ELSEVIER

Intern. J. of Research in Marketing 22 (2005) 441–457

International Journal of
Research in
Marketing

www.elsevier.com/locate/ijresmar

Consumer heterogeneity in the longer-term effects of price promotions

Jooseop Lim [a,1], Imran S. Currim [b,*], Rick L. Andrews [c,2]

[a] *John Molson School of Business, Concordia University, Montreal, Quebec, Canada H3G 1M8*
[b] *Paul Merage School of Business, University of California, Irvine, CA 92697-3125, USA*
[c] *Department of Marketing, Louisiana State University, Baton Rouge, LA 70803, USA*

Abstract

While a significant literature has emerged recently on the longer-term effects of price promotions, as inferred from persistence models, there is very little if any attention paid to whether such longer-term effects vary across different types of consumers. This paper takes a first step in that direction by exploring whether the adjustment, permanent, and total effects of price promotions, and the duration of the adjustment period, differ between consumers segmented based on their usage rates in a product category and their loyalty to a brand. We also investigate whether such consumer segmentation will improve the forecasting performance of persistence models at both product category and brand levels. Expectations are developed based on consumer behavior theory on various effects of price promotions, such as the post-deal trough, the mere purchase effect, the promotion usage effect, and responsiveness to competitor's reactions. Evidence from household-level supermarket scanner data on four product categories is provided. We find substantial differences between consumer segments and provide insights on how managers can increase the longer-term effectiveness of price promotions by targeting each consumer segment with a different promotion program. In addition, consumer segmentation is found to significantly improve the forecasting performance of the persistence model for two of the four product categories. For the other two product categories, consumer segmentation provides forecasting performance similar to that obtained from aggregate-level persistence models.

Keywords: Segmentation; Time-series models; Price promotions

Since the early 1970s, price promotions have accounted for the main share of the marketing budget in most consumer packaged good categories (e.g., Srinivasan, Pauwels, Hanssens, & Dekimpe, 2004). During the past two decades, a substantial academic literature has established the nature of *short-term* (immediate)[3] sales response to temporary price reductions, including an assessment of consumer heterogeneity in the effects of a temporary price reduction on sales. A key finding of this literature is that the immediate effect of temporary price reductions, as reflected in short-term (contemporaneous) changes in sales, is consistently found to be high (Neslin, 2002) and to vary substantially across consumer segments. For example, heavy users are found to be more price elastic than light

* Corresponding author. Tel.: +1 949 824 8368; fax: +1 949 725 2826.
E-mail addresses: jlim@jmsb.concordia.ca (J. Lim), iscurrim@uci.edu (I.S. Currim), randrews@lsu.edu (R.L. Andrews).
[1] Tel.: +1 514 848 2424x2772.
[2] Tel.: +1 225 578 2434.

[3] In this paper, the immediate effect of a price promotion is defined as the change in sales due to the promotion during the period in which the promotion is run.

0167-8116/$ - see front matter
doi:10.1016/j.ijresmar.2005.09.006

users (e.g., Neslin, Henderson, & Quelch, 1985), and non-loyal consumers are found to have higher (total[4]) price elasticity than loyal consumers (e.g., Krishnamurthi & Raj, 1991). Such information on how the short-term sales response to temporary price reductions varies across segments of customers is useful in designing and targeting temporary price reductions. For example, larger sizes can be promoted and targeted to attract heavy users, which can result in substantial increases in market share (Neslin et al., 1985, p. 160), and price cuts can be targeted to influence either switching or increased purchase (Krishnamurthi & Raj, 1991, p. 173).

Because the profitability of a promotion depends on *longer-term* as well as short-term effects, another important literature has emerged more recently on examining the longer-term effects[5] of price promotions, in particular, examining enduring effects through persistence modeling that does not assume mean reversion of the dependent variable (e.g., Dekimpe & Hanssens, 1995a,1995b, 1999; Dekimpe, Steenkamp, Hanssens, & Silva-Risso, 1999; Nijs, Dekimpe, & Hanssens, 2001; Srinivasan, Leszczyc, & Bass, 2000). Pauwels, Hanssens, and Siddarth (2002) define these different temporal effects, describe various streams of research in this area, including the advantages of persistence modeling relative to other approaches,[6] and describe the main findings of the research. In this literature, sales are first classified as stationary or evolving. When sales are stationary, promotions may have an immediate effect on sales that persists over the next several weeks (an adjustment period), but there is no permanent effect. In contrast, when sales are evolving they do not have a fixed mean and therefore could (but need not) be permanently affected by promotions. A key finding of this research is that while permanent effects of promotions are largely absent, there are adjustment period effects which vary by product category and brand, and which affect both total[7] promotion response and profitability.

While the effects of consumer heterogeneity on short-term promotion responses as inferred from multinomial logit models have been widely studied and have generated useful recommendations for marketing managers, to the best of our knowledge, there is no study that investigates the effect of consumer heterogeneity on longer-term promotion effects as inferred from persistence models. Consequently, as a first step, we explore differences in the longer-term responses to promotion among segmentation bases which are both basic and widely used by marketing managers: heavy vs. light users and loyal consumers vs. switchers. Usage- and loyalty-based segmentation has a long-standing tradition in the marketing literature beginning with early works by Boyd and Massy (1972) and Twedt (1967), respectively. Wedel and Kamakura (2000, p. 18) indicate that such segmentation "greatly enhances the usefulness of outcomes for management."

Specifically, we are interested in several research questions. Are the longer-term effects of temporary price promotions, as inferred from persistence models, different across segments of consumers? What aspects of longer-term effects are different (e.g., adjustment periods or effects, permanent effects, or total effects) across which types of customer segments (e.g., heavy vs. light users, loyal consumers vs. switchers), and how large are the differences? Alternatively, will segments of consumers who have been found to substantially differ in their immediate response to temporary price promotions also differ in their longer-term response to such promotions? To what extent? Can we improve the forecasting performance of persistence models by conducting a segment-level analysis?

Such an exploratory investigation can be an important first step towards generating valuable payoffs for marketing modelers and managers. First, if consumers are found to be heterogeneous in their longer-term responses to price promotions, marketing modelers ultimately will be able to attain richer and more accurate portraits of consumer longer-term response that are less subject to aggregation and specification errors, just as

[4] Total price elasticity includes elasticities of both brand choice and quantity purchased.

[5] In this paper, the longer-term effects are defined to include the adjustment and permanent effects, which occur subsequent to the immediate effect. The adjustment effect occurs during an adjustment period which is defined as the time period between when the immediate effect is observed, and the time at which sales (incremental sales in the case of evolving sales series) reach an equilibrium level.

[6] Pauwels et al. (2002, pp. 422–423) discuss the advantages of persistence modeling over approaches based on the Koyck model (e.g., Mela, Gupta, & Lehmann, 1997; Papatla & Krishnamurthi, 1996), flexible consumption functions (e.g., Ailawadi & Neslin, 1998), and multiplicative response models (e.g., Ailawadi, Lehmann, & Neslin, 2001). Basically, while both research streams model dynamic effects of price promotions, other approaches capture transient, not enduring effects, because they assume mean reversion of the dependent variable (e.g., Dekimpe & Hanssens, 1995a, 1999; Pauwels et al., 2002).

[7] The total promotion effect is defined as the sum of the immediate, adjustment, and permanent effects. If there is a permanent effect, the total effect of the promotion will be infinite.

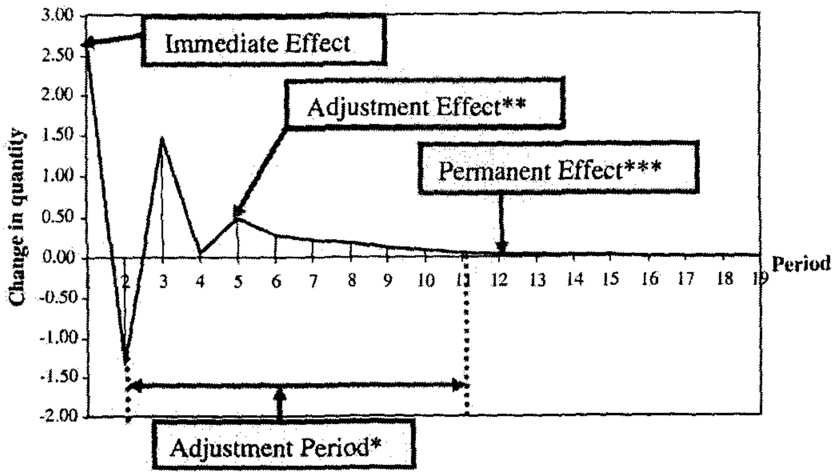

Fig. 1. An example of an impulse response function. *In this example, the promotion is in period 1 and the adjustment period begins at period 2. **The adjustment effect is the sum of the changes in quantity (the vertical solid lines) during the adjustment period. ***Beyond the 11th period (the end of the adjustment period), the changes in quantity are insignificantly different from 0, so that this example shows a lack of a permanent effect.

they have been able to do in studies of the short-term impact of sales promotion on brand choice (e.g., Chintagunta, Jain, & Vilcassim, 1991; Kamakura & Russell, 1989). Second, studying consumer heterogeneity in longer-term response to price promotions can ultimately help explain why longer-term effects vary across brands in a product category. For example, longer-term effects may vary across brands in a product category if the mix of heavy vs. light users, or loyal consumers vs. switchers varies across brands in the product category. Third, if the two important literatures on short- and longer-term effects can be integrated, managers will be able to design and target promotions to achieve short- and longer-term goals simultaneously.[8] For example, if heavy users, who have been found to be more price elastic in their immediate response than light users (e.g., Neslin et al., 1985), are also found to have shorter adjustment periods in their longer-term response to price promotions, managers could substantially increase market share (and profitability) by targeting this segment with more frequent promotions. Although these consumers buy more on promotion, they also return to their normal purchase behavior in the product category sooner than light users. In contrast, while promotions targeted to light users may have to offer price cuts that provide sufficient incentive to increase product category purchases, these promotions could be offered less frequently. While light users do make product category purchases in response to a promotion, they also return to their normal purchase quantity in the product category later than heavy users.[9] And the managerial gains from targeting heavy consumers more frequently will be larger if their adjustment effects are positive (above the zero line in Fig. 1) rather than negative (below the zero line in Fig. 1). Fig. 1 is described in more detail in the next section.

Both manufacturers and retailers can easily implement such recommendations. Identification of consumers belonging to either heavy or light user segments, or loyal vs. switcher segments, is easily accomplished at the store or chain level using purchase histories recorded when consumers use chain club cards (e.g., Ralph's Club Card or Vons/Pavillions' Value Club Card). Since address information is typically collected when applying for such club cards, it is possible to target the consumers identified with either retailer- or manufacturer-based promotions (or information on promotions). Alternatively, when the club card is swiped at the point of purchase, the member identification number can be easily used by retailers or manufacturers to access purchase history information and target promotions to different segments of consumers by printing

[8] This presumes that short- and longer-term effects do not have opposite signs. When effects have opposite signs, managerial decisions will involve tradeoffs between short- and longer-term goals so that goals are difficult to align.

