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Brand Loyalty and Price Promotion Strategies: An Empirical Analysis[☆]

William J. Allender*, Timothy J. Richards

Arizona State University, United States

Abstract

Though brand loyalty has been studied extensively in the marketing literature, the relationship between brand loyalty and retail pricing strategies is not well understood. Designing promotion strategies involves two key decisions: the percentage reduction in price from the existing price point (depth), and the frequency with which a product is promoted. These decisions, in turn, are critically dependent upon how many consumers can be convinced to switch to a brand by temporarily reducing its price, and how many are instead brand loyal. Theoretical models of how the strength of brand loyalty influence optimal promotion strategies have been developed, but there are no rigorous tests of their hypotheses that take into account wholesale price variation. We test how brand loyalty impacts promotion strategies for two frequently purchased consumer packaged good categories. Our results confirm that retailers promote strong brands shallower and more frequently compared to brands with weak loyalty. Our results highlight the importance of carefully modeling wholesale prices when testing behavioral models on retail pricing.

Keywords: Price promotion; Brand loyalty; Discrete choice model; Ice cream; Carbonated soft drinks

Introduction

Recent estimates indicate that consumer packaged good manufacturers allocate fully 58% of their marketing expenditure toward sales promotion (Low and Mohr 2000). Although not all of this investment is passed through to consumers by retailers, the importance of retailers' promotion decisions to their own economic performance is clear. What drives promotion by retailers, however, is only partly understood. While much of the early research focused exclusively on demand-side explanations for observed promotion behavior (Varian 1980; Butters 1977), more recent studies combine cost and demand considerations (Agrawal 1996; Gedenk and Neslin 1999; Raju, Srinivasan, and Lal 1990). Explaining how retailers make promotion decisions, and what these decisions are, is critical to understanding the retailing function more generally. In general, we know that retailers promote products because they can derive higher margins by price discriminating between groups of high and low demand. One way of defining high versus low demand considers whether consumers are brand loyal. Consumers often express loyalty to a particular consumer packaged good (CPG), so this study provides an empirical examination of how brand loyalty influences retail price-promotion decisions in two highly differentiated, frequently-purchased CPG categories: carbonated soft drinks (CSD) and ice cream.[1]

There are a number of competing theories as to how price promotions work, but common among them is the notion that the market can be segmented into groups of consumers that vary by the strength of their demand. Strength of demand, in turn, depends on whether the consumer is: informed or uninformed (Burdett and Judd 1983; Carlson and McAfee 1983; Varian 1980), high search-cost or low search-cost (Rob 1985; Stigler 1961), high or low willingness-to-pay (Jeuland and Narasimhan 1985; Pesendorfer 2002), high inventory-cost or low inventory-cost (Aguirregabiria 1999; Blattberg, Eppen, and Lieberman 1981) or are loyal to a brand or store (Agrawal 1996; Lal and

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* Corresponding author at: Morrison School of Management and Agribusiness, Arizona State University, 7001 E. Williams Field Rd. Bldg. 130, Mesa, AZ 85212, United States. Tel.: +1 480 727 1488; fax: +1 480 727 1961.

E-mail address: William.Allender@asu.edu (W.J. Allender).

1 A household is defined as being loyal to the brand that it is most likely to buy on each purchase occasion, controlling for all other factors that may influence purchase probability (Agrawal 1996). Strength of loyalty refers to the size of the price differential between a consumer's preferred brand, and one that is less preferred, before he or she will switch brands.

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Villas-Boas 1998; Raju, Srinivasan, and Lal 1990; Villas-Boas 1995). Promotions, or sales, allow retailers to price-discriminate between the two groups. For frequently-purchased consumer goods, however, information or inventory-based explanations are not likely given the nature of the product, so loyalty or intensity of demand is the more plausible explanation. Moreover, because loyalty and intensity are empirically similar according to the definition used by Agrawal (1996), we focus on brand loyalty to explain two aspects of promotion design: *depth* which is defined here as the percentage reduction in price from the existing price, and the *frequency*, or average number of times an individual brand is promoted over a specified time period (a year for example) (Raju 1992; Srinivasan et al. 2004).

Recognizing the connection between brand loyalty and promotion is not new. Raju, Srinivasan, and Lal (1990) develop a theoretical model of manufacturer competition that explains how differences in consumer loyalty leads to variations in the depth and frequency of price promotions offered by brands in the same product category. Recognizing that consumers buy from retailers, not manufacturers, Agrawal (1996) extends the theoretical model of Raju, Srinivasan, and Lal (1990) to include pricing behavior by retailers and the effect manufacturer advertising levels have on retailers' promotion decisions. His model suggests that a retailer will offer deeper discounts for brands with little brand loyalty, but promote them less often. Similarly, Jing and Wen (2008) assume consumers will switch to a preferred brand given a sufficient price discount, but also include the possibility of a consumer segment that is completely price sensitive. They find that the equilibrium promotional strategy depends critically on brand strength and the number of price sensitive consumers, therefore, models of brand loyalty and promotion should allow for switching behavior by consumers. We allow for both loyalty and brand substitution in our empirical models of CSD and ice cream demand.

It is also well-understood that retail pricing is strongly influenced by wholesale prices, although retail pass-through is not necessarily perfect (Nijs et al. 2010). This observation presents an empirical problem for researchers interested in explaining retail pricing decisions, however, as wholesale prices are rarely observed (Berto Villas-Boas 2007). Consequently, we estimate a model of vertical pricing relationships in both the CSD and ice cream markets to recover wholesale prices under only weak assumptions regarding wholesaler and retailer conduct. In this way, we are able to isolate changes in retail prices that are due solely to profit-maximizing decisions by retailers, conditioned on the prices they pay to wholesalers.

We empirically model the relationship between the strength of brand loyalty and retail promotion decisions, while controlling for variation in unobserved wholesale prices. Retailers are assumed to make two related decisions when promoting a particular brand: (1) the depth of the promotion, and (2) the frequency of promotions for that brand. As such, our study contributes to the literature on retail pricing and brand loyalty. Namely, our study is the first to investigate how brand loyalty affects the key decisions retailers face in designing promotions (depth and frequency) while accounting for variation in unobserved wholesale prices. While others admit the central role played by wholesalers in the retail promotion decision, none incorporate wholesale price information into their empirical analysis. Unobserved wholesale prices are included in our analysis using methods recently developed in the empirical industrial organization and quantitative marketing literatures.

This empirical framework allows us to test a number of hypotheses that emerge from the theoretical literature on the relationship between brand loyalty and the depth and frequency of promotion. The first hypothesis is that the average price discount at the retail level is negatively related to the strength of brand loyalty (Agrawal 1996). The second maintains that the frequency of price promotions is positively related to the strength of loyalty (Agrawal 1996). Our findings broadly support both hypotheses, even after controlling for variation in wholesale prices. The intuition behind these findings is straightforward – if retailers deeply discount strong brands, they not only forgo the price premium, but also the potential margin made on the weaker brand. Promotion decisions made by retailers differ from those made by manufacturers (Raju, Srinivasan, and Lal 1990), because retailers are concerned with category profit and not the profit from individual brands.

The remainder of the paper is organized as follows. In the next section, we provide a theoretical justification for the hypotheses tested with the empirical model. In the third section we describe the empirical techniques used to determine the relationship between brand loyalty and retail price promotions. We start by giving a general overview of the section followed by a description of the household demand model used to measure brand loyalty, then the market demand model used to estimate the wholesale prices paid by retailers. We conclude the third section with a detailed explanation of the retail price promotion models. The fourth section describes the econometric methods used to estimate each of the models. The fifth describes the data used in our empirical application while the results are presented in the sixth section. The final section concludes, offering some implications for the interaction between brand loyalty and promotional relationships in practice, and provides suggestions for future work in the area.

Theoretical brand loyalty background

In this section, we summarize the theoretical model of Agrawal (1996) and its predictions for retail price behavior. The model assumes two competing manufacturers sell through a common retailer.[2] The manufacturers play a three-stage game. In the first stage, they set advertising levels simultaneously without knowing each other's strategy. In the second stage, they quote wholesale prices to the retailer without knowing their rival's offer, but observing the prior stage advertising decisions. In the third stage, the retailer decides the prices to sell to the consumer and whether a price promotion is offered on one or more brands after observing wholesale prices. The market consists of consumers who are loyal to either one brand or the other, but can

[2] Although this abstracts from strategic pricing behavior by retailers, there is empirical evidence that retailers behave as local monopolists (Slade 1995).

be induced to switch if the price of their non-favored brand is low enough. In other words, brand loyalty is defined as the magnitude of a price promotion required to induce a consumer to switch from their preferred brand, or the one they are loyal to, to their non-preferred brand. Specifically, the brands are differentiated in the sense that consumers loyal to the stronger brand require a deeper discount to switch to the weaker brand relative to consumers loyal to the weaker brand. The game is solved by backward induction, and conclusions drawn for the optimal strategy at each stage. In this study, we focus on the latter two stages of this game as we are concerned only with retailer pricing strategies.

Retail pricing involves two key decisions: (1) the depth of the promotion (the percentage reduction in price from the existing price), and (2) the frequency with which a particular product is promoted (average number of promotions over an observed time period).[3] Agrawal (1996) finds that a monopoly retailer facing a market with asymmetric loyalty (a brand with strongly loyal customers and a brand with weakly loyal customers) faces three possible outcomes depending on his/her wholesale cost: (1) "... if the stronger brand is sufficiently cheaper than the weaker brand, promote the stronger brand and sell it to both consumer segments; (2) if the weaker brand is sufficiently cheaper than the stronger brand, promote the weaker brand and sell it to both consumer segments; and (3) if the two brands are not sufficiently different in wholesale prices then do not promote either brand, and sell each to its loyal segment" (p. 91). The intuition driving this conclusion is straightforward. Because retailers are only concerned about category profit, their pricing decisions seek to maximize the share of the product that provides the highest margin between the retail and wholesale prices. To make sense, a trade deal given by a wholesaler must ensure that the margin on the promoted product provides greater profit when sold to the entire market, relative to when each product is sold to its loyal segment at the non-promoted price.

This pricing rule leads to two hypotheses regarding the relationship between the frequency and depth of discounts as they relate to brand loyalty at the retail level. First, deeper price promotions are given for the weaker brand in comparison to the stronger brand. This result follows directly from the optimal pricing strategy because the weaker brand has to be offered by the retailer at a larger discount in order to attract the stronger brand's loyal customers. In other words,

- H_1: the average price discount at the retail level is negatively related to the strength of brand loyalty.

Second, because the likelihood of attracting consumers loyal to the stronger brand by promoting the weaker brand is low, the retailer will promote the stronger brand more frequently. In other words,

- H_2: the frequency of price promotions at the retail level is positively related to the strength of brand loyalty.

Because these hypotheses follow directly from the model described above, their support or rejection will give valuable insight into the underlying assumptions of the theoretical model. We test these hypotheses using an econometric model of price promotions in the CSD and ice cream market.

Econometric model of retail price promotion

Overview

Our econometric model is estimated in three stages.[4] Our objective in the first-stage is to obtain brand-specific measures of loyalty strength. For this purpose, we use household-level purchase data to estimate demand models for CSD and ice cream brands, from which we infer loyalty. In the second stage, our aim is to estimate supply-and-demand models of each vertical channel in order to calculate unobserved wholesale prices (Berto Villas-Boas 2007; Draganska and Klapper 2007). Because we need to model the entire market for CSD and ice cream, we use aggregate, store-level scanner data for stage two. In the third stage, we combine our household-level and market-level estimates to estimate the relationship between retailers' price promotion strategies – as measured by the depth and frequency of promotion for each brand – to the loyalty and wholesale prices obtained from the first two stages.

