and POST data we can collect. Without accounting for the above issues what we have analyzed is only part of the complete purchasing decisions. Still, we believe that the analysis in this paper is an important first step in separating PRE and POST on purchasing decisions and, as we will discuss later, helps to shed useful managerial insights on store promotions.

RESULTS

In this section, we will first present and discuss our model estimation results. We focus on the difference in behaviors between the two latent classes in our model. Based on the estimation results we will explore some “what-if” pricing experiments. Finally we discuss an extension of our model which also allows for the “zone of insensitivity”.

Estimation Results

To determine the number of latent classes we should allow for, we estimate our model with an increasing number of classes. With increase in the number of classes from one to three, log likelihood function improved along with the AIC and BIC criteria that penalize for increase in parameter in estimation model. Though with a 3-class model we get a statistically better fit, the size of the additional class 3, as we move from 2-class model to 3-class model, is only 5 percent of the total sample (comparison of the sizes of classes in different models is in Table 6). Marketers can customize their strategies for any customer segment only if it is large enough to pay for the effort; hence, the 3-class model may not provide more managerial insights compared with the 2-class model. Further, we find that estimation results for the two larger classes, from the 3-class model are similar to that of the 2-class model. Therefore, we consider the 2-class model only in our further analysis.

(Insert Table 6 about here)

The parameter estimates for PRE and POST formations and the purchase decision, from the 2-class model, are presented in table 7.

(Insert Table 7 about here)

From model estimation we find two distinct classes in our observations which are significantly different in purchase decision and PRE and POST formation. We will start with discussing the purchase decision phase estimates (the third panel in Table 7).

Purchase decision. The forward-looking class of purchasing decisions is more price sensitive than the transaction-utility class (estimated price coefficient -0.65 vs. -0.28). The most significant distinction between the two classes is that the most important variable in the purchase decision for the FL class is $\ln\left(PRICE/POST\right)$, that quantifies the difference between POST and current price. The coefficient for this variable (-1.77) is significantly larger ($t < 0.0001$) in magnitude than the coefficient for $\ln\left(PRICE/PRE\right)$ (-0.60) which quantifies the difference between PRE and current price. Thus, the purchases in the forward-looking class are mainly driven by the comparison of the cost of buying now vs. the expected cost buying in future. Consequently, we label this as the "forward-looking" (FL) class. Further, the coefficient of price display of this class is insignificant; as we discuss later, this may be because the forward-looking class is quite attentive to price changes.

In contrast, $\ln\left(PRICE / PRE\right)$ is the most important variable in determining the purchasing decision for the TU class, with estimated coefficient at -0.84. The variable $\ln\left(PRICE / POST\right)$ is significant with an anomalous positive sign, and in magnitude it is smaller than $\ln\left(PRICE / PRE\right)$ (0.41 vs. -0.84, t < 0.0001). As purchasing decisions in the TU class are primarily determined by the difference between actual price and PRE, we label it the "transaction-utility" (TU) class.

We note that the attention paid to price may be low for the TU class. First, the magnitude of the price coefficient is small, suggesting that a price promotion alone may not increase much purchase. Second, the effect of price displays ("*Display*" in table 7) is significantly positive, indicating that the purchase probability increases significantly for this class when the price reduction is accompanied with price display. This pattern of results is consistent with prior research. Specifically, Inman, McAlister and Hoyer (1990) find that a promotion cue is often used a signal for a deal, an assumption that is more likely for the TU (vs. FL) class of customers. Alba et al. 1999 also suggest that the effect of promotion is likely to stronger when the pricing environment is complex, as it typically is in a grocery store like ours. Our results suggest that price display may only be effective in increasing the propensity of purchasing when consumers are driven by transaction-utility but not when consumers are forward-looking.

If consumers were only forward-looking (e.g., Jacobson and Obermiller 1990), conditional on POST, PRE expectation should not impact purchasing decisions. However, we find that PRE is the major determinant for the TU class, which is larger than the FL class (we will discuss the segment size later). In contrast, the effect of PRE on purchasing decisions for the FL class is insignificant. Our results suggest that decisions for most grocery purchases may be made on the basis of psychological gains or losses. However, we note that purchase behavior in other product categories (especially high-priced ones) may be very different from that revealed by the present research.

PRE formation. The two classes of transactions also demonstrate distinct differences in PRE and POST formation (see the first and second panel in Table 7). For the FL class, PRE is affected more by the price observed in the previous visit than by the carry-over effect from their previous PRE (0.54 vs. 0.4, $t < 0.0001$). For the TU class, in contrast, the PRE formation has a higher carryover effect from their previous PRE and seem to be barely affected by the price they previously observed (0.84 vs. 0.12, $t < 0.0001$). This implies that the FL class is more attentive to the store prices in updating their price expectation than the TU class.

POST Formation. While PRE has dominant effect on the POST formation for both classes (0.96 and 0.97, respectively), the difference between current price and PRE has a stronger impact on POST for the FL class (0.73 vs. 0.02 for TU class, $t < 0.0001$). This seems to suggest that members of this class assimilate more of the price information and update their future expectation accordingly. On the other hand, members of the TU class have a strong carry-over effect of PRE and the effect of current price in formation of POST is not significant. In summary, we find that the classes behave consistently all three phases: While PRE is the dominant force in determining the PRE formation, POST formation and purchase decision for the TU class, it is less significant for the FL class.

Instead, the FL class updates PRE and POST quickly based on observed store prices, and its purchase decision is mainly driven by POST.

