A Comparative Analysis of Reference Price Models

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The effect of reference price on brand choice decisions has been well documented in the literature. Researchers, however, have differed in their conceptualizations and, therefore, in their modeling of reference price. In this article, we evaluate five alternative models of reference price of which two are *stimulus based* (i.e., based on information available at the point-of-purchase) and three that are *memory based* (i.e., based on price history and/or other contextual factors). We calibrate the models using scanner panel data for peanut butter, liquid detergent, ground coffee, and tissue. To account for heterogeneity in model parameters, we employ a latent class approach and select the best segmentation scheme for each model. The best model of reference price is then selected on the basis of fit and prediction, as well as on the basis of parsimony in cases where the fits of the models are not very different. In all four categories, we find that the best reference price model is a memory-based model, namely, one that is based on the brand's own price history. In the liquid detergent category, however, we find that one of the stimulus-based models, namely, the current price of a previously chosen brand, also performs fairly well. We discuss the implications of these findings.

It has long been recognized that consumers use some standard or reference point to evaluate the purchase price of a product (Emery 1970; Monroe 1973). More recently, researchers have empirically tested the effect of reference price in brand choice decisions by including a *positive difference* (termed a "gain") and a *negative difference* (termed a "loss") between the reference price and the purchase price of a brand as additional variables in the utility specification (Kalwani et al. 1990; Kalyanaram and Little 1994; Mayhew and Winer 1992; Winer 1986). Including these terms has consistently produced significant improvements in model fit over benchmark models that ignore the reference price effect (e.g., Guadagni and Little 1983). Incorporating reference price effects has also been shown to be important in developing optimal promotion strategies in the retail environment (e.g., Greenleaf 1995; Kopalle, Rao, and Assuncao 1996).

Although empirical results suggest that reference price plays an important role in consumer brand choice decisions, researchers have differed considerably in their conceptualizations and, therefore, operationalizations of the reference price construct (see Table 1 for a summary of different operationalizations). A majority of researchers have assumed that reference price is based on memory for prices encountered by consumers on previous occasions and, accordingly, have modeled reference price as a weighted average of *past prices* with varying carryover weights (Lattin and Bucklin 1989; Kalyanaram and Little 1994; Krishnamurthi, Mazumdar, and Raj 1992; Mayhew and Winer 1992). Others have extended this conceptualization by making reference price a function of not only the past prices but also other contextual factors such as deal proneness of the consumer, how frequently the brand is sold on deal, store characteristics, and price trend (Kalwani et al. 1990; Winer 1986). Yet others have argued that consumers may not have a strong memory for past

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TABLE 1

REFERENCE PRICE MODELS USED IN PAST RESEARCH

Author(s)	Model descriptions	Models and variables
1. Based on current prices:		
Hardie, Johnson, and Fader (1993)	Current price of the brand chosen on last purchase occasion	$RP_{ht} = P_{h(cb[t-1])t}$, where RP_{ht} = the reference price of household h on occasion t, $cb[t-1]$ = the chosen brand on occasion $t-1$, P = the shelf price
Rajendran and Tellis (1994)	An average of the highest, lowest, and mean of current price of a brand	$RP_{sjt} = (P^H_{sjt} + P^L_{sjt} + P^M_{sjt})/3$, where RP_{sjt} = the reference price of brand j in store s on occasion t, P^H, P^L, and P^M = highest, lowest, and mean shelf prices, respectively
Mazumdar and Papatla (1995)	Current prices of brands weighted by loyalties of the respective brands	$RP_{ht} = \Sigma_j LOY_{hjt} \cdot P_{jt}$, where LOY_{hjt} = loyalty of household h toward brand j on occasion t
2. Based on past prices:		
Mayhew and Winer (1992); Krishnamurthi, Mazumdar, and Raj (1992)	The respective brand's price on last purchase occasion	$RP_{hjt} = P_{hj(t-1)}$, where RP_{hjt} = household h's reference price for brand j on purchase occasion t, $P_{hj(t-1)}$ = the price of brand j faced by household h on occasion $(t-1)$
Rajendran and Tellis (1994)	A geometric mean of last three periods' prices of the respective brands	$RP_{hjt} = 0.571P_{hj(t-1)} + 0.286P_{hj(t-2)} + 0.143P_{hj(t-3)}$
Lattin and Bucklin (1989); Kalyanaraman and Little (1994); Mazumdar and Papatla (1995)	An exponentially smoothed composite of the prices of a brand faced by a consumer during entire purchase history	$RP_{hjt} = \lambda \cdot RP_{hj(t-1)} + (1-\lambda) \cdot P_{hj(t-1)}$, where λ = carryover weight
3. Based on past prices and other information:		
Winer (1986)	A function of last period's price, price trend, and market share of the brand	$RP_{hjt} = \delta_0 + \delta_1 P_{hj(t-1)} + \delta_2 \text{TREND}_{j(t-1)} + \delta_3 \text{MS}_{j(t-1)} + \varepsilon_{hjt}$, where $\text{TREND}_{j(t-1)}$ = price trend of brand j until occasion $(t-1)$, $\text{MS}_{j(t-1)}$ = market share of brand j until $(t-1)$
Kalwani et al. (1990)	A function of a brand's last five period prices, frequency of promotion, price trend, deal proneness of the household, and store characteristics	$RP_{hjt} = \delta_0 + \delta_1 \text{Pastpr}_{hj(t-1)} + \delta_2 \text{TREND}_{jt} + \delta_3 \text{FOP}_{jt} + \delta_4 \text{DP}_{Ht} + \delta_5 \text{ST}_1 + \delta_6 \text{ST}_2 + \delta_7 \text{ST}_2 + \varepsilon_{hjt}$, where $\text{Pastpr}_{hj(t-1)}$ = weighted log-mean of last five periods' prices (paid or faced) of brand j, FOP_{jt} = frequency of promotion of brand j until occasion t, DP_{Ht} = deal proneness of household H until occasion t, ST_i = store dummies

prices and, therefore, form the reference price at the point-of-purchase using *current price(s)* of certain brands (Hardie, Johnson, and Fader 1993; Rajendran and Tellis 1994).