Stage 1. Household-level brand-loyalty estimates

In the first stage, estimates of brand loyalty are obtained by estimating a random-utility household demand model for each product. Random-utility modeling in marketing is a well-understood method, so we summarize the unique features of our application here (Guadagni and Little 1983; Jain, Vilcassim, and Chintagunta 1994; Nevo 2001).[5] Random-utility models are ideally suited to estimating loyalty because they capture variation in demand for differentiated consumer products by households with heterogeneous tastes. Utility for a sample of $h = 1, 2, \ldots, H$ households and $b = 1, 2, \ldots, B$ brands and $t = 1, 2, \ldots, T$ purchase occasions is written as:

$$u_{hbt} = \eta_{0b} + \eta_1 dc_{bt} + \eta_2 dc_{bt} p_{bt} + \eta_3 pp_{hbt} - \eta_4 p_{bt} + \xi_{bt} + \epsilon_{hbt} \quad (1)$$

where η_{0b} is a set of binary variables that measure brand-specific preferences, dc_{bt} is a binary indicator of whether a brand is offered on a discount, which is equal to 1 if brand b was discounted more than 10% from one week to the next, and $dc_{bt}p_{bt}$ is an interaction term between the retail price and the discount

[3] Note that measuring frequency as the average number of promotions over a specified time period is equivalent to Agrawal's (1996) probability of offering a product on sale each week.

[4] For the sake of clarity there is a summary of the terms and definitions used throughout this section in an appendix at the end of the paper.

[5] Technical details are provided in the appendix.

(Chintagunta 2002). *The interaction term between prices and the discount variable ($dc_{bt}p_{bt}$) allows for the possibility that promotions both shift and rotate the demand curve so we allow items on promotion to become either more or less price-elastic*. Brand b's retail price at time t is represented by p_{bt} and ξ_{bt} is an error term that accounts for variation in demand that may be apparent to the household, but not the econometrician. We assume the error term ϵ_{hbt} is i.i.d. type I extreme value distributed, so the utility specification in Eq. (1) implies a multinomial logit (MNL) demand model. We address the "independence of irrelevant alternatives" (IIA) property of logit demand models by allowing the parameters η_3 and η_4 to vary randomly over households.

Utility also includes a measure of household "propensity" toward a brand (pp_{hbt}), where propensity is defined as a household's tendency to purchase the same brand on successive trips to the store. Propensity is defined more formally as a weighted-average of a household's propensity in the previous period (pp_{hbt-1}) and new information from the most recent purchase (y_{hbt-1}) so that propensity is written:

$$pp_{hbt} = \delta pp_{hbt-1} + (1+\delta)(y_{hbt-1} - pr^{I}_{hb}) \tag{2}$$

where y_{hbt-1} is equal to 1 if brand b was chosen at $t-1$ and 0 otherwise, δ is a smoothing parameter equal to 0.75 (Agrawal 1996) and pr^{I}_{hb} is the initial probability household h purchases brand b. Honoré and Kyriaziduo (2000) show that at least six purchase occasions are enough to obtain the initial estimate of pr^{I}_{hb}, so we use the first seven observations from each household's purchase history. This measure of propensity increases when a brand is chosen in successive periods, and decreases if not.

Next, we use estimates of Eq. (1) to determine each household's brand loyalty. We follow Agrawal (1996) in defining loyalty as the brand each household is most likely to purchase on each shopping trip, holding all elements of the marketing mix, including prior propensity to purchase, constant.[6] The purchase probability for each brand and household is calculated using the estimates of Eq. (1) and our logit demand assumption. Brand preference is then restricted to zero for all the other brands because, logically, a household can only be loyal to a single brand.

Once we have loyalty measures for each household, the strength of loyalty for each brand is calculated by averaging the implied purchase probability for each brand over all households loyal to brand b, or:

$$pref_b = \frac{1}{H_b}\sum_{h}\widehat{Pr_{hT}(b)} \tag{3}$$

where H_b is the number of household loyal to brand b. This measure reflects the average strength of loyalty among those households loyal to brand b.[7]

Stage 2. Pricing model for the CSD and ice cream markets

In the second stage, we obtain wholesale prices by estimating pricing models of the CSD and ice cream markets. Pricing models require the specification of both a demand and a supply side. On the demand side we model consumer purchases using a random-utility model similar to the one used in stage 1, but applied to aggregate, store-level data rather than household data. On the supply side we assume manufacturers and retailers compete among themselves in prices (Bertrand-Nash) as is common in the empirical marketing literature (Besanko, Dube, and Gupta 2003; Choi 1991; Draganska and Klapper 2007). Because wholesale prices are not observed in our scanner data, we use the margins implied by Bertrand-Nash competition and the nature of our demand estimates to infer a wholesale price series as in Draganska and Klapper (2007) and Berto Villas-Boas (2007). We begin by explaining the demand component, and then pricing decisions by retailers and manufacturers.

Consumer demand is represented by a random utility model in which consumers are assumed to make a hierarchical decision regarding the choice of store and, once this decision is made, the choice of brand from the set of all brands being offered, or make no purchase at all.[8] This latter alternative forms the outside option. Utility u_{ibkt} for consumer i obtained from purchasing product b on purchasing occasion t at store k is given by:

$$u_{ibkt} = \boldsymbol{\gamma}^{\top}\mathbf{z}_{bkt} - \alpha_i p_{bkt} + \xi_{bkt} + \varsigma_{ikt} + (1-\sigma_K)\varepsilon_{ibt} \tag{4}$$

where ξ_{bkt} is an error term that accounts for all product-specific variations in demand that are unobserved by the econometrician such as the amount of shelf space allocated to each product or the amount of national advertising. The set of brand-specific variables $\mathbf{z}_{bkt}$ contains an intercept term ($\boldsymbol{\gamma}_0$) which represents the average product-specific preference parameter, quarterly binary variables (Q_i) that accounts for differences in demand due to seasonal or weather changes, and other brand-specific attributes similar to those described above.[9] Product b's price in store k is represented by p_{bkt}. We explicitly account for the hierarchical nature of a consumer's choice process by using a generalized extreme value (GEV) or nested logit model (McFadden 1980). Partitioning the choice set by stores represents a natural choice because consumers are more likely to substitute among choices within a store than comparing the same choice across stores

[6] Brand loyalty is a complex concept, both theoretically and empirically. Guadagni and Little (1983) define loyalty in terms of the tendency toward repeat purchase of the same brand and package size using an exponential-smoothing algorithm. By this measure, if a household buys the same brand on successive shopping occasions, it is apparently brand loyal. However, such a construct is easily confounded with other mechanisms that may lead to state dependence in demand: learning, habit, transactions cost or even addiction. Agrawal (1996), on the other hand, recognizes that loyalty is an inherently latent construct that can be recovered as a component of unobserved differences among households. Therefore, we follow Agrawal (1996) closely in calculating brand loyalty using our sample households.

[7] The measures $pref_b$ closely follow Agrawal (1996), so we provide only a brief formal development of the construct here. Readers seeking more detail are referred to Agrawal (1996).

[8] We refer to the item of choice as a "brand" for simplicity although each brand may offer several unique universal product codes (UPC). The specific elements of the choice set are explained in more detail below.

[9] Note: $\gamma^{\top}z_{bkt} = \gamma_0 + \gamma_1 dc_{bt} + \gamma_2 dc_{bt}p_{bt} + \gamma_3 Q_1 + \gamma_4 Q_2 + \cdots$

(Smith 2004). In a nested logit model, the parameter σ_K measures utility-correlation within each nest (store). If $\sigma_K = 1$ the correlation among stores goes to 1 and stores are regarded as perfect substitutes, but if $\sigma_K = 0$ stores are not substitutes at all and a simple logit is more appropriate. As in the household-level model, we avoid the IIA property implied by our logit assumption by allowing the price response parameter (α_i) and the intercept term ($\boldsymbol{\gamma}_0$) to vary randomly.

Conditional on our demand estimates, retail and wholesale pricing decisions are modeled as the solutions to a pricing game between wholesalers and retailers in each product's supply chain. The nature of the game is wholesaler-Stackelberg (Berto Villas-Boas 2007; Besanko, Dube, and Gupta 2003; Choi 1991; Villas-Boas and Zhao 2005), meaning that wholesalers first set prices paid by retailers, who then set prices to consumers in Bertrand-Nash competition among themselves. The game is solved backwards – beginning with the retailers' problem and then solving the wholesalers' problem conditional on the retailers' choices. Details are available in the Appendix A. Because we do not observe wholesale prices, we exploit the Bertrand-Nash assumption and impute them from the retail first order conditions. Based on the imputed wholesale price estimates, we estimate manufacturing costs from the wholesalers' optimization problem. In other words, we obtain an estimate of the wholesale price (w_{bkt}) each retailer k pays for brand b at time t which is essential in isolating the effect brand loyalty has on the retailer's price promotion decision.

Stage 3. Retail price promotion model

In the third stage we test the hypotheses regarding the relationship between brand loyalty and the depth and frequency of price promotions using a regression model. Brand loyalty, however, is likely to be endogenous in this model. Therefore, we estimate the depth and frequency system using an instrumental variables estimator (systems generalized method of moments, SGMM). Our instruments include binary product indicators, on their own and interacted with quantity sales lagged one week. Further, we use wholesale prices from other markets, interacted with brand-specific indicators as additional identifying variables. This identifying assumption has been used elsewhere in data similar to that used here (Berto Villas-Boas 2007).

Our first hypothesis is that the strength of brand loyalty and the depth of retail price promotions are negatively related. Price promotions are used to attract consumers away from the other brand in order to increase category profit, so a retailer will only promote a strong brand if the profit from doing so is greater than what the retailer could otherwise obtain from selling both brands to their respective loyal cohorts (Agrawal 1996). Our second hypothesis concerning the frequency of price promotions suggests that it is positively related to the strength of brand loyalty. Because the stronger brands commands a significant price premium among its loyal customers the retailer earns higher margins on that brand even after a promotion, so the stronger brand is more likely to be promoted from one week to the next.

We define the depth and frequency of promotions in ways that are consistent with the empirical literature. Depth is defined as the percentage discount from the price in the previous week, and frequency is defined as the number of times a product is promoted over our observed time period (Raju, Srinivasan, and Lal 1990; Srinivasan et al. 2004).[10]

A retailer's promotion strategy is modeled as a function of the strength of brand loyalty ($pref_b$– described in Eq. (3) above), the wholesale price (w_{bkt}), and a vector of variables $\mathbf{v}$ which includes a time trend (t) measured in weeks, binary seasonal variables (S_i) to account for seasonal promotions effects, binary market variables (M_i), binary brand indicators to account for brand specific promotional strategies (B_i) that are independent of the brand's loyalty, and a variable indicating the discount offered in the previous week (d_{bkt-1}).[11] By including the previous week's discount as an explanatory variable we can account for the possible endogeneity of brand loyalty which can erode over time as a result of too many promotions (Gedenk and Neslin 1999). The estimated model for promotion depth is written as:

$$d_{bkt} = \phi_0 + \phi_{pref}\, pref_b + \phi_w w_{bkt} + \boldsymbol{\phi}^\top \mathbf{v} + \varepsilon_{1bt} \quad (5)$$

where ϕ_0 is the intercept term, ε_{1bt} is the error term which we assume is i.i.d., and $\boldsymbol{\phi}$ is a vector of parameters to be estimated. The hypothesis that the depth of the price discount at the retail level is negatively related to brand loyalty (H_1) implies: $\phi_{pref} < 0$.