[9] The two examples provided assume there is no permanent effect of promotion, which has been the major empirical finding in the literature. If there were differences in permanent effects such permanent effects would dominate all other effects such as the immediate and adjustment effects. For example, if the permanent effect was negative, because promotions in such a case would erode brand equity, managers would be recommended to resist running promotions even though there may be strong positive immediate effects.

promotions on the reverse side of purchase receipts. This latter approach does not rely on address information. A third approach is to target different promotions to heavy vs. light or loyal vs. switcher segments simply based on the products purchased (e.g., heavy users (switchers) tend to buy larger (smaller) sizes). Manufacturer promotions can be printed on or inserted inside packages of products offered by the manufacturer, or printed at point of purchase. This approach does not rely on address information or on the availability of purchase histories.

This work makes four types of unique contributions: substantive, managerial, methodological, and theoretical. The primary contribution is substantive, in studying whether the longer-term effects of promotions vary for heavy vs. light users, and loyals vs. switchers. This contribution is like the substantive contributions of the Krishnamurthi and Raj (1991) and Neslin et al. (1985) works that reported on the differences between heavy vs. light users and loyals vs. switchers, respectively, on the short-term or immediate effect of promotions. In addition, since these substantive differences result in recommendations for manufacturers and retailers that are easily implemented in retail settings, this work makes a managerial contribution. Also, this study shows that, in two of the four product categories studied, it is possible to substantially improve the forecasting performance of persistence models by incorporating information on consumer segments. In the other two product categories, segment-based model forecasts are close to their aggregate-model counterparts, so that segmentation is not found to negatively affect forecasting performance. This finding should be useful to marketing modelers in academic and corporate settings, in particular when forecasting accuracy of a model is less than desired. Finally, theoretical expectations are developed on how four effects of promotions, the post-deal trough, the mere purchase and promotion usage effects, and responsiveness of competitor's reactions, are likely to vary for heavy vs. light users at the category level and loyals vs. switchers at the brand level.

In the next section, we define the time frames for promotional effects and employ consumer behavior theory to develop hypotheses on different response patterns to a price promotion across heavy vs. light users, and loyal consumers vs. switchers. Subsequently, we present the persistence models, including unit root tests, category and brand level VARX (Vector Autoregression with Exogenous variables) models and impulse-response functions. Next, we briefly describe scanner panel data for four product categories, two storable products (detergent and paper towels) and two perishable[10] products (margarine and yogurt),[11] before presenting our results on how price promotion effects vary across consumer segments. Finally, we discuss the implications of the results for marketing modelers and managers.

1. Expected results

We follow Pauwels et al. (2002) in defining immediate, adjustment, permanent, and total effects,[12] and in the development of expectations regarding differences between consumer segments on the adjustment period and effects, and permanent and total effects of a promotion. While the immediate effect of a price promotion is the change in sales during the period in which the promotion is run, the adjustment effect refers to the effect of a price promotion during the transition period (called the adjustment period) between the immediate effect and the time at which sales (incremental sales in the case of evolving sales series) reach an equilibrium level (see Fig. 1). The adjustment effect can be either positive or negative (e.g., a temporary post-promotion dip as shown in Fig. 1), and the sign and magnitude of the effect greatly affect the overall profitability of the promotion (e.g., Blattberg & Neslin, 1990). Finally, a permanent effect of the promotion occurs when a proportion of the promotion's impact is carried forward to set a new equilibrium level (or level shift). This new equilibrium level is shown to be 0 in Fig. 1. For example, if the sales series is evolving with no fixed mean, the permanent effect of a marketing effort can be captured by relating the effort to the evolution of sales. The total effect is the total over-time impact of the price promotion, which includes the immediate, adjustment, and permanent effects.

Managers care most about the total effect of a promotion. If promotions have a permanent effect, the total effect will be infinite so that the permanent effect will dominate immediate and adjustment effects. In such a case, the immediate and adjustment effects are less relevant. However, if permanent effects do not exist, which is the dominant finding in the literature hereto-

[10] Our choice of the words "perishable" and "storable" follows Pauwels et al. (2002, p. 424).

[11] Pauwels et al. (2002) contrast one storable product (canned soup) and one perishable product (yogurt).

[12] Previous authors have introduced alternative terms that fit this framework; effects are either contemporaneous (immediate) or dynamic (longer-term), which could be transient (adjustment) or enduring (permanent).

fore (e.g., Dekimpe et al., 1999; Nijs et al., 2001), it is important to determine the size of the adjustment effect so that one can compute the total effect of a promotion. The adjustment period is an important component in the computation of the adjustment effect. In addition, the adjustment period, as outlined earlier, generates important managerial insights about the frequency of promotions. Consequently, the main focus of this paper is on the adjustment period and effect. Specifically, we are interested in whether the adjustment period and effect of a promotion is likely to be different for heavy vs. light users and loyal consumers vs. switchers. While there is a significant body of research on consumer heterogeneity in the immediate effects of price promotions (Neslin, 2002 provides an excellent review), there is no work that investigates whether there is likely to be any variation across consumer segments on the adjustment period or effects. Pauwels et al. (2002) indicate "the length of the adjustment period…has not received much attention in the context of price promotions." Secondarily, because permanent effects are possible (e.g., consumers could develop intrinsic preference for the brand subsequent to promotion-induced trial, or alternatively promotions could erode brand image), and the absence of a permanent effect in the data could be due to cancellation or dilution of permanent effects across different customer segments, we explore whether there is consumer heterogeneity in the permanent effect of price promotion. The effect of heterogeneity is explored at both product category and brand levels. Finally, we explore the differences in total over-time impact of a price promotion across different customer segments. This is the first paper that explores whether the length of the adjustment period, the adjustment effect, the permanent effect, and the total over-time impact of a price promotion vary across different segments of consumers.

1.1. Adjustment period

Past research on longer-term effects of promotions has identified four different forces that can influence the adjustment period (e.g., Pauwels et al., 2002). These forces include the post-deal trough, the mere purchase effect, the promotion usage effect, and the competitive reaction effect (Table 1).

Briefly, the post-deal trough results from promotion-induced timing and quantity acceleration. Quantity and timing acceleration results in stockpiling, after which consumers are expected to reduce their purchases in subsequent weeks (see Neslin, 2002, p. 22 for a review). In some product categories, consumers who stockpile can increase their consumption rates (e.g., Ailawadi & Neslin, 1998; see Neslin, 2002, pp. 25–26 for a review) which affects purchases in subsequent weeks.

The mere purchase effect posits that promotion-induced purchases increase future sales (e.g., Blattberg & Neslin, 1990) based on two behavioral theories, by (i) reminding consumers to buy the product category or

Table 1
Hypotheses on differences in the adjustment period between consumer segments

		Usage level segmentation[a]				Loyalty level segmentation[b]		
		Perishable products		Non-perishable products		Loyal[c]	Non-loyal[d]	Switcher
		Heavy[e]	Light	Heavy	Light			
Post-deal trough	Timing acceleration	Shorter	Longer	NA	NA	Shorter	Shorter	Longer
	Quantity acceleration	NA[f]	NA	Longer	Shorter	Shorter	Longer	Shorter
	Increase in consumption rate due to stockpiling	Shorter	Longer	NA	NA	NA	NA	NA
Mere purchase effect	Reinforcement	Shorter	Longer	Shorter	Longer	Shorter	Longer	Shorter
	Risk premium for trial	NA		NA		Shorter	Longer	Shorter
Promotion usage effect	Self-perception	Shorter	Longer	Shorter	Longer	Shorter	Longer	Shorter
	Price-perception	Shorter	Longer	Shorter	Longer	Shorter	Longer	Shorter
	Object-perception	NA	NA	NA	NA	Shorter	Longer	Shorter
Responsiveness to competitor's reactions		NE[g]	NE	NE	NE	Shorter	Longer	Shorter

[a] Applies to category sales.
[b] Applies to sales of the focal brand. Categorized into loyal, non-loyal, and switcher segments (Narasimhan, 1988).
[c] Loyal to the focal brand. Defined as customers whose focal brand share is more than 50% (Krishnamurthi & Raj 1991).
[d] Non-loyal to focal brand but loyal to another brand.
[e] Customers whose total purchase quantity is above the median purchase quantity across the entire sample of households over the calibration period (Neslin et al., 1985).
[f] Not applicable.
[g] No expectation.

brand and *reinforcing* their tastes (e.g., Erdem, 1996), and (ii) offering a *risk premium for trial* by new consumers, some who will like the product and repurchase it in the future (e.g., Mela et al., 1997).

The promotion usage effect posits that promotions affect consumer perceptions based on three behavioral theories; (i) *self-perception* theory (e.g., Bem, 1967; Dodson, Tybout, & Sternthal, 1978) which proposes that consumers purchasing on promotion will attribute their purchase to an external cause (promotion) rather than an internal cause (brand preference), (ii) *price-perception* theory (e.g., Briesch, Krishnamurthi, Mazumdar, & Raj, 1997; Kalyanaram & Winer, 1995; Winer, 1986) which proposes that consumers form a reference price for a brand based on past prices, and because promotions lower reference prices, consumers are less willing to purchase the brand off promotion, and (iii) *object-perception* theory (e.g., Blattberg, Briesch, & Fox, 1995) which proposes that promotions erode a brand's image. Finally, competitors may react to a focal brand's promotion (e.g., Ailawadi et al., 2001; Leeflang & Wittink, 1992, 1996).

1.1.1. Differences in the adjustment periods of heavy vs. light users for perishable products

Following Neslin et al. (1985), heavy users are defined as those consumers whose total purchase quantity is above the median purchase quantity across the entire sample of households over the calibration sample period.[13] The theoretical predictions of the adjustment period for heavy vs. light consumers (Table 1) are conditional on whether the product is perishable or not, because heavy users are more able than light users to adjust their consumption (relative to base quantity) depending on their inventory level (e.g., Wansink & Deshpande, 1994). In contrast, for non-perishable products no such increase in consumption is required if consumers stockpile on promotion. We first address differences in the adjustment periods of heavy vs. light users for perishable products.

1.1.1.1. Influence of post-deal trough and mere purchase effects. Based on an investigation of several product categories, Bell, Chiang, and Padmanabhan (1999) reported a 17 (incidence)/75 (choice)/8 (quantity) breakdown of elasticities[14] for perishable products relative to a 3/75/22 breakdown for non-perishable products, indicating that the extent of quantity acceleration in perishable products is low. Consequently, we focus on incidence (timing acceleration). Timing acceleration of purchases results in increased inventory. Heavy users are expected to engage in less timing acceleration (than light users) (Neslin et al., 1985, p. 158) and are expected to be more able to increase consumption relative to their base quantity (than light users) in order to deplete the additional inventory,[15] resulting in a shorter adjustment period before they return to their normal purchase quantity in the product category. Although light users have tried the product category, these users (because of their lower usage levels) are expected to be less familiar with the benefits of using the product category (than heavy users) and therefore more likely to be influenced or reinforced by a single promotional purchase. Such influence or reinforcement is likely to affect their behavior in subsequent periods so that we expect a longer adjustment period before they return to their normal purchase quantity in the product category. Because *all* users (heavy and light) have tried the product category, they do not require a risk premium for trial.

1.1.1.2. Influence of promotion usage effect and responsiveness to competitor's reactions. Because light users are more likely to attribute their purchase to external causes such as a promotion, resulting in reduced repeat purchase probability (Blattberg & Neslin, 1990), these users are more likely to deviate from their normal purchase quantity, resulting in a longer adjustment period.[16] Light users are also more likely to change their reference prices after a promotional purchase since they are less familiar with the product category and the average price level of the product category. Consequently, when the price reverts to its original level, these consumers are more likely to feel "sticker shock", or a "loss" relative to the lowered

[13] Note that the definition follows the literature and therefore is based only on total quantity purchased over a time period, and not purchase frequency.

