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Expanding the Role of Marketing: From Customer Equity to Market Capitalization

V. Kumar and Denish Shah

How can marketers prove the monetary value of their work? The framework proposed here enables marketing managers to deploy marketing initiatives at the customer level and to measure their outcome in the form of market capitalization.

Report Summary

How can marketers prove the monetary value of their work? This is one of the biggest challenges facing marketers today.

Here, V. Kumar and Denish Shah propose a novel approach to establish a link between customer equity (as determined by customer lifetime value) and market capitalization (as determined by the stock price of the firm). They ask three fundamental questions: Can customer equity predict the market capitalization of the firm? Can marketing strategies that increase customer equity also increase the stock price? And finally, can the marketer lift a firm's stock price through marketing strategies?

To answer these questions, the authors develop a framework and conduct an empirical field experiment on two Fortune 1000 companies—one a business-to-business (B2B) firm and one a business-to-consumer (B2C) firm. They use transaction data from the two companies over the period from January 2000 through April 2007. Both data sets contain longitudinal transaction data for each customer of the firm,

which allows the authors to compute customer lifetime value at an individual customer level and to explore how customer-centered marketing measures affect the market capitalization of the firms.

Their findings indicate that a customer equity-based framework reliably predicts the market capitalization of the firm, and furthermore, that marketing strategies directed at increasing customer equity not only increase the firm's stock price but also beat market expectations. The authors take into account two risk factors (volatility and vulnerability of cash flow from customers) that are typically not accounted for in the customer equity computation. The authors find that doing so improves the association between customer equity and market capitalization. They also divide customers into high-profitability, medium-to-low profitability, and negative-profitability categories and monetize the different segments' contributions to market capitalization. The findings reinforce the importance of the marketing function in any organization. ■

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Introduction

We are living in a customer-centered world, with firms increasingly focusing their organizations on customers. Of late, this trend has gathered momentum, with the CEOs of many firms expressing their intent to put customers at the top of the long list of issues that they must focus on for growth (New York Stock Exchange Group 2007). These developments have put marketing—the function that best knows and understands the firm’s customers—in the limelight. One would expect the CMO (chief marketing officer) to be the most sought-after executive in the boardroom, but in reality, the CMO is currently the most frequently fired C-level executive, with an average tenure of under 24 months (Fleener 2006). Furthermore, in a recent ANA-Booz Allen Hamilton survey, more than half of the executives surveyed claimed that the CEO’s agenda and marketing are not aligned in their organization (ANA-Booz Allen Hamilton 2004).

Clearly, there is a serious disconnect here. While an overwhelming majority of CEOs consider the marketing organization “highly influential and strategic in the enterprise,” a large majority still feel that CMOs don’t demonstrate adequate return on investment (ROI) and hence fail to demonstrate the true potential of marketing (CMO Council 2007). CEOs need CMOs to drive marketing strategies that will fetch the maximum value from customer relationships, but at the same time, the CMO must be held financially accountable for these strategies (Doyle 2000). To date, the marketing function across firms seems to be falling short on both imperatives.

Rust, Lemon, and Zeithaml (2004) note that marketing’s perceived lack of accountability undermines its credibility, threatens marketing’s standing in the firm, and even threatens the function’s very existence within the firm. The ominous premonition of Rust, Lemon, and Zeithaml (2004) resonates with the concerns raised by Webster, Malter, and Ganesan (2003),

who quoted a CMO as saying, “Marketing has lost its seat at the (boardroom) table” (p. 29). More damaging evidence comes from Nath and Mahajan (2008), who analyzed a multi-industry sample of 167 firms and concluded that CMO presence in top management teams has practically no impact on firm performance. What can be done about this situation? The answer is that marketing must shake off its image as a tactical function and show that it has strategic worth and is capable of helping the CEO drive growth and profitability (Kumar 2004). To demonstrate this worth, it must be able to show its effectiveness in influencing a financial metric that is of concern to the CEO.

Toward this endeavor, we propose a framework to link the outcome of marketing initiatives (as measured by customer equity) to the firm’s market capitalization (as determined by the stock price of the firm). It is generally accepted that the stock price of the firm is based on the expected future cash flows of the firm. If cash flow is generated primarily from customers, then there should be a relation between increases in customer equity (or cash flow from customers) and increases in market capitalization. Several managerially relevant questions emerge. To start with, can customer equity really predict the market capitalization of the firm? Following on that question, can marketing strategies that increase customer equity also increase the stock price? In such a scenario, can the marketer lift a firm’s stock price through marketing strategies?

We address these questions through empirical application of our framework to real-world data from a business-to-business (B2B) firm and a business-to-consumer (B2C) firm. Our results indicate that the customer equity metric will reliably predict the average market capitalization or the stock price of a firm within a maximum deviation range of 12% to 13%. We further demonstrate how marketing managers can leverage appropriate marketing strategies not only to lift the firm’s stock price,

but also to beat market expectations. Our results suggest that marketing is capable of augmenting firm value through strategic customer management initiatives.

Theory

How can marketing relate to firm value? Researchers have examined the link between marketing activities, metrics, and firm value in a number of different ways. For example, researchers have shown the relationship between satisfaction and firm value (e.g., Anderson, Fornell, and Mazvancheryl 2004; Fornell et al. 2006), brand and firm value (e.g., Kerin and Sethuraman 1998; Mizik and Jacobson 2008; Rao et al. 2004), advertisement and firm value (e.g., Joshi and Hanssens in press), new product announcements and firm value (Sorescu, Shankar, and Kushwaha 2007), and so on. See Srinivasan and Hanssens (in press) for a detailed review. In this study, we focus our attention on how customer equity (as determined from customer lifetime value) relates to firm value.

