Measuring Marketing Effects on Customer Equity for 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 adopting an *always-a-share* customer definition and using a probabilistic classification of active and inactive customers, 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 very different. As a result, the brands' customer equity levels may be evolving in different directions that are not readily apparent. We discuss the managerial implications of our findings and offer several areas for future research.

Key words: Customer Equity, Market Response Models, Time Series Models

Introduction

The customer equity (CE) paradigm proposes that firms can achieve superior performance by changing their focus from delivering competitive products to building good customer relationships (Blattberg, Getz, and Thomas 2001; Rust, Zeithaml, and Lemon 2000). Due to recent technological developments, firms now can utilize much richer information of their customers, such as histories of individual-level transactions. As a result, the CE paradigm is used in the practice of customer relationship management (CRM), and more researchers are investigating CE-related issues (e.g., Kumar and Reinartz 2006).

Under the CE 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[1]. However, such customer-centered thinking is also important in more conventional product-markets such as consumer packaged goods (CPG), because the consumers of these products ultimately generate the revenue flows for the suppliers, much like bank customers do.

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, 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).

[1] A notable exception is Rust et al. (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 *dynamic* relationship between the firm's marketing and the components of customer equity. For example, a price discount may initially bring in more new customers (i.e. a higher acquisition rate), but when prices don't return to normal quickly, the discount may become a "subsidy" that dampens or even nullifies the beneficial impact in the long run. Similarly, a successful customer-retention campaign may generate subsequent word-of-mouth that attracts more future new customers. Ignoring these dynamics can result in inaccurate assessment of marketing-mix effects on CE. In fact, several CE studies (e.g., Gupta, Lehmann, and Stuart 2004) avoid the problem by treating *acquisition rate* and *retention rate* as exogenous variables that are assumed to be determined by industry characteristics or product-life-cycle stage and that cannot be influenced by a single firm.

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 *stock* measures with long-run consequences, such as the gradual building or erosion of customer loyalty through marketing activity (Dekimpe and Hanssens 2008).

These realities motivate our development of a model that measures the value of customers and the impact of marketing activities such as price promotion in CPG industries, using readily-available scanner panel data. Our proposed model explains the dynamic interactions between the firm's marketing efforts and the two key components of CE, i.e., customer acquisition and retention. We focus on a mass-marketing and non-contractual transactions environment, which is common but has not been 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 product-marketing 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 starts from current CE measurement practice. We then propose a model that links product sales to CE and also measures the dynamic relationships among the key components of CE. 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

The Measurement of Customer Equity

A customer's lifetime value is measured as the net present value (NPV) of profit streams from the initial transaction (i.e. acquisition) and all future transactions generated by the customer (i.e. retention[2]). These two processes have been investigated in virtually all CE related literature (e.g., Blattberg, Getz, and Thomas 2001). 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.

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[2] Some researchers view cross-selling and up-selling as separate from the retention process (e.g., Blattberg, Getz, and Thomas 2001). However, a broader definition of retention can include cross-selling and up-selling processes as well.

Customer retention is directly observable only when the transaction frequency is nearly perfectly predictable, as in the case of a newspaper subscription. As a result, many customer equity models have been applied to industries with contractual relationships with customers (e.g., Wiesel, Skiera, and Villanueva 2008). However, if the transaction frequency is heterogeneous across consumers, measuring the incidence of retention and thereby retention rate is challenging, because attrition typically occurs silently. For instance, in CPG categories, a customer who has not repeat-purchased a product in a given recent time period is not necessarily "lost for good." Perhaps this consumer made her last purchase for an unusually large quantity because the product was on sale, and is therefore "out of the market" in the current time period. In the same vein, a manager should not de facto treat all customers in the firm's database as existing customers, since silent attrition cannot be measured without using sophisticated statistical models (Schmittlein, Morrison, and Colombo 1987; Schmittlein and Peterson 1994). Using the terminology of Dwyer (1997) we propose to measure CE in CPG industries based on *always-a-share* rather than *lost-for-good* buyer-seller relationships. We will use a stochastic model to determine the probability that a consumer is still a customer at any point in time, based on her purchase history.

The Impact of Marketing on Customer Equity

Even though CE has been suggested as an alternative paradigm for allocating a firm's marketing resources, the relationship between input (i.e., the firm's marketing mix efforts) and output (i.e., customers' acquisition and retention response) has not been examined extensively. The marketing-mix effects on key elements of CE are either not modeled explicitly (e.g., Berger and Nasr 1998) or are assumed to be instantaneous only (e.g., Blattberg and Deighton 1996; Blattberg, Getz, and Thomas 2001). The two key components of CE, acquisition rate and retention rate, are sometimes modeled as exogenous variables given to the firm (Gupta, Lehmann, and Stuart 2004).

The firm's marketing activities may affect customer equity through various routes. If for example a CPG brand implements a price promotion to acquire prospects and retain existing customers in a particular week, that promotion may increase the number of buyers from the prospect pool and the customer pool, as well as the purchase quantity of those buyers. Along with these positive effects, this price promotion can impact customer equity negatively as well, since the contribution margin will be lower due to the discounted price. Therefore, the net impact of marketing activities on CE should be carefully assessed via a cost-benefit analysis (Rust, Lemon, and Zeithaml 2004).

Another challenging task in investigating the impact of marketing on CE is to incorporate the dynamic nature of the relationship between marketing and CE, since CE is a forward-looking metric by definition. For example, higher marketing spending may increase customer retention, and this retention increase may in turn affect the manager's future marketing decisions. This simultaneity between marketing and CE has been singled out as a major challenge in modeling the relationship between the two (Berger et al. 2002).

In contrast, researchers in the product-marketing domain have conducted extensive studies on marketing's impact on sales response, including advertising (e.g., Assmus, Farley, and Lehmann 1984) and price promotions (e.g., Blattberg, Briesch, and Fox 1995). In addition, the long-run sales effects of these product-marketing actions are also well understood (Hanssens, Parsons, and Schultz 2001). However, these econometrically measured relationships occur in transactions space, with little or no reference to the consumers who generate them. In fairness, some researchers have addressed the difference between acquisition and retention behavior in the product-marketing domain. For example, Deighton et al. (1994) measured the effect of advertising on brand switching (akin to acquisition) and repeat purchasing (akin to retention). Roy, Chintagunta, and Haldar (1996) investigated repeat-purchase behavior by separating habit persistence and state dependence. However, we do not have a good understanding of the ways in which product-marketing actions either build or erode customer equity for the brands that initiate them.

Model Development

The Measurement of Customer Equity Using Scanner Panel Data

We evaluate CE by summing up all the existing and future customers' lifetime values (CLVs)[3] such that:

$$CE_t = \sum_{j=t}^{\infty} \frac{AV_j + RV_j}{(1+\delta)^{j-t}} \tag{1}$$

where CE_t is the magnitude of customer equity assessed at time t; AV_t is CLV from acquisition evaluated at time t; RV_t is CLV from retention evaluated at time t; and δ is a firm-specific time discount factor. More specifically, suppose a certain number of prospects[4] (N^a) purchase the firm's product at time t, then the value from acquisition can be expressed as:

$$AV_t = N_t^a q_t^a \pi_t^a \tag{2}$$

where q^a is average purchase quantity of acquisition buyers and π^a is contribution margin per sales unit, net of other acquisition costs. Likewise, the value from retention can be also written as:

[3] Some researchers only count the lifetime values of current customers when calculating the magnitude of CE at a certain point in time (Wiesel, Skiera, and Villanueva 2008). However, ignoring future acquisition will significantly underestimate the firm's CE.
[4] This prospect pool may include first-time buyers and competitors' customers.

