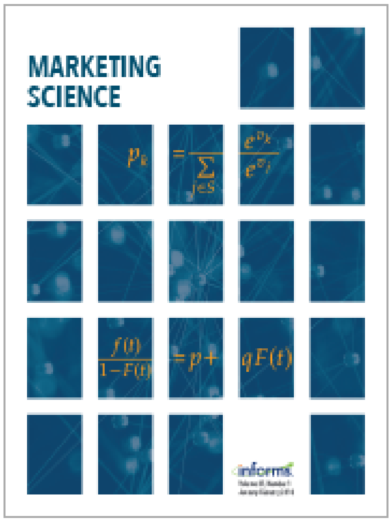


Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Looking for Loss Aversion in Scanner Panel Data: The Confounding Effect of Price Response Heterogeneity

David R. Bell, James M. Lattin,

Looking for Loss Aversion in Scanner Panel Data: The Confounding Effect of Price Response Heterogeneity

David R. Bell • James M. Lattin
The Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania 19104, davidb@mktgmail.wharton.upenn.edu
Graduate School of Business, Stanford University, Palo Alto, California 94305, jlattin@leland.stanford.edu

Abstract

Recent work in marketing has drawn on behavioral decision theory to advance the notion that consumers evaluate attributes (and therefore choice alternatives) not only in absolute terms, but as *deviations* from a reference point. The theory has important substantive and practical implications for the timing and execution of price promotions and other marketing activities.

Choice modelers using scanner panel data have tested for the presence of these "reference effects" in consumer response to an attribute such as price. In applications of the theory of reference-dependent choice (Tversky and Kahneman 1991), some modelers report empirical evidence of loss aversion: When a consumer encounters a price above his or her established reference point (a "loss"), the response is greater than for a price below the reference point (a "gain"). Researchers have gone so far as to suggest that evidence for the so-called reference effect make it an empirical generalization in marketing (e.g., Kalyanaram and Winer 1995, Meyer and Johnson 1995).

It is our contention that the measurement of loss aversion in empirical applications of the reference-dependent choice model is confounded by the presence of unaccounted-for heterogeneity in consumer price responsiveness. Our reasoning is that the kinked price response curve implied by loss aversion is confounded with the slopes of the response curves across segments that are differentially responsive to price. A more price-responsive consumer (with a steeper response function) tends to have a lower price level as a reference point. This consumer faces a larger proportion of prices above his reference point, thus the response curve is steeper in the domain of losses. Similarly, the less price-responsive consumer sees a greater proportion of prices below his reference point, so the response curve is less steep within the domain of gains. As a result, any cross-sectional estimate of loss aversion that does not take this into account will be biased upward—researchers who do not control for heterogeneity in price responsiveness may arrive at incorrect substantive conclusions about the phenomenon. It is interesting to note that in this instance, failure to control for heterogeneity induces a bias in *favor* of finding an effect, rather than the more typical case of attenuation of the effect toward zero.

We first test our assertion regarding the reference-dependent model using scanner panel data on refrigerated orange juice and subsequently extend this analysis to 11 additional product categories. In all cases we find, as predicted, that accounting for price-response heterogeneity leads to lower and frequently nonsignificant estimates of loss aversion. We do, however, find some categories in which the effect does not disappear altogether. We also estimate loss aversion using a "sticker shock" model of brand choice in which the reference prices are *brand-specific.* In line with the results of the majority of prior literature, we find smaller and insignificant estimates of loss aversion in this model. We show that this is because in the sticker shock model, there is no apparent correlation between the price responsiveness of the consumer and the representation of reference effects as losses or gains. Our findings strongly suggest that loss aversion may not in fact be a universal phenomenon, at least in the context of frequently purchased grocery products.

(*Choice Models*; *Reference Dependence*; *Loss Aversion*; *Sticker Shock*; *Reference Price*; *Empirical Generalization*)

Marketing Science © 2000 INFORMS
Vol. 19, No. 2, Spring 2000, pp. 185–200

0732-2399/00/1902/0185/$05.00
1526-548X electronic ISSN

1. Introduction

The literature on prospect theory (e.g., Kahnemann and Tversky 1979, Kahnemann et al. 1991, Tversky and Kahnemann 1991) has given choice modelers a number of things to think about. Working with scanner panel data, researchers have built increasingly elaborate models with the goal of testing these theories and gaining new insights into choice behavior.

Pricing is one area in which the findings of this research have been particularly promising. Prospect theory suggests two possible changes to the simple linear price response functions embodied in mainstream models of brand choice (e.g., Guadagni and Little 1983). First, consumer response to price should be framed relative to a point of reference, or *reference price.* Second, consumer response to price may exhibit *loss aversion,* where the response to a "loss" (i.e., an actual price above the reference point of the consumer) is greater than that for a "gain" of the same size. If consumer behavior is indeed consistent with these theories, this has a number of implications for researchers and for managers—particularly with respect to the timing and execution of price promotions (e.g., Hardie et al. 1993).

In recent years the number of empirical and analytical studies on reference effects has grown considerably. In particular, empirical models that incorporate both reference price effects and loss aversion include Kalwani et al. (1990), Krishnamurthi et al. (1992), Hardie et al. (1993), Kalyanaram and Little (1994), Briesch et al. (1997), and Chang et al. (1999).

It is interesting to note what while the empirical results with respect to loss aversion are somewhat mixed,[1] the "reference effect" has nevertheless attained the status of an empirical generalization in marketing (e.g., Meyer and Johnson 1995). In discussing the generalizability of the findings and in formulating an agenda for future research in this area, Kalyanaram and Winer (1995, p. G168) point out that "there is still some uncertainty about the impact of reference prices when cross-sectional variation in household heterogeneity is taken into account" and note that this is an important area for future research. This article contributes to filling this gap in the literature.

Loss Aversion and Heterogeneity in Price Responsiveness

In this research, we revisit the empirical findings on loss aversion obtained from models calibrated on cross-sectional panel data. Our goal is to show how the measurement of loss aversion along a given attribute (such as price) can be confounded if consumer heterogeneity with respect to that attribute is ignored. We do this by (a) developing an argument to show how this will happen, (b) testing our conjecture using data from a published study on reference-dependent choice, (c) extending our analysis to 11 additional product categories, and (d) further generalizing the result to the sticker shock formulation.

The intuition for our argument is as follows: Because the reference price is generally unobservable, it is usually modeled as some function of the prices encountered or paid by the consumer on previous (or current) choice occasions. For consumers who are highly responsive to price, this set of occasions will tend to involve a set of systematically lower prices, and hence a lower reference point. Conversely, less price-sensitive consumers will have a higher reference point for price. On any given choice occasion, a price-responsive consumer with a lower reference price level is more likely to be facing a "loss," while a price-insensitive consumer will more likely see his choice alternatives framed as "gains."

Now, imagine a situation where one wishes to take a series of consumer choices (such as those from a scanner panel dataset) and estimate the degree of loss aversion exhibited by those consumers. If consumers in the panel are differentially price responsive, the different mix of customers facing gains and losses may lead to something that only looks like loss aversion at the individual consumer level. This is because, in a cross-sectional model, what appears to be loss aversion (a steeper response function for losses than gains) can in fact be attributable to heterogeneity across households with respect to price responsiveness.[2]

[1]For example, Hardie et al. (1993) find evidence of loss aversion using a data on refrigerated orange juice, while Kalyanaram and Little (1994) find no significant loss aversion in coffee data.

[2]The idea that one can draw misleading conclusions about the nature of consumer choice behavior using cross-sectional data without accounting for heterogeneity is not new to marketing (see Massy et al. 1970, pp. 54–56).