[14] Van Heerde, Gupta, and Wittink (2003) note that the breakdowns are of elasticity and not of sales.

[15] This is supported by several theories. Assuncao and Meyer (1993) show that higher inventory levels provide the consumer with flexibility to consume at any desired rate. Folkes, Martin, and Gupta (1993) provide evidence for scarcity theory, in that smaller quantities are perceived to be more valuable and hence consumed more slowly. Wansink and Deshpande (1994) provide evidence that higher inventory levels create higher in-home awareness of the product, so that it is consumed more often. Soman and Gourville (2001) propose that stockpiling can influence consumers' perceptions of the sunk cost of their inventory investment and hence influence usage rates.

[16] Recall that light users are less able than heavy users to adjust their consumption depending on their inventory level (e.g., Wansink & Deshpande, 1994).

reference price, resulting in a longer adjustment period. Heavy consumers are more familiar with the product category, and with prices, both off and on promotion, and hence less likely to experience "sticker shock". Because usage level segmentation deals with category level predictions and object-perception deals with brand (or brand-size or SKU) level predictions, object perception effects do not apply to usage level segmentation. Finally, light users are more likely to attribute their purchase to an external cause (e.g., promotion) rather than an internal cause (e.g., preference), and as a result are more likely to wait for and respond to another promotion such as a competitor's retaliatory promotion, resulting in a longer adjustment period. However, it is also possible that heavy users, because of their greater knowledge of the category, are better trained to look for and wait for a promotion in the category so that the net result of these two possibilities cannot be predicted. Since all three effects (the post-deal trough, the mere purchase effect, and the promotion's usage effect) are expected to affect the adjustment period of heavy vs. light users of perishable products in a consistent way, our first expectation is:

H1. For perishable products and category level sales, light users are expected to have longer adjustment periods than heavy users.

1.1.2. Differences in the adjustment periods of heavy vs. light users for non-perishable products

In contrast to perishable products, for non-perishable or storable products, the consumer is more likely to engage in quantity rather than timing acceleration (Bell et al., 1999), and no increase in consumption is required if a consumer stockpiles on promotion. As a result, the corresponding expectations on the adjustment period will differ relative to the case for perishable products. For example, heavy users, who are more likely to engage in quantity acceleration (relative to their base quantity) on promotion (e.g., Neslin et al., 1985), no longer need to increase their consumption rate, so that adjustment periods will be longer before these consumers return to their normal purchase quantities in the product category. As a result, the three effects (the post-deal trough, the mere purchase effect, and the promotions usage effect) are no longer expected to affect the adjustment periods of heavy vs. light users of non-perishable products in a consistent way, so that the net effect of all four forces on the adjustment period remains as an important empirical question. The question is important because it affects the promotion frequency and targeting decisions of managers of leading brands that drive category sales.

1.1.3. Differences in the adjustment periods of loyal consumers vs. switchers

While usage level segmentation deals with category sales, loyalty-based segmentation deals with brand sales. Because consumers can be loyal to different brands, we follow Narasimhan (1988) in segmenting consumers into three groups: loyal to the focal brand, non-loyal to the focal brand but loyal to a brand other than the focal brand, and switchers. For ease of exposition, we henceforth refer to these segments as loyal, non-loyal, and switchers. If a consumer's brand share is above 50%, the consumer is classified as being loyal to that brand (e.g., Krishnamurthi & Raj, 1991).[17] In contrast to heavy vs. light users, the expectations regarding the adjustment period for loyal consumers vs. switchers are not conditional on whether the product category is perishable or non-perishable since increases in consumption depend on the usage level rather than the loyalty level (Ailawadi & Neslin, 1998; Wansink & Deshpande, 1994). The influence of the post-deal trough, the mere purchase effect, the promotion usage effect, and responsiveness to competitor's reaction, on the adjustment period of loyalty-based segments is discussed below.

1.1.3.1. Influence of post-deal trough. Switchers are more likely to accelerate purchase timing than loyals (e.g., Bucklin, Gupta, & Siddarth, 1998, Table 5) and, ceteris paribus (e.g., assuming similar consumption patterns for loyals and switchers), are expected to have a longer adjustment period before returning to their normal purchase quantity of the focal brand. The base quantity level of the focal brand will be the lowest for non-loyals. Consequently, when non-loyals purchase the focal brand on promotion, the change in quantity relative to the base quantity level will be higher than that for loyals or switchers, resulting in a longer adjustment period before they return to their normal purchase quantity of the focal brand.

1.1.3.2. Influence of mere purchase effect. The reinforcement effect is expected to be greater for non-loyal consumers than others. Non-loyal consumers are less familiar with the focal brand, so that the consumption

[17] There is always a theoretical possibility that some purchases of a brand are made on promotion. This does not necessarily imply the consumer is not loyal to that brand.

experience of the focal brand will have a relatively greater reinforcement effect (either positive or negative). If the reinforcement effect is positive (negative), non-loyal consumers are likely to purchase more (less) of the focal brand in weeks subsequent to the promotion week, so that they are likely to have a longer adjustment period before returning to their previous purchase quantity of the focal brand. Since non-loyal consumers are loyal to a brand other than the focal brand, these consumers are also expected to have longer adjustment periods before returning to their normal purchase quantity of the focal brand. Non-loyal consumers (who exhibit more loyalty to another brand than switchers) are most likely to require a risk premium for trial. If the risk premium is offered and the trial results in positive reinforcement, the purchase quantity of the focal brand in subsequent weeks will be affected, resulting in a longer adjustment period before they return to their normal purchase quantity of the focal brand.

1.1.3.3. Influence of promotion usage effect and responsiveness to competitor's reactions. Based on self-perception theory, non-loyal consumers, who are least familiar with the focal brand, are most likely to attribute their purchase of the focal brand to an external cause (promotion) rather than an internal cause (preference). Such an attribution will cause non-loyals to wait for another promotion on the focal brand, resulting in a longer adjustment period before returning to their normal purchase quantity of the focal brand.[18] Based on price perception theory, non-loyals are most likely to adjust their reference price downward, resulting in a longer adjustment period. And, based on object perception theory non-loyals could also adjust their perception of the focal brand (either upward or downward). Regardless of the direction of adjustment, any such adjustment in object perception will result in a longer adjustment period. Finally, since non-loyal consumers are most likely to attribute their purchase to an external cause (promotion), they are most likely to wait for another promotion and most likely to respond to competitors' retaliatory promotions, resulting in a longer adjustment period than others.

While the expectations of the length of the adjustment period for non-loyal consumers are less than perfectly consistent, much of the theoretical rationale suggests that non-loyal consumers will have a longer adjustment period for purchasing the focal brand than consumers loyal to the focal brand and switchers. Consequently, our second expectation is:

H2. For purchases of a focal brand, non-loyal consumers are more likely to have longer adjustment periods than consumers loyal to the focal brand and switchers.

1.2. Adjustment, permanent, and total effects

As defined earlier, the adjustment effect refers to the effect of a price promotion during the adjustment period between the immediate response and the time at which sales reach an equilibrium level (e.g., Pauwels et al., 2002). We separate our discussion for the adjustment period and effect because a longer adjustment period does not necessarily imply a greater adjustment effect. This is because the adjustment effect is a function of the duration of the adjustment period *and* the pattern of the impulse-response function (see Fig. 1). For example, there can be a negative post-promotion dip during a longer adjustment period that reduces the adjustment effect, or one can have a shorter adjustment period with stronger positive adjustment effects (longer solid vertical lines in Fig. 1), which increases the adjustment effect.

While we can hypothesize differences in the length of the adjustment period between heavy and light consumers for perishable products and also hypothesize differences in the length of the adjustment period between non-loyals and others, it is not possible to hypothesize (a) how large these differences will be and (b) the size and sign of the impulse-response function effect for each week (size and sign of the solid lines in Fig. 1). Therefore, it is not possible to hypothesize differences between consumer segments in the adjustment (or total) effects of promotions. However, studying the adjustment effects of promotion and whether these effects vary across segments of consumers is very important from a managerial point of view because (a) in the absence of permanent effects, which is most often the case in the literature heretofore, adjustment effects are a very important aspect of the total effect of promotions; and (b) studying how adjustment periods and effects vary across consumer segments can be useful in developing and targeting promotions that vary on frequency and in achieving different managerial objectives (e.g., either influence switching or increased purchase cf. Krishnamurthi & Raj, 1991, p. 173).

[18] Note the non-loyals do not purchase the focal brand often and hence their time between purchases of the focal brand may be large. However, when past purchase decisions are attributed to promotion rather than preference, ceteris paribus, adjustment periods are likely to be longer.

Following the previous literature, we expect to find that permanent effects of promotion are absent for usage- and loyalty-based segments of consumers. The present study is the first to empirically investigate whether the assumed absence of permanent promotional effects holds for different segments of consumers.

1.3. Forecasting performance of aggregate vs. segment-based persistence models

Persistence models calibrated separately for different kinds of users (e.g., heavy vs. light) may generate parameter estimates which are more representative of the behavior of each segment of users and hence could provide better forecasts of that behavior. For example, a priori (e.g., Currim, 1981) and post-hoc (e.g., Kamakura & Russell, 1989) segmentation methods have been shown to improve the forecasting performance of conjoint and logit model analyses (see Andrews, Ainslie, & Currim, 2002; Andrews, Ansari, & Currim, 2002; Wedel & Kamakura, 2000, Table 3.1). This is the first paper to test whether the forecasting performance of category (and brand level) persistence models can be improved through the use of consumer usage (and loyalty)-based segmentation concepts.

2. Methodology

2.1. Overview

The methodological framework consists of three major steps: (a) conducting unit root tests to identify whether each series (e.g., aggregate and segment level category and/or brand level sales) is stationary over time; (b) estimating aggregate and segment-based category and brand level VARX models in which variables are defined either in level or first-difference form depending on the outcome of (a); (c) using the aggregate and consumer segment-based VARX models to generate a corresponding impulse-response function (IRF) which traces the effect of a one standard deviation shock to one of the endogenous variables (e.g., price) on current and future values of other endogenous variables (category or brand sales). The immediate effect of a promotion is the effect of a price shock of one standard error on the response variable (e.g., Dekimpe et al., 1999; Srinivasan et al., 2000). The length of the adjustment period is the time needed for the IRF to stabilize so that the next four consecutive IRF values are insignificantly different from their asymptotic value (e.g., Nijs et al., 2001). This asymptotic value is zero in the case of stationary series, but may be different from zero in the case of non-stationary series. The adjustment effect is the effect of the promotion over the adjustment period, and the total effect of the promotion is the sum of immediate, adjustment, and permanent effects. As in the previous literature, all effects are impacts of a single marginal promotion, not a change in promotion structure.