A similar test is developed for the frequency of price promotions. Promotional frequency (f_{bk}) is operationalized as the average number of times the brand is discounted at least 10% from one week to the next over the sample period (Agrawal 1996). The loyalty-frequency model is written:

$$f_{bk} = \theta_0 + \theta_{pref}\ pref_b + \theta_w\ w_{bkt} + \boldsymbol{\theta}^\top \mathbf{v} + \varepsilon_{2bt} \quad (6)$$

where θ_0 is the intercept term, ε_{2bt} is the error term which we assume is i.i.d., and $\boldsymbol{\theta}$ is a vector of parameters to be estimated. The variables in $\mathbf{v}$ are the same as in Eq. (5).[12] The hypothesis that the frequency of retail price promotions is positively related to the strength of brand loyalty (H_2) implies: $\theta_{pref} > 0$. We test these hypotheses using the data described next.

Data description

Carbonated soft drinks

Estimating the entire model requires retail level data on prices, product characteristics, and household purchase information. We use Nielsen research group's Scantrack data for the CSD

[10] Note that frequency and probability are observationally equivalent when frequency is defined as the average number of promotions per period.

[11] The holidays include: Martin Luther King Day, Presidents' Day, Easter, Mother's Day. Memorial Day, Father's Day, 4th of July, Labor Day, Halloween, Veterans Day, Thanksgiving, and Christmas. Specifically, we include a binary variable equal to 1 if a holiday occured in that week and 0 otherwise.

[12] Because there are so many binary variables we could not indentify the price promotion equations when indicator variables were included for each brand. We therefore included as many brand indicator variables as possible, and focused on keeping those indicator variables for the brands with the highest market share. Specifically, we estimated models (5) and (6) with all of the indicator variables included and removed one at a time, starting with the brand that had the lowest market share, until we were able to identify the model.

category, which measures weekly retail sales, and their Homescan data which measures household purchases. Nielsen requires households participating in Homescan to submit all food purchase information each time they visit any type of retail food outlet. This data is used to obtain a brand's loyalty strength and size. The Scantrack data is necessary to obtain accurate data on retail price promotions, and allows us to impute unobserved wholesale prices. Previous studies combine retail sales data and household purchases in order to estimate steps 1 and 2 above in one model (e.g., Briesch, Chintagunta, and Fox 2008; Zhang, Gangwar, and Seetharaman 2008). While this method is certainly preferable to estimating two different demand models, some of the assumptions made in combining the household and store data may introduce more bias than is the case with our two-stage method. Specifically, the household-level purchase data provides information on the households location via their zip code and the retail outlet visited by the household, but only at the chain-level. On the other hand, the retail-level sales data provides the sales of specific stores and their respective chains, without providing detailed information on the store. Nevertheless, the same chain store can have several different retail outlets in the zip code so it is impossible to accurately match up which retail store the household went to. If the consumer is located on the edge of the zip code they could be visiting stores in entirely different zip codes. Because both models by themselves are efficient and consistent we estimate the demand models separately and combine the results in the third stage as described above.

Scantrack features weekly sales information at the UPC level for almost 10,000 retail outlets in nearly 3500 cities throughout the U.S. that sell CSDs. The data consist of dollar sales, unit volume (ounces), promotion attributes, and product specific identifiers. Covering all the cities would have been intractable so we focus on the 5 largest: Chicago, IL; Los Angeles, CA; New York, NY; Atlanta, GA; and Philadelphia, PA. There are 143 retail chains total used in our analysis of the CSD market. The chains collectively account for about $33.16 million dollars in sales in the CSD category throughout 2005. We have no specific information on the individual outlets covered by Scantrack. However, we do know that the supermarkets represented in the data are drawn from retail chains that operate relatively homogenous storefronts as a matter of corporate strategy. In terms of the representativeness of each store's specific market, we can only rely on Nielsen's assurances that their sample stores are representative of the broader population in each city. Because the Scantrack data features sales information for supermarkets only, the outside option consists of soft drink sales sold through all other distribution channels. Namely, the size of the potential market is calculated as the per capita consumption of soft drinks (USDA-ERS 2005) multiplied by the population of the respective markets. In total we have 163,593 weekly UPC retail sales observations in our CSD data.

The Homescan data consists of a panel of consumers that are selected to be demographically and geographically representative. Participating households submit all food purchase information each time they visit any type of retail food outlet. The data consists of detailed demographic information from all the members of the household and product specific information regarding the purchases they make. Demographic examples include age, employment, education, and income while purchase specific information includes such things as the brand, price, unit size, and quantities purchased. However, product reporting takes place in the home so items bought and immediately consumed may not be recorded and households that are generally hard to recruit (i.e., extremely high or low income households) are under-represented. Nevertheless the Homescan data in general has been found to be at least as accurate as other commonly used (government-collected) economic data sets (Einav, Leibtag, and Nevo 2008).

The Homescan data includes purchases by 38,856 households of which 35,232 made at least one purchase in the CSD category. Our dataset consists of daily purchases throughout 2005 which is long enough to observe several category purchases while short enough to assume consumer's preferences remain stable. It is well known that the choice set of discrete choice models must exhibit alternatives which are mutually exclusive from the decision maker's perspective (Train 2003). As a result, households were selected that live in the sampled markets that made one and only one brand selection on each shopping occasion.[13] Additionally Honoré and Kyriaziduo (2000) show that at least six purchase occasions are needed to identify the parameters of Eq. (A.1). Since the model is being estimated twice, once for the calibration period, and again with the propensity measure included, we select households that made at least 14 category purchases. Consequently our final dataset contained 848 households for a total of 23,933 CSD purchase occasions.

CSD is an ideal category for the purposes at hand because, first, the industry is highly concentrated at the manufacturing level and is largely dominated by two manufacturers.[14] Because our hypotheses were derived under assumptions of duopoly competition, the CSD industry is well-suited to the theoretical environment. Second, soft drink manufacturers often introduce new brands into a highly differentiated market, attempting to win consumers loyal to a competing brand. High concentration and strong brands lead to fierce brand rivalry in prices, sales promotion and product development. Further, the CSD category makes up a significant portion of consumer's grocery budget.

According to the Homescan data, the CSD category is also an important part of a typical consumer's grocery budget. In 2005, the baby milk and milk flavoring category accounts for the largest percentage of the food budget at 6%. The second highest category is beef at 4.5%, while the CSD category comes in 10th out of all 640 categories, or 3%. Moreover, we find that the proportion of Homecan respondents' food budget represented by CSDs ranges between 2.1 and 4.1%. Although we do not have data on the specific store-share of CSDs, given their evident

[13] While there are more flexible models that account for multiple brand purchases (i.e., Bhat 2008; Dube, 2004), the assumptions required of these models are in contrast to those in our study. Namely, that consumer's preferences are independent from one purchase occasion to the next. Since our measure of brand loyalty fundamentally contradicts this assumption, the standard RCL is a more appropriate specification because it is able to capture this phenomenon.

[14] Diet sodas were excluded because retail price information wasn't available.

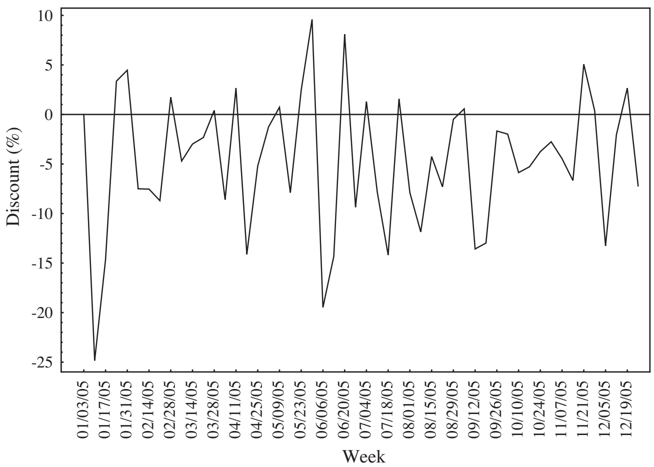

Fig. 1. Average discount over all brands throughout 2005.

importance in consumer's budgets, the CSD category is clearly important to retailers.

There are a large number of brands available in the CSD category – too large to model in a tractable way and obtain reliable estimates of brand loyalty. Therefore, we choose the thirty two most commonly purchased brands. The brands used are shown in Table 1 along with summary statistics on the price of each brand and information on the depth of the retail price discounts as well as the frequency of promotion throughout 2005. The fact that soft drinks are a differentiated food category is evident in the variability of prices among brands. Interestingly, the two most expensive brands, Red Bull and Monster, have the most shallow discounts on average. This is likely a result of the two brands being able to differentiate themselves from other carbonated soft drinks through early entry into the 'energy drink' market. Because differentiation implies less elastic demand, price promotion will be less effective as consumers are less price sensitive in general. Not surprisingly some of the most inexpensive brands are also discounted infrequently, while the medium price range brands show no apparent pattern. Additionally, Table 1 also shows there is a high degree of correlation between the discount depth and the discount frequency. Within the sampled brands of our 5 chosen markets the correlation between the average discount depth (measured as a percentage) and the average discount frequency for 2005 is 0.9652. On the surface, this finding supports the theoretical predication of Lal and Villas-Boas 1998. Furthermore, from the Scantrack data, the average discount across brands and all retailers shows that the CSD category is consistently discounted throughout the year with the largest discounts occurring during the summer and winter months (e.g., see Fig. 1). As one would expect, CSDs are heavily promoted during the week before the 4th of July, perhaps serving as loss-leaders to attract more consumers into the stores. However casual inspection of the summary statistics in Table 1 suggest that the brands can generally be broken up into four different categories. First there are brands that maintain everyday low prices and are rarely discounted such as I.B.C., Shasta, RC, Vintage, and Welch's. On the other hand, there are brands that seem to have carved out an advantage for themselves and are able to regularly maintain relatively high prices such as Monster, Red Bull, and Perrier. Finally, the brands that are discounted throughout the year generally see price cuts of 5-10% at a frequency of 18% – both metrics significantly higher than for the other brands. In summary, therefore, the data in Table 1 and Fig. 1 show that retail price promotions are common in the CSD category.

Ice cream

While the CSD category conforms nicely to the assumptions of the theoretical model described above, the fact that it is highly concentrated may mean that our results do not generalize to other categories. Therefore, we conduct the same empirical analysis with data from the ice cream category. Ice cream is nationally dominated by four major brands: Breyer's, Dreyers, Haagen Dazs, and Ben & Jerry's. However, in recent years their market share has been significantly reduced due to the rapid growth of private label and specialty regional brands. In 2004, retailers' own private label brands account for nearly 49% of retail ice cream sales (Reich, Paun and Davies 2005). Furthermore, 86% of all ice cream sales are sold through retail supermarkets so price promotions at the retail level are important to the entire marketing channel (IDFA).

The data used for the ice cream model is similar to the CSD data described above. That is, we use A.C. Nielsen's Homescan data to observe the household-specific ice cream purchases and IRI Infoscan to describe store-level movement and prices. IRI Infoscan is very similar to the Scantrack data described above in that it measures weekly sales information at the retail level. Our sample markets were as near to those used in the CSD category as possible, except that Atlanta and New York were replaced by Boston, MA and Baltimore, MD because Atlanta and New York were not available in the IRI data. For the ice cream category, the sample consists of 19 retailers that collectively account for about $688 million in ice cream sales throughout April 2007 to the end of December 2008. Because the IRI data features sales information for supermarkets only, the outside option is defined as the ice cream sales sold through all other distribution channels and calculated in the same way as that of the CSD market. In total we have 90,896 weekly Brand/Flavor retail sales observations for the final ice cream data.[15]

The households chosen for the ice cream model were selected using a similar strategy as in the CSD data described above. The household specific observations consist of daily purchases throughout April 2007 to the end of December 2008. Our final dataset consisted of 514 households for a total of 12,199 purchase observations. Finally, there are a large number of brands in the ice cream category with a multitude of flavor combinations. Therefore, we chose the 52 most popular brand/flavors measured by total sales over the observation period. The brands used in our analysis are shown in Table 2 along with their corresponding summary statistics. The summary statistics suggest

[15] There was considerable variation across UPC package sizes so we aggregated the data to the brand/flavor level to facilitate getting a larger sample that was consistent across all markets and retailers.

