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Rutger van Oest
BI Norwegian Business School

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* Rutger van Oest is Associate Professor of Marketing at BI Norwegian Business School, Nydalsveien 37, 0442 Oslo, Norway, (email) rutger.d.oest@bi.no (tel) +47 46410653 (fax) +47 21048000. The author thanks Els Gijsbrechts, Auke Hunneman and Ken Wathne for useful comments.

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Abstract

The literature has produced mixed support for loss aversion in a reference price context and the outcome may depend on the type of reference price. One extant study has reported empirical evidence that consumers are less loss averse in internal than external reference prices, but without discussing causes or implications. In the current study, we reconcile relevant literature and propose this asymmetric loss aversion result as an empirical generalization. Next, we provide and test an explanation: two empirical regularities in pricing cause that consumers tend to observe few losses for external reference price and many losses for internal reference price, making them less sensitive to internal than external losses. We use two scanner panel data sets to show that the two empirical regularities contribute to asymmetric loss aversion, while accounting for alternative explanations. We explore the implications of loss aversion asymmetry for the effectiveness of price promotions by simulation.

KEY WORDS:

Internal reference price, External reference price, Loss aversion, Scanner panel data

INTRODUCTION

A large body of literature has considered the impact of reference prices on brand

choice, resulting in the empirical generalization that consumers do not merely judge the

absolute price, but evaluate it against reference points (Winer 1986; Blattberg et al. 1995;

Kalyanaram and Winer 1995; Meyer and Johnson 1995). They construct an external

reference price (ERP) from *current* shelf prices in the product category[1] and an internal

reference price (IRP) for each brand based on recalled *previous* prices. Though price

recall studies indicate that consumers have limited price memory (Dickson and Sawyer

1990; Vanhuele and Dreze 2002), both reference price types drive brand choice and have

been incorporated into brand choice models simultaneously (Kumar et al. 1998; Mayhew

and Winer 1992; Rajendran and Tellis 1994; Mazumdar and Papatla 2000).

Consistent with prospect theory (Kahneman and Tversky 1979) and mental

accounting (Thaler 1985), a second empirical generalization is that consumers are loss

averse: they react more strongly to prices above the reference price (i.e., losses) than to

prices below (i.e., gains) (Kalyanaram and Winer 1995). However, while there is strong

consensus on reference prices influencing brand choice, the existence of loss aversion in

a reference price context is debated (Bell and Lattin 2000; Mazumdar et al. 2005) and

studies have found opposite results (Briesch et al. 1997; Krishnamurthi et al. 1992).

The presence of loss aversion could depend on whether the reference price is

external or internal: Mazumdar and Papatla (2000, p. 254) conclude from a thorough

empirical analysis on four product categories that "ERP segments are found to be more

loss averse than the IRP ones", but without providing discussion. It is unclear what the

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[1] We focus on ERP that is the current price of a reference brand (Hardie et al. 1993). The literature also
contains other forms such as the retailer-supplied comparative price (Kopalle and Lindsey-Mullikin 2003).

implications are for pricing strategies and also to what extent this loss aversion asymmetry between ERP and IRP is a universal phenomenon. Moreover, from a theoretical perspective, the mechanisms triggering the asymmetry remain not well-understood. While the literature has identified household-level characteristics influencing loss aversion, these have only been tested for IRP (Erdem et al. 2001; Krishnamurthi et al. 1992) or found to work in the same direction for ERP and IRP (Klapper et al. 2005); they have not been connected to loss aversion asymmetry.

The current paper addresses these issues. It establishes Mazumdar and Papatla's loss aversion asymmetry as an empirical generalization (Bass and Wind 1995) and explains the asymmetry by two empirical regularities in pricing: (1) brands with larger choice shares tend to be more expensive, and (2) brand prices tend to increase over time. The mechanism we propose and test is that these regularities trigger ERP gains and IRP losses, respectively, and that the larger number of IRP losses than ERP losses makes consumers relatively less sensitive to the former type. We find empirical support from two scanner panel data sets that the two regularities drive loss aversion asymmetry, while controlling for several alternative explanations. We further contribute to the literature by exploring the implications of loss aversion asymmetry for the long-run (cumulative) impact of price promotions through simulation.

In this article, we start by defining loss aversion asymmetry in a utility framework and reconcile empirical evidence from the literature to come up with our empirical generalization. Next, we lay out the rationale for consumers usually being less loss averse in IRP than ERP, and we discuss the role of the two empirical regularities in detail; two scanner panel data sets show the connection between the regularities and loss aversion

asymmetry. Finally, we conduct the simulation experiment to present managerial implications.

LOSS AVERSION ASYMMETRY

We focus on the role of reference prices in brand choice and add non-price factors in a later stage. In so doing, we define utility resulting from brand j as

$$(1) \qquad U_j = \beta_E\big(\text{ERPGAIN}_j + \lambda\text{ERPLOSS}_j\big) + \beta_I\big(\text{IRPGAIN}_j + \lambda\mu\text{IRPLOSS}_j\big),$$

where ERPGAIN_j is the difference between the external reference price and the observed price of brand j when the reference price is above the observed price, ERPLOSS_j is this difference when the reference price is below the observed price, and IRPGAIN_j and IRPLOSS_j are defined similarly for the internal reference price. The coefficients β_E and β_I capture the effects of ERP gains and IRP gains, respectively, and λ is the loss aversion parameter for ERP (Bell and Lattin 2000; Hardie et al. 1993): $\lambda > 1$ indicates loss aversion, i.e., higher responsiveness to losses than to equal-sized gains. As loss aversion in IRP is defined by $\lambda\mu$, parameter μ is the ratio of loss aversion in IRP relative to ERP: consumers are less loss averse in IRP than ERP when $\mu < 1$. We expect all four coefficients β_E, β_I, λ and μ to be positive, as all gain and loss variables in (1) are framed as the reference price minus the observed price (Bell and Lattin 2000; Hardie et al. 1993). Equation (1) does not have a separate price term, as it is not jointly identified with the ERP gain-loss components (Briesch et al. 1997; Moon et al. 2006; Niedrich et al. 2009).[2]

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[2] Neither ERP nor the response coefficients in (1) are brand-specific, causing that price drops out when the ERP gain and loss terms are included.