2.2. Unit-root tests

The Augmented Dickey–Fuller (ADF) test (e.g., Dekimpe et al., 1999; Pauwels et al., 2002) is performed on the sales series at the aggregate and consumer segment levels. The general form of the test equation is given by:

$$\Delta y_t = \alpha_0 + \alpha_1 t + \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t \qquad (1)$$

where y_t is the variable of interest (aggregate and consumer segment-based category-level and brand-level sales series) and t is a deterministic trend variable. Without t, the assumption is that there is no time trend. If the series is found to be non-stationary without t, we can do a stricter test by assuming that there is a time trend and, in this case, we want to determine whether or not the non-stationarity stems from the time trend. To determine the number of lagged difference terms, k is varied from 1 to 8, and the model specification selected is the one with the best value of the BIC criterion (e.g., Pauwels et al., 2002). If we do not reject the null hypothesis of γ equals zero, the series is non-stationary. If there are structural breaks (e.g., new product introductions), corresponding tests (Perron, 1990) need to be conducted before we reject stationarity. Consistent with prior research, if sales are non-stationary there is a potential for permanent effects (e.g., Dekimpe et al., 1999). We followed Enders (1995) to determine whether or not a series is stationary. Dummy variables can also be added to the specification to investigate seasonal effects.

2.3. VARX model

The category level VARX models are estimated with category level quantity (Q) and market-share weighted[19] average price (P) as endogenous variables, and three exogenous variables: intercepts ($\alpha_{0,Q}$ and $\alpha_{0,P}$), feature variables (F), and display variables (D). At the brand level, we estimate a separate VARX model for each brand to avoid potential degrees-of-freedom

[19] Dynamic weights were used to derive the weighted price.

problems when estimating extended VARX models (e.g., when several competitors' performance and marketing-mix variables are included simultaneously as endogenous variables). In the absence of unit roots, variables will be written in levels form, while for unit-root series (or equivalently, non-stationary series) variables will be written in first-difference form. When two or more series are found to be non-stationary and co-integrated, one can run a Vector Error Correction (VEC) Model in place of the VARX model. Our model for category level demand follows Nijs et al. (2001) and is represented as follows under the assumption that all the endogenous variables are stationary:

$$\begin{bmatrix} Q_t \\ P_t \end{bmatrix} = \begin{bmatrix} \alpha_{0,Q} \\ \alpha_{0,P} \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \beta^i_{11} & \beta^i_{12} \\ \beta^i_{21} & \beta^i_{22} \end{bmatrix} \times \begin{bmatrix} Q_{t-i} \\ P_{t-i} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \times \begin{bmatrix} F_t \\ D_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{Q,t} \\ \varepsilon_{P,t} \end{bmatrix} \tag{2}$$

where $[\varepsilon_{Q,t}\ \varepsilon_{P,t}]' \sim N(0, \Sigma)$.

Similarly, the brand level model (e.g., 3 brands) can be specified as:

$$\begin{bmatrix} Q_{j,t} \\ P_{1,t} \\ P_{2,t} \\ P_{3,t} \end{bmatrix} = \begin{bmatrix} \alpha_{Q_j} \\ \alpha_{P_1} \\ \alpha_{P_2} \\ \alpha_{P_3} \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \beta^i_{11} & \beta^i_{12} & \beta^i_{13} & \beta^i_{14} \\ \beta^i_{21} & \beta^i_{22} & \beta^i_{23} & \beta^i_{24} \\ \beta^i_{31} & \beta^i_{32} & \beta^i_{33} & \beta^i_{34} \\ \beta^i_{41} & \beta^i_{42} & \beta^i_{43} & \beta^i_{44} \end{bmatrix} \times \begin{bmatrix} Q_{j,t-i} \\ P_{1,t-i} \\ P_{2,t-i} \\ P_{3,t-i} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} & \gamma_{16} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} & \gamma_{25} & \gamma_{26} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} & \gamma_{35} & \gamma_{36} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} & \gamma_{45} & \gamma_{46} \end{bmatrix} \times \begin{bmatrix} F_{1,t} \\ F_{2,t} \\ F_{3,t} \\ D_{1,t} \\ D_{2,t} \\ D_{3,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Q_j,t} \\ \varepsilon_{P_1,t} \\ \varepsilon_{P_2,t} \\ \varepsilon_{P_3,t} \end{bmatrix} \tag{3}$$

where $[\varepsilon_{Q_j,t}\ \varepsilon_{P_1,t}\ \varepsilon_{P_2,t}\ \varepsilon_{P_3,t}] \sim N(0, \Sigma)$, j=1,2, and 3. This linear specification is preferred (over a multiplicative model which is linear in logs), because it yields an elasticity that is increasing (rather than constant) in price (Pauwels et al., 2002; Van Heerde et al., 2000). The linear specification is also less sensitive to aggregation bias (Christen, Gupta, Porter, Staelin, & Wittink, 1997). The order of a VARX model is determined by the best BIC criterion (e.g., Pauwels et al., 2002).

2.4. Impulse-response function

The impulse-response function traces the effect of one standard deviation shock to one of the endogenous variables on current and future values of the endogenous variables (for more details on impulse-response function, see Dekimpe & Hanssens, 1999; Nijs et al., 2001). A shock to the i-th variable directly affects the i-th variable, and is also transmitted to all of the endogenous variables through the dynamic structure of the VARX. The over-time price promotion impact is derived under the assumption that the initiating price promotion does not alter the data-generating process (Pesaran & Samiei, 1991).

Finally, all the estimated impulse-response functions are transformed to unit-free elasticities (rather than absolute quantity changes) to measure the size of the immediate, adjustment, and permanent effects (Srinivasan et al., 2000). This is because the results of impulse-response functions provide the incremental units (e.g., in ounces) sold by the price promotion, which are not comparable across product categories and consumer segments. The conversion of the results of the impulse-response functions to price elasticities is based on the following equation:

$$\varepsilon(Q) = \frac{P}{Q} \times \frac{dQ}{dP} \tag{4}$$

where dP is found by Cholesky decomposition of the residual variance–covariance matrix, dQ is the result of the impulse-response function, and P and Q are average price and purchase quantity, respectively. Following Pauwels et al. (2002, p. 428), for category analysis we shock price first, allowing for contemporaneous effects on category level quantity, and for brand level analysis we shock the focal brand's price, allowing for contemporaneous effects on brand level quantity.

2.5. Repeated sampling

We employed repeated sampling (Currim & Schneider, 1991; Efron, 1979) to test the significance of differences in the duration of the adjustment periods, adjustment effects, and total effects across consumer segments. Specifically, we generated purchase quantity and marketing mix variables by randomly selecting 90% of the total households in each segment and estimated VARX models using the generated data series.[20] The above procedure was repeated 100 times and, as a result, we could generate 100 impulse-response functions for each segment level analysis. Based on the mean and standard deviation of the 100 replications, we performed t-tests to verify whether the differences across consumer segments are significant. This approach is different from that advocated in Dekimpe and Hanssens (1999) and easier to implement because of access to household-level data.[21]

3. Data

We use scanner data on four product categories: yogurt, margarine, paper towels, and detergent. The yogurt data was collected by A.C. Nielsen in Sioux Falls, South Dakota, over 138 weeks, and the margarine, paper towels, and detergent data sets were collected by IRI in Chicago over 112 weeks. The yogurt data have been made available through the Marketing Science Institute and A.C. Nielsen and have been widely used in marketing research. The total number of households are 2556 (yogurt), 1539 (margarine), 1513 (paper towels), and 1525 (detergent). The total number of purchases are 78,527 (yogurt), 30,259 (margarine), 28,287 (paper towels), and 19,752 (detergent). We consider paper towels and detergent as non-perishable (or storable) products with a high ability to stockpile and margarine and yogurt as perishable products with a low ability to stockpile (Narasimhan, Neslin, & Sen, 1996; Pauwels et al., 2002). Three leading brands are considered from each product category since a VARX model (e.g., with a 1-period lag) requires estimation of 36 parameters with 112–138 weekly observations. The data sets were divided into calibration and holdout samples (10 weeks from each data set) to compare the forecasting performance of aggregate-level and segment-level analyses.

In this research, we employ price, feature, and display variables. The quantity variable represents per week sales volume in ounces for margarine, detergent, and yogurt, and square yards for paper towel. The category level price variable is calculated using the average unit price of brands weighted by their market shares. The feature and display variables are dummy variables indicating presence (or absence) of a feature or display during each week.

4. Results

4.1. Unit root tests

An augmented Dickey–Fuller (ADF)[22] test was conducted on each of the following series: category sales (at the aggregate level, and separately for heavy, and light consumers), and sales for each of 3 brands (at the aggregate level, and for each of 3 segments, loyals, non-loyals, and switchers). These 15 tests were conducted for each of the 4 product categories. All 60 tests[23] conducted indicated that the corresponding series were stationary (values between -3.1 and -11.3 were compared to McKinnon critical values of -2.88 (5% level)). Since the category and brand level sales series at both aggregate and segment levels are found to be stationary, there are no permanent effects, either at the aggregate or consumer segment levels.

The aggregate level results are consistent with the previous findings in time series research that most purchase quantity or sales series are stationary (e.g., Nijs et al., 2001). Based on this research, we can extend the previous findings of the absence of permanent effects of promotions to the segment level. Therefore, regardless of consumers' behavioral characteristics, such as heavy, light, loyal, and non-loyal consumers and switchers, manufacturers (or retailers) cannot expect consumers to permanently increase their purchase quantities in response to temporary price promotions.

4.2. Adjustment period

The results on the duration of the adjustment periods for the various consumer segments are summarized in Table 2.

4.2.1. Heavy vs. light users

First, for perishable products (margarine and yogurt) we find that light users have longer adjustment periods than heavy users (3.25 vs. 2.87 ($p<0.00$) weeks for margarine and 3.99 vs. 1.98 ($p<0.00$) weeks for yogurt). Consequently, H1 is supported. For non-perishable products, it was not possible to

[20] 90% is based on Currim and Schneider (1991). They repeatedly generated random samples with replacement in a way that any given random sample comprised 90% of the household's purchase history.

[21] We thank a reviewer for pointing this out.

[22] Inclusion of seasonal effect dummy variables did not improve the fit of the model.

[23] Detailed results are available from the authors.

Table 2
Results on the duration of adjustment period in weeks[a]

		Usage level segmentation[b]			Loyalty level segmentation[c]						
		Heavy[d]	Light		L	NL	S	Significance			
								ANOVA	L vs. NL	L vs. S	NL vs. S
Perishable	Margarine	2.87	3.25	$P<0.00$	1.25	1.71	0.49	$p<0.00$	$p<0.00$	$p<0.00$	$p<0.00$
	Yogurt	1.98	3.99	$P<0.00$	4.09	3.97	3.44	$p<0.04$	$p<0.70$	$p<0.02$	$p<0.01$
Non-perishable	Detergent	1.32	1.29	$P<0.65$	1.57	1.97	1.36	$p<0.00$	$p<0.00$	$p<0.01$	$p<0.00$
	Paper towel	1.09	1.13	$P<0.53$	1.74	2.52	1.51	$p<0.00$	$p<0.00$	$p<0.00$	$p<0.00$

[a] L represents Loyals, NL represents Non-loyals, and S represents Switchers in this table.
[b] Applies to category sales.
[c] Applies to sales of the focal brand, averaged over three brands.
[d] See footnotes of Table 1 for definitions of category usage and brand loyalty level based consumer segments.

hypothesize the difference in duration of adjustment period between heavy and light users because the four different effects (post-deal trough, the mere purchase effect, the promotions usage effect, and responsiveness to competitor's promotions) did not affect the duration of the adjustment period in a consistent fashion. Our finding for non-perishable products is that there is no difference in the duration of adjustment period between heavy and light users (1.32 vs. 1.29 ($p<0.65$) weeks for detergent and 1.09 vs. 1.13 ($p<0.53$) weeks for paper towel). This second result implies that the effect of quantity acceleration by heavy users on the duration of their adjustment period (making it longer than that for light users) is about equal to the effects of timing acceleration, reinforcement, self and price perception (making it shorter than that for light users). This second result is intuitively appealing given that heavy users are found to be substantially more price elastic than light users (e.g., Neslin et al., 1985).