Our argument and analysis complements that of Chang et al. (1999), who show that symmetric reference effects in the sticker shock model may be spurious. Our work here differs in three important respects. First, because our interest is in the phenomenon of loss aversion, we focus initially on the reference-dependent model in which loss aversion is obtained directly from theory.[3] Second, our argument for bias results soley from an analysis of heterogeneity in price responsiveness, whereas Chang et al. (1999) demonstrate the biasing effect of unaccounted for heterogeneity in purchase timing. Third, we generalize our result across 12 product categories.

The paper is organized as follows. In §2 we present an intuitive and illustrative example to show how this misattribution can occur and then estimate a reference-dependent choice model on scanner panel data from the refrigerated orange juice category.[4] Our results suggest that as one accounts for heterogeneity in price response (using a finite mixture model), the degree of loss aversion implied by model parameters decreases substantially and significantly. We then conduct a series of posterior analyses to show that, consistent with our earlier conjecture, households are segmented according to whether they see primarily losses or gains, and this is systematically related to their overall price sensitivity.

In §3 we extend the analysis using additional product categories and find that the single-segment loss aversion parameter estimates are all greater than the estimates after heterogeneity is accounted for. Thus, we are able to show that our finding is not limited to a single product category. Finally, in §4 we address the issue of loss aversion in sticker shock models of brand choice that contain a main effect for price in addition to the reference effects for gains and losses. We find no evidence of asymmetric sticker shock effects (loss aversion) for all categories studied and show that there is no apparent correlation between reference price and the representation of gains and losses in this model. Therefore, our argument is not limited to a particular model of the reference effect.

[3]In §4 and in the appendix, we also investigate the impact of price response heterogeneity on loss aversion in the so-called sticker shock model of reference price effects (e.g., Winer 1986).

[4]This dataset was used by Hardie et al. (1993) in their analysis of reference-dependent choice.

2. Models of Loss Aversion

We begin by reviewing the theory of reference-dependent choice and empirical results from prior research. We then proceed to outline our intuition for the heterogeneity confound and present our findings from the refrigerated orange juice category.

2.1. Loss Aversion and Reference-Dependent Choice

The theory of reference-dependent riskless choice is presented in Tversky and Kahneman (1991). For choice an alternative j, defined by a single attribute x, there exists a reference structure $R(x)$ such that $U_r^j(x) = R^j(x)$. In words: The utility of alternative j evaluated from reference point r is captured by the reference function $R(x)$. Furthermore, the additive reference structure model exhibits constant loss aversion

$$R^j(x) = \begin{cases} u^j(x) - u^j(r) & \text{if } u^j \geq r^j, \\ \lambda[u^j(x) - u^j(r)] & \text{if } u^j < r^j, \end{cases} \tag{1}$$

with $\lambda > 1$. The restriction $\lambda > 1$ captures asymmetric response to deviations above and below the reference point. In particular, $\lambda > 1$ implies that the decision maker is loss averse and that the response function is steeper in the domain of losses than in the domain of gains. In empirical applications, a natural test for the presence of loss aversion is that the estimated value of λ is significantly greater than one.

The theory also implies that *all* alternatives in the choice set are evaluated with respect to a *common* reference point (i.e., there is only one reference point per choice occasion, against which all alternatives are compared). It is silent with respect to the origin of the reference points, so empirical models typically operationalize them as a function of the idiosyncratic experience of the chooser; see Briesch et al. (1997) for a review.

To implement the theory in an empirical setting, it is necessary to specify the utility structure in Equation (1) and to provide a mapping into choice probabilities. In a direct adaptation of Equation (1), Hardie et al. (1993) specify the following model:[5]

[5]They also consider quality. Because our goal is to demonstrate the confounding effect of heterogeneity, we focus (without loss of generality) on a single attribute: price.

$$U_{it}^h = \alpha_i + \beta_1 FEAT_{it} + \beta_2(PGAIN_{it}^h + \lambda PLOSS_{it}^h) + \beta_3 BLOY_{it}^{h6} + \epsilon_{it}^h, \qquad (2)$$

where

$FEAT_{it}$ = a 0/1 indicator of feature advertising activity,
$PGAIN_{it}^h$ = the difference between the reference price and the observed price when the observed price is *below* the reference point,
$PLOSS_{it}^h$ = the difference between the reference price and the observed price when the observed price is *above* the reference point,
$BLOY_{it}^h$ = loyalty of household h to brand i at time t (e.g., Guadagni and Little 1983),
α_i, β_1, β_2,
λ, β_3 = parameters to be estimated.

$\lambda > 1$ constitutes evidence for "loss aversion" (Hardie et al. 1993, p. 83). With ϵ_{it}^h distributed double exponential, the probability of choice is given by

$$p_t^h(i) = \frac{\exp(V_{it}^h)}{\sum_k \exp(V_{kt}^h)}, \qquad (3)$$

where V_{it}^h denotes the deterministic component of utility for each alternative i, given in Equation (2). Hardie et al. (1993) find that this theory-based reference-dependent model fits their data better than a model without reference dependence (in which the terms *PGAIN* and *PLOSS* are replaced by a single *PRICE* variable). They also find strong evidence of loss aversion.

2.2. Other Models of Reference Price

The reference-dependent choice model presented in Equations (2) and (3) presents somewhat of a departure from the approach used by many choice modelers to capture the effect of reference price. Lattin and Bucklin (1989), Kalwani et al. (1990), Mayhew and Winer (1992), and Kalynaram and Little (1994), among others, have all used a variant of the sticker shock model introduced by Winer (1986). The sticker shock model includes both a main effect of price and a term to capture the difference between the actual price and the reference price of the consumer. Winer's initial notion for reference price, based on a rational expectations model, was brand-specific (unlike the reference-dependent model, where each alternative is compared to a single reference point). Winer's original model was not developed with the idea of testing for loss aversion. Subsequently, others have modified the form of the utility function to allow for asymmetric sticker shock effects. Kalwani et al. (1990), for example, find significant asymmetry in their analysis of coffee data, and they interpret the result as being consistent with prospect theory.

In the remainder of §2 and in §3 we focus principally on the reference-dependent choice model. It is, in fact, a more parsimonious model and was developed from theory expressly for the purpose of investigating loss aversion (which is our focus). In §4 we return to the sticker shock model and ask whether our inferences involving loss aversion are similarly affected by price-response heterogeneity for this different model form.

2.3. Heterogeneity in Price Response and Loss Aversion

The theory embodied in Equation (1) refers to an individual-level phenomenon, and if the parameters in Equation (2) were estimated at the level of the individual household any evidence of loss aversion would be unambiguous.[7] However, model calibration using cross-sectional panel data (as done in most empirical applications in the literature) introduces sources of heterogeneity that could potentially bias λ, the estimate of loss aversion.

If consumers differ with respect to price responsiveness, those who are most price responsive will tend to favor and purchase the least expensive brands, *ceteris paribus*. For these consumers who establish relatively low reference points, prevailing prices will tend to be at or above the reference point (i.e., will be perceived as losses). Consumers who are least price responsive will have a higher point of reference for price and will tend to perceive prevailing prices as gains. Under these

[6]The smoothing parameter embedded in the loyalty term is estimated simultaneously with other parameters following the method proposed by Fader et al. (1992).

[7]In these type of datasets with limited choice observations per consumer, individual-level estimation has its own problems. Effects that are significant cross-sectionally may not show up at the individual level. See Seetharaman et al. (1999) for a discussion of this point.

circumstances, it may be possible to better fit consumer choice behavior in a cross-sectional model with a kinked price response curve (with a steeper slope for losses than for gains), even in the absence of any true loss aversion behavior. This is because the "kinked" price response curve better accounts for underlying heterogeneity in price responsiveness.

