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The Impact of Introducing a Customer Loyalty Program On Category Sales and Profitability

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ABSTRACT

The authors propose and empirically investigate the effect of category-specific attributes as important factors associated with the change in pre- versus post-loyalty program introduction category sales and profits. Category penetration and frequency are positively correlated with loyalty program success with an increase in sales and profits, whereas impulse buying and ability to stockpile show negative correlations. Furthermore, although introducing a loyalty program generates immediate spikes in sales and profits in most categories; its impact is generally short-lived. It results in an initial redistribution of category expenditures during the program launch, where consumers seemingly shift consumption from lightly purchased categories to heavily purchased categories. But the effect soon erodes. Nevertheless, by modeling the diffusion process of loyalty program performance, this paper finds that penetration rate and private label share are key drivers of a category's sustainable growth. The evolution of consumer price elasticities and promotion sensitivities are tracked pre- and post-loyalty program introduction, and profit-driving categories are identified according to their category characteristics. New insights are offered on category management and long-term program planning.

Key Words: loyalty programs, category management, performance metrics

§1 INTRODUCTION

Customer loyalty programs are "structured marketing efforts" (Sharp and Sharp 1997) designed to reward and encourage loyal behavior, and increase usage of the company's product or service offerings. According to Forrester Research (Kelley, Delhagen and Yuen 2003), in 2003, 62% of U.S. consumers were enrolled in at least one customer loyalty program. Their collective penetration would certainly exceed that level today. It was estimated that in the fourth quarter of 2006, the average U.S. citizen belonged to 12 loyalty programs, yet was active in only 4.7 of these (Ferguson and Hlavinka 2007).

Despite the prevalence of loyalty programs across a variety of industries, there have long been doubts about their effectiveness. While some studies maintain that loyalty programs have a positive impact on re-patronage decisions and share-of-wallet (e.g., Lewis 2004; Verhoef 2003), many researchers claim that the proliferation of customer loyalty programs is a 'me-too' scheme and the term 'loyalty' is a misnomer (Shugan 2005). Sharp and Sharp (1997) claim that, at best, only one-third of loyalty programs 'work'. In the retail industry where loyalty programs are most widely in use, there are successful models such as Tesco's Clubcard, as well as unsatisfactory examples such as Safeway's ABC card program (Humby, Hunt and Philips 2003). McKinsey's research (Cigliano et al. 2000) indicates that while 48 percent of those who join grocery store loyalty programs spend more, only 18 percent do so in casual apparel programs.

The seeming paradox of high popularity of customer loyalty programs and large variability in their performance, and the ongoing debate about their effectiveness necessitate a better understanding of such programs for both researchers and retailers. A focus on effective category management processes has gained prominence in business practice. Recognizing retailers' concerns related to category management, marketing research has responded with a shift from brand level analysis to cross-category or multi-category analysis of pricing (Chintagunta 2002), assortment (Kalyanam, Borle and Boatwright 2007), price promotions (Nijs et al. 2001) and other marketing mix variables (Dhar, Hoch and Kumar 2001). Understanding how marketing actions and resulting consumer sensitivities differ or correlate across category types will give retailers insight on effective resource allocation across stores and categories (Seetharaman et al. 2005). Surprisingly, loyalty programs, one of the most expensive marketing investments that potentially link customer metrics to financial performance (Gupta and Zeithaml 2006), have rarely been examined in a cross-category setting.

This research addresses this issue by: First, investigating the impact of a rewards program and other elements of the marketing mix on sales and profitability over time by studying before and after the introduction of a loyalty program by a major grocery retail chain; Second, identifying the moderating effect of category characteristics on category-level performance using penetration, purchase frequency, impulse buying and ability to stockpile as key dimensions; Third, tracking the evolution of loyalty program performance following program launch and identifying drivers of long term program success. We focus on the six months following program launch, which is distinguished from longer time horizons that may allow for revised segmentations and/or household-level targeting based on longer purchase histories of program members that are collected.

Using store data from Dominick's Finer Foods, our research contributes to the literature in the following ways: First, it is the first empirical analysis that longitudinally examines the impact of loyalty program introduction on category sales and profits using pre- and post-program store transaction data. We find evidence that introducing a loyalty program is effective in most categories. Second, we demonstrate that while loyalty program performance is not universally satisfactory, category characteristics are an important moderator: Categories with high penetration, high frequency, low impulse and low ability to stockpile perform best, resulting in an increase in sales and profits. By contrast, categories with low penetration, low purchase frequency, but high impulse and high degree of stockpiling experience a decline in sales and profits following program introduction. In other words, a loyalty program is most effective in high-penetration, high-frequency, fast-moving consumption goods categories that consumers have planned for. Third, we model the diffusion process and offer valuable insights on the evolution of loyalty program performance. We find that, while a loyalty program's effect in most of the categories studied is short-lived, penetration rate and private label share are key to a category's sustainable growth in sales and profits post-introduction. Significant benefits from a loyalty program may only be realized over a longer time horizon, when the firm can utilize the customer database to develop better behavior-based segments and/or household-level promotions.

The rest of this paper is organized as follows: The next sections review the related literature, describe the data, and then construct the empirical model. We conclude with managerial implications, and possible future research directions.

§2 LITERATURE REVIEW

2.1 Loyalty Programs: Are They Effective?

The debate over loyalty program effectiveness has long been of interest to researchers. Table 1 presents a summary of findings from a representative sample of related research. Advocates of customer loyalty programs argue that they accelerate the loyalty life cycle and increase brand loyalty, while lowering operational costs by decreasing price competition. This is achieved in a number of ways. First, loyal customers provide favorable recommendations to potential customers (Biyalogorsky, Gerstner and Libai 2001) and allow firms to manage capacity in a more flexible manner (Kim, Shi and Srinivasan 2004). Second, loyalty programs provide data that help firms identify their most valuable customers, track purchasing patterns, and understand more about consumers' behavior at an individual level, as opposed to merely at an aggregate level (Kopalle et al. 2011). Third, loyalty program members have lower price sensitivity than nonmembers (Van Heerde and Bijmolt 2005), and weigh negative experiences with the firm less than nonmembers (Bolton, Kannan and Bramlett 2000).

On the other hand, there is substantial criticism related to the effectiveness of loyalty programs to increase firm profitability and create competitive advantage. Lal and Bell (2003) analyze data from a U.S. supermarket chain, finding that, while loyalty programs are profitable, it is only because substantial incremental sales to casual shoppers (cherry pickers) offset subsidies to already loyal customers. Dowling and Uncles (1997) argue that a loyalty program is unlikely to alter customer behavior fundamentally, especially in established competitive markets. In some sectors, it is believed that loyalty programs have little potential to create competitive advantages and firms may end up playing a zero-sum game (Humby et al. 2003). Examining two years of single source BehaviorScan data, Meyer-Waarden and Benavent (2009) find that more frequent customers of a store enroll in a loyalty program earlier; buying behavior changes only slightly after buyers join a program; and, the small changes in loyalty that do occur appear to erode 6-9 months after buyers join.

While the marketing literature does not provide a conclusive answer to whether loyalty programs are an effective tool to boost sales and profits, the discrepancy of research results may be due to a number of reasons: First, while existing research using attitudinal and behavioral measures address the effectiveness of loyalty programs on individual customers, few studies establish the link between a loyalty program and store and/or category performance, which is a concern of management. Researchers have been using customer-level metrics such as spending levels and purchase frequencies, and customer-level motivators such as reward types and memberships from household panel data. Other research also examines the impact on brand market share (Sharp and Sharp 1997) and on sales in a single category (Drèze and Hoch 1998). However, relatively little empirical research exists investigating whether and how a loyalty program works in the store and across stores from the firm's perspective. The limited existing research that does investigate store-level performance (Leenheer et al. 2007; Van Heerde and Bijmolt 2005) and draws comparisons on members versus nonmembers, has been criticized for methodological limitations such as self-selection bias and endogeneity.

Secondly, the methodological limitations are also a result of an inappropriately selected observation window. For studies that only use post-program introduction period data, most use only the membership database to examine the impact between heavy users and light users without having nonmembers as a control group (Kim, Shi and Srinivasan 2001; Liu 2007; Taylor and Neslin 2005). Leenheer et al. (2007), using both members and nonmembers information, adopted a 2SLS approach to account for endogeneity. Other useful approaches include switching regression models (Taylor and Neslin 2005) and dynamic structural models that capture the optimizing behavior of consumers (Kopalle and Neslin 2003; Lewis 2004). There are few studies, however, that use time series analysis in which a loyalty program is introduced within the observation period. Drèze and Hoch (1998) compare sales in a single category with its historical level. Sharp and Sharp (1997) conduct a survey on 5000 respondents before and after the program introduction. Taylor and Neslin (2005), and Lal and Bell (2003) both examine promotions that reward members for achieving target purchase levels over a short term (6-8 weeks) period, which is fundamentally different from conventional loyalty programs that require a longer-term commitment from both retailers and consumers. Ideally, we would like to examine both the pre- and post-program introduction period as if it was a 'natural experiment', which is what is done in this paper. Table 2 summarizes selective studies along with the unit of analysis and observation window dimensions. Our study is unique in using longitudinal store-level data to examine the performance of a customer loyalty program, addressing managerial concerns on linking a loyalty program to store performance.

