The Effect of Reference Price and Loss Aversion on Consumer Brand Choice, Category Purchase and Quantity Decisions

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ABSTRACT

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In this study I investigate the effects of reference price on three consumer purchase decisions: consumer brand choice, purchase incidence, and purchase quantity. First, I compare the impact of internal reference price (IRP) and external reference price (ERP) on the three consumer purchase decisions. I hypothesize that (a) consumers rely more on ERP (vs. IRP) in brand choice and purchase quantity decisions, and more on IRP (vs. ERP) in purchase incidence decision; and (b) consumers use both IRP and ERP simultaneously to evaluate shelf price in all three consumer purchase decisions. Second, I examine the impact of consumers' loss aversion tendencies on the three consumer purchase decisions. I hypothesize that loss aversion affects all three consumer purchase decisions; that is, consumers respond more sensitively to a loss than to a corresponding gain. I estimate models of brand choice, purchase incidence and purchase quantity using multinomial logistic regression, binary logistic regression, and Poisson regression, respectively.

Hypotheses are generally supported based on empirical analyses of scanner data for a battery product category. This study contributes to the literature in two ways. First, it is the first study to test the direct impact of reference price on purchase incidence decisions. Second, it is the first study to incorporate both IRP and ERP variables into purchase incidence and purchase quantity decisions. Overall, this study contributes an understanding of the influence of reference price on three consumer purchase decisions, which provides both manufactures and retailers with valuable knowledge to formulate optimal pricing and promotion strategies.

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INTRODUCTION

When consumers shop for a certain product, they must make three critical decisions: a) whether to buy in a product category (purchase incidence), b) which brand to buy once they decide to buy (brand choice), and c) what quantity to buy (purchase quantity). These three decisions are influenced by both consumer heterogeneities in brand loyalty and deal-proneness, and price and promotion characteristics of products (Bucklin et al. 1998). Traditional brand choice studies have found that consumers evaluate the utilities of brands based on their observed shelf prices (Guadagni and Little 1983). Another stream of research, however, shows that consumer purchase decisions are influenced by gain and loss perceptions based on reference prices (Bell and Bucklin 1999, Briesch, Krishnamurthi and Raj 1997, Kopalle et al. 2012, Kumar, Karande and Reinartz 1998, Krishnamurthi, Mazumdar and Raj 1992, Mayhew and Winer 1992). In other words, consumers do not directly respond to the observed shelf prices when they make purchase decisions; instead, they are influenced by the difference between the observed price and a reference price which has been established by past purchase memory of the price paid (internal reference price; IRP hereafter) or by stimuli received within the shopping environment (external reference price; ERP hereafter).

Most of the literature has investigated the impact of these reference prices in terms of consumers' brand choice decisions (e.g., Briesch et al. 1997). However, as noted above, the consumer purchase process is a series of decisions, including not only brand choice decisions, but also category and quantity decisions. These three purchase decisions—purchase incidence, brand choice, purchase quantity--are influenced by several factors, such as price, brand loyalty and promotion (Bucklin et al. 1998). To this list of influencing factors, one could add reference price. It is important to address the reference price effect in one model incorporating all three consumer purchase decisions because a more comprehensive understanding helps manufacturers and retailers find a balanced pricing and promotion strategy to maximize their profits. For instance, continuous promotions (constant lowering reference price) in a category lead to increase in purchase quantity but a decrease in purchase incidence and brand equity (Pauwels et al. 2002). Hence, not accounting for the effects of reference prices on any of the three purchase decisions could result in suboptimal promotion strategies.

Only a very limited number of studies have explored the effects of reference price on purchase incidence and purchase quantity. Furthermore, none of the past studies examined the simultaneous effects of IRP and EPR on purchase incidence and purchase quantity. One paper addressed only the effect of IRP on purchase quantity decisions (Krishnamurthi, Mazumdar and Raj 1992), leaving the ERP effect on purchase quantity decisions unknown. Moreover, a concrete link between reference price and purchase incidence has not been established yet. It also is important to address the impacts of both IRP and ERP in one model incorporating the three consumer purchase decisions because consumers will simultaneously employ their reference points developed by their past purchase experiences (IRP) as well as by external stimuli (ERP) in their shopping-decisions. Manufactures and retailers can utilize the findings from this study in the design of their promotional strategies. Hypothetically, if consumers rely more on ERP to make brand choices but IRP to make category purchase decisions, manufactures and retailers may need to carefully design the promotion frequency to consider customers' memory of past promotional prices, but determine prices of competing brands to promote the brand choice of the focal brand. Thus, understanding both IRP and ERP effects on these three purchase decisions in a holistic manner is important for retailers to maximize their profits. Considering that households are likely to have different levels of inventories for different products at the time of shopping, a critical issue is to understand how customers process the gap between the shelf price and their reference prices to determine whether to make a purchase or increase the purchase quantity (Bell and Bucklin 1999). Consequently, the primary goal of this paper is to investigate the effects of IRP and ERP on the three consumer purchase decisions: purchase incidence, brand choice, and purchase quantity.

First, I explore whether consumers adopt both IRP and ERP in their evaluation of shelf prices when shopping and how each type of reference price (IRP or ERP) affects the three purchase decisions. Findings in the literature are mixed, possibly because of varying consumer characteristics and contextual conditions (Kalyanaram and Winer 1995, Kumar et al. 1998). For instance, after controlling for household heterogeneity, models adopting the memory-based IRP variable are found to outperform ERP based models in four product categories on brand choices (Briesch et al. 1997). In contrast, the gap between ERP and shelf price affects more than IRP on brand choices when deal-prone consumers face a stock-out situation (Kumar et al. 1998).

Considering that IRP and ERP are two distinct price comparison systems with no correlation or conflict in between, it is possible to argue that consumers could use both standards at the same time when making a buying decision. While most studies have adopted only one of the price comparison systems--i.e., either IRP or ERP, in a single model--a few studies included both IRP and ERP in one model and demonstrated an improvement in model fit in brand choice (Mayhew and Winer 1992, Rajendran and Tellis 1994). The improvement can be even more evident when consumer heterogeneity is considered in the models (Mazumdar and Papatla 2000). In sum, the comparison between IRP and ERP has been mainly undertaken in a brand choice model context, but not in purchase incidence and quantity decision contexts.

Second, the existence of customers' loss aversion is investigated with respect to consumers' purchase incidence and quantity decisions. When the reference price is lower than the observed price, it is perceived as a sense of loss. In contrary, when the reference price is higher than the observed price, it is perceived as a sense of gain (Kalwani et al. 1990). Although Prospect Theory states that consumers' reaction to the sense of loss is stronger than to the sense of gain (Kalwani et al. 1990; Pulter 1992; Kahneman and Tversky 1979), loss aversion has not been not found to be a universal phenomenon in the literature on brand choice (Bell and Lattin 2000). For example, loyal consumers are found to be equally sensitive to gain and loss, while brand switchers respond more to the sense of gain rather than loss (Krishnamurthi, Mazumdar, and Raj 1992). In another study on brand choice decisions, the impact of loss was found to be greater than the gain in a margarine product category, but the results were reversed in a Cola beverage product category (Kopalle et al. 2012). This study fills a gap in terms of the lack of empirical support on the existence of loss aversion on the purchase incidence and quantity decisions in addition to the brand choice decision.

Third, the above stated research questions are addressed for a new product category: primary batteries (AAA and AA). Past studies on reference price have utilized product retail data, including yogurt, baking chips, crackers, coffees, peanut butter, tissues, and detergent product categories. No study has addressed research questions with battery data. However, it is worth in-depth investigation due to its unique product characteristics. Compared to food and beverages, batteries are much more storable and could have fairly long usage life depending on

the appliances, which leads to longer inter-purchase cycles. Compared to tissues and detergent, batteries are easier to stockpile due to their small size. Often times, consumers are unable to increase purchase incidence or quantity on promotion if the size of product is large, because the larger size limits the consumers' stockpiling capability. These unique characteristics of the battery product are expected to exert significant impact especially on category and quantity decisions. Therefore, consumers' responses to price changes are expected to be sensitive to batteries on purchase incident and quantity decisions.

In the next section, theories related to reference price will be presented as well as the impact of reference price on consumer behavior. Based on this literature review, I develop hypotheses to be tested. Subsequently, I present the proposed quantitative decision models. Closely following Bucklin, Gupta and Siddarth's (1998) study, I estimate models of brand choice, purchase incidence, and purchase quantity with multinomial logistic regression, binary logistic regression, and Poisson regression, respectively. A detailed description on AC Nielsen's scanner panel data in the batteries product category is presented in the data section. Finally, model results are reported and managerial implications are discussed.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Reference Price

A reference price is an internal or an external standard against which observed prices are evaluated (Briesch et al. 1997). Internal reference prices (IRP; also known as memory-based reference prices) are formed from price information a consumer gained on past purchase occasions. Consumers enter the current purchase environment with an idea of how much they are willing to pay for the same product based on how much they paid on previous shopping trips. External reference prices (ERP) are established during a purchase occasion based on the current shelf prices of one or several other brands (also known as stimulus-based reference prices; Mazumdar and Papatla 2000). Evidence shows that when making a purchase decision, consumers use IRP, EPR, or both to evaluate the utility of brands instead of directly responding to observed prices (Conover 1986; Mazumdar and Papatla 2000). In addition, various types of IRPs and ERPs have been shown to be influential on and compared in brand choice models. Nevertheless, little research on this topic has been done on purchase incidence and quantity decisions.