(3) $$RV_t = N_t^r q_t^r \pi_t^r$$

where N^r is the number of buyers from the existing-customer pool; q^r is average purchase quantity of these retention buyers; and π^r is contribution margin per sales unit, net of other retention costs. Therefore, the firm's customer equity evaluated at time t can be written as:

(4) $$CE_t = \underbrace{\sum_{j=t}^{\infty} \frac{N_j^a \pi_j^a q_j^a}{(1+\delta)^{j-t}}}_{\text{value from acquisition}} + \underbrace{\sum_{j=t}^{\infty} \frac{N_j^r \pi_j^r q_j^r}{(1+\delta)^{j-t}}}_{\text{value from retention}}$$

This modeling approach is different from that of Gupta, Lehmann, and Stuart (2004), who track future retention of a customer cohort acquired at a period of time based upon a "lost-for-good" definition of the buyer-seller relationship. Since buyers in CPG categories typically keep changing their membership status (i.e. they oscillate back and forth between prospect status and existing-customer status) over the duration of their purchasing lifetime, it is meaningless to analyze the lifetime value of each customer or cohort by successive future retention rates. Instead, we propose to decompose the long-term value stream they generate for the firm from a *product consumption* point of view. Under the *always-a-share* scenario typical in CPG industries, if a buyer is classified as an existing customer at a certain point of time, her purchase will be regarded as a successful "retention sale" regardless of when she was first 'acquired' by the firm. Similarly, if the buyer does not meet the existing-customer criterion at that point in time, the sale will be classified as an 'acquisition sale" (in most cases it is a "re-acquisition" sale). Therefore, the number of buyers in acquisition and retention will be directly calculated from this definition of "existing customers." As a result, the firm's CE will be obtained from future expected values of (1) number of buyers, (2) purchase quantity, and (3) contribution margin.

How Do We Analyze Acquisition and Retention in CPG Industries?

The traditional definition of an existing customer is based on “ownership” or “usage” of a product or service. This definition works well in relationship businesses where a contract exists between the firm and the customer (e.g., insurance). It also works well for consumer and industrial durables where a customer makes a longer-term commitment to ownership or usage, so that brand switching is costly and infrequent (e.g. automobiles). However, the definition easily breaks down when customers switch easily and frequently among brands, when their inter-purchase times vary widely and when they may consume multiple brands at the same time, as is the case in CPG.

We propose to use the stochastic purchase behavior model by Schmittlein, Morrison, and Colombo (1987) and modified by Fader, Hardie, and Lee (2005) to define an existing customer for a specific CPG brand. This model calculates each individual’s probability of being a specific brand’s active customer at any point in time, based on her transactions history, which is readily available in scanner panel data. A customer whose probability of being active is higher than a critical value will be categorized as an existing customer (Reinartz and Kumar 2000; 2003). For example, if a customer buys a carton of brand A yogurt at time *t*, this purchase is recorded as a retention sale if that customer frequently purchased brand A’s product before time *t,* so that the probability of being an active customer for brand A is sufficiently high. Otherwise, i.e. if the customer mainly purchased competitors’ products before time *t*, the purchase is recorded as an acquisition sale for brand A[5].

[5] Note that this definition of an existing customer is not exclusive, i.e., a consumer can be considered to be an existing customer of several brands at the same time. This is a main difference between the *lost-for-good* and the *always-a-share* definition of a buyer-seller relationship.

Using the Beta-Geometric Negative Binomial Distribution (BG/NBD) model proposed by Fader, Hardie, and Lee (2005), we calculate a customer's probability of being active for a brand at each point in time given her purchase history. As an illustration in our empirical analysis, a customer's probability of being active with Dannon yogurt in week 138 is .79 if she purchased Dannon 17 times in 137 prior weeks, and her last purchase was recorded in week 121. Another customer who purchased Dannon 13 times with the last purchase occurring in week 88 would have an existing-customer probability of only .06. Therefore, if the latter customer purchases Dannon yogurt in week 138, the sale is recorded as "acquisition" for the brand, while the former customer's purchase is recorded as "retention", assuming a .5 cutoff value for the probability of being active.

The BG/NBD model calculates the probability of being active at a point of time based on the number of past purchases ($x > 0$), the time of the most recent purchase (t_x), and the length of observation period (T) such that:

$$E\left[\Pr\left(\text{active at } T \mid X = x, t_x, T, \gamma, \alpha, a, b\right)\right] = \frac{1}{1 + \frac{a}{x+b-1} \cdot \left(\frac{\alpha + T}{\alpha + t_x}\right)^{x+\gamma}} \tag{5}$$

where γ, α, a, b are BG/NBD model parameters[6].

[6] For detailed assumptions and derivations of the BG/NBD model, see Fader, Hardie, and Lee (2005).

Impact of Marketing on Customer Equity

Equation (4) shows that the firm's marketing actions can affect the magnitude of customer equity in three ways. First, a firm's marketing activities may increase the number of customers or prospects who purchase the firm's product (N_t^a and N_t^r respectively). For example, newspaper advertisements by brand A in a certain week may increase the purchase incidence probability among existing customers of the brand so that more people buy the brand's product in that week. This *purchase incidence effect* is expected to be positive. Second, a firm's marketing can affect the purchase volume per customer as well (q_t^a and q_t^r). It has been shown that a firm's marketing actions affect not only brand choice but also purchase timing and quantity (e.g., Gupta 1988), and that these effects are different in the short run and the long run (Pauwels, Hanssens, and Siddarth 2002). For example, a brand's price promotion may make consumers stockpile the brand's products. This *volume effect* is also expected to positively affect CE. Third, since the firm's marketing actions are costly, there can be a negative impact of marketing on CE through lower contribution margins (π_t^a and π_t^r), as with price promotion or advertising spending[7]. 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 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 the components of CE and their dynamic interactions. The VAR model has been used to decompose short-run and long-run impacts and to

[7] Note that we do not separately model marketing that is a variable cost (e.g., price discounting) and marketing that is a fixed cost (e.g., media advertising). The contribution margin per sales unit (π) in our model is assumed to contain the cost information of both types.

investigate the dynamics among key variables in a system. For instance, Bronnenberg et al. (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; 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. Third, the VAR model is flexible in dealing with endogeneity, since it is inherently a *systems* approach that regards all variables as jointly endogenous. 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 an acquisition process and a retention process, the following VAR model is constructed.

(6) $$\mathbf{Y_t} = \mathbf{c_t} + \sum_{i=1}^{k} \mathbf{\Phi_i Y_{t-i}} + \mathbf{\Psi Z_t} + \boldsymbol{\varepsilon}_\mathbf{t}$$

where $\mathbf{Y_t} = (AQ_t\ RQ_t\ AN_t\ RN_t\ OM_t\ CM_t)'$ is a vector of endogenous variables; AQ_t is average purchase quantity in acquisition; RQ_t is average purchase quantity in retention; AN_t is the number of buyers originating from the prospect pool, RN_t is the number of buyers among the existing customers; OM_t is own marketing efforts; CM_t is competitive marketing efforts; $\mathbf{Z_t}$ is other covariates affecting the VAR system; $\mathbf{c_t}$ is a vector of intercepts[8]; $\mathbf{\Phi}$ and $\mathbf{\Psi}$ are coefficient matrices; k is the lag order; and $\boldsymbol{\varepsilon}_\mathbf{t}$ is a vector of white noise processes with zero mean and covariance matrix $\mathbf{\Sigma}$.