Lastly, while researchers have examined loyalty programs in a variety of categories, any one study is almost always limited to a single category. It is not only difficult to make comparisons across airlines (Sharp and Sharp 1997), financial services (Bolton et al. 2000), and retailers (Lewis 2004), but results are also vulnerable to potential moderating effects of category characteristics on store loyalty (Zhang, Gangwar and Seetharaman 2010). In fact, category performance may be systematically driven by the role of the category (Dhar et al. 2001). Although previous research focuses on consumer factors, program factors and competition factors as drivers for successful loyalty programs (Liu and Yang 2009), category factors such as category expandability and product substitutability are often implicitly captured by competition factors, particularly when analysis is conducted at one category.

Fok et al. (2006) summarize the literature on the determinants of price promotions effectiveness. Thirteen out of 15 papers they examined listed category characteristics as their explanatory variables[1]. Similarly, marketing actions such as loyalty program performance may be influenced by category characteristics (Fader and Lodish 1990). In fact, previous literature has documented some evidence of moderating effects of usage levels, though not necessarily emphasizing category characteristics. For example, Lewis (2004) finds that the level of reward received by a customer in a prior period positively affects the probability of making larger-sized

[1] The detailed review is available in the web appendix.

transactions in the current period. Liu (2007) finds that consumers with low or moderate initial patronage levels gradually purchase more and become more loyal to the firm after joining its loyalty program. Leenheer et al.'s (2007) study also shows a slight increase in share of wallet for loyalty program members. Sharp and Sharp (1997) investigate the impact of Australia's Fly Buys program by comparing observed purchase frequencies with the Dirichlet baseline and find only a weak improvement in repeat-purchase behavior. In this paper, we are interested in examining the impact of category characteristics on loyalty program performance, and drawing implications on category management for retailers.

In summary, the marketing literature has shown mixed support for loyalty program effectiveness, largely due to managerial limitations that include linking store performance with attitudinal or behavioral measures, operational limitations to address self-selection with the post-program observation period, and theoretical limitations to investigate the moderating effect of category characteristics. This study enriches the existing research on loyalty programs by: First, empirically examining the impact of introducing a loyalty program on sales and profitability using store data in a retail chain setting; Second, including both the pre- and post-program introduction period as if it was a 'natural experiment'; Third, discussing how the impact of introducing a loyalty program varies across categories as a result of category characteristics.

2.2 Category Factors Governing the Effectiveness of Loyalty Programs

To identify category, store and brand characteristics, we draw primarily on recent studies by Fok et al. (2006) and Macé and Neslin (2004) to ensure an adequate representation of characteristics. We find the following commonly studied category characteristics based on Fok et al. (2006)'s summary: Household penetration; Purchase frequency; Average deals; and, Category expensiveness.

These variables are consistent with Fader and Lodish's (1990) earlier framework as well as the popular scheme promoted by the Food Marketing Institute (FMI), which also utilizes consumer-based category roles defined according to penetration and frequency. Therefore, categories are classified into four groups respectively: *staples* (high penetration/high frequency), *niches* (low penetration/high frequency), *variety enhancers* (high penetration/low frequency) and *fill-ins* (low penetration/low frequency). With different consumer motivations across four groups, it is highly likely that the effectiveness of marketing actions also differs by category (Dhar et al. 2001). For example, the heavy user effect (Hoch et al., 1995) would predict that consumers are more responsive in categories that are purchased more often and heavily such as staples, and less so in fill-ins.

Another important work is by Narasimhan et al. (1996), who examine the relationship between promotional elasticities and characteristics in the framework of brand switching, store switching, category expansion and purchase acceleration. They hypothesize that category penetration, interpurchase time, price, private label share, number of brands, impulse buying and ability to stockpile are correlated with promotional response. We include all above variables as well as deals (average percent off), which is used as a dependent variable in their paper.

Higher category penetration means a larger potential customer base that can generate a steady stream of revenues and data with the loyalty program; shorter purchase cycle encourages repeated purchases within a short time frame; price levels and deals are directly related to customers' experiences and expectations about the loyalty program; Categories with greater private label share allow flexible use of advertising and promotion; brand proliferation within a category suggests room for product differentiation and thus data applications on in-depth customer segmentation. Rather than inducing one-time impulse buying and strategic stockpiling behavior through temporary promotions, loyalty programs foster customer knowledge and nurture long-term relationships.

3.2 Other Factors

To fully understand the impact of loyalty programs, we also include the following characteristics: Price; Promotion frequency; Promotion types (e.g., bundles, bonus buys, coupons); Competitive price; Competitive promotion; Private label versus national brand; Brand assortment; and, Store traffic.

Promotions, coupled with unpublicized communications to program members, incentivize more customers to join the loyalty program. While bonus buys may be more apparent in perceived savings, targeted coupons are idiosyncratic to members' personal consumption habits. Competitive prices and promotions enable customers to form a price image of a particular store and/or brand. Store brands can help retailers drive store traffic and increase loyalty due to a unique identification with the store, thereby contributing to better program performance. Brands with greater depth may have greater accessibility to frequent buyers, as well as greater utility for accumulating rewards. Lastly, modeling store traffic provides insight on whether the revenue impact, if any, is a result of increasing expenditures from the existing customers, or a result of a greater number of shoppers.

§3. DATA AND MODEL

Dominick's Finer Foods (DFF) introduced its "Fresh Values" frequent shopper card program on December 5, 1996. Like many other loyalty programs in place today, it is a free membership that provides exclusive savings and benefits for members[2]. According to the Chicago Sun-Times (Dec 4th, 1996), during the first week of introduction, Dominick's mailed

[2] See website at http://www.dominicks.com/IFL/Grocery/Club-Card. The website lists three major benefits: savings, earning money for education and gasoline. The latter two options were not available when the program was first introduced.

500,000 cards to shoppers who already held its check-cashing card. Customers were also encouraged to sign up at the check-out counters.

The Dominick's Research Database, hosted by the University of Chicago (http://research.chicagobooth.edu/marketing/databases/dominicks/index.aspx), provides weekly store data for 399 weeks from September 1989 to May 1997, with week 378 being the week that the loyalty program was introduced. Our analysis includes all 29 categories, making this study one of the few to examine the complete dataset. Available measures include unit sales, retail shelf prices, which are usually the same as transaction prices as in Van Heerde et al. (2000) and Levy et al. (2010), profit margins, which are obtained from the computation of wholesale prices, and indicator variables describing promotion activities: bonus buy, coupons, and sales. Category characteristics are obtained from multiple sources and presented in Table 3. Category penetration, interpurchase time, price level and average deal are available from the (1998) IRI *Marketing Factbook* (these are national-level metrics). Measures for impulse buying and ability-to-stockpile are from by Narasimhan, Neslin and Sen (1996). Lastly, we computed the number of brands and private label share in each category from the Dominick's dataset.

For each category, UPC-level data are aggregated to the store-brand level. Data available for estimation of the model parameters are: brands' average per unit scanner price adjusted for pack size (equal to a brand's sales divided by its total volume sold), dollar sales, gross margins (profits), and three types of promotions: *PromoB* (bonus buy), *PromoC* (coupon) and *PromoS* (sales). We decompose the effect of the loyalty program into two components: An indicator variable, *LoyPgm,* to describe the presence of the loyalty program, and a diffusion variable, *LoyPgm_Diff*, to capture the program's adoption and penetration effects. In addition we also create a variable, *StoreBrand*, to indicate whether a particular brand is a private label. We introduce three brand assortment variables: *UpcCount*, to measure the number of UPCs a brand carries; *Brand_New* and *Brand_Discontinued*, to control for the number of UPCs within a brand that were introduced or discontinued after the program introduction. In addition, we create a market share variable, *BrandShare,* to assess the share of a brand in a store; and a traffic variable, *CustomerCount*, to capture customer traffic in a given store. Holidays, seasonality and trend are also captured as independent demand shifters to facilitate identification. Moreover, for each store-brand, we calculate the average price, and average promotions of all competitors of that particular brand at the same store in the same week. Table 4 provides a description of the variables.