Table 1
Carbonated soft drink summary statistics.

	Price (cents per oz.)				Ave. Disc. (%)	Disc.[1] Freq. (%)
	Mean	Std. Dev	Max	Min		
Overall	*0.0275*	*0.0268*	*0.2880*	*0.0003*	*−7.44*	*18.42*
A &W	0.0166	0.0032	0.0247	0.0047	−7.68	19.51
Barq's	0.0186	0.0035	0.0249	0.0077	−6.58	19.23
Canada Dry	0.0176	0.0066	0.0530	0.0074	−7.31	20.97
Coca-Cola Cherry	0.0214	0.0042	0.0347	0.0081	−8.59	24.59
Coca-Cola Caffeine Free	0.0229	0.0048	0.0353	0.0117	−12.92	35.10
Coca-Cola Classic	0.0320	0.0175	0.0725	0.0069	−6.76	16.09
Private Label	0.0116	0.0039	0.0208	0.0074	−1.84	5.77
Dr. Pepper Caffeine Free	0.0229	0.0037	0.0284	0.0125	−10.70	32.69
Dr. Pepper	0.0184	0.0038	0.0328	0.0030	−8.16	21.59
Fanta	0.0177	0.0041	0.0331	0.0053	−4.61	13.60
I.B.C.	0.0512	0.0075	0.0554	0.0347	−1.95	3.85
Monster	0.1337	0.0076	0.1369	0.0994	−1.24	3.85
Mountain Dew Code Red	0.0154	0.0028	0.0226	0.0086	−10.89	26.92
Mountain Dew	0.0319	0.0205	0.0740	0.0047	−6.78	17.12
MUG	0.0171	0.0028	0.0250	0.0089	−9.67	27.24
Pepsi Caffeine Free	0.0167	0.0036	0.0247	0.0072	−14.74	32.50
Pepsi	0.0315	0.0197	0.0710	0.0044	−6.81	16.53
Pepsi Vanilla	0.0164	0.0040	0.0220	0.0055	−23.50	44.23
Pepsi Wild Cherry	0.0165	0.0033	0.0247	0.0030	−13.16	31.70
Perrier	0.0601	0.0202	0.0876	0.0296	−2.37	5.77
RC	0.0149	0.0010	0.0189	0.0102	−2.48	7.69
Red Bull	0.2399	0.0146	0.2880	0.1955	−0.80	3.05
S. Pellegrino	0.0663	0.0097	0.0707	0.0296	−3.85	9.62
Schweppes	0.0225	0.0123	0.0536	0.0058	−8.25	20.30
Seagram's	0.0185	0.0047	0.0312	0.0108	−13.02	29.23
7 Up	0.0109	0.0145	0.0526	0.0003	−6.85	18.25
Shasta	0.0152	0.0038	0.0267	0.0069	−1.42	2.56
Sierra Mist	0.0265	0.0191	0.0695	0.0038	−9.01	21.70
Sprite	0.0307	0.0188	0.0730	0.0033	−7.45	17.17
Squirt	0.0178	0.0033	0.0277	0.0069	−5.42	17.90
Sunkist	0.0166	0.0050	0.0645	0.0044	−6.82	17.32
Vintage	0.0152	0.0033	0.0204	0.0074	−1.83	5.20
Welch's	0.0148	0.0010	0.0185	0.0102	−1.98	5.77

[1] Discount Frequency is measured as the percentage of 2005 that the brand was discounted more than 10%.

that the pricing strategy is fairly consistent across flavors within a brand, but varies significantly across brands. For example, the Ben & Jerry's and Haagen Dazs brands are consistently priced higher than the other brands on average, while the Private Label brands are priced the lowest. In contrast to the discounting pattern observed in the CSD market, it appears from Table 2 that the Breyers and Dreyers brands are discounted the most often while the premium brands that sell for more are discounted less often. However, the correlation between discount depth and the promotion frequency is −0.7680 – opposite to that observed in the CSD market as brands that promote more deeply tend to discount prices less frequently. This reversal may be due to short-run category expansion effects. Specifically (Nijs et al. 2010) find that price promotions are more effective in stimulating category demand in markets with fewer brands, as the CSD category has, and short-run price promotion effectiveness is diminished by major new product introductions which is commonly observed in the ice cream category. Nonetheless, the summary statistics in Table 2 suggest that price discounts are an important element to ice cream promotions at the retail level.

Empirical results and discussion

In this section, we present the results from the CSD demand models and then follow with the retailer promotion models for both the CSD and ice cream category.[16] In each case, the validity of the estimated model is established through a series of specification tests, followed by a discussion of the parameter estimate implications. The household demand results supply the necessary measures of brand loyalty which are then used with the wholesale price estimates from the market demand model. Combining the results of these two models we test the hypotheses that the depth and frequency of retail price promotion is negatively related to the strength of brand loyalty, and the frequency of promotion is positively related to the size of the brand's loyal cohort.

[16] For brevity we exclude the ice cream demand model results which are, for the most part, qualitatively similar to the CSD demand model results, however they are available from the authors upon request.

Table 2
Ice cream summary statistics.

	Price (cents per oz.)				Ave. Disc. (%)	Disc.[1] Freq. (%)
	Mean	Std. Dev	Max	Min		
Overall	20.3997	11.7606	64.6118	3.4950	−3.61	35.13
Ben &Jerry's - Heath Bar Crunch	35.7726	5.3932	49.8167	19.3834	−1.34	29.06
Ben &Jerry's - Cherry Garcia	34.2916	5.0205	49.7000	19.3857	−1.08	29.92
Ben &Jerry's - Choc. Chip Cookie Dough	39.0579	5.8947	64.6118	19.6215	−0.65	30.38
Ben &Jerry's - Chocolate Fudge Brownie	36.0900	5.2750	49.7846	17.7377	−1.21	29.29
Ben &Jerry's - Chunky Monkey	35.4947	5.5961	49.9000	19.1794	−1.37	28.66
Ben &Jerry's - Mint Chocolate Chip	35.9195	5.3705	49.8200	19.4938	−1.35	28.95
Ben &Jerry's - NY Spring Fudge Chunk	35.8129	5.4156	49.6895	19.2389	−1.39	29.46
Ben &Jerry's - Peanut Butter Cup	35.7316	5.4637	49.7333	19.5958	−1.32	29.18
Ben &Jerry's - Phish Food	35.8947	5.3360	49.7125	19.6818	−1.30	29.46
Ben &Jerry's - Vanilla Heath Bar	35.7833	5.4180	49.8070	19.7860	−1.28	29.63
Ben &Jerry's - Half Baked	35.9613	5.3233	49.8574	19.7297	−1.28	29.06
Breyers - Chocolate	13.7348	3.3007	22.2933	5.7797	−3.81	36.38
Breyers - French Vanilla	13.0681	3.1109	22.2777	5.7298	−4.14	36.04
Breyers - Mint Chocolate Chip	13.6136	3.3138	22.3718	5.7437	−4.12	36.04
Breyers - Natural Vanilla	13.1084	2.8548	26.3541	5.7826	−2.80	36.16
Breyers - Strawberry	13.6715	3.4372	22.3730	5.7331	−4.05	37.41
Breyers - Vanilla Chocolate Strawberry	13.0261	3.1011	22.2612	5.7052	−4.12	35.98
Breyers - Reeses Peanut Butter Cup	13.2238	3.1929	22.3000	5.7618	−4.33	37.13
Dreyers - Limited Edition	12.5582	3.2232	20.9667	5.5323	−5.85	39.13
Dreyers - Butter Pecan	12.6591	3.2970	20.9667	5.4906	−5.96	39.30
Dreyers - Chocolate	12.6551	3.3098	20.9667	5.4952	−6.06	39.07
Dreyers - Cookie Dough	12.7409	3.2627	20.9667	5.4808	−5.85	38.90
Dreyers - Drumstick Sundae Cone	12.5979	3.3012	20.9667	5.4925	−6.09	38.79
Dreyers - Mint Chocolate Chip	12.6160	3.2390	20.9667	5.5234	−5.91	38.96
Dreyers - Neapolitan	12.5329	3.2736	20.9667	5.5061	−6.02	39.47
Dreyers - Vanilla	12.7488	3.2851	20.9667	5.5779	−5.88	38.67
Dreyers - Vanilla Bean	12.6950	3.2889	20.9667	5.5431	−5.95	39.13
Dreyers - Chocolate Chip Cookie Dough	12.7923	3.2531	20.9667	5.5860	−5.74	39.87
Dreyers - Chocolate Peanut Butter Cup	12.7634	3.2589	20.9667	5.5989	−5.92	39.99
Dreyers - Nestle Butterfinger	12.7651	3.2622	20.9667	5.5493	−5.93	39.93
Dreyers - Butter Pecan	12.8296	3.2304	20.9667	5.6907	−5.73	39.82
Dreyers - Caramel Delight	12.7013	3.2057	20.9667	5.6584	−5.81	39.65
Dreyers - Chocolate	12.6741	3.1966	20.9667	5.6504	−5.72	39.87
Dreyers - Double Fudge Brownie	12.7496	3.2592	20.9667	5.5793	−5.96	39.24
Dreyers - French Silk	12.7360	3.2432	20.9667	5.5112	−5.97	39.07
Dreyers - French Vanilla	12.8804	3.2290	20.9667	5.5426	−5.71	38.50
Dreyers - Fudge Tracks	12.8291	3.2004	20.8938	5.6366	−5.76	39.30
Dreyers - Neapolitan	12.7327	3.2150	20.7483	5.6671	−5.70	40.56
Dreyers - Peanut Butter Cup	12.8039	3.2485	20.9667	5.6255	−5.87	40.10
Dreyers - Pumpkin	12.2814	3.0231	20.9667	5.6374	−5.71	39.24
Dreyers - Vanilla	12.8610	3.1745	20.9667	5.1658	−5.59	38.39
Dreyers - Vanilla Bean	12.8556	3.2300	20.9667	5.6428	−5.72	39.13
Haagen Dazs - Chocolate	34.0287	3.4630	45.0521	22.7984	−0.37	31.12
Haagen Dazs - Coffee	34.6024	3.9083	46.9000	22.6849	−0.58	30.15
Haagen Dazs - Dulce De Leche Caramel	35.0627	4.1891	46.9000	24.8731	−0.66	31.18
Haagen Dazs - Rum Raisin	36.1469	4.8908	46.9000	20.1974	−1.10	29.58
Haagen Dazs - Strawberry	34.6081	4.0254	46.9193	22.6309	−0.60	30.72
Haagen Dazs - Vanilla	33.2320	3.1322	42.5391	22.7685	−0.25	30.09
Haagen Dazs - Vanilla Bean	36.2600	4.8497	46.9000	20.2366	−1.11	29.23
Private Label - Chocolate	7.4963	1.8083	15.7080	3.9493	−0.80	33.70
Private Label - Neapolitan	7.2005	1.2280	11.5596	3.4950	−0.34	28.83
Private Label - Vanilla	7.8317	2.3036	15.5861	3.7500	−0.60	29.92

[1] Discount Frequency is measured as the percentage of Apr. 2007 to Dec. 2008 that the brand was discounted more than 10%. $N = 1748$ for each brand.