Such divergent views of the reference price concept raise important theoretical questions. Is there a particular model of reference price that best captures the concept? Can there be multiple valid conceptualizations and, hence, operationalizations of reference price (e.g., Winer 1988)? Addressing these questions is also important from an empirical standpoint because a misspecification of the reference price model may result in incorrect parameter estimates of the brand choice models. Moreover, future researchers may use the specification that is most parsimonious and computationally simple if a comparison of different reference price specifications shows little or no difference in the performance of the choice models. Finally, practitioners would be interested to know which model is appropriate for making substantive decisions if the estimated effects of price and promotion are found to be sensitive to the type of reference price model used.

Motivated by these implications, we present an empirical comparison of five reference price models. These models are selected in such a way that they differ in the degree to which consumers are postulated to use *past* information from memory versus *current* information available at the point-of-purchase. We incorporate the reference price models in the utility specifications and calibrate brand choice models using four data sets—peanut butter, liquid laundry detergent, and toilet tissue data from A. C. Nielsen and ground coffee data from Information Resources, Inc. Criteria of model fit, prediction, and parsimony are used to select the best model.

A CONCEPTUAL FRAMEWORK

Not only do the different models used in past research reflect divergent views of the reference price construct, they also assume very different price judgment strategies employed by consumers. When *previously encountered* price and/or other information is used to model reference price, the price judgment is assumed to be *memory based* because the information is retrieved from memory and compared with current prices.[1] By contrast, when the *current* price of another brand is used as a reference price, the price judgment is assumed to be *stimulus based* in which consumers rely on information available in the external environment (Biehal and Chakravarti 1983; Lynch and Srull 1982).

The consumer information processing literature offers some insights into the conditions under which a judgment is likely to be memory based or stimulus based (Hastie and Park 1986; Lynch and Srull 1982). It has been suggested that the likelihood that a judgment will be memory based is a function of, among other factors, the accessibility of relevant information in memory and the extent to which the accessible information is diagnostic for the judgment task in question (Feldman and Lynch 1988; Lynch, Marmorstein, and Weigold 1988). These findings, applied in the current context, suggest that memory-based price judgments are likely to occur when consumers are able and are motivated to recall past prices from memory and use this information for the task at hand. In the absence of these conditions, consumers may rely either on price information available externally or on prior evaluations to make the decision (Lynch et al. 1988).

Evidence of Price Memory. Beginning with Gabor and Granger (1961), a number of researchers have examined the extent to which consumers pay attention to supermarket prices and retain this information in memory for later use (Allen, Harrell, and Hutt 1976; Conover 1986; Dickson and Sawyer 1990; Heller 1974; Monroe, Powell, and Choudhury 1986). In the Dickson and Sawyer study, 58 percent of shoppers surveyed were found to check prices at the point-of-purchase to decide which brand to buy, how much to buy, or simply out of habit (see Dickson and Sawyer 1986). The study also reports that 47 percent of consumers recalled exactly the right prices, 32 percent offered price estimates that were not exactly accurate, and 21 percent of consumers had no recollection of the prices they paid and therefore could not offer any estimate. Of the shoppers who provided price estimates, 56 percent were able to offer price estimates that deviated from the actual prices by only ±5 percent. Somewhat similar results are also reported in a study by Conover (1986) in which about 51 percent of consumers offered exactly correct price estimates and the overall absolute deviation from actual prices was only ±6 percent.

This stream of research collectively suggests that a relatively large proportion of consumers are fairly accurate in their estimates of supermarket prices and, therefore, may rely on their memories for past prices when evaluating purchase prices of different brands. Thus, overall, memory-based models may be valid conceptualizations of reference price. It is important to note also that a sizable percentage of shoppers have little or no recollection of the prices paid, primarily because price is not considered an important attribute in making the purchase decision (Dickson and Sawyer 1986). These consumers may either base their decisions on nonprice attributes or carry out price comparisons at the point-of-purchase. Thus, for some consumers, and possibly in some product categories, we may expect reference prices to be formed at the point-of-purchase.

Price Memory across Product Categories. Price awareness research has also shown that consumers' ability to recall prices accurately varies across product classes. For example, in the Dickson and Sawyer (1986) study, shoppers are found to be most accurate for toothpaste and margarine prices, least accurate for cold breakfast cereal prices, and the accuracy for coffee prices is somewhere in between. Conover (1986) found that more than 50 percent of shoppers could accurately recall prices for bread, paper towels, coffee, mayonnaise, and cola. The accuracies were lower in products such as margarine, detergent, and milk. Thus, attempts to link price recall accuracies to specific product categories have produced mixed results.

Variations in consumers' memories for prices can occur when the accessibility of price information in memory and the diagnosticity of this information differ across product categories. One factor that has been shown to influence accessibility is the time elapsed since previous exposure. For example, Dickson and Sawyer (1986) find the accuracies in immediate recall tests to be significantly greater than in delayed recall tests. Thus, prices for categories with long interpurchase time may be less accessible in memory and therefore less prone to be used in price judgments than more frequently purchased categories, ceteris paribus. Diagnosticity of past prices may be a function of price volatility and price spreads across brands. When there are frequent price changes over time and when price differences across brands are small, past prices may no longer be very useful in making choice decisions.[2]

[1]A judgment task that requires consumers to combine information retrieved from memory with externally available information is usually referred to as a *mixed judgment* task. In this article, however, we consider a price judgment to be memory based when previously encountered information is used to compare current prices.

[2]These are to be treated only as plausible tendencies rather than as testable hypotheses because numerous other factors can cause product category differences with regard to memory for prices. Since we utilize data from naturally occurring choice environments, we cannot control

In summary, a large proportion of supermarket shoppers have relatively accurate knowledge of past prices and, therefore, may employ memory-based price judgment strategies. There are also customers, however, who may form reference prices based on externally available information and, therefore, employ stimulus-based price judgment strategies. Relative use of memory or external information may vary across product classes.

ALTERNATIVE CONCEPTUALIZATIONS OF REFERENCE PRICE

Recognizing that both memory-based and stimulus-based price judgments are possible, we conceptualize a continuum that captures the degree to which consumers may be required to draw on their memory or external information in forming a reference price. For example, at one extreme, we could conceive of a reference price model that requires no memory for past information and, therefore, consumers form the reference price at the point-of-purchase (e.g., Hardie et al. 1993). At the other extreme, we could consider a reference price model that requires consumers to retrieve historical prices as well as other information of each brand from memory with a reasonable degree of accuracy (e.g., Kalwani et al. 1990). On this continuum, we select five reference price models which can be grouped as stimulus-based reference prices, which are formed at the point-of-purchase, or memory-based reference prices, which utilize price and/or other information stored in consumers' memory.