Class Membership. Table 8 reports the parameter estimates in the probability function for the FL class (see Equation 7). A positive coefficient implies that the higher the value of the variable increases the probability of belonging to the FL class (and correspondingly decreases the probability of belonging to the TU class). The coefficient of the indicator for favorite brand is significantly positive at 0.70. Thus, purchases of favorite brands are likely to belong to the FL class. As consumers are more likely to be motivated to process information carefully when buying their favorite brand (e.g., Cacioppo and Petty 1984), this coefficient is consistent with the previously-discussed behavior of the FL class being more active in assimilating the price information to update expectations and make purchasing decisions.

The positive coefficient for *PreConfidence* implies that consumers are more likely to belong to the FL class if their confidence level of PRE is high. There may be two explanations for this result. First, a more confident consumer will find the deviation of actual price from her expectation more unexpected; hence, she is more ready to update her price expectations and be attentive to price changes, which are behaviors exhibited by the FL class. Alternatively, a forward-looking type consumer may be more knowledgeable about prices; hence, is also more confident of her PRE. Therefore, we observe a positive correlation between confidence level and probability of belonging to this class.

Coefficients for other variables such as frequent shopper indicator, income level and price display are insignificant. This reaffirms findings from previous studies that the most commonly captured demographic indicators in scanner panel data are not good indicators of membership of a class, especially "analyzing brand choice behavior of households" (Gupta and Chintagunta 1994 p. 135). Finally, the intercept term is significantly negative at -1.44, implying that on average the size of the FL class is smaller than that of the TU class. Indeed, we find that in our sample observations only about 35% are forward-looking (vs. 65% belonging to the TU class), perhaps indicating that the grocery shopping behavior of most of the consumers is consistent with the transaction utility explanation, i.e., the purchasing decisions may rely more on departures of price from PRE expectations. However, consumers may switch to the forward-looking type when buying for their favorite brand or being more knowledgeable about price.

(Insert Table 8 about here)

Some "What-If" Experiments

To compare the difference in behaviors between the FL and TU class, we conduct some "what-if" pricing experiments. The first experiment demonstrates the consumer responses when price shifts to a permanently higher level. We arbitrarily choose one SKU (Campbell soup 18.6 oz) and increase its price by 15% (normal price \$2.60, rise to \$2.99) in period 1. Price stays at this level in subsequent periods. We assume that the PRE of consumers before they know the price change in period 1 is at \$2.60. Figure 2 shows the dynamic changes in PRE and POST and purchasing probabilities of the two classes for 10 periods. The differences in the two classes are similar for both PRE and POST: PRE and POST of the forward-looking type quickly catches up with the new price level, while that of the transaction-utility driven type is updated slowly and though rising they do not catch up with the new price level till period 10.

(Insert Figure 2 about here)

The updating process of PRE and POST will also generate differential effect on purchasing probability in the two classes, which is shown in Figure 3. Price increase reduces the purchase probability for both classes, but has a stronger effect on FL class. However, as the price stays at the higher level in subsequent periods, members of this class quickly update their expectations and their purchase probability reverts to normal level by fifth period. On the other hand, due to slower updating behavior of the TU class, the price increase in period 1 depresses the purchase probability for a greater number of periods. The dotted line in Figure 3 shows this effect which is lower in magnitude for period 1 (compared to the FL class) but lingers much longer. It takes all of ten periods for purchase probability to get back to usual level for this class.

(Insert Figure 3 about here)

Our second pricing experiment demonstrates the effect of a temporary price promotion on future sales. We choose the same Campbell soup 18.6 oz and reduce its price by 15% (normal price $2.60, falls to $2.21) in period 1. Price returns to the normal level from period 2 onwards. We assume that the price cut in period 1 is accompanied by a price display. Again we assume that consumers' PRE before knowing the price change in period 1 is at $2.60. Figure 4 shows the changes of purchase probability of each class relative to the level when the price is fixed at the normal level from period 1 to period 5. The increase in purchasing probability of the FL class during the promotion period is much higher than that of the TU class (9% vs. 3%, respectively). Another interesting result is that for the FL class, we observe a well-documented post-promotion sales dip in period 2 – purchasing probability is decreased by about 1 percent after the temporary price promotion. However, such dip is almost non-existent for the TU class. This result may help to explain why empirical evidence for the post-promotion sales dip is intermittent (Neslin and Schneider 1996). Specifically, the extent to which a temporary price promotion will hurt future sales depends on the relative size of the FL vs. TU classes. This is consistent with prior research that has found the post-promotion sales dip to be a small effect that is detectable only after controlling for household heterogeneity (Hendel and Nevo 2003).

(Insert Figure 4 about here)

Zone of Insensitivity

In our analysis, we have assumed that consumers respond to any disconfirmation of actual price and price expectations by updating their POST and adjusting purchasing decisions. In their research Kalwani and Yim (1992) have shown that consumers have a zone of insensitivity around their expected prices and they change their expectations only when the magnitude of changes is large enough to be outside this zone. This "threshold effect" has been confirmed in several other papers (Kalyanaram and Little 1994; Raman and Bass 2002; Monroe 1971). As an extension of our model, we explore the existence of this zone in the POST formation and purchasing decisions. In the POST formation, we assume that consumers will only update if the absolute difference between actual price and PRE is above a positive cut-off point k_1. The formula for POST formation is modified as the following:

$$\ln(POST_{ijt}) = \beta_0^s + \beta_1^s \ln(PRE_{ijt}) + \beta_2^s (DIFF_{ijt}) \cdot \left\{ \left| \frac{PRICE_{jt}}{PRE_{ijt}} - 1 \right| > k_1 \right\} + \eta_{ijt} \tag{4'}$$

where $\{\cdot\}$ is an indicator function which is equal to one if the logical expression inside brackets is true and zero otherwise. The above equation implies that consumers will only update their POST if the ratio $\left| \frac{PRICE_{jt} - PRE_{ijt}}{PRE_{ijt}} \right|$ is large enough.