To make this intuition clear, consider the following simple example. A category of consumer packaged goods contains six distinct but comparable brands (A,B,C,D,E,F) ranging in price from \$1.00 to \$2.50. Furthermore, there are two segments of consumers who buy in the product category; the first segment is more price responsive than the second. As a result, consumers in segment 1 chose predominantly from the lower-priced brands—A, B, and C—while the consumers in segment 2 choose from the higher-priced brands—D, E, and F.

In this simple example, neither segment of consumers exhibits any loss aversion. The best fit to the data is given by a model that allows for different levels of price responsiveness for the two segments (as shown by the dashed lines in Figure 1).

What happens if we do not allow for heterogeneity in price response? Clearly, such a model will not fit the data as well. We can, however, improve the flexibility of the model by adding reference price. The construction of reference price will differ by segment. Consumers in segment 1 who chose primarily from among brands A, B, and C will have a reference price in the range of \$1.00–\$1.60, and for them most of the choice alternatives will be framed as losses (i.e., actual prices will be above the reference points). Consumers in segment 2 who chose primarily from among brands D, E, and F will have a reference point in the range of \$1.90–\$2.50, and most of their choice alternatives will be framed as gains.

The reference price formulation allows us to fit a kinked curve to the data (as shown by the solid line in the figure), steeper in the domain of losses than in the domain of gains. What we are really doing in the context of this example is simply segmenting the market: a steeper curve for the more price-responsive consumers (who predominantly face losses) and a shallower curve for less price-responsive households (who predominantly face gains). Thus, the slope in the domain of losses is essentially determined by the relatively price-sensitive households, while the slope in the domain of gains is being estimated over data points drawn primarily from the more price-insensitive households.

To summarize, the example suggests three things: (1) A reference-dependent model estimated with a single loss aversion parameter will fit the data better than a model that does not allow for this effect; (2) it will do so because it mimics the underlying heterogeneity; and (3) after accounting for heterogeneity in price responsiveness, the estimate of loss aversion will decrease.

2.3.1. Testing for the Impact of Heterogeneity In light of the concerns raised by our example, we allow for preference and response heterogeneity using a finite-mixture model (Kamakura and Russell 1989). The deterministic utility for the mixture model is a straightforward extension of Equation (2):

$$V_{it|s}^{h} = \alpha_{is} + \beta_{1s}FEAT_{it} + \beta_{2s}(PGAIN_{it}^{h} + \lambda_s PLOSS_{it}^{h}) + \beta_{3s}BLOY_{it}^{h}, \tag{4}$$

where α_{is} and β_{ms} vary across the segments $s = 1, 2, \ldots, S$, for each brand $i = 1, 2, \ldots, I - 1$ and each explanatory variable $m = 1, 2, \ldots, M$, respectively. We model the segment sizes ψ_s indirectly (e.g., Kamakura and Russell 1989, Bucklin and Gupta 1992) via ϕ_s,

$$\psi_s = \frac{\exp(\phi_s)}{\sum_r \exp(\phi_r)}, \tag{5}$$

where ϕ_1 is normalized to zero.[8]

2.4. Operationalizing Reference Price

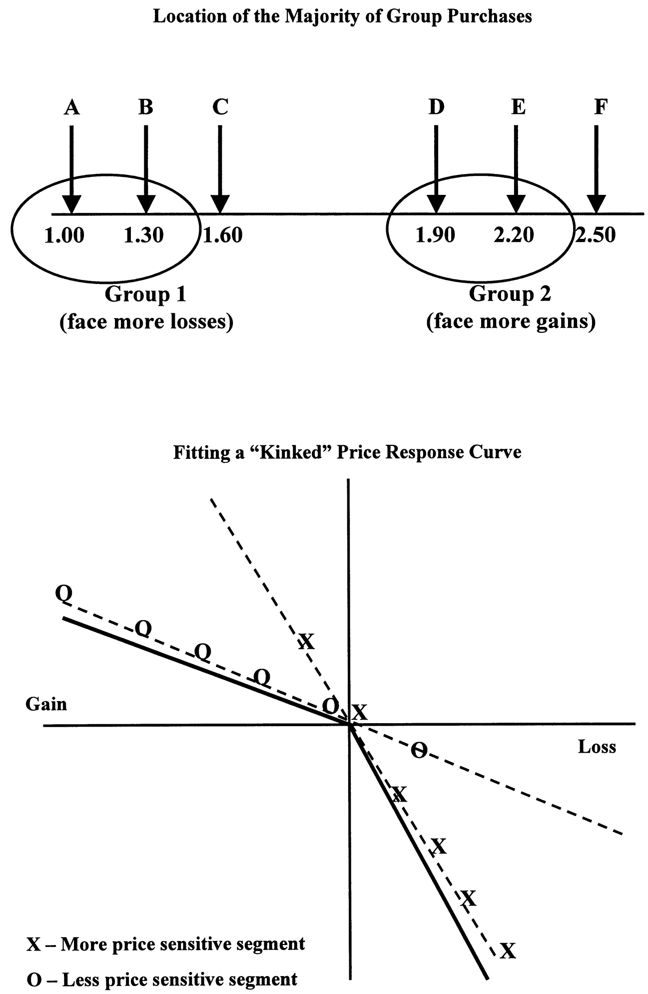
There is little conceptual guidance for the operational definition of the reference point because several approaches are arguably consistent with the theoretical model of Tversky and Kahneman (1991). Hardie et al. (1993) tackled this problem empirically by estimating their models under five alternative reference point schemes (see their Appendix 2 for details). They found

[8]Parameters are estimated by maximum likelihood and we determine S, the number of choice segments to estimate, using the BIC criterion. BIC $= -\text{LL} - (k/2)\ln(n)$, where k is the number of parameters and n is the number of observations.

the current price of the brand last purchased to be the reference point that produced the best fitting models. This operationalization can also be justified by work that shows consumers have poor memory for prices (e.g., Dickson and Sawyer 1990), which suggests it is therefore appropriate to assume consumers remember the brand bought at the last purchase occasion rather than remember the last price paid.

Briesch et al. (1997) conduct explicit empirical performance comparisons for a variety of reference point formulations. They find that reference points based on prices paid at previous purchase occasions yield the best fit (they also consider exponentially smoothed reference prices). Therefore, in our empirical work we use two measures, and following the terminology of Briesch et al. (1997), we refer to them as *stimulus-based* (current price of last brand bought) and *memory-based* (last price paid) measures. One practical advantage of using two measures is that we are able to show that our heterogeneity argument is robust to the specification of the reference point.

Figure 1 Price Responsiveness and Gains and Losses



2.5. Empirical Results for Orange Juice

We begin with our investigation of the effects of heterogeneity in loss aversion, using the same set of data used by Hardie et al. (1993): refrigerated orange juice. The data are from Marion, Indiana, and cover 3745 purchase occasions by 200 randomly selected households over a 130-week period (January 1983–July 1985). At least 80% of the purchases made by the households come from the following brands: Tropicana Regular, Citrus Hill, Minute Maid, Tropicana Premium, one store brand, and a regional brand. All six brands are the 64-ounce size. In accordance with Hardie et al. (1993), we divide the data as follows: The first 1490 purchase occasions (those made in 1983) are used to initialize the loyalty variable, the next 1589 (those made in 1984) are used to estimate the model parameters, and the remaining 666 purchases are kept aside for model validation.

2.5.1. Replication Results *Results from Models without Heterogeneity.* Table 1 presents the model fits and parameter estimates for three models: (1) A null model with a main effect for price, (2) a reference-dependent model that relies on stimulus-based reference points, and (3) a reference-dependent model that relies on memory-based reference points. As shown in Table 1, the reference-dependent models provide a better fit to the data than the null model does, and this holds up out of sample. All parameters have the expected signs and magnitudes, and the two reference-dependent models both provide estimates of λ that would lead one to view consumers as loss averse. The memory-based reference point model provides the best fit to the data.[9]

[9]In the remainder of the paper we report results for the memory-based reference point models because they provide the better fit in each of the 12 categories we analyzed. The substantive results for the stimulus-based reference point models are identical. Full results are available from the authors upon request.