Demand model results

Household demand

Household-level demand for both CSDs and ice cream is modeled using a random coefficient logit (RCL) model. We first estimate the model in Eq. (A.1) for the first seven purchase observations of each household. Using the likelihood-ratio (LR) test both the MNL and RCL logit were significantly better than a naive model that restricts all the parameters to zero except the intercept term. Furthermore, the RCL model fit the data better when their respective likelihood-ratio indices (LRI) were compared. Finally almost all of the variable's t-statistics were significant at the 5% level of significance in the RCL model.[17] We therefore used the predicted probabilities of the RCL to calculate the propensity measure given in Eq. (2).

Table 3 presents results of the CSD household-level demand model and, for comparison purposes, MNL estimates with the propensity variable included. Once again, we find a naive model is rejected using the LR test. While it is certainly understood that the IIA problem is prevalent in the MNL model there are several methods that can be used to test whether or not the data conform to the IIA assumption. The first test we do follows Hausman and McFadden (1984) in which the MNL model is re-estimated on a subset of the choices. For this purpose we exclude the choice of purchasing the brand Red Bull and re-estimate the MNL under this restriction. We obtain a test statistic of 2963.26 which is Chi-square distributed with 1 degree of freedom. Therefore, we reject the null hypothesis and conclude that the data does not conform to the IIA assumption and the MNL is inappropriate. Because the MNL with the IIA assumption is a special case that arises from the RCL when the mixing distributions have zero variance we can also test the IIA assumption by testing whether these parameters are zero (Train 2003). We test the hypothesis $H_0 : \sigma_p = \sigma_{pp} = 0$ formally using a F-test. We obtain a test statistic of 20.2117 which is Chi-square distributed with 2 degrees of freedom (critical value of 5.9914 at the 5% level of significance). Therefore, we reject the hypothesis and conclude that our data does not conform to the IIA assumption and the RCL is a more appropriate specification than the MNL, which is consistent with the conclusion of the Hausman and McFadden (1984) statistic above.

While the IIA test above suggest that the RCL model is more appropriate for the data, it does not indicate to what degree this is true. We therefore include several measures of fit for the MNL and RCL models. First Ben-Akiva and Lerman (1985) (R^2_{BL}) suggest measuring and comparing the average probability of correct predictions by the prediction rule. This measure suggests that the MNL model has a better predication rate than the RCL which is in contrast to the IIA test above. However, this measure does not account for the fact that the less frequent outcomes will usually predict very badly by the standard procedure so we also included the measure of fit suggested by Cramér (1999) (λ_c) which accounts for this. From Table 3 we see that the measure suggested by Cramér (1999) is indeed lower than the measure suggested by Ben-Akiva and Lerman (1985) for both the RCL and MNL models. However, comparing across models it seems the prediction rule that comes from the MNL is again marginally better than that of the RCL. Looking at how well the data fit the two different models we also include the LRI and the measure of fit developed by McKelvey and Zavoina (1975) (R^2_{VZ}) which modifies the LRI. The LRI (R^2_{VZ}) for the RCL model is 0.881 (0.900) and for the MNL model is 0.555 (0.602). Both measures suggest, consistent with the IIA test results above, the RCL fit the data better than the MNL model. Hence, we maintain our results interpretation from the RCL model because it does not need the IIA assumption and the RCL specification fit the data better.

There are several parameters of inherent interest both from a managerial and theoretical perspective. First, using a standard t-test, the results in Table 3 show the own-price effect (α_{hbt}), averaged over the 32 brands, is negative as expected. Consistent with the theoretical model, this suggests that households will have a reservation price r, at which they will no longer make a purchase. Second, the coefficient on discount-effect (dc_{bt}) is negative and the discount price interaction term ($dc_{bt}p_{bt}$) is positive, both of which are statistically different from zero. This implies that discounting a brand will shift the demand curve inwards, and rotate it counter clockwise. While this may not be the intended result from the retailer's perspective, it is consistent with literature that argues for enhanced price competition due to price promotion (Hosken and Reiffen 2001; MacDonald 2000). Finally, the parameter estimate on the propensity variable (pp_{bt}) is positive and significantly different from zero, as expected. Additionally, the standard deviation of the propensity variable's estimate (σ_{pp}) is significantly different from zero and estimated to be greater than 2. This suggests that while a household's propensity towards a brand will increase the likelihood it is purchased, this effect differs significantly across households. The importance of this result is supported by comparing the parameter estimates of propensity measure between the logit and RCL models. Table 3 shows the parameter estimate of propensity in the MNL case is biased downward when the parameter is assumed fixed.

Finally, the intercept terms capture the brand specific effect on the probability of purchasing that particular brand. Consequently it captures the average weight each brand has with respect to purchasing that brand such as unobserved brand specific advertising, and manufacturer effects such as a stronger distribution method. Table 3 shows that Cherry Coke and Red Bull have significantly negative brand specific intercept terms while almost all the others are significantly positive. Because the outside option brand for this model was Monster one could interpret the brand specific intercept terms as the average weight of each brand on the probability of purchasing that brand relative to the outside option brand holding all of the other explanatory variables constant. As a result, all of the brands with significantly positive intercept terms would be preferred more than the outside option brand, Monster, while the Monster brand would be preferred to that of Cherry Coke and Red Bull. Those brands that have intercept terms that are not significantly different from zero would be preferred equally to that of the Monster brand. However, because the random parameter model is inherently non-linear it is difficult to comment on the specific magnitude of the parameters relative to the others. However, it is clear that a larger intercept term would suggest a brand is preferred over another brand with a smaller intercept term. For example Coca-Cola Classic has the largest intercept term while Pepsi has the second largest. This suggests that, holding everything else constant, Coca-Cola is the most preferred brand while Pepsi is the second most preferred brand.

[17] The results of this model are available from the authors upon request.

Table 3
Random coefficient logit demand estimates: carbonated soft drinks.

	Random Coef. Logit Model		Multinomial Logit Model	
Variable	Estimate	t-ratio.	Estimate	t-ratio.
Price (p_{bt})	−0.1779*	−6.42	−0.0045	−0.47
Discount Dummy (dc_{bt})	−0.2375*	−2.84	−0.1134	−1.72
Discount Price Interaction ($dc_{bt}p_{bt}$)	0.1075*	3.25	0.0567*	2.40
Propensity (pp_{bt})	4.1020*	39.90	3.8024 *	93.29
	(η_{0b}) Brand Intercept parameters			
Private Label	11.0881*	6.26	1.6833*	4.80
Coca-Cola Classic	17.2641*	9.78	6.0117*	18.46
Pepsi	17.0881*	9.68	5.8323*	17.88
Sprite	15.3369*	8.70	4.1455	12.66
Dr. Pepper	10.4421*	5.76	0.1569*	0.36
Seven Up	8.9546*	4.42	−2.2674	−2.16
Canadian Dry	10.8963*	6.08	0.2507	0.59
Mountain Dew	10.0061*	5.40	0.0471	0.11
Sierra Mist	9.9847*	5.40	−0.8899	−1.49
Pepsi - Caffeine Free	−4.5918	−0.01	−1.5699*	−2.02
A &W	10.7409*	5.94	−0.1905	−0.40
Schweppes	9.5474*	5.06	−1.5857*	−2.04
Shasta	10.3669*	5.74	0.5927	1.47
Sunkist	10.3072*	5.63	−0.1912	−0.40
Vintage	9.1265*	4.82	−0.2658	−0.55
Pepsi - Wild Cherry	10.8362*	6.03	0.0226	0.05
Mug	10.1770*	5.50	−0.8765	−1.47
Coca-Cola - Cherry	−6.1388*	−2.61	−0.8796	−1.47
Seagram's	9.7529*	5.13	0.0273	0.06
Fanta	10.8465*	6.02	−0.0846	−0.18
Coca-Cola Classic - Caffeine Free	10.9674*	6.08	0.0116	0.03
RC	−7.3382	0.00	0.4545	1.10
Barq's	10.1242*	5.46	−1.1678	−1.76
Pepsi - Vanilla	10.7752*	5.97	−0.3341	−0.67
Mountain Dew - Code Red	9.7165*	5.12	−0.8811	−1.48
Squirt	9.4994*	5.03	−0.0812	−0.17
Welch's	10.9014*	6.06	−0.3215	−0.64
Perrier	9.1659*	4.91	−0.5403	−1.04
I.B.C.	11.1695*	6.21	−0.1933	−0.40
Vernors	9.0804*	4.49	−2.2627*	−2.15
Red Bull	−11.4074*	−2.20	−0.2246	−0.46
	Distributions			
Price (σ_p)	0.4973*	19.27		
Propensity (σ_{pp})	2.1219*	20.21		
Log-Likelihood at conversion	−7477.67		−8251.92	
LR	−110761.0		−109212.0	
LRI	0.8811		0.5544	
R^2_{BL}	0.9836		0.9870	
λ_c	0.7307		0.7852	
R^2_{VZ}	0.9001		0.6021	

Dependent variable: binary variable equal to 1 if brand b was chosen. The outside option brand is Monster.
* Indicates significance at the 5% level.

From the above model we are able to estimate the strength and size of each brand's loyalty following Eq. (3). The results are presented in Table 4. The estimates suggest that Coca-Cola has the greatest brand strength and size among all the brands with Pepsi closely following. This is consistent with the intercept estimates of Table 3. While the strength and size measures of Coca-Cola and Pepsi dominate all of the rest of the brands we do find that the brand with the third largest strength and size measure is Sprite, followed by Private Label brands, Canadian Dry, and Mountain Dew. All of the other brands have strength and size measures of 0. In Table 1 the above mentioned brands with positive strength and size measures are in bold. We see that the average price discount of these brands is about 7% and are discounted roughly 9 of the 52 weeks (or 17%) of the year except for the private label brands which are discounted much less frequently.

Table 4
Brand strength and size measures for the carbonated soft drink market.

Brand	Strength[1]
Private Label	0.0023641
Coca-Cola Classic	0.3583365
Pepsi	0.3034285
Sprite	0.0391628
Canadian Dry	0.0007279
Mountain Dew	0.0007164
All Others	0

[1] Brand Strength – see Eq. (3).

Market demand model

Market-level demand is modeled using a random coefficient nested logit (RCNL) model for CSDs and ice cream. As a first step to interpreting the results we test the validity of the RCNL model against a MNL alternative. A simple specification test involves testing the significance of the GEV scale parameter, σ_K. If $\sigma_K = 0$, then the GEV model collapses to a standard RCL model. In the results shown in Table 5, the *t*-statistic for the null hypothesis that $\sigma_K = 0$ is 815.57, so we easily reject the null hypothesis and conclude that the GEV model is preferred. Furthermore, it is common in the retailing literature to assume that individual stores price as local monopolists (Chintagunta 2002). However, the GEV scale parameter, σ_K, which represents a measure of the extent to which consumers substitute among stores, does not support this assumption as the stores in the sampled markets are regarded as very good – but not perfect – substitutes for each other ($\sigma_K = 0.926$, while $\sigma_K = 1.0$ implies perfect substitutability).[18] In other words most (but not all) consumers substitute among products across stores just as much as products in stores. Consequently the consumer information and comparison of the brands in the CSD category across stores is quite high so consumers on average show little loyalty for a particular retailer. So the parameter estimate would imply that retailer competition via price promotions and other means would indeed be effective in capturing market share away from competing retailers.

Next, we compare the RCNL to a constant parameter alternative by testing whether or not the data conform to the IIA assumption. We use the test suggested by Train (2003) and test the IIA assumption under the hypothesis $H_0: \sigma_\upsilon = \sigma_\alpha = 0$ using the *F*-test. We obtain a test statistic of 686.3 which is Chi-square distributed with 2 degrees of freedom. We therefore reject the hypothesis and conclude that the retail level sales data does not conform to the IIA assumption so the RCNL is the preferred model to the constant parameter nested logit (NL) alternative based on the IIA test.