Similarly, for the purchasing decision phase, let k_2 and k_3 be two positive numbers. We assume that the consumer utility will only be affected if the disconfirmations between actual price and price expectations are large enough. The purchase utility function in Equation 5 is modified as the following:

$$\begin{aligned} u_{ijt} = {} & \delta_0^s + \delta_1^s \ln(PRICE_{jt}) + \delta_2^s \ln\left(\frac{PRICE_{jt}}{PRE_{ijt}}\right) \cdot \left\{ \left| \frac{PRICE_{jt}}{PRE_{ijt}} - 1 \right| > k_2 \right\} \\ & + \delta_3^s \ln\left(\frac{PRICE_{jt}}{POST_{ijt}}\right) \cdot \left\{ \left| \frac{PRICE_{jt}}{POST_{ijt}} - 1 \right| > k_3 \right\} + \delta_4^s Display_{jt} + \upsilon_{ijt} \end{aligned} \tag{5'}$$

That is, impacts of PRE and POST will only enter the consumer utility if the absolute difference between actual price and PRE or POST is larger than k_2 or k_3, respectively. The binary logit purchasing probability function in Equation 6 is similarly modified. The estimates of k_1, k_2 and k_3 for two classes are reported in table 9.

For the FL class the value of k_1 is 13% and is statistically significant. This result should be seen in conjunction with the parameter estimate (0.733 for *Diff* – panel 2 of table 6). This indicates that once the absolute difference between PRE and price is beyond the threshold, the effect is quite strong. In contrast to previous findings of threshold effects, our results show that all the other $k's$ are small in magnitude and are not statistically significant. This might be because the participants know that they are taking part in an experiment and, hence, are in a heightened state of awareness. Finally, we also find a clear emergence of two classes with distinctive updating and purchasing process similar to the model without the zone of insensitivity, signifying that our results are robust to various model specifications.

(Table 9 about here)

CONCLUSION

Despite the large amount of previous research on price expectations, no study has examined to what extent PRE and POST price expectations separately affect consumers' purchase decisions. Further, no research has simultaneously studied how consumers form PRE and POST price expectations. The main reason is that PRE and POST are unobservable in consumer panel data and not separately identifiable based on observed purchases and prices. To address these issues, we set up a controlled online store shopping environment allowing participant consumers to make real purchasing decisions in a five-week window. Rich data including consumers' PRE and POST expectations are collected to enable us to simultaneously estimate the PRE and POST formation as well as to identify their impacts on the purchasing decisions.

We find from estimation results that two distinct classes of shopping behaviors exist in our data. Purchase decisions of the FL class are determined by the perceived difference between actual price and POST price expectations, while that of the TU class are mainly driven by the perceived difference between actual price and PRE price expectations. Price display has significant effect on purchases for the TU class. Moreover, when store prices change, the updating processes of PRE and POST are much faster for the FL (vs. TU) class. We also find that the TU class is a much larger segment in our data with a 65% share (vs. 35% for FL). However, consumers purchasing a favorite brand or those with a high level of confidence in PRE are more likely to belong to the FL class.

Thus, our results suggest that differing messages to FL and TU classes may be effective in increasing the impact of sales promotions. To increase purchases of a product which buyers more likely belong to the TU class (e.g. products without strong brand preferences), the message should compare the promoted price with past prices (e.g., “Today’s price $1.99, was $2.59!”). In contrast, to increase purchases of a product which buyers more likely belong to the FL class (e.g. favorite brands for most consumers), the message should emphasize that the current promoted price is only temporary (e.g., “price cut at $1.99, only this week!”), decreasing consumer expectation of better deals in the future. Through some “what-if” pricing experiments we demonstrate the differential dynamic impacts on future purchases following permanent change in prices or temporary price promotions in the two classes. Results show that it is important for managers to understand the differences in purchasing behaviors as well as the size of these two consumer segments in order to formulate effective promotion policies targeting different consumer segments.

We acknowledge some of the major limitations in the current study, which may become important avenues for future research. First, as we have discussed, we only model the binary purchasing decisions due to data limitation; hence, we ignore the competitive effects from other products. Further, our analysis is conditional on the list of products that our participants intend to purchase. We do not model how this list is generated. We also do not model the purchasing decisions of products outside the list. Without accounting for all these issues, we only analyze part of the consumer purchasing decisions. Second, though we have tried our best to create a realistic shopping environment, our participants understand that they are shopping in a controlled lab. Hence, their PRE and POST formations as well as responses to price promotions may not have high external validity. To make sure that our results can be replicated in real shopping environments, we should conduct field experiments where consumers are not aware that they are studied and prices are controlled for research purpose.