Table 1 Orange Juice: Single Segment Estimation Results

			Reference-Dependent Models			
	Null Model		Stimulus-Based		Memory-Based	
Variable	Parameter	Std. Err.	Parameter	Std. Err.	Parameter	Std. Err.
Constants						
Regional Brand	0.188	0.174	0.074	0.172	0.015	0.188
Citrus Hill	1.116[a]	0.170	0.984[a]	0.167	0.905[a]	0.167
Minute Maid	1.068[a]	0.190	0.936[a]	0.184	0.907[a]	0.187
Tropicana Reg.	0.353[b]	0.158	0.234	0.158	0.227	0.154
Tropicana Prem.	0.814[a]	0.253	0.611[b]	0.239	0.547[b]	0.248
Store Brand	0.000	—	0.000	—	0.000	—
Marketing Mix						
β_1 ($FEAT_{it}$)	0.596[a]	0.099	0.669[a]	0.080	0.703[a]	0.098
β_2 ($PRICE^h_{it}$)	−2.410[a]	0.200	—	—	—	—
β_2 ($PGAIN^h_{it}$)	—	—	1.330[a]	0.239	0.510	0.279
λ ($PLOSS^h_{it}$)	—	—	2.650*	0.509	6.925*	1.183
β_3 ($BLOY^h_{it}$)	3.928[a]	0.137	3.655[a]	0.177	3.710[a]	0.187
γ ($BLOY^h_{it}$ smoothing)	0.831[a]	0.062	0.844[a]	0.084	0.858[a]	0.085
Calibration Fit						
−LL	−1438.3		−1426.6		−1408.8	
BIC	−1471.5		−1462.9		−1445.8	
ρ^2	0.418		0.488		0.429	
Forecast						
−LL	−620.9		−609.3		−608.8	

[a]Parameter is significantly different from zero, $p < 0.01$.
[b]Parameter is significantly different from zero, $p < 0.05$.
*Fail to accept the null hypothesis H_0: $\lambda = 1$, $p < 0.01$.

Results from Models with Heterogeneity. Table 2 presents the model fits for the null and reference-dependent models, but this time we account for heterogeneity using two different models. In the first, we allow for heterogeneity across all parameters in the model *except* for loss aversion. In effect, we constrain λ to be the same across all segments of the finite-mixture model. By comparing this model to the model without heterogeneity, we can assess the improvement in fit that comes from allowing differences in response parameters across households and compare the estimates of λ of evidence for bias. In the second model, we allow for heterogeneity across all parameters of the model *including* loss aversion. Comparing the second model to the first allows us to assess whether or not different segments of consumers exhibit differing amounts of loss aversion.

Initially, we focus on the models that allow for heterogeneity in price response but not heterogeneity in loss aversion. As indicated in Table 2, the two-segment reference-dependent model with the memory-based reference points and $\lambda_1 = \lambda_2$ provides the best fit to the data, adjusted for degrees of freedom (i.e., $BIC = -1{,}440.3$). The estimated parameters for the best-fitting two segment models are shown in Table 3.

Using these results, we test our assertion that the

Table 2 Orange Juice: Summary of Model Fits

	Number of Parameters	Log Likelihood	BIC
Null Model			
One Segment	9	−1,438.3	−1,471.5
Two Segments	**17**	**−1,383.3**	**−1,446.0**
Three Segments	26	−1,370.6	−1,466.4
Reference-Dependence (Stimulus-Based)			
One Segment	10	−1,426.1	−1,462.9
Two Segments	19	−1,378.1	−1,448.1
Two Segments ($\lambda_1 = \lambda_2$)	**18**	**−1,381.7**	**−1,448.0**
Three Segments	29	−1,366.2	−1,473.1
Three Segments ($\lambda_1 = \lambda_2 = \lambda_3$)	27	−1,372.2	−1,471.7
Reference-Dependence (Memory-Based)			
One Segment	10	−1,408.9	−1,445.8
Two Segments	19	−1,372.7	−1,442.7
Two Segments ($\lambda_1 = \lambda_2$)	**18**	**−1,374.0**	**−1,440.3**
Three Segments	29	−1,362.8	−1,469.7
Three Segments ($\lambda_1 = \lambda_2 = \lambda_3$)	27	−1,362.6	−1,462.1

single-segment parameter estimates for λ will be biased upward. For the estimates of λ accounting for heterogeneity in price responsiveness, we compute the associated 95% confidence intervals. In the far right column, we report the single-segment estimates of λ and the standard errors.

	Accounting for Heterogeneity			No Heterogeneity	
	Estimated λ	Std. Err.	95% C.I.	Estimated λ	*t*-ratio
Stimulus-Based	1.95	0.29	[1.38, 2.52]	2.65	3.24
Memory-Based	3.35	0.99	[1.41, 5.29]	6.93	5.01

First, note that under both formulations of the reference price, the single-segment (unadjusted) parameter estimate lies outside a 95% confidence interval around the heterogeneity-adjusted parameter estimate. This finding is in accordance with our expectations: the parameter estimated from the single-segment model is biased upwards. Loss aversion does not disappear completely: Even after accounting for heterogeneity in price responsiveness, the estimates of λ are still significantly greater than one.

Is there evidence of heterogeneity across households in the loss aversion parameter? The results reported in

Table 3 Orange Juice: Parameter Estimates from Segmented Models*

	Null Model		Reference-Dependent Models			
			Stimulus-Based		Memory-Based	
Variable	Segment 1 (47%)	Segment 2 (53%)	Segment 1 (52%)	Segment 2 (48%)	Segment 1 (49%)	Segment 2 (51%)
Marketing Mix						
β_1 ($FEAT_{it}$)	1.013[a]	0.158	1.080[a]	0.154	1.165[a]	0.208
	(0.160)	(0.172)	(0.163)	(0.204)	(0.175)	(0.177)
β_2 ($PRICE_{it}^{h}$)	−3.822[a]	−1.534[a]	—	—	—	—
	(0.352)	(0.297)				
β_2 ($PGAIN_{it}^{h}$)	—	—	2.865[a]	1.391[a]	1.291[a]	0.821[a]
			(0.443)	(0.351)	(0.421)	(0.238)
λ ($PLOSS_{it}^{h}$)	—	—	1.950[#]	—	3.357[#]	—
			(0.292)		(0.991)	
β_3 ($BLOY_{it}^{h}$)	3.528[a]	4.175[a]	3.206[a]	4.169[a]	3.177[a]	4.026[a]
	(0.239)	(0.202)	(0.282)	(0.209)	(0.284)	(0.206)

*Standard errors in parentheses, brand constants not reported.

[a]Parameter is significantly different from zero, $p < 0.01$.

[#]The hypothesis H_0: $\lambda = 1$ is rejected at $p < 0.01$.

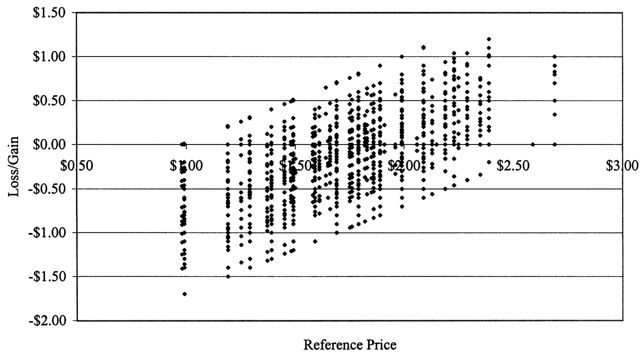
Table 2 suggest not. Judging from BIC, the improvement in fit is more than offset by the decrease in parsimony (i.e., BIC increases from $-1{,}440.3$ to $-1{,}442.7$). Furthermore, the hypothesis $\lambda_1 = \lambda_2 = \lambda$ cannot be rejected based on asymptotic t-statistics.