< TABLE 1 ABOUT HERE >

To investigate the hypothesis $\mu < 1$, as suggested by Mazumdar and Papatla (2000), we compute μ from other empirical studies that report loss aversion coefficients for both ERP and IRP; these extant studies do not provide μ directly. Table 1 summarizes the results. Bell and Lattin (2000) report significant loss aversion in ERP, i.e. $\lambda > 1$, for 7 out of 12 product categories (without showing the actual coefficients) and no evidence of asymmetric price response for IRP in any category ($\lambda\mu = 1$), consistent with consumers being less loss averse in IRP ($\mu < 1$). Briesch et al. (1997) show parameter estimates for ERP and IRP in the liquid detergent category. Their estimates amount to $\mu = .47$. Both Bell and Lattin (2000) and Briesch et al. (1997) have accounted for unobserved heterogeneity via latent classes. Hardie et al. (1993) do not consider unobserved heterogeneity in response to marketing mix; their estimated loss aversion coefficients for ERP and IRP in the orange juice category are $\lambda = 1.66$ and $\lambda\mu = 1.46$, implying that $\mu = .88$. Mazumdar and Papatla (1995) consider two product categories and distinguish between two deterministic segments driven by ERP and IRP, respectively; their parameter estimates in the margarine category are consistent with $\mu < 1$, but the numbers for liquid detergent run counter to the results of Briesch et al. (1997) for the same category and our expectations. Moon et al. (2006) employ a latent class structural heterogeneity model of reference price usage; they find evidence of loss aversion in the toilet tissue category for both ERP and IRP, but much stronger for the former reference price type ($\mu = .27$). Finally, Pauwels et al. (2007) use aggregate brand sales data for twenty product categories and find "increased price sensitivity for gains, but decreased price sensitivity for losses" regarding IRP, but no significant differences for ERP; their

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parameter estimates imply that $\mu = .65$. We conclude from these studies from different authors in different settings that loss aversion asymmetry between ERP and IRP is commonplace and propose it as an empirical generalization.

RATIONALE FOR LOSS AVERSION AYMMETRY

The mechanism connecting the two empirical regularities in pricing to loss aversion asymmetry is that these regularities lead to less ERP losses and more IRP losses, making consumers relatively less sensitive to the latter. The notion that high-frequency events receive less weight has roots in social psychology (Nisbett and Ross 1980). In making probability judgments, chances of high-frequency events are underestimated, while low-frequency events are overestimated (Kahneman et al. 1982). Similarly, respondents underreport high-frequency events and over-report low-frequency events in recall-based tasks, as low-frequency events are more salient (Schroder et al. 2003). Analogous findings exist for non-recall based tasks (Fiske 1980; Kanouse and Hanson 1972).

The two empirical regularities (or conditions[3]) are (1) brands with larger choice shares tend to be more expensive, and (2) brand prices tend to increase over time; they appear at the product category (or market) level, but can also be defined at the level of the individual consumer (or household) that can be viewed as a market segment of size one. As the theoretical link with loss aversion asymmetry is made at the consumer rather than category level, an individual level analysis is the most natural way to go. For testing purposes, an advantage of the disaggregate approach is that it offers ample variation in the outcomes of the two conditions. While the empirical regularities typically hold at the

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[3] We use the terms empirical regularity and condition interchangeably, though an empirical regularity is observed at the category level and the corresponding condition can also be measured at the individual level.

category level (offering little variation unless many categories are considered), there is substantial variation across individual purchase occasions. For instance, chosen brands vary and as a result choice shares of expensive versus cheap brands vary as well (variation in Condition 1). Similarly, consumers observe different price sequences (variation in Condition 2), as brand prices vary over time and purchasing patterns differ in terms of average cycle, degree of regularity and when the bulk of the purchases was made.[4] Below we argue that the two empirical regularities trigger more ERP gains and IRP losses, respectively, making losses more frequent for IRP than ERP (reducing loss aversion in IRP relative to ERP via the frequency-importance mechanism described earlier).

Condition 1: brands with larger choice shares are more expensive

Most scanner panel data used in published studies originate from the eighties and nineties. Consistent with Condition 1, these data often contain a positive correlation between brand price and choice share (Bolton 1989; Klapper et al. 2005). The majority of reference price studies have operationalized ERP as the current shelf price of the previously chosen brand (Bell and Lattin 2000; Briesch et al. 1997; Hardie et al. 1993; Kopalle et al. 1996; Moon et al. 2006), meaning that at many purchase occasions ERP is the price of a brand with a large choice share. As according to Condition 1 large-share brands tend to have higher prices, there are many high ERPs and hence many gains relative to these high ERPs.