Table 5 has several parameters that are of interest from a managerial and theoretical point of view. First the coefficient on price (α_{hbt}) is significantly different from zero and negative as expected. Additionally the standard deviation of the price parameter is significantly bigger than 1, so there is a considerable amount of household heterogeneity present. Because this heterogeneity would have been swept into the mean parameter estimate of the NL one would expect the two parameter estimates to differ. However, interestingly the mean parameter estimate of the NL and the RCNL are strikingly similar despite the amount of heterogeneity the RCNL is picking up. Second, the coefficient on discount dummy (dc_{bt}) is positive and the discount price interaction term ($dc_{bt}p_{bt}$) is negative, both of which are statistically different from zero. This implies that discounting a brand will shift the demand curve inwards, and rotate it clockwise which suggests that CSDs are conducive to price promotions. Third, the results in this table indicate that all of the binary quarterly and store variables are significantly different from zero. Therefore, seasonality and weather effects represented by each quarterly dummy have positive effects on the probability of purchasing a brand in the CSD category. Interestingly, all of the market specific binary variables are negative. These binary variables pick up the market-specific effect of all brand purchases within the respective markets. The negative coefficient estimate on Chicago, IL for example, suggests that the mean utility of all brands purchased by consumers in Chicago, IL is 0.6258 lower than the excluded market (Philadelphia, 4th quarter). Because we exclude Q_4 from the regression, the benchmark for mean utility is Philadelphia in the 4th quarter.

Retail price promotion results

Our primary interest lies in the results of the third-stage retail price promotion models, or the relationships between the strength of brand loyalty and the depth and frequency of price promotion. The results of the SGMM and seemingly unrelated regression (SUR) estimates of Eqs. (5) and (6) are presented in Tables 6 and 7. For clarity the results are presented equation by equation, but bear in mind that Eqs. (5) and (6) are estimated together using SGMM and SUR for the CSD category and then for the ice cream category. Prior to presenting these results, however, we first conduct tests of the loyalty-regression specifications. First, we test the null hypothesis that the calculated wholesale price is exogenous using a Wu-Hausman test statistic. In the case of both the depth and frequency of retail price promotion we find a Wu-Hausman test statistic of 14,442.5 and 11,855.9 for the CSD and ice cream categories, respectively, clearly rejecting the null hypothesis of exogeneity in either case. Consequently, we interpret the results from the SGMM models. Second, we examine the goodness-of-fit for each model using a LR test in which we compare the likelihood function value of the estimated model to a naive model in which all the parameters are zero except the intercept term. The LR statistic from the depth and frequency models are 190,687.9 and 145,871.2, respectively, for the CSD market and 23,297.8 and 30,353.8 for the ice cream market, all of which are significant at the 5% level thus rejecting the naive models.

Discount model

The primary parameter of interest in the depth of retail promotion model is the effect of the strength of brand loyalty (ϕ_{pref}).

[18] A formal test of the hypothesis: $H_o: \sigma_K = 1$ produces a *t*-statistic of 63.127, so we reject the null hypothesis and conclude that soft drinks from different stores are not perfect substitutes.

Table 5
Random coefficient nested logit demand estimates: carbonated soft drinks.

	Random Coef. Nested Logit Model		Nested Logit Model	
Variable	Estimate	t-ratio.	Estimate	t-ratio.
Constant (γ_0)	−8.5657*	−1455.09	−8.5659*	−1402.79
Price (p_{bkt})	−0.3699*	−24.48	−0.3681*	−24.74
Discount Dummy (dc_{bt})	0.1595*	33.73	0.1595*	32.99
Discount Price Interaction ($dc_{bt}p_{bt}$)	−0.4317*	−11.89	−0.4323*	−11.99
Q_1	0.1021*	24.55	0.1019*	24.56
Q_2	0.0361*	8.64	0.0361*	8.88
Q_3	0.0722*	17.67	0.0722*	17.77
Chicago IL	−0.6258*	−129.55	−0.6258*	−151.05
Los Angeles CA	−0.9165*	−239.15	−0.9165*	−222.45
New York NY	−0.8270*	−161.32	−0.8269*	−136.28
Atlanta GA	−0.5484*	−99.58	−0.5486*	−117.07
σ_K	0.9255*	815.57	0.9255*	782.06
	Distribution			
Constant (σ_υ)	0.0136*	9.27		
Price (σ_α)	3.8050*	379.28		
Log-Likelihood at conversion	−146,210.40		−146,212.47	
AIC	1.7876		−1.0502	
R^2	–		0.8412	

Dependent variable: Probability brand j was puchased in store k.
* Indicates significance at the 5% level.

The loyalty test provides evidence in support of the equilibrium model – brand loyalty is clearly an important determinant of retail promotion strategies. Consistent with Agrawal (1996), our estimates indicate that the average price discount at the retail level is negatively related to the strength of brand loyalty ($\phi_{pref} < 0$). In other words, retailers will promote a brand with weak loyalty more aggressively than a strong one, which is contrary to the theoretical predictions of Raju, Srinivasan, and Lal (1990). Further, the sign of the key parameter (i.e., ϕ_{pref}) is consistent for both the CSD and ice cream market, which lends evidence to suggest that the implications of the theoretical model described above may extend to markets with fundamentally different competitive structures. Note that if the null hypothesis was rejected (i.e., $\phi_{pref} \geq 0$) it would suggest a brand with strong brand loyalty is promoted deeper than a weak brand – a fundamental contradiction of the distinction between strong and weak brands. Consequently, the parameter estimates provide support for the operationalization of brand loyalty within the confines of the theoretical model of Agrawal (1996). These results, however, are conditional on constant wholesale prices. Holding the strength of brand loyalty constant and focusing on wholesale-price effects, we find a negative parameter estimate on the wholesale price ($\phi_w < 0$) for both categories. Hence, retailers tend to offer deeper discounts when the wholesale price is reduced – a result that is consistent with previous research (e.g., Ailawadi 2001). In other words, retailers pass along at least some of the manufacturer trade-deals to consumers.

In terms of retail decision making, it makes sense to offer deeper price promotions on brands with weak brand loyalty only if the wholesale price is significantly lower. If retailers deeply discount strong brands they not only forgo the price premium, but also the potential margin made on the weaker brand. As Table 1 suggests, there is a high correlation between the depth and frequency of the discounts offered by specific brands. At first this seems counterintuitive because one would expect the retailer would decrease profits by deeply and frequently discounting brands. However, a high correlation makes more sense if manufacturers of weaker brands incentivize retailers to offer deep and frequent price promotions. This notion is further supported by the fact that there is a positive correlation between the depth and frequency of discounts in the ice cream market. The parameter estimate on the ice cream wholesale price (ϕ_w) in Table 6 is smaller (in absolute terms) than the same parameter for the CSD market. This suggests that pass-through is lower in a more competitive wholesale market, which is, again, to be expected because retailers are in a stronger bargaining position when there are more suppliers. In general our findings show that the results of Agrawal (1996) hold in our empirical contexts, while those of Raju, Srinivasan, and Lal (1990) may not necessarily describe the observed patterns in retail prices because Agrawal (1996) incorporates an active retailer, while Raju, Srinivasan, and Lal (1990) do not.

There are several managerial implications that follow from our results. First, Sirohi, McLaughlin, and Wittink (1998) find a positive link between store loyalty and price promotions. Consequently, retailers are better off using a HI-LO strategy compared to an every day low price (EDLP) strategy. While our results do lend evidence to suggest a retailing model that ignores competition is not invalid, retailers can further strengthen this notion by building their own store loyalty. Moreover Manning, Bearden, and Rose (1998) find that HI-LO retailers often find EDLP pricing programs unattractive because they fear losing trade deals. Trade deals can have a significant positive impact on retailer's

Table 6
Relationship of brand strength and discount depth.

Dependent Var.: d_{bkt}	Carbonated Soft Drinks				Ice Cream			
	SGMM		SUR		SGMM		SUR	
Variable	Estimate	t-ratio.	Estimate	t-ratio.	Estimate	t-ratio.	Estimate	t-ratio.
Constant (ϕ_0)	0.4101*	87.85	0.1168*	78.87	0.8706*	155.11	0.3754*	124.44
Brand Loyalty (ϕ_{pref})	−2.0122*	−79.38	−0.1547*	−41.32	−0.1488*	−18.22	−0.0078	−1.18
Wholesale Price (ϕ_w)	−0.2197*	−18.47	−0.0110*	−3.50	−0.1817*	−141.32	−0.0575*	−96.97
Time Trend (ϕ_t)	0.0004*	5.91	0.0002*	6.28	−0.0009*	−27.47	−0.0004*	−15.71
Lagged Discount (d_{bkt-1})	−0.4073*	−78.07	−0.1430*	−56.94	0.0004*	10.41	0.0002*	7.38
Chicago, IL	−0.0203*	−3.97	−0.0159*	−13.20	0.0006	0.23	0.0011	0.52
Los Angeles, CA	−0.4016*	−75.58	−0.0814*	−67.85	−0.0621*	−25.48	−0.0520*	−26.07
New York, NY	−0.3374*	−34.46	−0.0775*	−44.27	–		–	
Atlanta, GA	−0.1979*	−36.30	−0.0560*	−41.32	–		–	
Baltimore, MD	–		–		−0.0726*	−23.93	−0.0731*	−29.37
Boston, MA	–		–		−0.0904*	−39.36	−0.0794*	−42.20
Martin Luther King Day	0.0006	0.10	−0.0024	−0.77	−0.0075	−0.94	−0.0141*	−2.14
President's Day	−0.0322*	−5.49	−0.0368*	−11.80	−0.0056	−0.69	−0.0134*	−2.05
Easter	0.0069	1.19	0.0137*	4.41	0.0113	1.41	−0.0022	−0.33
Mother's Day	0.0204*	3.54	0.0169*	5.49	0.0157*	2.76	0.0109*	2.32
Memorial Day	0.0203*	3.53	0.0196*	6.39	0.0109	1.92	0.0068	1.46
Father's Day	0.0025	0.43	0.0072*	2.36	0.0228*	4.00	0.0252*	5.40
4th of July	0.0211*	3.67	0.0126*	4.10	−0.0031	−0.53	−0.0130*	−2.78
Labor Day	−0.0064	−1.10	−0.0088*	−2.85	0.0038	0.67	0.0021	0.46
Halloween	−0.0222*	−3.79	−0.0210*	−6.71	0.0408*	7.16	0.0391*	8.36
Veteran's Day	−0.0489*	−8.32	−0.0431*	−13.76	0.0590*	9.06	0.0712*	13.32
Thanksgiving	−0.0288*	−4.89	−0.0158*	−5.03	0.0265*	4.07	0.0151*	2.83
Christmas	−0.0041	−0.69	0.0076*	2.39	0.0101	1.77	−0.0012	−0.27
Private Label (Private Label - Vanilla)	0.5877*	72.71	0.0832*	34.96	−0.1406*	−22.91	−0.0537*	−10.75
Coca-Cola (Private Label - Choc.)	0.5772*	73.48	0.0933*	39.36	1.3088*	14.62	−0.0723	−0.99
Pepsi (Breyers - Vanilla Light)	0.0138*	3.43	0.0193*	9.23	−0.3272*	−51.84	−0.1591*	−31.58
Sprite (Breyers - Natural Vanilla)	0.3772*	63.79	0.0446*	20.60	0.1447*	23.08	−0.0075	−1.50
Dr. Pepper (Dreyers - Vanilla Light)	0.3065*	58.93	0.0497*	23.26	−0.1073*	−17.42	−0.0071	−1.42
⋮								
Log-Likelihood at conversion	−43731.29		57244.68		−2752.80		15118.61	
Likelihood Ratio Stat.	190687.9		11263.5		23297.8		12445.1	
Hausman Statisitic	14442.5		–		11855.9		–	
R^2	−2.283		0.068		−0.296		0.129	

(⋮) The rest of the binary brand estimates are excluded for the sake of space, but were very similar. The specific ice cream brands are in parentheses.
* Indicates significance at the 5% level.

profits if they are deep enough to make promotions attractive, but also if they aren't. When trade deals that lead to price promotions that are too shallow to overcome the other brand's consumer loyalty they help to significantly increase retail margins because the retailer is able to sell both brands at the regular price, but incur a lower cost. Therefore, a HI-LO strategy is likely to be more attractive than EDLP.

