

# **Marketing and the Evolution of Customer Equity of Frequently Purchased Brands**

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## **Abstract**

The customer equity paradigm is readily implemented in relationship businesses where the distinction between a prospect and an existing customer is unambiguous. That enables firms in such industries to be customer and long-term focused in the allocation of their marketing resources. This is not the case in frequently purchased product categories, where customers may switch back and forth between competing brands, and even consume multiple brands in the same time period. However, by using stochastic models for purchase quantity and purchase frequency, we demonstrate that measures of customer equity may still be obtained in such categories, using readily available scanner panel data. We illustrate our approach for the leading national and private-label brands in two CPG categories and show that the brands' sources of customer equity and the impact of their marketing activities are different. As a result, the brands' customer equity levels may be evolving in different directions that are not readily apparent from their revenue or market share positions. We discuss the managerial implications of our findings and offer several areas for future research.

*Key words: Customer Equity, Consumer Packaged Goods, Stochastic Purchase Models, Time Series Models*

## Introduction

The customer equity (CE) paradigm proposes that firms can achieve superior performance by changing their focus from selling products to securing strong customer relationships (Blattberg, Getz, and Thomas 2001; Rust, Zeithaml, and Lemon 2000). Under this perspective, a firm's marketing efforts are guided by the quality and profitability of its relationship with customers and prospects. Not surprisingly, the paradigm has been applied mainly to the relationship-marketing domain, for example in the banking and telecommunications sectors<sup>1</sup>. However, such customer-centered thinking is also important in more conventional product markets such as consumer packaged goods (CPG). The consumers of a CPG brand are usually defined at the household level, and these households vary widely in their *brand purchase quantities*, their *purchase frequencies*, and their *willingness to pay*. These components create a stream of household revenues for the brand, and as such they may be viewed as creating a customer's lifetime value (CLV). The sum of these CLVs across the brand's customer base is the brand's customer equity.

Managers in product-markets such as CPG find it difficult to use customer equity thinking because several CE-related metrics are not easily observed in product-centered sales data. For example, unless the firm has a contractual relationship with its customers, loyalty or repeat-purchase (retention) rates are difficult to measure since customer attrition occurs silently. Thus it is not easy to answer even the simple question of how many customers the firm currently has (Schmittlein, Morrison, and Colombo 1987).

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<sup>1</sup> A notable exception is Rust, Zeithaml, and Lemon (2004), who use CE in consumer goods sectors such as electronics, retailing, and facial tissues. However, their approach is based on extensive consumer surveys, which are often costly and time consuming.

Measuring the impact of marketing activities on CE is even more difficult, because of the *indirect* and *dynamic* relationship between the firm's marketing and the three components of customer equity. For example, a price discount of brand A may make a customer switch from brand B to brand A, and this brand switching (and subsequent consumption) may affect the consumer's future purchase behavior. In addition, though the price promotion may increase sales from less loyal customers in the short run, the discount may become a "subsidy" that dampens or even nullifies the beneficial impact of the sales increase in the long run when prices do not return to normal quickly. Ignoring these indirect and dynamic effects can result in an inaccurate assessment of marketing-mix effects on firm performance, especially in the long run.

With CE metrics that are difficult to define, and marketing impact on CE difficult to estimate, managers in CPG and related product markets typically do not know or do not consider the CE ramifications of their actions. Instead, they rely on conventional product-centered performance metrics such as units sold and market share. Such *flow* measures of performance are short-run and often volatile in nature, and ignore possibly important evolution in *stock* measures, such as the gradual strengthening or erosion of customer loyalty through marketing activity (Hanssens and Dekimpe 2008).

These realities motivate our development of a model that measures the long-term value of customers and the impact of marketing activities such as price promotion in frequently purchased categories such as CPG, using readily-available scanner panel data. Our proposed model explains how marketing efforts either build or destroy customer equity through sales-lift effects. We focus on a mass-marketing and non-contractual transactions environment, which is common but has not been extensively studied in the CE literature. By providing a linkage between product marketing and CE, we develop a unifying CE framework for long-run marketing resource

allocation that spans both direct marketing and mass marketing in transactions-focused as well as relationship businesses. In so doing, we aim at making the benefits of customer equity thinking available to managers in traditionally product-focused categories.

Our paper begins with current CE measurement practice. We then propose a model that links product marketing to CE and also measures the dynamic relationships between them. The proposed model is applied to two CPG categories, using A.C. Nielsen household scanner panel data. Conclusions and directions for future research are discussed in the last section.

### **Customer Equity: Measurement and Relationship with Marketing Activities**

A customer's lifetime value (CLV) is measured as the net present value (NPV) of all expected profit streams from the customer during his or her tenure with the firm. The CLVs of all customers are summed to obtain a firm's customer equity<sup>2</sup>. Many researchers measured CE through well defined customer life-cycle stages such as acquisition, retention, and expansion. For instance, Blattberg and Deighton (1996) proposed a simple CE formula that assumes acquisition and retention rate are constant over time and homogenous across customers. In their framework, each customer's relationship duration is *implied* (i.e. measured indirectly) by his or her retention rate. Rust, Lemon, and Zeithaml (2004) measured CE based on stated switching probability (i.e., acquisition vs. retention) of customers among competitive brands. Customer equity can also be measured by an aggregate approach (Kumar and George 2007) in which a typical customer's lifetime value is calculated by revealed information (e.g., churn rate in the mobile telecommunications industry) and multiplied by the number of customers to obtain CE (Gupta, Lehmann, and Stuart 2004).

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<sup>2</sup> In the calculation of CE, one may include expected future customer acquisition (i.e., dynamic customer equity) or restrict to the existing customer pool (i.e., static customer equity). This paper uses the latter, conservative definition since we use balanced scanner panel data that do not show customer exit or entry during the observation period.

However, characteristics of CPG categories prevent researchers from obtaining such CE assessment. First, customer acquisition or retention is not easily observable and, moreover, does not provide useful diagnostics to understand the total value of a CPG brand's customers. The transaction amount and frequency are heterogeneous across consumers, and customer attrition (i.e., switching to other brands) typically occurs silently. Therefore we will use stochastic models to predict individuals' future expected purchases, from which we derive a *forward looking* customer equity metric. We view the evolution in this metric as an indicator of *brand health*, and investigate how this health is impacted by marketing activities.

Our effort is motivated by the observation that, while managers are generally interested in long-term metrics such as brand health, short-term sales quota and profit pressures typically force them to focus on the short-term fluctuations of conventional performance metrics (e.g., sales and market share). Such focus could result in resource allocations that diminish the brand's customer equity, or conversely, a lack of allocations that would increase customer equity.

## **Model Development**

### *The Measurement of Customer Equity Using Scanner Panel Data*

We first evaluate customer  $i$ 's lifetime value at time  $t$  by the number of expected transactions ( $ET$ ), purchase quantity per transaction ( $PQ$ ), price per purchased unit ( $PR$ ), contribution margin ( $CM$ ), and any expected discretionary marketing investments ( $FC$ ) such that:

$$(1) \quad CLV_{it} = \sum_{j=t}^{\infty} (1+d)^{-(j-t)} [ET_{it} PQ_{it} PR_{it} CM_{it} - FC_{it}]$$

where  $d$  is a time discount factor. Customer equity (CE) can be obtained by summing up all customers' CLV at a certain point in time. We focus our modeling efforts on future expected

purchases, i.e., number of transactions (*ET*) and purchase quantity per transaction (*PQ*). These are *response* variables among the components of CLV calculation, while price, margin, and marketing investments are *decision* variables for the brand.

### *Number of Expected Transactions (ET)*

Since typical scanner panel data contain information about each individual's purchase history during an observation period, we can predict when and how much a customer will buy a certain product by describing his or her current purchase behavior with probability models. Since Schmittlein, Morrison, and Colombo (1987) suggested a model structure to analyze a company's customer base, there have been several approaches to explain a customer's purchase behavior by probability mixtures. In particular, Fader, Hardie, and Lee (2005) proposed a Beta-Geometric / Negative Binomial Distribution (BG/NBD) model by modifying the original Pareto/NBD model (Schmittlein, Morrison, and Colombo 1987) to improve parameter tractability. We will use a more recently developed Beta-Geometric / Beta-Bernoulli (BG / BB) model (Fader, Hardie, and Shang 2010) to model purchase behavior in CPG categories, for the following reasons. First, as Fader, Hardie, and Shang (2010) pointed out, the BG / BB model fits well when repeat purchases are tracked on a discrete-time basis. Typical purchases in CPG categories (e.g., ketchup or yogurt) are generally discrete. Second, we empirically compared the performance of the three models above and found that the BG / BB model outperformed the other models in both in-sample fit (6 out of 6 cases) and out-of-sample fit (3 out of 6 cases).

The BG / BB model assumes that a customer buys a firm's product at a purchase opportunity, given her active relationship with the brand with probability  $p$ , and "drops out" ("dies") at the beginning of a transaction opportunity with probability  $q$ . The two probabilities  $p$

and  $q$  are heterogeneous across customers, each of them following a separate beta distribution:  $p \sim \text{beta}(\alpha, \beta)$  and  $q \sim \text{beta}(\gamma, \delta)$ . Furthermore, the model enables analysts to obtain two relevant metrics for CE computation: (1) the probability of being active (*PACT*) and (2) the discounted sum of future expected number of transactions (*DET*) (Fader, Hardie, and Shang 2010). These two metrics can be obtained from a customer's purchase history - i.e. the number of transactions ( $x$ ), the time at which the last transaction occurred ( $t_x$ ), and the total number of observation periods ( $n$ ) – along with the four BG/BB model parameters, such that:

$$(2) \quad PACT(n+1 | \alpha, \beta, \gamma, \delta, x, t_x, n) = \frac{B(\alpha+x, \beta+n-x)B(\gamma, \delta+n+1)}{B(\alpha, \beta)B(\gamma, \delta)L(\alpha, \beta, \gamma, \delta | x, t_x, n)}$$

$$(3) \quad DET(d | \alpha, \beta, \gamma, \delta, x, t_x, n) = \frac{B(\alpha+x+1, \beta+n-x)B(\gamma, \delta+n+1)}{B(\alpha, \beta)B(\gamma, \delta)L(\alpha, \beta, \gamma, \delta | x, t_x, n)} \\ \times \frac{{}_2F_1\left(1, \delta+n+1; \gamma+\delta+n+1; \frac{1}{1+d}\right)}{1+d}$$

where  $L(\cdot)$  stands for the likelihood function of the joint probabilities  $p$  and  $q$ , given model parameters and purchase history, and  ${}_2F_1(\cdot)$  is the Gaussian hypergeometric function.