Finally, our study addresses “how” but not “why” PRE and POST are formed and impact final purchasing decisions. For example, it is important to understand why the TU class is less attentive to price changes and less affected by POST than the FL class. One possible explanation may be that the cognitive effort required to collect and assimilate information leads consumers in the TU class to satisfice (Simon 1955). However, certain stimuli may prompt these consumers to switch from a non-attentive to an attentive mode. We believe that these are important research questions waiting to be studied in future.

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FOOTNOTES

[1]To minimize the substantial delivery cost, not every participant would get her chosen groceries home delivered. Instead, a coin was tossed at the end of each interaction cycle to find out whether the participant would get her groceries or $15 in cash. That is, those who decided to purchase from the online store had a 50 percent chance of getting their groceries delivered. Overall there were 290 participant-weeks of which 143 resulted in home deliveries.

[2] Our "price display" in this experiment is to make participants aware of the price promotion, which is close to the function of product displays in grocery stores.

[3] We only asked participants to report PRE for those SKUs they planned to purchase because of two reasons: first, it would be too time consuming if participants had to report PREs for all 89 SKUs every week. Second and more importantly, it is not realistic that participants would be able to form price expectations for all 89 SKUs including those they had never purchased (or never intended to purchase).

[4] If POST represents the price expectations for consumers during their next visit to our online store, it may become their PRE for next period (after accounting for memory decay and/or exposure to outside prices in the interim). However, we find strong evidence that for most of our participants the POST is the expected price at outside stores. Therefore, we choose to model POST and PRE separately.

[5] To test the robustness of model specifications we also estimate a single class model allowing θ_0 to be different across products and find the results very similar to that of the single class model without product-specific θ_0 . This implies that our assumption of the homogeneity of θ's across categories under the log specification may be reasonable.

[6] We have also asked participants to report the POSTs of those products they did not intend to buy but chose to purchase after knowing the actual prices.

TABLE 1: HOUSEHOLD CHARACTERISTICS OF PARTICIPANTS

Household Characteristics	**Max.**	**Min.**	**Mode**	**Mean**
Family size (including children)	6	1	2	2.54
Number of children	3	0	0	.39
Shopping trips in a month	12	2	5	5.39

TABLE 2: PRICE CHANGE AT SKU LEVEL

Direction of Price Change	Number	% of Total
Increase	608	17%
Decrease	615	17%
No Change	2337	66%
Total	3560	100%

TABLE 3: CATEGORY-WISE BREAK-UP OF DATA USED FOR ANALYSIS

Category (1)	**No. of SKUs (2)**	**Number of Intended Purchases (3)**	**Number of Purchase Instances (4)**	**% Conversion[a] (5)**
Milk	13	117	61	52%
Soft Drinks	19	104	45	43%
Yogurt	13	236	146	62%
Orange Juice	11	83	26	31%
Canned Soup	11	159	67	42%
Pasta	4	121	32	26%
Pasta Sauce	11	129	39	30%
Bath Tissue	4	118	35	30%
Paper Towel	3	116	24	21%
Total	89	1183	475	40%

[a] % Conversion is from purchase intention to actual purchase instances

TABLE 4: PRICE DISPERSION AND AVERAGE PRE AND POST ACROSS CATEGORIES (ALL FIGURES IN $)

Category	**Max. Price**	**Min. Price**	**Avg. Price**	**Avg. PRE**	**Avg. POST**
Milk	2.69	1.19	2.25	2.35	2.31
Soft Drinks	3.67	0.89	2.14	2.05	2.00
Yogurt	3.09	0.50	1.00	1.05	1.02
Orange Juice	5.99	1.65	3.52	3.10	3.10
Canned Soup	3.29	1.99	2.56	1.94	2.09
Pasta	2.49	0.50	1.07	1.21	1.16
Pasta Sauce	3.49	0.89	2.06	2.18	2.23
Bath Tissue	3.79	1.65	2.85	2.67	2.62
Paper Towel	7.59	0.89	2.86	2.19	2.15

TABLE 5: PRICE DISPLAY OF SKUS
IN THE LAST THREE WEEKS OF THE DATA COLLECTION

Category	**Cumulative SKU Price Display**[a]
Milk	4
Soft Drinks	38
Yogurt	10
Orange Juice	28
Canned Soup	20
Pasta	20
Pasta Sauce	20
Bath Tissue	5
Paper Towel	0
Total	145

[a] Same SKU, if on display for several weeks, gets counted multiple times

TABLE 6: SIZE OF EACH CLASS IN ESTIMATION MODELS

	Class Size		
	Single-class model	Two-class model	Three-class model
Class 1	100%	35%	31%
Class 2	NA	65%	64%
Class 3	NA	NA	5%

TABLE 7: PARAMETER ESTIMATES OF THE 2-CLASS MODEL

	Parameter	Class: Forward-looking (FL) Estimate	SE	Class: Transaction-utility (TU) Estimate	SE
PRE Formation	*Const1*	.029	.011*	.018	.006*
	$\ln(PRICE_{(t-1)})$	.540	.011*	.122	.007*
	$\ln(PRE_{(t-1)})$	.395	.012*	.838	.008*
POST Formation	*Const2*	.000	.008	-.003	.006
	$\ln(PRE_{t})$	.957	.011*	.970	.008*
	$\ln(PRICE_{jt} / PRE_{ijt})$	.733	.030*	.017	.015
Purchase Decision	*Const3*	.012	.141*	-.843	.097*
	$\ln(PRICE_{jt})$	-.652	.156*	-.282	.119*
	$\ln(PRICE_{jt} / PRE_{ijt})$	-.599	.425	-.839	.208*
	$\ln(PRICE_{\mathrm{jt}} / POST_{ijt})$	-.768	.822*	.405	.193*
	$Display_{jt}$	-.123	.767	.826	.365*