Understanding customer lifetime value (CLV)

In recent years, the idea of managing customers based on the customer lifetime value (or customer equity) metric has become extremely popular. The appeal of the CLV metric lies in its ability to foster profitable customer relationship management through its support for appropriate marketing interventions (Villanueva and Hanssens 2007). Several methods of computing CLV have been suggested (e.g., Fader, Hardie, and Lee 2005; Gupta, Lehmann, and Stuart 2004; Lewis 2004; Kumar et al. 2008; Reinartz and Kumar 2000; Rust, Lemon, and Zeithaml 2004; Venkatesan and Kumar 2004; Venkatesan, Kumar, and Boehling 2007). In essence, CLV computation requires predicting the future cash flow from each customer by combining the elements of revenue, expense, and customer behavior that drive customer profitabil-

ity. This is then discounted by the cost of capital to arrive at the net present value of all future cash flows expected from a customer, or the lifetime value of the customer. The sum total of the lifetime value of all the firm's customers represents the customer equity (CE) of the firm. In other words, CLV is the disaggregate measure and CE is the aggregated measure of customer profitability. Interestingly, CLV computation is conceptually analogous to the discounted cash flow system used by accounting to value firms. But can the CLV concept be extended to relate to the market capitalization of the firm?

Customer value and firm value

Several researchers in the recent past have proposed strong theoretical arguments in favor of linking customer value to firm value, shareholder value, or the market capitalization of the firm (Bauer, Hammerschmidt, and Braehler 2003; Berger et al. 2006; Srivastava, Shervani, and Fahey 1998). Consistent with their theoretical arguments are empirical studies that have validated the claim that customer value can be used as a proxy for a firm's market value. For example, Kim, Mahajan, and Srivastava (1995) used the popular discounted cash flow method to estimate the value of business in the wireless communications industry. Gupta, Lehmann, and Stuart (2004) conducted an analysis across multiple firms to show that customer value can be as good as or a better method of firm valuation than traditional accounting. Rust, Lemon, and Zeithaml (2004) showed that when they multiplied the average CLV of American Airlines' customers by the total number of airline passengers in the United States, the total customer value so obtained was more or less consistent with the market capitalization of the firm. Libai, Muller, and Peres (2006) estimated firm value for five different companies from customer-based measures and found that for four of the five companies, they could correctly estimate the firm value within an average deviation of 11.5%.

Furthermore, past studies have reported sub-

stantive findings that underscore the link between marketing and firm value. For example, the Gupta, Lehmann, and Stuart (2004) study showed that a 1% improvement in retention, margin, or acquisition cost could improve firm value by 5%, 1%, and .1%, respectively. Similarly, the Rust, Lemon, and Zeithaml (2004) study showed how their customer equity framework could be applied to project ROI from marketing expenditures.

Collectively, these findings contribute to a growing and exciting stream of research that demonstrates the power of customer-based measures in shaping firm value. We propose to advance these findings in several important ways. First, we apply the customer lifetime value computation at the customer level rather than the industry level (Kim, Mahajan, and Srivastava 1995) or the firm level (Gupta, Lehmann, and Stuart 2004; Libai, Muller, and Peres 2006). By doing so, our study can help firms differentiate the lifetime value of each customer and thereby help them deploy differentiated marketing strategies that are relevant to each customer, based on his or her lifetime value. For example, Gupta, Lehmann, and Stuart (2004) showed that on average, a 1% improvement in acquisition cost would increase firm value by .1%. By using customer-level data, our study proposes to advance these findings by showing that a 1% improvement in acquisition rate can have a varying outcome on firm value, ranging from a positive to a negative impact depending on whether the 1% improvement is directed toward highly profitable customers, less profitable customers, or unprofitable customers. This is a necessary consideration for firms that have a highly skewed distribution of lifetime value across customers. In fact, most firms are governed by the 80-20 Pareto principle. That is, the top 20% of the customers usually provide close to 80% of the overall revenue and/or profits of the firm. Recent studies have empirically demonstrated the disparity of customer value (see Kumar, Shah, and Venkatesan 2006; Rust, Lemon, and Zeithaml 2004). In such a sce-

nario, marketing initiatives (such as cross-selling) will be wasteful (or less efficient at best) if they are uniformly applied across all the firm's customers.

One of the most important constituents of firm valuation is future cash flow. To date, studies on CLV have focused on computing the value of future cash flows, but they have not provided any insight into the nature of the cash flows. Srivastava, Shervani, and Fahey (1998) contend that any firm's future cash flow is subject to inherent risks that make the future revenue stream vulnerable and/or volatile, thereby impacting firm valuation. In other words, given the same value of future cash flows for two firms, a firm with lower risk (i.e., the firm whose cash flows have lower volatility and vulnerability) will get a higher valuation than a firm with higher risk. The vulnerability of cash flows is reduced when customer stickiness increases, as indicated by higher customer satisfaction, loyalty, and retention. Similarly, the volatility of cash flow is reduced when revenue streams from customers become more stable (Srivastava, Shervani, and Fahey 1998). We account for volatility and vulnerability in our framework and empirically demonstrate that exclusion of these measures can attenuate the link between customer equity and the market capitalization of the firm (i.e., firm value as determined by the firm's stock price).

Finally, research studies to date have focused their attention only on linking customer value to firm value. To the best of our knowledge, no study has continuously tracked the impact of marketing strategies on the stock price of the firm over time. In this study, we empirically demonstrate which differentiated customer management strategies can be deployed successfully and how the effects of the strategies may be tracked by following the changes in the stock price of the firm over time.

What drives the lifetime value of each customer? Managers are interested in uncovering

and measuring these drivers so they can deploy appropriate customer relationship management (CRM) strategies to influence CLV. Previous research has identified these drivers as exchange characteristics and customer heterogeneity variables (Reinartz and Kumar 2003). Exchange characteristics consist of variables such as purchase propensity, contribution margin (including past customer spending level), cross-buying behavior, purchase frequency, recency of purchase, past buying behavior, and marketing contacts by the firm (Reinartz and Kumar 2003). Customer heterogeneity variables include demographic variables such as age, income, gender, place of residence, type of residence, and marital status in the case of retail customers (Kumar, Shah, and Venkatesan 2006). For business customers, customer heterogeneity variables include firm-related variables such as industry type, number of employees, annual revenue, annual growth, number of branch offices, and indicators for domestic or multinational operations (Venkatesan and Kumar 2004). Collectively, these factors create variability at the individual customer level and hence help in measuring the lifetime value of each customer.