### *Purchase Quantity per Transaction (PQ)*

Schmittlein and Peterson (1994) proposed a Normal/Normal structure to incorporate the monetary value of each purchase in a customer base analysis. They assume that a customer's purchase amount per transaction is distributed normal with a mean value across time, and that the mean is characterized by a normal distribution across customers. Colombo and Jiang (1999) suggested a Gamma-Gamma structure to handle the high skewness problem associated with the

Normal/Normal model. They model the variability of purchase amounts within customers using a gamma distribution, and the mean of each individual's purchase amount varies across customers as another gamma distribution. We consider both models to predict future purchase amounts per transaction for each individual<sup>3</sup>. The key result of both models is an expected purchase amount ( $PQ$ ) that a customer will buy given her purchase history. For example, the Normal/Normal model expresses the expected value of  $PQ$  for customer  $i$  as;

$$(4) \quad E[PQ_i | q_{i1}, \dots, q_{ix}] = \rho \bar{q}_i + (1 - \rho) \overline{PQ}, \quad \rho = \frac{x\sigma_A^2}{x\sigma_A^2 + \sigma_i^2}$$

Where  $q_{it}$  is the purchase quantity at transaction  $t$ ,  $\bar{q}_i$  is the mean purchase quantity for customer  $i$ ,  $\overline{PQ}$  is a mean value of purchases across all customers. In addition,  $\sigma_A^2$  is the purchase quantity variance across customers, and  $\sigma_i^2$  is the variance within a customer. We tested both models and found that the Normal/Normal model provided a better in-sample fit for 4 out of 6 category-brand cases. Therefore we use equation (4) in calculating CLV for each customer.

#### *Evolution of the Discounted Sum of Purchase Quantities by Recursive Estimation*

We multiply the discounted expected number of transactions ( $DET$ ) by the expected purchase quantity per transaction ( $PQ$ ) to obtain the discounted sum of purchase quantities ( $DPQ$ ).  $DPQ$  plays a critical role in investigating the evolution of customer equity and its linkage to marketing actions, due to the chain reactions among marketing, sales,  $DPQ$ , and finally  $CE$ . In the empirical illustration we first obtain a time series of  $DPQ$  for each brand by recursively estimating the

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<sup>3</sup> Though the original models were applied to monetary value (i.e., quantity times price) per transaction, we only model purchase quantity in this approach since in CPG categories, the price decision is typically not made at the individual-consumer level. Instead, we will make predictions of future price movements by a time series model explained hereafter.

BG/BB and Normal/Normal model parameters after an initialization period. More specifically, we add one more data point per week to obtain new parameter sets for the BG/BB and Normal/Normal models, and calculate a new value of each brand's DPQ for each individual in our panel data. In this way, we can construct time series of DPQs for each brand and be ready for investigating the influence of marketing upon that series and thereby upon CE.

*Linking Marketing to Customer Equity through the Discounted Sum of Purchase Quantities*

Equation (1) shows that the firm's marketing actions can affect the magnitude of customer equity in two ways. First, a firm's marketing activities may increase the expected value of the future number of transactions and purchase quantities per transaction. This increase occurs through the short-term sales lift of a marketed product. For example, a customer currently using a competitor's product may switch to a brand that offers a price promotion, and her future expected purchases of this focal brand may increase due to the switch. Likewise, if a customer repeat purchases a brand's product due to a feature advertisement, her discounted sum of purchase quantities may increase as well. Second, since the firm's marketing actions are costly, there can be a negative impact of marketing on CE through lower price and therefore margin, or through higher discretionary spending such as advertising. Such negative effects may persist over time due to performance feedback loops or decision inertia, as shown in two frequently-purchased product categories (Dekimpe and Hanssens 1999). A performance feedback loop occurs when managers respond to past market performance in their marketing decisions (Nijs, Srinivasan, Pauwels 2007). A common occurrence of decision inertia is when future marketing spending is set in function of past budgets, even though the effectiveness of that spending has worn out.

In order to accommodate these different impact routes of marketing on customer equity, we use a vector-autoregressive (VAR) model on marketing actions, short-term sales lift, and long-term expectation on customer value. The VAR model has been used to decompose short-run and long-run impacts and to investigate the dynamics among key variables in a system. For instance, Bronnenberg, Mahajan, and Vanhonacker (2000) examine the temporal relationship between market share and distribution share using rolling-window impulse-response functions (IRF) estimated from a VAR model.

VAR models offer several appealing advantages in our context (see Dekimpe and Hanssens 1995; Dekimpe and Hanssens 1999 for a more detailed description). First, VAR models can capture not only contemporaneous effects but also lagged effects among and within variables. This property enables researchers to decompose the short-run and long-run effects among variables. Second, in contrast to other approaches that disentangle the long-run effects (e.g., Koyck-type regressions in time-varying parameter models by Mela, Gupta, and Lehmann 1997), VAR models do not impose any *a priori* restrictions on the stationarity of variables, i.e., evolving variables with a unit root can be analyzed as well. Dekimpe and Hanssens (1999) show that long-run marketing- resource allocation should be adjusted when there is persistence in the marketing-mix and sales variables. This characteristic is particularly important in our context since we aim to investigate the evolutionary nature of a long-run metric, customer equity. Third, the VAR model is flexible in dealing with endogeneity, since it is inherently a *systems* approach that regards all variables as jointly endogenous, while allowing for hypothesized short-term and long-term restrictions on the relationship among variables. Consequently, a future outcome of one variable is the result of the dynamic interactions of *all* variables in the system.

The impact of an unexpected shock in one variable on the others is measured by IRF analysis (see Lütkepohl 1993 for a more formal discussion).

To investigate the system that generates CE through marketing actions (*MKT*) and sales (*SLS*), the following VAR model is constructed.

$$(5) \quad \begin{pmatrix} MKT_t \\ SLS_t \\ DPQ_t \end{pmatrix} = \begin{pmatrix} \mathbf{c}_{1t} \\ \mathbf{c}_{2t} \\ \mathbf{c}_{3t} \end{pmatrix} + \sum_{l=1}^L \begin{pmatrix} \varphi_{11}^l & \varphi_{12}^l & \varphi_{13}^l \\ \varphi_{21}^l & \varphi_{22}^l & \varphi_{23}^l \\ \varphi_{31}^l & \varphi_{32}^l & \varphi_{33}^l \end{pmatrix} \begin{pmatrix} MKT_{t-l} \\ SLS_{t-l} \\ DPQ_{t-l} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix}$$

Where the  $\mathbf{c}$  vectors can contain the impact of other exogenous variables on the system, such as seasonality, competitive activity and macro-economic conditions;  $L$  is the lag order of the system; and  $\varepsilon$  is a vector of white noise processes with zero mean and covariance matrix  $\Sigma$ .

Since the model coefficients ( $\varphi$ 's) only capture the lagged effects among variables in the VAR system, contemporaneous relationships among the variables are obtained by placing restrictions on the residual covariance matrix  $\Sigma$ . We use a causal ordering of  $MKT \rightarrow SLS \rightarrow DPQ$  to make a Cholesky decomposition of the residual covariance matrix, as in Dekimpe and Hanssens (1995). Once we have the model parameters of Equation (5), we can investigate how the firm's marketing actions affect current and future DPQs, which is the long-run consequence of these marketing efforts. The net impact of marketing on CE can be positive or negative<sup>4</sup>. It is determined by comparing the magnitude of increases in DPQ due to changes in marketing activities to the long-run change in costs and margins. We can also juxtapose the impact of marketing on sales versus that on customer equity to evaluate its short-run vs. long-run marketing effects.

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<sup>4</sup> See Dekimpe and Hanssens (1999) for an elaboration of different scenarios.

In sum, we replace the traditional approach of modeling the effect of marketing, such as a brand's price promotion, on a consumer's brand choice probability by a *forward looking* model that assesses the impact of the same price promotion on the future expected brand purchases of that consumer. We achieve this by combining stochastic purchase behavior models (e.g., Schmittlein, Morrison, and Colombo 1987; Fader, Hardie, and Lee 2005) that typically lack marketing components with econometric time series models (e.g., Dekimpe and Hanssens 1995) on brand-relevant response variables such as sales and market share.

### **Empirical Illustration**

#### *Data*

We use A.C. Nielsen household scanner panel data observed for 138 weeks in the ketchup and yogurt product categories in Sioux Falls, South Dakota. This dataset was made available through the Kilts Center for Marketing at the University of Chicago and has been widely used in the marketing literature (e.g., Chintagunta 1993). As package sizes differ across brands and product categories, we calculate sales by the number of ounces sold and aggregate them to the brand level. We then compute the price paid per ounce by subtracting coupon values redeemed from regular prices. Three top-selling brands are selected for the ketchup category (Heinz, Hunts and Del Monte) and the yogurt category (Yoplait, a private-label brand, Dannon). Table 1 shows the descriptive statistics of the data.

Insert Table 1 about here

#### *Model Selection*

We first tested the performance of three competing models for estimating the discounted sum of future transactions: Pareto/NBD (Schmittlein, Morrison, and Colombo 1987), BG/NBD (Fader,

Hardie, and Lee 2005), and BG/BB (Fader, Hardie, and Shang 2010). We divided our full dataset in a calibration sample (weeks 1 to 92) and a prediction sample (weeks 93 to 138). In-sample fit was tested on the calibration data, and out-of-sample fit was tested on the prediction data based on the model results from calibration. We predicted customers' average number of transactions in the hold-out period based on the number of transactions in the calibration period by comparing eight customer groups, ranging from zero to seven or more transactions. In addition, we verified the performance of two competing models for estimating future purchase quantities per transaction: the Normal/Normal (Schmittlein and Peterson 1994) and the Gamma-Gamma model (Colombo and Jiang 1999).