We report summary statistics for unit retail prices, average promotions, sales and profit margins for periods before and after the introduction of the "Fresh Values" loyalty program in the web appendix. Similar to Macé and Neslin (2004), our analysis contains 200 weeks from week 200 to 399, with week 200 being the time around the first frequent shoppers' program was introduced in the Chicago area by DFF's largest competitor, Jewel Osco. Due to seasonality concerns, we match the data by comparing statistics during the 22 weeks after program launch with statistics during the same period one year earlier. Hotelling's T-statistic shows a different mean vector across all categories. We observe an increase in sales and profits in categories such as cereal (CER), cheese (CHE), soft drinks (SDR) and etc, while a decrease in categories such as bath soap (BAT), cigarettes (CIG), grooming products (GRO).

We are aware that, after the introduction of the loyalty program by a grocery store, cashiers are typically provided a 'store' loyalty card to ensure non-members received the discount price at checkout during the rollout period. Nevertheless, it is possible that there were some purchases made by nonmembers who did not use a card. We contacted Dominick's corporate offices to ask for data on nonmembers' checkout prices, but were not successful in acquiring this data. Therefore, in this paper, we construct nonmembers' prices using the following procedure: Distinguish between the following three price definitions: A: Regular price, which is the price in regular (non-promotional) conditions. B: Current nonmembers' price, which in our case is the actual price that a nonmember pays at the check-out. C: Current members' price, which is the price a member pays at the checkout. Definitions A and B are well studied in the literature (Tijmolt, Van Heerde and Pieters 2005; Wedel and Zhang 2004). We take the first step in understanding and disentangling the effect of B and C as a result of the program introduction. The relationships between the three prices are as follows:

If A=B, there is no promotion;

If A>B, there is a promotion; promotion indicator =1, and price promotion = A-B[3]

If B=C, there is no members' discount;

If B>C, there is a members' discount; members' discount= B-C

If A=C, there is no promotion or members' discount;

Because B and C price are not directly in the dataset, we sought out store managers for guidance as to how to use available measures to create measures for members' and nonmembers' price. Figure 1 illustrates an example of members' and nonmembers' price in a typical retail store.

The Dominick's Database records the actual price (posted shelf price, or transaction price). For example, after the introduction of the loyalty program, if an item was originally \$3.89, its new shelf tag would take the following form: \$3.49 (with card, was \$3.89). Therefore, members pay \$3.49 at the check-out. This price is then recorded in the database and we denote it

[3] We follow Macé and Neslin (2004)'s algorithm for computing prices. We also thank Xavier Drèze, who helped to set up much of the database and Jie Zhang for clarifications on price definitions via personal communications.

as *MemPrice*. By contrast, nonmembers pay the regular price (without promotion or members' discount) of $3.89, which we denote as *NonMemPrice*. If a regular promotion occurs, then the above item would, for exposition, have a price of $2.33, which all customers are entitled to regardless of membership. In this case, $2.33 will be recorded in the system. This has been common practice in many retail stores. For example, Figure 1 presents the two scenarios of 1) members receive the posted shelf price/actual price, and 2) general promotions to both members and nonmembers. Therefore, we denote members' discount as *DPrice,* which is the difference between *NonMemPrice and MemPrice.* It is equal to zero before the program was introduced, and when there is a general promotion applied to all customers. Since our data only records actual transaction price (*MemPrice*) at the store level, our approach makes the assumption that there is an unobservable mix of members and nonmembers that were previously both paying *MemPrice,* but when loyalty program is in place, nonmembers have to pay *NonMemPrice* at the stores with *highest* price in the same week. Furthermore, we seek to accommodate this loyalty program effect by using *LoyPgm* and *LoyPgm_Diff*, and note that the underlying actual data is unobservable and confidential.

Since the loyalty program was introduced in week 378, which we refer to as t_{intro}, we have

(1) $$LoyPgm_t = 1 \text{ if } t \geq t_{intro}; \qquad 0 \text{ otherwise}$$

We note that program diffusion is likely to vary across store areas as a function of store demographics. In fact, individual stores may have distinct response profiles for price and promotion (Hoch et al., 1995). While this paper focuses on loyalty program performance at the category level, it is necessary to control for variations across stores by incorporating store demographics into the diffusion function:

(2) $LoyPgm\_Diff_{st}$ = F $(StoreDemo_s)_t$

$= StoreDemo * ((t/\ t_{intro}) + (t/\ t_{intro})^2 + (t/\ t_{intro})^3)$ if $t \geq t_{intro}$; 0 otherwise

We allow the effect of loyalty program to diffuse over time by multiplying StoreDemo with a flexible cubic function of time[4]. Hoch et al. (1995) examine eleven consumer and competitive characteristics that impact store-level price elasticities using the same dataset: ELDERLY, EDUC, ETHNIC, FAM_SIZE, INCOME, HOUSE_VAL, WORK_WOM, SUPER_DIS, WARE_DIS, SUPER_VOL and WARE_DIS. Therefore, we use their estimates (which was pooled across categories) and set *StoreDemo* to be a compound of all the eleven variables. Across all 107 stores, the value for *StoreDemo* varies between -1.250 to -0.143. To make the interpretation easier, we take the absolute values of *StoreDemo* (0.143, 1.250) so that $LoyPgm\_Diff_{st}$ would be positive.

Following Macé and Neslin (2004) and Van Heerde et al. (2000, 2004), we use four periods lags and leads for sales, prices, and promotions in a regression model at the store-brand level. For each of the 29 categories, we set up the sales equation as follows:

(3)

$$\ln(Sales_{ist}) =$$

$$\beta_0 + \sum_{u=1}^{4} \beta_{1u} \ln(Sales_{is,t-u}) + \sum_{v=1}^{4} \beta_{2v} \ln(Sales_{is,t+v}) + \sum_{l=1}^{4} \beta_{3w} \ln(MemPrice_{is,t-w}) +$$

$$\sum_{m=1}^{4} \beta_{4l} \ln(MemPrice_{is,t+l}) + \sum_{o=1}^{4} \beta_{5o} \ln(CompMemPrice_{is,t-o})\, s +$$

$$\sum_{p=1}^{4} \beta_{6p} \ln(CompMemPrice_{is,t+p}) + \beta_7 LoyPgm_t + \beta_8 LoyPgm\_Diff_{st} + \Pi Z_{ist} +$$

$$\Phi LoyPgm_t \times Z_{ist} + \Psi LoyPgm\_Diff_{st} \times Z_{ist} + \beta_9 Holiday + \beta_{10} Season_t + \beta_{11} t + u_{ist}$$

where,

[4] In the empirical analysis, we examine other functional forms as robustness checks.

Z_{ist}

$$= \begin{bmatrix} \ln(MemPrice_{ist}), \ln(CompMemPrice_{ist}), \ln(DPrice_{ist}), \\ PromoB_{ist}, PromoC_{ist}, PromoS_{ist}, CompPromoB_{ist} \\ , CompPromoC_{ist}, CompPromoS_{ist}, StoreBrand_{i}, \\ UpcCount_{ist}, Brand\_New_{ist}, Brand\_Discontinued_{ist}, BrandShare_{ist}, CustomerCount_{st}, \end{bmatrix}$$

and, $u_{ist} =$ an error term for brand *i* in store *s* during week *t*. In the empirical analysis, we also examined a linear and a nonlinear, non-monotone functional form for the process function, but did not find either to fit the data better than a nonlinear, monotone functional form.

Similarly, we set up the profits equation separately using ln($Profits_{ist}$) as the dependent variable. The same set of independent variables is used except now we have four periods lag and lead profits instead of sales. In that equation, we are mainly concerned about the effect of $LoyPgm_t$ and $LoyPgm\_Diff_t$ on profit margins.

Sales and *Profits* are the geometric means of sales and profit margins, respectively, across all UPC's for a given store-brand combination in week *t*. The variable $LoyPgm_t$ is an indicator describing whether the retailer's customer loyalty program was running in period *t*. The variable $LoyPgm\_Diff_t$ simulates the adoption and diffusion effect of loyalty program membership. The intrinsic synergy between the customer loyalty program and marketing mix efforts are captured using interactions involving the two loyalty program variables, $LoyPgm_t$ and $LoyPgm\_Diff_{st}$, and marketing action variables that describe own and competitive prices and promotions in the form of bonus buys, coupons and sales, brand assortments, store traffic, and whether the brand is a store brand.