4.2.2. Loyal vs. non-loyal vs. switchers

Third, we find that non-loyal (to the focal brand but loyal to another brand) consumers have longer adjustment periods to a promotion of the focal brand than other consumers (loyals and switchers) for 3 of the 4 product categories studied; 1.97 (non-loyals) vs. 1.57 (loyals) and 1.36 (switchers) (both $p<0.00$) for detergent; 2.52 (non-loyals) vs. 1.74 (loyals) and 1.51 (switchers) (both $p<0.00$) for paper towels; and 1.71 (non-loyals) vs. 1.25 (loyals) and 0.49 (switchers) (both $p<0.00$) for margarine. For yogurt, non-loyals have a longer adjustment period than switchers ($p<0.01$) but the difference between non-loyals and loyals was found to be statistically insignificant ($p<0.70$). Consequently, H2 is largely supported. Overall, across both segmentation schemes at the category and brand levels the results are strongly indicative of the fact that the adjustment periods can vary substantially across consumer segments.

4.3. Adjustment and total effects

The results on the adjustment and total effects of a temporary price promotion on the aggregate sample population and the consumer segments are summarized in Table 3.

4.3.1. Heavy vs. light users

For perishable products, we find that heavy users have a lower adjustment ($p<0.00$) and higher total effect ($p<0.00$) than light users (the adjustment effect is 0.69 for heavy users vs. 0.88 for light users,

Table 3
Results on the adjustment and total effects of a price promotion

	Usage level segmentation[a]						Loyalty level segmentation[b]						
	Perishable products			Non-perishable products			L	NL	S	Significance			
	Heavy[c]	Light	Significance	Heavy	Light	Significance				ANOVA	L vs. NL	L vs. S	NL vs. S
Total effects	2.54	2.18	$p<0.00$	1.07	1.41	$p<0.00$	4.12	5.69	5.53	$p<0.00$	$p<0.00$	$p<0.00$	$p<0.64$
Adjustment effects	0.69	0.88	$p<0.00$	−0.06	−0.02	$p<0.02$	1.70	2.30	1.38	$p<0.00$	$p<0.01$	$p<0.14$	$p<0.00$

[a] Applies to category sales.
[b] Applies to sales of the focal brand, averaged across three brands.
[c] See footnotes of Table 1 for definitions of category usage and brand loyalty level based consumer segments.

while the total effect is 2.54 for heavy users vs. 2.18 for light users). Our results indicate that for perishable products, heavy users have a shorter adjustment period and lower adjustment effect, than light users. The larger total effect is intuitively appealing given that heavy users have been found to have larger immediate effects (e.g., Neslin et al., 1985). For non-perishable (or storable) products, heavy users are found to have a smaller adjustment effect ($p<0.02$) than light users (-0.06 for heavy users vs. -0.02 for light users. The negative (or negligible) adjustment effect is indicative of a post-promotion dip, which is more likely in non-perishable product categories because heavy users do not have to increase their consumption when they engage in quantity acceleration in response to a single, temporary price reduction. This post-promotion dip lowers the total promotion effect in the non-perishable product category relative to that for light users (1.07 vs. 1.41 ($p<0.00$)).

4.3.2. Loyal vs. non-loyal vs. switcher

Earlier we found that non-loyal customers had the longest adjustment period to promotions of the focal brand (H2). For this segment of consumers, the longest adjustment period also translates into the highest adjustment effect (2.3 for non-loyals vs. 1.7 for loyals ($p<0.00$) and 1.38 for switchers ($p<0.00$)), and total effects of a promotion (5.69 for non-loyals vs. 4.12 for loyals ($p<0.00$) and 5.53 for switchers (n.s.)).

4.4. Forecasting performance of aggregate vs. segment-based persistence models

To compare the forecasting performances between aggregate and segment-level analyses, we calculated Root Mean Squared Error (RMSE) for the 10 out-of-sample periods:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{T} (\hat{Q}_t - Q_t)^2}{T}} \tag{5}$$

At the aggregate level, $\hat{Q}_t$ can be directly estimated from the VARX system. At the segment level, we (i) estimated $\hat{Q}_{st}$, where s indicates heavy and light segments at the category level and loyal, non-loyal, and switchers at the brand level, (ii) calculated $\hat{Q}_t$ by summing $\hat{Q}_{st}$ over s segments, and (iii) compared $\hat{Q}_t$ and Q_t. The results on forecasting performance of aggregate and segment-level analyses are summarized in Table 4.

First, segment analysis produces better forecasting performance for yogurt and detergent categories, while aggregate analysis produces better forecasting performance for margarine and paper towel categories, indicating that there is more difference between consumer segments (heavy vs. light, loyal vs. non-loyal vs. switchers) in yogurt and detergent categories than margarine and paper towel categories, in how sensitive the consumer segments' purchase quantity decisions are to prices, features and displays.

Second, although segmentation does not result in better predictions for all product categories, we observe from inspecting Table 4 that the gain in forecasting performance achieved through segment-based analyses is often larger than the loss in forecasting performance achieved when conducting a segment based analysis. In most cases wherein segment analysis produces worse forecasting performance than aggregate analysis, the segment level RMSE is very close to the aggregate level RMSE (except yogurt brand 1 and margarine brand 3). However, when segment analysis generates

Table 4
Comparison of the forecasting performance of VARX models as measured by RMSE[a]

	Margarine		Yogurt		Detergent		Paper towel	
	Aggregate level analysis	Segment level analysis	Aggregate level analysis	Segment level analysis	Aggregate level analysis	Segment level analysis	Aggregate level analysis	Segment level analysis
Category level demand	910.68	935.39 (−2.7%)	1,519.56	1,190.72 (21.6%)	4,714.92	4,574.81 (3%)	1031.54	1056.56 (−2.4%)
Quantity for brand 1	636.53	464.93 (27%)	187.14	217.33 (−16.1%)	1527.66	1514.30 (0.9%)	294.26	298.25 (−1.4)
Quantity for brand 2	276.83	279.23 (−0.9%)	1,299.32	1,110.85 (14.5%)	2019.59	1859.82 (7.9%)	863.58	874.47 (−1.3)
Quantity for brand 3	221.48	240.29 (−8.5%)	217.85	169.29 (22.3%)	2826.37	2763.27 (2.2%)	423.25	425.59 (−0.6)

[a] For category level demand, we use usage-based segmentation, while for brand level demand (quantity) we use loyalty-based segmentation. The percentage improvement of segment level analysis over aggregate level analysis is in parenthesis.

better forecasts, the segment level RMSE is often considerably better than the aggregate level RMSE. Consequently, there is a definite potential for improving the forecasting performance of category and brand level persistence models by conducting consumer segment-based analyses.

5. Summary, managerial implications, limitations, and future research

While the effect of consumer heterogeneity on short-term response to promotion as inferred from multinomial logit models has been widely studied, no study has investigated the effect of consumer heterogeneity on longer-term effects of promotion as inferred from persistence models. This paper takes a first step in that direction by investigating whether there are differences in the longer-term response to promotion between heavy vs. light users, and loyal vs. non-loyal vs. switcher segments. Specifically, we focus on the adjustment period and the adjustment, permanent, and total effects of a promotion in four product categories. Usage- and loyalty-based segmentation has a long-standing tradition in the marketing literature (Boyd & Massy, 1972; Twedt, 1967) and Wedel and Kamakura (2000, p. 18) indicate that such segmentation "greatly enhances the usefulness of outcomes for management."

5.1. Main results, managerial implications and implementation

Our main results and associated managerial implications are as follows:

1. For perishable products, while light users have longer adjustment periods than heavy users, heavy users have larger total effects. This result implies that managers may be able to substantially increase market share by targeting the heavy user segment with more frequent promotions than light users because heavy users buy more on promotion and also return to their normal purchase behavior in the product category sooner than light users. It is important, however, that the frequency of promotion be below a threshold level beyond which more frequent promotions begin to lower the effect of promotions (e.g., Foekens, Leeflang, & Wittink, 1999; Raju, 1992). In contrast, while promotions targeted to light users have to offer price cuts that provide sufficient incentive to increase product category purchases, these promotions could be offered less frequently because light users take a longer time to return to their normal purchase quantity in the product category. Because light users have positive adjustment effects, the longer adjustment period for light users implies that promotion can be effectively used to educate these consumers about the benefits of using the product category.
2. For non-perishable products, heavy users have the same adjustment period as light users. We find a negative adjustment effect for heavy users, which results in a lower total promotion effect for these users. This result implies that the strategy of targeting heavy users with more frequent promotions on the perishable items they buy may not work as well for non-perishable products. These consumers stockpile and exit the market rather than increase their consumption and return quickly to their normal purchase quantity in the product category.
3. Consumers who are non-loyal to a focal brand but loyal to another brand have longer adjustment periods than other consumers when responding to a promotion of the focal brand. For this segment, a longer adjustment period results in a larger adjustment effect and a larger total effect of promotion. Currently, managers are more likely to target switchers because consumers who are loyal to another brand are thought to be difficult to attract to the focal brand. However, this result suggests that consumers who are non-loyal to the focal brand but loyal to another brand are likely to provide a larger total effect in response to a promotion of the focal brand than switchers in a longer term.
4. There are no permanent effects of a promotion for any of the segments studied. This result implies that the absence of permanent effects is prevalent not only across different product categories (e.g., Nijs et al., 2001) but also across different usage- and loyalty-based consumer segments.
5. At the category level, a segment-based analysis improves the forecasting performance of a persistence model in 2 of the 4 product categories studied. At both category and brand levels, when a segment-based analysis does improve forecasting performance, the improvement is often large. In contrast, when segment-based analysis does not improve forecasting performance, the loss is often small. Consequently, managers are likely to find that the segmentation-based analysis is particularly important when persistence models provide less accurate forecasts.

Overall, at both category and brand levels, the results strongly indicate that (a) the adjustment period and the adjustment, permanent, and total effects of a promotion vary significantly across consumer segments, and that consideration of such differences can be useful in (b) improving the forecasting performance of persistence models and (c) designing manufacturer and/or retailer-based promotion programs targeted at different segments in a way that can be easily implemented in retail settings. Managerial implementation is possible using a variety of approaches, some of which rely on address information or the ability to customize promotions at point of purchase, while other approaches do not.

5.2. Limitations and future research

First, while this work considers the immediate and post-promotion effects, like the majority of published works in persistence modeling, it does not consider lead effects due to anticipation of promotions (Van Heerde et al., 2000), which if present would further reduce the total effect of a promotion. It is also possible that lead effects are to some extent indirectly reflected in changing baseline values, and hence in a reduced shock content of a nominal price reduction. Future research could study whether there are differences in the extent to which different consumer segments anticipate promotions, and whether such potential differences result in differences in total promotion effects including pre- and post-promotion dips (across segments).

Second, although our operationalization of heavy vs. light users is consistent with previous work (e.g., Neslin et al., 1985), we do not distinguish between heavy users based on their frequency of purchase. Future research could consider whether differences in frequency of purchase result in differences in the adjustment period and effects. Perhaps adjustment periods are more likely to be impacted by inter-purchase time for infrequent purchasers and by usage rates for frequent purchasers.