Insert Table 2 about here

As a result, the BG/BB and Normal/Normal models were selected for calculating each customer's discounted sum of purchase quantities (DPQ). First, the BG/BB model for purchase incidence outperforms the other two models in all cases for in-sample fit (evaluated by log-likelihood) and in 3 out of 6 cases for out-of-sample fit (evaluated by chi-square statistics). It predicts that customers on average make 4.16 (vs. 4.06 actual) transactions for ketchup, and 7.20 (vs. 6.53 actual) transactions for yogurt in the 46 weeks of the holdout period. Second, the Normal/Normal model for purchase quantity explains the calibration data better (as evaluated by MAPE) for 6 out of 8 cases and shows better predictive performance (evaluated by chi-square statistics) for 4 out of 8 cases than the Gamma/Gamma model. Table 2 presents the model selection results. The selected Normal/Normal model predicts that purchase amount per transaction is 32.85 (vs. 33.76 actual) ounces for ketchup, and 22.78 (vs. 23.55 actual) ounces for yogurt during the holdout period. These results provide evidence that the BG/BB and

Normal/Normal models will accurately predict an individual customer's future purchase behavior based on his or her transactions history.

### *Customer Equity Evolution of Different Brands*

To capture the evolution of customer equity, we first estimated all model parameters using the first 46 weeks of our data. After this initialization to minimize the effect of left-censoring, we *recursively* estimate model parameters by adding one new data point, i.e., a new individual-level purchase record in a subsequent week. Therefore, we do not utilize any information from the future in our parameter estimation. This resembles a typical manager's situation where he or she has to make a marketing decision based on information available up to the current period.

Based on model parameters for each week, we calculate the discounted<sup>5</sup> number of future transactions (DET) and expected purchase quantity per transaction (PQ) for each individual in that week. We then multiply DET by PQ to obtain the discounted sum of purchase quantity (DPQ) that will be a basis for calculating customer equity for each brand. Figure 1 shows the evolution of DPQ along with sales movements for each brand in the two product categories.

Insert Figure 1 about here

Based on an individual's DPQ and a brand's contribution margin, we calculate the CLV of each individual for that brand. We then sum up all the individual CLVs to obtain the brand's customer equity over time as in Figure 2. As individual-brand contribution margin data are not available, we multiply 52-week moving-averages of brand prices by a fixed contribution margin rate of 60% for all brands. Therefore, in making comparisons, it will be more relevant to interpret the evolutionary path (rather than the absolute magnitude) of CE for each brand.

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<sup>5</sup> We used an annual time discount factor of 10% for our empirical illustration.

Insert Figure 2 about here

The CE indicators in Figure 2 show evolution (i.e. noticeable trending) for several brands. Specifically, in the ketchup category, all three brands' CE are declining during the first half of the analysis period, but Heinz and Hunt's later recover their CEs at the expense of Del Monte. In the yogurt category, none of the brands grow their CE, but on a relative scale, Yoplait becomes stronger (approximately .8% point CE share increase in the second half of the analysis period) while the private-label brand loses its CE share (about .8% point).

Figure 3 compares the movement of customer equity share with that of revenue-based market share for the three brands. *Unlike the highly volatile weekly market shares, the CE metric shows stable but clear direction in a brand's health status.* For example, the private-label yogurt brand maintains a stable average CE share of 16.1%, but its market share fluctuates widely around 17.9% (by revenue) and 34.9% (by units sold). Similarly, the dominance of Heinz in the ketchup category is accentuated with a CE share of 81.6%, while the brand's market share fluctuates around 77.0% (by revenue) and 73.2% (by units sold). Put differently, the long-term financial strength of the yogurt private label brand is not as high as short-term indicators indicate, whereas that of the Heinz ketchup brand is higher than it appears.

Next, we examine the question whether or not the sources of CE evolution are the same across brands. Using the customer's calculated probability of being active (PACT) in each time period, we derive total customer value from three sources: low, medium, and highly active customer groups. This is done by repeatedly sorting out customers with respect to their probability of being active, which is time-varying and different across brands. Figure 4 shows the average decompositions by brand. It demonstrates that yogurt brands rely more heavily on customers with a high probability of being active (i.e. high loyalty) than do ketchup brands. In

addition, market leaders in both categories (i.e. Heinz and Yoplait) have the lowest proportion of high-PACT customer segments and the highest proportion of low-PACT customer segments among their direct competitors. Thus brand loyalty is financially more relevant in yogurt than it is in ketchup, and the marketing of leading brands is more customer-base-expanding than that of others. The first result may be attributed to category differences in brand differentiation (for example yogurt brands may have more distinctive tastes than ketchup brands). The second result is in line with the findings that market leaders enjoy a higher retail pass-through of their trade promotions than smaller brands (Ailawadi and Harlam 2009) and have superior promotion effectiveness (Blattberg and Wisniewski 1989; Allenby and Rossi 1991).

Insert Figure 4 and Figure 5 about here

Our methodology also enables to investigate the dynamics of the decomposed customer equity as presented in Figure 5. For example, as already reported, the CE of ketchup brand Del Monte is decreasing while that of Hunt's is increasing, especially in the latter part of the data sample. According to Figure 5, a main driving force of this difference lies in the value of high PACT customers, where the gap between the two brands grows over time. Similarly, the CE gap between Dannon and the private-label brand is driven mainly by the difference in the value of their high-PACT customers. We note that the private-label brand promotes more frequently and more deeply than Dannon, resulting in much lower customer values from loyals than from switchers.

#### *Modeling Marketing Effects on Customer Equity*

We use average price per ounce after coupon redemption as a focal marketing variable in this study. Therefore, a VAR model with three endogenous variables (i.e., price, sales, and DPQ) will

be constructed to investigate the impact of marketing on customer equity. The non-stationarity of each endogenous variable is verified by the Augmented Dickey-Fuller (ADF) test (Dekimpe, Hanssens, and Silva-Risso 1999) to prevent spurious regression (Granger and Newbold 1974). *The ADF test reveals that only the long-term metric, DPQ, evolves over time*<sup>6</sup>. The DPQs of all brands in the ketchup and yogurt category are found to be non-stationary even though their prices and sales are stationary. This is an interesting finding in its own right: while the *visible* performance metrics such as sales and prices appear to be mean-reverting, there is underlying evolution in an “*invisible*” metric such as CE, which suggests that some brands are quietly gaining ground over others.

We determined an appropriate lag order of one by comparing Schwarz’s criterion for various possible lag orders (Lütkepohl 1993). As a result, the following VAR model is constructed for each brand (recognizing that DPQ is an evolving series):

$$(6) \quad \begin{pmatrix} PRICE_t \\ SALES_t \\ \Delta DPQ_t \end{pmatrix} = \begin{pmatrix} c_{10} + \sum_{s=1}^{12} c_{1s} SD_s \\ c_{20} + \sum_{s=1}^{12} c_{2s} SD_s \\ c_{30} + \sum_{s=1}^{12} c_{3s} SD_s \end{pmatrix} + \sum_{l=1}^L \begin{pmatrix} \phi_{11}^l & \phi_{12}^l & \phi_{13}^l \\ \phi_{21}^l & \phi_{22}^l & \phi_{23}^l \\ \phi_{31}^l & \phi_{32}^l & \phi_{33}^l \end{pmatrix} \begin{pmatrix} PRICE_{t-l} \\ SALES_{t-l} \\ \Delta DPQ_{t-l} \end{pmatrix} \\ + \sum_{k=1}^K \begin{pmatrix} \psi_{11}^k & \psi_{12}^k & \psi_{13}^k \\ \psi_{21}^k & \psi_{22}^k & \psi_{23}^k \\ \psi_{31}^k & \psi_{32}^k & \psi_{33}^k \end{pmatrix} \begin{pmatrix} PRICE_{kt} \\ FEAT_{kt} \\ DISP_{kt} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix}$$

where  $\psi$  parameters control own ( $k = 1$ ) and competitive ( $k \neq 1$ ) marketing effects such as price, feature ad (FEAT), and in-store display (DISP). Since own price is included in the VAR system as a focal endogenous variable,  $[\psi_{11}^1 \quad \psi_{21}^1 \quad \psi_{31}^1]'$  will be restricted to be zero.  $FEAT_{kt}$  and  $DISP_{kt}$  are binary variables that indicate whether or not there is feature ad or display

<sup>6</sup> The ADF test results are available from the first author.

implemented by brand  $k$  at time  $t$ , respectively. SDs are 4-week dummy variables to control for seasonality, and  $\Delta$  is a difference operator. Note that all three endogenous variables are expressed in logarithms, in order to easily obtain response elasticities among the variables (Nijs et al. 2001)<sup>7</sup>.

The over-time response of CE to a firm's marketing intervention (e.g. an unexpected price change) is measured by impulse response functions (IRFs) based on the model parameters of Equation (6). More specifically, the future response of a firm's CE when there is a price shock of  $\theta$  can be expressed as;

$$(7) \quad IR(CE_{t+h} | PRICE_t^{shock} = \theta) = \sum_{i=1}^N (CLV_{i(t+h)} | E[PRICE_t]) - \sum_{i=1}^N (CLV_{i(t+h)} | E[PRICE_t] + \theta)$$

$$= \underbrace{IR(DPQ_{t+h} | PRICE_t^{shock} = \theta)}_{\text{response of discounted sum of purchase quantity}} \times \underbrace{IR(PRICE_{t+h} | PRICE_t^{shock} = \theta)}_{\text{response of future price}} \times \underbrace{E[CM_{t+h}]}_{\text{margin ratio}}$$

where zero-base marketing spending is assumed without loss of generality. If there exists an interaction among marketing activities (e.g., between advertising and price), the interaction can be included in the VAR system, and the future response of marketing action A to the shock of marketing action B can be easily incorporated in the calculation. In the empirical illustration we assume a fixed profit margin of 60%<sup>8</sup> and we set the baseline discretionary marketing costs (e.g., advertising spending) to zero.

### *The Impact of a Price Promotion*

We examine both short-term and long-term consequences of a 30% price shock on sales, weekly gross revenue, and customer equity, using same-week, 4-week and 13-week horizons. The

<sup>7</sup> The complete VAR estimation results are available from the first author.