The coefficient matrix $\mathbf{\Phi}$ captures the dynamic interactions among endogenous variables. Let φ_{ij} be the ij^{th} element of $\mathbf{\Phi}$ matrix. The lagged volume effects in acquisition and retention are captured by φ_{15} and φ_{25}, respectively. The lagged purchase-incidence effects in acquisition and retention are represented by φ_{35} and φ_{45}, respectively. However, the total marketing-mix effects could be overestimated if the *feedback effects* due to retention and acquisition (measured by φ_{51} through φ_{54}) are ignored. Since the firm's marketing decisions may be dependent upon its own past decisions and competitors' actions, the dynamic behavior of the firm's marketing efforts could show *decision inertia* (measured by φ_{55}) and/or *competitive reactions* (measured by φ_{56}). Consumers' purchase decisions are affected not only by companies' activities but also by other people's decisions. This word-of-mouth or network externality effect is captured by φ_{11} through φ_{44}.

Since the coefficient matrix $\mathbf{\Phi}$ includes only the lagged effects among variables in the VAR system, contemporaneous relationships among the variables are obtained by placing restrictions on the residual covariance matrix $\mathbf{\Sigma}$. Marketing researchers have conventionally used either a Cholesky ordering among the variables (e.g., Dekimpe and Hanssens 1995) or a simultaneous-shocking approach based on the multivariate normality of the residuals (e.g., Pauwels and Srinivasan 2004). However, we use a structural factorization method to identify the contemporaneous relationship among variables, since there is no theory-driven causal ordering

[8] Note that the intercepts have a t subscript to include a deterministic trend and seasonal dummy variables

among the endogenous variables, and it is unreasonable to allow for contemporaneous effects among all endogenous variables. For example, the acquisition quantity cannot affect the price level in the same week, but the effect may exist in the opposite direction. Therefore, we construct a restriction matrix that defines the possible contemporaneous relationships among the endogenous variables. We only allow the contemporaneous impact of marketing variables (i.e., *OM* and *CM*) on response variables (i.e., *AQ*, *RQ*, *AN*, and *RN*). The IRFs can be identified by pre-multiplying the inverse of a restriction matrix to the VAR system. As a result, the VAR model (6) then becomes:

$$\mathbf{Y_t} = \mathbf{A}^{-1}\mathbf{c_t} + \mathbf{A}^{-1}\sum_{i=1}^{k}\mathbf{\Phi_i Y_{t\text{-}i}} + \mathbf{A}^{-1}\mathbf{\Psi Z_t} + \mathbf{A}^{-1}\boldsymbol{\varepsilon}_\mathbf{t} \tag{7}$$

where the restriction matrix A can be defined as:

$$\mathbf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 & -\gamma_{15} & -\gamma_{16} \\ 0 & 1 & 0 & 0 & -\gamma_{25} & -\gamma_{26} \\ 0 & 0 & 1 & 0 & -\gamma_{35} & -\gamma_{36} \\ 0 & 0 & 0 & 1 & -\gamma_{45} & -\gamma_{46} \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{8}$$

The γ parameters show the contemporaneous influence of marketing activities on purchase quantity and the number of buyers.

Empirical Illustration

Data

We construct weekly time series of sales and marketing activities (e.g., price, feature, and display) using A.C. Nielsen household scanner panel data in the ketchup and yogurt product categories in Sioux Falls, South Dakota for 138 weeks. 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 (Dannon, Yoplait and a private-label brand). Table 1 shows the descriptive statistics of the data.

Insert Table 1 about here

Variable Operationalization

One of the main tasks in this study is to decompose average purchase quantity and number of buyers into two parts: acquisition and retention. To achieve this task, we first estimate four BG/NBD model parameters for each brand. We then calculate the probability of being an active customer for each brand at each point of time, based on a panel member's purchase history data. Using a cutoff value of .5 as in Reinartz and Kumar (2000; 2003) we determine whether a customer is a member of the "prospect" group or the "existing customer" group for each brand at each point of time[9]. This information enables us to construct separate average purchase quantities and numbers of buyers in prospect mode (acquisition) and in existing-customer mode (retention). Figure 1 shows an example of sales decomposition and the number of existing customers based on the proposed method. Note that we use the first 26 weeks for initialization to minimize the effect of left censoring.

Insert Figure 1 about here

[9] The cutoff value of .5 is intuitively appealing and has been frequently used in classification and survival analysis (e.g., Helsen and Schmittlein 1993). However, different firms may use different cutoff values to define their existing customers.

We use average price per ounce after coupon redemption as a focal marketing variable in this study. However, other marketing activities such as feature ad and in-store display are also included in the VAR system as exogenous variables. Since these two variables are recorded in the dataset as binary variables, we calculate the proportion of product volume for each brand that is sold under feature ad or display conditions to obtain a proxy for the depth of these marketing activities. We use market-share weighted competitive price as a composite index for competitors' marketing to reduce the dimension of the VAR system. Three 13-week seasonal dummy variables and a trend variable are also constructed to control for possible seasonality and a deterministic trend in the data generating process.

Model Specification and Estimation

The non-stationarity of each endogenous variable is verified by the Augmented Dickey-Fuller (ADF) test procedure (Dekimpe, Hanssens, and Silva-Risso 1999). Since all variables are found to be stationary, first-differencing of the variables and co-integration tests are not necessary. The lag order of one is determined by comparing Schwarz's criteria for various possible lag orders (Lütkepohl 1993). As a result, the following VAR model is constructed for each brand:

$$
(9)\quad
\begin{pmatrix} aquant_t \\ rquant_t \\ apurch_t \\ rpurch_t \\ oprice_t \\ cprice_t \end{pmatrix}
=
\begin{pmatrix}
c_{10} + \sum_{s=1}^{3} c_{1s} sdummy_{st} + c_{14}t \\
c_{20} + \sum_{s=1}^{3} c_{2s} sdummy_{st} + c_{24}t \\
c_{30} + \sum_{s=1}^{3} c_{3s} sdummy_{st} + c_{34}t \\
c_{40} + \sum_{s=1}^{3} c_{4s} sdummy_{st} + c_{44}t \\
c_{50} + \sum_{s=1}^{3} c_{5s} sdummy_{st} + c_{54}t \\
c_{60} + \sum_{s=1}^{3} c_{6s} sdummy_{st} + c_{64}t
\end{pmatrix}
+
\begin{pmatrix}
\varphi_{11} & \varphi_{12} & \varphi_{13} & \varphi_{14} & \varphi_{15} & \varphi_{16} \\
\varphi_{21} & \varphi_{22} & \varphi_{23} & \varphi_{24} & \varphi_{25} & \varphi_{26} \\
\varphi_{31} & \varphi_{32} & \varphi_{33} & \varphi_{34} & \varphi_{35} & \varphi_{36} \\
\varphi_{41} & \varphi_{42} & \varphi_{43} & \varphi_{44} & \varphi_{45} & \varphi_{46} \\
\varphi_{51} & \varphi_{52} & \varphi_{53} & \varphi_{54} & \varphi_{55} & \varphi_{56} \\
\varphi_{61} & \varphi_{62} & \varphi_{63} & \varphi_{64} & \varphi_{65} & \varphi_{66}
\end{pmatrix}
\begin{pmatrix} aquant_{t-1} \\ rquant_{t-1} \\ apurch_{t-1} \\ rpurch_{t-1} \\ oprice_{t-1} \\ cprice_{t-1} \end{pmatrix}
+
\begin{pmatrix}
\psi_{11} & \psi_{12} \\
\psi_{21} & \psi_{22} \\
\psi_{31} & \psi_{32} \\
\psi_{41} & \psi_{42} \\
\psi_{51} & \psi_{52} \\
\psi_{61} & \psi_{62}
\end{pmatrix}
\begin{pmatrix} feature_t \\ display_t \end{pmatrix}
+
\begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \end{pmatrix}
$$

where *aquant* and *rquant* are average purchase quantity per customer in acquisition and retention mode, respectively; *apurch* and *rpurch* are number of buyers in acquisition and retention respectively; *oprice* refers to own price; *cprice* refers to competitive price; and *sdummy* stands for 13-week seasonal dummy variables. Note that all 6 endogenous variables are expressed in logarithms, in order to easily obtain response elasticities among the variables.