Measuring customer lifetime value

Several methods have been proposed by past researchers to estimate CLV. However, given the objectives of this study, we need a CLV computation approach that can: (a) estimate the lifetime value of each customer separately and account for customer-level heterogeneity, (b) specify the lifetime value of each customer as a function of customer-centric drivers that may be controlled by the firm through appropriate marketing interventions, and (c) be easy to implement in the real world. Recently, Kumar et al. (2008) computed the lifetime value of IBM's customers using a system of seemingly unrelated regression equations whose parameters were estimated using a Bayesian methodology. Their model was successfully implemented by IBM in a pilot study with 35,000 customers. Encouraged by this real-world case study, we adapt and extend the work of Kumar et al.

(2008) to compute the lifetime value of each customer. We do this by accounting for customer-level heterogeneity in covariates and by inferring customer transactions with competitors using share-of-wallet information (further explained in the next section).

Calculating customer equity

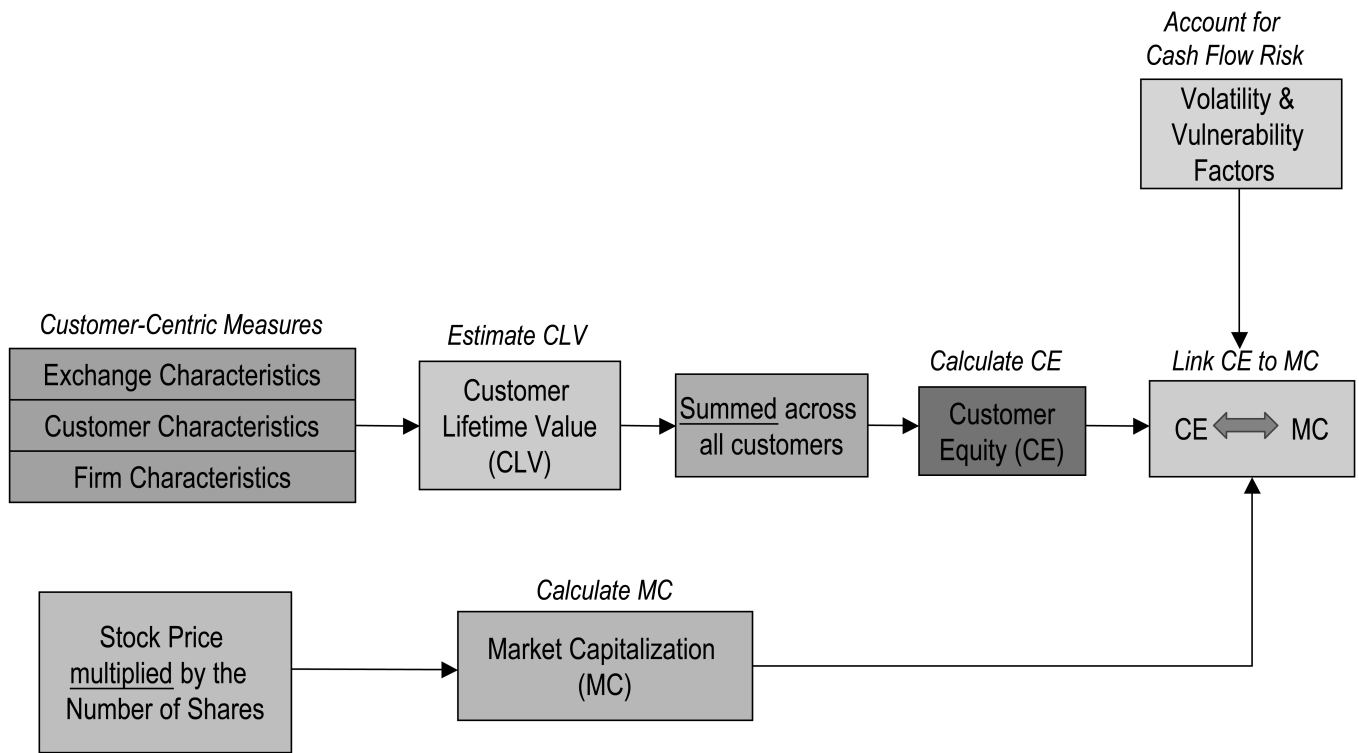
CE is calculated as the sum of the lifetime value of all existing customers as well as the new customers that the firm is expected to acquire in future.

Calculating market capitalization

One popular measure of firm value is market capitalization (MC), which is based on the stock price of the firm. The firm value is computed as the product of the stock price of the firm and the number of outstanding shares in the market. According to the efficient-market theory, stock prices incorporate all information about expected future earnings (Fama 1970). Thus, measures based on stock price can be assumed to be a good proxy for the long-term performance of the firm. Another measure of firm value is based on Tobin's q . A firm's q value is the ratio of its market value to the current replacement cost of its assets (Tobin 1969). An advantage of this measure is that it normalizes the market value of the firm (as determined by the stock price) to a natural common baseline in the form of the replacement cost of the assets of the firm. Such normalization facilitates comparison across multiple firms.

Both approaches have been used by marketing studies in the past (Anderson, Fornell, and Mazvancheryl 2004; Gupta, Lehmann, and Stuart 2004; Rust, Lemon, and Zeithaml 2004). In this study, we choose to use the market capitalization approach because the stock price of the firm offers a straightforward, forward-looking measure of the market value of the firm, whereas computation of Tobin's q is relatively involved. Computation of the replacement cost of the firm (denominator of Tobin's q) is complicated and excludes the

Figure 1
Linking Customer Equity and Market Capitalization



intangible assets of the firm (Anderson, Fornell, and Mazvancheryl 2004). Furthermore, our study is longitudinal and involves an in-depth (and independent) analysis of two firms. Hence, we do not need to normalize the stock price to facilitate comparison across multiple firms.