Various operationalizations of the reference price concept have been proposed and studied. Specifically, four IRP models have been widely used in past studies. The most parsimonious model of IRP is the price of a brand purchased in the last purchase occasion, which was often used in earlier research (Krishnamurthi et al. 1992; Mayhew and Winer 1992; Kumar et al. 1998). Those studies assume that consumers form a unique IRP for each brand; the IRP of a certain brand is the paid price of that brand on the last purchase occasion. The second type of IRP was relatively less studied in previous research. Rajendran and Tellis (1994) constructed two measures of IRPs: a) a simple average price of past prices paid on last three purchase occasions and b) a declining weighted average price of each brand's past prices on the last three purchase occasions, with declining weights (0.571, 0.286, and 0.143) of a geometric function of a common ratio of 0.5. They argue that this operationalization works better considering consumer memory builds not only on one shopping occasion, but also on numerous shopping occasions. The third model of IRP is a single reference price for all brands, as in an exponentially smoothing shelf price of previously chosen brands, constructed and tested by Briesch et al. (1997). The rationale

behind this was that consumers tend to have stronger memory for product information for chosen brands than for rejected brands (Biehal and Chakravarti 1983). Consequently, memory of the previously chosen brand's price should be accessible to consumers' memory and ready to be used as a reference point to evaluate the observed price. Finally, the fourth IRP model is also an exponentially smoothing shelf price faced by consumers on previous shopping occasions, but unique to each brand. This is the most commonly used IRP model in the literature (Moon et al. 2006; Mazumdar and Papatla 2000; Kalyanaram and Little 1994; Mazumdar and Papatla 1995; Hardie et al. 1993). Research indicates that consumers are able to distinguish price information of different brands and build up separate memory trace for each brand (Briesch et al. 1997). Thus, this type of IRP is purely temporal and precisely reflects the past price information of one specific brand, and each brand's price is in comparison with its own history.

In terms of ERPs, four operationalizations have generally been adopted in buying decision studies. The most common ERP model is the current price of the last chosen brand, under the assumption that consumers are not able to recall the exact price paid but the brand purchased on last occasion. Thus, they use the current price of the last purchased brand to evaluate shelf price of a focal brand (Hardie et al. 1993; Bell and Lattin 2000; Moon et al. 2006; Kopalle et al. 2012). Hardie et al. (1993) tested five different ERP models: a) the price of the same brand (which has the highest market share) as reference price for all shopping occasions, b) the price of each household's most frequently purchased brand in the initialization period, c) the price of each household's most frequently purchased brand across all purchase occasions, d) the price of each household's most loyal brand, and e) the current price of the brand purchased on the most recent shopping occasion. Results indicate that the current price of last chosen brand provided the best model fit of all five models, which was then widely used in subsequent studies. The second model of ERP is the current price of a random brand on the shelf (Briesch et al.1997). This operationalization assumes that consumers cannot or do not make an effort to remember the last price paid or last brand purchased, nor are they able to decide which brand should be used as the reference brand; instead, they select a random brand on the shelf and use its current price as a reference point. The third model of ERP is the lowest price of brands on a shopping occasion. Rajendran and Tellis (1994) tested three measures of ERP: the highest, the lowest, and the mean of prices of all brands on shelf at that shopping occasion. While the mean price captures the

information of all brands, the highest and lowest prices have more influence on consumers' choices because they are the most salient and observable (Biswas and Blair 1991). Moreover, the lowest price was the most effective because it is often featured in in-store promotions or special display. Results validated that the lowest current price was the most influential one of all three, which was then used in Kumar et al.'s (1998) study and shown to have more impact than IRP models. The fourth, and last, model of ERP is a weighted average price of all brands based on brand loyalty (Mazumdar and Papatla 1995, Mazumdar and Papatla 2000). They argued that the most used ERP model--current price of last chosen brand--was restrictive if consumers have more than one brand in their consideration sets, and a weighted average price includes the price information of all acceptable brands. Above that, the price information of the most loyal brand of a consumer should exert the strongest impact on his buying decision. Hence, it is a weighted average price based on brand loyalty levels.

Aside from the commonly used IRP and ERP operational definitions discussed above, several less frequently used reference price models have been constructed with temporal prices, price trends, promotion information, and characteristics of households. As summarized in Briesch et al.'s (1997) study, there are three prominent models: a) a brand-specific reference price model including past price, price trend, and market share of the brand (Winer 1986), b) an extended function with additional store and consumer information (Kalwani et al. 1990), and c) a model consisting of the brand's prices of the last five periods, frequency of promotion, price trend, deal proneness of the household, and store information. This model was tested against other four reference price models by Briesch et al. (1997) and it did not perform as well as the purely temporal reference models.

In this study, I operationalize IRP as an exponentially smoothing shelf price faced by consumers on previous shopping occasions unique to each brand (Moon et al. 2006; Mazumdar and Papatla 2000; Kalyanaram and Little 1994; Mazumdar and Papatla 1995; Hardie et al. 1993), and ERP as the current price of last purchase brand (Briesch et al.1997; Hardie et al. 1993), because they have been tested repeatedly by numerous studies and proven to be the most influential among all operationalization of reference prices.

Reference Effects on Consumer Brand Choice, Purchase Incidence, and Purchase Quantity

The majority of studies on reference effects have been based on brand choice models. Many studies have shown that reference prices have significant influence on consumer brand choices in various product categories (For example, Briesch et al. 1997, Kumar et al. 1998). More specifically, IRP and ERP separately affect consumer brand choices in yogurt, baking chips, crackers, coffees, peanut butter, tissues, and detergent product categories (Briesch et al. 1997). After taking consumer heterogeneity and product characteristics into account, IRP and ERP are also significant influential factors in consumer brand choices (e.g., Kumar et al. 1998, Mazumdar and Papatla 2000). Therefore, I expect significant impact of reference price on consumer brand choices.

Hypothesis 1a: Reference price influences consumer brand choice.

Brand choices are only a single part of a series of purchase decisions. Consumers must also decide *whether* to buy and *what quantity* to buy. Investigations of reference price effects on incidence and quantity decisions helps us gain a deeper understanding of the consumer decision-making process. Moreover, from a methodological point of view, neglecting the decision of incidence could result in incorrect inferences, because all the existing asymmetric effects are assumed to raise from brand choices, while some of it could result from the "whether" decision (Sivakumar and Raj 1997). However, only a limited amount of research has incorporated reference effects in purchase incidence and quantity models. The most relevant study intended to assess reference price effects on purchase incidence is Kopalle et al. (2012). However, the study only incorporated reference price variables in a brand choice model, used the estimates of a brand choice model to construct category value, and then tested the purchase incidence model with category value alone. Aside from neglecting many other potential drivers in the model, such as consumption rate and household inventory levels (Bucklin and Gupta 1992), it failed to establish a solid association between category incidence and reference price effects. As a result, no study has validated the impact of internal and external reference price on purchase incidence decision or the asymmetric effect of gain and loss on category purchase.

Sivakumar and Raj (1997) investigated the asymmetric effect in product quality tier

competition and how price changes impact brand and category choices. Results demonstrate that price reduction led to more gain on high-quality brands than low-quality brands in both brand and incidence decisions. Although the research focus was quality tier competition rather than reference price effects as the variables of price increase and decrease were manipulated by regular and promotional prices (but not reference prices), it did raise the point that price discrepancy does impact purchase incidence. Moreover, an investigation of the effect of internal reference points on purchase incidence included IRP in the brand choice model, and used the estimated results to calculate category value (CV) (Bell and Bucklin 1999). Next, the expectation of category value (E [CV]) was set as a reference point to estimate reference category value effects in the incidence model. Results indicate that the reference effects of category attractiveness do influence the purchase incidence decision. The above discussion provides evidence of the relation of reference points and purchase incidence. The current study will be the first to test the reference effects directly on purchase incidence rather than conditioned on the results of brand choice model.

Hypothesis 2a: Reference price influences category purchase decisions.

The association between reference price and purchase quantity decision was examined by Krishnamurthi et al. (1992). Using two types of coffee data, they constructed gain and loss terms with IRP to inspect asymmetric response to price in purchase quantity decisions. Results indicate that IRP has a significant impact on product purchase quantity. Thus, I expect significant impact of reference price on purchase quantity in battery category:

Hypothesis 3a: Reference price influences purchase quantity decisions.

The Impact of Internal and External Reference Prices on Consumer Purchase Decisions

One main stream of research on reference price has investigated whether consumers are more responsive to IRP or ERP (Hardie et al. 1993; Briesch et al. 1997; Kumar et al. 1998; Moon et al. 2006; Kopalle et al. 2012). The results have been mixed. On the one hand, some researchers have found that the best reference price model is an IRP model. An IRP model of past price of a specific brand outperformed four other reference price models in four product

categories (Briesch et al. 1997). In this study, five different reference price models were compared in a brand choice model. As IRPs, prices of previously chosen brands, past price of each brand, and past price of a specific brand and other information (price trend and frequency of discounts) were included in the test. As ERPs, current price of a random brand and current price of last chosen brand were included in the test. The five reference prices were incorporated separately in brand choice models with four different product categories' datasets (peanut butter, liquid detergent, tissue, and grand coffee). Also, a latent class segmentation method was applied to account for consumer heterogeneity. The results showed that the model of past price of a specific brand produced the best model fit in all four product categories. In another study of loss aversion, IRP was confirmed to be more influential than ERP (Bell and Lattin 2000). IRP and ERP were tested separately in a brand choice model for loss aversion effect with orange juice data. Comparing two models without heterogeneity, the IRP model provided the best model fit. Moreover, a finite mixture model was adopted to account for heterogeneity of consumers' sensitivities to price. Both models suggested a two-segment solution, and consistent with the one-segment model, the IRP model still provided the best fit to the data.