Stimulus-Based Reference Prices

Consumers may enter a store with no knowledge of the historical prices of different brands. If price is considered an important attribute, consumers may use the current price of *any* brand or the current price of a *known* brand as a reference point for price judgments.

Random Brand's Current Price (RNDBR). We begin with an extreme case in which the consumer not only has no knowledge of brand prices but also is unable to determine which brand's current price should be used to compare prices of other brands. Under this condition, the consumer may randomly select a brand available on the current purchase occasion (e.g., the first brand in the aisle) and use its price as a reference point for price judgments. Thus, a *common* reference price is used to compare the prices of all other brands, resulting in either gains or losses for these brands.[3]

Reference Brand's Current Price (REFBR). This model of reference price is the same as the model used by Hardie et al. (1993) and is based on the notion that the consumer cannot remember the price paid but does have a *reference brand* (e.g., the brand chosen on last occasion) in memory. When evaluating prices of other brands, the consumer, therefore, uses the *current* price of this brand for comparing prices of all other brands. This conceptualization also assumes a common reference price for judging prices of all brands.

Memory-Based Reference Prices

We consider three memory-based reference prices. The first one assumes that consumers do not distinguish among prices of different brands and use the price of the brand chosen on the prior occasion as the common reference price to judge prices of different choice alternatives. The second one assumes that each brand's price history constitutes its own reference price specific to the brand. Finally, the third type of reference price is also brand-specific but it additionally utilizes other historical information about a brand in forming the reference price.

Prices of Previously Chosen Brands (PASTCHBR). Consumers are believed to have a stronger memory for attribute information of the *chosen* brand than for the rejected brand (Biehal and Chakravarti 1983). The rationale behind this thesis is that consumers cursorily examine product information during the initial stage of the choice process and quickly eliminate the brands that are not considered acceptable. Greater attention is then directed to the brands that survive the initial screening. This line of reasoning suggests that the price of the brand previously chosen, rather than prices of all brands encountered, during past purchase occasions should be readily accessible in consumer memory and used as a common reference point for comparing the current prices.

Brand-Specific Past Prices (PASTBRSP). This model of reference price assumes that consumers are able to distinguish among the prices of different brands encountered during past purchase occasions. Thus, reference price is *unique* for each brand in that each brand's price is compared against its own price history. The reference price effect is therefore purely temporal. As can be seen from Table 1, a majority of researchers have used this model of reference price with different carryover weights to account for several lags in price.

Brand-Specific Past Prices and Other Information (PASTINFO). Among all the models described above, this conceptualization of reference price places the greatest demands on consumer memory. Following Kalwani et al. (1990) and Winer (1986), we assume that consumers not only remember specific prices of each brand (as in

for these factors. Thus, we leave the formal tests of specific hypotheses linking product categories to memory for prices to experimental research. In the discussion section, however, we make a qualitative attempt to check if the conjectures hold.

[3] This type of price comparison is similar to the interbrand price comparisons assumed in traditional brand choice models (e.g., Guadagni and Little 1983). The only distinction here is that the difference between a brand's price and the reference price is perceived as a gain or a loss, and that the responsiveness to gains and losses may be different. It can be shown that a model that assumes a common reference price for all brands reduces to the traditional model when gain and loss sensitivities are the same.

PASTBRSP above), but they also use other information such as price trend and frequency of deals for each brand. In addition, a consumer's propensity to buy a brand on deal (i.e., deal proneness) affects the reference price.

MODELS AND VARIABLE DESCRIPTIONS

Reference Price Models

RNDBR. Based on our previous explanation, this reference price is the shelf price[4] (SP) of a randomly picked brand (denoted by *rb*) by household *h* on purchase occasion *t*. Therefore,

$$RP_{ht} = SP_{h(rb[t])t}. \tag{1}$$

Note that this reference price is common for all brands but may vary on each occasion depending on the brand picked at random as a referent.

REFBR. Following Hardie et al. (1993), we assume that the brand chosen (*cb*) by a consumer on the last purchase occasion becomes the reference brand (denoted as $cb[t - 1]$) for the consumer on the current purchase occasion. The current shelf price (SP) of the reference brand is the reference price for all the brands. Therefore,

$$RP_{ht} = SP_{h(cb[t-1])t}. \tag{2}$$

Again, RP has no brand subscript because it is a common reference price for all brands.

PASTCHBR. We model this reference price by exponentially smoothing the shelf prices (SP) of the brands chosen by household *h* on past purchase occasions. Therefore,

$$RP_{ht} = \alpha RP_{h(t-1)} + (1 - \alpha)SP_{h(cb[t-1])(t-1)}, \tag{3}$$

where α is the carryover parameter. Again, RP is common for all brands.

PASTBRSP. This model of reference price is brand-specific. Following other researchers (e.g., Kalyanaram and Little 1994; Lattin and Bucklin 1989), the reference price of brand *j* is modeled by exponentially smoothing its own shelf prices (SP) faced by household *h* on previous purchase occasions. Therefore,

$$RP_{hjt} = \alpha RP_{hj(t-1)} + (1 - \alpha)SP_{hj(t-1)}. \tag{4}$$

Note that the reference price is unique to each brand and therefore includes a brand subscript *j*.

PASTINFO. This model is similar to the one proposed by Kalwani et al (1990). This brand-specific reference price is made a function of the brand's immediately past shelf price, price trend, and deal frequency as well as the deal proneness of the household. Therefore,

$$\begin{aligned} RP_{hjt} = {} & \gamma_0 + \gamma_1 SP_{hj(t-1)} + \gamma_2 TREND_{jt} \\ & + \gamma_3 DP_{ht} + \gamma_4 DF_{jt} + \varepsilon_{hjt}, \end{aligned} \tag{5}$$

where DP_{ht} is deal proneness of household *h* on occasion *t*, DF_{jt} is deal frequency of brand *j* on occasion *t*, and $TREND_{jt}$ is the price trend of brand *j* on occasion *t*. And γ_0, γ_1, γ_2, γ_3, and γ_4 are parameters of the reference price model, which are estimated separately by regressing the current shelf price of brand *j* faced by household *h* on occasion *t* against the predictor variables in Equation 5.