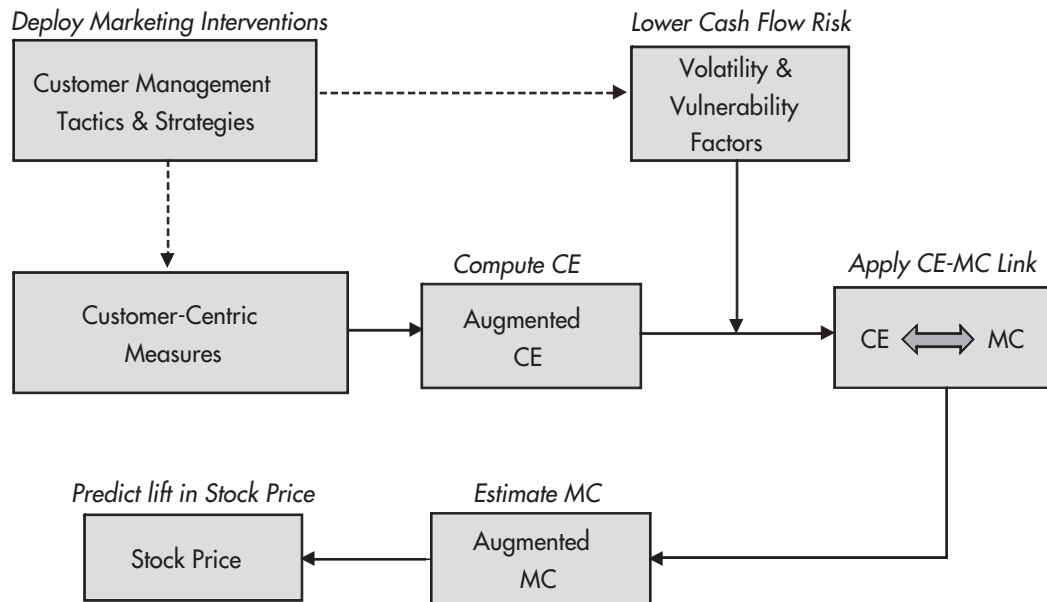
Linking customer equity to market capitalization

The ultimate objective of Figure 1 is to establish the link between the CE and the MC of the firm. Before establishing this relationship, it is important to conceptually understand that while the stock price (assuming efficient-market theory) is risk adjusted, the cash flow from CLV computation is not. Ignoring this aspect of firm valuation could attenuate the relationship between CE and MC. Srivastava, Shervani, and Fahey (1998) contend that risks associated with future cash flows can be addressed through customer-based measures that relate to the volatility and vulnerability of

cash flows from customers. Towards this endeavor, we propose to use variance in CE computation as a proxy variable to capture the volatility of cash flows from individual customers and share of wallet as a measure of vulnerability of future cash flows.

The variance in CE computation can be defined as a measure of the level of uncertainty in firms' estimation of the total lifetime value of their customers. Share of wallet is defined as the approximate proportion of relevant business a customer conducts with the concerned firm. For example, if Firm X has 100% of Customer A's share of wallet for apparel sales, it implies that Customer A makes all his or her apparel purchases from Firm X alone. When a high share of a customer's wallet goes to a particular firm, the customer is likely to exhibit high likelihood of repurchase, high retention, and high overall customer satisfaction (Perkins-Munn et al. 2005). Consequently, high share of wallet implies more stability and

Figure 2
Leveraging Customer Management Strategies to Increase Stock Price



hence low vulnerability of future cash flows. In sum, lower volatility (or variance in CE computation) and lower vulnerability (i.e., higher share of wallet) implies a stronger association between CE and MC.

Leveraging customer management strategies to increase stock price

A concept that goes hand in hand with the notion of shareholder value is the notion of shareholder value creation. The primary agenda of CEOs is typically to create value for the firm's shareholders. The firm creates value for its shareholders when the shareholders' return exceeds the cost of capital (i.e., the required return on equity). Consequently, a firm can create shareholder value if its stock price outperforms market expectations, which are typically based on historic performance and expected future returns. In this section, we discuss how firms can increase stock price (and potentially create shareholder value) by applying CLV-based customer management strategies (see Figure 2).

As discussed earlier, the CLV of each customer

is driven by a set of customer-specific drivers. From the managerial standpoint, one can think of these drivers as customer-specific levers that may be influenced through appropriate marketing interventions in the form of customer management tactics and strategies. Since our modeling framework and data set facilitate the computation of the lifetime value of *each* of the firm's customers, firms gain the ability to deploy different marketing tactics and strategies for different customers (or customer segments) based on individual CLV (or average CLV of a customer segment). For example, a manager may want to increase the marketing resources for a high-CLV customer (or segment) while curtailing resources for a customer or segment with negative CLV. Such marketing interventions will increase the overall lifetime value of the firm's customers (i.e., CE, as shown in Figure 2) and may also help in lowering cash flow risk by stabilizing the future expected cash flows. The increase in CE of the firm's customers can be used to predict an increase in the MC of the firm by applying the CE–MC relationship developed in the previous section (depicted in Figure 1). We define

the resultant MC as augmented MC in Figure 2. If augmented MC exceeds market expectations, it will result in shareholder value creation. By dividing the augmented MC by the number of the firm's shares outstanding, we can estimate the lift in the firm's stock price.

Our modeling framework (discussed in the next section) will help quantify the effects of different market activities directed at different customers (or customer segments) on the stock price, or MC, of the firm. We operationalize the conceptual frameworks presented in figures 1 and 2 by dividing our methodology and analysis into two parts. In Part 1, we explain how to use our model to compute CLV/CE and link it to the MC of the firm (as illustrated in Figure 1). In Part 2, we show how to use the results from Part 1 to increase the MC (or the stock price) of the firm.