Similar to Macé and Neslin (2004)'s specification, the model is nonlinear of a multiplicative form, and potential endogeneity is addressed by incorporating lag and lead variables. We also include only direct effects of bonus buys, coupons and sales promotions, but do not include feature or display due to data availability. However, in their paper, price index (the ratio of actual price to regular price) instead of actual retail price is used for compatibility across categories. Our analysis is performed category-by-category. Yet, we found similar estimates for the loyalty program whether they were calculated on the basis of price indices or retail prices. The price elasticities of brand *i* at store *s* at time *t* can be computed by summating across the coefficients of the following variables:

(4) $\text{PriceElasticity}_{\text{ist}} = \ln(MemPrice_{ist}) + \ln(DPrice_{ist}) + LoyPgm_t * \ln(MemPrice_{ist})$
$+ (LoyPgm\_Diff_{st}) * \ln(MemPrice_{ist}) + LoyPgm\_Diff_{st} * \ln(DPrice_{ist})$

In Equation 4, $\ln(MemPrice_{ist})$ serves as the baseline price, and is equal to $\ln(NonMemPrice_{ist})$ before the program introduction or when there is a general promotion to all customers; $\ln(DPrice_{ist})$ captures members' discounts after the program introduction; $LoyPgm_t * \ln(MemPrice_{ist})$ denotes the change in price sensitivities due to the introduction. For example, customers may form certain expectations about receiving better prices, or they may better understand store's pricing policy and track their consumption habits with the loyalty card and related communication efforts; Lastly, $(LoyPgm\_Diff_{st}) * \ln(MemPrice_{ist})$ and $LoyPgm\_Diff_{st} * \ln(DPrice_{ist})$ reflects the adoption and penetration effect over time for both baseline price and members' discounts.

The Arellano-Bond test indicates autocorrelation in the panel data. Therefore, a random-effects GLS model, adjusted for autocorrelation, is used for parameter estimation. The assumption is that the random effects are uncorrelated with the independent variables. Therefore, we have

(5) $$u_{ist} = a_{is} + \varepsilon_{ist}$$

Where

a_{is} are random effects, ε_{ist} are the random error and both follow an iid normal distribution, and we have $\mathrm{E}(a_{is}, \varepsilon_{ist}) = 0$. In such a model, each intercept is a random deviation from some mean intercept. It is used when some omitted variables are constant over time but vary between cases, and others may be fixed between cases but vary over time. Managerially this implies that different marketing strategies might be implemented across store-brand combinations, or across time. The Hausman-Wu test results also support using the random-effects specification.

§4. RESULTS

Tables 5a to 7e present the results from our model. We focus our discussion on the effect of the loyalty program on sales, profits, price elasticities, and promotion elasticities across the 29 categories. Complete results including all variables are available in the web appendix. In summary, the model fit (R-square) is acceptable and almost all coefficients are significantly different from zero. Across all the categories, the lag and lead effects are positive. In the sales equation, there is a negative association between price and sales. In addition, promotional activities are positively associated with sales. The average price of competing brands is positively associated with sales of a particular brand at the same store in a given week, whereas average promotional activities of competing brands is negatively associated with the sales. In general, positive correlations are found between sales and brands that are private labels, or enjoy large market share, or have large assortments, or attract greater store traffic. Similar patterns are observed in the profit equation except that the direction of association between price and profit margins is inconclusive.

We are primarily interested in the parameters associated with the loyalty program. We break the results down and present them in five tables (Tables 5a to 5e). The following sections discuss the effect of the loyalty program introduction on sales, profits, price elasticities, and promotion elasticities.

4.1 Category Sales and Profits

Table 5a shows the impact on category sales and profits. *LoyPgm_Sales* and *LoyPgmDiff_ Sales* are the estimates for *LoyPgm* and *LoyPgm_Diff* from the sales equation, respectively. *LoyPgmFinal_ Sales* is the impact of the loyalty program in the final week (Week 399) of the observation window. It is computed as *LoyPgm_Sales* + *LoyPgmDiff_Sales* × StoreDemo× $((399/378) + (399/378)^2 + (399/378)^3)$. Since *StoreDemo* takes a range between 0.143 and 1.250, we also report the upper and lower bounds for the final effect of loyalty program. We observe vast differences in parameter estimates across categories. The direct loyalty program effect, *LoyPgm_Sales,* ranges from -6.637 in the frozen juice (FRJ) category to 5.782 in the soft drinks (SDR) category. Interestingly, positive signs seem to occur most often in categories that are purchased heavily and frequently, such as cheese (CHE), laundry detergent (LND), beer (BER) and so on. In contrast, negative signs occur most often in categories that have fewer or infrequent purchases, such as fabric softener (FSF), cookies (COO), grooming products (GRO) and others.

However, the number of positive effects (19 categories) is higher than that of negative effects (10 categories). Also, effect size is much larger in categories with positive signs. Overall, consistent with Drèze and Hoch (1998), a loyalty program helps boost sales in most of the categories during its introduction period.

Furthermore, in nearly half of all the 29 categories, while the signs of *LoyPgm_Sales* suggest mixed directions of loyalty program effectiveness, the estimates for *LoyPgmDiff_Sales* seem to neutralize that effect with opposite signs from the estimates for *LoyPgm_Sales.* In other words, the main loyalty program effect is most prominent during the introduction period, and then decays over time. Categories that benefit from the introduction of the loyalty program gradually experience a diminishing effect, whereas categories that suffer from a sales hit at the beginning eventually recover.

Similar patterns are found for the effect on profits, price elasticities and promotion sensitivities. Again *LoyPgm_Profits* and *LoyPgmDiff_Profits* are the estimates for *LoyPgm* and *LoyPgm_Diff* from the profits equation, respectively. *LoyPgmFinal_Profits* is the impact on loyalty program in the final week (Week 399) of the observation window. Consistent with our findings on sales, Table 7b suggests three interesting phenomena associated with category profitability: First, the directions for loyalty program effectiveness are different across categories. The introduction of a loyalty program is associated with a quick impulse response, upwards or downwards, on category profits. Next, a loyalty program is effective in extracting higher profit margins in many categories (21 out of 29 categories) during its launch. In addition, the large spikes in profits in these categories outweigh the small losses that occur in other categories. Lastly, while we suspect that category characteristics might be influencing the program performance, we find that in majority of categories, the program effect gets attenuated over time.

4.2 Price and Promotion Elasticities

Table 5b reports the estimates for the effect of loyalty program on prices. Since a log-log specification is used in our model, price elasticities are computed as coefficients of the price variables. The negative sign of members' discount, *ln(DPrice),* indicates members are in general less price sensitive than nonmembers (Bolton et al., 2000). In addition, the estimate for *LoyPgm*×*ln(MemPrice)* is positive in 18 out of 29 categories. This is consistent with the common belief that loyalty programs reduce price sensitivity (Dowling and Uncles 1997).

We compare our estimates with Hoch et al. (1995)'s, who examine the same Dominick's data using fewer categories and a shorter observation period at the UPC level. Our estimates are in general a little less negative than Hoch et al.'s. Due to the nature of scanner data, our price elasticities are likely to be biased upwards (Bijmolt et al. 2005).

Table 7c, 7d and 7e report the estimates for the effect of introducing a loyalty program on bonus buys, coupons and sales promotions from the sales equation. Similar to Leenheer and Bijmolt (2003) who find no effect of promotions on perceived effectiveness in their survey, we observe that the interaction between general promotions and loyalty program has mixed outcomes across categories. While there is strong presence of synergies among marketing actions in some categories, others seem to experience a negative interaction between the two tools. Managerially, in these categories, short-term promotions tend to work in opposition to a structured loyalty program which is built upon long-term customer knowledge and customer loyalty, and they may become substitutes for each other. For those categories which do enjoy synergistic effects between the two, coupon promotions seem to perform better than sales and bonus buys. In practice, a common targeting effort is sending out coupons that are tailored to consumers' purchase preferences, which are inferred from the program membership database (though Dominick's may not have had that degree of sophistication at the time of the program launch).

Furthermore, similar to the patterns in category sales and profits, the diffusion variables for price and promotion wash out the immediate spikes or dips associated with program launch. Despite the short-term impulses, price and promotion elasticities tend to revert to their original level approximately six months after introduction.

4.3 Category Characteristics

Since we observe significant differences in loyalty program effectiveness across categories, we propose category characteristics as a potential moderator. Following Narasimhan et al. (1996) and Fok et al. (2006), we regress loyalty program effect on penetration, frequency, price, deals, impulse, ability to stockpile, number of bands and private label. As shown in Table 8, category penetration and frequency are positively correlated with *LoyPgm_Sales* and *LoyPgm_Profits*. This is consistent with Narasimhan et al.'s finding which uses promotional response as a dependent variable. However, contrary to their hypotheses on impulse and ability to stockpile, we find that *LoyPgm_Sales* and *LoyPgm_Profits* are negatively correlated with these two category characteristics. In other words, loyalty program works best in high penetration, high frequency fast moving consumption goods (FMCG) that consumers have planned for. Managerially, it suggests that a loyalty program is best viewed as a long-term promotional effort that tracks consumption habits, rather than encouraging one-time impulsive buying.

Furthermore, we notice that the direction of loyalty program diffusion also varies by category. Understanding evolutions of loyalty program performance over time and identifying drivers of sustainable growth is crucial to long-term promotion planning and program design. For example, managers may adjust program reward structure in anticipation of changes in penetration and reach (due to advertising), brand composition (due to new brand introduction) and category pricing. We find that a loyalty program is increasingly effective in boosting sales and profits in some categories such as cheese (CHE), canned soup (CSO) and bottled juice (BJC) . Categories such as bath soaps (BAT), fabric softeners (FSF), grooming products (GRO) and shampoos (SHA) continue to suffer from a greater decline in sales and profits. The effect of loyalty program is short-lived for the rest of the categories: previous effects of introducing a loyalty program, regardless of the sign, gradually revert to the mean within 22 weeks of program introduction.