On the other hand, a considerable amount of literature has demonstrated the superiority of ERP to IRP in choice models. In a study to address the concepts of reference effects and loss aversion, both IRP and ERP models were tested in brand choice models with refrigerated orange juice data. IRP was defined as an exponentially smoothed average of past price for a specific brand, and ERP as the current price of last purchased brand. Results indicated that although both models were significant and confirmed the existence of loss aversion, the ERP model produced a better fit than the IRP model (Hardie et al. 1993). Similarly, Kumar et al. (1998) argue that the effect of ERP discrepancy (ERP-observed price) carries stronger influence on brand choice decisions than that of IRP discrepancy (IRP-observed price), because contextual information is the most immediate and direct factor for brand evaluation at the time of purchase (Rajendran and Tellis 1994). Moreover, with two contextual variables--household stockpile situation and deal-proneness--added to the brand choice model with reference prices, ERP discrepancy still has a greater impact on brand choice than IRP discrepancy in following scenarios: a) when ERP discrepancy and IRP discrepancy are tested separately without accounting for heterogeneity of stockpile situation and deal proneness; b) when ERP discrepancy and IRP discrepancy are tested

simultaneously without accounting for heterogeneity of stockpile situation and deal-proneness; c) when consumers are facing a stock-out situations; and d) when consumers are deal-prone (Kumar et al. 1998). On the contrary, when consumers are not facing a stock-out and are not deal-prone, ERP discrepancy and IRP discrepancy have similar influences on brand choices. Another study applied a structural heterogeneity analysis on toilet tissue data to categorize consumers based on their tendency of using different reference prices, which categorized consumers into three segments: no reference price users, IRP users, and ERP users (Moon et al. 2006). In their study, significantly more ERP consumers were found than IRP consumers, which indirectly certified the importance of ERP.

Beyond the two scenarios discussed, a few studies yielded mixed results on whether IRP or ERP imposes stronger influence. Rajendran and Tellis's (1994) argued that ERP effects should be stronger than IRP effects, because contextual information and prices are more salient at the point of purchase. Also it takes efforts to memorize and recall temporal information on consumers' side. Moreover, the expected price of a brand is determined initially by current prices of that brand and other brands on the shelf (Jacobson and Obermiller 1990). However, the results do not fully support their argument. When not contemplating consumer heterogeneity in the model, the strength of IRP and ERP effects differ among different cities and categories using saltine crackers (salted and unsalted). For salted crackers, the impacts of ERP and IRP on brand choices were not statistically different in Milland and Willamsport; in Rome, the influence of ERP was even significantly smaller than IRP. Only in an unsalted category, ERP, especially the observed lowest price, appeared to be more influential than IRP. After dissection of consumer heterogeneity of brand preference, brand sampling, and purchase frequency, the results still diverged. As a result, the dominance of ERP and IRP vary by cities and categories.

As discussed above, we cannot draw concrete conclusions on whether IRP or ERP imposes a stronger influence on consumer brand choice decisions, because the effect differs depending on consumer heterogeneity and product characteristics. From the perspective of a product, given that batteries are easy to stockpile and have a long inter-purchase span, consumers have more difficulties remembering the last purchased price, which results in heavier dependence on ERP (Mazumdar and Papatla 2000). Furthermore, the contextual information is

more salient at the point of sale of batteries. Because of relatively small volume/packaging, the shelf space of batteries is usually small and compact comparing to large volume products such as breakfast cereals. Consequently, it is easier for consumers to attain holistic information with a quick scan and to compare prices between brands. Thus, I hypothesize that consumers rely more on ERP than IRP to make a brand and quantity choice when shop for batteries.

Hypothesis 1b: ERP (vs. IRP) imposes stronger effects on brand choice decisions.

Hypothesis 3b: ERP (vs. IRP) imposes stronger effects on quantity decisions.

The situation should be different in purchase incidence, however. While evaluating brand choices is more of a horizontal comparison, where information of brands on the shelf contribute a great deal to the decision making process, a category choice is more of a vertical comparison where consumers assess whether the utility of making a purchase of any brand at this trip is superior to the utility gained from the last trip. In other words, to make a buy/no buy decision, consumers are inclined to evaluate whether the overall situation improves compared to the last time rather than make inter-brand comparisons (Jain and Vilcassim 1991). In this sense, internal reference effects naturally become a key factor (Bell and Bucklin 1999). Therefore, I expect consumers to rely more on IRP rather than ERP in a category purchase incidence decision.

Hypothesis 2b: IRP (vs. ERP) imposes a stronger effect on category purchase decisions.

Aside from the comparison between the impact of ERP and IRP, three studies have attempted to prove that the simultaneous effects of ERP and IRP is stronger than that of either one of them alone (Rajendran and Tellis 1994; Kumar, Karande, and Reinartz 1998; Mazumdar and Papatla 2000). All three studies conclude that the model fit improved significantly with both IRP and ERP in brand choice models. Models containing both IRP and ERP worked better comparing to models containing either one of the reference prices (Rajendran and Tellis 1994, Kumar et al. 1998). A more in-depth study proposed that not only do consumers use both IRP and ERP to evaluate the utility of a brand, but they also rely more on one than the other (Mazumdar and Papatla 2000). To test this hypothesis, a carryover parameter λ ($0<\lambda<1$) was

assigned to measure the relative weight between IRP and ERP. The outcome revealed that not only did the model containing two types of reference price produce a better fit than models containing either one alone, but also that the model with an unconstrained λ was superior to the model with a constrained λ to set equal weight between IRP and ERP. Considering that IRP and ERP are two distinct price comparison systems with no correlation or conflict in between, I argue that consumers use both standards at the same time when making buying decisions.

Hypothesis 1c: The additive effects of both IRP and ERP on brand choice decisions are stronger than either one of IRP or ERP alone.

Hypothesis 2c: The additive effects of both IRP and ERP on category purchase decisions are stronger than either one of IRP or ERP alone.

Hypothesis 3c: The additive effects of both IRP and ERP on purchase quantity decisions are stronger than either one of IRP or ERP alone.

The Effects of Gain and Loss on Consumer Purchase Decisions

Another area of reference price research has sought to inspect consumers' asymmetric reaction to the sense of gain and loss when comparing reference prices to observed prices (Krishnamurthi et al. 1992; Mayhew and Winer 1992; Hardie et al. 1993; Kalyanaram and Little 1994; Briesch et al. 1997; Sivakumar and Raj 1997; Mazumdar and Papatla 2000; Bell and Lattin 2000; Han et al. 2001; Moon et al. 2006; Kopalle et al. 2012). When the reference price is higher than the observed price, consumers achieve a sense of gain; in contrast, when the reference price is lower than the observed price, consumers achieve a sense of loss. This research stream has provided evidence that consumers have asymmetric responses to loss and gain in purchase decisions; that is, consumers tend to react more negatively to loss than positively to gain (Kalwani et al. 1990; Pulter 1992), which is consistent with Prospect Theory in part (Kahneman and Tversky 1979). An asymmetric response to loss and gain was discovered when examining the latitude of price acceptance of consumers, as the absolute value of coefficient of loss is greater than that of gain (Kalyanaram and Little 1994); however, the difference did not reach

significance. Another study verified the existence of reference dependence and loss aversion by incorporating gain and loss variables into a consumer brand choice model with orange juice data (Hardie et al. 1993). Gain was defined as "reference price – price" when reference price is higher than price, and loss as "price – reference price" when price is higher than reference price; an unconstrained parameter to the loss term was added to measure the extent of loss aversion. Results show that the model that included gain and loss variables resulted in a better fit than traditional brand choice models, and demonstrated the existence of loss aversion (Hardie et al. 1993; Bell and Lattin 2000). Moreover, after segmenting consumers based on latent heterogeneity, loss aversion was tested with eleven product categories in brand choice models (Bell and Lattin 2000). Although results yielded small and insignificant estimates, consumer loss aversion does exist but is not a universal phenomenon in frequently purchased products. Using another a latent class structural heterogeneity model, Moon et al. (2006) profiled consumers into three categories based on their reference price usage proneness, Non-reference price based consumers (NRP), memory based reference price consumers (MBR), and stimulus based reference consumers (SBR), to inspect the differences in price sensitivity. Comparison of absolute values of coefficients suggested that both MBR and SBR consumers (accounting for 91% of the population) respond to loss more negatively than they did to gain positively, which is in line with Prospect Theory; additionally, a segment-level estimation of price elasticities was developed and further validated the results.

In contrast, a considerable number of studies have demonstrated that under certain circumstances consumers respond to gain more intensely than to loss. For example, brand loyal consumers are equally sensitive to gain and loss, while brand switchers are significantly more sensitive to gain than to loss when making brand choice decisions (Krishnamurthi et al. 1992). Because switchers do not have strong attachment to certain brands, price differences may have more influence on a brand choice decision; and the decisions are more likely guided by motivation of obtaining value rather than avoiding loss. Similar conclusions were made in Briesch et al.'s (1997) study, when comparing five different reference price effects in brand choice decisions of four different product categories, gain has significantly greater impact than an equal loss does in all four product categories.