Third, while our operationalization of loyalty is consistent with previous work (e.g., Krishnamurthi & Raj, 1991), it is possible that some of the purchases were made when the brand was on promotion. Although this does not necessarily imply that the consumer is less loyal to the brand, future research could investigate whether alternative ways of operationalizing brand loyalty result in differences in adjustment periods and effects across loyal vs. non-loyal vs. switcher segments.

Fourth, while our specification of the VARX model (Eqs. (2) and (3)) is consistent with previous research (e.g., Nijs et al., 2001), such a specification results in three different equations for each brand's price (in Eq. (3)). An alternative specification is one in which there is one (instead of 3) system of equations with all brand level quantities and prices as endogenous variables. Of course the latter specification will involve estimation of many more parameters than the former, which is a concern when we have limited data on the number of weeks. The empirical effect of this tradeoff can be assessed in future research. In addition, while Eq. (2) is a model for category level demand one can ask whether the model could be improved by considering a four-equation model as in Eq. (3). One can also investigate the implications of only considering the top three brands by including a larger number of brands. Large (small) share brands are likely to be high (low) tier, high (low) price brands which are impacted quite differently by the marketing activities of small (large) share brands than by the activities of other large (small) share brands (see Neslin, 2002, pp. 8–12 for a review of such asymmetric effects caused by preference heterogeneity, loss aversion, and income and dominance effects). Small share brands are likely to be niche brands that appeal to a certain segment of consumers, who are likely to differ from consumers that purchase large share brands. How these asymmetries and differences impact the differences in duration of the adjustment period, the adjustment effect, and the total effect of promotion across different segments investigated in this paper is an empirical question for future research.

Fifth, this work is consistent with previous published work in that the model assumes constant parameters. Alternatively, one can investigate the performance of a varying parameter model, one in which the effects of promotion are allowed to vary over time. And one can investigate the results of allowing for non-zero covariances between adjustment period effects of different segments. Future research could consider the pros and cons of alternative modeling strategies.

Finally, in this study, we used an exploratory a priori segmentation approach to demonstrate that substantial differences exists between consumer segments in terms of their longer-term purchase responses to promotions. In future research, it would be valuable to investigate an a posteriori segmentation approach to investigate whether there is any heterogeneity among consumers, how many segments describe the data best, and what the behavioral characteristics are for each segment. Given that the consumer heterogeneity issue in persistence modeling has been neglected heretofore, we believe our research can serve as a useful starting point for further investigation of this issue.

Acknowledgements

The authors thank David Brownstone, Cornelia Pechmann, and Rajeev Tyagi (all at UCI) for their helpful comments.

References

Ailawadi, K. L., Lehmann, D. R., & Neslin, S. A. (2001, January). Market response to a major policy change in the marketing mix: Learning from Proctor and Gamble's value pricing strategy. *Journal of Marketing*, *65*, 44–61.

Ailawadi, K. L., & Neslin, S. A. (1998, August). The effect of promotion on consumption: Buying more and consuming it faster. *Journal of Marketing Research*, *35*, 390–398.

Andrews, R. L., Ainslie, A., & Currim, I. S. (2002, November). An empirical comparison of logit choice models with discrete versus continuous representations of heterogeneity. *Journal of Marketing Research*, *39*, 479–487.

Andrews, R. L., Ansari, A., & Currim, I. S. (2002, February). Hierarchical bayes versus finite mixture conjoint analysis models: A comparison of fit, prediction, and partworth recovery. *Journal of Marketing Research*, *39*, 87–98.

Assuncao, J. L., & Meyer, R. J. (1993). The rational effect of price promotions on sales and consumption. *Management Science*, *39*(5), 517–535.

Bell, D. R., Chiang, J., & Padmanabhan, V. (1999). The decomposition of promotional response: An empirical generalization. *Marketing Science*, *18*(4), 504–526.

Bem, D. J. (1967). Self-perception: An alternative explanation of cognitive dissonance phenomena. *Psychological Review*, *74*, 183–200.

Blattberg, R. C., Briesch, R. A., & Fox, E. J. (1995). How promotions work. *Marketing Science*, *14*(3), G122–G132.

Blattberg, R. C., & Neslin, S. A. (1990). Sales promotion concepts, methods, and strategies. Englewood Cliffs, NJ: Prentice-Hall.

Boyd, H. W., & Massy, W. F. (1972). Marketing management. New York: Harcourt Brace Jovanovich.

Briesch, R. A., Krishnamurthi, L., Mazumdar, T., & Raj, S. P. (1997, September). A comparative analysis of reference price models. *Journal of Consumer Research*, *24*, 202–214.

Bucklin, R. E., Gupta, S., & Siddarth, S. (1998, May). Determining segmentation in sales response across consumer purchase behaviors. *Journal of Marketing Research*, *35*, 189–197.

Chintagunta, P. K., Jain, D. C., & Vilcassim, N. J. (1991, November). Investigating heterogeneity in brand preferences in logit models for panel data. *Journal of Marketing Research*, *28*, 417–428.

Christen, M., Gupta, S., Porter, J., Staelin, R., & Wittink, D. R. (1997, August). Using market-level data to understand promotion effects in a nonlinear model. *Journal of Marketing Research*, *34*, 322–334.

Currim, I. S. (1981, August). Using segmentation approaches for better prediction and understanding from consumer choice models. *Journal of Marketing Research*, *18*, 301–309.

Currim, I. S., & Schneider, L. G. (1991). A taxonomy of consumer purchase strategies in a promotion intensive environment. *Marketing Science*, *10*(2), 91–110.

Dekimpe, M. G., & Hanssens, D. M. (1995). Empirical generalizations about market evolution and stationarity. *Marketing Science*, *14*(3), G109–G121.

Dekimpe, M. G., & Hanssens, D. M. (1995). The persistence of marketing effects on sales. *Marketing Science*, *14*(1), 1–21.

Dekimpe, M. G., & Hanssens, D. M. (1999, November). Sustained spending and persistent response: A new look at long-term marketing profitability. *Journal of Marketing Research*, *36*, 397–412.

Dekimpe, M. G., Hanssens, D. M., & Silva-Risso, J. M. (1999). Long-run effects of price promotions in scanner markets. *Journal of Econometrics*, *89*(1/2), 269–291.

Dodson, J. A., Tybout, A. M., & Sternthal, B. (1978, February). Impact of deals and deal retraction on brand switching. *Journal of Marketing Research*, *15*, 72–81.

Efron, B. (1979). Bootstrap methods—another look at the jackknife. *Annals of Statistics*, *7*, 1–26.

Enders, W. (1995). *Applied econometric time series* (1st ed.). New York: John Wiley and Sons, Inc.

Erdem, T. (1996). A dynamic analysis of market structure based on panel data. *Marketing Science*, *15*(4), 359–378.

Foekens, E. W., Leeflang, P. S. H., & Wittink, D. R. (1999). Varying parameter models to accommodate dynamic promotion effects. *Journal of Econometrics*, *89*(1/2), 249.

Folkes, V. S., Martin, I. M., & Gupta, K. (1993, December). When to say when: Effect of supply on usage. *Journal of Consumer Research*, *20*, 467–477.

Kalyanaram, G., & Winer, R. S. (1995). Empirical generalizations from reference price research. *Marketing Science*, *14*(3), G161–G169.

Kamakura, W. A., & Russell, G. J. (1989, November). A probabilistic choice model for market segmentation and elasticity structure. *Journal of Marketing Research*, *26*, 379–390.

Krishnamurthi, L., & Raj, S. P. (1991). An empirical analysis of the relationship between brand loyalty and consumer price elasticity. *Marketing Science*, *10*(2), 172–183.

Leeflang, P. S. H., & Wittink, D. R. (1992). Diagnosing competitive reactions using (aggregated) scanner data. *International Journal of Research in Marketing*, *9*(1), 39–57.

Leeflang, P. S. H., & Wittink, D. R. (1996). Competitive reaction versus consumer response: Do managers overreact? *International Journal of Research in Marketing*, *13*(2), 103–119.

Mela, C. F., Gupta, S., & Lehmann, D. R. (1997, May). The long-term impact of promotion and advertising on consumer brand choice. *Journal of Marketing Research*, *34*, 248–261.

Narasimhan, C. (1988). Competitive promotional strategies. *Journal of Business*, *61*(4), 427–449.

Narasimhan, C., Neslin, S. A., & Sen, S. K. (1996, October). Promotional elasticities and category characteristics. *Journal of Marketing*, *60*, 17–30.

Neslin, S. A. (2002). *Sales promotions*. Cambridge, MA: Marketing Science Institute Relevant Knowledge Series.

Neslin, S. A., Henderson, C., & Quelch, J. (1985). Consumer promotions and the acceleration of product purchases. *Marketing Science*, *4*(2), 147–165.

Nijs, V. R., Dekimpe, M. G., Steenkamp, J. E. M., & Hanssens, D. H. (2001). The category-demand effects of price promotions. *Marketing Science*, *20*(1), 1–22.

Papatla, P., & Krishnamurthi, L. (1996, February). Measuring the dynamic effects of promotions on brand choice. *Journal of Marketing Research*, *33*, 20–35.

Pauwels, K., Hanssens, D. H., & Siddarth, S. (2002, November). The long-term effects of price promotions on category incidence, brand choice and purchase quantity. *Journal of Marketing Research*, *39*, 421–439.

Perron, P. (1990). Testing for a unit root in a time series with a changing mean. *Journal of Business and Economic Statistics*, *8*(2), 153–162.

Pesaran, M. H., & Samiei, H. (1991). Persistence, seasonality and trend in the UK egg production. *Applied Economics*, *23*(3), 479–484.

Raju, J. S. (1992). The effect of price promotions on variability in product category sales. *Marketing Science*, *11*(3), 207–220.

Soman, D., & Gourville, J. T. (2001, February). Transaction decoupling: How price bundling affects the decision to consumer. *Journal of Marketing Research*, *38*, 30–44.

Srinivasan, S., Leszczyc, P. T. L., & Bass, F. M. (2000). Market share response and competitive interaction: The impact of temporary, evolving and structural changes in prices. *International Journal of Research in Marketing*, *17*(4), 281–305.

Srinivasan, S., Pauwels, K., Hanssens, D. M., & Dekimpe, M. G. (2004). Do promotions benefit manufacturers, retailers, or both? *Management Science*, *50*(2), 617–629.

Twedt, D. W. (1967). How does awareness-attitude affect marketing strategy? *Journal of Marketing*, *31*, 64–66.

Van Heerde, H. J., Gupta, S., & Wittink, D. R. (2003, November). Is 75% of the sales promotion bump due to brand switching? No, only 33% is. *Journal of Marketing Research*, *40*, 481–491.

Van Heerde, H. J., Leeflang, P. S. H., & Wittink, D. R. (2000, August). The estimation of pre- and postpromotion dips with store-level scanner data. *Journal of Marketing Research*, *37*, 383–395.

Wansink, B., & Deshpande, R. (1994, January). Out of sight, out of mind: Pantry stockpiling and brand-usage frequency. *Marketing Letters*, 91–100.

Wedel, M., & Kamakura, W. A. (2000). Market segmentation: Conceptual and methodological foundation (2nd ed.). Boston, MA: Kluwer Academic Publishers.