Brand Choice Model

We specify the brand choice model as a multinomial logit model so that the conditional probability that brand *j* will be chosen by household *h* on purchase occasion *t* is given by

$$p(j_{ht}) = \exp(u_{hjt}) / \textstyle\sum_i^n \exp(u_{hit}), \tag{6}$$

where u_{hjt} is the utility of brand *j* for household *h* on occasion *t* and $i = 1, 2, \ldots, n$, the number of brands.

Utility Specifications. The specification of the utility function containing a brand-specific reference price (i.e., PASTBRSP and PASTINFO) is different from that containing a common reference price (i.e., RNDBR, REFBR, and PASTCHBR). Note that when reference price is brand-specific, the difference between the reference price and the paid price (i.e., the gain or the loss) term in the utility specification accounts for only the temporal difference of a brand's own past prices and the current price. To account for the competitive effects of the prices of other brands in the choice set, we need a separate price variable in the utility function. Therefore, when reference price is brand-specific,

$$\begin{aligned} u_{hjt} = {} & \beta_{0,j} + \beta_P P_{hjt} + \beta_G G(RP_{hjt} - P_{hjt}) \\ & + \beta_L L(P_{hjt} - RP_{hjt}) + \beta_F F_{jt} \\ & + \beta_D D_{jt} + \beta_L LOY_{hjt} + \varepsilon_{hjt}, \end{aligned} \tag{7}$$

where $G = 1$ and $L = 0$ when $RP_{hjt} > P_{hjt}$, $G = 0$ and $L = 1$ when $RP_{hjt} < P_{hjt}$, $G = 0$, $L = 0$ when $RP_{hjt} = P_{hjt}$; P_{hjt} is price paid or faced by household *h* for brand *j* on occasion *t*; F_{jt} and D_{jt} indicate whether brand *j* is featured or displayed, respectively, on occasion *t*; LOY_{hjt} is household *h*'s loyalty toward brand *j* on purchase occasion *t*.

When reference price for a household *h* on a purchase occasion is common for all brands (as in RNDBR, REFBR, and PASTBRSP), the gain or loss term on that occasion is computed by subtracting a fixed quantity (RP) from the respective prices. Therefore, a separate price term cannot be included in a model with common reference price because the price parameter cannot be separately identified. Therefore, when reference price is common for all brands,

$$\begin{aligned} u_{hjt} = {} & \beta_{0,j} + \beta_G G(RP_{ht} - P_{hjt}) + \beta_L L(P_{hjt} - RP_{ht}) \\ & + \beta_F F_{jt} + \beta_D D_{jt} + \beta_L LOY_{hjt} + \varepsilon_{hjt}. \end{aligned} \tag{8}$$

[4]Shelf price differs from the paid price only when a coupon is used.

Note that there is no temporal effect of reference price when it is common for all brands.

In addition to the above two utility specifications, we consider a Guadagni and Little (1983) type model that assumes no reference price effect. Constraining $\beta_G = \beta_L = 0$ in Equation 7 (or constraining $\beta_G = -\beta_L$ in Eq. 8), we get the following NOREF model:

$$u_{hjt} = \beta_{0,j} + \beta_P P_{hjt} + \beta_F F_{jt} + \beta_D D_{jt} + \beta_L LOY_{hjt} + \varepsilon_{hjt}. \quad (9)$$

Variable Descriptions

SP_{hjt}: Shelf price in cents per ounce for brand j faced by household h on purchase occasion t.

P_{hjt}: Price in cents per ounce paid by household h for brand j on purchase occasion t. This quantity is computed by subtracting the value of the coupon (if one is used) from the shelf price and dividing it by the size (in ounces) of the item.

D_{jt} and F_{jt}: Take the value of 0 or 1, indicating a presence or absence of display and feature, respectively, for brand j on purchase occasion t.

LOY_{hjt}: Following Guadagni and Little (1983), we define loyalty of household h to brand j on occasion t as

$$LOY_{hjt} = \lambda LOY_{hj(t-1)} + (1 - \lambda) I_{hj(t-1)}, \quad (10)$$

where $I_{hj(t-1)} = 1$ if brand j is purchased by household h at $(t - 1)$, 0 otherwise. We estimate the carryover parameter α along with other parameters of the model using the procedure described in Fader, Little, and Lattin (1992).

DATA

The data for peanut butter, liquid detergent, and tissue come from Nielsen's Scantrak markets in Sioux Falls, South Dakota, and Springfield, Missouri. The ground coffee data are from the Information Resources, Inc., panel in the Pittsfield, Massachusetts market.

Peanut Butter

We select four brands, namely, Jif, Skippy, Peter Pan, and private label. Collectively, these four brands account for 94 percent of market share in this category. The data cover 120 weeks—the first 30 weeks of data are used for initialization, the next 60 weeks of data are used for model estimation, and the last 30 weeks of data are used for prediction. We exclude families that do not make at least two purchases during the initialization period *and* during the estimation period. The remaining families are ordered by the number of purchases made and a systematic sample of 236 families is drawn.[5] These households account for 1,873 choices during the estimation period and 717 choices in the prediction sample. The average interpurchase time for the sample is 8.7 weeks.

Liquid Detergent

We select five brands of liquid laundry detergent, namely, Surf, Bold, Tide, Era, and Wisk. Collectively, these five brands account for over 67.7 percent of the liquid detergent purchases. The data cover 138 weeks. The data for the first 52 weeks are used for initialization, the next 52 weeks of data are used for model estimation, and the last 34 weeks of data are used for prediction. We use the same purchase criteria as in peanut butter but select all the 423 families. These households account for 1,918 choices during the estimation period and 891 choices in the prediction sample. The average interpurchase time for the sample is 11.4 weeks.

Tissue

We select five brands—Scott, Charmin, Northern, White Cloud, and Cottonelle, which collectively account for about 92 percent share of the category. As in peanut butter, this data set covers 120 weeks. The data for the first 30 weeks are used for initialization, the next 60 weeks of data are used for model estimation, and the last 30 weeks of data are used for prediction. We use the same purchase criteria for selecting families as in the other two categories. As in peanut butter, we order the remaining families on number of purchases made and draw a systematic sample of 216 families. These families account for 3,030 choices during the estimation period and 1,113 choices in the prediction sample. The average interpurchase time for the sample is 5.2 weeks.