In conclusion, the extent of consumers' responsiveness to gain and loss depends on consumer heterogeneity and product characteristics. For instance, the impact of gain was greater in a margarine category while the impact of loss was greater in liquid detergent category (Mazumdar and Papatla 1995). Similarly, in a cola beverage category, the impact of gain was greater on brand choice decision than a corresponding loss; however, the results were reversed in margarine product category (Kopalle et al. 2012). Although a consistent pattern of influence of product characteristics on consumers' reaction to gain and loss have not been identified, loss aversion is more likely to exist in product categories that are easy to stockpile with a higher price level in brand choice decisions (Mazumdar and Papatla 1995, Kopalle et al. 2012). Moreover, empirical studies also provided evidence on loss aversion. A survey to measure consumer responsiveness to price changes by 5%, 10%, and 15% indicated that consumers are significantly more sensitive to price increase than price decrease (Uhl and Brown 1971). As for category purchase decision, no direct evidence supports the loss aversion caused by price discrepancies. However, one study investigated the effect of internal reference points in purchase incidence by constructing category value discrepancy. Results show that the purchase delay caused by the sense of loss outstripped the acceleration motivated by a gain, namely the asymmetric effects in purchase incidence (Bell and Bucklin 1999). Furthermore, consumers' sensitivity to gain and loss in quantity decisions is moderated by household stock situation and varies across brand loyal consumers and brand switchers. Facing a stock-out situation, loyal consumers are more responsive to gain than to loss, while before a stock-out situation, loyal consumers are influenced more by loss than gain. As for brand switchers, the asymmetric response to gain and loss was not found in quantity decisions (Krishnamurthi et al. 1992). While the outcomes are insightful, I argue that given that batteries are easy to stockpile and their inter-purchase span is relatively long, consumers face a stock-out of batteries less frequently than perishable food products. In addition, Krishnamurthi et al. (1992) tested gain and loss constructed only by IRP in the purchase quantity model. However, if ERP exerts stronger influence on purchase quantity than IRP as hypothesized, the results of loss aversion could be different. To sum up, I propose the following.

Hypothesis 1d: Consumers respond more strongly to a sense of loss than a corresponding level of gain in brand choice decisions.

Hypothesis 2d: Consumers respond more strongly to a sense of loss than a corresponding level of gain in category purchase decisions.

Hypothesis 3d: Consumers respond more strongly to a sense of loss than a corresponding level of gain in purchase quantity decisions.

Table 1 Summary of Literature

	Year	IRP	ERP	IRP & ERP	Gain & Loss	Brand Choice	Category Purchase	Quantity	Summary of Results
Krishnamurthi Mazumdar, Raj	1992	✓			✓	✓		✓	Loyal consumers/no stock-out: gain≈loss; Switchers/stock-out: gain>loss
Mayhew and Winer	1992			✓	✓	✓			Consumers use both IRP and ERP
Hardie et al.	1993	✓	✓		✓	✓			ERP>IRP
Rajendran and Tellis	1994			✓		✓			Mixed results in different cities and sub-categories.
Briesch, Krishamurthi, Mazumdar	1997	✓	✓		✓	✓			IRP>ERP; Gain>Loss
Kumar, Karande, and Reinartz	1998			✓		✓			Consumers use both IRP and ERP; Stock-out/deal-prone: ERP>IRP; Otherwise: ERP≈IRP

	Year	IRP	ERP	IRP & ERP	Gain & Loss	Brand Choice	Category Purchase	Quantity	Summary of Results
Mazumdar and Papatla	2000			✓	✓	✓			Consumers use both IRP and ERP; Higher price/Shorter inter-purchase period: IRP>ERP; Lower price/more promotion: ERP>IRP
Bell and Lattin	2000	✓	✓		✓	✓			IRP>ERP; Loss aversion is not universal
Han, Gupta, and Lehmann	2001	✓			✓	✓			Higher price volatility: Gain>Loss; Intense price promotion: more sensitive to loss.
Moon, Russell, and Duwuri	2006	✓	✓		✓	✓			ERP consumers are more sensitive to price
Kopalle et al.	2012	✓	✓		✓	✓			IRP≈ERP; Cola: Gain>Loss; Margarine: Loss>Gain
Current study	2016	✓	✓	✓	✓	✓	✓	✓	

MODEL FORMULATION AND MODEL VARIABLES

The models of consumer purchase choices seek to capture the impact of IRP and ERP discrepancies (both positive and negative) and other marketing variables at the disaggregate level on three purchase decisions. The consumer purchase decisions are conceptualized as a three-step decision respectively. When a consumer walks into a store, he decides whether to make a purchase from a curtain product category, in this study, batteries. Next, he decides which brand to purchase from a set of choices. Given the brand choice, he then decides how many units of that brand to purchase. This scenario can be translated in to a probabilistic choice framework with three separate probability models consisting of a multinomial logistic model for brand choice, a binary logistic model for category choice, and a Poisson regression model for quantity choice.

As for model variables, consumer choice models--as in brand choice model, purchase incident model, and purchase quantity model--have been very well developed and adopted to various research topics. Although scholars have made minor adjustments to the variables tested in the models to better fit their research questions, the general framework of these models does not vary significantly. In this study, I use the most-adopted and parsimonious models to test the hypotheses with the addition of reference price variables. Especially, I closely follow Bucklin, Gupta and Siddarth's (1998) methodology and model building for all three choice models. IRP is operationalized as an exponentially smoothing shelf price faced by consumers on previous shopping occasions unique to each brand, and ERP as the current price of last purchase brand.

Operationalization of IRP

Following past literature, I operationalize IRP as the last purchased price of specific brands, which has been shown to provide the best model fit among all five types of reference price in brand choice model in Briesch et al.'s (1997) study. In addition, it is the most used IRP in brand choice models (For example, Kumar, Karande and Reinartz, 1998; Alvarez and Casielles, 2005; Moon, Russell and Duvvuri, 2006; Han, Gupta and Lehmann 2001). It assumes

that consumers use the past price of one specific brand to evaluate the current price of that brand. Therefore, the IRP is unique to each brand and purely temporal:

(1) $IRP_{hjt} = \lambda\ IRP_{hj(t-1)} + (1 - \lambda)\ P_{hj(t-1)}$

where λ ($0 \leq \lambda \leq 1$) is a smoothing parameter that determines the number of past prices that influence the current reference price value (Lattin and Bucklin 1989), which should be estimated by maximum likelihood method. However, due to mature estimation of this parameter in past research and the time constrains, I set λ equals to 0.65 following Briesch et al.'s (1997) estimation on tissue data, which has the more product similarity with batteries than other perishable products.

Operationalization of ERP

I operationalize ERP as the current price of the last purchased brand. This operationalization assumes that consumers have better memory for the brand name they purchased on the last shopping trip rather than the actual price. This is a fairly reasonable assumption for a product with commonly low purchase frequency, and itis the most extensively used ERP in past research (for example, Hardie et al. 1993, Bell and Lattin 2000) The mathematical expression of ERP of a household *h* at purchase occasion *t* is written as follow:

(2) $ERP_{ht} = P_{ht(\text{last purchased})}$

Note that this reference price is not brand specific, but it varies on each purchase occasion due to different brands being picked as reference brands.

Model and Variables of Brand Choice

Multinomial logistic regression uses maximum likelihood estimation to evaluate the probability of category membership on a dependent variable with a basis of multiple explanatory variables. It is an extension of binary logistic regression that allows for more than two categories of the outcome variable (Aldrich and Nelson 1984). It has been used extensively assorted choice studies, including automobile buyers' choices of dealers (Mahajan et al. 1978) and students' choices of business schools (Punj and Staelin 1978). Furthermore, Guadagni and Little's (1983)

study examining brand choices with multinomial logistic regression has become the standard of brand choice studies. Thus, in this study I employ multinomial logistic regression to examine brand choices of batteries with the addition of reference price variables.

The probability of household *h* buying brand *i* among *k* brand choices on a store trip at time *t* is given by the multinomial logistic regression (Guadagni and Little 1983):

(3) $P^h_t(i) = \exp(u_i+\beta X_{it}^h) / \sum_k \exp(u_k+ \beta X_{kt}^h)$

X_{it}^h represents a vector of household-specific marketing including brand loyalty and unit price, and reference price variables. The model estimates a vector of brand specific intercept u_i and a vector of response coefficients β for X_{it}^h.