Our results thus far raise the following questions: Given that the single-segment estimate is biased upward, is it possible that studies based on cross-sectional scanner panel data have been reporting evidence of loss aversion when in fact none exists, and is it ever the case that accounting for heterogeneity causes the effect to disappear completely? Are there some contexts (or product categories) in which loss aversion is a real phenomenon, and some in which it is not? We return to these questions in §3, where we conduct a multicategory investigation. Prior to doing this, we use the orange juice data to perform posterior checks on the second implication from our intuitive argument in §2.3 (i.e., that the form of the reference price allows the model to mimic the underlying heterogeneity in price responsiveness).

2.5.2. Posterior Analysis of the Orange Juice Data Our argument regarding the price-responsiveness confound (Figure 1 and §2.2) rests on the notions that the price responsiveness of a household influences our measure of reference price, and that our measure of reference price determines whether we code price as a loss or gain. More price-responsive consumers pay lower prices and see more losses, and less price-responsive consumers pay higher prices and see more gains. One way to illustrate the relationship is to plot, for each household and choice occasion, the reference price of the household versus the gain or loss experienced. Figure 2 shows the plot for the 200 households in the orange juice data set. There is a clear positive correlation between these two variables ($r = 0.627$). Households who, on average, pay lower prices have their reference points defined at lower price levels, and they tend to evaluate other brands in the choice set as "price losses." This phenomenon drives the confounding effect of price-response heterogeneity on cross-sectional estimates of loss aversion.

One limitation with the plot in Figure 2 is that in the reference-dependent formulation, "reference price" reflects both the price sensitivity of the household as well as reference point used in the model (which is tautologically related to whether gains or losses are faced by the household). A different approach involves segmenting households by price responsiveness by using posterior probabilities calculated from the two-segment model reported in Table 3:

Figure 2 **Reference Price and Reference Effects in the Reference-Dependent Model** ($r = 0.627$)



$$\text{post}_1^h = \frac{L(X^h \mid 1)\psi_1}{L(X^h \mid 1)\psi_1 + L(X_2^h \mid 2)\psi_2}, \tag{6}$$

where X^h denotes the choice history of household h, $L(X^h \mid s)$ is the likelihood of observing history X^h given household membership in segment s, and ψ_1 and ψ_2 are the prior segment sizes for segments 1 and 2, respectively. The assignment procedure places 90 households in the more price-sensitive segment ($\beta_{21} = -3.82$, t-ratio $= -10.86$) and 110 households to the less price-sensitive segment ($\beta_{22} = -1.53$, t-ratio $= -5.17$).

Table 4 shows the average number of gains, average number of losses, and net gains (average number of gains minus average number of losses) for households in the two segments. The table verifies that households in the more price-sensitive segment (segment 1) see relatively fewer gains than those in the less price-sensitive segment (segment 2), and the difference is significant (t-ratio $= -9.40$). Further, they face a larger number of losses (t-ratio $= 5.22$).

We have now found evidence for all three conjectures: (1) The single-segment reference-dependent model fits better than the null model; (2) as shown

Table 4 Orange Juice: Average Gains and Losses Faced by Each Segment

	More Price Sensitive ($\beta_{21} = -3.82$)	Less Price Sensitive ($\beta_{22} = -1.53$)	Difference
NUMGAINS	0.675	1.411	−0.736
t-ratio			−9.397
NUMLOSSES	2.623	2.011	0.612
t-ratio			5.216
NETGAINS	−1.948	−0.600	−1.348
t-ratio			−8.928

above, this is because there is a systematic relationship between gains and losses faced and price sensitivity; and (3) estimates of loss aversion are smaller when one accounts for heterogeneity.

3. Cross-Category Validation

Our analysis of the orange juice data shows that attenuation in the estimate of loss aversion is substantial and statistically significant, once heterogeneity in price responsiveness is taken into account. This finding is interesting and presents a new twist on the usual effect of failure to account for heterogeneity. In most instances, the presence of unaccounted-for heterogeneity biases effect sizes toward zero; yet in the case of reference-dependent choice, the opposite result holds.

In addition to the issue of our heterogeneity argument extending across categories, the question posed at the end of §2.4.1 remains: Are there cases where the effect goes away completely? We use additional market basket data to (1) ascertain the generality of our key result and (2) identify cases where loss aversion disappears and instances where it remains.

3.1. Market Basket Data

These data come from a large midwestern city and cover the two-year period June 1991–June 1993. We use a wide range of categories: bacon, butter, margarine, crackers, sugar, paper towels, ice cream, liquid detergents, hot dogs, bathroom tissue, and soft drinks. Summary statistics for these categories are provided in Table 5.

3.2. Estimation Results

For each of the 11 additional product categories we estimate three models: (1) The single-segment model of loss aversion; (2) the finite-mixture model, which allows for preference and price response heterogeneity, but not heterogeneity in loss aversion; and (3) the most general model, which allows for preference, price-response, and loss aversion heterogeneity.[10] Model fits for all three models are given in Table 6. In this table the letter "c" denotes a model that allows for heterogeneity in price response, but not loss aversion (i.e., constrains the loss aversion parameter to be equal across segments).[11]

Heterogeneity in Price Responsiveness. Table 6 indicates that in 9 of 11 categories (detergent and hot dogs are an exception) there is no statistical evidence of differences in loss aversion across categories. Once heterogeneity in price response is accounted for, there appears to be little need to further relax the model and allow for heterogeneity in loss aversion. This corroborates our finding from the orange juice data.

Table 7 shows the estimates of loss aversion obtained from the best fitting models. Three important

Table 5 Cross-Category Data: Description

Category	Brands	Sizes	Total[a]	Observations
Bacon	7	1	7	1126
Butter	5	1	5	1156
Margarine	11	1	11	3323
Crackers	6	1	6	739
Sugar	7	1	7	1124
Paper towels	11	1	11	4155
Ice cream	12	3	18	2098
Detergent	9	4	32	1198
Hot dogs	10	2	16	1433
Tissue	9	4	26	5692
Soft drinks	7	7	29	3197

[a]Number of unique brand-size combinations.

[10]Unlike orange juice, some of the market basket categories contain multiple sizes. In these cases we follow Fader and Hardie (1996) and estimate size and brand-specific intercepts. In addition, we replace the Guadagni and Little loyalty variable with two variables (loyalty and last brand purchased) to separate cross-sectional and longitudinal heterogeneity (e.g., Bucklin and Gupta 1992).

[11]As with the orange juice data, results for the models that use stimulus-based reference points are substantively identical; however, the memory-based models are preferred on the basis of fit. Stimulus-based results are available from the authors upon request.