The left panel of Figure 1 illustrates the principle for a consumer with a purchasing pattern that is consistent with the empirical regularity: the expensive brand

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[4] In line with extant panel data studies of brand choice, an implicit assumption is that households only observe brand prices at purchase occasions and not at other shopping trips (Chang et al.1999).

has a choice share of 80%, i.e., it has been the previous choice at 4 out of 5 purchase

occasions, while the cheap brand has been picked only once. As the expensive brand is

more often the previously chosen brand and therefore tends to be the reference brand (the

exception is occasion 3), the consumer indeed experiences more ERP gains than losses.

For expository purposes, the illustration focuses on one "cheap" brand and one

"expensive" brand, with prices fixed over time, so that price level and price ranking

coincide at every occasion. In an extended scenario with price variation due to price

shifts and promotional offers, the mechanism remains valid. However, brands that are

more expensive on average no longer need to be more expensive at every occasion. As

the frequency of ERP gains is determined by each occasion's price ranking of the

previously chosen brand, we measure the extent to which Condition 1 is met by the

average price ranking of chosen brands across purchase occasions.[5]

< FIGURE 1 ABOUT HERE >

In a different context, Bell and Lattin (2000) have also employed the mechanism

that consumers purchasing more expensive brands face more gains relative to ERP.

These authors use it to point out that not properly accounting for unobserved

heterogeneity results in a price response curve with spurious loss aversion; less price

sensitive consumers (flatter price response and buying more expensive brands) tend to be

concentrated in the gains part of the price response curve, while price sensitive

consumers (steeper price response and cheaper brands) are located in the losses part; this

could falsely suggest the presence of loss aversion when individual consumers are not

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[5] This definition of expensiveness is most strongly connected to ERP gains and losses. We verified that the empirical findings are robust to replacing the price rankings by price levels in dollar cents.

loss averse. Their seminal work emphasizes a measurement issue regarding loss aversion, while we focus on a behavioral explanation of loss aversion asymmetry between ERP and IRP. Nevertheless, the findings of Bell and Lattin imply that ignored unobserved heterogeneity could be an alternative explanation for loss aversion asymmetry, as it would cause overestimation of loss aversion in ERP. We rule out this alternative explanation by incorporating unobserved heterogeneity into our empirical analysis.

Condition 2: brand prices increase over time

It is well-established that prices show upward trends due to inflation. As (a) this implies that past prices tend to be lower than the current price and (b) IRP is based on these lower past prices, consumers experience many losses when comparing current prices to IRPs. The right panel of Figure 1 illustrates this mechanism for a consumer observing a price pattern that is consistent with the empirical regularity. For expository purposes, we define IRP as the brand's previous price, a special case of the more general IRP employed in the empirical analysis. Indeed, the current price is higher than the previous price (which serves as the IRP), causing perceived losses.

In the illustration, IRP is determined by the brand's price at the previous occasion, implying that the number of IRP losses coincides with the number of occasions that the price has increased: it is the frequency that matters. However, extant reference price studies indicate that IRP is shaped by a substantially larger number of past purchase occasions (Briesch et al. 1997; Niedrich et al. 2009). Under these more realistic circumstances, the gap between the brand's price and its IRP is not only the result of the frequency of price increases versus decreases but is the net effect of both the frequency

and magnitude. We therefore measure the extent to which Condition 2 is met by the average price change between all subsequent purchase occasions across all brands.

FORMAL LINK BETWEEN CONDITIONS AND LOSS AVERSION

To formally connect the two pricing conditions to loss aversion in ERP (i.e., λ) and loss aversion in IRP (i.e., $\lambda\mu$), we consider a situation with a high outcome (H) and a situation with a low outcome (L) for each of these conditions. We define $COND1^{(H)} > COND1^{(L)}$ for Condition 1, with the values of $COND1^{(H)}$ and $COND1^{(L)}$ being average price rankings of chosen brands. Similarly, $COND2^{(H)} > COND2^{(L)}$ for Condition 2, where the values of $COND2^{(H)}$ and $COND2^{(L)}$ correspond to average price change between subsequent purchase occasions.

As Condition 1 affects the number of ERP gains but is not related to the number of IRP gains, it may influence loss aversion λ in ERP, even though $\lambda\mu$ for IRP remains constant. If we define

$$(2) \qquad\qquad \lambda^{(H)} = (1/\theta_1)\,\lambda^{(L)},$$

for some $\theta_1 > 0$, then $\lambda^{(H)}\mu^{(H)} = \lambda^{(L)}\mu^{(L)}$ (i.e., constant $\lambda\mu$) yields

$$(3) \qquad\qquad \mu^{(H)} = \theta_1\,\mu^{(L)}.$$

As Condition 1 should lead to more ERP gains, i.e., less losses, and we expect that consumers become more loss averse if losses are less frequent, we hypothesize that $\lambda^{(H)} > \lambda^{(L)}$; this corresponds to the hypothesis $\theta_1 < 1$ in (2) and (3).

We follow a similar logic for Condition 2. It affects the number of IRP losses but is not related to the number of ERP losses. Hence, while λ remains constant for ERP, loss aversion $\lambda\mu$ for IRP may change via the loss aversion asymmetry parameter μ; we define

$$(4) \qquad\qquad \mu^{(H)} = \theta_2\, \mu^{(L)}$$

for some $\theta_2 > 0$. As Condition 2 should lead to more IRP losses and we expect less loss aversion if the frequency of losses increases, we hypothesize that $\mu^{(H)} < \mu^{(L)}$, amounting to $\theta_2 < 1$ in (4).