Note: * indicates a significance level of 5% or better

TABLE 8: PROBABILITY FUNCTION ESTIMATES FOR THE FORWARD-LOOKING CLASS

Parameter	Estimate	SE
Const	-1.435	.097*
Fav_Brand	.703	.111*
PreConfidence	.046	.014*
Display	-.286	.499
Freq_Shop	-.050	.168
ln(Inc)	.000	.001

Note: * indicates a significance level of 5% or better

TABLE 9: ESTIMATES OF ZONE OF INSENSITIVITY

	Class			
	Forward-looking		Transaction utility-driven	
Parameter	Estimate	SE	Estimate	SE
k_1	.130	.037*	.004	.040
k_2	.017	.123	.007	.112
k_3	.002	.366	.012	.283

Note: * indicates a significance level of 5% or better

Figure 1: Relationship of PRE, POST, Price and Purchase Decision

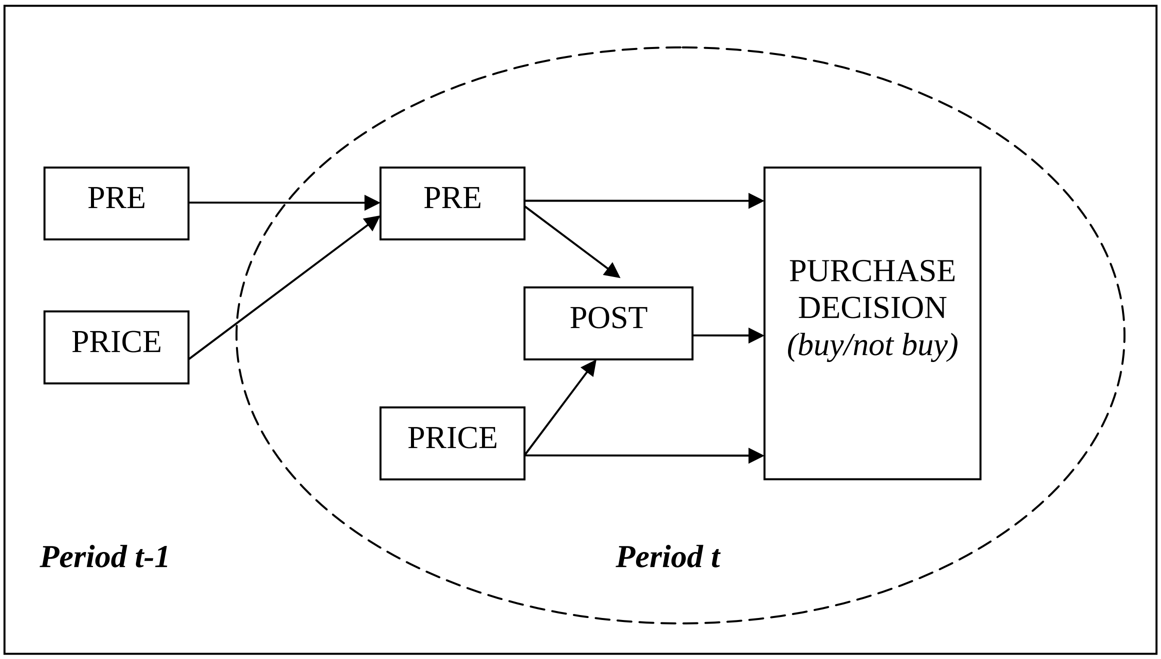


Figure 2: Changes in PRE and POST for Forward Looking (FL) class and Transaction-utility (TU) class as Price Increases in Period 1