Coffee

We select four brands, namely, Hill Brothers, Folgers, Maxwell House, and Chock Full O' Nuts. These four brands account for over 80 percent of purchases in the category. The data cover 106 weeks. The first 32 weeks of data are used for initialization, the next 42 weeks of data are used for model estimation, and the last 32 weeks of data are used for prediction. We again use the same purchase criteria and exclude families that do not make at least two purchases during the initialization period *and* during the estimation period. Like in peanut butter and tissue categories, the remaining families are ordered according to the number of purchases made and a systematic sample of 238 families is drawn. These households account for 2,050 choices during the estimation period and 1,287 choice occasions in the prediction sample. The average interpurchase time for the sample is 6.5 weeks.

DATA ANALYSIS AND RESULTS

We first compare the performance of the models in the estimation and prediction samples and select the "best"

[5]This procedure was adopted to make the size of the data set manageable for estimation of model parameters. As explained subsequently, we drew a systematic sample in tissue and coffee also. A proper representation of households is assured by this sampling scheme.

model(s) in each product category. In the interest of space, we only report the parameter estimates of the chosen models.

Model Comparison and Selection

Overview of the Approach. As described earlier, we have six utility specifications—one with no reference price (NOREF) and five with reference price terms, each incorporating a different operationalization of reference price (RNDBR, REFBR, PASTCHBR, PASTBRSP, and PASTINFO). To select the best model(s), we take a two-step approach. First, researchers have suggested that consumer heterogeneity should be accounted for before assessing the effects of reference price (Bell and Lattin 1996). Accordingly, we use the estimation sample data to calibrate each of the six models by employing a latent class segmentation methodology (e.g., Kamakura and Russell 1989), which allows all parameters in the brand choice model to be heterogeneous.[6] We use the Bayesian Information Criteria (BIC) to decide how many segments are appropriate. The BIC is widely used to compare nonnested models (see, e.g., Gupta and Chintagunta 1994).

After deciding how many segments are appropriate for each reference price model as well as the NOREF model, we proceed to compare the performances of the "best" segment level models *across* the different reference price definitions and the NOREF model. We again use BIC as a basis for comparison because most of the competing models are nonnested. Even for models that are nested (e.g., the one-segment NOREF model is nested within one-segment PASTBRSP and PASTINFO models), we use BIC because it favors the more parsimonious models (i.e., models with fewer parameters; see Judge et al. 1985, p. 873 for an elaboration). Moreover, by using BIC in all model comparisons, we are able to remain consistent throughout the model selection process.

In the prediction sample, we use the "best" segment level model for each reference price definition and the NOREF model identified in the estimation sample. For example, if a two-segment NOREF model is found to be the best segmentation scheme in the estimation sample, we use a two-segment NOREF model on the prediction sample data. As in the case of the estimation sample, we use BIC to compare across the models and pick the best model. When the "best" model in the estimation sample and the "best" model in the prediction sample differ, we either pick the model that is more parsimonious or select both models as appropriate.

Tables 2–5 report the number of choices, number of parameters, log-likelihoods, and the BICs for the estimation as well as the prediction samples for the peanut butter, liquid detergent, coffee, and tissue data, respectively. Recall from the model section that the NOREF model includes price but not the gain and loss terms; the common reference price models (i.e., RNDBR, REFBR, PASTCHBR) contain the gain and loss terms but not the price term; and the brand-specific reference price models (i.e., PASTBRSP and PASTINFO) include price as well as the gain and loss terms in the utility specification. In the PASTINFO model, we exogenously estimate the unique reference price for each brand as a function of the brand's shelf price on the last purchase occasion, price trend, deal frequency, and deal proneness and then incorporate it in the brand choice model (see Kalwani et al. [1990] for a similar approach). Since the gain and loss terms are generated regressors, the standard errors of the coefficients in the PASTINFO models are approximate.[7]

Peanut Butter Data. In Table 2, we present the results of the analysis of the peanut butter data. We first consider the results for the estimation sample in part A of Table 2. For each reference price definition, the segment level model likelihoods and BICs are reported. One segment is appropriate for the PASTBRSP model. For all other models (i.e., NOREF, RNDBR, REFBR, PASTCHBR, and PASTINFO), however, the best segmentation scheme is one that permits two segments. Now comparing the BICs of the best segmentation schemes *across* the difference reference price definitions, we find that the single-segment PASTBRSP model has the best log-likelihood with fewest parameters and therefore has the smallest BIC. Thus, in the estimation sample, the PASTBRSP is the best model. The prediction results essentially support the results from the estimation sample. We again find that the single segment PASTBRSP model performs the best. Thus, in the peanut butter category, reference price effects exist, and operationalizing reference price as PASTBRSP provides the best fit of the data.

Liquid Detergent Data. The estimation sample results are presented in part A of Table 3. Allowing for multiple segments does not significantly improve the fit of any model over the single-segment model. Thus, we need only to compare the single-segment results across the different models. Between the two stimulus-based models, the REFBR definition does better than the RNDBR definition. Among memory-based models, PASTBRSP performs better than the other two reference price definitions. Comparing the BICs of these two reference price models with that of the NOREF model, we find that both REFBR and PASTBRSP models perform better, suggesting that reference price effects do exist in this category. Overall,

[6]An alternative way of addressing unobserved heterogeneity is by allowing the price and gain or loss parameters to be random, say, by following a normal distribution. In principle, the Kamakura-Russell method that we have adopted, which assumes the underlying distribution of the parameters to be discrete, is a special case of the random coefficient model, which typically assumes a continuous distribution. In addition, the Kamakura-Russell method allows for the identification of distinct consumer segments, which is not possible with the commonly employed unimodal random coefficient model.

[7]Since the reference price is estimated separately, the PASTINFO model does not have a price carryover parameter. Thus, the utility function containing PASTINFO model has one fewer parameter than that for the PASTBRSP model.