Part 1: Linking Customer Equity and Market Capitalization

We adapt the approach of Kumar et al. (2008) to compute the lifetime value of each customer, with two important extensions to their methodology: first, we allow *all* parameters (pertaining to CLV prediction) to be customer specific in order to capture heterogeneity of customer responses, whereas Kumar et al. (2008) allow only the intercept terms to be customer specific, and second, we use share-of-wallet information to impute customers' transactions with competitors. Inclusion of these refinements serves to improve the accuracy of CLV prediction.

Computing CLV for each customer

We define CLV as the net present value of cash flows provided by a customer over a future time horizon of three years (or 36 months). The prediction horizon is held at three years and not the natural lifespan of the customer because, given the dynamic environment that firms typically operate in, a prediction window of three years offers a good

tradeoff between prediction accuracy and prediction horizon when computing CLV at individual customer level. Several research studies in the past have used a similar time horizon when estimating CLV at the individual customer level (e.g., Kumar et al. 2008; Venkatesan and Kumar 2004; Venkatesan, Kumar, and Boehling 2007). Furthermore, the act of discounting future cash flows generally results in a majority of the customer's lifetime value being captured within the first three years (Gupta and Lehmann 2005). Hence, the CLV for a customer i can be specified as:

$$CLV_i = \sum_{j=T+1}^{T+36} \frac{p(Buy_{ij} = 1) * \hat{CM}_{ij}}{(1+r)^{j-T}} - \frac{\hat{MT}_{ij} * \overline{MC}}{(1+r)^{j-T}} \quad (1)$$

where CLV_i = lifetime value for customer i ; $p(Buy_{ij} = 1)$ = predicted probability that customer i will purchase in time period j ; \hat{CM}_{ij} = predicted contribution margin provided by customer i in time period j ; \hat{MT}_{ij} = predicted level of marketing contact (touches) directed toward customer i in time period j ; \overline{MC} = average cost of a single marketing contact; j = index for future time periods (months in this case); T = the end of the calibration or observation time frame; and r = monthly discount factor (.0125 in this case; equivalent to a 15% annual rate).

Such a formulation assumes an always-a-share approach. That is, every customer is assumed always to be associated with the firm. Any period in which the customer does not transact with the firm is assumed to be a period of temporary dormancy. Such an approach is appropriate for non-contractual settings (Rust, Lemon, and Zeithaml 2004; Venkatesan and Kumar 2004) such as those that apply in our case. For contractual settings, firms can employ the lost-for-good approach to compute CLV (e.g., Berger and Nasr 1998; Lewis 2005).

Equation 1 contains the following three terms that need to be predicted for each customer:

- The expected level of marketing contact, \hat{MT}_{ij}
- The probability of purchase, $p(Buy_{ij} = 1)$
- The contribution margin, \hat{CM}_{ij}

We model the log of the level of marketing contact for customer i in time j as:

$$\log(\hat{MT}_{ij}) = \alpha_{1i} + x_{1ij}^T \beta_{1i} + u_{1ij} \quad (2)$$

where x_{1ij} , β_{1i} , α_{1i} , and u_{1ij} are a vector of predictor variables, a vector of corresponding customer-level coefficients, a customer-level intercept, and an error term, respectively. Using a logarithmic form of marketing contact helps to account for the diminishing returns of marketing efforts (Venkatesan and Kumar 2004).

To model the probability of purchase, we first specify the latent utility for customer i of purchasing from the firm in time period j as a linear function of predictor variables:

$$Buy_{ij}^* = \alpha_{2i} + x_{2ij}^T \beta_{2i} + u_{2ij} \quad (3)$$

where x_{2ij} , β_{2i} , α_{2i} , and u_{2ij} are a vector of predictor variables, a vector of corresponding customer-level coefficients, a customer-level intercept, and an error term, respectively.

We assume that customer i purchases from the firm only when the latent utility for the customer of purchasing from the firm Buy_{ij}^* exceeds a certain threshold, set to zero in this case. We do not observe the latent utility for the customer but observe a binary outcome variable Buy_{ij} , indicating whether the customer purchased or did not purchase in time period j . Consequently, we map the latent utility to the observed binary outcome variable Buy_{ij} as follows:

$$\begin{aligned} Buy_{ij}^* > 0, & \text{ if } Buy_{ij} = 1 \\ Buy_{ij}^* \leq 0, & \text{ if } Buy_{ij} = 0 \end{aligned}$$

Finally, we model the contribution margin from customer i in time period j as:

$$\hat{CM}_{ij} = \alpha_{3i} + x_{3ij}^T \beta_{3i} + u_{3ij} \quad (4)$$

where x_{3ij} , β_{3i} , α_{3i} , and u_{3ij} are a vector of predictor variables, a vector of corresponding customer-level coefficients, a customer-level intercept, and an error term, respectively.

In equations 2, 3, and 4, the intercept and other coefficients are specified as customer-specific parameters. Hence, they vary by customer. The variability in parameters is induced by customer heterogeneity as captured by select firm-related and demographic variables. (See Table 1 for a complete list of variables used in this study.)

Accounting for missing transactions

For any given Firm A, the contribution margin from a customer is realized only when Firm A's database records a purchase incidence (i.e., $Buy_{ij} = 1$). However, there may be instances when the customer does not purchase anything from Firm A. This could be either because the customer does not have any need to make a purchase or because the customer chooses to buy from a competitor. In either case, the proprietary data set of Firm A will not observe CM_{ij} when $Buy_{ij} = 0$. This is summarized by Equation 4A.

$$\begin{aligned} CM_{ij} &= CM_{ij}^* \text{ if } Buy_{ij} = 1 \\ CM_{ij} &= Unobserved \text{ if } Buy_{ij} = 0 \end{aligned} \quad (4A)$$

The unobserved CM_{ij} includes missed-purchase incidences when the customer chooses to buy from competitor firms. The lack of information regarding customers' transactions with competitors can result in an estimation bias (of customer response elasticity) due to missing data. Kumar et al. (2008) address this issue by imputing the missing contribution margin (when a purchase incidence does not occur as expected) based on the customer's historic average interpurchase time. In such a scenario, the missing contribution margin is imputed as random realizations of a normally distributed prior distribution. However, the Kumar et al. (2008) approach

assumes that the customer will spend at the same level with Firm A as with the competitor. In reality, the customer's spending level with the competitor will depend upon the customer's share of wallet with Firm A. In other words, a 70% share of wallet for Firm A would imply that the customer spends the remaining 30% of the total category spending with competitors.