Above, we have described the mathematical link between the two pricing conditions and loss aversion asymmetry by comparing a "high" with a "low" outcome. Empirically, however, such an approach with one parameter in one pairwise comparison would not leave any degrees of freedom. We therefore put (2), (3) and (4) with associated hypotheses $\theta_1 < 1$ and $\theta_2 < 1$ in a format that allows us to simultaneously consider the entire range of outcomes of COND1 and COND2. In so doing, we redefine the homogeneous loss aversion parameter λ in (1) as

$$(5) \qquad\qquad \lambda \equiv \lambda \exp(-\delta_1 COND1)$$

and we redefine the homogeneous asymmetry parameter μ in (1) as

$$(6) \qquad\qquad \mu \equiv \mu \exp(\delta_1 COND1) \exp(\delta_2 COND2).$$

Our hypothesis $\theta_1 < 1$ in (2) and (3) maps one-to-one into $\delta_1 < 0$ in (5) and (6), while $\theta_2 < 1$ in (4) coincides with $\delta_2 < 0$ in (6). We can verify this easily: if $COND1^{(H)} >$

COND1$^{(L)}$, $\lambda^{(H)} \equiv \lambda \exp(-\delta_1 \text{COND1}^{(H)})$ in (5) and $\lambda^{(L)} \equiv \lambda \exp(-\delta_1 \text{COND1}^{(L)})$ in (5),

then $\delta_1 < 0$ implies that $\lambda^{(H)} > \lambda^{(L)}$, which is (2) with $\theta_1 < 1$. Similarly, if $\mu^{(H)} \equiv$

$\mu \exp(\delta_1 \text{COND1}^{(H)}) \exp(\delta_2 \text{COND2})$ and $\mu^{(L)}$ is defined analogously in (6), then $\delta_1 < 0$

leads to $\mu^{(H)} < \mu^{(L)}$ while still satisfying $\lambda^{(H)} \mu^{(H)} = \lambda^{(L)} \mu^{(L)}$; this is (3) with $\theta_1 < 1$.

Analogously, there is a one-to-one correspondence between (6) with $\delta_2 < 0$ and (4) with

$\theta_2 < 1$. In sum, we have two hypotheses about the empirical regularities triggering loss

aversion asymmetry; one hypothesis connects the first condition to more loss aversion in

ERP, while the other connects the second condition to less loss aversion in IRP.

Hypothesis for Condition 1: the higher the average price ranking of chosen brands, the

more loss aversion there will be in ERP, i.e., $\delta_1 < 0$.

Hypothesis for Condition 2: the higher the average price change between subsequent

purchase occasions, the less loss aversion there will be in IRP, i.e., $\delta_2 < 0$.

EMPIRICAL ANALYSIS

We use two A.C. Nielsen scanner panel data sets of brand choice and marketing mix

in the ketchup and peanut butter categories in the Sioux Falls SD market. The data run

from June 1986 to October 1988 and cover 124 weeks. We consider households with at

least 10 purchases in the category: 732 households who together made 12,681 purchases

in the ketchup category and 1047 households whose number of purchases totaled 19,664

for peanut butter. The analysis includes the ketchup brands Heinz, Hunts, Del Monte and

Store brand and the peanut butter brands Jif, Peter Pan, Skippy and Store brand (Erdem et

al. 2001). Each household's first five purchases serve as an initialization period to "warm up" the internal reference prices and a brand loyalty variable.

< TABLE 2 ABOUT HERE >

Frequencies of gains and losses

Table 2 reports the percentages of gains and losses that households experienced in brand prices across all purchase occasions in the calibration period and all brands[6]. As anticipated, there are more gains (and fewer losses) for ERP than IRP in both product categories. For ketchup, the percentage of ERP gains is 68 and the percentage of IRP gains is 50, implying a differential of 18 points. Similarly, the percentages are 54 and 30 for peanut butter, a differential of 24 points. Chi-square tests show that the frequency differentials between ERP and IRP are significant in both categories (p < .0001). We further note that for both ERP and IRP the percentage of gains is larger for ketchup than for peanut butter. This is consistent with the two pricing conditions: (1) Heinz is the undisputed market leader in the ketchup category and by far the most expensive brand, while this positive share-expensiveness relationship is less pronounced for peanut butter (Condition 1; more ERP gains for ketchup); (2) the prices of all brands have increased over time in the peanut butter category, but some ketchup brands have become cheaper (Condition 2; more IRP gains for ketchup).

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[6] To compute the number of IRP losses, we use the estimated IRP carry-over parameter in our base model.

Base model of brand choice and presence of loss aversion asymmetry

To verify that our data sets contain loss aversion asymmetry and are in line with the extant studies in Table 1, we first estimate μ from a base model of brand choice that is similar to what has been done in the literature; we allow for loss aversion in both ERP and IRP but do not yet try to explain these loss aversion estimates. In so doing, we extend utility specification (1) by accounting for the household's previous brand choices (i.e., brand-specific loyalty), the brand's feature advertising and display activities as well as unobserved heterogeneity. As explained earlier, in particular the last addition is important: heterogeneity not accounted for may result in spurious loss aversion (Bell and Lattin 2000) and may bias the estimated loss aversion asymmetry. We capture unobserved heterogeneity by allowing for latent classes and determining the optimal number of segments by the Bayes Information criterion (BIC). This criterion results in three segments for ketchup and four segments for peanut butter. Furthermore, consistent with the approach and findings of Bell and Lattin (2000), the BIC values indicate that a parsimonious model with segment-independent loss aversion parameter λ and asymmetry parameter μ is appropriate.[7] The level of deterministic utility for household i (in segment s) choosing brand j on purchase occasion t is