Second, Blattberg, Briesch, and Fox (1995) and Neslin (2002) suggest that deep promotions on a brand draw too much attention to the promotion and not the positive attributes of the brand itself. Empirically, DelVecchio, Henard, and Freling (2006) found, in a meta-analysis, that large promotions (+20%) had detrimental effects on brand preference over time. Retailers should therefore be cautious in passing along trade deals that lead to really deep price promotions. Third, research also finds that price promotions on unfamiliar brands are quite harmful to the brand's long term loyalty so new and/or unfamiliar brands should utilize avenues other than price promotions such as in store sampling.

Finally, consistent with the "promotion usage effect", coupons require some effort on the part of the consumer. As the effort needed to redeem a given promotion increases, the consumer is more likely to attribute their brand choice to their affinity toward the brand instead of the promotion. Hence, price discounts via coupons can lead to favorable post-promotion brand preference and are encouraged (DelVecchio, Henard, and Freling 2006; Macé and Neslin 2004). Moreover, coupons have the added benefit of capturing the consumer segment that can be persuaded to switch brands if the promotion is sufficiently deep enough to overcome their brand strength. Consequently, the retailer is able to maintain a higher price on the brand being promoted for those consumers who are already loyal to that brand, while also increasing the volume sold at a price that captures the segment switching to the promoted brand.

Table 7
Relationship of a brand's strength and size on promotion frequency.

Dependent Var.: f_{bk}	Carbonated Soft Drinks				Ice Cream			
	SGMM		SUR		SGMM		SUR	
Variable	Estimate	*t*-ratio.	Estimate	*t*-ratio.	Estimate	*t*-ratio.	Estimate	*t*-ratio.
Constant (θ_0)	0.4454*	170.04	0.4105*	268.25	0.4580*	207.00	0.3754*	124.44
Brand Loyalty (θ_{pref})	0.1832*	12.88	−0.0175*	−4.54	0.0292*	9.07	−0.0078	−1.18
Wholesale Price (θ_w)	−0.4001*	−59.97	−0.1678*	−51.72	−0.0432*	−85.30	−0.0575*	−96.97
Time Trend (θ_t)	−0.0022*	−61.06	−0.0022*	−63.44	−0.0002*	−13.21	−0.0004*	−15.71
Lagged Discount (d_{bkt-1})	−0.0056	−1.90	−0.0203*	−7.84	−0.0001	−1.73	0.0002*	7.38
Chicago, IL	0.0623*	21.71	0.0453*	36.51	−0.0106*	−10.11	0.0011	0.52
Los Angeles, CA	0.0187*	6.28	−0.0109*	−8.76	−0.0582*	−60.59	−0.0520*	−26.07
New York, NY	−0.0106	−1.93	−0.0437*	−24.18	–		–	
Atlanta, GA	0.0329*	10.74	0.0199*	14.22	–		–	
Baltimore, MD	–		–		−0.0334*	−27.92	−0.0731*	−29.37
Boston, MA	–		–		−0.0632 *	−69.84	−0.0794*	−42.20
Martin Luther King Day	−0.0432*	−13.03	−0.0425*	−13.07	0.0023	0.74	−0.0141*	−2.14
President's Day	0.0505*	15.36	0.0502*	15.58	0.0028	0.89	−0.0134*	−2.05
Easter	−0.0173*	−5.30	−0.0137*	−4.29	0.0047	1.51	−0.0022	−0.33
Mother's Day	−0.0229*	−7.06	−0.0205*	−6.47	0.0017	0.76	0.0109*	2.32
Memorial Day	−0.0228*	−7.08	−0.0201*	−6.34	0.0015	0.64	0.0068	1.46
Father's Day	−0.0504*	−15.65	−0.0496*	−15.69	−0.0008	−0.37	0.0252*	5.40
4th of July	0.0187*	5.80	0.0216*	6.82	0.0035	1.56	−0.0130*	−2.78
Labor Day	−0.0346*	−10.66	−0.0358*	−11.24	0.0007	0.29	0.0021	0.46
Halloween	−0.0242*	−7.37	−0.0233*	−7.22	0.0007	0.31	0.0391*	8.36
Veteran's Day	0.0003	0.10	−0.0008	−0.26	−0.0042	−1.62	0.0712*	13.32
Thanksgiving	0.0225*	6.82	0.0235*	7.24	0.0040	1.57	0.0151*	2.83
Christmas	0.0396*	11.82	0.0412*	12.54	0.0041	1.80	−0.0012	−0.27
Private Label (Private Label - Vanilla)	0.5785*	127.55	0.6553*	266.61	−0.0277*	−11.46	−0.0537*	−10.75
Coca-Cola (Private Label - Choc.)	0.4903*	111.23	0.5673*	231.75	−0.5462*	−15.48	−0.0723	−0.99
Pepsi (Breyers - Vanilla Light)	0.4462*	197.36	0.4680*	216.65	−0.2309*	−92.82	−0.1591*	−31.58
Sprite (Breyers - Natural Vanilla)	0.0067*	2.03	0.0343*	15.33	−0.0995*	−40.28	−0.0075	−1.50
Dr. Pepper (Dreyers - Vanilla Light)	0.0808*	27.70	0.1080*	49.02	0.0300*	12.35	−0.0071	−1.42
⋮								
Log-Likelihood at conversion	48973.08		52063.05		80956.31		81412.24	
Likelihood Ratio Stat.	145871.2		152051.0		30353.8		31265.6	
Hausman Statistic:	14442.5		–		11855.9		–	
R^2	0.597		0.612		0.286		0.294	

(⋮) The rest of the binary brand estimates are excluded for the sake of space, but were very similar. The specific ice cream brands are in parentheses.
* Indicates significance at the 5% level.

Frequency model

The results of the SGMM and SUR estimates of Eq. (6) are presented in Table 7 for both the CSD and ice cream markets. Our central hypotheses concern the parameter estimates for the strength of brand loyalty. If $\theta_{pref} > 0$ the frequency of retail price promotions is positively related to the strength of brand loyalty. Our results confirm the hypothesis for the CSD and ice cream market.

The finding that retailers promote stronger brands more often is consistent with Agrawal (1996). The retailer is concerned with category profits, not individual brand profits as the manufacturer is. Since the stronger brand commands a significant price premium among consumers, the retailer enjoys a higher margin on the stronger brand even after a price promotion so it is discounted more often. The manufacturer-based model of Raju, Srinivasan, and Lal (1990), which Agrawal (1996) builds upon, suggests retailers promote brands with weak loyalty more often than those with stronger brand loyalty, which their empirical tests support. That proposition is driven by the idea that manufacturers of brands with weak loyalty promote often as a way to attract consumer attention. However, that model does not take into account the retailer's strategy being fundamentally different from the manufacturer's. Namely, retailers are concerned with the overall category profits, not the profitability of individual brands. Our results, therefore, confirm the importance of accounting for the retail level of the supply chain which if ignored, can lead to erroneous conclusions about the relationship between brand loyalty and retail price promotions.

These findings also highlight the importance of carefully controlling for wholesale price variation. Intuition suggests that the frequency of price promotions should be negatively related to the wholesale price. In other words, as the wholesale prices are decreasing we would expect to find retailers promoting the brands more often. Our model confirms this for both the ice cream and CSD categories. Specifically, we find the wholesale price is negatively related to the frequency of brand promotion

($\phi_w < 0$). Frequently discounting brands erode retailer profits unless the manufacturer makes it profitable to do so. This, in turn, suggests that the frequency a brand is promoted is driven, at least partially, by the discounts a retailer receives from the manufacturer. Therefore, while retailers use the depth of promotion as a tool to price discriminate among consumers loyal to one or the other brands, they frequently promote the brands that manufacturers provide incentives for.

In general, the results lend evidence to suggest that a simple model that assumes only two manufacturers and a single retailer may be applicable to a wider context. The results confirm, at least at the retail level, the hypotheses for the relationship between brand loyalty and retail promotion strategies for the CSD category, as expected, and the ice cream category. It is well known that the CSD category is primarily dominated by two manufacturers so one would expect the theoretical model to hold in this case unless retail competition lends evidence to suggest otherwise. However, the fact that the results also extend to the ice cream category which is nationally dominated by four major brands who in recent years have had their market share reduced by the rapid growth of private label and specialty regional brands implies the theoretical model may generalize to other cases as well. It is often difficult and cumbersome to relax assumptions to more closely represent reality and impossible to remove them altogether. Therefore, evidence suggesting that simple models are indeed applicable to a wider range of contexts is always valuable.

Our CSD and ice cream results imply retailers understand that the stronger brand does not need to be promoted as deeply as the weak brand because it commands a higher price premium among its loyal consumers. Thus promoting the stronger brand more steeply will erode the retailer's profit margin and forego profits it makes on the weaker brand. Although our results are only directly applicable to retail promotion behavior, they nonetheless have significant implications for consumer packaged goods manufacturers. Focusing on their own brand, the weak brand manufacturer increases profits by attracting the strong brand's customers. The weak brand manufacturer must therefore, offer deep discounts on their brand in order to induce the retailer to pass the trade deal through to the consumer. Shallow trade deals will not be passed through to the consumer because the discount will not be deep enough to overcome the brand loyalty strength of the rival brand's consumers who are more loyal. As a result, shallow trade deals on the part of the weak brand manufacturer will only increase the retailer's profit as they will sell both brands at the regular price and simply make a higher margin on the weaker brand.

The strong brand manufacturer on the other hand, can retain its loyal customer base by offering trade deals that are deep enough to overcome the loyalty of the weaker brand's consumers while also making it profitable for the retailer to promote the brand. The strong brand manufacturer does not need to offer trade deals as deeply as the weak brand manufacturer because their consumer's loyalty is by definition, weak. Further, since the strong brand manufacturer is primarily interested in retaining their loyal customers they do not need to offer trade deals as frequently because the retailer will naturally do so. Therefore, weak brand manufacturers should offer deep trade deals, while the strong brand manufacturer can offer attractive trade deals less frequently to help maintain its loyal consumer base.

Finally, retailers are cautioned against offering price promotions too often because consumers may begin to postpone a category purchase on the expectation of a promotion in the near future. Sawyer and Dickson (1984) suggest that infrequent price promotions induce consumers to purchase a product because the brand's regular price is taken as the reference price and the brand is seen as being discounted. However, frequent price promotions lower the brand's expected price in the consumer's mind and lead consumers to defer purchases of the brand when it is being sold at the regular price (DelVecchio, Henard, and Freling 2006; Jedidi, Mela, and Gupta 1999; Kalwani and Yim 1992). As a corollary, Kalwani and Yim (1992) also find that unfulfilled promotion expectations will have an adverse impact on the brand because frequent price promotions reduce the expected price of the brand and lead consumers to wait for a sale instead of buying the product at its regular price. The specific answer of what constitutes 'too frequent', is beyond the scope of this paper. Nevertheless, retailers should monitor long-term sales frequency to make sure that promotions are not eroding the brand's regular price in the consumer's mind and leading them to postpone a purchase on the expectation of a discount in the near future.