TABLE 2

MODEL COMPARISONS FOR PEANUT BUTTER

		Stimulus-based		Memory-based		
Models	NOREF	RNDBR	REFBR	PASTCHBR	PASTBRSP	PASTINFO
A. Estimation sample:						
Number of choices	1,873	1,873	1,873	1,873	1,873	1,873
Number of segments = 1:						
Number of parameters	8	9	9	10	11	10
Log-likelihood	−1,114.96	−1,113.76	−1,114.33	−1,110.11	−1,072.62	−1,109.55
BIC	−1,145.10	−1,147.67	−1,148.24	−1,147.78	*−1,114.06*	−1,147.23
Number of segments = 2:						
Number of parameters	16	18	18	19	21	20
Log-likelihood	−1,056.55	−1,055.54	−1,069.07	−1,061.37	−1,054.66	−1,049.92
BIC	*−1,116.83*	*−1,123.26*	*−1,136.89*	*−1,132.95*	−1,133.78	*−1,125.28*
Selected model in					✓	
B. Prediction sample:						
Number of choices:	717	717	717	717	717	717
Log-likelihood	−444.39	−444.81	−439.35	−445.84	−419.71	−448.71
BIC	−496.99	−503.99	−498.53	−508.30	*−455.87*	−547.33
Selected model in					✓	
Overall selection					✓	

NOTE.—BIC = Bayesian Information Criteria. Italicized values are best models in their respective classes.

TABLE 3

MODEL COMPARISONS FOR LIQUID LAUNDRY DETERGENT

		Stimulus-based		Memory-based		
Models	NOREF	RNDBR	REFBR	PASTCHBR	PASTBRSP	PASTINFO
A. Estimation sample:						
Number of choices	1,918	1,918	1,918	1,918	1,918	1,918
Number of segments = 1:						
Number of parameters	9	10	10	11	12	11
Log-likelihood	−1,201.10	−1,172.86	−1,168.40	−1,196.10	−1,154.15	−1,162.10
BIC	*−1,235.12*	*−1,210.65*	*−1,206.20*	*−1,237.67*	*−1,199.50*	*−1,203.68*
Number of segments = 2:						
Number of parameters	18	20	20	21	23	22
Log-likelihood	−1,179.15	−1,151.20	−1,143.70	−1,169.34	−1,131.02	−1,144.74
BIC	−1,247.18	−1,226.79	−1,219.29	−1,248.71	−1,217.94	−1,227.89
Selected model in					✓	
B. Prediction sample:						
Number of choices:	891	891	891	891	891	891
Log-likelihood	−605.51	−604.53	−597.56	−619.75	−593.28	−602.16
BIC	−636.08	−638.49	*−631.52*	−657.11	−634.03	−639.52
Selected model in			✓			
Overall selection			✓		✓	

NOTE.—BIC = Bayesian Information Criteria. Italicized values are best models in their respective classes.

in the estimation sample, the PASTBRSP model performs the best, followed by the REFBR model.

In the prediction sample, REFBR is the better stimulus-based model and PASTBRSP is the best memory-based model. Comparing the BICs of these two models, we find that the REFBR model with two fewer parameters performs a little better even though its likelihood value is somewhat worse. Thus, the PASTBRSP model is the best in the estimation sample and REFBR is the best model in the prediction sample. Neither model is computationally more demanding than the other and both models have been used in past research. Accordingly, we select both PASTBRSP and REFBR as appropriate models in this category.

Coffee Data. The results for the coffee data are presented in Table 4. For the NOREF model, allowing for heterogeneity results in a two-segment scheme. For all the models containing reference price, single-segment models

TABLE 4

MODEL COMPARISONS FOR COFFEE

		Stimulus-based		Memory-based		
Models	NOREF	RNDBR	REFBR	PASTCHBR	PASTBRSP	PASTINFO
A. Estimation sample:						
Number of choices	2,050	2,050	2,050	2,050	2,050	2,050
Number of segments = 1:						
Number of parameters	8	9	9	10	11	10
Log-likelihood	−902.80	−900.63	−902.64	−902.78	−889.46	−895.86
BIC	−933.31	*−934.95*	*−936.96*	*−940.91*	*−931.40*	*−933.99*
Number of segments = 2:						
Number of parameters	16	18	18	19	21	20
Log-likelihood	−870.86	−870.49	−870.82	−872.13	−866.25	−860.61
BIC	*−931.86*	−939.12	−939.45	−944.58	−946.32	−936.87
Selected model in	✓				✓	
B. Prediction sample:						
Number of choices:	1,287	1,287	1,287	1,287	1,287	1,287
Log-likelihood	−717.10	−731.31	−732.90	−733.28	−726.17	−726.14
BIC	−774.38	−763.53	−765.12	−769.08	−765.55	*−761.94*
Selected model in						✓
Overall selection					✓	

NOTE.—BIC = Bayesian Information Criteria. Italicized values are best models in their respective classes.

are adequate. Among all the reference price models, the PASTBRSP model performs the best. This model also performs marginally better than the two-segment NOREF model. In the prediction sample, we find that the PASTINFO model, which is a memory-based model, performs the best. The two-segment NOREF model has the worst BIC in the prediction sample.

Thus, the results for this category are somewhat mixed. In the estimation sample, allowing for heterogeneity improves the fit of the NOREF model but the single-segment PASTBRSP is still the best model here. The two-segment NOREF model performs the worst in the prediction sample, and PASTINFO is the best here. Overall, we feel that the one-segment PASTBRSP model is the most parsimonious model, because it is computationally much simpler than either the two-segment NOREF model (which has five additional parameters) or the PASTINFO model. Recall that the PASTINFO model requires the reference price to be exogenously estimated and then incorporated in the brand choice model. Strictly speaking, this model contains five additional parameters over and above the 10 parameters in the choice model. Thus, on balance, we select the PASTBRSP model.

Tissue Data. The tissue data results are reported in Table 5. The estimation sample results show that allowing for two segments is the best segmentation scheme for all reference price models as well as for the NOREF model. Comparing across these models, we find that the PASTBRSP model has the smallest log-likelihood and BIC and is clearly the best model. The prediction sample results are similar to that of the estimation sample. Once again, the BIC for PASTBRSP is the smallest. Thus, overall, in this product category, a reference price effect is present and PASTBRSP is the most appropriate operationalization of reference price.

Summary of Model Comparison Results. In summary, PASTBRSP is the best operationalization of reference price in all four product categories. In the liquid detergent category, however, the REFBR model performs better than the PASTBRSP model in the prediction sample. We therefore select both these models as appropriate in this category. In the coffee category, a two-segment NOREF model performs nearly as well as the one-segment PASTBRSP model in the estimation sample, but the NOREF model fits the prediction sample data quite poorly.

Parameter Estimates

The parameter estimates of the selected models are reported in Table 6. This includes the one-segment PASTBRSP models for peanut butter, liquid detergent, and coffee data and the two-segment PASTBRSP model for the tissue data. In addition, since the single segment REFBR model performs fairly well for the liquid detergent data, we report the parameters of this model also.