<sup>8</sup> We do not have access to these cost data. Including them will make improve the CE estimates, but will not change our substantive conclusions.

customer equity metric is a multiplication of discounted purchase quantity (DPQ) and expected margin in each corresponding time period. Since we are able to estimate the future responses of DPQs and price variables from the IRF analysis, a new level of CE emerges for different scenarios.

Insert Table 3 about here

All brands in both product categories successfully increase short-term sales by additional price promotions. The short-term price elasticity ranges between 1.03 and 2.31 in absolute value, resulting in a 30.8% to 69.4% sales lift in the same week due to a 30% price discount. In addition, 4 out of 6 brands improve their revenue in the week of the price promotion. However, after a thirteen-week dust-settling period, the sales and revenues of all brands revert to their pre-shock level. During this 13-week period, the average weekly sales increase is 5.4% (or equivalently a .18 elasticity) and the revenue increase is 1.3% (or equivalently a .04 elasticity), a significant portion of which is realized in the first few weeks after the shock.

However, the price effects on customer equity are starkly different from those on sales and revenue. First, the positive impact of the marketing intervention is not immediately realized, but instead is gradually manifested over a prolonged period of time. Eventually, after the 13-week dust-settling period, all brands not only recuperate their original level of CE but benefit from an increase in CE. Second, different brands show different patterns of CE evolution after the price shock. For example, while Hunt's shows a CE increase after four weeks, Del Monte's promotion deteriorates the brand's CE compared to the pre-promotion level.

A primary reason for the difference between sales effects and CE effects lies in price inertia. All brands show significant and positive price inertia, though its magnitude differs. For example, Del Monte in the ketchup category and the private-label brand in the yogurt category

have significantly higher accumulated inertia than Hunt's and Dannon, respectively. While Hunt's and Dannon's prices return to normal – defined as  $\pm 0.5\%$  of the original price – within two to three weeks after a promotional price shock, Del Monte and the private-label brand exhibit six weeks of sustenance of the price shock. A similar result was found in Nijs, Srinivasan, and Pauwels (2007), who demonstrated that retailers whose prices are heavily dependent on past prices are less profitable.

Do CPG brands increase their customer equity by price promotion? The answer to this question depends on the brand's promotional practice. According to our analysis, some brands may deteriorate their CEs by an additional price promotion within 4 weeks, while they may increase CEs over a longer horizon. For example, if the private-label yogurt brand implements heavy (i.e., deeper than 30% in our case) price cuts more than once in a four-week period, it cannot increase its customer equity due to this practice.

We examined all brands' promotion practices during the 92-week observation period to evaluate the net impact of their price promotion strategy on CE. In the ketchup category, the number of weeks with 30 percent or deeper price cuts (compared to regular price) are 8 for Del Monte and Heinz (or equivalently 1 occurrence per 11.5 weeks) and 6 for Hunt's (1 per 15.3 weeks). In the yogurt category the numbers are 26 for Dannon (1 per 3.5 weeks), 64 for Yoplait (1 per 1.4 weeks) and 84 for the private-label brand (1 per 1.1 weeks). We then compare these promotional practices with the *number of weeks required to recover* the status quo CE estimates to evaluate the net impact of price promotion on CE as presented in Table 4. In our example, all three ketchup brands and a yogurt brand Dannon are found to successfully increase their customer equity by a “disciplined” price promotion strategy (i.e. restricting the promotion

frequency). However, Yoplait and the private yogurt brand deteriorate their CE levels by running promotional price cuts too frequently.

Insert Table 4 about here

### **Validation with a Household Level Choice Model**

We have proposed an approach to assess CPG brands' customer equity and investigated the effect of marketing activities on CE. But how can one ascertain that the proposed model measures what it intends to measure? We examine the validity of the proposed model by applying a household-level choice model to the same dataset and by comparing the simulated DPQs from the comparison choice model with those from the proposed model<sup>9</sup>. Similar results from the two models would support the validity of the proposed model.

We first estimate models of purchase incidence, brand choice, and purchase quantity (Bucklin, Gupta, and Siddarth 1998) on the same data that were used in our proposed model. Then, using the estimated parameter values, the effect of a 30% price promotion on sales is simulated for a focal brand, and repeated for each brand in each week. Based on the simulated sales, a new DPQ is calculated for five randomly chosen weeks. Because DPQ is the key component in the proposed CE metric, the average of the five new DPQs is compared with the results in Table 3. Details of the validation models are described in the Appendix. Table 5 shows the estimation results of the household-level model.

Insert Table 5 about here

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<sup>9</sup> We choose a household-level choice model for our validation purpose, because it is one of the most widely used models in the literature on marketing effectiveness for CPG brands.

The signs of all the parameter estimates are as expected. Price promotion increases the probability of purchase incidence, the likelihood of the promoted brand being chosen, and the expected purchase quantity. Display and feature advertising have the anticipated signs. Overall, the greater is the daily consumption of a household, the higher the probability of purchase incidence and the greater expected purchase quantity. In addition, brand loyalty has a strong positive effect on brand choice.

Insert Table 6 about here

Table 6 shows that our approach provides realistic results compared to a conventional household-level choice model. The estimates of price elasticity of sales (Table 6(a)) and of the percentage change in DPQs due to a 30 percent price promotion (Table 6(b)) are close to each other.

This result not only validates the proposed approach but also suggests several advantages of our approach. First, our model is simpler than the comparison choice model, because it benefits from the analytical solutions for  $DPQ_{it}$ , a key element of  $CE^{10}$ . Since the effect of marketing on CE is computed recursively by adding future time points one-by-one, having an analytical solution for  $DPQ_{it}$  is a significant advantage. Second, our model takes advantage of the flexibility of the VAR model framework. The VAR model incorporates various effects of marketing activities in a dynamic simultaneous but simple linear manner (DeKimpe and Hanssens 1995). In addition, its inherent systems approach naturally incorporates endogeneity, relieving researchers of the burden of modeling the complex supply side behavior. In sum, our approach is practically appealing because of its simplicity and flexibility while producing reasonable computation results for the effect of marketing on CE.

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<sup>10</sup> The choice model does not produce an analytical solution for  $DPQ_{it}$ , which requires simulation to calculate  $DPQ_{it}$ .

## Conclusions and Further Research

Customer equity is an alternative long-run objective of the firm to prosper in the information age. It gives the firm a clearer insight of how it generates customer value and how it should allocate its scarce marketing resources. However, academic research to date has been relatively silent in applying the CE concept to frequently purchased categories such as consumer packaged goods. This paper has proposed a method to measure the magnitude of CE and the impact of marketing activities on CE, using readily-available scanner panel data. We calculate the magnitude of CE based on non-contractual buyer-seller relationships in CPG categories, while the conventional CE literature has focused on contractual relationships. We also use the VAR model as a method to investigate the impact of marketing activities on CE, which is a long-term metric by its very nature.

In an empirical illustration on six brands in two product categories, ketchup and yogurt, we found that the positive impact of a price promotion on short-term sales does not always translate immediately to higher CE. The CPG brands need a longer time horizon to recover their CEs due to price inertia, though the speed of recovery is different across brands. On average across six brands, four post-promotion weeks are necessary to achieve at least a *status quo* level of customer equity. However, some brands (e.g., Yoplait and the private yogurt brand) fail to recover their CEs due to heavy price promotions that are run too frequently.

We also found that some brands' customer equity relies more on highly active customers than others. For example, while Heinz derives only 53.4% of its CE from highly active customers (High PACT in Figure 4), Del Monte receives as much as 62.5% of its CE from this source. Comparing the two product categories, we also found that competition in the highly-active segment is more important in yogurt than in ketchup: the three yogurt brands derive on average 72.4% of their value from such highly active customers, vs. 56.8% for the ketchup

brands. Therefore, a brand manager in the ketchup category should focus more on customers who have experienced the brand's products in the past but do not show recent purchase activity. Finally, we established that the evolution of customer equity is different across brands, as is the evolution in the high versus low active customer groups.

Our paper has some limitations that provide directions for future research. First, our model is developed for a one-brand-one-category scenario, i.e., we exclude possible cross-selling of brand customers into other categories (such as Heinz mustard or barbeque sauce). Since brand purchase behaviors may be correlated across categories (Ainslie and Rossi 1998), cross-selling opportunities exist for multi-category brands. Moreover, if the focal brand is a retailer as opposed to a manufacturer, our methodology should be modified in the direction of total-category sales. Second, this paper has examined two mature CPG categories with mass-marketing activities. Future research should consider additional product categories including newly emerging products, where new-customer acquisition occurs mainly at the category level, and with direct-marketing components such as catalog and email marketing. By analyzing more product categories, we will also be able to identify the brand / product characteristics that describe the impact of marketing on CE. Third, we have provided a descriptive model of the CE consequences of managers' product-marketing activities. Future work should prescribe an optimal marketing policy, for example a dynamic resource allocation among customers to maximize customer equity. Fourth, since our results are based on a constant-elasticity model, we did not capture possible non-monotonic or asymmetric effects of marketing on customer equity. For example, repetitive deep (e.g., 50%) price promotions may profoundly change consumer attitudes and thus disproportionately influence CE compared to shallow (e.g., 5%) price cuts.

Threshold-based models (Pauwels, Srinivasan & Franses 2007) or regime-switching models may shed light on this issue.

The business performance of brands in frequently purchased categories such as CPG is *fast-moving* and *volatile*, especially when brand competition involves price promotions, as illustrated in Figure 1. In such environments it is difficult to assess if a brand's health is evolving positively or negatively. Perhaps the greatest managerial benefit of our proposed CE modeling approach is that it provides a *slow-moving* diagnostic – as illustrated in Figure 3 – that is based on extant consumer behavior principles, is long-run focused and can be related to marketing actions. As such we hope that this approach will contribute to the practice of marketing for long-run value improvement as opposed to short-run sales stimulation, in the interest of consumers as well as shareholders.