Brand choice models are some of the most developed consumer choice models since Guadagni and Little's (1983) study. Variables commonly and repeatedly constructed in this model consist of brand loyalty, last purchased brand, size loyalty, last purchased size, product display, product features, promotion, price, coupon (Erdem, Mayhew, and Sun 2001; Bell and Lattin 2000; Mazumdar and Papatla 2000; Han, Gupta and Lehmann's 2001). In this study, due to data source restrictions and research focus, I build the most parsimonious brand choice model with brand loyalty to capture cross-sectional brand preference, and with price to describe consumer price sensitivity. I assume that consumers are more likely to purchase their preferred brands, and brands with a more appealing price. Starting with the null model without any reference price variables, I add reference prices related variables subsequently to build four models to compare different reference effects of IRP effect, ERP effect, IRP and ERP effects:

(4.1) $X^h_{it} = \beta_1 BL^h_i + \beta_2 PRICE_{it}$

(4.2) $X^h_{it} = \beta_1 BL^h_i + \beta_2 PRICE_{it}$
$+ \beta_{inL} L(PRICE_{it} - IRP^h_{it}) + \beta_{inG} G(IRP^h_{it} - PRICE_{it})$

(4.3) $X^h_{it} = \beta_1 BL^h_i + \beta_2 PRICE_{it}$
$+ \beta_{exL} L(PRICE_{it} - ERP^h_{it}) + \beta_{exG} G(ERP^h_{it} - PRICE_{it})$

(4.4) $X^h_{it} = \beta_1 BL^h_i + \beta_2 PRICE_{it}$

$$+ \beta_{inL}L(PRICE_{it} - IRP^{h}_{it}) + \beta_{inG}G(IRP^{h}_{it} - PRICE_{it}) + \beta_{exL}L(PRICE_{it} - ERP^{h}_{it})$$
$$+ \beta_{exG}G(ERP^{h}_{it} - PRICE_{it})$$

Where L=1 if $PRICE_{it} > RP^{h}_{it}$, 0 otherwise.
G =1 if $PRICE_{it} < RP^{h}_{it}$, 0 otherwise.

Brand loyalty (BL^{h}_{i}) is household-specific market share of each brand during a 39-week initialization period, which should exert a positive influence on brand choice. Unlike the specification of brand loyalty in Guadagni and Little's (1983) study, BL^{h}_{it} only captures cross-sectional heterogeneity, which does not vary over time but varies across households. It is calculated by the total units of each brand purchased in the initialization period divided by the total units purchased of all brands in initialization period. Price ($PRICE_{it}$) is the price of each unit of batteries; that is, the shelf price divided by number of batteries in one package. I predict that unit price imposes a negative impact on brand choice. Controversy exists about whether the current price of the brand should be added to the ERP models along with gain and loss terms. This study follows Moon et al. (2006), who reason that current price presents substitution among brands, while gain and loss reflects the influence of reference price on utility. Consequently, all three variables are included in the model. In addition, I expect a higher likelihood to purchase a brand when consumers achieve a sense of gain, and a lower probability of purchase with a sense of loss. Also, loss should exert stronger influence on brand choice than gain.

Model and Variables of Purchase Incidence

A binary logistic regression model was adopted to examine the reference effects on purchase incidence. Logistic regression measures the probability of a binary response, buy/no buy in this study, based on one or more independent variables (Tversky and Sattath 1979). In previous studies, the universal method to test purchase incidence is nested logit model (For example, Bucklin and Gupta 1992), in which brand choices are conditional on purchase incidence. It is a generalization of multinomial choice model with unobserved variables (Heiss 2002). In such case, reference prices would be unobserved variables only constructed in brand choice models and imposed on purchase incidence through category value (CV). However, this study aims to examine the direction relationship between reference prices and purchase

incidence. Thus, I construct the reference price variables directly into the purchase incidence model and test it with binary logistic regression.

Purchase incidence is the probability that a household *h* buys from a product category on a store trip at time *t*, which can be expressed by a binary logistic regression (Bucklin, Gupta and Siddarth 1998):

(5) $P^h_t(\text{inc}) = \exp(\gamma_0 + \gamma Y_t^h) / 1 + \exp(\gamma_0 + \gamma Y_t^h)$

Y_t^h represents a vector of explanatory factors, including household inventory, consumption rate, and unit price. γ_0 is the vector of estimated intercept and γ is the vector of response coefficients for Y_t^h.

I assume that households with high usage rates of batteries are more likely to make a purchase while others who do not use as many batteries are more likely to postpone the purchase. Similarly, households with a sufficient stock have a higher possibility to delay new purchases while households facing a stock-out are expected to accelerate a new purchase. Thus, the utility for making a purchase of a household h on a shopping trip at time t should consider the effects of consumption rate, household inventory, and the reference price variables. The equation is expressed as (Bucklin and Gupta 1992):

(6.1) $Y_t^h = \gamma_0 + \gamma_1 CR^h + \gamma_2 INV^h_t + \gamma_3\, PRICE_{it}$

(6.2) $Y_t^h = \gamma_0 + \gamma_1 CR^h + \gamma_2 INV^h_t + \gamma_3\, PRICE_{it}$
$+ \gamma_{inL} L(PRICE_{it} - IRP^h_{it}) + \gamma_{inG} G(IRP^h_{it} - PRICE_{it})$

(6.3) $Y_t^h = \gamma_0 + \gamma_1 CR^h + \gamma_2 INV^h_t + \gamma_3\, PRICE_{it}$
$+ \gamma_{exL} L(PRICE_{it} - ERP^h_{it}) + \gamma_{exG} G(ERP^h_{it} - PRICE_{it})$

(6.4) $Y_t^h = \gamma_0 + \gamma_1 CR^h + \gamma_2 INV^h_t + \gamma_3\, PRICE_{it}$
$+ \gamma_{inL} L(PRICE_{it} - IRP^h_{it}) + \gamma_{inG} G(IRP^h_{it} - PRICE_{it}) + \gamma_{exL} L(PRICE_{it} - ERP^h_{it})$
$+ \gamma_{exG} G(ERP^h_{it} - PRICE_{it})$

Where L=1 if $PRICE_{it} > RP^h_{it}$, 0 otherwise.

G =1 if $PRICE_{it} < RP^h_{it}$, 0 otherwise.

Consumption rate (CR^h) captures a household h's weekly consumption of batteries. It varies across households but does not vary over time, and it catches household heterogeneity in incident probabilities. It is computed as the total number of units of batteries purchased by household h in the initialization period divided by the number of weeks in the initialization period. Inventory (INV^h_t) is another variable to capture household heterogeneity but in a time-varying way. It is the household stock level starting from zero, adding the units purchased at t, and subtracting the amount consumed between time t and t-1. Thus, inventory is constructed as a recursive equation:

(7) $INV^h_t = INV^h_{t-1} + Q^h_{t-1} - CR^h * I_{t-1,t}$

Q^h_{t-1} is the total units of batteries purchased at shopping trip t-1 by household h. $I_{t-1,t}$ is the time interval of that between shopping trip t-1 and t; it is calculated by week as is the consumption rate. In the estimation of incident probabilities, I mean-centered inventory using calculated inventory level subtracting each household's average inventory level during the estimation period. This procedure makes inventory become a household-specific relative measure (considering in our construction, inventory is allowed to be below zero) and in turn minimizes the possible collinearity between consumption rate and inventory (Bucklin and Gupta 1992). The operationalization of the unit price ($PRICE_{it}$) variable is different from the brand choice model. In the incidence model, I set the unit price of non-battery purchase occasions as the current unit price of the most purchased brand, assuming that consumers' attention is drawn to information of the brand that they are most loyal to, because when facing a category of choices in a shopping environment, consumers are inclined to pay more and prior attention on their most chosen brands over others (Fournier 1998).

Note that in this study, the purchase incidence model is not explained by category value (the log of the denominator of brand choice probability computed by the coefficients estimated by brand choice model) as in most past literature. The current study focuses on the direct effect of IRP and ERP on category purchase incidence. Therefore, the price variable along with the

gain and loss terms are directly included in the binary logistic equations instead of estimating by the brand choice model first.

Model and Variables of Purchase Quantity

Poisson regression is a form of regression analysis adopted to model count data and is believed to be appropriate to estimating purchase quantity. In most purchase situations, the discrete number of units purchased is a more natural measurement of products than ounces or kilograms etc. In studies using product categories such as yogurt or liquid detergent, quantity is usually modeled as a continuous variable (Krishnamurthi and Raj 1988; Neslin et al. 1985), which can result in estimation bias since quantity purchase is often discrete (McKelvey and Zavoina 1975). Unlike such product categories, the nature of how batteries are packaged dictates that the quantity of such product cannot be measured as a continuous variable. Therefore, Poisson regression is chosen to estimate the purchase quantity model.

The probability that a household *h* buys a discrete number of brand *i* on a shopping trip at time *t* can be captured by a Poisson regression model where the outcome q_{it}^{h} =1, 2, 3……n units of batteries (Bucklin, Gupta and Siddarth 1998):

(8) $P(Q_{it}^{h} = q_{it}^{h} | Q_{it}^{h} > 0) = [\exp(-\lambda_{it}^{h})(\lambda_{it}^{h})^{qith}] / [1 - \exp(-\lambda_{it}^{h})]\, q_{it}^{h}!$

λ_{it}^{h} is a household-specific and brand-specific purchase rate at time *t*, which is a function of household characteristics and marketing activity, including purchase rate, inventory, brand loyalty and unit price.