The model parameters can be estimated by ordinary least squares (OLS) since all regressors are the same in each sub-equation in the system. After estimating the VAR model parameters, additional parameters in the structural factor matrix (8) are estimated by maximum likelihood, in order to obtain the contemporaneous relationships among the variables. All parameter estimations were carried out in Eviews 6.0.

The Impact of Price on the Components of Customer Equity

To measure the impact of price on CE, both short-term and long-term price effects on average purchase quantity (i.e., *volume effects*), number of buyers (i.e., *purchase incidence effects*), and price itself (i.e., *decision inertia effects*) are measured by impulse response functions (IRFs).

IRFs are used to investigate the response of one variable to an unexpected shock in other variable within a *system*. That response is the result of a chain reaction among the variables in the system, set in motion by the initial shock in the focal variable. Consequently, we may obtain different IRF estimates, even though the *direct effect* of, say, a price change on sales is the same for two brands.

The IRFs up to 13-week lags are obtained by the VAR model parameters and structural factor matrix, as shown in Table 2. Since the VAR model is specified in log-log form, IRFs show the elasticity among variables so that the IRF values among different brands are comparable (Nijs et al. 2001). Table 3 shows the contemporaneous and accumulated IRFs over 13 weeks (i.e., long-term effects). Since all endogenous variables are found to be stationary (i.e. mean-reverting), there are no permanent or persistent effects among the variables.

Insert Table 2 and Table 3 about here

The short-term impact of price on average purchase quantity and number of buyers is found to be either significantly negative or insignificant (5 out of 24 cases). However, these impacts are different for acquisition versus retention. For example, while a price change for Heinz, a dominant brand with over 65% market share, has a bigger impact on new customer acquisition than retention, Del Monte's has a bigger impact on retention. This difference shows that, in the short run, some brands' marketing actions result mainly in customer acquisition ("offense"), while others achieve more customer retention ("defense") from similar activities. Though it is widely accepted that loyal customers are less price sensitive than brand switchers (e.g., Guadagni and Little 1983), this principle does not apply equally to all brands in a product category.

We also identified a notable difference between the two product categories in terms of quantity effects and purchase incidence effects. While purchase incidence is more affected by price promotion in the ketchup category (-.957 vs. -.436 on average), price effects on average purchase quantity are higher (in absolute values) in the yogurt category (-.681 vs. -.573 on average). In other words, in the yogurt category, CE is driven mainly by consumption rate, whereas in the ketchup category, purchase incidence is the more important CE driver. This result is consistent with Ailawadi and Neslin's (1998) finding that ketchup shows a more stable consumption pattern than yogurt.

The long-term quantity and purchase incidence effects are not always consistent with the short-term ones. For example, the price effects on purchase incidence for Del Monte are higher in acquisition than in retention in the long run, but lower in the short run. On the other hand, Heinz shows the opposite pattern in that the brand's price promotion has a higher long-term impact on retention than acquisition. This result is not to Heinz's advantage, as it indicates that brand loyalty (i.e. repeat buying by existing customers) is promotion-dependent, which lowers customer equity. Note that these long-term effects include possible indirect effects such as performance feedback, decision inertia, and competitive reactions. The results also extend our understanding about the long-term promotion effects on category incidence and purchase quantity reported in Pauwels, Hanssens, and Siddarth (2002), as we decompose the sources of these effects into customer retention and acquisition.

All but one brands show significant and positive decision inertia in price, though its magnitude differs. For example, the private-label brand in the yogurt category shows significantly higher accumulated decision inertia than Dannon. While Dannon returns back to its usual price after a promotional price shock (resulting in an accumulated effect of 1.0), the private- label brand exhibits 90% sustenance of the price shock (resulting in an accumulated effect of 1.9). Note that, the higher a brand's decision inertia (with respect to price in this case), the more negatively its CE will be affected. For example, Nijs, Srinivasan, and Pauwels (2007) found that retailers whose prices are heavily dependent on past prices have lower profit margins.

In order to obtain the net impact of marketing on CE, we should combine this decision inertia effect with the positive impacts through increased purchase quantity and increased number of buyers. In the next section we conduct a scenario analysis of the impact of price promotion on CE for different brands.

Net Impact of Price on Customer Equity

The numerical simulation of the net price impact on CE starts with an initial condition using the sample average of purchase quantity (in acquisition and retention), number of buyers (in acquisition and retention), and price for each brand. We then calculate the "gross" value from prospects (i.e., acquisition) and from existing customers (i.e., retention) in 13 weeks of time by setting the contribution margin rate to 60% and other marketing costs (e.g., advertising spending) to zero[10]. As a result, we obtain the current value of CE in 13 weeks using a weekly time discount factor of .002. We then calculate a new value of CE based on a scenario that an unexpected 30% price discounting is implemented by a brand in week 1. We apply the IRF results of average purchase quantity, number of buyers, and price to obtain this new magnitude of CE. The results are shown in Table 4.

Insert Table 4 about here

In the ketchup category, the market leader, Heinz obtains most of its customer equity from existing customers (about 92%). However, the brand's price promotion negatively affects its CE, as the positive impacts of price promotion through increased purchase quantity and number of

[10] We do not have access to these cost data. Including them will make improve the CE estimates, but will not change our substantive conclusions.

buyers are insufficient to cover the negative impact due to decision inertia. As a result, the brand loses about .04% of its customer equity in the 13 weeks following a sales promotion. The other two brands, Del Monte and Hunt's successfully increase their CE by about 1.3% and 1.8% respectively. Since Heinz already has a significant number of loyal customers who are willing to pay a price premium, the brand fails to increase its CE by price-related promotions.

All three brands in the yogurt category derive more customer value from retention than from acquisition, since variety seeking is more common in this category than in ketchup, resulting in more users of multiple brands. Though Dannon, Yoplait and a private brand show similar market shares (15.6%, 18.3%, and 16.2% respectively), only the private brand can increase its CE by price promotion, due to relatively high price effects on both average purchase quantity and number of buyers. However, note also that the private brand's CE is significantly lower than Dannon or Yoplait due to the brand's sharply lower base price.

How do these price effects on CE compare to their more readily observable impact on sales? Figure 2 reveals that three out of six brands show a *sign reversal* of the effect. Specifically, an extra price promotion of Heinz, Dannon, and Yoplait has the expected positive impact on sales while it deteriorates the brands' CE. In addition, the most sales-effective price promotion may not be the most CE-effective one. For example, in the ketchup category, Del Monte shows the highest price impact on sales among three brands, while Hunt's enjoys the highest CE effect.

Insert Figure 2 about here

The uneven effects of price promotions on customer equity across brands and categories suggest that the brands' evolution of their CE over an extended time period may be different as well. We explore this in the next section.