Peanut Butter Data. All the parameter estimates for the PASTBRSP model have correct signs, displaying face validity of the selected model. The price coefficient is negative and significant, which suggests a high degree of interbrand price sensitivity. The gain parameter is positive and significant; the loss parameter is negative but not statistically significant. The price carryover parameter of $\alpha = 0.47$ indicates that several periods of past prices (about five) influence formation of reference price.

Liquid Detergent Data. As noted earlier, we report the

TABLE 5

MODEL COMPARISONS FOR TISSUE

Models	Stimulus-based NOREF	Stimulus-based RNDBR	Stimulus-based REFBR	Memory-based PASTCHBR	Memory-based PASTBRSP	Memory-based PASTINFO
A. Estimation sample:						
Number of choices	3,030	3,030	3,030	3,030	3,030	3,030
Number of segments = 1:						
Number of parameters	9	10	10	11	12	11
Log-likelihood	−2,325.80	−2,325.46	−2,324.47	−2,317.65	−2,179.41	−2,313.13
BIC	−2,361.87	−2,365.54	−2,364.55	−2,361.74	−2,227.51	−2,357.22
Number of segments = 2:						
Number of parameters	18	20	20	21	23	22
Log-likelihood	−2,261.62	−2,258.83	−2,258.70	−2,254.59	−2,130.89	−2,261.55
BIC	*−2,333.76*	*−2,339.00*	*−2,338.87*	*−2,338.76*	*−2,223.08*	*−2,349.73*
Selected model in					✓	
B. Prediction sample:						
Number of choices:	1,113	1,113	1,113	1,113	1,113	1,113
Log-likelihood	−945.17	−941.00	−940.18	−944.82	−891.96	−940.27
BIC	−1,008.30	−1,011.15	−1,010.33	−1,018.48	*−972.63*	−1,017.44
Selected model in					✓	
Overall selection					✓	

NOTE.—BIC = Bayesian Information Criteria. Italicized values are best models in their respective classes.

TABLE 6

PARAMETER ESTIMATES OF THE SELECTED MODEL

	Product category					
	Peanut butter (4 brands)	Liquid detergent (5 brands)		Coffee (4 brands)	Tissue (5 brands)	
					PASTBRSP (2 segments)	
Selected model	PASTBRSP (1 segment)	PASTBRSP (1 segment)	REFBR (1 segment)	PASTBRSP (1 segment)	Segment 1	Segment 2
Brand 1	1.48	.34	.73	−.62	−1.80	−.49
	(8.0)	(2.3)	(5.1)	(−3.8)	(−7.8)	(−1.6)
Brand 2	1.22	.98	1.38	.32	−.44	−.63
	(7.2)	(7.8)	(11.4)	(2.9)	(−3.8)	(−2.2)
Brand 3	1.18	.32	.33	.27	−.32	−.22
	(7.8)	(2.7)	(2.7)	(2.3)	(−2.9)	(−.9)
Brand 4	Base	1.26	1.70	Base	−.10	−.20
		(9.6)	(13.8)		(−.4)	(−.5)
Brand 5	NA	Base	Base	NA	Base	Base
Loyalty	4.34	5.42	5.42	5.00	4.24	4.15
	(28.0)	(29.0)	(29.2)	(24.1)	(23.4)	(15.2)
Price	−.67	−1.01	NA	−.39	−.76	−.33
	(−9.6)	(−12.2)		(−6.6)	(−8.1)	(−2.9)
Gain	.85	1.12	1.78	.27	1.15	.83
	(8.6)	(9.1)	(24.0)	(4.4)	(12.3)	(5.4)
Loss	−.11	−.23	−.78	−.13	.01	.02
	(−1.7)	(−2.8)	(−8.4)	(−2.4)	(.2)	(.1)
Feature	.77	1.40	1.43	1.30	.94	−.65
	(5.9)	(5.7)	(6.0)	(8.0)	(9.2)	(−2.0)
Display	.63	1.20	1.29	.85	1.13	.80
	(3.1)	(6.6)	(7.2)	(6.1)	(8.6)	(3.4)
Loyalty carryover	.80	.77	.69	.88	.84	
Price carryover	.47	.57		.58	.65	
Masspoint					.74	

NOTE.—*t*-values are in parentheses.

parameter estimates of the PASTBRSP as well as that of the REFBR model. All the parameters for the PASTBRSP model have correct signs. The price coefficient in this model is negative and large. The gain coefficient is significant but the loss coefficient is not. Also, the price carryover parameter ($\alpha = 0.57$) implies about six period lag in the formation of reference price in this category.

The parameters in the REFBR model also have correct signs and are very similar to those of the PASTBRSP model. The brand constants have the same order, the parameters associated with the promotional variables, brand loyalty, and the loyalty carryover are all very similar to the corresponding parameters estimated by using the PASTBRSP model. Since the REFBR model does not contain a separate price term, the effect of price differences across brands are captured by the gain and loss terms. Both gain and loss parameters are statistically significant.

Coffee Data. We report the estimates for the PASTBRSP model. All parameters in the PASTBRSP model have the correct signs. The price coefficient is negative and significant; the gain coefficient is positive and the loss coefficient is negative, both statistically significant. The price carryover parameter ($\alpha = 0.57$) implies effects of price history of six periods on reference price formation.

Tissue Data. As mentioned earlier, we have two sets of parameter estimates (one for each segment) for the PASTBRSP model. The order of the brand constants for the two segments are similar except for brand 1 and brand 2 whose orders are switched. The brand loyalty effects of both segments are similar and have correct signs. The two segments, however, differ in the price sensitivities, responsiveness to gains, and to the two promotional variables, namely, features and displays. Segment 1 is more sensitive to price and promotions than segment 2. In segment 2, the feature parameter is negative and significant, contrary to expectation. The price carryover parameter ($\alpha = 0.65$) again implies effects of price history on the reference price formation. The loyalty carryover is similar to that found in the other categories.

To summarize, all model parameters of the selected models have correct signs. The PASTBRSP models for all four product categories produce a similar pattern of results, with large negative price and positive gain coefficients and relatively smaller negative loss parameters. The loyalty carryover parameters are within 0.77–0.88, except in the REFBR model (0.69) for the liquid detergent category. The price carryover parameters for the PASTBRSP models range from 0.47 to 0.65, suggesting effects of price history in reference price formation in all four products. We now discuss the results of our analyses of the four product categories and summarize the key findings.