**Table 1**  
**Descriptive Statistics of the Data**

A. Ketchup

	Del Monte	Heinz	Hunt's	Category
Number of Panels	652	1,608	834	1,693
Number of Shopping Trips	1,733	13,594	2,931	19,841
Weekly Sales (oz.)	420	3,305	771	4,841
<i>Share</i>	8.7%	68.3%	15.9%	
Regular Price (cents/oz.)	3.20	3.91	3.27	3.68
Price Paid (cents/oz.)	2.91	3.39	2.80	3.20
<i>Ratio</i>	90.7%	86.6%	85.5%	87.1%
Feature AD (0-1)	0.29	0.34	0.30	0.31
Display (0-1)	0.07	0.11	0.12	0.10

B. Yogurt

	Dannon	Yoplait	Private	Category
Number of Panels	797	879	625	1,435
Number of Shopping Trips	8,037	13,434	7,529	59,201
Weekly Sales (oz.)	762	892	791	4,878
<i>Share</i>	15.7%	18.4%	16.3%	
Regular Price (cents/oz.)	7.14	9.37	4.29	6.34
Price Paid (cents/oz.)	5.35	6.19	2.43	4.14
<i>Ratio</i>	74.8%	66.1%	56.8%	65.4%
Feature AD (0-1)	0.13	0.10	0.27	0.24
Display (0-1)	0.01	0.03	0.11	0.07

(Note) "Number of Panels" for each brand refers to the number of households that purchase each brand at least once in the observation period.

**Table 2**  
**Model Selection Results**

A. Model Comparison for Number of Transactions

	In-Sample Fit (Log Likelihood)			Out-of-Sample Fit (Chi2 Stat.)		
	Pareto/NBD	BG/NBD	BG/BB	Pareto/NBD	BG/NBD	BG/BB
Del Monte	-3,079.52	-3,079.60	<b>-3,061.10</b>	0.667	<b>0.653</b>	0.679
Heinz	-24,804.51	-24,803.16	<b>-24,331.90</b>	0.221	<b>0.218</b>	0.220
Hunt's	-4,666.37	-4,666.36	<b>-4,639.17</b>	0.515	0.522	<b>0.493</b>
Ketchup Category	-35,724.69	-35,723.38	<b>-34,853.00</b>	0.141	0.144	<b>0.073</b>
Dannon	-8,569.47	-8,567.19	<b>-8,204.61</b>	3.435	3.612	<b>3.011</b>
Yoplait	-11,001.05	-10,991.84	<b>-10,387.46</b>	2.669	2.558	<b>2.235</b>
Private Brand	-5,735.86	-5,734.68	<b>-5,533.60</b>	5.751	<b>5.583</b>	5.640
Yogurt Category	-37,260.42	-37,254.98	<b>-34,401.23</b>	0.986	<b>0.937</b>	1.472

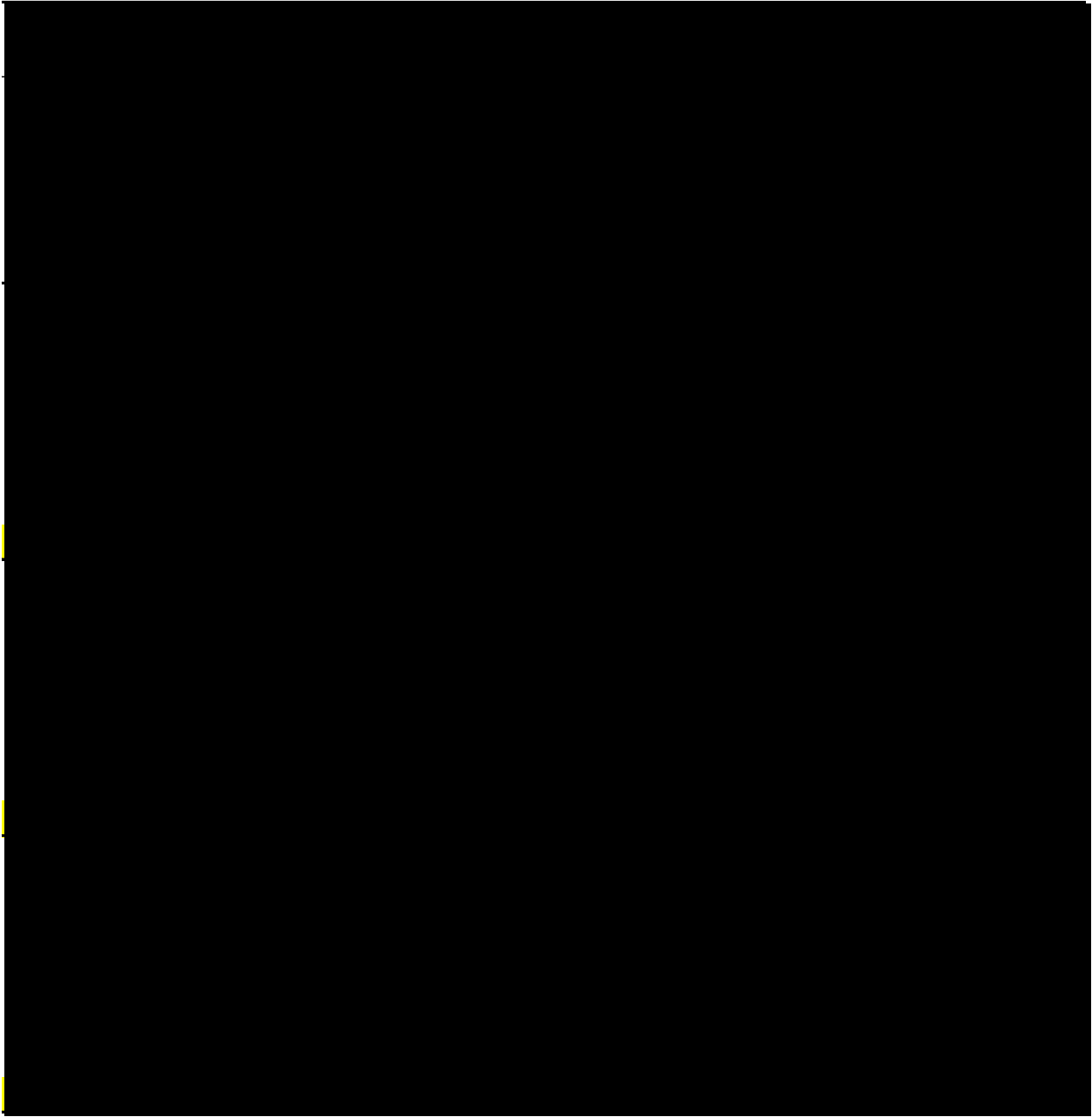
B. Model Comparison for Amount of Purchase Per Transaction

	In-Sample Fit (MAPE)		Out-of-Sample Fit (Chi2 Stat.)	
	Normal/Normal	Gamma/Gamma	Normal/Normal	Gamma/Gamma
Del Monte	<b>1.153</b>	2.203	1.130	<b>0.767</b>
Heinz	<b>2.358</b>	6.506	<b>0.574</b>	1.093
Hunt's	0.973	<b>0.049</b>	5.664	<b>1.565</b>
Ketchup Category	<b>2.529</b>	5.328	<b>0.557</b>	0.837
Dannon	2.225	<b>0.520</b>	<b>5.410</b>	5.721
Yoplait	<b>2.982</b>	10.986	9.929	<b>7.065</b>
Private Brand	<b>2.332</b>	21.954	<b>5.422</b>	9.451
Yogurt Category	<b>2.759</b>	7.409	19.223	<b>12.289</b>

\*Bold letters indicate the best model.

\*The chi-square test for out-of-sample fit is on 8 customer groups based on number of transactions in the calibration period. (d.f. = 7, critical value for 95% of confidence level = 14.07)

**Table 3**  
**Customer Equity Effects of Price Promotion**



(Note) The results are based on dynamic responses of price, sales, and DPQ to a shock of 30% price decrease (i.e., promotion).

**Table 4**  
**Customer Equity and Promotion Practice**

Brand	Number of Weeks Necessary for CE Recovery	Number of Weeks with 30% or Deeper Price Promotion	Average Frequency (in 92 weeks)	CE Lifting Due to Price Promotion?
Del Monte	5	8	11.5	Yes
Heinz	4	8	11.5	Yes
Hunt's	3	6	15.3	Yes
Dannon	3	26	3.5	Yes
Yoplait	4	64	1.4	No
Private	5	84	1.1	No

**Table 5**  
**Estimation Results of the Household Level Model**

		Ketchup	Yogurt
Purchase Incidence	Daily Consumption	0.143 (27.639)	0.461 (78.757)
	Category Value	0.240 (32.967)	0.048 (4.388)
Brand Choice	Price	-1.055 (-24.296)	-0.190 (-18.893)
	Display	0.965 (11.260)	1.094 (14.821)
	Feature	1.417 (25.524)	1.045 (26.535)
	Brand Loyalty	4.991 (73.629)	3.627 (102.602)
Purchase Quantity	Daily Consumption	N.A.	0.562 (56.815)
	Price	N.A.	-0.126 (-56.755)
	Display	N.A.	1.112 (16.880)
	Feature	N.A.	0.943 (23.475)

(Note) The purchase quantity model does not apply very well to the ketchup category since there is too little variation in the units purchased in this category.