Customer Equity Evolution of Different Brands

Based on the CE derivation shown in Equation (4), we calculate the magnitude of customer equity for each brand as shown in Figure 3. The weekly dynamics of CE value between the 35th week of 1987 and the 34th week of 1988 are obtained based on 52-week moving-averages of number of customers (N), purchase quantity (q), and contribution margin (π) (Pauwels and Hanssens 2007). Since the contribution margin data by brand are not available, we assume the same contribution margin rate of 60% for all brands. Therefore, it will be more relevant to interpret the evolutionary path (rather than the absolute magnitude) of CE for each brand.

Insert Figure 3 about here

The CE indicators in Figure 3 show evolution (i.e. significant trend) in all 6 cases (the range of trend |t|-statistics is between 2.51 and 34.30). Specifically, in the ketchup market, Hunt's customer equity is growing, while that of Heinz is stable and Del Monte is declining. In the yogurt market, none of the brands can grow their CE, but on a relative scale, Dannon and Yoplait are becoming stronger, at the expense of private label. These patterns occur because consumer response to marketing (in casu, price promotions) is different in acquisition vs. retention mode, and because brands differ in the level of inertia in their marketing spending.

Figure 4 decomposes the brands' CE evolution, so we may diagnose the sources of their CE movements. For example, the growing CE of Hunt's is mainly due to retention while the CE decline of Del Monte is attributable mainly to acquisition. Even though Yoplait's CE is decreasing slightly, the brand is successfully maintaining the value from its existing customers (i.e., retention). Since the private brand in the yogurt category is losing its CE from existing customers, a private-label brand manager would be advised to focus her marketing on increasing the repeat purchase rate of the brand.

Insert Figure 4 about here

The CE value presented in Figure 3 and Table 4 is obtained from a sample of 1,693 households for ketchup and 1,435 households for yogurt, respectively. Since there were 39,790 households in Sioux Falls according to the 1990 U.S. census, we can calculate a city-level customer value by multiplying by a factor of 23.5 for ketchup and 27.7 for yogurt. Other marketing costs assumed to be zero should also be included to obtain a more accurate estimate of customer equity. Nevertheless, the methodology presented in the current study will provide managers with good guidance to assess customer equity and its responsiveness to marketing activities. Overall, we conclude that, even in frequently purchased product categories, computing and tracking customer equity provides valuable information about the long-term health trajectory of competing brands.

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 consumer packaged goods industries. 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 an *always-a-share* definition of a customer in CPG categories, while the conventional CE literature has focused on relationship businesses where a *lost-for-good* definition is more appropriate. 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 two product categories, ketchup and yogurt, we found that the positive impact of price promotion on increasing average purchase quantity and number of buyers does not always translate to higher CE, due to decision inertia effects. While a leading brand in the ketchup category, Heinz, fails to increase its CE by implementing an extra price promotion, the other two major brands, Del Monte and Hunt's, succeed. In the yogurt category, only a private-label brand is found to increase its CE by price promotions, mainly because they increase the average purchase quantity and number of buyers among existing customers.

We also found that some brands' financial performance relies more on acquisition than others. For example, while Heinz derives only 7.9% of its customer equity from acquisition, Del Monte receives as much as 61.5% of its CE from this source. Comparing the two product categories, we also found that competition in the yogurt category is more important in retention than in acquisition, since all three brands of interest derive over 75% of their value from retaining existing customers. Therefore, a brand manager in the yogurt category should focus more on customers who have already experienced her brand's products in the past. Finally, we established that the evolution of customer equity is different across brands, as is the evolution in the CE components of acquisition and retention.

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 more 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 between existing customers (i.e. retention) and prospects (i.e. acquisition) that maximizes customer equity.

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.

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
Sales (oz.)	57,948	456,116	106,359	668,104
Average Market Share	8.7%	68.3%	15.9%	
Average Price (cents / oz.)	2.91	3.39	2.80	3.20
Sales with Display (oz.)	4,116	47,596	12,992	66,332
(% of total sales)	(7.1%)	(10.4%)	(12.2%)	(9.9%)
Sales with Feature AD (oz.)	18,208	156,188	31,504	211,698
(% of total sales)	(31.4%)	(34.2%)	(29.6%)	(31.7%)

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
Sales (oz.)	105,116	123,099	109,178	673,186
Average Market Share	15.6%	18.3%	16.2%	
Average Price (cents / oz.)	5.35	6.19	2.43	4.14
Sales with Display (oz.)	632	3,580	12,592	50,916
(% of total sales)	(0.6%)	(2.9%)	(11.5%)	(7.6%)
Sales with Feature AD (oz.)	12,958	12,132	28,498	154,210
(% of total sales)	(12.3%)	(9.9%)	(26.1%)	(22.9%)

(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
Structural Parameters for Impulse Response Identification

A. Ketchup

	Purchase Quantity		Number of Purchasers	
	Acquisition	Retention	Acquisition	Retention
Del Monte				
Price	-0.396 ***	-0.433 ***	-0.565	-0.988 **
	(0.105)	(0.087)	(0.499)	(0.489)
Competitors' Price	0.061	0.033	0.512	1.170 **
	(0.118)	(0.098)	(0.559)	(0.548)
Heinz				
Price	-0.512 ***	-0.097 *	-1.363 **	-1.143 ***
	(0.158)	(0.058)	(0.533)	(0.215)
Competitors' Price	0.287	-0.043	0.250	-0.149
	(0.180)	(0.066)	(0.608)	(0.245)
Hunt's				
Price	-0.904 ***	-0.276 ***	-0.669 *	-1.016 ***
	(0.123)	(0.058)	(0.362)	(0.262)
Competitors' Price	-0.060	0.046	0.000	0.310
	(0.168)	(0.079)	(0.496)	(0.359)

B. Yogurt

	Purchase Quantity		Number of Purchasers	
	Acquisition	Retention	Acquisition	Retention
Dannon				
Price	-0.452 **	-1.000 ***	-0.394	0.039
	(0.186)	(0.086)	(0.489)	(0.214)
Competitors' Price	-0.459 *	0.053	0.501	0.132
	(0.249)	(0.116)	(0.656)	(0.287)
Yoplait				
Price	-0.355 *	-0.696 ***	-2.128 ***	-0.118
	(0.200)	(0.070)	(0.509)	(0.238)
Competitors' Price	0.036	-0.038	0.880 **	-0.149
	(0.176)	(0.061)	(0.449)	(0.210)
Private Brand				
Price	-0.725 ***	-0.857 ***	-0.096	-0.739 ***
	(0.136)	(0.044)	(0.301)	(0.172)
Competitors' Price	-0.046	-0.079	0.749	0.489
	(0.331)	(0.108)	(0.733)	(0.420)

*p < .1, **p <.05, ***p <.01
(Note) Standard errors are in parentheses

Table 3

Impact of an Unexpected Price Shock

A. Ketchup

	Del Monte		Heinz		Hunt's	
	Short-Term	Long-Term	Short-Term	Long-Term	Short-Term	Long-Term
Volume Effects (Average Purchase Quantity)						
Acquisition	-0.396 ***	-0.397 **	-0.512 ***	-0.703 **	-0.904 ***	-0.985 ***
	(0.109)	(0.158)	(0.162)	(0.351)	(0.137)	(0.266)
Retention	-0.433 ***	-0.555 ***	-0.097 *	0.067	-0.276 ***	-0.340 ***
	(0.092)	(0.160)	(0.058)	(0.125)	(0.061)	(0.113)
Purchase Incidence Effects (Number of Purchasers)						
Acquisition	-0.565	-2.594 *	-1.363 **	-1.387	-0.669 *	-1.956 **
	(0.500)	(1.373)	(0.541)	(1.089)	(0.365)	(0.876)
Retention	-0.988 *	-1.630	-1.143 ***	-2.054 ***	-1.016 ***	-1.833 ***
	(0.494)	(1.037)	(0.229)	(0.634)	(0.271)	(0.613)
Decision Inertia Effects (Future Price)						
	1.000 ***	1.744 ***	1.000 ***	1.598 ***	1.000 ***	1.325 ***
	(0.069)	(0.278)	(0.068)	(0.268)	(0.068)	(0.225)