SUMMARY AND DISCUSSION

Although several studies have demonstrated reference price effects in consumer brand choice decisions, the manner in which the reference price construct has been conceptualized and modeled has varied widely. In this article, we utilize consumer purchase history data for four frequently purchased product categories (peanut butter, liquid detergent, tissue, and ground coffee) and empirically compare the performances of different operationalizations of reference price to ascertain which model of reference price best captures the construct.

A notable result of our analysis is that certain specifications of reference price (e.g., PASTCHBR in all four data sets) do not produce any improvement in the fit over a model that contains no reference price term (i.e., the NOREF model). This finding is significant because it demonstrates that a misspecified reference price model can obscure the reference price effect, even when it may actually exist. Conversely, we also find that in some instances (e.g., in liquid detergent category), reference price models perform better than the NOREF model regardless of how the reference price is operationalized. Thus, it is important to establish whether there is an appropriate specification of reference price, and whether inclusion of this specification explains consumer choices better than a simpler model that does not consider the reference price effect.

"Best" Reference Price Specification

Focusing first on the three memory-based models of reference price, we note that these models differ in the amount of information required to be retrieved from memory and used in price judgments. The least burdensome for consumers is the PASTCHBR model in which consumers are assumed to use the past prices of the brands (any brands) chosen on past occasions without distinguishing among the brands. Unfortunately, this model performs the worst in all four product categories. Thus, although the notion that consumers may have a *category level* (rather than brand-specific) reference price is appealing, our analysis shows that specifying a single reference price for all brands is not appropriate and reference price is brand-specific.

Between the two brand-specific memory-based models considered here, the PASTINFO model assumes that consumers use not only past prices but also other information in the formation of reference price. Consequently, this model is also computationally more complex because one has to invoke the rational expectation hypothesis (Muth 1961) to estimate the reference price by regressing the current shelf price of a brand against the variables described in Equation 5. Except in the prediction sample in the coffee category, this added complexity does not produce improvements in the model fit over the PASTBRSP model in any of the product categories.

The PASTBRSP model is also based on the assumption that consumers have a separate reference price for each brand. This is a simpler model, however, in that only price history of the brand is used in the reference price formation, with more recently encountered price information receiving greater weight. In all four product categories, this model outperforms all other memory-based models of reference price. Moreover, this model performs better than the two stimulus-based models in all categories except in the prediction sample of the liquid detergent category. Thus, based on our analysis of the four data sets, the PASTBRSP model appears overall to be the best model of reference price. We also find that consumers go back several periods into their choice histories in forming this reference price.

The finding that past prices of a brand is the best model of reference price implies that consumers have a fairly accurate knowledge of past prices. This implication is not inconsistent with the price awareness research reviewed earlier, which shows that a sizeable proportion of consumers are capable of recalling prices with ±6–7 percent accuracy, which usually falls within the normal variation of prices. The second feature of the PASTBRSP model is that each brand has its own reference price. Even though storing the price histories of each brand in memory appears cognitively burdensome, the prices of different brands may be perceived by consumers to be distinctive enough to construct separate reference prices for each brand.

From a methodological standpoint, our finding that PASTBRSP reference price is the best memory-based model in all four product categories is reassuring because a majority of previous researchers have used the same basic operationalization of reference price, although some researchers have assumed the carryover weight to be 0. Thus, the findings in this research, involving empirical comparison of five alternative models using four different data sets, lend confidence to the body of evidence accumulated since Winer (1986).

From a managerial perspective, the evidence that consumers use past prices of a brand as its reference price implies that it is not enough to set a brand's price lower than that of competing brands. The price of the brand should also compare favorably to what has been charged in the past. To assess the relative effect of these two types of price comparisons (i.e., prices of other brands and past prices of the same brand), the brand manager should examine the price effect (i.e., the price parameter) as well as the reference price effect (i.e., the gain and loss parameters).

Accounting for Heterogeneity in Price Sensitivity

As noted earlier, researchers have recommended that the reference price effect, especially the phenomenon of loss aversion, should be assessed *after* accounting for consumer heterogeneity in the parameter estimates (e.g., Bell and Lattin 1996). Following this suggestion, we have utilized the latent class approach that accounts for such heterogeneity while estimating the reference price model as well as the NOREF model. We find that allowing multiple segments does improve the performance of the NOREF model in all categories except in liquid detergent and brings the model performance closer to that of the single-segment reference price model. Despite this improvement, the PASTBRSP model performs significantly better in three of the four categories and somewhat better in the ground coffee category. Thus, our results do not support the notion that the reference price effects are simply a result of consumer heterogeneity.

Future Research Directions

Overall, we find that PASTBRSP is the best model. However, in one case, in the prediction sample for the liquid detergent category, the REFBR model provides a better fit than the PASTBRSP model. It is possible that some consumers of this category may neither remember nor feel motivated to use past prices as the reference price for price judgments. Instead, they may simply use the current price of the brand chosen on the last occasion as a basis for comparing the prices of other brands. To provide some explanation for this finding, we examine certain characteristics of this product category. The interpurchase time for liquid detergent purchase (11.4 weeks) is greater than that of coffee (6.5 weeks), tissue (5.2 weeks), and peanut butter (8.7 weeks). For some consumers, longer intervals between purchases may have caused past prices to be less readily accessible in memory and not used in price judgments. Moreover, the price spread between the highest and the lowest priced brand in the liquid detergent category is the smallest (3.2 cents per ounce vs. 8.23 cents per ounce for coffee, 7.79 cents per ounce for tissue, and 5.0 cents per ounce for peanut butter). Given the narrow price spread in the detergent category, some consumers probably judged past prices as not sufficiently diagnostic to be stored in memory. These explanations are, however, tentative and need to be formally tested through a field or laboratory experiment.

Another issue to note is that our analysis is based on the assumption that all consumers use the same type of reference price. It is possible that there are two consumer segments, with one relying on their memory for past prices whereas the other uses current price information as a reference point (Kalyanaram and Winer 1995; Mazumdar and Papatla 1995). Also, consumers may use different types of reference price on different purchase occasions. If this is indeed the case, then future research should account for this and identify appropriate consumer segments based on the *type* of reference price used.

[Received March 1996. Revised December 1996. Brian Sternthal served as editor and Russell S. Winer served as associate editor for this article.]

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