(7) $U_{i,j,t|s} = \alpha_s + \beta_{1,s}\text{BLOY}_{i,j,t} + \beta_{2,s}\text{FEATURE}_{i,j,t} + \beta_{3,s}\text{DISPLAY}_{i,j,t}$

$\qquad + \beta_{E,s}\big(\text{ERPGAIN}_{i,j,t} + \lambda\text{ERPLOSS}_{i,j,t}\big) + \beta_{I,s}\big(\text{IRPGAIN}_{i,j,t} + \lambda\mu\text{IRPLOSS}_{i,j,t}\big),$

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[7] We do keep the price responsiveness coefficients β_E and β_I heterogeneous in order to avoid bias from ignored heterogeneity in price sensitivity (Klapper et al. 2005). Substantive results are preserved if λ and μ would be heterogeneous too.

where $\text{BLOY}_{i,j,t} = \kappa_{\text{BLOY}}\text{BLOY}_{i,j,t-1} + (1 - \kappa_{\text{BLOY}})I(y_{i,t-1} = j)$ is the brand-specific

loyalty measure of Guadagni and Little (1983), with smoothing parameter $0 \leq \kappa_{\text{BLOY}} \leq$

1 and $I(y_{i,t-1} = j)$ being a 0/1 dummy variable indicating whether household i chose

brand j at the previous purchase occasion $t - 1$. Similar to choice shares, $\sum_j \text{BLOY}_{i,j,t} =$

1, i.e., brand loyalty scores sum to one across brands. For initialization, $\text{BLOY}_{i,j,1} =$

κ_{BLOY} if brand j was chosen, while it is $(1 - \kappa_{\text{BLOY}})/(\# \text{ brands} - 1)$ otherwise

(Guadagni and Little 1983). We translate the utilities in (7) to logit brand choice

probabilities by computing

$$(8) \qquad\qquad p_{i,j,t|s} = \frac{\exp(U_{i,j,t|s})}{\sum_k \exp(U_{i,k,t|s})}$$

and obtain all parameter estimates by numerically maximizing the log-likelihood

$$(9) \qquad\qquad \ln L = \sum_i \ln\left(\sum_s \pi_s \left[\prod_t \prod_j p_{i,j,t|s}{}^{I(y_{i,t}=j)}\right]\right),$$

where π_s is the relative size of segment s and $I(y_{i,t} = j)$ is a 0/1 dummy variable

indicating whether household i chose brand j at occasion t.

      Consistent with most extant studies, we operationalize ERP in (7) as the current

shelf price of the previously chosen brand; this ERP is household-specific but common

for all brands, is behaviorally plausible and has been shown to perform well empirically

(Hardie et al. 1993). We verified that it fits our scanner panel data better than other ERP

operationalizations such as the current average shelf price across brands, the highest shelf

price or the lowest price (Kumar et al. 1998; Rajendran and Tellis 1994) as well as a

loyalty-weighted ERP (Mazumdar and Papatla 1995; 2000). We define IRP as an exponentially smoothed average of the brand's past prices, i.e., $\text{IRP}_{i,j,t} = \kappa_{\text{IRP}}\text{IRP}_{i,j,t-1} + (1 - \kappa_{\text{IRP}})\text{PRICE}_{i,j,t-1}$, with the smoothing parameter $0 \leq \kappa_{\text{IRP}} \leq 1$ reflecting the amount of price memory (Kalyanaram and Little 1994; Niedrich et al. 2009). This brand-specific IRP performed best in an extensive comparison of alternative reference price specifications (Briesch et al. 1997) and is most frequently used in the literature (Erdem et al. 2001). Consistent with the findings of Briesch et al. (1997) and Rajendran and Tellis (1994), the brand-specific IRP fits our data substantially better than an IRP based on prices paid for previously chosen brands. Our estimates of μ in (7) are $.39$ for ketchup and $.48$ for peanut butter; both are significantly smaller than 1, which is in line with the extant studies in Table 1 and provides further evidence of loss aversion asymmetry.

Full model of brand choice with asymmetry and pricing conditions

We build the full model of brand choice by incorporating the two pricing conditions $\text{COND1}_{i,t}$ and $\text{COND2}_{i,t}$ into the base model via (5) and (6). Furthermore, we extend (6) with other variables that may affect loss aversion asymmetry in μ and serve as alternative explanations; we add these variables in the same way as $\text{COND1}_{i,t}$ and $\text{COND2}_{i,t}$ and mean-center the variables in (5) and (6). As control variables in (6), we consider two measures of purchase behavior (the household's brand loyalty and average interpurchase time until occasion *t*) and two socio-demographic characteristics (household size and income). Findings by Klapper et al. (2005) and Krishnamurthi et al. (1992) indicate that loss aversion becomes stronger for households with stronger brand loyalty, reflected by a larger Herfindahl index $\sum_j \text{BLOY}_{i,j,t}^2$; an explanation is that loyal

customers are relatively insensitive to price discounts (gains) but may switch if they

encounter a bad price (loss) for their preferred brand. Klapper et al. also report evidence

that longer interpurchase times are associated with more loss aversion, but note that

causality may be in the opposite direction: highly loss averse households may postpone

category purchases more often until they encounter acceptable prices. We include

household size and income as socio-demographic variables, as financially constrained

households may be more loss sensitive with regard to IRP (Erdem et al. 2001); this would

imply less loss aversion asymmetry, i.e. larger μ, for large and low-income households.