Winer, R. S. (1986). A reference price model of brand choice for frequently purchased products. *Journal of Consumer Research*, *13*(2), 250–256.

African Journal of Business Management pp. 092-098, July 2007
Available online http://www.academicjournals.org/ajbm
ISSN 1993-8233 ©2007 Academic Journals

Full Length Research Paper

The effect of consumer price knowledge and gender on retail marketing strategy

Louise van Scheers* and M C Cant

University of South Africa, School of Marketing Unisa PO Box 392 Pretoria, South Africa.

Accepted 1, June 2007

Secondary research shows that consumer price knowledge and gender has an effect on retail management strategy. Consumer knowledge and expertise of industries prices, products and store location add to the ease at which consumers are able to cherry pick. Consumers are informed of discounted prices on products as well as the product assortment of a particular store, through marketing and store promotions. Cherry picking can be defined as taking the best and leaving the rest and therefore cherry picking is used to portray both buyer and seller behaviour in retailing. Various sellers can be viewed as those who are selective about which consumer profile they choose to target, whereas consumers are selective about which products or services they purchase. This article aims to establish the effect of consumer price knowledge and gender on retail management strategy. Consumers who are branded as cherry pickers are price sensitive shoppers with no brand loyalty but this market segment has been found to be sizable, heterogeneous, and potentially attractive for retailers, contrary to the myth that they are a retailers' nemesis. Price knowledge means the ability of buyers to keep prices in mind; it influences what, when, where and how much they buy. Cherry pickers build price competitions between retailers'; therefore they should strive to have the most attractive offers and weekly advertisements, in order to draw the cherry pickers in and obtaining a greater turnover.

Key words: Cherry picking Consumer knowledge consumer price knowledge price sensitive shoppers

INTRODUCTION

It has long been said that that consumer price knowledge and gender has an effect on retail marketing strategy. Consumer price knowledge and expertise of an industries prices, products and store location add to the ease at which consumers are able to cherry pick. They are informed of discounted prices on products as well as the product assortment of a particular store, through marketing and promotions. Price knowledge means the ability of buyers to keep prices in mind. Commodity prices in the market play a relevant role in consumer decision-making as they influence what, when, where and how much consumers buy (Alba et al., 1999). It is of utmost importance that retailers incorporate strategies that target and meet the needs of this type of consumer, as it will ensure a larger market share and in turn a greater ROI. The study aims to establish the effect of consumer price knowledge and gender on retail marketing strategy. The study also aims to establish whether consumer price knowledge and gender has a positive effect on cherry picking in selecting groceries and whether there is a relationship between consumer knowledge and gender.

Retail marketing strategy serve as the fundamental underpinning of marketing plans designed to reach marketing objectives. A good retail marketing strategy should integrate an organization's marketing goals, policies, and action sequences (tactics) into a cohesive whole. The objective of a marketing strategy is to provide a foundation from which a tactical plan is developed. This allows the organization to carry out its mission effectively and efficiently. Cherry picking can be described as taking the best and leaving the rest according to Fox and Hoch (2003). Cherry picking is used to portray both buyer and seller. Various sellers can be viewed as those who are selective about which consumer profile they choose to target, whereas consumers are selective about which products or services they purchase.

*Corresponding author. Email: vscheml@unisa.ac.za

Consumers who are branded as cherry pickers are price sensitive shoppers who tend to delay purchases or move from one shop to another looking for a better deal with regards to price, product variety and assortment. Levy and Weitz (2004) define cherry picking as"... consumers who visit a store and only buy merchandise sold at big discounts". Other factors that influence a consumer to cherry pick are store location, and store preference and consumer expertise/knowledge.

REASON FOR THE STUDY

There has been numerous studies conducted on the effect of cherry picking on consumer price knowledge and gender in selecting groceries in the USA and Europe but very limited research has been conducted on these two constructs in a South African context.

OBJECTIVES OF THE STUDY

The study aims to establish the relationship between consumer knowledge and gender in selecting grocery items. The study also aims to establish whether consumer price knowledge and gender has a positive effect on cherry picking in selecting groceries and whether there is a relationship between consumer knowledge and gender. To achieve these objectives of the study the following hypotheses were set:

H_1: Consumer price knowledge and gender has a positive effect on retail marketing strategy.
H_2: Consumer price knowledge and gender has a positive effect on cherry picking in selecting groceries.
H_3: There is a significant relationship between consumer knowledge and gender.

LIMITATIONS OF THE STUDY

Research was only conducted in shopping malls within the Pretoria (Tshwane) area, therefore this study is not truly representative of the South African population. No research was conducted over weekends and in the early evening; this could therefore have an impact on the final results of this study as some people conduct their shopping trips during this time. A larger percentage of females than males completed the questionnaire, and therefore this may have a bearing on the stronger results shown on females to that of males.

LITERATURE REVIEW

The literature explored in this section focuses on the effect of consumer price knowledge and gender on cherry picking in selecting groceries.

The effect of consumer price knowledge and gender on retail marketing strategy

Commodity prices in the market play a relevant role in consumer decision-making, as they influence what, when, where and how many consumers buy (Alba et al., 1999) and therefore studying consumers' price awareness is highly relevant. Price awareness or price knowledge means the ability of buyers to keep prices in mind (Aalto-Setala and Raijas, 2003). The majority of past studies on pricing have pointed out that consumers generally have very limited knowledge of prices. Price knowledge has therefore become the subject of increasing research interest. The consumers' price knowledge and genders effect on consumers' selection of grocery items can be influenced by numerous factors, which may be related to the characteristic of the consumer or the product category (Estelami, 1998). The demographic background (example; age, gender and income) of a consumer may affect their interest in products as well as their expertise as to their prices. It has been researched that females, who account for the larger percentage of pur-chases of grocery products, would be more knowledgeable about prices in this category than males (Market Research Bureau. 2004). Estelami (1998) researched the influence of demographics on price knowledge in the grocery shopping industry and therefore the following hypothesis was set.

H_1: Consumer price knowledge and gender has a positive effect on retail marketing strategy.

Venhuele and Dreze (2002) found that there are different levels of price knowledge that a consumer can be found in. In the first level, there is no price knowledge, the second level reflects recognition of large price differences but this is still not perfect. The third level represents a consumers' ability to recall a price within a 5% difference from the actual price set. The last level represents a consumer's ability to accurately recognise the actual price of a product. This level is representative of the highest and rarest form of price recall. Venhuele and Dreze (2002) also deduced that cherry picking has no impact on price knowledge, due to their increased task complexity from the average shopper.

The effect of consumer price knowledge and gender on cherry picking in selecting groceries

There are many definitions and descriptions of cherry pickers that have been compiled by various researchers (Fox and Hoch, 2003; Gauri et al., 2005; Levy and Weitz, 2004), based on these definitions, cherry pickers can be defined as ".... purchasers who cherry pickers can be

Table 1. Description of typical cherry pickers.

Type of household	Probability for cherry picking to occur
Larger households	More likely to cherry pick
Household with senior citizens	More likely to cherry pick
Household with homeownership	More likely to cherry pick
Wealthy household	Less likely to cherry pick
Household with a working adult female	Less likely to cherry pick

defined as ".... purchasers who examine the different proposals of several retailers and pick out the best over one or more days. They are characterised as price sensitive and well informed customers, as they construct pre-determined shopping trips from promotions and sales advertisements previously viewed so that the best deals are utilised".

The American Marketing Association (2004) defines cherry picking as "..... a buyer selection of only a few items from one's line and others from another line, failing to purchase a complete line or classification of merchantdise from one source". Due to the shopping style of these customers, many affected retailers question their brand and store loyalty. Gauri et al., (2005), argue against the loyalty aspect of this definition as they found that cherry pickers can indeed be store loyal as they delay their shopping trip over time in order to get a better price deal at the same store.

Secondary research done by the American Marketing Association (2004) shows that cherry pickers either keep a different reference price for each store they pick from or create an average reference price from several different sources. This may also lead to the lack of price knowledge. We will investigate if this statement holds true for the South African industry, therefore the following hypothesis was set:

H_2: Consumer price knowledge and gender has a positive effect on cherry picking in selecting groceries.

Although it is important that consumers are informed of the different prices offered at various places, it will benefit them even more if they have a general understanding of the retail industry as a whole. Findings from the research conducted by Fox and Hoch (2003) indicate that this market segment is sizable, heterogeneous, and potentially attractive for retailers, contrary to the myth that they are a retailers' nemesis. The composition of the main decision-makers in a household and their different characteristics could determine cherry picking to a greater or lesser extent (Fox and Hoch. 2003). See Table 1 below for a better description.

Adapted from: Fox and Hoch, 2003. Cherry Picking. Journal of Marketing. 69(1). [Online] Available from: http://proquest.umi.com [Accessed: 24/01/2006]. From the deductions made above in Table 1, one can conclude that cherry picking has a meaningful influence on the retail industry from an economic point of view, and therefore is a cause of concern for the affected retailers of today. A consumers understanding and intellect of the retail industry has a significant influence on their propensity to cherry pick. Consumer knowledge will therefore be discussed as the next important construct put under investigation in this study.

Consumer knowledge and gender

Consumer knowledge or expertise is generally defined as a consumers' confidence or experience in shopping. Knowledgeable consumers are those who are well informed or "clued up" on the prices of products, the types of stores as well as product assortment. These consumers generally feel comfortable in sharing this knowledge with others as they see themselves as a good source of reference. Consumers inform themselves by searching for information on promotional material and constantly updating themselves on the latest product on the market or price specials at certain stores. If a consumer is enlightened through various media channels and word of mouth, they begin to store this information in their memory and begin to feel confident in their knowledge and therefore if information is required from them, they share it with the thought of being a good source of information.

H_3: There is a significant relationship between consumer knowledge and gender

The method of analysis chosen and the results thereof will is discussed next.

METHODOLOGY

The sampling, data collections and measures of the research is analysed in this section.

Sampling

Grocery shoppers were the targeted population of this study. The sample was targeted through the use of mall intercept and interviewer-administrated personal interviews at a variety of shopping malls. The sampling frame was obtained from different shopping malls found in Pretoria (Tshwane), South Africa, based on convenience. Shopping malls found in areas representing the different

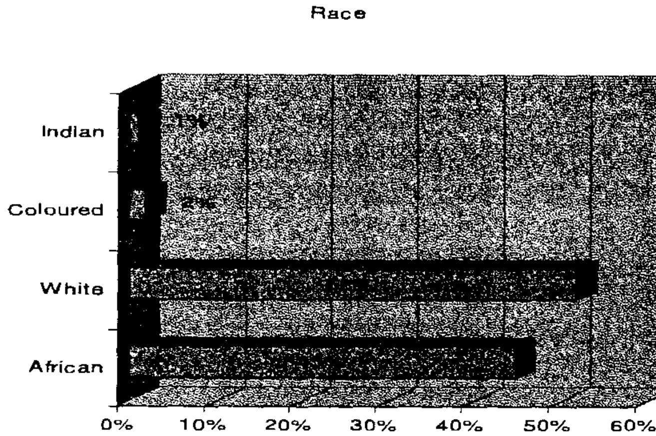

Figure 1. Socio-demographic profile – race.