Table 6 Cross-Category Data: Reference-Dependence Model Fits

Category	Obs	Seg	NP	− LL	BIC	Category	Obs	Seg	NP	− LL	BIC
Bacon	1126	1	12	−924.5	−966.6	Butter	1156	1	10	−528.7	−564.0
		2	25	−875.9	−963.7			2	21	−481.0	−555.1
		2c	**24**	**−876.0**	**−960.4**			**2c**	**20**	**−481.9**	**−552.5**
		3	38	−837.4	−970.9			3	32	−469.2	−582.0
		3c	36	−841.5	−968.0			3c	30	−468.0	−573.8
Margarine	3323	1	16	−3,889.2	−3,954.0	Crackers	739	1	11	−638.3	−674.6
		2	33	−3,778.4	−3,912.2			2	23	−597.3	−673.2
		2c	32	−3,774.9	−3,904.6			**2c**	**22**	**−599.5**	**−672.2**
		3	50	−3,666.3	−3,869.0			3	50	−583.6	−748.7
		3c	**48**	**−3,673.9**	**−3,868.5**			3c	48	−584.0	−742.5
Sugar	1124	1	12	−886.3	−928.5	Paper towels	4155	1	16	−4,627.5	−4,694.1
		2	25	−828.5	−916.3			2	33	−4,457.4	−4,594.8
		2c	**24**	**−829.2**	**−913.5**			2c	32	−4,457.5	−4,590.8
		3	38	−796.9	−930.4			3	50	−4,360.6	−4,568.9
		3c	36	−798.4	−924.8			**3c**	**48**	**−4,359.8**	**−4,559.8**
Ice cream	2098	1	21	−2,451.6	−2,531.9	Detergent	1198	1	19	−1,871.2	−1,938.6
		2	43	−2,276.4	−2,440.9			**2**	**39**	**−1,769.4**	**−1,907.6**
		2c	**42**	**−2,276.8**	**−2,437.5**			2c	38	−1,780.1	−1,914.8
		3	65	−2,240.0	−2,488.6			3	59	−1,713.5	−1,922.6
		3c	63	−2,240.5	−2,481.4			3c	57	−1,716.1	−1,918.1
Hot dogs	1433	1	18	−1,668.9	−1,734.3	Bath tissue	5692	1	19	−7,759.5	−7,841.7
		2	37	−1,586.5	−1,720.9			2	39	−6,915.2	−7,081.9
		2c	36	−1,588.2	−1,719.0			**2c**	**38**	**−6,915.2**	**−7,079.5**
		3	**56**	**−1,510.5**	**−1,714.0**			3	59	−6,829.2	−7,084.3
		3c	54	−1,562.9	−1,759.1			3c	57	−6,840.4	−7,086.8
Soft drinks	3197	1	20	−5,450.8	−5,531.5						
		2	41	−5,187.8	−5,353.2						
		2c	40	−5,187.8	−5,349.2						
		3	65	−4,785.9	−5,048.1						
		3c	**63**	**−4,792.4**	**−5,046.6**						

findings emerge. First, in all categories the single-segment estimate of loss aversion is greater than that obtained when heterogeneity is taken into account. Thus, we have a cross-category validation of the result from the orange juice data: Failure to account for heterogeneity in the reference-dependent model results in an upward bias in the estimate of loss aversion. Second, there are five categories (bacon, butter, crackers, sugar, and ice cream) where previously significant loss aversion disappears as one accounts for heterogeneity in price responsiveness. (The confidence interval for the heterogeneity-adjusted parameter contains one, while the single segment estimate is significantly different from one.) Third, we see that even after controlling for heterogeneity in price responsiveness, loss aversion persists in 6 of the 11 categories: margarine, paper towels, detergents, hot dogs, bathroom tissue, and soft drinks. Three of these categories (paper towels, detergents, and bathroom tissue) have been shown to exhibit stockpiling effects in response to promotions (Bell et al. 1999). It could be that consumers are more likely to be loss averse, or defer choices, in categories that can be stockpiled when prices are favorable.

Heterogeneity in Loss Aversion. In most of the categories we examine, heterogeneity in loss aversion cannot be supported on the basis of fit. Nonetheless, it is

Table 7 Cross-Category Data: λ With and Without Heterogeneity Accounted for

	Heterogeneity Adjusted			Unadjusted	
	True λ_p	(Std. Err.)	95% cl: [Lower, Upper]	Biased λ_p	(Std. Err.)
Bacon	1.24	(0.25)	[0.75, 1.72]	1.99[a]	(0.49)
Butter	2.33	(0.71)	[0.94, 3.71]	4.21[c]	(2.45)
Margarine	1.32[a]	(0.11)	[1.10, 1.53]	1.99[a]	(2.30)
Crackers	2.37	(0.84)	[0.73, 4.01]	3.20[b]	(1.29)
Sugar	1.56	(0.40)	[0.78, 2.33]	2.34[c]	(0.67)
Paper towels	1.69[a]	(0.14)	[1.42, 1.97]	2.49[a]	(0.35)
Ice cream	1.13	(0.10)	[0.94, 1.32]	1.70[a]	(0.20)
Detergent	1.43[a]	(0.14)	[1.16, 1.69]	1.94[a]	(0.23)
Hot dogs	2.01[a]	(0.39)	[1.25, 2.77]	2.14[a]	(0.39)
Tissue	1.69[a]	(0.14)	[1.41, 1.97]	1.86[a]	(0.18)
Soft drinks	2.18[a]	(0.16)	[1.85, 2.50]	2.99[a]	(0.63)

[a] $\lambda > 1.0$, $p < 0.01$. [b] $\lambda > 1.0$, $p < 0.05$. [c] $\lambda > 1.0$, $p < 0.10$.

instructive to examine the parameters of the models that allow for heterogeneity in loss aversion. Table 8 shows these segment-specific loss aversion parameters.

For two categories (detergents and hot dogs), heterogeneity in both price response *and* loss aversion are important. In these two categories the improvement in fit from allowing λ to differ across segments at least outweighs the added costs in degrees of freedom. In both categories, there appears to be one segment of consumers exhibiting measurable loss aversion, while the remainder do not. Although the differences in model fit are not significant, some of the other categories show a similar pattern (e.g., margarine and ice cream each have a segment of consumers with estimated parameter λ greater than one and larger than the single segment estimate for λ). The findings suggest that loss aversion may not in fact be a universal phenomenon, at least in the context of frequently purchased grocery products.

4. Discussion and Conclusion

In recent years the marketing research community in general, and choice modelers in particular, have paid considerable attention to decision making under uncertainty and the theory of reference-dependent choice (e.g., Kahneman and Tversky 1979, Tversky and Kahneman 1991). A number of papers that present empirical applications of the theory have appeared in the major marketing journals, and the effect has attained some stature as an empirical generalization (e.g., Kalyanaram and Winer 1995, Meyer and Johnson 1995).

Table 8 Cross-Category Data: Heterogeneity in Loss Aversion

	Segment-Specific λ's and Standard Errors						Segment Sizes		
	Seg 1	(S.E.)	Seg 2	(S.E.)	Seg 3	(S.E.)	Seg 1	Seg 2	Seg 3
Bacon	1.437	(1.13)	1.110	(0.13)	—		0.33	0.67	—
Butter	2.238[b]	(1.37)	0.009	(0.57)	—		0.71	0.29	—
Margarine	2.741[a]	(0.30)	1.545[a]	(0.17)	0.987	(0.04)	0.41	0.26	0.33
Crackers	2.629	(1.99)	1.632	(0.77)	—		0.62	0.38	—
Sugar	2.620	(1.43)	1.169	(0.33)	—		0.39	0.61	—
Paper towels	2.095[a]	(0.18)	0.652	(0.15)	0.053	(0.44)	0.61	0.27	0.12
Ice cream	2.348[a]	(0.37)	0.114	(0.72)	—		0.40	0.60	—
Detergent	3.333[a]	(0.64)	1.048	(0.13)	—		0.48	0.52	—
Hot dogs	2.719[a]	(0.32)	1.313	(0.30)	0.380	(0.16)	0.41	0.54	0.05
Bath tissue	2.076[a]	(0.13)	1.194	(0.14)	0.871	(0.02)	0.64	0.04	0.32
Soft drinks	3.515[b]	(0.14)	2.223[a]	(0.22)	2.028[a]	(0.21)	0.37	0.13	0.50

[a] $\lambda > 1$, $p < 0.01$. [b] $\lambda > 1.0$, $p < 0.05$. [c] $\lambda > 1.0$, $p < 0.10$.