Similar to buy/no buy probability, the purchase quantity decisions are assumed to be influenced by inventory level, as a high stock level would lead to lower quantity purchased. Brand loyalty describes the potential impact of households' brand preference on quantity decisions, as consumers tend to increase quantity of their preferred brands. Also, purchase quantity is expected to be correlated with household past purchase quantity history, captured as purchase rate. Similar to the brand choice model, I add reference price related variables to a base model to build four models to compare different reference effects of IRP effect, ERP effect, IRP

and ERP effects. Based on Krishnamurthi et al. (1992) and Bucklin et al. (1998), I construct the purchase quantity utility of the quantity of brand *i* purchased by household *h* at a shopping trip time *t* as follows:

(9.1) $\lambda_{it}^{h} = \exp(\alpha_{i0} + \alpha_{i1}PR^{h} + \alpha_{i2}INV^{h}_{t} + \alpha_{i3}BL^{h}_{i} + \alpha_{i4}PRICE_{it})$

(9.2) $\lambda_{it}^{h} = \exp(\alpha_{i0} + \alpha_{i1}PR^{h} + \alpha_{i2}INV^{h}_{t} + \alpha_{i3}BL^{h}_{i} + \alpha_{i4}PRICE_{it}$
$+ \alpha_{inL}L(P_{it} - IRP^{h}_{it}) + \alpha_{inG}G(IRP^{h}_{it} - P_{it}))$

(9.3) $\lambda_{it}^{h} = \exp(\alpha_{i0} + \alpha_{i1}PR^{h} + \alpha_{i2}INV^{h}_{t} + \alpha_{i3}BL^{h}_{i} + \alpha_{i4}PRICE_{it}$
$+ \alpha_{exL}L(P_{it} - ERP^{h}_{it}) + \alpha_{exG}G(ERP^{h}_{it} - P_{it}))$

(9.4) $\lambda_{it}^{h} = \exp(\alpha_{i0} + \alpha_{i1}PR^{h} + \alpha_{i2}INV^{h}_{t} + \alpha_{i3}BL^{h}_{i} + \alpha_{i4}PRICE_{it}$
$+ \alpha_{inL}L(P_{it} - IRP^{h}_{it}) + \alpha_{inG}G(IRP^{h}_{it} - P_{it}) + \alpha_{exL}L(P_{it} - ERP^{h}_{it}) + \alpha_{exG}G(ERP^{h}_{it} - P_{it}))$

Where $L=1$ if $P_{it} > RP^{h}_{it}$, 0 otherwise.
$G=1$ if $P_{it} < RP^{h}_{it}$, 0 otherwise.

Purchase rate is the average quantity of batteries purchased by household h, which is included in the estimation to capture cross-sectional heterogeneity in purchase inclination, namely time-invariance. It is calculated as the total number of units of batteries purchased in the initialization period divided by the number of battery purchase occasions in the initialization period. Inventory (INV^{h}_{t}), Brand loyalty (BL^{h}_{i}), and price ($PRICE_{it}$) are defined as discussed above.

DATA DESCRIPTION AND RESULTS

Data and Sample Descriptions

A.C. Nielsen scanner panel data in a battery product category are used to test the proposed models. It includes battery purchase history in six provinces in Canada, from December 31st 2007 to June 28th 2009, for seventy-eight weeks. The complete dataset consists of purchase records of 9678 respondents' shopping trips for batteries of all types, and their non-battery purchase shopping trips. Due to the heterogeneity and popularity of battery usage, only AAA and AA batteries are included in the study. The dataset is divided into two periods, the initialization period (the first thirty-nine weeks), and the estimation period (the last thirty-nine weeks). Households were qualified to be included in the sample if they made at least four purchases of batteries in the initialization period and four purchases in the estimation period. In total, 158 samples were qualified, which includes 8875 observations, with 4655 observations in the initialization period and 4220 observations in the estimation period. On average, each panelist went on 11.23 shopping trips, with 5.89 trips in the initialization period and 5.34 trips in the estimation period (refer to Table 2). Due to a lack of sample data, I did not conduct further screening by store type and location.

Table 2 Description of Samples

	Sample	Observations	Average trips
Total	158	8875	11.23
Initialization	158	4655	5.89
Estimation	158	4220	5.34

I limited the study to the four top-selling brands in the market; all other brands are grouped into one as 'others'. No brand was eliminated to ensure the completeness of information. The four top selling brands, with their market share in brackets, are Duracell (29.41%), Energizer (27.38%), Panasonic (13.06%), Rayovac (6.52%), and others (23.62%) (refer to Table 3).

Table 3 Description of Brands

Brand	Purchase Frequency	Market Share	Average Unit Price
Duracell	454	29.41	1.44 dollars
Energizer	489	27.38	2.26 dollars
Panasonic	325	13.06	0.60 dollars
Rayovac	135	6.52	0.77 dollars
Others	372	23.62	1.03 dollars

Model Comparison

As noted previously, I estimate the brand choice model with multinomial logistic regression, the purchase incidence model with binary logistic regression, and the quantity model with Poisson regression. Four models are estimated for each purchase decision: a) a null model with no reference price variable (model4.1, model6.1, model9.1), b) a model with gain and loss terms constructed with IRP (model4.2, model6.2, model9.2), c) a model with gain and loss terms constructed with ERP (model4.3, model6.3, model9.3), and d) a model with gain and loss terms constructed with both IRP and ERP (model4.4, model6.4, model9.4). Table 4 presents the results of the model comparison for each decision.

Table 4 Model Comparisons

Brand choice model				
	Model 4.1 *(Null Model)*	**Model 4.2** *(IPR)*	**Model 4.3** *(ERP)*	**Model 4.4** *(IRP and ERP)*
Likelihood ratio	669.47 (<.0001)	686.71 (<.0001)	719.61 (<.0001)	746.48 (<.0001)
-2 Log Likelihood	4979	4962	4929	**4902**
BIC	4992	4989	4956	**4942**
Purchase incidence model				
	Model 6.1 *(Null Model)*	**Model 6.2** *(IPR)*	**Model 6.3** *(ERP)*	**Model 6.4** *(IRP and ERP)*
Likelihood ratio	1635.3640 (<.0001)	2693.2097 (<.0001)	2548.4318 (<.0001)	4075.2235 (<.0001)
-2 Log Likelihood	6242	5184	5329	**3802**
BIC	6283	5246	5391	**3885**
Purchase quantity model				
	Model 9.1 *(Null Model)*	**Model 9.2** *(IPR)*	**Model 9.3** *(ERP)*	**Model 9.4** *(IRP and ERP)*
Log Likelihood	12057	12061	12063	**12067**
AIC	7197	7193	7188	**7185**
BIC	7221	7226	**7221**	7227

Convergence criterion (GCONV=1E-8) is satisfied for all four brand choice models. Likelihood ratio of Chi-square is to test the null hypothesis of Beta equals to zero. All *p*-values are smaller than .0001, indicating that in each model at least one of the coefficients is significantly different from zero. Thus, the null hypothesis is rejected. -2 Log Likelihood and BIC are to compare model fit and select the best model. -2 Log Likelihood shows that model fit improved significantly with reference price variables compared to the null model with no reference price variable. Furthermore, while model (4.3) with external gain and loss terms performs better than model (4.2) with internal gain and loss terms, the model (4.4) constructed with both IRP and ERP variables is the best fit of all four models. BICs demonstrate the exact

same results. Hence, hypothesis 1(c) is fully supported; that is, the effects of both IRP and ERP on brand choice decisions are stronger than either one of IRP or ERP alone.

As for the purchase incidence model, all four models are valid, as the F-test of Likelihood ratio is significant and so the null can be rejected. -2 Log Likelihood indicates models with reference price variables perform better than the null model. Moreover, the model with both IRP and ERP effects shows significant improvement compared to the model with either only IRP or ERP effects. Similarly, BICs suggest the exact same results as -2 Log Likelihood does. Thus, hypothesis 2(c), that the effects of both IRP and ERP on category purchase decisions are stronger than either one of IRP or ERP alone, is supported. Moreover, as expected, in contrast to the brand choice model, the model with IRP (Model 6.2) shows better fit than the model with ERP (Model 6.3).

Algorithm of all four quantity models are converged. Log Likelihood (the larger the better) illustrates that models with reference price effects perform better than the null model. In agreement with brand choice results, ERP also provides better model fit than IRP in quantity models. Furthermore, the model with both ERP and IRP (Model 9.4) effects is significantly better fit than the other three models. Although BICs suggest different results, AICs are in line with the indication of Log Likelihood and suggest the exact same implication. Therefore, hypothesis 3(c) is supported; that is, the effects of both IRP and ERP on purchase quantity decisions are stronger than either one of IRP or ERP alone.

Results of Brand Choice Models

Table 5 Results of Brand Choice Models

Variables	**Model 4.1** *(Null Model)*	**Model 4.2** *(IPR)*	**Model 4.3** *(ERP)*	**Model 4.4** *(IRP and ERP)*
Unit Price	-0.10213 ***	0.02334	0.01410	0.22610 ***
Brand Loyalty	2.54666 ***	2.56677 ***	2.34319 ***	2.36214 ***
Internal Gain	-	-0.01461	-	-0.01073
Internal Loss	-	-0.25062 ***	-	-0.34382 ***
External Gain	-	-	-0.05796	-0.04330
External Loss	-	-	-0.34338 ***	-0.41077***

*Note: *** represents p-value<.05*

Table 5 presents maximum likelihood estimations of brand choice models. The coefficient of unit price in model 4.1 is negative and significant as expected. The coefficients of unit price in models 4.2, 4.3, and 4.4 are positive. However, because these three models include reference price variables (internal gain and loss, external gain and loss) constructed by unit price, the effect of unit price should be presented by the coefficients of unit price added to the coefficients reference price variables. That is, unit price is negatively related to brand choice.