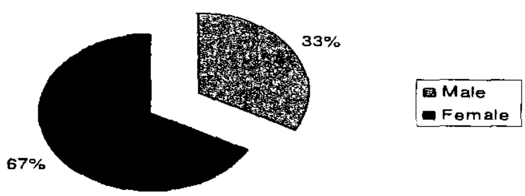

Figure 2. Socio-demographic profile – gender

LSM groups were targeted, thus affording the researchers a closely representative sample of the population of Pretoria (Tshwane).

A realised sample size of 176 was obtained from a target sample size of 250 with 100% of the questionnaires being usable. This could be attributed to the use of personal interviews as a data collection method. The data collection method is now discussed in more detail.

Data collection

A pilot study was conducted on the questionnaire through 10 quasi interviews. Respondents were selected based on convenience and only the "main family grocery shopper" was allowed to participate.

Data collection took place over a span of three days through the use of personal interviews at ten different shopping malls within the Pretoria (Tshwane) region. Well trained interviewees were used to conduct the research, thus decreasing the chance of error and bias. According to Tustin et al (2005) personal interviews are regarded as one of the most viable options to use in testing variables like cherry picking and consumer knowledge. Three different times slots in the day where used (morning, afternoon and early evening) where upon research was conducted, thus allowing the researches to capture a wider spread of respondents

Measures

This study's main constructs of consumer price knowledge, cherry picking and gender was measured through the use of Likert-type scales as opposed to the demographic variables (income, age, and gender) whose questions delivered only nominal data. The basic scale design therefore consisted of a Likert-type scale with five scale points (with labels ranging from strongly agree to strongly disagree and not well informed to very well informed). This scale was found to be highly reliable with a Cronbach's Alpha of above 0.7. No items on any of these scales were reverse scored. The results of the study are shown below.

RESEARCH RESULTS

In this study the research results were described by using descriptive statistics and inferential statistics.

Descriptive statistics

The study shows that the majority of respondents who participated in this study were female (67%) with an average age of between 24 and 28 years (30%). A relatively diverse spread of language across respondents was obtained with most respondent's preferred language being Afrikaans (50%) and 37% of the respondents English as their preferred language while only 13% speak North Sotho. The race of the respondents was an important variable in indicating what effect price knowled-ge and gender has on a consumers' propensity to cherry pick and the response is summarized in Figure 1.

From the data represented above in Figure 1, the response with regards to the race of the respondents, it seems that 52% of the respondents were white and 45% were African, compared to 2 percent coloured and one percent Indian respondents. The outcome of this statistic can possibly be explained due to the selection of shopping centres during data collection.

It can be clearly seen from Figure 2 that the majority of the respondents who completed the questionnaires where females, showing a strong 67% compared to the 33% of male respondents. This can also be explained due to the time periods in which data collection took place. The bulk of the data collection took place in the morning, early afternoon and late afternoon, therefore the majority of the respondents were housewives and senior citizens with a

Table 2. Pearson correlation between consumer price knowledge, gender and retail marketing strategy.

Data		Correlation between consumer price knowledge, gender and retail marketing strategy	Total: consumer price knowledge, gender and retail marketing strategy
Correlation between consumer price knowledge, gender and retail marketing strategy	Pearson Correlation	1	.047
	Sig. (2-tailed)	.	.348
	N	167	166

Table 3. Cross-tabulation of price knowledge and gender

		Male	Female
How informed are female and male respondents with regard to prices of products?	Not very well informed	60%	30%
	Indifferent	16%	17%
	Very well informed	24%	53%
Total		100%	100%

smaller percentage of the working population. The hypotheses set for this study are stated in the next section from which the above was tested and analyzed.

Inferential statistics

In this study the researchers describe the sample data as means, standard deviation and proportions but also wish to make inferences about the population based on what was observed in the sample. Inferential statistics allow researchers to make inferences concerning the true differences in the population (Tustin et al., 2005).

The effect of consumer price knowledge and gender on retail marketing strategy

The gender of consumers may have an influence on their interest in products and their expertise as to their prices which may affect the retail marketing strategy. It has been researched that females, who account for the larger percentage of purchases of grocery products, would be more knowledgeable about prices in this category than males (Market Research Bureau, 2004). This study would like to investigate if this statement holds true for grocery items purchased in South Africa. To achieve the objecttives of the study, to determine the price knowledge and gender relationship of consumers when they do grocery shopping, the following hypotheses were formulated:

H_{01}: $\mu 1 \neq \mu 2$
H_{A1}: $\mu 1 = \mu 2$

In analysing $H0_2$, the researchers conducted a Pearson Correlation test between the variables; consumer price knowledge and gender. From the results indicated in Table 2, it shows that there is a significant relationship between the two as the p-value is 0.047 for both at a 0.05 significant level. When conducting the z-test, H02 was rejected therefore accepting Ha1. Therefore, by accepting Ha1, one may conclude that there is a significant correlation between price knowledge and gender. The table below portrays the results of a cross tabulation between the two constructs tested in this hypothesis.

Table 3 shows that 53% of the female respon-dents are of the opinion that they are well informed about prices of grocery products compared to 24% of the male respondents. Table 3 also shows that 60% of the male respondents admit that they are not very well informed compared to only 30% of the female respondents. The study shows that females are more knowledgeable about prices of grocery products.

The effect of consumer price knowledge and gender on cherry picking in selecting groceries

The research aims to establish whether consumer price knowledge and gender has a positive effect on cherry picking in selecting groceries in South Africa and therefore the following hypotheses were set:

H_{02}: $\mu 1 \neq \mu 2$
H_{A2}: $\mu 1 = \mu 2$

Table 4 indicates the Pearson correlation on the effect of consumer price knowledge and gender on cherry picking in selecting groceries. These variables were correlated through the use of the Pearson Correlation test. The results show that there is a significant relationship between these variables with the p-value of 0.037 on a 0.05

Table 4. Pearson correlation on the effect of consumer price knowledge and gender on cherry picking.

Data		Effect of cherry picking on consumer price knowledge and gender	Total: price shop across stores and gender
Effect of cherry picking on consumer price knowledge and gender	Pearson Correlation	1	.037
	Sig. (2-tailed)	.	.348
	N	167	166

Table 5. Pearson correlation between consumer knowledge and gender.

Data		Correlation between price knowledge and gender	Total: price knowledge and gender
Correlation between price knowledge and gender	Pearson Correlation	1	.045
	Sig. (2-tailed)	.	.348
	N	167	166

significant level, therefore the null hypothesis is rejected as 0.037 is smaller than the p-value. The study shows that consumer price knowledge and gender has a positive effect on cherry picking in selecting groceries.

From the results found above it can be concluded that South African consumers are able to confidently cherry pick over more than one day due to their increased knowledge of prices offered on different products at different stores. If consumers have a broader knowledge of prices they are able to participate in the act of cherry picking easier than a consumer who has selected knowledge thereof.

Consumer knowledge about product prices, type of stores and product assortment and gender

Consumer knowledge as indicated in paragraph 5 is the consumers' confidence or experience in shopping. Knowledgeable consumers are those who are well informed on the prices of products, type of stores as well as product assortment. The respondents were asked whether they know a lot about product prices, type of stores as well as product assortment. The response is summarized in Figure 3.

From Figure 3 it is clear that female respondents are more knowledgeable about product prices, type of stores and product assortment. From the female respondents, 65% indicated that they are well informed, compared to 35% of male respondents.

The research also aimed to establish whether gender has an influence on the knowledge that the South African consumers have on the prices of products, type of store and product assortment and therefore the following hypotheses were set:

H_{03}: $\mu1 \neq \mu2$
H_{A3}: $\mu1 = \mu2$

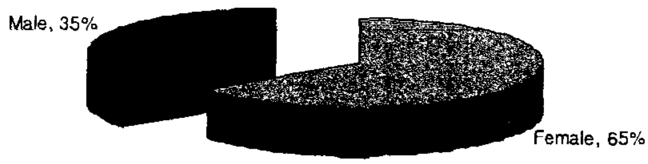

Figure 3. Knowledge about product prices, type of stores as well as product assortment.

In Table 5, the variables were correlated through the use of the Pearson Correlation test. The results show that there is a significant relationship between these two variables with the p-value of 0.045 on a 0.05 significant level, thus the null hypothesis is rejected as 0.045 is smaller than the p-value. From the results found above it can be concluded that there is a significant relationship between consumer knowledge and gender and that gender has an influence on the knowledge that the South African consumers have on product prices, type of stores and product assortment.

MANAGERIAL IMPLICATIONS

Knowledge regarding cherry picking behaviour will enable retailers to get a higher wallet share from even its price sensitive shoppers, while at the same time charging higher prices for its price insensitive customers. The retailers must be aware of the fact that much of the savings on cherry picking trips is due to the purchase of more promotional items, where savings is subsidised by manufacturer discounting. Thus, the burden of cherry picking is borne by both retailer and manufacturer. The implication of marketing for retailers is what they need to find a balance between "specials" and cherry pickers as well as "regular" customers. This is important for the survival of the retailer over time.

Retailers must also make an effort to embrace this segment as it accounts for such a large percentage of the population. Cherry pickers build price competitions between retailers', therefore they should strive to have the most attractive offers and weekly advertisements, in order to draw the cherry pickers in and obtaining a greater turnover.

RECOMMENDATIONS FOR FUTURE RESEARCH

Research could be extended and conducted over weekends and in the earlier evening, thus taking into consideration the working population who only get the chance to conduct their shopping trips during these periods. A larger sample of South Africa needs to be considered in order to create a "truer" representation of the shopping habits of South Africans. A 50-50 sample population with regards to men and women should be attained in order to measure the true level of price knowledge and consumer knowledge.

REFERENCES

Aalto-Setala V, Raijas A (2003). Actual market prices and consumer price knowledge. J. Prod. Brand Manage. 12(3):180-192

Alba JW, Mela CF, Shimp TA, Urbany JE (1999). The effect of discount frequency and depth on consumer price judgements. J. Consumer Res. 26: 99 -114

American Marketing Association. 2004. Cherry picking. [Online] Available from: http://www.marketing power.com/mg-dictionary-view541.

Blackwell RD, Miniard PW, Engel JF (2006). Consumer behaviour: Mason: Thomson South-Western. pp. 34-78

Brink A, Berndt A (2004).. Customer Relationship Management.
South Africa:Juta. pp 25-62

Cant MC, Brink A, Brijball S (2006). Consumer behaviour. South Africa: Juta. . p. 65

Churchill GA, Iacobucci D (2002). Marketing research- Methodological Foundations:Orlando: Harcourt College Publishers. pp 234-238

Estelami H, (1998). The price is right... or is it? Demographic and category effects on consumer price knowledge. J. prod. brand manage. I 7 (3):254-266

Fox EJ, Hoch, SJ (2003). Cherry Picking. J. Mark. 69(1). [Online] Available from: http://proquest.umi.com

Gauri DK, Sudhir K, Talukdar D (2005). "When" and "Where" to Cherry Pick? The Temporal and Spatial Dimensions of Price Search. [Online] Available from: www.google.com

Levy M, Weitz BA (2004). Retailing Management. 5th edtion. New York: McGraw-Hill Irwin. pp. 142-149

Popkowski Leszczyc, PL Timmermans HJP (1997). Store switching behaviour. Marketing letter 8:2. Netherlands. Kluwer Academic Publishers. pp. 2-6.

Simmons Market Research Bureau. (1994). *Choices II System.* Simmons Inc. New York. P. 54

Vanhuele M, Dreze X (2002). Measuring the price knowledge shoppers bring to the store. J. mark. 66: pp 72-85