To show how the measurement of important substantive effects (e.g., loss aversion) implied by the theory of reference dependence can be confounded by consumer heterogeneity, we (1) developed an argument and example to show why the confound arises, (2) tested our conjectures using data from another published study on reference-dependent choice, and (3) generalized our results across categories.

4.1. Loss Aversion in the Sticker Shock Model

While there has been considerable agreement regarding the representation of loss aversion in the utility function of choice models (as a kinked, linear response curve, with steeper response for losses than gains), there has been more diversity with respect to the approach used to capture the reference effect. As outlined in §2.2, many researchers have used a sticker shock model (featuring brand-specific reference points and an absolute as well as relative price term) to capture the reference price effect. Because the sticker shock model is widely used to capture reference price effects (and has been used to test for asymmetric price response), we look to see whether the same problems with bias resulting from unaccounted-for heterogeneity might also be an issue in this case.

Because the mechanics of the analysis are completely analogous to the approach presented in §§2 and 3, the details have been relegated to the appendix. Only the highlights are summarized below.

- The (symmetric) sticker shock effect is significant at the 0.01 level in 8 of the 12 categories, and at the 0.05 level in 2 categories. (There is no significant effect for soft drinks and orange juice.)
- There is no evidence of asymmetric price response (i.e., a higher coefficient on the relative price term when the actual price is higher than the reference price) for any of the 12 categories (even before accounting for heterogeneity).

What could account for such a dramatic difference between the sticker shock model and the reference-dependent model with respect to their findings on price response asymmetry? We contend that the difference is primarily a result of the operationalization of reference price: in the sticker shock model there is a different reference price for each brand and choice occasion (defined as the price of the brand—not necessarily the price paid—on the previous purchase occasion(s)). This brand-specific reference point undoes the strong correlation between price paid and the net gains faced by the household. Figure 3 shows the plot of reference price against the gains and losses for the 200 households in the orange juice data set (this plot is directly analogous to Figure 2 for the reference-dependent model). As is clear from the plot, the correlation is nearly zero ($r = -0.085$).

It should also be noted that the findings on the symmetric sticker shock may not be without bias. Chang et al. (1999) show that heterogeneity in price response coupled with heterogeneity in purchase timing, when not accounted for, may lead to a positive bias in the sticker shock.[12] And 10 years earlier, Lattin and Bucklin (1989) pointed out that the sticker shock effect might be capturing the difference between long-run price elasticity and short-run promotional price elasticity.

We believe that our findings at least raise some questions about the evidence for loss aversion as estimated from cross-sectional scanner panel data. In the sticker shock model where there is no apparent correlation between household price responsiveness and the representation of price as a loss or a gain, there is no evidence of asymmetric price response whatsoever. In the reference-dependent model formulation, accounting for heterogeneity significantly reduced the estimate of loss aversion in most categories. In considering these findings, one must keep in mind that our method for

[12]Their pattern of results for two categories (ketchup and yogurt) also mirrors ours. They find a (spurious) symmetric sticker shock but do not find evidence for asymmetry.

Figure 3 **Reference Price and Reference Effects in the Sticker Shock Model** ($r = -0.085$)

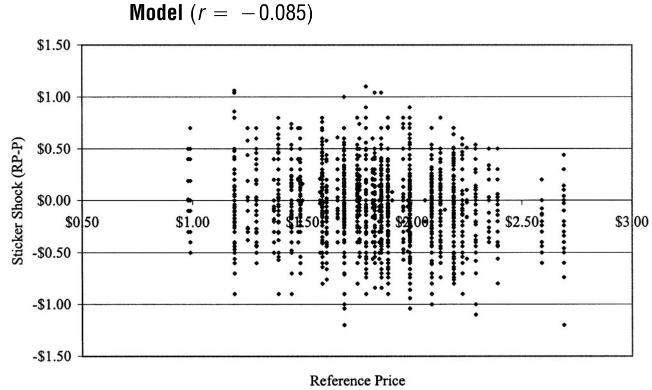


Table A1 Model Fits and Estimates for Sticker Shock

	Symmetric SS (A.1) Test H_0: $\beta_3 = 0$				Asymmetric SS (A.2) Test H_{01}: $\gamma_4 - \gamma_3 = 0$ and Test H_{02}: $\gamma_4/\gamma_3 = 1$					
	LL	BIC	β_3	(S.E.)	LL	BIC	$\gamma_4 - \gamma_3$	t-ratio	γ_4/γ_3	(S.E.)
Bacon	−929.2	−971.4	0.226[b]	(0.11)	−928.6	−974.3	0.220	0.812	2.560	(3.58)
Butter	−535.0	−570.0	1.071[a]	(0.29)	−536.3	−575.1	0.767	1.269	3.230	(3.55)
Margarine	−3,919.0	−3,983.9	1.049[a]	(0.18)	−3,918.9	−3,987.8	0.123	0.295	1.124	(0.46)
Crackers	−644.3	−680.6	0.591[a]	(0.21)	−644.3	−684.0	0.308	0.657	1.810	(1.46)
Sugar	−886.2	−928.4	0.889[a]	(0.24)	−885.5	−931.2	0.255	0.551	0.751	(0.41)
Paper Towels	−4,660.4	−4,727.1	1.176[a]	(0.20)	−4,660.4	−4,731.2	0.280	0.610	1.277	(0.54)
Ice Cream	−2,462.2	−2,542.5	0.605[a]	(0.18)	−2,461.8	−2,546.0	0.352	0.856	1.839	(1.31)
Detergents	−1,896.9	−1,964.2	0.548[a]	(0.19)	−1,899.7	−1,970.6	0.480	1.031	2.461	(2.42)
Hot Dogs	−1,682.9	−1,748.3	0.232[b]	(0.13)	−1,682.7	−1,751.8	−0.200	−0.625	0.401	(0.39)
Bath Tissue	−7,783.3	−7,865.4	2.273[a]	(0.47)	−7,782.5	−7,868.9	−1.312	−1.340	0.542	(0.49)
Soft Drinks	−5,476.0	−5,556.7	−0.044	(0.04)	−5,468.5	−5,553.3	−1.110	−1.040	1.721	(1.12)
Orange Juice	−1,440.3	−1,473.5	0.152	(0.19)	−1,440.1	−1,477.0	−0.140	−0.049	0.496	(5.09)

[a]Fail to accept null at $p < 0.01$. [b]$p < 0.05$.

accounting for heterogeneity is limited. Allenby et al. (1998) point out that there is still substantial heterogeneity not accounted for by a finite mixture model. It is possible that applying another, more sophisticated model of heterogeneity might further reduce the estimates of loss aversion.

4.2. Future Research on Loss Aversion

The argument and findings presented in this paper are relevant both to the large number of researchers who wish to adapt behavioral decision theory to an econometric choice model setting and to researchers building models of promotion theory. Our findings also have important practical implications. For example, promotional decisions will be very different depending on the degree to which one believes consumers are reference dependent or loss averse, and as shown in §3.4, there is disparity across categories in terms of evidence for loss aversion.