**Table 6**  
**Validation of the Proposed Model**

**(a) Sales Elasticity**

		Ketchup				Yogurt			
		Del Monte	Heinz	Hunt's	Category	Dannon	Yoplait	Private	Category
VAR Model (Table 3)	Simulation Elas.	-2.304	-2.194	-1.728	-2.123	-1.029	-1.236	-1.458	-1.261
Household Level Model	Simulation Elas.	-2.427	-1.161	-2.134	-1.415	-1.488	-1.630	-0.504	-1.298
	Point Elas.	-2.700	-1.670	-2.446	-2.163	-1.167	-1.374	-0.729	-0.971

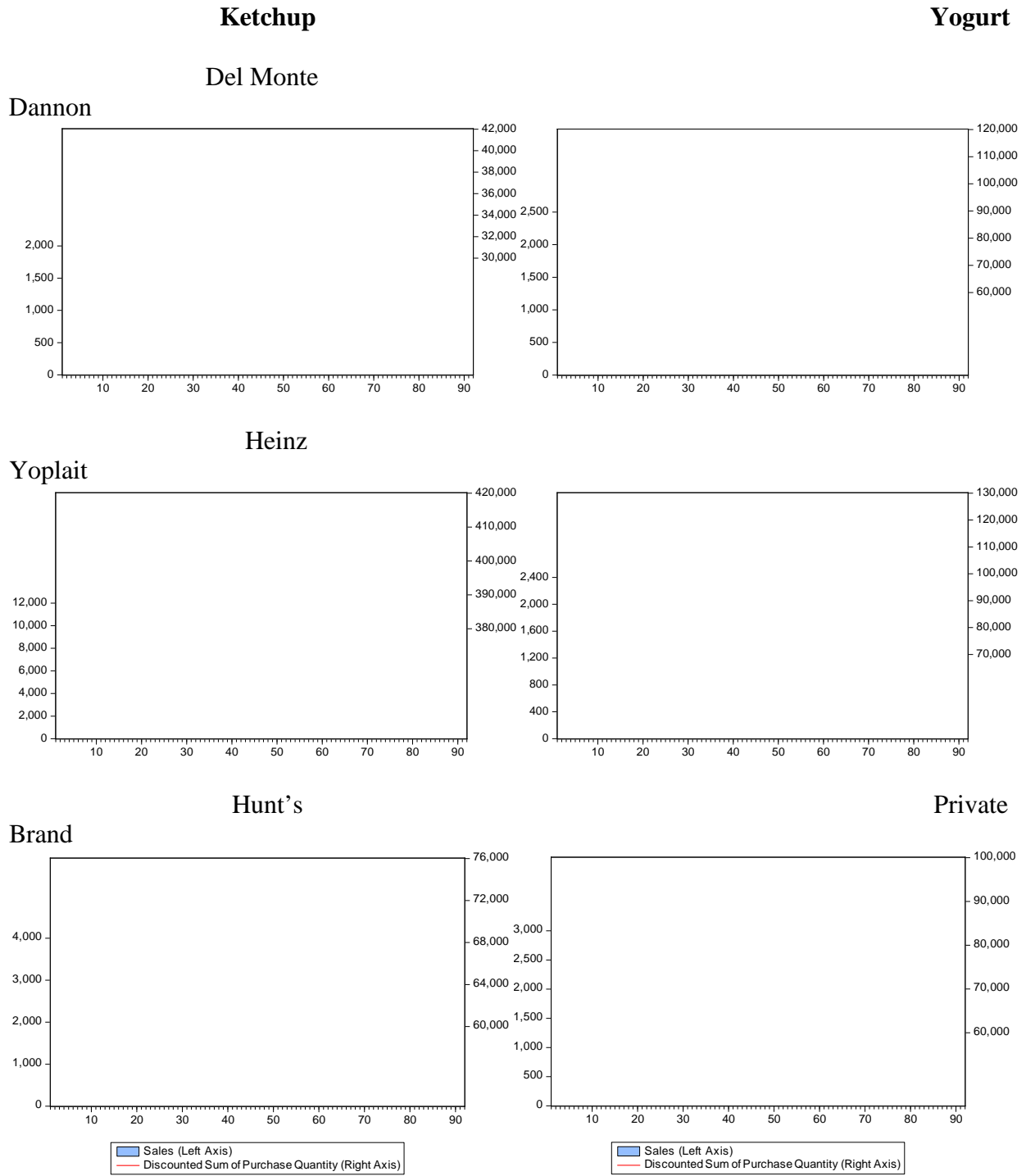
(Note) The simulation elasticity calculated from the simulated sales data due to 30% price promotion. The point elasticity is calculated from the elasticity formula in the Appendix.

**(b) Percentage Change in DPQ due to 30% Price Promotion**

		Ketchup				Yogurt			
		Del Monte	Heinz	Hunt's	Category	Dannon	Yoplait	Private	Category
VAR Model (Table 3)	Same Week	0.88%	0.83%	0.71%	0.82%	0.54%	0.27%	0.52%	0.43%
	After 4 Weeks	1.36%	0.87%	0.66%	0.87%	0.76%	0.34%	0.83%	0.63%
	After 13 Weeks	1.38%	0.87%	0.66%	0.88%	0.76%	0.34%	0.84%	0.63%
Household Level Model	Same Week	1.75%	0.75%	1.35%	0.88%	1.29%	0.73%	0.18%	0.75%
	After 4 Weeks	1.65%	0.70%	1.25%	0.82%	1.23%	0.71%	0.17%	0.72%
	After 13 Weeks	1.32%	0.57%	1.06%	0.67%	0.36%	0.73%	0.08%	0.45%

**Figure 1**

**Evolution of the Discounted Sum of Purchase Quantities**

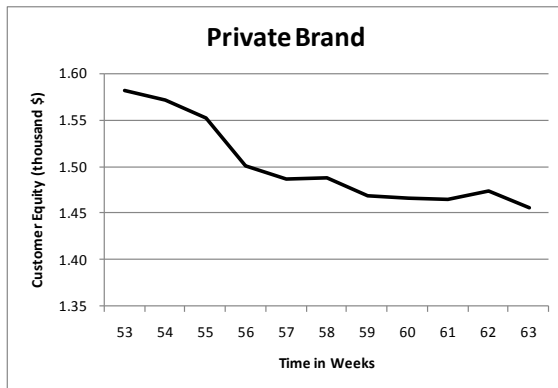
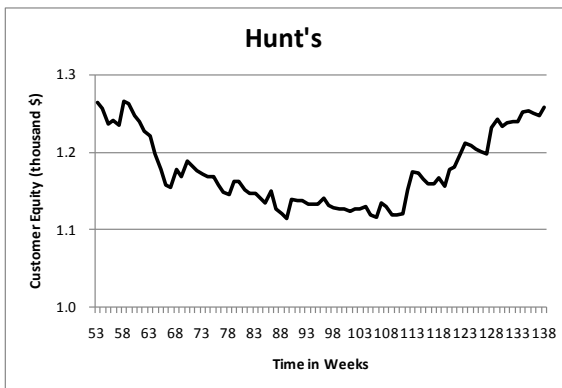
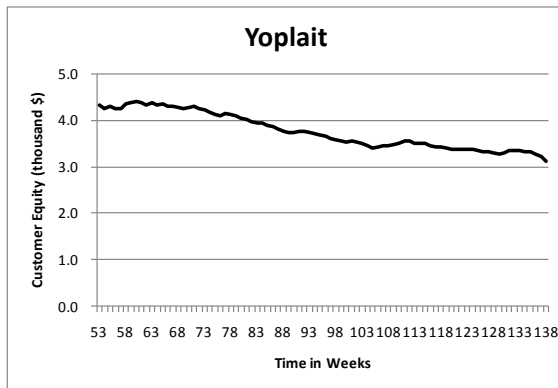
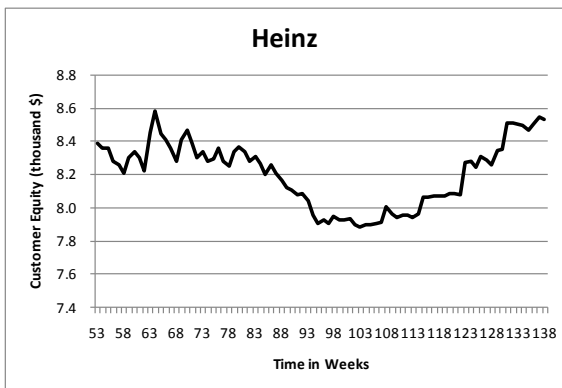
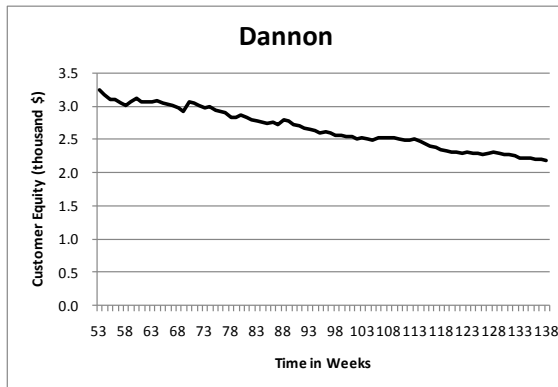
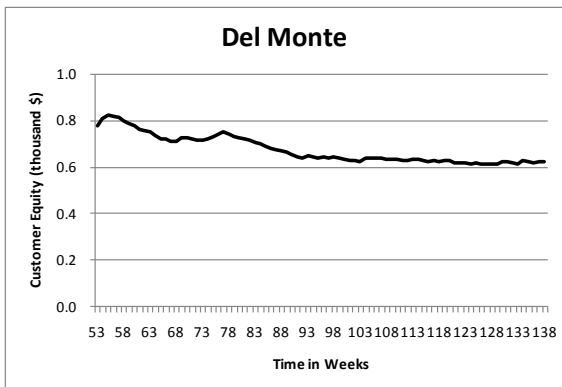


(Note) Vertical axis is ounces sold, and horizontal axis is weekly time periods.