In this study, we assume the mean of the prior distribution to be the product of the customer's average overall contribution margin and the share of purchases made with competitors (as inferred from observed average contribution margin with Firm A and share-of-wallet data). The data augmentation process for imputing missing values is discussed in Kumar et al. (2008) and Cowles, Carlin, and Connett (1996); in the interest of space, we do not repeat the explanation here. However, note that the data augmentation process is used only for obtaining nonbiased estimates of response elasticities. It is not used for CLV prediction.

The three terms in equations 2, 3, and 4 relate to the same customer and thus are inherently correlated. Hence, we model these three terms jointly as a system of equations. The corresponding likelihood function will be:

$$L(MT, Buy, CM) \propto \prod_{i=1}^N \prod_{j=1}^T \Pr(Buy_{ij}^* \leq 0, MT_{ij})^{1-Buy_{ij}^*} \Pr(CM_{ij}^* = CM_{ij}, Buy_{ij}^* > 0, MT_{ij})^{Buy_{ij}^*} \quad (5)$$

where Buy_{ij}^* = the latent utility for customer i of purchasing in time period j .

The likelihood function is estimated using a Bayesian estimation procedure. The technical details of the estimation procedure are included in the appendix.

Segmentation and profiling

Once the CLV scores are computed, managers are interested in maximizing customer equity.

Computation of CLV at the individual level offers the flexibility of aggregating customers in any number of discrete segments. In this study, we employ data from two firms—a manufacturing firm catering to business customers and an apparel firm catering to retail customers. The manufacturing firm prefers to create customer segments containing only one member as each customer represents a business establishment with a relatively high volume of business, and the manufacturing firm prefers to customize its marketing touches and customer relationship efforts to each of its customers. In contrast, the retailer firm has millions of customers and a relatively low volume of business per customer. Consequently, the retailer firm prefers to group its customers into segments. In either case, for the purpose of this study, we shall represent the database of both firms as comprising three segments—high CLV, medium/low CLV, and negative CLV—to convey the heterogeneity of customer profitability. Once the segments are defined, it is managerially useful to profile the segments to evaluate which demographic (or firm-related) variables vary significantly across segments. We can empirically determine the probability that a customer i will belong to segment q by employing a multinomial logit.

$$prob_{iq} = \frac{\exp(\delta_{iq})}{\sum_{q=1}^Q \exp(\delta_{iq})}$$

$$where: \delta_{iq} = \beta_0 + \sum_{k=1}^K \beta_k X_{ik} \quad (6)$$

where $prob_{iq}$ = probability of customer i to be in segment q ; δ_{iq} = latent utility of customer i belonging to segment q ; X_{ik} = 'K' demographic/firm-related variables corresponding to customer i of segment q ; β_0, β_k = coefficients estimated from the data.

Computing CE at the firm level

After estimating the CLV for each customer i of the firm, we calculate the customer equity of N existing or retained customers (CE_R) as the summation of each customer's lifetime value:

$$CE_R = \sum_{i=1}^N CLV_i \quad (7)$$

New customers that the firm expects to acquire in the future represent another important source of customer value for the firm.

One way to take new customers into account is to predict the growth of the customer base using a diffusion-based model (e.g., Gupta, Lehmann, and Stuart 2004; Kim, Mahajan, and Srivastava 1995). Such an approach can account for nonlinear growth rates and diminishing returns, which are naturally observed due to market saturation over time. In the context of our study, we are dealing with two large corporations and predicting the future value of their customers over a relatively short time horizon of time years (as opposed to the infinite time horizon of Gupta, Lehmann, and Stuart 2004). Moreover, both firms are highly diversified in their respective industries and growing over time. Consequently, we use the average acquisition rate of customers as reported by the two firms to compute the growth of customers over the next three years, an average annual growth rate of 6% and 3% for the B2B and B2C firms, respectively. Both firms deemed these growth rates appropriate for the next three years after accounting for their future business growth plans in terms of acquisitions (for the B2B firm) and the opening of new stores (for the B2C firm).

Consequently, if M customers are expected to be acquired over the next three years, then CE_A represents the customer equity from M newly acquired customers:

$$CE_A = \sum_{k=1}^M (CLV_k - A_k) \quad (8)$$

where CLV_k is the estimated lifetime value of each customer k acquired and A_k is the corresponding acquisition cost. We assume CLV_k to be equal to the average CLV of existing customers of the firm and A_k is assumed to be equal to the average acquisition cost per customer for the purpose of estimation. Such an assumption may not be an accurate representation of CLV at the individual customer level.

However, since this information is eventually aggregated (in the form of CE_A), average CLV measures suffice as a convenient way to estimate the CE of new customers for the purpose of this study. Alternatively, some sophistication can be introduced in this computation depending on the firms' sales cycle, nature of business, industry, and availability of data pertaining to customers in the prospect pool. For example, B2B firms typically have long sales cycles, and many B2B firms maintain a sales pipeline report that contains details about each prospective customer. In such a scenario, probability of acquisition can be assigned to each customer and multiplied by the expected CLV. The expected CLV can be determined by matching the profile of the prospective customer with the average CLV of all retained customers of the firm having a similar profile.