The above observation offers an interesting fact: the dynamic effect of introducing a loyalty program and program diffusion are different, not only in terms of magnitude, but also in terms of direction, across different categories. Since the direction of the effect is jointly determined by the sign of *LoyPgm* and *LoyPgm_Diff*, we define a direction variable, *LoyPgm_Direction_Sales* and *LoyPgm_Direction_Profits*, as:

$$(6) LoyPgm\_Direction\ \_Sales(Profits) = \begin{matrix} 4\ if\ LoyPgm \geq 0\ and\ LoyPgm_{Diff} \geq 0 \\ 3\ if\ LoyPgm \geq 0\ and\ LoyPgm_{Diff} \leq 0 \\ 2\ if\ LoyPgm < 0\ and\ LoyPgm_{Diff} \geq 0 \\ 1\ if\ LoyPgm < 0\ and\ LoyPgm_{Diff} < 0 \end{matrix}$$

Since the coding is categorical, we add the direction values for *sales* and *profits* together to yield in a range of 2 to 8 for *LoyPgm_Direction*, where an 8 indicates best performance and a 2 indicates worst performance. The most flexible coding is 15 indicator variables (4 directions for sales times 4 directions for profits less one). We also examine more parsimonious operationalizations and the substantive conclusions do not change including using *LoyPgm_Direction*, a single variable. We then regress the category characteristics on direction values again. As shown in Table 6, high penetration and high private label share categories are positively correlated with a strong positive diffusion effect. They are the drivers of category's sustainable growth. We do not find a significant association between category characteristics and the effect of loyalty program on price elasticities or promotion sensitivities.

4.4 Robustness Checks

First, while the nature of the data creates endogeneity concerns, we perform the two-stage least-squares (2SLS) estimation with prices and promotions being instrumented. We use average prices and promotions in the other categories during the same week, as well as own prices and promotions during the same week a year ago as the instrumental variables. The 2SLS results do not differ from our GLS results.

Next, we use a subset of stores as the hold-out sample. We predict the sales and profits for each store-brand combinations in these stores using our model, and compute the symmetric average mean absolute percentage error (sMAPE)[5]. Across 29 categories the value is around 9.17% for sales and 20.46% for profits, indicating satisfactory predictive power. Next, in order to test whether the loyalty program causes a structural break in sales and profit margins, we perform the Zivot-Andrews unit root test, which allows a structural break at an unknown point in the intercept, the linear trend, or both. The minimum t-statistics from 29 categories indicate strong presence of a structural break in sales and profits around the time when the loyalty program is introduced, without a significant change in store traffic. In fact, the interaction between loyalty program and store traffic (*CustomerCount*) is mostly nonsignificant and close to zero. We also examined models that included *CustomerCount* as a dependent measure and did not find significant results.

The category-by-category MAPE and structural break test results are available in the web appendix. In addition, our results hold as we vary the length of our observation window, or use different functional forms (we tried a second order term, and/or use $t\text{-}t_{intro}$ instead of t/t_{intro}) for the diffusion effect, or use aggregate measures of promotional activities.

§5. DISCUSSION AND MANAGERIAL IMPLICATIONS

First, as previous empirical research and industrial practice suggests the effect of a loyalty program on a retail chain's sales and profitability is largely mixed, that published results from multiple categories do not converge. However, in Dominick's case, the introduction of its loyalty program is associated with an immediate boost in sales and profit margins in most of the categories. It could be that customers who are already loyal to the supermarket chain increase

[5] sMAPE is bound between 0 and 1, and is preferred to MAPE when a few number of observations with high values may distort the mean MAPE, as MAPE does not have an upper bound.

their spending levels following the program introduction (Lewis 2004; Liu 2007). But it is also likely that substantial incremental sales to casual shoppers that are attracted to the store offset subsidies to those already loyal customers (Lal and Bell 2003). This is because if the first explanation holds, the change in loyal customers' consumption patterns would persist, rather than only generate short-term spikes in many categories. Our findings seem to suggest that a loyalty program is effective in arousing shoppers' interests and attracting revenue streams in the short run. In reality, Dominick's loyalty program reported strong acceptance of its Fresh Values loyalty card with a 3.2 percent sales increase and a 7.8 percent profit increase in the subsequent fiscal quarter. According to Morgan Stanley (the investments firm), Dominick's quadrupled its earnings per share during the first quarter of 1997. As its President and Chief Executive Officer Robert A. Mariano put, in spite of some initial losses attributed to remodeling activities, they "conservatively approached the introduction of our Fresh Values card. As a result, cash flow was stronger than would have been the case had the company been more promotional during the introductory phase of the card program".

Secondly, while the 29 categories do not yield convergent and determinant results, category characteristics moderate the effectiveness of loyalty programs. Specifically, a loyalty program performs best in categories with high penetration rate, high purchase frequency (the *staples*), low impulse and low ability to stockpile; each is associated with an increase in sales and profit margins. By contrast, in categories with low penetration rate, low purchase frequency (the *fill-ins*) but high impulse and high ability to stockpile, there is a decline in sales and profit margins. The categories in the middle experience a moderate impact as compared to the extreme categories.

A loyalty program seems to be most effective in heavily purchased FMCG categories for several reasons. First, these categories allow more accesses and purchases, thereby providing more incentives and greater involvement for customers enrolled in the loyalty program (Kivets and Simonson 2003; Yi and Jeon 2003). In that case, a $1 reward from $100 purchase would be perceived as less valuable than a $10 reward from $1000 purchase (Tversky and Kahneman 1981). Secondly, our findings are consistent with the Recency-Frequency-Monetary Value (RFM) framework in CRM applications in that high penetration and high purchase frequency imply large repeat purchases and customer base which provides adequate input for managers to analyze their patterns and preferences. It is through long-run customer knowledge and loyalty that which store performance is improved (Humby et al. 2003). Once consumption habits are established (through consumers' better understanding of the program structure) and tracked, impulsive and stockpiling behavior would be discouraged. In addition, high penetration, as a proxy for market size, makes the expenses incurred in administrating such expensive programs more justifiable. Moreover, it can be argued that Dominick's, as a grocery retailer, has very few categories that are extremely low in penetration or in purchase frequency, yet strong category differences are present even on a relative scale. We would expect the moderating effect of category characteristics to be more salient when applied to other retail programs with a wider range of categories.

The payoff for a loyalty program is worthwhile only when it is complemented with category-specific marketing strategies. Despite the mixed evidence for its performance, we observe encouraging results from many categories that are the highest selling for grocery retailers: cheese and cereal, for example, are the profit-driving categories compared to less frequently purchased categories such as bath soaps and fabric softeners. Therefore, retailers should focus on their core competencies by investing more marketing efforts in promoting the high penetration and high frequency FMCG categories, while preventing (or preparing for) undesirable performance in the low penetration and low frequency categories. Different pricing policies can be implemented for different categories. The most purchased categories require more marketing actions that foster customer knowledge and nurture long-term relationships, whereas infrequently purchased categories may have to compete even more intensively on prices. For example, more coupons tailored to consumer preferences can be generated for the heavily purchased categories, whereas more sales promotions can be organized to encourage purchases in the infrequently purchased categories. In summary, a loyalty program is an integrative tool for better category management and targeting.

Lastly, although a loyalty program generates an immediate impulse on sales and profits during the launch period, its effect gets attenuated over the six months following introduction in many categories. Categories that benefit from the introduction of a loyalty program gradually experience a diminishing effect, whereas categories that suffer from a hit at the beginning largely get compensated. Our findings are consistent with Meyer-Waarden and Benavent (2009)'s and Lal and Bell (2003)'s findings that while loyalty programs are profitable, the effect is short-lived. While previous literature extensively discusses how loyalty programs affect spending levels (Liu 2007), our investigation on category characteristics and the decay effect for the loyalty program provides an alternative interpretation: The impact of a loyalty program is largely on redistribution of category expenditures, rather than on expansion of total spending. Redistribution implies a short-term abrupt change in consumption patterns during program launch (Macé and Neslin 2004), postponing consumption (deceleration) of less heavily and less frequently purchased products while increasing consumption (stockpiling) of the everyday products in order to receive larger program benefits (for example, more coupons). However, as consumers get familiar with the program, the fever of "join-the-program-now-and-enjoy-the-savings" cools down. Consumers (in aggregate) seem to be shifting back to their original consumption patterns. Category shares are re-balanced in the long run, without necessarily an absolute increase in total expenditures.