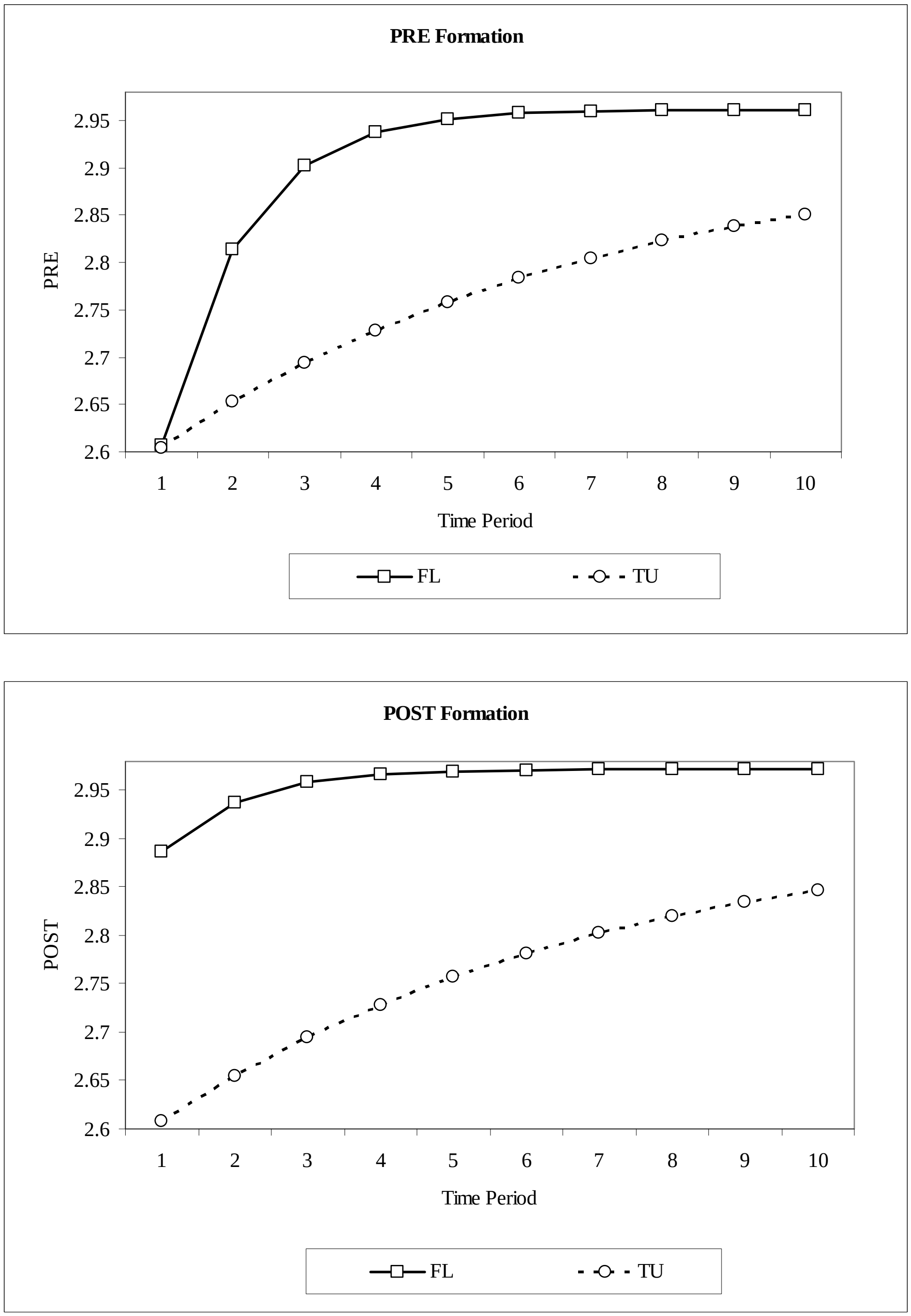


Figure 3: Dynamic Change in Market Share for Forward Looking (FL) class and Transaction-utility (TU) class as Price Increases in Period 1

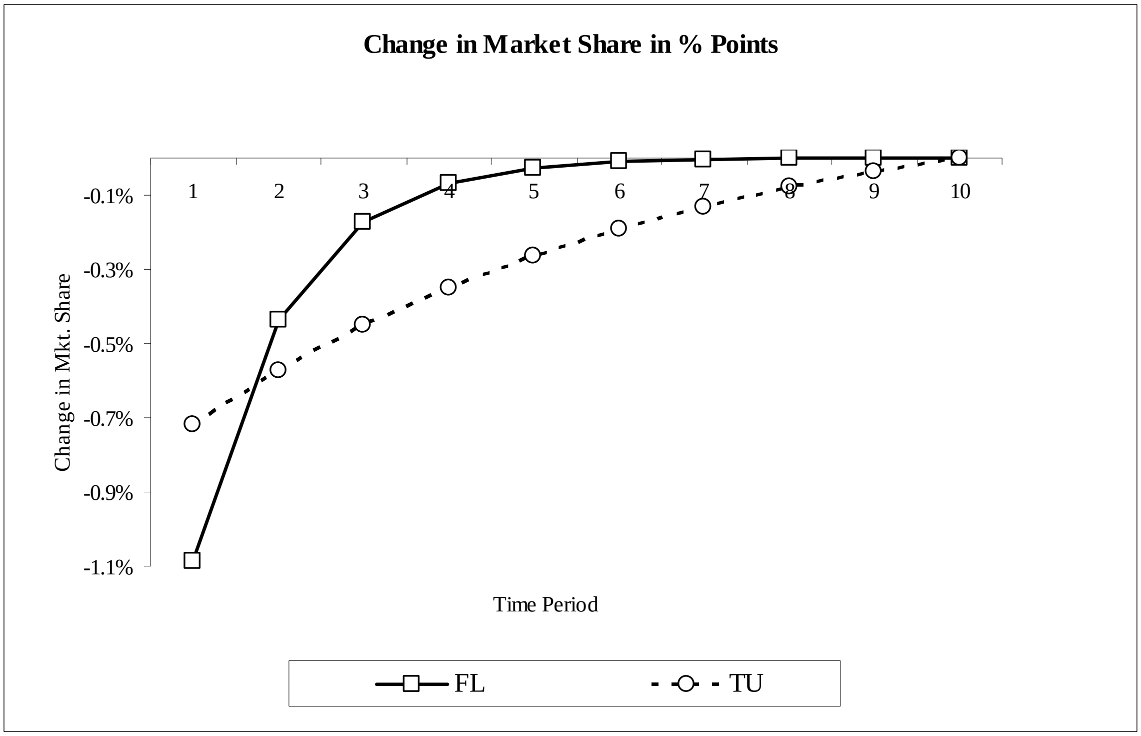
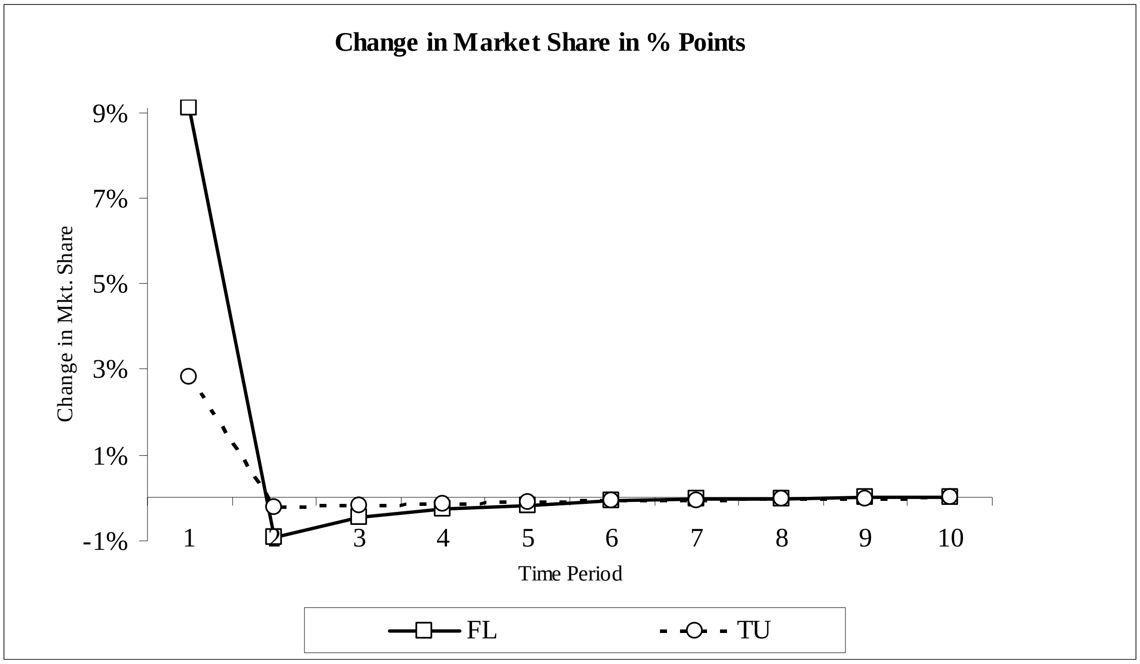