The customer equity (CE) of all customers of the firm will be the summation of the CLV of N retained customers and M customers expected to be acquired, as depicted by Equation 9:

$$CE = CE_R + CE_A \quad (9)$$

Computing market capitalization (MC)

Consistent with the efficient-market theory and earlier studies, we compute MC as the market value of the firm. For publicly listed firms, the MC of a firm at time t can be computed as the product of the average stock price (ASP) of the firm and the average number of outstanding shares P of the firm at time t :

$$MC_t = ASP_t * P_t \quad (10)$$

Linking customer equity to market capitalization

The MC of the firm is linked to CE as of time t by the following equation:¹

$$MC_t = \gamma_0 + \gamma_1 * CE_t + \varepsilon_t \quad (11)$$

where γ_0 and γ_1 are parameters to be estimated and ε_t is the residual term that is assumed to

be normally distributed. In this study, the time period t represents a month.

The term ε_t represents the difference between the actual and predicted MC in month t , and it represents aspects of firm valuation that CE_t does not account for. The estimate of MC based on CE can be poor if ε is large. To address this issue, we let ε be a function of factors that are not accounted for in the CLV (and hence CE) computation. As discussed earlier, there are some inherent risks associated with cash flows that are reflected in the MC of the firm (assuming efficient-market theory) but not in the CE computation. Consequently, we use the variance in CE calculation (VAR_CE) and share-of-wallet (SOW) information to capture the volatility and vulnerability in cash flow from customers.

The variance in CE represents the uncertainty (from the firm's standpoint) in estimating the total lifetime value of customers based on the parameter estimates of the drivers (or covariates) of CLV because of the variance associated with these parameter estimates (of equations 2, 3, and 4) that are used to compute CLV. Consequently, we estimate the lifetime value of each customer by making a draw of customer-level parameter estimates. Then we add up the CLV of each customer to get the total CLV (i.e., CE). If we repeat this process 10,000 times, then each process/iteration will generate a different value of CE. Consequently, a distribution of CE is generated, thus facilitating the calculation of VAR_CE . Based on such an operationalization, VAR_CE will be expected to have a negative impact on MC. In other words, the power of CE in predicting MC is diminished (enhanced) by a higher (lower) variance in CE.

The vulnerability of cash flows is another dimension of risk. We capture this through the share-of-wallet (SOW) information. We operationalize average SOW across customers as a weighted average (weighted by the contribution margin of the customers) to give more

importance to high-value customers and less importance to low-value customers. We expect SOW to exert a positive influence on MC, as discussed earlier. High SOW implies greater stability of cash flow from customers, which lowers the riskiness of the firm's operations and hence raises the firm's valuation.

Inclusion of these risk factors can help explain why two firms having similar CE values can still have dissimilar market valuation due to the differences in perceived riskiness of the two firms. Consequently, these risks moderate the relationship between CE and MC and hence exert their influence as both main effects and interaction terms as specified in Equation 12.

Besides cash flow risks, there may still be some unobserved effects related to the environment and the market (such as investor sentiments and macroeconomic factors) that could possibly bias the parameter estimates. To mitigate this problem, we employ one-period lagged value of market capitalization as a proxy for omitted variables. Therefore, we can express ε in time t as:

$$\varepsilon_t = \lambda_0 + \lambda_1 SOW_t + \lambda_2 (CE_t * SOW_t) + \lambda_3 VAR_CE_t + \lambda_4 (CE_t * VAR_CE_t) + \lambda_5 MC_{t-1} + \xi \quad (12)$$

where λ is a vector of parameters to be estimated representing the effect of risk factors and unobserved factors that are accounted in the MC but not in the CE. Note that the impact of these factors on the MC of the firm is constrained by the magnitude of the residual term ε_t . This ensures that the relationship between CE and MC is maximized and not confounded by potential collinearity with terms specified in Equation 12.²

The CE_t term (in equations 11 and 12) represents the total lifetime value of customers with the limitation of a finite future time horizon of three years. It may be argued that some alternative future time horizon for CE computation

(i.e., less than or more than three years) may provide a stronger relationship between CE and MC. To address this issue, we test the linkage between CE and MC by plugging in CE estimates (as per equations 1, 2, 3, and 4) for different future time horizons.

Data Description for Part 1

As mentioned earlier, we make use of customer transaction data sets from a B2B firm and a B2C firm. Both firms are large, publicly traded companies.

The B2B data set comes from a Fortune 1000 high-tech manufacturing firm that sells computer-related hardware and supporting software. The company's database contains monthly transaction data for all of its customers (i.e., client businesses) from January 2000 to April 2007. The product categories in the database represent different spectrums among high-technology products. In these product categories, the buyer and the seller must choose to develop a mutual relationship, and both parties benefit significantly by maintaining the relationship. Even though these products are durable goods, they require constant maintenance and frequent upgrades; this provides the variance required in modeling the customer response. In order to help managers make their decisions, they have at their disposal for each customer information on the date of each purchase, the product category purchased (and hence the level of cross-buying within the firm), the channel used by the customer to transact business (for example, online versus direct sales), and the amount spent by each customer on each purchase occasion. The SOW information is obtained from a third-party external research firm hired by the B2B high-tech firm. In addition, the high-tech firm has developed a sophisticated approach to impute the SOW for each of its customers. We use both sources of information to reconcile the differences in SOW, if any.