**Figure 2**  
**The Evolution of CPG Brands' Customer Equity**

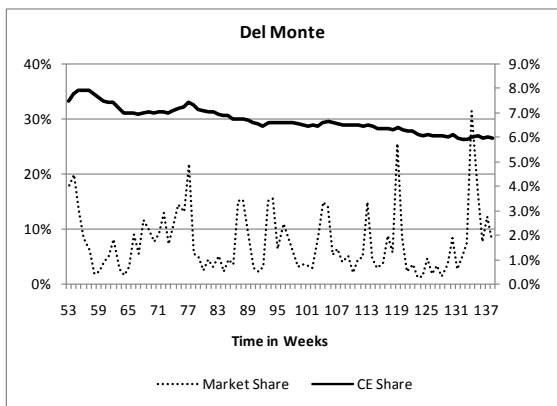
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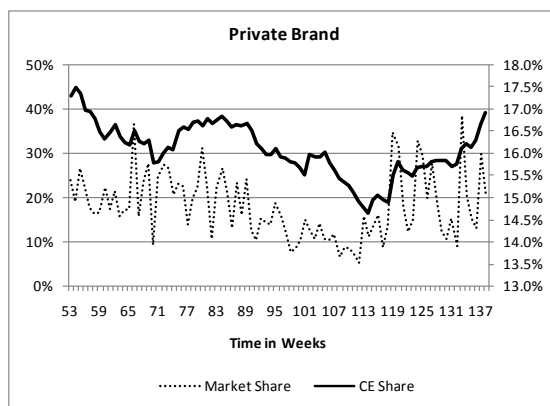
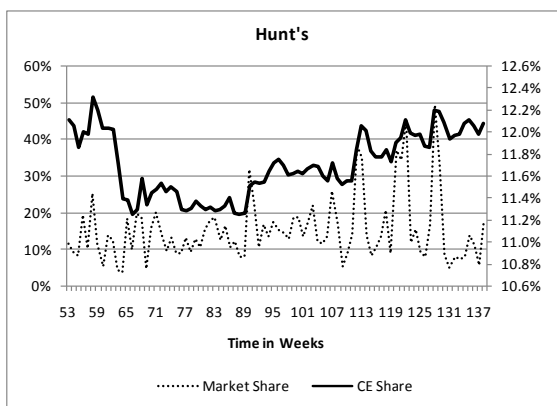
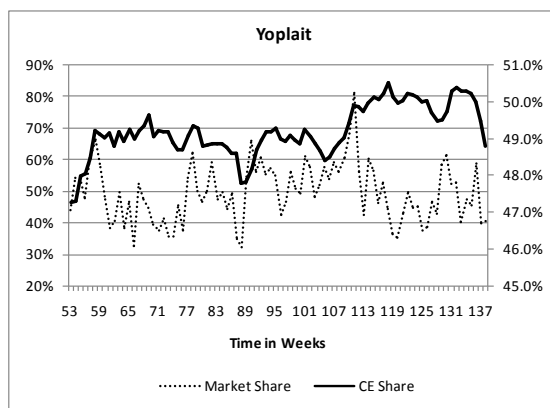
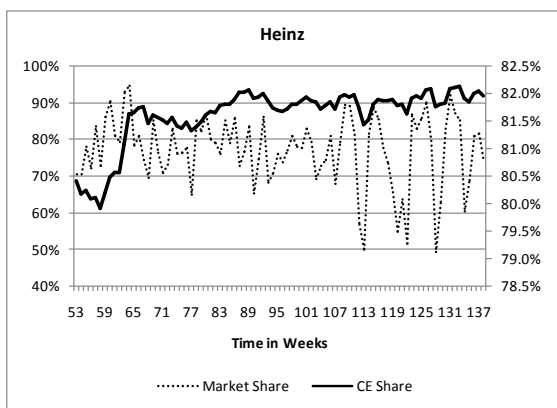
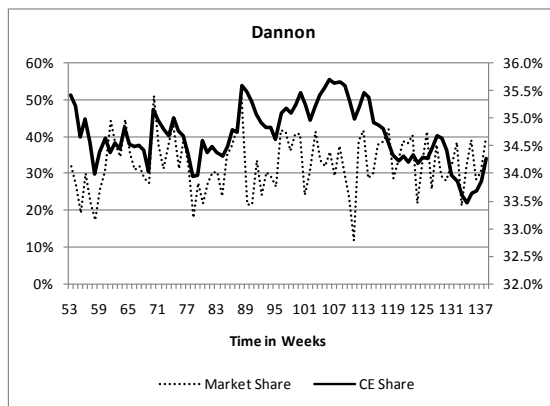


**Figure 3**  
**Share of Customer Equity and Share of Revenue**

**<Ketchup>**

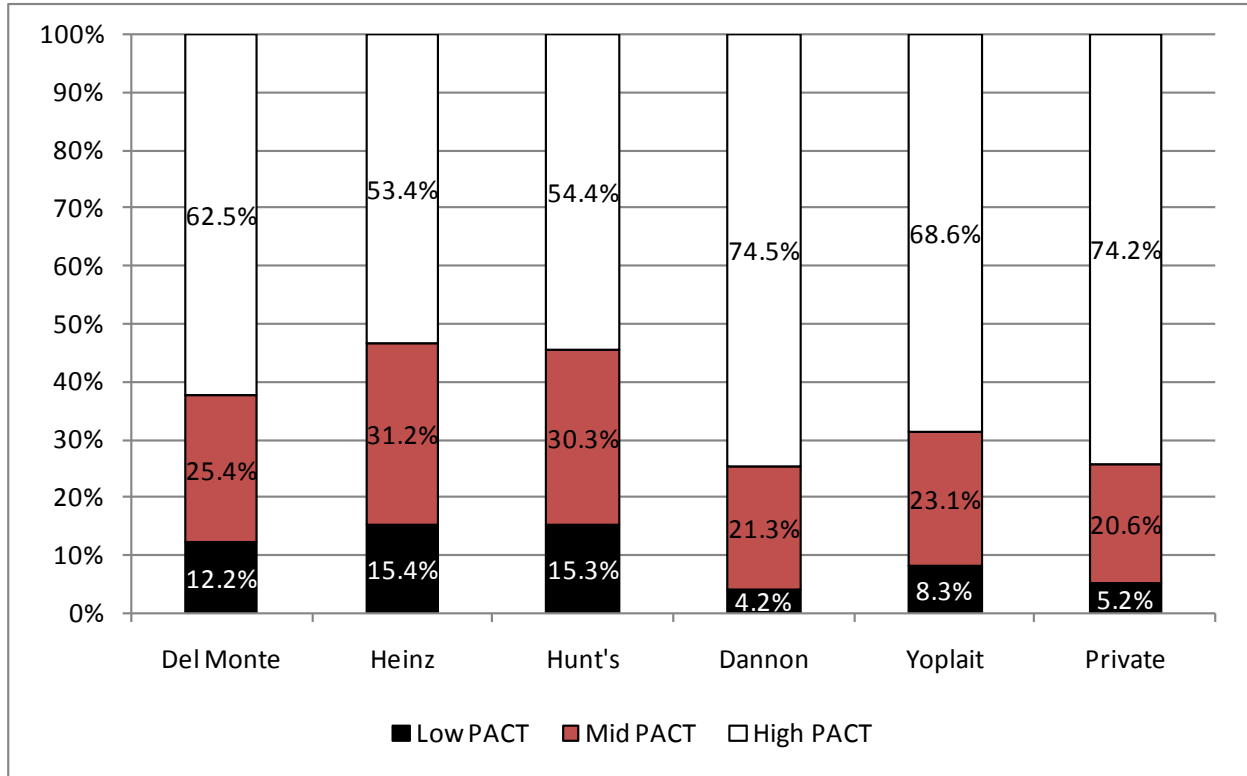


**<Yogurt>**



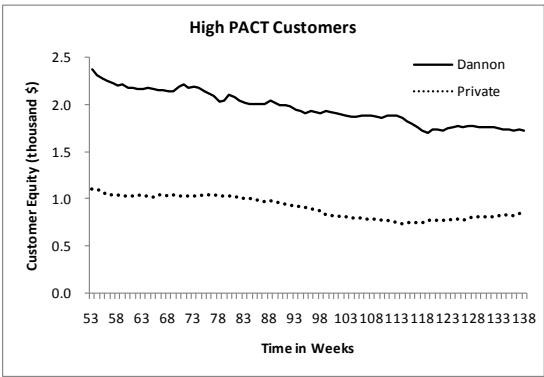
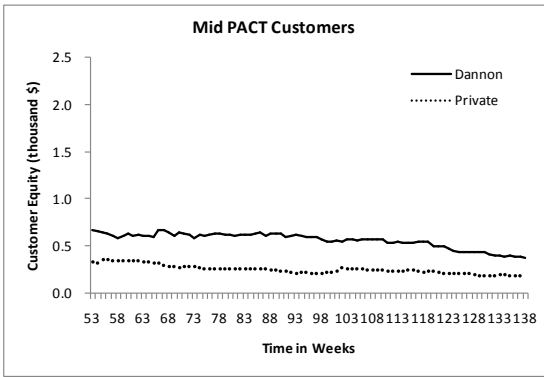
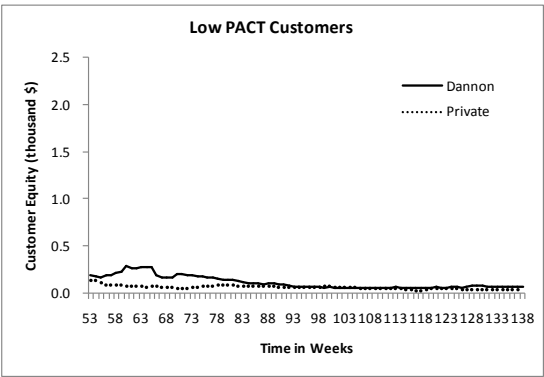
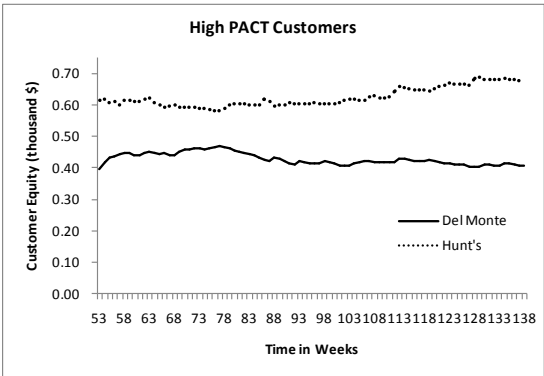
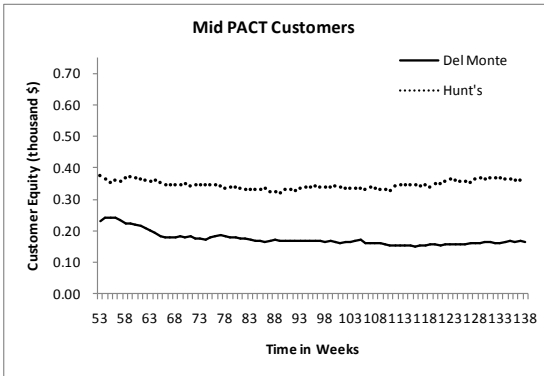
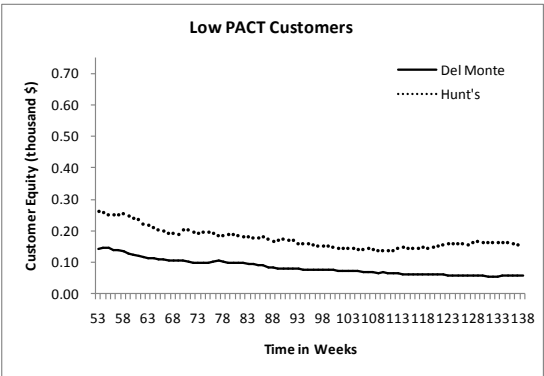
(Note) Both CE (right axis) and market shares (left axis) are relative to the three brands in each category.