B. Yogurt

	Dannon		Yoplait		Private Brand	
	Short-Term	Long-Term	Short-Term	Long-Term	Short-Term	Long-Term
Volume Effects (Average Purchase Quantity)						
Acquisition	-0.452 ***	-0.523 *	-0.355 *	-0.330	-0.725 ***	-1.423 ***
	(0.188)	(0.310)	(0.201)	(0.280)	(0.144)	(0.352)
Retention	-1.000 ***	-1.076 ***	-0.696 ***	-0.839 ***	-0.857 ***	-1.606 ***
	(0.109)	(0.215)	(0.084)	(0.165)	(0.073)	(0.323)
Purchase Incidence Effects (Number of Purchasers)						
Acquisition	-0.394	-0.193	-2.128 ***	-2.181 **	-0.096	-0.096
	(0.490)	(0.849)	(0.528)	(0.907)	(0.301)	(0.788)
Retention	0.039	0.320	-0.118	-0.092	-0.739 ***	-1.489 *
	(0.214)	(0.418)	(0.239)	(0.651)	(0.179)	(0.554)
Decision Inertia Effects (Future Price)						
	1.000 ***	0.988 ***	1.000 ***	1.253 ***	1.000 ***	1.888 ***
	(0.067)	(0.132)	(0.067)	(0.160)	(0.067)	(0.355)

*p < .1, **p <.05, ***p <.01
(Notes) Standard errors are in parentheses. Short-term effects refer to the impulse responses in the same week. Long-term effects refer to the accumulated impulse responses in 13 weeks.

Table 4

Customer Equity Change Due to a Price Promotion Shock

A. Ketchup

	Initial Condition		30% Price Promotion		% Change
Del Monte					
Number of Purchasers	146		153		5.15%
Among Prospects (Acquisition)	91		96		5.99%
Among Own Customers (Retention)	55		57		3.76%
Average Purchase Quantity (oz.)	32.06		32.39		1.03%
Among Prospects (Acquisition)	31.56		31.85		0.92%
Among Own Customers (Retention)	32.88		33.30		1.28%
Average Price (cents per oz.)	2.91		2.77		-4.76%
Customer Equity in 13 Weeks ($)	80.36	(100.0%)	81.43	(100.0%)	1.32%
Among Prospects (Acquisition)	49.41	(61.5%)	50.42	(61.9%)	2.04%
From Own Customers (Retention)	30.96	(38.5%)	31.01	(38.1%)	0.17%
Heinz					
Number of Purchasers	1,308		1,368		4.60%
Among Prospects (Acquisition)	117		121		3.20%
Among Own Customers (Retention)	1,191		1,247		4.74%
Average Purchase Quantity (oz.)	33.37		33.37		0.00%
Among Prospects (Acquisition)	29.32		29.80		1.62%
Among Own Customers (Retention)	33.77		33.71		-0.15%
Average Price (cents per oz.)	3.39		3.23		-4.52%
Customer Equity in 13 Weeks ($)	876.03	(100.0%)	875.65	(100.0%)	-0.04%
Among Prospects (Acquisition)	68.81	(7.9%)	68.91	(7.9%)	0.16%
From Own Customers (Retention)	807.22	(92.1%)	806.74	(92.1%)	-0.06%
Hunt's					
Number of Purchasers	274		285		4.34%
Among Prospects (Acquisition)	110		115		4.51%
Among Own Customers (Retention)	164		171		4.23%
Average Purchase Quantity (oz.)	36.15		36.64		1.37%
Among Prospects (Acquisition)	36.68		37.51		2.27%
Among Own Customers (Retention)	35.79		36.07		0.78%
Average Price (cents per oz.)	2.80		2.68		-3.99%
Customer Equity in 13 Weeks ($)	163.87	(100.0%)	166.87	(100.0%)	1.83%
Among Prospects (Acquisition)	66.74	(40.7%)	68.64	(41.1%)	2.84%
From Own Customers (Retention)	97.13	(59.3%)	98.23	(58.9%)	1.13%

Table 4

Customer Equity Change Due to a Price Promotion Shock (Cont'd)

B. Yogurt

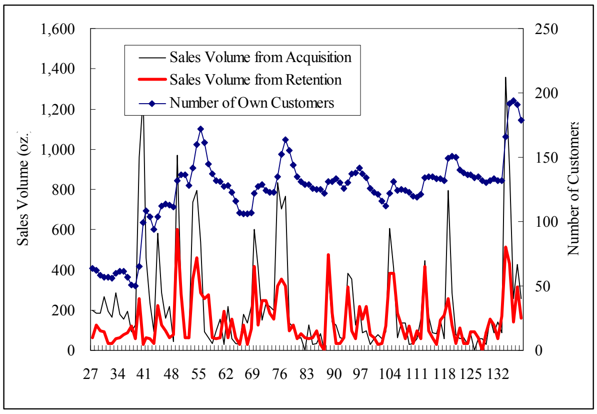
	Initial Condition		30% Price Promotion		% Change
Dannon					
Number of Purchasers	638		635		-0.42%
Among Prospects (Acquisition)	169		170		0.45%
Among Own Customers (Retention)	469		465		-0.74%
Average Purchase Quantity (oz.)	14.03		14.33		2.11%
Among Prospects (Acquisition)	11.89		12.04		1.21%
Among Own Customers (Retention)	14.80		15.17		2.48%
Average Price (cents per oz.)	5.35		5.19		-2.88%
Customer Equity in 13 Weeks ($)	283.81	(100.0%)	280.35	(100.0%)	-1.22%
Among Prospects (Acquisition)	63.84	(22.5%)	63.11	(22.5%)	-1.14%
From Own Customers (Retention)	219.97	(77.5%)	217.24	(77.5%)	-1.24%
Yoplait					
Number of Purchasers	1,156		1,171		1.26%
Among Prospects (Acquisition)	251		264		5.03%
Among Own Customers (Retention)	905		907		0.21%
Average Purchase Quantity (oz.)	8.93		9.07		1.51%
Among Prospects (Acquisition)	7.81		7.87		0.76%
Among Own Customers (Retention)	9.24		9.42		1.94%
Average Price (cents per oz.)	6.19		5.97		-3.63%
Customer Equity in 13 Weeks ($)	379.27	(100.0%)	376.39	(100.0%)	-0.76%
Among Prospects (Acquisition)	72.04	(19.0%)	73.17	(19.4%)	1.56%
From Own Customers (Retention)	307.23	(81.0%)	303.23	(80.6%)	-1.30%
Private Brand					
Number of Purchasers	703		721		2.54%
Among Prospects (Acquisition)	196		196		0.22%
Among Own Customers (Retention)	507		525		3.44%
Average Purchase Quantity (oz.)	15.07		15.63		3.72%
Among Prospects (Acquisition)	13.29		13.73		3.28%
Among Own Customers (Retention)	15.76		16.35		3.71%
Average Price (cents per oz.)	2.43		2.30		-5.35%
Customer Equity in 13 Weeks ($)	152.89	(100.0%)	154.40	(100.0%)	0.98%
Among Prospects (Acquisition)	37.58	(24.6%)	37.00	(24.0%)	-1.55%
From Own Customers (Retention)	115.31	(75.4%)	117.40	(76.0%)	1.81%