The first condition $\text{COND1}_{i,t}$ is that the household's brand choices correspond to

expensive brands. Consistent with earlier conceptualization, we capture the extent to

which this is met for household i at purchase occasion t by computing the average price

ranking of the household's previously chosen brands:

$$(10) \qquad \text{COND1}_{i,t} = \frac{1}{J(t-1)} \sum_{\tau=1}^{t-1} \sum_{j=1}^{J} I(\text{PRICE}_{i,j,\tau} < \text{PRICE}_{i,y_{i,\tau},\tau}) \, ,$$

where $\text{PRICE}_{i,j,\tau}$ is the price of brand j observed by household i at purchase occasion τ,

$\text{PRICE}_{i,y_{i,\tau},\tau}$ is the price of the chosen brand at that occasion and $I(\text{PRICE}_{i,j,\tau} <$

$\text{PRICE}_{i,y_{i,\tau},\tau})$ is a 0/1 dummy variable indicating whether $\text{PRICE}_{i,j,\tau} < \text{PRICE}_{i,y_{i,\tau},\tau}$. We

represent the second condition $\text{COND2}_{i,t}$ that the household experiences upward prices

by the average price change for all brands and all purchase occasions at which the

household could observe brand prices:

$$(11) \qquad \text{COND2}_{i,t} = \frac{1}{J(t-1)} \sum_{\tau=2}^{t} \sum_{j=1}^{J} (\text{PRICE}_{i,j,\tau} - \text{PRICE}_{i,j,\tau-1}) .$$

The variables in (10) and (11) are indeed strongly connected to the gain frequency

differential between ERP and IRP; linear regression with the gain frequency differential

for household i at occasion t acting as the dependent variable and $\text{COND1}_{i,t}$ and

$\text{COND2}_{i,t}$ being the independent variables results in highly significant coefficients (p <

.0001) in both product categories ($R^2_{\text{ketchup}} = .64$; $R^2_{\text{peanut butter}} = .57$).

< TABLE 3 ABOUT HERE >

Table 3 contains the parameter estimates of the full model. All segment-specific

response coefficients in the first part of the table have the expected sign and most of them

are significant at the 1% level. For ketchup, the first two segments are almost equally

large (41% and 37%) and both of them are sensitive to reference prices, while the third

segment is smaller (22%) and not driven by reference prices (Moon et al. 2006).

Regarding feature and display, the second segment is most responsive and the third

segment is least responsive. For peanut butter, the first two segments together capture

75% of the market. Households are responsive to marketing mix in both segments, but

segment 2 is more responsive than segment 1. Furthermore, households in segment 2

dislike the store brand; they use price and promotion to choose between national brands.

The second part of Table 3 provides the loss aversion estimates. Most

importantly, the coefficients δ_1 and δ_2 of the two pricing conditions are negative and

significant at the 1% level in both product categories; this confirms our hypotheses that

the first condition leads to more asymmetry by increasing loss aversion in ERP and the second condition does so by decreasing loss aversion in IRP. [8] The effects of the four alternative explanations are weaker: three of them (interpurchase time, household size and income) are as anticipated in both product categories, but only two of the six coefficients are significant at the 5% level.

Impact of loss aversion asymmetry on the effectiveness of price promotions

To explore the implications of loss aversion asymmetry, we run a simulation in which we use the brand prices and response parameters from the base model in the peanut butter category, but vary the values of λ and μ in four different scenarios. We consider a one-time price cut by one of the brands that equals 10 percent of the category price, while keeping the prices of all other brands fixed (Moon et al. 2006; Rajendran and Tellis 1994); this is consistent with the empirical finding that the most common competitive response is no response (Steenkamp et al. 2005). For each scenario, Table 4 provides (a) the percentage-point increase in the focal brand's choice probability at the current purchase occasion with the one-time price promotion and (b) the net cumulative change across both current and future occasions, expressed in the same unit.

< TABLE 4 ABOUT HERE >

Compared to scenario 1 ($\lambda = 1$ and $\mu = 1$), scenario 2 keeps loss aversion for IRP constant at $\lambda\mu = 1$ but induces loss aversion asymmetry ($\mu = 0.5$) by increasing loss aversion for ERP ($\lambda = 2$): the adverse impact of losses with regard to ERP becomes

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[8] The two pricing conditions are strongly connected to the gain frequency differential between ERP and IRP. Replacing them in the full model, the coefficient of the gain frequency differential has the expected sign in both categories; it is significant at 5% for ketchup and significant at 1% for peanut putter.

larger in scenario 2, making it more rewarding to use a price discount to decrease ERP losses than to increase corresponding gains. As a price cut mainly reduces ERP losses for expensive brands, while it tends to increase gains for cheap brands, expensive brands benefit most. This is reflected in both the instantaneous (current) and cumulative (current plus future) effects of the simulated price promotion in scenario 2.