**Figure 4**  
**Customer Equity Decomposition**



(Note) PACT = probability of being active, obtained from BG/BB model estimation.

**Figure 5**  
**The Evolution of Decomposed Customer Equity**



## References

- Ainslie, Andrew and Peter E. Rossi (1998), "Similarities in choice behavior across product categories," *Marketing Science*, 17 (2), 91-106.
- Ailawadi, Kusum L. and Bari A. Harlam (2009), "Findings—Retailer Promotion Pass-Through: A Measure, Its Magnitude, and Its Determinants," *Marketing Science*, 28 (4), 782-91.
- and Scott A. Neslin (1998), "The Effect of Promotion on Consumption: Buying More and Consuming It Faster," *Journal of Marketing Research*, 35 (3), 390-8.
- Allenby, Greg M. and Peter E. Rossi (1991), "Quality Perceptions and Asymmetric Switching between Brands," *Marketing Science*, 10 (3), 185-204.
- Blattberg, Robert C. and John Deighton (1996), "Manage marketing by the customer equity test," *Harvard Business Review*, 74 (4), 136-44.
- , Gary Getz, and Jacquelyn S. Thomas (2001), *Customer Equity: Building and Managing Relationships as Valuable Assets*, Boston, Massachusetts: Harvard Business School Press.
- and Kenneth J. Wisniewski (1989), "Price-Induced Patterns of Competition," *Marketing Science*, 8 (4), 291-309.
- Bronnenberg, Bart J., Vijay Mahajan, and Wilfried R. Vanhonacker (2000), "The Emergence of Market Structure in New Repeat-Purchase Categories: The Interplay of Market Share and Retailer Distribution," *Journal of Marketing Research*, 37 (1), 16-31.
- Bucklin, Randolph E, Sunil Gupta, and S. Siddarth (1998), "Determining Segmentation in Sales Response Across Consumer Purchase Behaviors," *Journal of Marketing Research*, 35 (2), 189-97.
- Chintagunta, Pradeep K. (1993), "Investigating Purchase Incidence, Brand Choice and Purchase Quantity Decisions of Households," *Marketing Science*, 12 (2), 184-208.
- Colombo, Richard and Jiang Weina (1999), "A Stochastic RFM Model," *Journal of Interactive Marketing*, 14 (2), 2-12.
- Dekimpe, Marnik G. and Dominique M. Hanssens (1995), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14 (1), 1-21.
- and ---- (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability," *Journal of Marketing Research*, 36 (4), 397-412.
- , ----, and Jorge M. Silva-Risso (1999), "Long-run effects of price promotions in scanner markets," *Journal of Econometrics*, 89 (1-2), 269-91.

Fader, Peter S., Bruce G. S. Hardie, and Ka Lok Lee (2005), "Counting Your Customers the Easy Way: An Alternative to the Pareto / NBD Model," *Marketing Science*, 24 (2), 275 - 84.

----, ----, and Jen Shang (2010), "Customer-Base Analysis in a Discrete-Time Noncontractual Setting," *Marketing Science*, 29 (6), 1086 – 108.

Granger, Clive W.J. and Paul Newbold (1974), "Spurious Regressions in Econometrics," *Journal of Econometrics*, 2 (2), 111-20.

Gupta, Sunil, Donald R. Lehmann, and Jennifer Ames Stuart (2004), "Valuing Customers," *Journal of Marketing Research*, 41 (1), 7-18.

Hanssens, Dominique M. and Marnik G. Dekimpe (2008), "Models for the Financial Performance Effects of Marketing," in *Handbook of Marketing Decision Models*, Berend Wierenga, ed.: Springer Science.

Kumar, V., and Morris George (2007), "Measuring and Maximizing Customer Equity: A Critical Analysis," *Journal of the Academy of Marketing Science*, 35 (2), 157-71.

Lütkepohl, Helmut (1993), *Introduction to Multiple Time Series Analysis*, Germany: Springer-Verlag.

Mela, Carl F., Sunil Gupta, and Donald R. Lehmann (1997), "The Long-term Impact of Promotion and Advertising on Consumer Brand Choice," *Journal of Marketing Research*, 34 (2), 248-61.

Nijs, Vincent R., Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamp, and Dominique M. Hanssens (2001), "The Category-Demand Effects of Price Promotions," *Marketing Science*, 20 (1), 1-22.

----, Shuba Srinivasan, and Koen Pauwels (2007), "Retail-Price Drivers and Retailer Profits," *Marketing Science*, 26 (4), 473-87.

Pauwels, Koen, Shuba Srinivasan, and Philip Hans Franses (2007), "When Do Price Thresholds Matter in Retail Categories?," *Marketing Science*, 26 (1), 83-100.

Rust, Roland T., Katherine N. Lemon, and Valarie A. Zeithaml (2004), "Return on Marketing: Using Customer Equity to Focus Marketing Strategy," *Journal of Marketing*, 68 (1), 109-27.

----, Valarie A. Zeithaml, and Katherine N. Lemon (2000), *Driving Customer Equity: How Customer Lifetime Value Is Reshaping Corporate Strategy*, New York, NY: The Free Press.

Schmittlein, David C., Donald G. Morrison, and Richard Colombo (1987), "Counting Your Customers: Who Are They and What Will They Do Next?," *Management Science*, 33 (1), 1-24.

---, Robert A. Peterson (1994), "Customer Base Analysis: An Industrial Purchase Process Application, " *Marketing Science*, 13 (1), 41-67.

### Appendix: The household level choice model

The household level choice model (choice model hereafter) consists of three sub-models: a brand choice model, a purchase incidence model, and a purchase quantity model. The brand choice model and the purchase incidence model are linked in the standard nested logit model framework. Purchase quantity is modeled by a truncated-at-zero Poisson model.

#### *Brand choice model*

$$P(J_t^h | inc_t^h = 1) = \frac{\exp(U_{jt}^h)}{\sum_{k=1}^4 \exp(U_{kt}^h)}$$

(A-1)

where

$$U_{jt}^h = \gamma_0 + \gamma_1 \cdot \text{Price}_{jt} + \gamma_2 \cdot \text{Display}_{jt} + \gamma_3 \cdot \text{Feature}_{jt} + \gamma_4 \cdot \text{BLoyalty}_j^h \\ + \gamma_5 \cdot \text{Brand1} + \gamma_6 \cdot \text{Brand2} + \gamma_7 \cdot \text{Brand3}$$

Brand1, Brand2, and Brand 3 are the brand dummy variables. The brand loyalty variable of household h for brand j,  $\text{BLoyalty}_j^h$ , is calculated as the share of brand j during household h's total shopping trips. The marketing variables (i.e. price, display, and feature) of brand j are volume-averaged across different UPCs of the brand.

#### *Purchase incidence model*

$$P(inc_t^h = 1) = \frac{\exp(V_t^h)}{1 + \exp(V_t^h)}$$

(A-2)

where

$$V_t^h = \beta_0 + \beta_1 \cdot \text{Daily Consumption}^h + \beta_2 \cdot \log\left(\sum_k \exp(U_{kt}^h)\right)$$

Daily consumption is the average daily consumption (oz.) of the category of household h. We do not include an inventory-level variable as in Ailawadi and Neslin (1998) since our sample includes both static and non-static households.

*Purchase quantity model*

$$P(q_{jt}^h | j_t^h \& inc_t^h = 1) = \frac{(\lambda_{jt}^h)^{q_{jt}^h}}{(e^{\lambda_{jt}^h} - 1)q_{jt}^h!}$$

(A-3)

where

$$\lambda_{jt}^h = \pi_0 + \pi_1 \cdot \text{Daily Consumption}^h + \pi_2 \cdot \text{Price}_{jt} + \pi_3 \cdot \text{Display}_{jt} + \pi_4 \cdot \text{Feature}_{jt}.$$

The model is estimated by maximum likelihood. The nested logit of purchase incidence and brand choice is estimated sequentially, by first estimating the brand choice model and then estimating the purchase incidence model. For the ketchup category we do not estimate the purchase quantity model since the households in the sample purchased only one unit of ketchup in virtually all purchase occasions.

*Point elasticity of demand*

The demand, i.e. expected purchase quantity (oz) of brand j in week t is given by

$$\begin{aligned} E(Q_{jt}) &= \sum_{h=1}^H E(q_{jt}^h) = \sum_{h=1}^H E(q_{jt}^h | j_t^h \& inc_t^h = 1) \times \Pr(j_t^h | inc_t^h = 1) \times \Pr(inc_t^h = 1) \\ (A-4) \quad &= \sum_{h=1}^H \left( \frac{\lambda_{jt}^h}{1 - e^{-\lambda_{jt}^h}} \frac{e^{U_{jt}^h}}{\sum_{k \in K_{st}} e^{U_{kt}^h}} \frac{e^{V_t^h}}{1 + e^{V_t^h}} \right). \end{aligned}$$

Then for brand  $j$  and household  $h$ , the price elasticity of the expected purchase quantity (oz) is

$$\eta_{p_j}^h = \eta_{p_j, E(q|inc, j)}^h + \eta_{p_j, Pr(j|inc)}^h + \eta_{p_j, Pr(inc)}^h$$

where

$$(A-5) \quad \eta_{p_j, E(q|inc, j)}^h = \pi_2 \frac{1 - (1 + \lambda_j^h) e^{-\lambda_j^h}}{1 - e^{-\lambda_j^h}} \frac{p_j}{E(q_j^h | inc^h \& j^h)}$$

$$\eta_{p_j, Pr(j|inc)}^h = \gamma_1 p_j (1 - Pr(j^h | inc^h))$$

$$\eta_{p_j, Pr(inc)}^h = \beta_2 \gamma_1 \frac{e^{\gamma_{0j} + \gamma_1 p_j}}{\sum_k e^{\gamma_{0k} + \gamma_1 p_k}} p_j (1 - Pr(inc^h)).$$

The market-level elasticity is the average of the individual households' elasticities computed in (A-5).