Figure 1

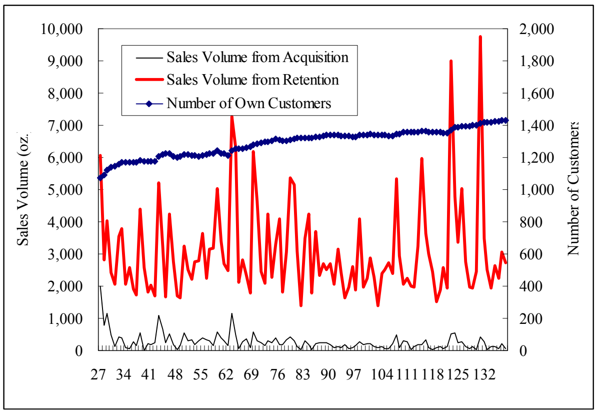
Number of Customers and Decomposed Sales

A. Ketchup

Del Monte



Heinz



Hunt's

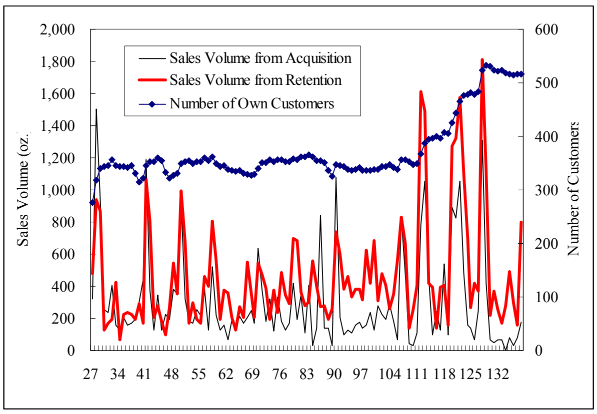
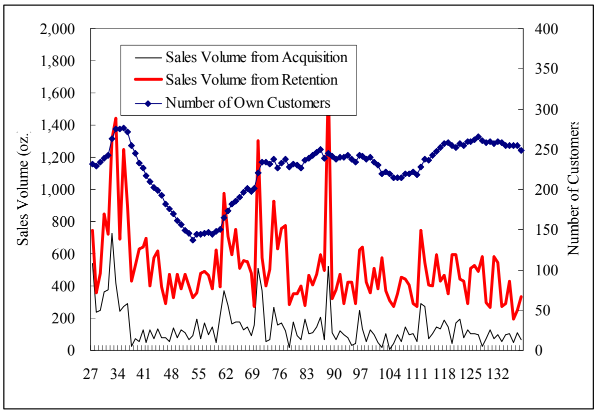


Figure 1

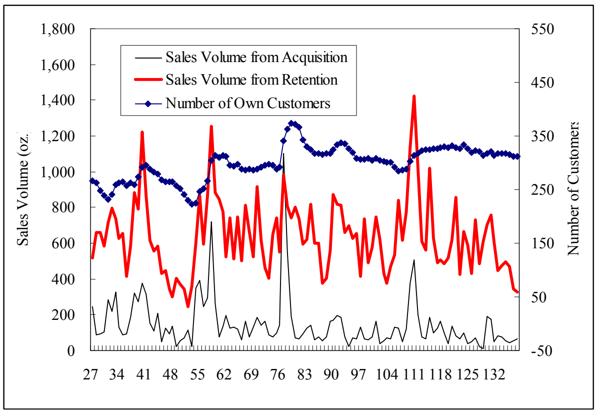
Number of Customers and Decomposed Sales (cont'd)

B. Yogurt

Dannon



Yoplait



Private Brand

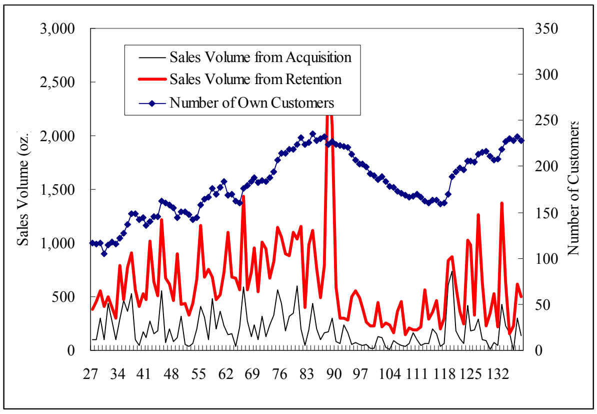
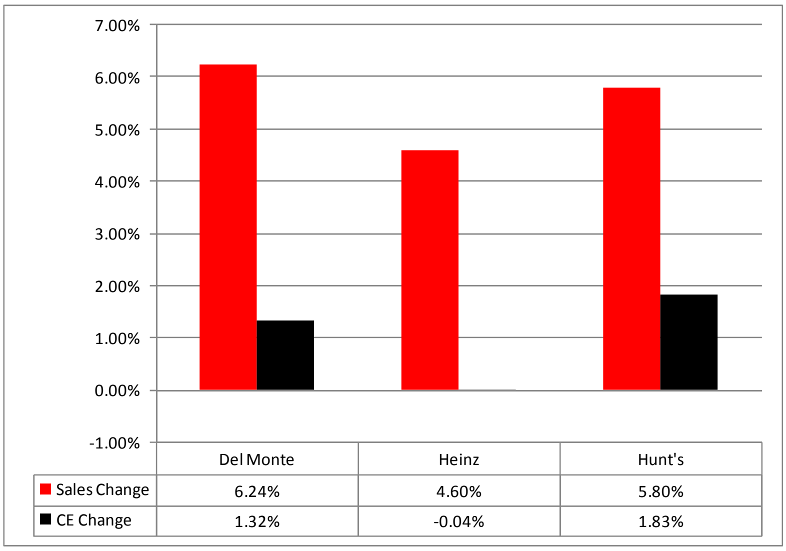
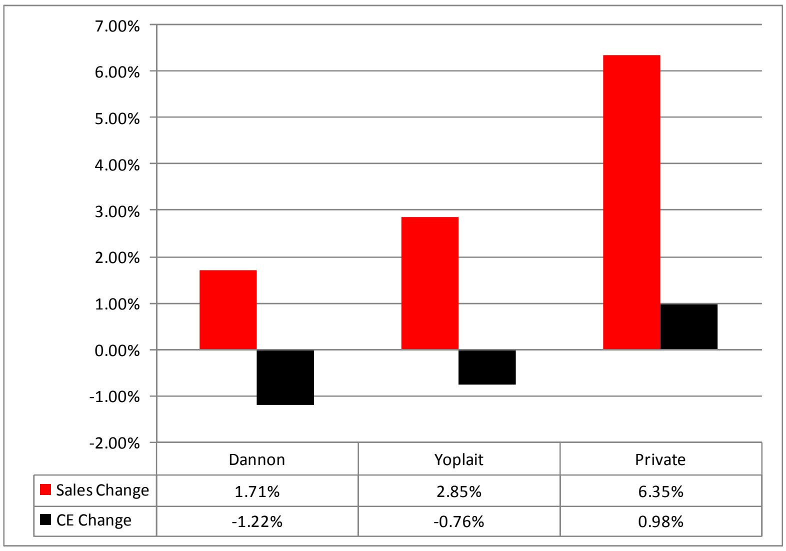