Comparing scenario 2 and scenario 3, loss aversion for ERP is kept constant at $\lambda = 2$, but asymmetry is brought into scenario 2 by decreasing loss aversion in IRP. Table 4 shows that the instantaneous effect of the price promotion on brand choice probability is identical in the two scenarios, due to the same ERP coefficients. However, the cumulative net effect is positive in scenario 2 but negative in scenario 3, meaning that without loss aversion asymmetry (scenario 3) the promotion's negative future carry-over outweighs the immediate positive impact. Intuitively, a price reduction triggers future IRP losses in both scenarios, but these losses are penalized much more in the symmetric scenario 3 than in the asymmetric scenario 2. In this case, the mechanism is so strong that loss aversion asymmetry makes the difference between an effective and an ineffective price promotion in terms of cumulative net effect.

Scenarios 2 and 4 share the same asymmetry coefficient $\mu = 0.5$. The simulation results demonstrate that differences in promotional effectiveness between expensive and cheap brands —due to a fixed loss aversion asymmetry— become more pronounced if the amount of loss aversion λ increases. Moreover, the effectiveness gap can become so large that price promotions are effective for expensive brands but ineffective for cheaper brands. Overall, we conclude from the simulation that asymmetric loss aversion makes it more attractive to promote frequently, but more so for higher-price brands.

DISCUSSION AND CONCLUSION

Loss aversion has been much debated in the reference price literature. A possible reason for the mixed support is that the presence of loss aversion depends on the type of reference price: ERP or IRP. Mazumdar and Papatla (2000) found empirical evidence that ERP-oriented customer segments are more sensitive to losses, while IRP segments are more sensitive to gains. More broadly, this suggests that consumers are less loss averse in IRP than ERP, which is intriguing but puzzling: other studies remained silent on asymmetric loss aversion and neither explanation nor implications have been provided so far. In the current study, we attempted to fill this gap. First, we considered several loss aversion estimates from the literature to establish that asymmetric loss aversion is commonplace. Next, we postulated that the lower degree of loss aversion in IRP as compared to ERP is driven by two empirical regularities triggering ERP gains and IRP losses, and that the larger number of IRP losses makes households less loss averse in that type. We found empirical support in two product categories, while four alternative explanations of loss aversion asymmetry did not have much explanatory power.

By proposing the asymmetric loss aversion finding of Mazumdar and Papatla (2000) –which was only a relatively small part of their paper– as an empirical generalization, we hope this result will become more influential and salient. Rajendran and Tellis (1994) conclude that only the inclusion of both ERP and IRP can justify a pricing scheme with both high regular prices and low discount prices, but do not consider loss aversion. The literature also reports that loss aversion in IRP makes it more profitable to smooth out price fluctuations, while gain seeking increases the net payoff of

price promotions (Greenleaf 1995; Kalwani and Yim 1992; Kopalle et al. 1996).[9] However, none of the abovementioned studies have incorporated loss aversion in both ERP and IRP, which is needed to understand the implications of loss aversion asymmetry for long-run (cumulative) promotional impact. Our simulation shows that the presence of asymmetry makes it more effective to have price promotions frequently, in particular for expensive brands. It provides a rationale for the existence of both Every-Day-Low-Price brands that are not on discount and Hi-Lo premium brands that are promoted relatively often: expensive brands can use temporary price cuts to transform ERP losses into ERP gains without heavy penalization of induced future IRP losses, while cheaper brands already tend to correspond to ERP gains and therefore have less need (and margins) to promote often. Furthermore, the frequency-importance connection for losses suggests that brands can be promoted more often in times of price inflation when consumers are desensitized toward IRP losses following price promotions.

This study suggests several avenues for further research. First, we have used data from two product categories and implemented within-category individual-level tests. An important extension is to assess what percentage of variation in loss aversion estimates across categories is explained by the two pricing conditions and other characteristics at the category level. In a similar vein as a meta analysis, this may help to clarify why loss aversion is found in some extant studies but not in others. Second, our empirical modeling approach is reduced-form; one could attempt to build a more structural model or do an analytical study (Putler 1992). Third, the model of brand choice may be extended with a latitude of price acceptance within which the consumer does not respond

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[9] Kopalle et al. (1996) also derive implications of loss aversion in ERP for optimal pricing policies, but their model does not consider ERP and IRP simultaneously.

to deviations from the reference price (Gupta and Cooper 1992; Kalyanaram and Little 1994) and the thresholds for gains and losses may be asymmetric (Han et al. 2001). While extant studies with loss aversion in both ERP and IRP do not incorporate a latitude of price acceptance, it would drive the frequencies of gains and losses. Similarly, consideration set formation may influence the percentages of gains versus losses, for example, if brands that are on promotion are more likely to enter the consumer's consideration set (Andrews and Srinivasan 1995; Bronnenberg and Vanhonacker 1996).

Finally, reference prices are not observed in scanner panel data and need to be inferred from observed shelf prices, which may deviate from consumers' perceived prices. For instance, consumers tend to underestimate the prices they paid (Dickson and Sawyer 1990; Vanhuele and Dreze 2002), increasing the perceived number of IRP losses. To resolve the price perception (and possibly other) issues, one may complement our scanner data analysis with controlled experiments (Kalwani and Yim 1992). Reference price studies based on scanner data versus experiments constitute "two fairly independent streams of research" (Mazumdar et al. 2005, p. 84), but have the potential to strengthen each other in order to better understand actual purchase behavior and its underlying psychology.

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Table 1

Overview of estimates of loss aversion asymmetry, computed from the literature.