By tracking program diffusion over time and coding the signs of its directions, our analysis offers new insights on long term program planning and design with respect to category management. We further put directions of loyalty program in a 2×2 matrix as in Table 7. Table 7 presents the values and managerial implications for the evolution of loyalty program effect. The cell *Value Enhancer* represents categories that enjoy growth at increasing positive diffusion rates; The cell *Double Jeopardy* denotes categories that suffer from continuous and larger losses over time; The cells *Wear-out* and *Climb-out*, respectively, summarizes the rest categories that experience a short-term spike or dip at the introduction but the effect gets gradually attenuated in the long run. Examining variations in the direction of program evolution, and we find that penetration and private label share are key drivers of a category's sustainable growth.

There are three actions that managers can take: First, marketing campaigns that increase category reach and promote private labels can be designed in order to strengthen the positive impact of loyalty program. Secondly, anticipating the shift in category shares, managers can plan and adjust promotion design, shelf space and inventory levels according to specific category demands. Lastly, while a loyalty program may seem to be influential for many categories only in the short run, managers could identify and approach the customer as an individual through complex segmentation strategies and targeted communications. In that way, a loyalty program creates superior value for customers to earn their true lifetime loyalty (Humby et al. 2003).

§6. CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

Despite the growing suspicion towards loyalty programs' effectiveness at the customer level in attitudinal and behavioral marketing research, there is little solid empirical evidence on how a loyalty program influences store and category performance over time. This research sheds light on the literature in four ways: First, it is the first empirical analysis that longitudinally examines the impact of loyalty program introduction on category sales and profits using pre- and post- program store transaction data. We find evidence that introducing a loyalty program is effective in most categories. Secondly, this research demonstrates that while loyalty program performance is not universally satisfactory, category characteristics are an important moderator. Category penetration and frequency are positively correlated with loyalty program success, whereas impulse buying and ability to stockpile show negative correlations. Lastly, we model the diffusion process and offer valuable insights on the evolution of loyalty program performance. We find while the effect for most of the categories is short-lived, penetration rate and private label share are key to a category's sustainable growth.

This research provides a first snapshot in examining the impact of introducing a loyalty program over time in a natural setting. Due to data availability, this paper examines only one retailer and where all stores in the dataset introduced the loyalty program at the same time. Future research could investigate dynamic and competitive structure of loyalty programs. For example, we have access to only 22 weeks of observations after the introduction of the program. It would be interesting if we were able to collect a much longer time series (We did seek this by asking both U. Chicago and Dominick's, but did not obtain this data). It is also interesting to note that Dominick's major competitor, Jewel Osco, introduced its reward program in 1993 and revamped it in 1998. Future research can examine how competition moderates loyalty program performance (Dowling and Uncles 1997) and how loyalty programs combat competition (Kim et al 2001). For example, we would expect a saturating effect when the program matures and a dip in performance when the competitor launches a similar program. We have collected advertising expenditures of both retail chains over eight years. As shown in Figure 2, when Jewel-Osco launched its loyalty program, it maintained a low level of advertising expenditures around 1993 and 1994. The effect diminished soon after Dominick's introduced its program in 1996 and Jewel-Osco increased advertising expenditure dramatically presumably to safeguard its sales. There is obvious evidence of defensive advertising as a competitive reaction.

Secondly, our analysis on loyalty program diffusion provides insights on category management and planning. However, since the focus of this paper is category performance, little can be drawn on individual customer behavior from this study. We are not able to decompose the revenue increase for members versus nonmembers, or for increased consumption versus greater reach. It would be interesting to model the adoption and diffusion process at the individual consumer level: How does his/her behavior change after the program introduction? What are the drivers of this change?

Lastly, our unit of analysis is the store-brand combination. Future research can investigate which specific brands benefit more from the loyalty program and derive a corresponding optimal pricing policy for managers. Given that promotion plays a more crucial role after the introduction of a loyalty program, what is the optimal promotion depth and frequency? If the retailer is able to make profits at a higher price charged, should manufactures give more or less price discount to the retailer? Implications on retail pass-through and brand market share could be drawn. All the above have implications for data collection.

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TABLE 1: Related Literature on Loyalty Programs

Study	Independent Variables	Dependent Variable(s)	Representative Findings
Dowling, Uncles (1997)	Loyalty programs	Performance	A major reason for the launch of many customer loyalty schemes is competition
Sharp, Sharp (1997)	Loyalty programs	Repeat-purchase	Panel data were used to develop Dirichlet estimates of expected repeat-purchase loyalty statistics by brand. Overall a trend towards a weak level of excess loyalty was observed
Drèze, Hoch (1998)	Category designation program	Sales	Loyalty program increases sales and profits
Bolton et. al (2000)	Repatronage intention	Decision to stay loyal	Members discount negative evaluations of the company vis-à-vis competition
Kim et. al (2001)	Reward type and amount	Prices	Reward programs weaken price competition
Lal, Bell (2003)	Loyalty program and pricing	Profits	These programs are profitable because substantial incremental sales to casual shoppers (cherry pickers) offset subsidies to already loyal customers
Reinartz, Kumar (2003)	Customer characteristics	Profitable lifetime duration	Long-life customers are not necessarily profitable customers
Yi, Jeon (2003)	Timing and type of reward, involvement	Value perception, loyalty	Involvement moderates the effects of loyalty programs on customer loyalty
Lewis (2004)	Loyalty Program	Repeated purchase	Loyalty program increases repeated purchase
Taylor, Neslin (2005)	Frequency Reward Program	Sales	Frequency reward program can be profitable
Van Heerde, Bijmolt (2005)	Loyalty program membership	Response to price discounts	Members are less sensitive to price discounts than nonmembers
Liu (2007)	Loyalty program membership	Usage level	Members increase usage level
Leenheer et. al (2007)	Loyalty program membership	Customer share-of-wallet	Creating loyalty program membership is a crucial step to enhance share-of-wallet
This Study	**Program and Marketing Variables**	**Sales and Profits**	**Loyalty program increases sales and profits in the heavily purchased categories, but decreases sales and profits in the lightly purchased categories in the short-term**

TABLE 2: Characterizing Research on Customer Loyalty Programs

	Observation Window	
Unit-of-Analysis	Post-Introduction Only	Pre- and Post-Introduction
Customer	Bolton et al (2000) Verhoef (2003) Lewis (2004) Liu (2007)	Taylor and Neslin (2005) Lal and Bell (2003)
Brand and/or Single Category	Dowling and Uncles (1997) Shugan (2005)	Sharp and Sharp (1997) Dréze and Hoch (1997)
Store/Multi-category	Van Heerde and Bijmolt (2005) Leenheer et al (2007) Meyer-Waarden and Benavent (2006)	This study

TABLE 3: Category Characteristics (National-Level) for All 29 Dominick's Categories

Category Name	Category Code	% HH's Buying (Penetration)	Purchase Cycle (365/Freq)	Avg % off Price Deals (Deals)	Avg. Price/Vol Paid (Price)	Impulse	Stockpiling	No. of Brands	Private Label Share
Analgesics	ANA	0.810	4.563	0.270	4.740	0.092	0.456	54	0.133
Bath soap	BAT	0.226	3.826	0.268	1.830	1.044	0.246	57	0.115
Beer	BER	0.446	6.518	0.139	12.360	0.252	-0.425	108	0.001
Bottled juices	BJC	0.912	7.620	0.257	0.580	0.039	0.285	55	0.144
Cereals	CER	0.958	11.406	0.298	2.690	-0.111	0.052	22	0.035
Cheese	CHE	0.985	13.469	0.226	3.290	0.071	-0.723	78	0.322
Cigarette	CIG	0.293	12.718	0.137	18.460	0.012	0.580	18	0.000
Cookies	COO	0.957	10.311	0.228	2.470	0.886	0.612	77	0.086
Crackers	CRA	0.975	8.838	0.235	2.610	0.296	0.146	56	0.069
Canned soup	CSO	0.976	8.816	0.277	1.350	-0.132	0.937	20	0.031
Dish detergent	DID	0.912	5.177	0.257	0.920	-0.126	0.436	17	0.055
Front-end-candies	FEC	0.936	7.935	0.243	3.270	1.040	-0.059	29	0.000
Frozen dinners	FRD	0.890	8.129	0.254	2.070	0.611	-0.118	12	0.000
Frozen entrees	FRE	0.890	8.129	0.254	2.070	-0.025	-0.492	46	0.003
Frozen juices	FRJ	0.578	6.822	0.240	0.360	0.747	0.193	23	0.283
Fabric softeners	FSF	0.444	4.728	0.170	1.020	-0.035	-0.463	29	0.078
Grooming products	GRO	0.609	4.015	0.303	0.590	-0.187	0.389	40	0.000
Laundry detergent	LND	0.898	5.650	0.225	0.840	-0.126	0.181	25	0.016
Oatmeal	OAT	0.659	4.225	0.254	2.030	0.280	-0.313	15	0.053
Paper towels	PTW	0.908	6.261	0.272	1.380	-0.047	0.465	11	0.106
Refrigerated juices	RFJ	0.849	8.295	0.276	0.480	-0.193	-0.394	31	0.155
Soft drinks	SDR	0.983	16.820	0.269	3.650	0.424	0.100	90	0.066
Shampoos	SHA	0.794	4.926	0.270	2.670	0.001	0.433	113	0.004
Snacks	SNA	0.601	6.565	0.226	4.390	0.825	0.117	45	0.033
Soaps	SOA	0.906	5.624	0.254	2.500	-0.345	0.565	20	0.003
Toothbrushes	TBR	0.574	3.806	0.318	2.060	-	-[6]	29	0.048
Canned tuna	TNA	0.812	5.887	0.236	2.370	-0.202	0.781	45	0.064
Toothpaste	TPA	0.886	4.815	0.302	6.400	-	-	30	0.013
Bathroom tissues	TTI	0.946	7.060	0.257	0.360	-0.263	0.653	10	0.053

[6] The measures for toothbrush and toothpaste are not available from Narasimhan et al. (1996)'s study. However, we try to approximate their impulse and stockpiling values using similar categories (e.g. grooming products, shaving creams etc.) and find little difference in results.