Figure 2
The Impact of a Price Shock on Sales vs. Customer Equity

A. Ketchup



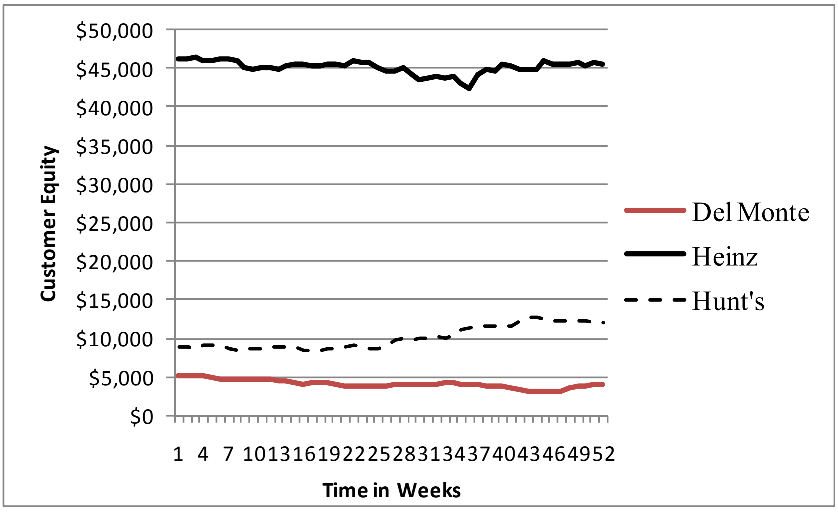
B. Yogurt



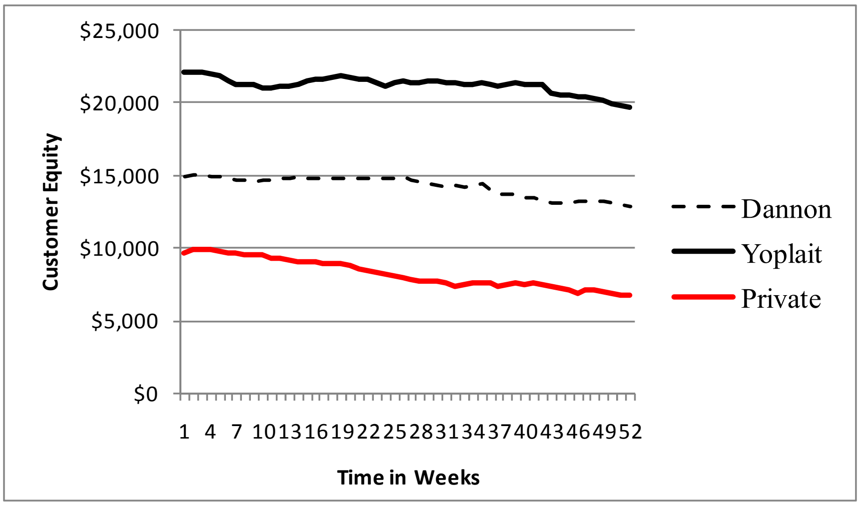
(Note) The effects are based on the 13-week cumulative impulse responses of unit sales and customer equity to a 30% unexpected price discounting.

Figure 3
The Evolution of Brands' Customer Equity

A. Ketchup



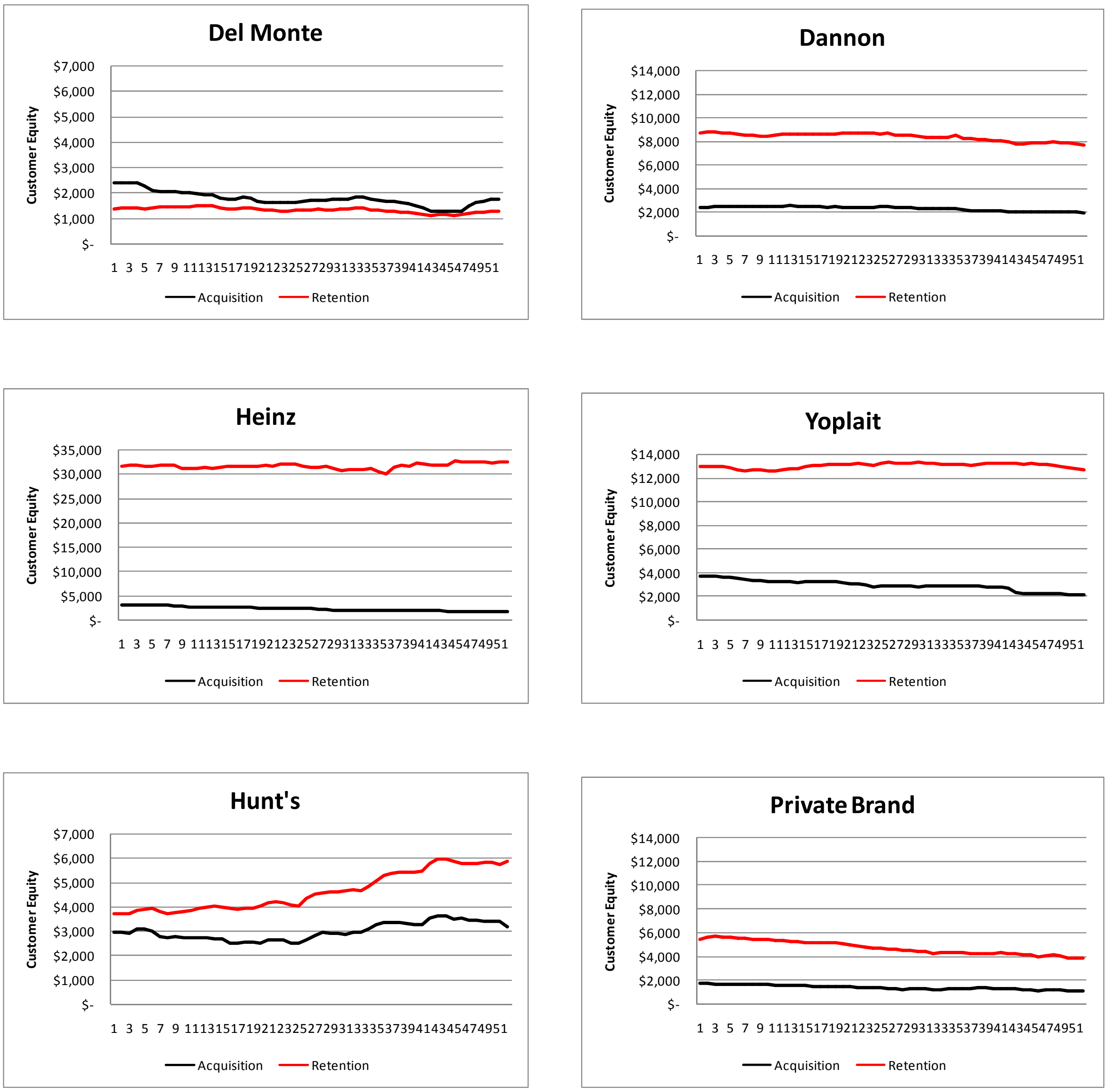
B. Yogurt



(Note) The horizontal axis refers to calendar weeks between the 35th week of 1987 and the 34th week of 1988. We use the past one year's information to obtain number of customers, purchase quantity, and contribution margin. A contribution margin rate of 60% is used to calculate the CE value.

Figure 4
Customer Equity Decomposition: Acquisition vs. Retention

<Ketchup> **<Yogurt>**



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