Study	Level of analysis	Unobserved heterogeneity	Product categories	ERP (λ)	IRP ($\lambda\mu$)	Ratio (μ)
Bell and Lattin (2000)	Individual	Latent class	Orange juice and 11 other categories	Loss aversion in ERP for 7 out of 12 categories, no loss aversion in IRP for all 12 categories		
Briesch et al. (1997)	Individual	Latent class	Both ERP and IRP are reported for liquid detergent	0.44	0.20	0.47
Hardie et al. (1993)	Individual	No	Orange juice	1.66	1.46	0.88
Mazumdar and Papatla (1995)	Individual	Deterministic segmentation	Margarine and liquid detergent	$\lambda\mu$ virtually zero for margarine ($\mu \approx 0$), while $\lambda\mu$ very large for liquid detergent (μ very large)		
Moon et al. (2006)	Individual	Latent class structural heterogeneity	Toilet tissue	18.04	4.88	0.27
Pauwels et al. (2007)	Aggregate	Not applicable	Combination of brands from 20 categories	0.91	0.59	0.65

Table 2

Frequencies of gains and losses for ERP and IRP.

		ERP	IRP	differential	p-value
ketchup	% gain	68	50	18	0.000
	% loss	32	50		
peanut butter	% gain	54	30	24	0.000
	% loss	46	70		
across-category differential		14	20		
p-value		0.000	0.000		

Table 3

Parameter estimates of the full model (standard errors in parentheses). All brand constants are relative to the Store brand. For the two pricing conditions and the alternative-explanation variables, negative coefficients indicate more asymmetry.

	ketchup				peanut butter			
segment number	1	2	3		1	2	3	4
segment size	41%	37%	22%		46%	29%	19%	6%
HEINZ / JIF	1.249^a	2.985^a	2.794^a		0.725^a	3.370^a	1.746^a	4.931^a
	(0.159)	(0.258)	(0.336)		(0.111)	(0.251)	(0.311)	(0.748)
HUNTS / PETER PAN	-0.181^b	1.575^a	2.152^a		0.174^c	3.009^a	0.933^a	0.237
	(0.091)	(0.250)	(0.309)		(0.094)	(0.219)	(0.258)	(1.071)
DEL MONTE / SKIPPY	-0.377^a	0.932^a	0.767^b		0.610^a	3.309^a	1.470^a	4.359^a
	(0.087)	(0.244)	(0.379)		(0.083)	(0.220)	(0.230)	(0.695)
BLOY	0.238^a	0.119^a	0.188^a		0.313^a	0.145^a	0.292^a	0.156^a
	(0.013)	(0.018)	(0.015)		(0.006)	(0.014)	(0.023)	(0.024)
FEATURE	0.164^a	0.282^a	0.088^a		0.109^a	0.298^a	0.524^a	0.446^a
	(0.017)	(0.024)	(0.032)		(0.021)	(0.034)	(0.074)	(0.107)
DISPLAY	0.163^a	0.437^a	0.138^a		0.162^a	0.528^a	0.515^a	0.122
	(0.034)	(0.067)	(0.037)		(0.049)	(0.110)	(0.168)	(0.207)
ERPGAIN	0.115^a	0.121^a	0.015		0.022^a	0.063^a	0.081^a	0.026^b
	(0.015)	(0.016)	(0.018)		(0.004)	(0.009)	(0.012)	(0.012)
IRPGAIN	0.087^a	0.124^a	0.024		0.036^a	0.054^a	0.080^a	0.033
	(0.019)	(0.030)	(0.034)		(0.008)	(0.011)	(0.017)	(0.030)
LOSS AVERSION (λ)	1.066	(0.078)			1.631^a	(0.154)		
ASYMMETRY (μ)	0.356^a	(0.238)			0.459^a	(0.113)		
CONDITION 1 (δ_1)	-1.006^a	(0.088)			-1.978^a	(0.145)		
CONDITION 2 (δ_2)	-3.203^a	(0.854)			-0.895^a	(0.243)		
LOYALTY	-4.299^c	(2.212)			1.059	(0.757)		
INTERPURCH TIME	0.052	(0.062)			0.121^b	(0.050)		
HHOLD SIZE	0.283^b	(0.134)			0.081	(0.093)		
HHOLD INCOME	-0.258	(0.210)			-0.021	(0.047)		
κ_{BLOY}	0.790^a	(0.010)			0.807^a	(0.005)		
κ_{IRP}	0.643^a	(0.012)			0.295^a	(0.068)		
Log-likelihood	-8035.86				-12919.49			

[a] significant at 1%, [b] significant at 5%, [c] significant at 10% (significance of λ and μ relative to 1).

Table 4

Instantaneous and cumulative effects of price promotions.

	scenario 1		scenario 2		scenario 3		scenario 4	
loss aversion	$\lambda = 1$		$\lambda = 2$		$\lambda = 2$		$\lambda = 3$	
asymmetry	$\mu = 1$		$\mu = 0.5$		$\mu = 1$		$\mu = 0.5$	
brand (price)	instant	cumul	instant	cumul	instant	cumul	instant	cumul
1 (9.85c)	12.18	9.25	13.98	14.85	13.98	−6.68	15.63	9.76
2 (9.34c)	12.18	9.25	13.45	13.61	13.45	−7.71	14.53	6.62
3 (9.31c)	12.18	9.25	13.39	13.45	13.39	−7.83	14.43	6.44
4 (8.00c)	12.18	9.25	11.24	10.13	11.24	−11.12	10.01	−0.27

Figure 1

Illustration of the two pricing conditions triggering ERP gains and IRP losses.

Condition 1:
"expensive brand has larger share"

Condition 2:
"brand price increases over time"