TABLE 4: Variable Operationalizations

Variable	Description	Expected Sign of the Coefficient
Ln($Sales_{ist}$), or Ln($Profits_{ist}$)	Log sales (or gross margins) of a brand-store combination during a given week	**DV**
$MemPrice_{ist}$	Per unit retail price of brand i at store s during a given week averaging across all UPCs	**-**
$CompMemPrice_{ist}$	Average price of competing brands for a particular brand at a given store during a given week	**+**
$DPrice_{ist}$	Members' discount, as the difference between $MemPrice_{ist}$ and the highest retail price across stores during that week in the absence of general promotion	**-**
$PromoB_{ist}$, $PromoC_{ist}$, $PromoS_{ist}$	An ACV-weighted variable indicating the presence of promotional activities in the form of bonus buys, coupons, or sales	**+**
$CompPromoB_{ist}$, $CompPromoC_{ist}$, $CompPromoS_{ist}$	Promotional activities of competing brands for a particular brand at a given store in a given week in the form of bonus buys, coupons or sales	**-**
$StoreBrand_{i}$	Indicator indicating whether a particular UPC is a private label	**+**
$BrandShare_{ist}$	Brand I's market share at store s during a given week	**+**
$UpcCount_{ist}$	A count variable describing the number of UPCs a brand carries in a given store during a given week	**+**
$Brand\_New_{ist}$	Number of UPCs for a brand that are new after the introduction of the loyalty program	**+/-**
$Brand\_Discontinued_{ist}$	Number of UPCs for a brand that are discontinued after the introduction of the loyalty program	**+/-**
$Holiday_{t}$	Indicator for the presence of a holiday in a given week	**+**
$Season_{t}$	A seasonality variable	**+/-**
$LoyPgm_{t}$	Indicator variable for the presence of a customer loyalty program	**+**
$LoyPgm\_Diff_{t}$	Diffusion variable for the effect of a customer loyalty program	-

TABLE 5a: Results for the Effect of Loyalty Program on Sales and Profits

Category	LoyPgm_Sales	LoyPgm_Diff_Sales	Min(LoyPgm_Final_Sales)	Max(LoyPgm_Final_Sales)	LoyPgm_Profits	LoyPgm_Diff_Profits	Min(LoyPgm_Final_Profits)	Max(LoyPgm_Final_Profits)
ANA	0.419***	-0.125	-0.105	0.360	0.474***	-0.151**	-0.159	0.402
BAT	-6.637***	-0.228***	-7.594	-6.746	-4.537***	-0.174***	-5.265	-4.62
BER	2.534***	0.417	2.734	4.282	3.071***	0.313	3.222	4.385
BJC	0.294	0.354	0.464	1.776	-2.003**	0.451	-1.789	-0.117
CER	1.321	-0.171	0.605	1.239	-1.308	-0.255	-2.378	-1.431
CHE	4.017***	1.058***	4.522	8.446	4.447***	0.772***	4.815	7.678
CIG	0.072	-0.083	-0.277	0.032	1.093***	-0.277***	-0.068	0.961
COO	0.180	0.007	0.184	0.211	-0.498	0.099	-0.452	-0.084
CRA	-0.408	0.114	-0.354	0.069	1.445***	-0.230	0.480	1.335
CSO	2.504***	0.327	2.661	3.876	2.552***	0.533***	2.806	4.782
DID	-0.388***	-0.037	-0.548	-0.407	-0.409**	0.031	-0.394	-0.278
FEC	-0.134	0.258***	-0.011	0.947	0.603***	0.012	0.610	0.656
FRD	2.596***	0.025	2.609	2.704	1.389	-0.242	0.376	1.274
FRE	2.808***	0.085	2.849	3.165	2.947***	0.449*	3.161	4.826
FRJ	3.465***	0.483	3.697	5.488	2.101*	0.660	2.416	4.866
FSF	-0.037	-0.031	-0.022	0.096	-0.085	-0.077	-0.049	0.238
GRO	-0.091*	-0.038**	-0.074	0.067	-0.070	-0.062***	-0.040	0.193
LND	4.356***	-0.878***	0.683	3.938	6.470***	-1.940***	-1.646	5.545
OAT	1.252***	-0.415***	-0.487	1.054	1.095***	-0.395***	-0.561	0.906
PTW	-0.078	-0.030	-0.206	-0.093	0.177	-0.024	0.074	0.166
RFJ	3.033***	-1.745***	-4.267	2.200	2.208***	-1.286***	-3.172	1.595
SDR	5.782***	-1.088***	1.231	5.264	5.057***	-1.985***	-3.248	4.110
SHA	-0.354***	-0.088***	-0.312	0.016	-0.326***	-0.049	-0.303	-0.119
SNA	-0.787	0.092	-0.743	-0.400	-0.688	-0.027	-0.805	-0.701
SOA	1.626***	-0.373***	0.062	1.448	2.036***	-0.389***	0.409	1.851
TBR	1.299***	-0.222***	0.370	1.194	1.355***	-0.409***	-0.358	1.160
TNA	0.468***	0.059	0.497	0.719	0.369**	-0.013	0.315	0.364
TPA	-0.058	0.054	-0.032	0.172	0.345***	-0.003	0.329	0.344
TTI	0.370	-0.070	0.075	0.337	0.812***	-0.019	0.733	0.804

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

TABLE 5b: Results for the Effect of Loyalty Program on Price

Category	MemPrice	LoyPgm _MemPrice	LoyPgm_Diff _MemPrice	dPrice	LoyPgm_Diff _DPrice	Min(LoyPgm _Final_MemP rice)	Max(LoyPgm _Final_MemP rice)	Hoch et al.
ANA	0.156***	0.022	-0.030***	-0.002***	0.001	0.057	0.163	
BAT	-0.135***	0.067***	-0.017***	-0.019***	-0.008***	-0.193	-0.098	
BER	-1.565***	0.458***	0.007	-0.056***	0.009***	-1.156	-1.092	
BJC	-1.562***	-0.210***	0.023***	-0.016***	0.007***	-1.775	-1.661	-1.49
CER	-.610***	-0.268***	-0.053	0.003***	-0.006***	-.1.129	-0.904	-1.14
CHE	-1.127***	0.034	-0.033***	-0.032***	0.006***	-1.238	-1.137	-1.44
CIG	0.627***	-0.151***	0.046	(omitted)	(omitted)	(omitted)	(omitted)	
COO	-0.341***	-0.331***	0.055***	-0.018***	0.006***	-0.660	-0.430	-0.90
CRA	-1.194***	-0.028	0.038***	-0.004***	-0.002***	-1.210	-1.077	
CSO	-2.014	0.341***	0.012	-0.029***	0.011***	-1.691	-1.604	-1.66
DID	-0.405***	0.013	0.014**	-0.008***	0.006***	-0.390	-0.314	
FEC	-1.080***	0.081	0.065***	-0.001***	-0.006***	-0.972	-0.752	
FRD	-1.028*	-0.228**	0.181***	0.005***	-0.007***	-1.169	-0.523	
FRE	-2.045***	0.334***	0.138***	-0.015***	0.003***	-1.659	-1.132	-1.65
FRJ	-2.788***	1.763***	0.048	-0.005***	-0.006***	-1.010	-0.854	-1.95
FSF	-2.035***	0.095***	-0.020***	0.001***	0.011***	-1.973	-1.852	-1.99
GRO	0.246***	0.029***	0.021***	-0.041***	0.014***	0.252	0.384	
LND	-1.187***	-0.049	-0.088***	-0.052***	0.020***	-1.575	-1.322	-1.99
OAT	-0.160***	-0.070**	-0.040***	-0.001	-0.000	-0.402	-0.251	
PTW	-1.004***	0.075***	-0.014	-0.008***	0.000	-0.998	-0.945	-1.21
RFJ	-1.502***	0.310***	-0.125***	-0.015***	0.016***	-1.665	-1.260	-2.24
SDR	-2.051***	0.132***	-0.102***	-0.030***	-0.005***	-2.397	-1.990	-2.59
SHA	-0.103***	0.014	0.000	-0.032***	0.001	-0.119	-0.113	
SNA	-0.092***	-0.371***	0.042***	-0.013***	0.006***	-0.454	-0.271	-0.79
SOA	-0.117***	0.010	-0.013	-0.013***	0.019***	-0.116	-0.096	
TBR	-0.230***	-0.722***	0.110***	-0.006***	0.002***	-0.904	-0.487	
TNA	-0.237***	0.087***	-0.042***	0.002***	-0.000	-0.325	-0.168	
TPA	-2.178***	0.101***	0.041***	-0.000	0.011***	-2.051	-1.852	-2.00
TTI	-2.115***	-0.320***	0.092***	-0.001***	-0.000	-2.392	-2.051	-2.28