Figure 4: Dynamic Change in Market Share for Forward Looking (FL) class and Transaction-utility (TU) class following Temporary Price Promotion in Period 1



Appendix A

PRODUCT LIST

S. No.	Category	Brand	Pack Size
1	Bath Tissue	Angel Soft Bath Tissue, Double Rolls, White	4 ct
2	Bath Tissue	Kleenex 4 Pk Double Roll White Bath Tissue	4 ct
3	Bath Tissue	Schnuck True Soft Premium Bath Tissue Double Roll	4 ct
4	Bath Tissue	Scott Bath Tissue, White	4 ct
5	Canned Soup	Campbell Home Cooking Chicken with Noodles	18.6 oz
6	Canned Soup	Campbell Home Cooking Potato Roast Garlic	18.8 oz
7	Canned Soup	Campbell Roasted Chicken	18.6 oz
8	Canned Soup	Campbell Roasted Chicken Rice Soup	18.6 oz
9	Canned Soup	Campbell Chunky Chicken with Vegetables	18.8 oz
10	Canned Soup	Campbell Chunky Vegetables	18.8 oz
11	Canned Soup	Progresso Chicken Noodles Soup	19 oz
12	Canned Soup	Progresso Chicken Rice Soup	19 oz
13	Canned Soup	Progresso Hearty Tomato	19 oz
14	Canned Soup	Progresso Soup Beef & Baked Potato	18.5 oz
15	Canned Soup	Progresso Vegetable Soup	19 oz
16	Milk	Pevely Milk, Homogenized	64 oz
17	Milk	Schnuck Milk, 1% - Half Gallon	64 oz
18	Milk	Schnuck Milk, 1/2% - Gallon	128 oz
19	Milk	Schnuck Milk, 2% - Gallon	128 oz
20	Milk	Schnuck Milk, 2% - Half Gallon	64 oz
21	Milk	Schnuck Milk, 2% - Quart	32 oz
22	Milk	Schnuck Milk, Homogenized - Gallon	128 oz
23	Milk	Schnuck Milk, Homogenized - Half Gallon	64 oz
24	Milk	Schnuck Milk, Homogenized - Quart	32 oz
25	Milk	Schnuck Milk, Lite One - Gallon	128 oz
26	Milk	Schnuck Milk, Skim - Gallon	128 oz
27	Milk	Schnuck Milk, Skim - Half Gallon	64 oz
28	Milk	Schnuck Milk, Skim - Quart	32 oz
29	Orange Juice	Schnuck Orange Juice, Gallon	128 oz
30	Orange Juice	Schnuck Orange Juice, Select w/Calcium	64 oz
31	Orange Juice	Florida Natural, Orange Juice	64 oz
32	Orange Juice	Florida Natural, Orange Juice w/Calcium	64 oz
33	Orange Juice	Minute Maid Orange Juice, Calcium Fortified	64 oz
34	Orange Juice	Minute Maid Orange Juice, Premium, Original Calcium Low Pulp	128 oz
35	Orange Juice	Schnuck Orange Juice	64 oz
36	Orange Juice	Tropicana Orange Juice, Premium Grove Stand	64 oz