The cross-category findings, in particular, raise some interesting new issues for future research. For example, why do some categories still appear to exhibit loss aversion and others do not? What is different about them? Is it just the salience of price? Or the structure of brand competition within the category? Are there theoretical reasons to expect that context plays a role in the overall degree of reference dependence? Another interesting angle to consider is the prevalence of loss aversion throughout the population. Is it possible that this is a trait exhibited by only a subset of the population? (See Ainslie and Rossi 1998 for evidence that price sensitivity is a fundamental consumer trait.) Further empirical work and theoretical developments are necessary to help resolve these issues.[13]

Appendix A. Loss Aversion and Sticker Stock Choice

In its original formulation, the sticker shock model of brand choice (Winer 1986) derived from adaptation level theory (Helsen 1964) contains a main effect and a symmetric reference price effect

$$U_{it}^h = \alpha_i + \beta_1 FEAT_{it} + \beta_2 PRICE_{it}^h + \beta_3(RP_{it}^h - PRICE_{it}^h) + \beta_4 BLOY_{it}^h + \epsilon_{it}^h, \quad \text{(A.1)}$$

where RP_{it}^h is the reference price. Equation (A.1) differs from Equation (2) in two ways. First, it contains a main effect for price; and second, the reference points are *brand-specific.* That is, as the term "sticker shock" implies, the price and reference price deviations are

[13]The authors thank John Carstens, Pete Fader, Bruce Hardie, Kevin Keller, Bob Meyer, Dave Montgomery, Don Morrison, Paddy Padmanabhan, S. Siddarth, Seenu Srinivasan, and especially Randy Bucklin for many helpful comments on an earlier draft. They are also very grateful to the editor, area editor, previous editor (Richard Staelin), and three anonymous *Marketing Science* reviewers for many valuable comments and suggestions.

with respect to a given brand. β_3 captures a symmetric reference effect, or sticker shock. Over time, researchers have experimented with various formulations for reference price, but most have converged on either the last posted price of the brand or some similar variation such as an exponentially smoothed combination of several previous prices (see Briesch et al. 1997 for a review), and these have become the accepted operationalizations in the literature.

Several researchers (e.g., Kalwani et al. 1990, Kalyaranam and Little 1994, Chang et al. 1999) have modified Equation (A.1) to examine possible asymmetries in response to positive and negative values of the sticker shock term ($RP_{it}^h - PRICE_{it}^h$):

$$U_{it}^h = \alpha_i + \gamma_1 FEAT_{it} + \gamma_2 PRICE_{it}^h + \gamma_3 PGAIN_{it}^h + \gamma_4 PLOSS_{it} + \gamma_5 BLOY_{it}^h + \epsilon_{it}^h, \tag{A.2}$$

where one can infer loss aversion from testing $\gamma_4/\gamma_3 > 1$. Empirical results on loss aversion in the sticker shock model of (A.2) suggest much lower estimates than those obtained from the reference-dependent model. Furthermore, the magnitude of difference between the gain and loss parameters is typically not different from zero, either can one reject the null hypothesis that $\gamma_4/\gamma_3 = 1$. The most recent example is Chang et al. (1999), who estimate Equation (A.2) on ketchup and yogurt and find no significant difference between the parameters, and that the ratio of parameters is not different from one. As discussed in §4, we estimated both Equations (A.1) and (A.2) on 12 data sets. The complete results are given in Table A1.

References

Allenby, Greg A., Neeraj Arora, James L. Ginter. 1998. On the heterogeneity of demand. *J. Marketing Res.* **35** (August) 384–389.

Ainslie, Andrew, Peter E. Rossi. 1998. Similarities in choice behavior across multiple categories. *Marketing Sci.* **17** (2) 91–106.

Bell, David R., Randolph E. Bucklin. 1999. The role of internal reference points in the category purchase decision. *J. Consumer Res.* **26** (September) 128–143.

——, Jeongwen Chiang, V. Padmanabhan. 1999. The decomposition of promotional response: an empirical generalization. *Marketing Sci.* **18**(4) 504–526.

Briesch, Richard A., Lakshaman Krishnamurthi, Tridib Mazumdar, S. P. Raj. 1997. A comparative analysis of reference price models. *J. Consumer Res.* **24** (September) 202–214.

Bucklin, Randolph E., Sunil Gupta. 1992. Brand choice, purchase incidence, and segmentation: an integrated modeling approach. *J. Marketing Res.* **29** (May) 201–215.

Chang, Kwangpil, S. Siddarth, Charles B. Weinberg. 1999. The impact of heterogeneity in purchase timing and price responsiveness on estimates of sticker shock effects. *Marketing Sci.* **18**(2) 178–190.

Dickson, P. R., A. G. Sawyer. 1990. The price knowledge of supermarket shoppers. *J. Marketing* **54** (July) 42–53.

Fader, Peter S., Bruce G. S. Hardie. 1996. Modeling consumer choice among SKUs. *J. Marketing Res.* **33** (November) 442–452.

——, James M. Lattin, John D. C. Little. 1992. Estimating nonlinear parameters in the multinomial logit model. *Marketing Sci.* **11** (2) 372–385.

Greenleaf, Eric. 1994. The impact of reference price effects on the profitability of price promotions. *Marketing Sci.* **14** (Winter) 82–104.

Guadagni, Peter M., John D. C. Little. 1983. A logit model of brand choice calibrated on scanner data. *Marketing Sci.* **2** (Summer) 203–238.

Hardie, Bruce G. S., Eric J. Johnson, Peter S. Fader. 1993. Modeling loss aversion and reference dependence effects on brand choice. *Marketing Sci.* **12** (Fall) 378–394.

Helson, Harry. 1964. *Adaptation-Level Theory.* Harper and Row, New York.

Kahneman, D., J. L. Knetsch, R. H. Thaler. 1991. The endowment effect, loss aversion and status quo bias. *J. Economic Perspectives* **17** (Winter) 193–206.

——, A. Tversky. 1979. Prospect theory: an analysis of decision under risk. *Econometrica* **47** (March) 263–291.

Kalwani, M. U., C. H. Yim, Heikki J. Rinne, Yoshi Sugita. 1990. A price expectations model of customer brand choice. *J. Marketing Res.* **27** (August) 251–262.

Kalyanaram, G. K., John D. C. Little. 1994. An empirical analysis of the latitude of price acceptance in consumer packaged goods. *J. Consumer Res.* **21** (December) 408–418.

——, Russell S. Winer. 1995. Empirical generalizations from reference price research. *Marketing Sci.* **14** (Summer) G161–G169.

Kamakura, Wagner A., Gary J. Russell. 1989. A probabilistic choice model for market segmentation and elasticity structure. *J. Marketing Res.* **26** (November) 379–390.

Kopalle, Praveen K., Ambar Rao, Joao Assuncao. 1996. Asymmetric reference pricing effects and dynamic pricing policies. *Marketing Sci.* **15** (1) 60–85.

Krishnamurthi, Lakshaman, Tridib Mazumdar, S. P. Raj. 1992. Asymmetric response to price in consumer choice and purchase quantity decisions. *J. Consumer Res.* **19** (December) 387–400.

Lattin, James M., Randolph E. Bucklin. 1989. Reference effects of price and promotion on brand choice behavior. *J. Marketing Res.* **26** (August) 299–310.

Massy, Montgomery, Morrison. 1970. *Stochastic Models of Buying Behavior.* The MIT Press, Cambridge, MA.

Mayhew, Glenn E., Russell S. Winer. 1992. An empirical analysis of internal and external reference prices using scanner data. *J. Consumer Res.* **19** (June) 62–70.

Meyer, Robert, Eric J. Johnson. 1995. Empirical generalizations in the modeling of consumer choice. *Marketing Sci.* **14** (Summer) G180–G189.

Putler, Daniel. 1992. Incorporating reference price effects into a theory of consumer choice. *Marketing Sci.* **11** (Summer) 287–309.

Rajendran, K. N., Gerard J. Tellis. 1994. Contextual and temporal components of reference price. *J. Marketing* **58** (January) 22–34.

Seetharaman, P. B., Andrew Ainslie, Pradeep K. Chintagunta. 1999.

Investigating household state dependence effects across categories. *J. Marketing Res.* **36** (November) 488–500.
Tversky, A., D. Kahneman. 1991. Loss aversion and riskless choice: a reference-dependent model. *Quart. J. Economics* **106** (November) 1039–1061.
Winer, Russell S. 1986. A reference price model of brand choice for frequently purchased consumer products. *J. Consumer Res.* **13** (September) 250–256.

This paper was received May 1996 and was with the authors 33 months for 3 revisions; processed by Greg Allenby.