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

TABLE 5c: Results for the Effect of Loyalty Program on Bonus Buy Promotions

Category	PromoB	LoyPgm_PromoB	LoyPgm_Diff_PromoB	Min(LoyPgm_Final_PromoB)	Max(LoyPgm_Final_PromoB)
ANA	14.98***	-9.020**	3.258	7.514	19.591
BAT	-0.086	-0.330	-0.044	-0.602	-0.438
BER	14.89***	9.383***	-6.448***	-2.695	21.206
BJC	20.57***	-17.99***	4.089***	4.532	19.687
CER	101.6***	-23.54***	-8.099***	44.262	74.281
CHE	82.31***	95.50***	-32.83***	40.472	162.161
CIG	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
COO	105.2***	5.263	3.221	112.002	123.941
CRA	15.33***	16.27***	-6.265***	5.402	28.625
CSO	37.86***	-56.35***	16.06***	-10.827	48.699
DID	15.01***	-0.996	1.424	14.702	19.980
FEC	6.735***	-7.804	-0.216	-1.976	-1.172
FRD	25.06***	-28.97***	2.051	-2.937	4.667
FRE	73.25***	-27.69**	-10.04	3.526	40.757
FRJ	19.67***	10.76***	-3.713***	14.905	28.670
FSF	26.42***	-3.164	-4.217	5.616	21.248
GRO	42.27***	65.80***	1.850	108.959	115.816
LND	19.50***	24.56***	-5.511***	21.015	41.441
OAT	11.08***	9.758***	-3.402***	6.608	19.217
PTW	4.650***	10.61***	-3.054***	2.483	13.804
RFJ	14.53***	28.30***	-4.735***	23.030	40.580
SDR	231.2***	-8.190	22.30***	233.668	316.325
SHA	21.59***	50.14***	-17.46***	-1.345	63.403
SNA	16.80***	19.63***	-3.531	21.663	34.752
SOA	10.43***	-10.27	-1.845	-7.553	-0.714
TBR	7.421***	-9.506***	1.504**	-1.367	4.210
TNA	14.44***	-5.196*	-0.132	8.694	9.184
TPA	20.20***	-6.904***	3.841***	15.134	29.371
TTI	11.13***	-0.238	-0.005	10.870	10.889

***Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

TABLE 5d: Results for the Effect of Loyalty Program on Coupon Promotions

Category	PromoC	LoyPgm_PromoC	LoyPgm_Diff_PromoC	Min(LoyPgm_Final_PromoC)	Max(LoyPgm_Final_PromoC)
ANA	25.27***	(omitted)	(omitted)	(omitted)	(omitted)
BAT	1.885***	17.52	-2.947	7.085	18.009
BER	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
BJC	8.669***	(omitted)	(omitted)	(omitted)	(omitted)
CER	111.5***	-330.2	182.2	-131.751	543.682
CHE	147.9***	31.02	-37.32***	22.832	161.151
CIG	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
COO	94.58***	-3.808	-6.402	63.996	87.725
CRA	4.269***	-32.62	4.533	-26.194	-9.393
CSO	-98.14***	86.61***	6.698*	-8.334	16.493
DID	12.92***	(omitted)	(omitted)	(omitted)	(omitted)

FEC	28.89***	-0.662	-13.72***	-29.164	21.686
FRD	45.58***	(omitted)	(omitted)	(omitted)	(omitted)
FRE	95.95***	27.35***	1.278	123.926	128.666
FRJ	17.56***	(omitted)	(omitted)	(omitted)	(omitted)
FSF	30.68***	(omitted)	(omitted)	(omitted)	(omitted)
GRO	148.3***	266.6***	-58.88***	168.678	386.925
LND	38.87***	22.63***	-9.251***	22.807	57.097
OAT	17.04***	7.518	-2.407	14.494	23.417
PTW	1.269***	(omitted)	(omitted)	(omitted)	(omitted)
RFJ	9.386***	(omitted)	(omitted)	(omitted)	(omitted)
SDR	234.3***	46.37	-21.47	190.902	270.494
SHA	95.46***	-104.4***	7.273	-5.483	21.474
SNA	49.77***	(omitted)	(omitted)	(omitted)	(omitted)
SOA	44.78***	31.46**	5.963	79.095	101.197
TBR	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
TNA	19.73***	1.791	-1.237	16.347	20.932
TPA	16.66***	-1.003	14.20***	22.435	75.077
TTI	10.22***	(omitted)	(omitted)	(omitted)	(omitted)

***Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

TABLE 5e: Results for the Effect of Loyalty Program on Sales Promotions

Category	PromoS	LoyPgm_PromoS	LoyPgm_Diff_PromoS	Min(LoyPgm_Final_PromoS)	Max(LoyPgm_Final_PromoS)
ANA	20.24***	-4.919	-2.260	5.871	14.250
BAT	0.116	-1.157	0.503	-0.800	1.067
BER	18.19***	(omitted)	(omitted)	(omitted)	(omitted)
BJC	9.614***	34.55***	-6.927***	15.194	40.868
CER	92.66***	-4.435	-6.987***	58.994	84.892
CHE	68.94***	1.391	-3.089**	57.410	68.862
CIG	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
COO	67.09***	-14.78	2.903	53.694	64.454
CRA	9.950***	-45.08***	8.736***	-30.962	1.418
CSO	44.64***	-50.61***	7.000***	-2.638	23.307
DID	9.982***	16.90***	-1.937***	18.782	25.962
FEC	1.218	15.49***	-0.638	14.039	16.406
FRD	36.02***	-11.37***	-3.457***	10.180	22.994
FRE	77.41***	55.82***	-24.79***	29.492	121.405
FRJ	15.22***	6.174***	-1.973***	13.143	20.456
FSF	18.28***	-7.932	-1.226	5.216	9.763
GRO	128.5***	206.9***	-44.93***	147.525	314.058
LND	16.03***	27.86***	-9.100***	5.834	39.563
OAT	16.95***	-4.478	-0.916	8.641	12.039
PTW	4.266***	4.591***	-2.121***	-0.019	7.845
RFJ	9.533***	43.80***	-7.395***	22.403	49.812
SDR	228.2***	84.27***	-31.52***	180.595	297.451
SHA	17.90***	-14.54**	3.660	5.102	18.669
SNA	19.44***	6.328	-0.550	23.465	25.506
SOA	11.78***	-13.77	2.303	-0.889	7.648

TBR	4.837***	-5.735**	1.078	-0.383	3.616
TNA	11.23***	-11.63***	1.509	0.329	5.923
TPA	17.80***	-22.20***	6.944***	-1.081	24.658
TTI	6.632***	3.962***	-0.593***	8.114	10.312

***Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

TABLE 6: The Effect of Category Characteristics on Loyalty Program Performance

Dependent Variable	LoyPgm_Sales	LoyPgm_Profits	LoyPgm_Direction
Penetration	4.165*	4.027**	5.297***
Frequency	0.261*	0.235*	0.023
Price	-0.030	-0.022	0.232
Deals	-12.356	-15.216	-5.061
Impulse	-1.570*	-1.663***	0.048
Stockpiling	-1.596*	-1.359*	-0.838
BrandNum	-0.003	0.001	-0.013
StorebrandShare	1.244	-0.072	7.751*
Constant	-0.499	0.655	1.957
Adj R-square	0.373	0.408	0.162

***Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

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TABLE 7: Evolution of Loyalty Program Effect

Loyalty Program Diffusion Effect		
Positive	***2: Climb-out***	***4: Value Enhancer***
Negative	***1: Double Jeopardy***	***3: Wear-out***
	Negative	**Positive**

Loyalty Program Main Effect

FIGURE 1: Example of Members' and Nonmembers' Prices

FIGURE 2: Advertising Expenditures for Dominick's Finer Foods and Jewel-Osco