Next, in line with predictions, the coefficients of brand loyalty are positive and significant, illustrating that consumers tend to choose a brand to which they are more loyal. In all three models, the coefficients of internal and external gain are negative, opposite to what I expected, however, its influence on brand choice is not significant. On the other hand, in agreement with our prediction and past literatures, both internal and external loss terms in all three models are negative and significant. Thus, hypothesis 1(a) is partially supported, that is, reference price effect (gain and loss) does influence on brand choice decisions. In addition, the absolute vales of the estimates of loss are significant and larger than those of gain in all three models. It fully supports hypothesis 1(d) that consumers respond more strongly to a sense of loss than a corresponding level of gain in brand choice decisions. Moreover, in addition to the fact that ERP better fits the model as stated in last section, the coefficients of ERP are more deviate

from zero than those of IRP in model 4.4, indicating a larger influence on brand choice. Thus, Hypothesis 1(b) is valid: ERP imposes stronger effects on brand choice decisions than IRP does.

Results of Purchase Incidence Models

Table 6 Results of Purchase Incidence Models

Variables	**Model 6.1** *(Null Model)*	**Model 6.2** *(IPR)*	**Model 6.3** *(ERP)*	**Model 6.4** *(IRP and ERP)*
Intercept	4.0643 ***	4.1568***	3.8847***	4.3513***
Unit Price	-0.00378 ***	-0.00001	-0.00676***	-0.00194***
Consumption Rate	0.2237***	0.1713***	0.3152***	0.0959
Inventory	-0.00430***	-0.00284***	-0.00309***	6.549E-6
Internal Gain	-	-0.00193***	-	-0.00302***
Internal Loss	-	-0.00786***	-	-0.0359***
External Gain	-	-	0.00106***	0.00159***
External Loss	-	-	0.000305***	0.0359***

*Note: *** represents p-value<.05*

Table 6 presents parameter estimates of purchase incidence models. Unit price in all four models have the correct sign and are significant, demonstrating that consumers have a higher probability of making a purchase of batteries when the price is lower. Both coefficients of consumption rate and inventory have the correct sign and significant as expected, except for model 6.4. This illustrates that consumers with higher-level consumption of batteries and lower level inventory are inclined to make a purchase. But the contribution of these variables are very limited, and price evaluation is the key influential factor for category purchase decisions. The estimates of internal gain in model 6.2 and 6.4 are negative and significant, opposite to expectation, while the coefficients of external gain in model 6.3 and 6.4 are positive and significant as expected. Contradictory to the results of gain variables, estimates of internal loss are all negative and significant as predicted, whereas the coefficients of external loss are with the wrong signs but significant. This implies that although both IRP and ERP effects contribute to consumer decision-making processes, consumers are more likely to make a purchase when comparing the price to the prices of other brands on the shelf and are less likely to buy when comparing the price to past purchased prices. However, significant signs do show support for

hypothesis 2(a) that reference price effect does influence (accelerate or delay) on category purchase decisions. Moreover, the absolute values of loss coefficients are larger than those of gain except for model 6.3. This partially supports hypothesis 2(d) that consumers respond more strongly to a sense of loss than a corresponding level of gain in category purchase decisions. Overall, the estimates of internal gain and loss are slightly larger than those of external gain and loss. Thus, from both model fit statistics and estimates, I conclude that IRP imposes stronger effects on category purchase decisions than ERP does. Therefore, Hypothesis 2(b) is supported.

Results of Purchase Quantity Models

Table 7 Results of Purchase Quantity Models

Variables	**Model 9.1** *(Null Model)*	**Model 9.2** *(IPR)*	**Model 9.3** *(ERP)*	**Model 9.4** *(IRP and ERP)*
Intercept	1.9475 ***	1.9105 ***	1.9241***	1.8887***
Unit Price	-0.1392 ***	-0.1212 ***	-0.1233***	-0.1053***
Purchase Rate	0.0518 ***	0.0519 ***	0.0521***	0.0523***
Inventory	-0.0002 ***	-0.0002***	-0.0002***	-0.0002***
Brand loyalty	0.0802***	0.0981***	0.0768***	0.0935***
Internal Gain	-	0.0135***	-	0.0129***
Internal Loss	-	-0.0404	-	-0.0402
External Gain	-	-	0.0133***	0.0126***
External Loss	-	-	-0.0508***	-0.052***

*Note: *** represents p-value<.05*

Table 7 presents parameter estimates of purchase quantity models. All of the coefficients have the right signs and are significant as expected, except for internal loss terms in model 9.2 and 9.4. The coefficients of unit price in the quantity models are negative and significant, indicating consumers tend to decrease purchase quantity when the unit price increases. Estimates of purchase rate and inventory have the correct sign and are significant, demonstrating that consumers who purchase batteries more frequently and have lower inventory are more likely to purchase larger quantity of batteries. The coefficients of brand loyalty are positive and

significant, implying that consumers are inclined to purchase larger quantity batteries of their loyal brands. Estimates of internal and external gain terms in model 9.2, 9.3, and 9.4 are positive and significant, indicating consumers purchase larger quantity when they achieve a sense of gain. Estimates of external loss terms in model 9.3 and 9.4 are negative and significant as expected, meaning that consumers buy less if the chosen brand's unit price is higher than other competing brands. The results provide full evidence for hypothesis 3(a) that reference price effect does influence (increase or decrease) on purchase quantity decisions. Moreover, although both internal loss terms are not significant, external loss appears to have stronger impact on purchase quantity than external gain does, which partially supports Hypothesis 3(d): consumers respond more strongly to a sense of loss than a corresponding level of gain in purchase quantity decisions. Last, quantity model with ERP performs better than the model with IRP, and all ERP variables are significant while internal loss terms are not. Thus, Hypothesis 3(b) is supported: ERP imposes stronger effects on purchase quantity decisions than IRP does.

Overall, unexpected signs of estimates appear in brand choice and purchase incidence models on reference price variables. Estimates of internal gain and external gain in brand choice models (4.2, 4.3, and 4.4) are negative. Internal gain and external loss in purchase incidence models (6.2, 6.3, and 6.4) are opposite to expectations. To investigate whether these puzzling results are a result from collinearity, I examine the correlation matrix (refer to APPENDIX, Table 9, Table 11, and Table 13) and find that the correlations among variables are very low except for Unit Price and four reference price variables (Internal gain and loss, External gain and loss). However, these correlations are expected considering that gain and loss variables are computed by unit price and reference prices, and they do not interfere with the results. One of the possible causes could be missing promotion and coupon usage information, which leads to part of the model remaining unexplained. Another issue with the results is the latitude of some variables, which are too close to zero, indicating only minor influence on purchase decisions. This could contribute to the difference in latitude of variables in the model (refer to APPENDIX, Table 8, Table 10, and Table 12) or the absence of other potential influencers, such as features and display.

DISCUSSION

Conclusion and Managerial Implications

The results of this study agree with past literature to a certain extent. First, parameter estimates of all three models indicate that IRP and ERP effects impact on consumer purchase decisions of brand choice, category incidence and purchase quantity. Furthermore, in all purchase decisions, when consumer evaluate the price of a brand, they use both IRP and ERP as standards rather than either one of them alone. Second, in battery brand choice and quantity decisions, consumers rely more on ERP than IRP to assessing the unit price of a target brand, yet rely more on IRP than ERP in purchase incidence decisions. Last, consumers respond to the sense of loss more strongly than the sense of gain in brand choice and category incidence decisions. However, consumers only react more heavily to the sense of loss constructed with ERP than the sense of gain in purchase quantity decisions. In conclusion, most hypothesis stated above are fully or partially supported, aside from the incorrect signs of certain parameters.

The current study makes both theoretical and practical contributions to marketing pricing decisions. The major theoretical contributions of this study are twofold: (1) validating the impact of reference price effects on purchase incidence and quantity decisions, and (2) identifying that consumers rely heavily on different types of reference price when making the three key purchase decisions.

Additionally, several major managerial implications can be drawn from this study for both manufacturers and retail outlets. From a manufacturer's perspective, first, to boost the purchase incidence of a brand, it is crucial to set the price of the brand favorably comparing to its own price history, since consumers rely more on IRP rather than ERP when deciding whether to make a purchase. Second, segment consumers and identify the most possible brand consideration sets, and set the price favorably compared to other brands in consumers' consideration sets. Third, avoid continuously lowering IRP for consumers by carefully planning the duration and frequency of price reduction or promotions. In a long-term, constant promotion and discount would decrease the likelihood of category purchase incidence, but increase purchase quantity (Mela et al. 1998). Thus, finding the threshold of price sensitivity is crucial to ensure product

profitability. Past study suggests that irregular promotion can maximize profit based on reference effects (Greenleaf 1995).

From retails' perspective, first, the main focus is to simulate consumers to make a purchase of large quantity. This can be achieved by manipulating shelf space and arrangement of products. For example, to boost the sale of the most profitable brand in the store, place it next to brands with higher price and away from lower price brands to maximize the sense of gain and to avoid the sense of loss. Second, to simulate category purchase, retailers could distribute more shelf space to brands on sale and arrange all discounted brands together in the most eye-catching place, which grant consumers a conspicuous cue that the current prices are lower than the previous.