Conclusion and implications

Most theoretical explanations of price promotions rely on some form of price discrimination between identifiable market segments. There are few empirical tests of how the nature of these segments – how large they are or how strong their membership – influences retailers' price promotion strategies. In this study, we develop and test an empirical model of price promotion in which brand loyalty determines the depth and frequency of discounts.

Our econometric model is estimated in three stages for two different product categories: carbonated soft drinks and ice cream. In the first stage we model household demand using a random coefficient logit specification yielding estimates of brand loyalty. In the second stage, we estimate a market demand model which allows us to estimate the wholesale price each retailer observes for each brand. The third stage of the model determines how the strength of brand loyalty influences retail promotion decisions, defined in terms of their depth and frequency, conditional on estimates of the wholesale price. In particular, we model the frequency and depth of retail promotion as functions of the strength of loyalty to a particular brand and test hypotheses regarding these relationships developed in the theoretical literature.

The results of our retail price promotion model are consistent with existing theory on the relationships between brand loyalty and the depth and frequency of price promotion. We find that retailers should promote weaker brands more aggressively than strong brands when designing price promotions. By not aggressively pricing weak brands retailers will forego their margin because consumers loyal to a strong brand will not switch. Our findings also suggest that weaker brands are promoted less frequently compared to stronger brands. Because the stronger brand commands a significant price premium among its loyal consumers the retailer enjoys a higher margin on the stronger brand even after a price promotion so it is naturally discounted more often compared to the weaker brand. In general, while the strength of a brand's loyalty is certainly an important determinant in a retailer's decision to discount, we find that the wholesale price has a significant effect on the retailer's price promotion strategy. Consequently, our results suggest that it is important to take this crucial aspect of the retailer's decision into account when testing the relationship between brand loyalty and retail price promotion. As the article shows, while the specific wholesale prices may not be available, they can be recovered with minimal assumptions and market level retail data.

There are several managerial implications from our results. First, retailers should not pass on shallow trade deals from manufacturers of weak brands. Since the price promotion that results from such trade deals will not be enough to overcome the loyalty of the strong brand consumer and make the promotion profitable, retailers should instead sell both brands to the respective loyal cohorts and pocket the added margin. As a corollary, retailers should also be cautious when offering really deep price promotions because these can have a detrimental effect on brand preference over time (DelVecchio, Henard, and Freling 2006). Second, Promotions can re-set consumers' reference prices for frequently purchased brands such that they become reluctant to purchase at the brand's normal, or non-discounted price (Kalwani and Yim 1992). If consumer's references prices are adjusted down they may shy away from making a category purchase all together which will significantly decrease category profits. Therefore, retailers should be cautious in too frequently passing trade deals through to the consumer and make sure that category sales in the long run are not adversely affected.

Third, retailers should use a HI-LO pricing strategy instead of an EDLP strategy. Our empirical results show that the wholesale price has a significant effect on retailer's promotion decisions and EDLP strategies often result in few, if any trade deals offered by manufacturers (Bearden and Rose's 1998). Fourth, new and/or unfamiliar brands should avoid price promotions and instead use other advertising techniques such as in store sampling. Finally retailers are encouraged to use coupons as the primary means of price promotion. The effort needed to redeem the coupon on the part of the consumer points the consumer's reasoning for making a brand selection in the direction of their brand affinity instead of the promotion itself. Moreover coupons have the added benefit of increasing profits by capturing new market share via the discounted price, while also retaining the higher price for those consumers already loyal to the particular brand being discounted.

There is much that remains for both theoretical and empirical research. First, retailers may not behave as local monopolists. If retailers instead make decisions regarding promotion depth and frequency in a strategic way, then our hypotheses may be significantly different, and certainly more complicated. Further, future empirical research would benefit from studying the effect of a price sensitive segment on retailers' promotional strategies. If researchers could identify the size of such a segment, it would be possible to provide insight into the effect of the degree of brand loyalty on retailers' incentives to offer price promotions. Future theoretical research in the study of retailer promotional strategies may consider markets that consist of more than two brands. Most retail markets are inherently multiproduct so such models are likely to be more relevant than those currently in the literature. Accordingly, one could investigate the possibility of complementary products and their effect on retailer's promotional decisions. Research may also benefit from looking at the dynamic long run game theoretic aspects of promotional strategies. This would allow models to relax the assumption that the manufacturer sets prices simultaneously, and assume a sequential price setting game. This is a more realistic assumption and would allow theoretical applications to investigate the effect trade deals have on the opposing manufacturer and the resulting equilibrium. Lastly, theoretical extensions to markets whereby two manufacturers sell multiple brands would certainly have relevance. Because many highly concentrated industries have only a few manufacturers selling multiple products, it follows that individual manufacturers may be able to capitalize on varying degrees of brand loyalty within their own product listing, and offer trade deals to retailers accordingly.

Appendix A.

In this appendix, we describe our random utility demand model in more detail. To account for household heterogeneity and avoid the "independence of irrelevant alternatives" (IIA) property the parameters on both the price and propensity variables are allowed to vary randomly over households following a normal distribution (Train 2003). Specifically, define the densities of p_{bt} and pp_{hbt} as $f(p_{bt})$ and $f(pp_{hbt})$, respectively. Letting the parameter on price vary randomly over households accounts for the notion that some consumers may be more or less sensitive to price. Similarly the random parameter assumption on propensity simply acknowledges the likelihood that households may differ in their implicit desire to purchase the same brand repeatedly. These assumptions merely add an additional degree of flexibility to the model. Namely, if households are quite homogenous in their sensitivity to price and their preference for variety the estimated standard deviation of the density functions will be zero and the model will revert back to a MNL model.

Finally, the probability of household h purchasing brand b on purchasing occasion t is achieved by integrating over the conditional probability and the mixing distribution just defined, to obtain:

$$Pr_{ht}(b) = \int\int\prod_{t=1}^{T}\frac{e^{\zeta_{hbt}}}{1+\sum_{i=b}^{N-1}e^{\zeta_{hbt}}}f(p_{bt})\,f(pp_{hbt})\,dp_{bt}\,dpp_{hbt} \tag{A.1}$$

where $\zeta_{hbt} = u_{hbt} - \epsilon_{hbt}$ is the mean utility.

Because there is no analytical closed form we estimate the demand models for the household level brand loyalty estimates

(A.1) and the demand pricing model using simulated maximum likelihood (Train 2003).[19] Simulated maximum likelihood provides consistent parameter estimates under general error assumptions and is readily able to accommodate complex structures regarding consumer heterogeneity. To aid in the speed and efficiency of estimation, we include a Halton draw sequence. Halton draws can significantly reduce the number of draws with no degradation to simulation performance (Bhat, 2003). We found that $R = 100$ draws are sufficient to produce stable estimates without excessive estimation time. Bhat (2003) provides experimental evidence that suggests Halton sequences can reduce the number of draws required to produce estimates at a given accuracy by a factor of 10.

Retailer decision

Each retailer, k, chooses prices p_j for all brands to maximize category profits. In other words, the retailer solves:

$$\Pi^k = \max_{p_j} Q \sum_{j=1}^{J} (p_j - w_j) s_j,\ \forall j \tag{A.2}$$

where Q is the total market, w_j is the wholesale price, p_j is the price retailers charge, and s_j is the market share of brand j. To simplify our derivation, and without loss of generality, we assume unit retailing costs are zero. Eq. (A.2) assumes retailers maximize profits across all product categories, and not just on a category by category basis. In other words, retail prices reflect the implicit assumption that retailers internalize all pricing externalities across categories. We assume that retailers compete as Bertrand-Nash oligopolists so our first order condition for product j is given by:

$$s_j + \sum_{l=1}^{J} \frac{\partial s_l}{\partial p_j}(p_l - w_l) = 0,\ \forall j \tag{A.3}$$

for each retailer k. Stacking the first-order conditions for all retailers and solving for retail prices in matrix notation yields:

$$\mathbf{w} = \mathbf{p} - \mathbf{S}_p^{-1}\mathbf{S} \tag{A.4}$$

where $\mathbf{p}$ is a $J \times 1$ vector of retail prices, $\mathbf{w}$ is a $J \times 1$ vector of wholesale prices, $\mathbf{S}$ is a $J \times 1$ vector of market shares, and $\mathbf{S}_p$ is a $J \times J$ matrix of share derivatives with respect to all retail prices. Calculating $\mathbf{w}$ (which we refer to as w_{bkt}, below) in Eq. (A.4) provides an estimate of the wholesale price each retailer k pay for brand b at time t which is essential in isolating the effect brand loyalty has on the retailer's price promotion decision.

[19] We also estimate Eq. (A.1) as a multinomial probit model on a restricted number of choices and compare the results to those obtained with a RCL specification on the same choice set. Our results are robust to the choice of specification and, because the RCL allows us to estimate the demand model on an unrestricted number of choices, we employ the RCL model throughout.

Definition of terms

- Variables in the household level demand model include:
  - p_{bt}: Observed retail price of brand b at time t.
    σ_{α_h}: Estimated standard deviation of the random parameter.
  - γ_b: Brand-specific intercept terms.
  - dc_{bt}: An indicator of whether brand b is offered on a temporary discount during week t which is equal to 1 if the brand was discounted more than 10% from 1 week to the next.
  - $dc_{bt}p_{bt}$: An interaction term between the retail price and the discount indicator variable that accounts for demand rotations as a result of promotions.
  - pp_{hbt}: A measure of household propensity towards a brand defined in Eq. (2).
    * $\sigma_{pp_{hbt}}$: Estimated standard deviation of the propensity parameter which is allowed to vary randomly over households.
- ϵ_{hbt}: Error term in the household demand model which is assumed to be i.i.d. type I extreme value distributed and accounts for household-specific heterogeneity in preferences.
- ξ_{bt}: Error term in the household demand model that accounts for all product-specific variations in demand that are unobserved by the econometrician.
- pr^I_{hb}: Predicted probability of brand b used in the calculation of pp_{hbt} in Eq. (2).
  - A household is deemed *loyal to the brand* for which it has the highest brand preference, defined as the highest predicted probability of purchase $\left(\widehat{Pr_{hT}(b)}\right)$.
- $pref_b = (1H_b)/\sum_h \widehat{Pr_{hT}(b)}$: The measure of brand b's loyalty strength.
- $(\boldsymbol{\gamma})\ \mathbf{z}_{jkt}$: Vector of (parameters) variables in the retail level demand model which include variables similar to the ones described in $\mathbf{x}_{hbt}$ (excluding pp_{hbt}), and
  - α_i: Parameter on price which is allowed to vary randomly.
    * σ_α: Estimated standard deviation of the random parameter.
  - υ_{ijkt}: Intercept term that is allowed to vary randomly.
    * σ_υ: Estimated standard deviation of the random parameter.
- w_{bkt}: Estimate of the wholesale price each retailer k pays for brand b at time t.
- d_{bkt}: Depth of the discount offered on brand b by retailer k during week t. More precisley it is negative 1 times the percentage change in prices from one week to the next.
- f_{bk}: Promotional frequency of brand b in retailer k – the average number of times the brand is discounted at least 10% from one week to the next throughout 2005.
- $\mathbf{v}$: Vector of variables in the retail promotion models that include:
  - t: A time trend measured in weeks.
  - S_i: Binary seasonal variables to account for seasonal promotions effects.
  - M_i: Binary market variables.

- d_{bkt-1}: A variable indicating the discount offered for brand b in retailer k in the previous week.
- B_i: Binary brand indicator variables.

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