37	Orange Juice	Tropicana Orange Juice, Premium Grove Stand	96 oz
38	Orange Juice	Tropicana Orange Juice, Premium Homestyle	64 oz
39	Orange Juice	Tropicana Orange Juice, Pure Premium, Calcium Fortified	64 oz
40	Paper Towel	VIVA Big Roll White Towel	1 Each
41	Paper Towel	Schnuck Paper Towels White 1 Roll	1 ct
42	Paper Towel	Schnuck Paper Towels White 6 Roll	6 ct
43	Pasta	R&F Spaghetti	16 oz
44	Pasta	R&F Thin Spaghetti	16 oz
45	Pasta	Schnuck Spaghetti	16 oz
46	Pasta	Schnuck Spaghetti	32 oz
47	Pasta Sauce	Brilla Pasta Sauce, Mushroom Garlic	26 oz
48	Pasta Sauce	Brilla Pasta Sauce, Tomato Basil	26 oz
49	Pasta Sauce	Del Monte D'Italia Pasta Sauce, Four Cheese	26.5 oz
50	Pasta Sauce	Del Monte Pasta Sauce, Garlic & Onion	26.5 oz
51	Pasta Sauce	Del Monte Pasta Sauce, Meat	26.5 oz
52	Pasta Sauce	Hunt's Pasta Sauce, Meat	26.5 oz
53	Pasta Sauce	Hunt's Pasta Sauce, Parmesan	26 oz
54	Pasta Sauce	Hunt's Pasta Sauce, Traditional	26.5 oz
55	Pasta Sauce	PREGO GARLIC PARMESAN SAUCE	26 oz
56	Pasta Sauce	Prego Pasta Sauce, Meat	48 oz
57	Pasta Sauce	Prego Pasta Sauce, Regular	26 oz
58	Soda	Coke Classic, 2-Liter	67.6 oz
59	Soda	Coke Classic, 6-Pack Bottles	48 oz
60	Soda	Diet Coke, 6-Pack Bottles	48 oz
61	Soda	Diet Coke, 6-Pack Cans	72 oz
62	Soda	Diet Coke, Caffeine-Free, 2-Liter	67.6 oz
63	Soda	Pepsi, 2-liter	67.6 oz
64	Soda	Pepsi, 6 Pk Bottles	144 oz
65	Soda	Pepsi, 6-Pack Cans	72 oz
66	Soda	Pepsi, Caffeine-Free, 2-Liter	67.6 oz
67	Soda	Diet Pepsi, 2-Liter	67.6 oz
68	Soda	Diet Pepsi, 6 Pk Bottles	144 oz
69	Soda	Diet Pepsi, 6-Pack Cans	72 oz
70	Soda	Diet Pepsi, Caffeine-Free, 2-Liter	67.6 oz
71	Soda	Diet Sprite, 2-Liter	67.6 oz
72	Soda	Dr. Pepper .5 Liter	101.4 oz
73	Soda	Dr. Pepper Diet .5 Liter	101.4 oz
74	Soda	Dr. Pepper, 2-Liter	67.6 oz
75	Soda	Mountain Dew, 2-liter	67.6 oz
76	Soda	Mountain Dew, 6 Pk Bottles	144 oz
77	Yogurt	Dannon Yogurt, Non-Fat Plain	32 oz
78	Yogurt	Dannon Yogurt, Plain	32 oz
79	Yogurt	Dannon Yogurt, Plain	6 oz
80	Yogurt	Dannon Yogurt, Raspberry	6 oz

81	Yogurt	Dannon Yogurt, Vanilla	32 oz
82	Yogurt	Yoplait Go-Gurt, Portable Yogurt Strawberry & Berry Blue 2.25 Oz	18 oz
83	Yogurt	Yoplait Yogurt, Light Apricot Mango Fat Free	6 oz
84	Yogurt	Yoplait Yogurt, Light Banana Cream Pie Fat Free	6 oz
85	Yogurt	Yoplait Yogurt, Light Blueberry Patch Fat Free	6 oz
86	Yogurt	Yoplait Yogurt, Light Strawberries 'N Bananas Fat Free	6 oz
87	Yogurt	Yoplait Yogurt, LightWhite Chocolate Strawberry Fat Free	6 oz
88	Yogurt	Yoplait Yogurt, Original Cherry Orchard 99% Fat Free	6 oz
89	Yogurt	Yoplait Yogurt, Original French Vanilla 99% Fat Free	6 oz

Appendix B

DEMOGRAPHIC AND OTHER BACKGROUND INFORMATION

Question	**Response**
Number of people in your household (all inclusive)	Number
Number of children in your household (those below 14 years)	Number
Are you the primary grocery shopper for the family?	Yes/No
On an average, how many times a month do you go for grocery shopping?	Number
Where do you shop most often for your grocery? (Name of the primary grocery store)	1 Name
If you shop at other grocery stores, please list them below	Up to 5 Names
In your estimate, how long (number of days) does it take for your household to consume each of the following items. If you buy some other pack sizes, please make appropriate conversions. If you do not buy them at all, please indicate. MILK 1 Gallon (128 oz) 12 cans of SODA/SOFT DRINK A tub (32 oz) of YOGURT (e.g. Dannon's tub) A carton (64 oz) of ORANGE JUICE 6 small cans (11 oz) of SOUP (e.g. Campbell's small cans) A small pack (16 oz) of PASTA A pack (26 oz) of PASTA SAUCE 6-roll pack BATH TISSUE A single roll of PAPER TOWEL	Response for each can either be: (a) No. of days, OR (b) Do not buy at all
Your Age	Years
Your Annual Household Income	Dollars per annum