Limitations and Future Research

Though both theoretical and methodological care were taken in the current study, some unavoidable limitations are nevertheless present. I discuss limitations in terms of data analysis, model building and consumer characteristics. In terms of data analysis, several limitations must be discussed. First, different battery sizes (AAA and AA) should also be treated as alternatives. As Guadagni and Little (1983) selected five coffee brands with two sizes (small and large) each, ten alternatives entered the model. This procedure is even more crucial for battery product, because practically speaking, different size of batteries is used on different appliances and they are not interchangeable; thus when a consumer makes the decisions of whether and how many to buy, it depends on the inventory of each type of batteries rather than the total inventory of all batteries. This issue might be responsible for the abnormal signs in the results, especially in purchase incidence and quantity models. Second, the durability of batteries should be taken into consideration as well. Commonly, manufactures produce various selections for one type of batteries based on different durability (i.e. 30 hours and 50 hours); and it is most likely that the price of batteries with high durability are higher than that of the ones with low durability. Unfortunately, this information was not able to be extracted from the dataset, which results in the abnormal positive coefficients of unit price parameters. Third, the dataset for estimation was only screened by battery type and panelist purchase occasions, while store type should be another important screening factor. The original dataset contains outlets of all type in Canada,

including convenient stores, supermarkets, electronic stores, dollar stores, and so on. Depending on the different nature of these outlets, brand selections, product display, and price range should all be different. However, due to limited sample size after screening by product type and purchase occasions, I was not able to do further screening on store type, which might be another contributor to the abnormal signs of parameters, especially price variables.

In terms of model building, several issues are worthy of attention. First, several important variables were not included in the models, such as product display, discount feathers, and promotion information. In traditional brand choice models, the influences of such variables have been shown to be important (for example, Guadagni and Little 1983, Hardie et al. 1993). For instance, product features and promotion are positively related to brand choices; that is, consumers tend to choose a brand when it is on sale or on display. Unfortunately, the original data of battery in current study does not include any promotional or display information. The absence of this information might have affected model fit and abnormal coefficients. Second, the operationalization of IRP (the past shelf price of a specific brand) could be improved. The smoothing parameter λ ($0 \leq \lambda \leq 1$) in the IRP equation is supposed be estimated by maximum likelihood method (Briesch et al. 1997). It various based on different brands and different product categories. However, due to estimation of this parameter in past research and the time constrains of this study, I set λ equal to 0.65, following Briesch et al.'s (1997) estimation on tissue data, which has more product similarity with batteries than other perishable products. Further correction of λ might provide better model fit and parameter estimation. Third, various or better manipulations of unit price in the incidence model could be discovered. This study uses the current price of most purchased brand as the shelf price of non-battery purchase occasions in purchase incidence model, while other operationalizations may produce better results. For example, one could examine the current price of a random brand, under the assumption that consumers have little memory of past purchase records. Also, the average price of existing brands or weighted average price based on brand loyalty could be considered, as consumers tend to evaluate the price level of the entire category when facing a category purchase (Rajendran and Tellis 1994). The manipulations of unit price of non-battery purchase occasions in the purchase incidence model are crucial, because consumers may not be exposed to battery products at all during their non-battery purchase shopping trips. Fourth, only one operationalization of IRP and

ERP are tested in the model due to time constrains. However, in battery category purchase, other alternative models of reference prices may produce better results, especially further investigation on IRP effects in battery purchase is valuable. Last, this study estimated three models independently; that is, category value estimated by brand choice model does not account for variation of purchase incidence, which could lead to partial information unexplained since purchase incidence is conditional on brand choice. Due to time and technical constrains, I could not do joint estimation of the three purchase decision models. It should be realized in future research.

In terms of consumer characteristics, another major limitation of this study is that consumer heterogeneity and other contextual conditions are not included in the models. Past research has proven that the effects of IRP and ERP on consumer purchase decisions varies depending on the types of consumers (Mazumdar and Papatla 1995). For example, consumers have no symmetric responses to gain and loss when they are loyal to a brand, while brand switchers react more strongly to gain than loss (Krishnamurthi et al. 1992). Brand preference, brand sampling and purchase frequency also moderate the effect of reference price (Rajendran and Tellis 1994). Moreover, contextual conditions are also an influential factor. For instance, when consumers are facing a stock-out situation, ERP exerts more impact on brand choice than IRP does; otherwise, the impact of ERP and IRP are similar (Kumar, Karande and Reinartz 1998). In addition, categories that have greater frequency of in-store promotional activities are more likely to be influenced by ERP than IRP (Mazumdar and Papatla 2000). Consumer characteristics and contextual situations should be entered into the model in future research to gain a deeper understanding of how reference price affect consumer decisions.

In addition to addressing the issues stated above, future research could work on simultaneous estimation of brand choice, purchased incidence, and quantity models, which would produce estimates that maximize the fit of all three models. A latent class model or hierarchical Bayes model could be adopted for segmentation of consumers to interpret the effects of reference price in a more specific and practical way.

Another research direction could be comparison of reference effect or loss aversion among different product categories, especially between perishable and non-perishable products.

Loss aversion appears in some categories but not in others (Bell and Lattin 2000), which could attribute to different structure of brand competition, different purchase frequency and so on. Further empirical work on this matter would provide more practical implications targeting specific product categories.

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APPENDIX

Table 8 Descriptive Analysis of Brand Choice Model

Variable	Mean	Std Dev	Sum	Minimum	Maximum
Unit Price	2.26599	3.51958	9562	0.10944	69.98
Brand Loyalty	0.2	0.29442	844	0	1
Internal Gain	0.82877	2.11135	3497	0	39.41886
Internal Loss	0.79828	2.84385	3369	0	67.35696
External Gain	0.68604	1.74681	2895	0	25.6075
External Loss	1.02875	3.21085	4341	0	69.10625

Table 9 Correlations between Variables in Brand Choice Model

Pearson Correlation Coefficients						
	Unit Price	Brand Loyalty	Internal Gain	Internal Loss	External Gain	External Loss
Unit Price	1	-0.054	-0.13	0.91	-0.12	0.93
Brand Loyalty	-0.054	1	-0.078	-0.03	-0.08	-0.102
Internal Gain	-0.13	-0.08	1	-0.11	0.1	-0.103
Internal Loss	0.91	-0.03	-0.11	1	-0.078	0.87
External Gain	-0.12	-0.08	0.1	-0.078	1	-0.13
External Loss	0.93	-0.102	-0.1	0.87	-0.13	1

Table 10 Descriptive Analysis of Purchase Incidence Model

Variable	Mean	Std Dev	Sum	Minimum	Maximum
Consumption Rate	1.40614	1.08892	47030	0.30769	6.92308
Inventory	0	1.21042	0	-9.20049	8.86101
Unit Price	3.40975	4.09254	114043	0	35.184
Internal Gain	5.44973	5.68193	182272	0	39.97994
Internal Loss	0.94372	2.20559	31563	0	26.178
External Gain	5.21196	6.16268	174319	0	99.99
External Loss	0.70103	1.75815	23447	0	24.83143

Table 11 Correlations between Variables in Purchase Incidence Model

Pearson Correlation Coefficients							
	Consumption Rate	Inventory	Unit Price	Internal Gain	Internal Loss	External Gain	External Loss
Consumption Rate	1	0	0.054	0.164	-0.0695	0.023	-0.008
Inventory	0	1	0.013	-0.057	0.0016	-0.018	-0.0006
Unit Price	0.054	0.013	1	-0.45	0.625	-0.38	0.49
Internal Gain	0.16	-0.057	-0.45	1	-0.41	0.36	-0.305
Internal Loss	-0.07	0.002	0.63	-0.41	1	-0.22	0.588
External Gain	0.023	-0.018	-0.384	0.36	-0.22	1	-0.34
External Loss	-0.008	-0.0006	0.49	-0.305	0.588	-0.34	1

Table 12 Descriptive Analysis of Purchase Quantity Model

Variable	Mean	Std Dev	Sum	Minimum	Maximum
Unit Price	2.26599	3.51958	9562	0.10944	69.98
Purchase Rate	8.98568	5.92396	37920	2.4	36.8
Brand Loyalty	0.2	0.29442	844	0	1
Inventory	1.97948	114.057	8353	-790.66414	502.9564
Internal Gain	0.82877	2.11135	3497	0	39.41886
Internal Loss	0.79828	2.84385	3369	0	67.35696
External Gain	0.68604	1.74681	2895	0	25.6075
External Loss	1.02875	3.21085	4341	0	69.10625

Table 13 Correlations between Variables in Purchase Quantity Model

Pearson Correlation Coefficients								
	Unit Price	Purchase Rate	Brand Loyalty	Inventory	Internal Gain	Internal Loss	External Gain	External Loss
Unit Price	1	-0.025	-0.054	0.001	-0.13	0.92	-0.12	0.93
Purchase Rate	-0.025	1	0	-0.06	-0.024	-0.015	-0.012	-0.018
Brand Loyalty	-0.054	0	1	0	-0.078	-0.03	-0.08	-0.103
Inventory	0.001	-0.06	0	1	0.007	0.001	-0.01	0.001
Internal Gain	-0.13	-0.024	-0.08	0.007	1	-0.11	0.1	-0.103
Internal Loss	0.91	-0.015	-0.03	0.001	-0.11	1	-0.08	0.87
External Gain	-0.12	-0.012	-0.08	-0.01	0.1	-0.078	1	-0.126
External Loss	0.93	-0.018	-0.102	0.01	-0.1	0.87	-0.126	1