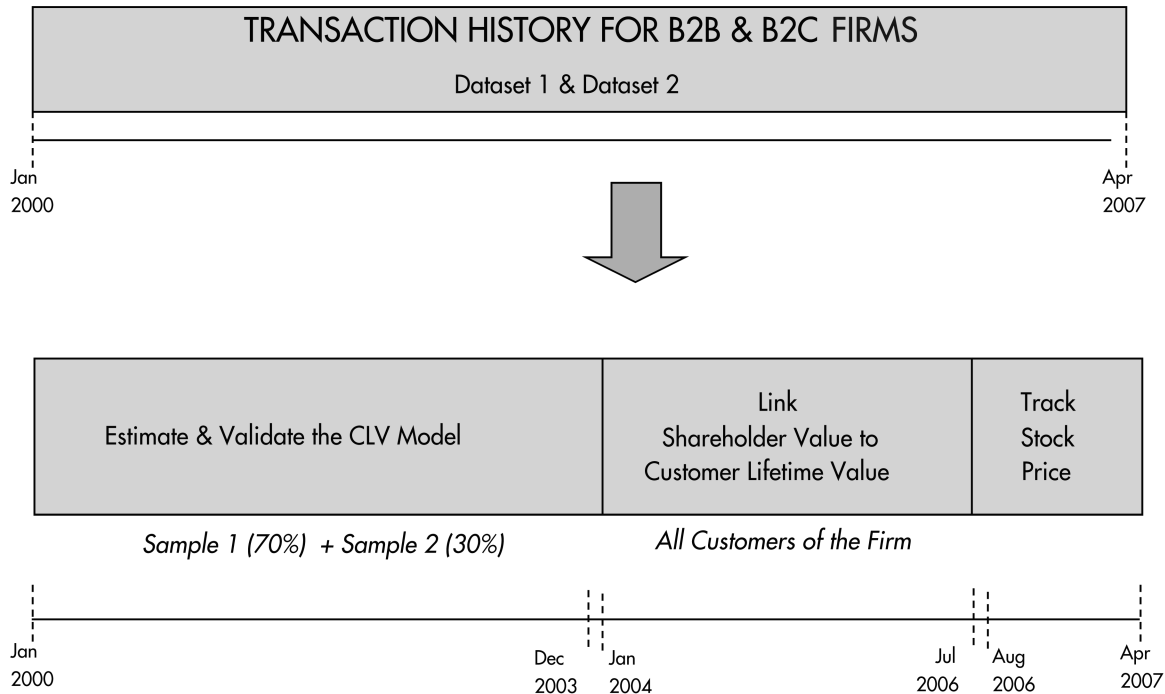
The B2C data set comes from a large retailer selling apparel, shoes, and accessories for both men and women. The retailer's data set contains customer-level, monthly transaction data for all customers (more than 1 million) who made purchases between January 2000 and April 2007. The retailer offers its customers three ways to make their purchases: through any of the company's 30 retail stores in the United States, through a catalog, or through the company's website. Hence, the data set captures information on multichannel shopping behavior.

The data set also contains rich information on different product categories being sold by the retailer. Purchase transaction details such as frequency of purchase, average purchase value, type of product purchased, number of product categories in which purchases were made, channel through which purchase was made, and number and type of marketing communications the firm directed toward the customer are available for each month. The retailer calculates the SOW information as the ratio of the total amount of dollars spent by a given customer in one year with the retailer and the estimated total amount of dollars the customer is capable of spending on similar products in one year. The denominator is imputed on the basis of available demographic information about the customer such as zip code, gender, marital status, family size, income, and age.

We divide both data sets into two samples of customers: Sample 1 and Sample 2. Sample 1 is the model-building sample and comprises 70% of the firm's total customers. Sample 2 is the model validation sample and comprises 30% of the firm's customers. We use Sample 1 to calibrate the model and Sample 2 to validate the calibrated model. The final model is then used to compute the CLV for the entire data set. Figure 3 depicts the data set in terms of associated timelines used for data analyses and prediction.

The unique strength of the two data sets is that they contain longitudinal transaction data

Figure 3
Data Analyses – Timelines



for each customer of the firm. This enables us to compute CLV at an individual customer level, uncover customer-centric measures that drive CLV, and subsequently test the impact of customer-centric tactics and strategies on the MC of the firm. Most importantly, disaggregated data facilitate deployment of marketing strategies at even single-member customer segments.

Available variables

Table 1 summarizes the set of customer-level variables that are employed from the two data sets to estimate the propensity to buy, contribution margin, and marketing contacts for each customer and hence the lifetime value of each customer. The choice of variables is drawn from past research as well as theoretical and practical considerations that typically govern CLV prediction (see Venkatesan and Kumar 2004; Kumar, Shah, and Venkatesan 2006; or Venkatesan, Kumar, and Boehling 2007 for a discussion). The availability of firm-related (for the B2B customers) and demographic (for

the B2C customers) variables corresponding to customers in Data Set 1 and Data Set 2 respectively will help in estimating the customer-specific parameters of equations 2, 3, and 4 as well as in conducting profile analyses, as specified in Equation 6. For the B2B firm, we use average customer revenue (bearing in mind that for the B2B firm, the customers are also firms), customer size (determined by the number of employees), and industry type to estimate customer-specific coefficients. For the B2C firm, we use gender, household income, and distance from the store (as determined from zip code) to estimate customer-specific coefficients.

Estimation for part 1

The objective of estimation is to recover two sets of parameters: Θ_1 and Θ_2 . Let Θ_1 represent the set of parameters pertaining to CLV computation (i.e., customer-level parameters corresponding to equations 2, 3, and 4), and Θ_2 represent the set of parameters pertaining to linking CE to MC (i.e., firm-level parameters

Table 1
List of Available Variables

Exchange Characteristics

Variable	Operationalization
Level of marketing communication	Number of firm-initiated marketing touches in a given month
Product purchase	Indicator variable = 1 if product is purchased; otherwise, indicator variable = 0
Number of purchases	Number of purchase transactions in a given month
Recency of purchase	Time (in months) since previous purchase
Contribution margin	Amount of profit (in dollars) contributed by a customer in a given month
Spending level	Share of wallet
Multichannel behavior	Number of channels used by a customer in a given year
Majority product category	Indicator variable = 1 if customer makes a purchase in a prespecified major product category in a given year; otherwise, indicator variable = 0
Cross-buying	Total number of product categories in which a customer makes a purchase in a given year
Product return	Amount of returns (in dollars) made by a customer in a given year
Referral credit earned	Amount of credit (in dollars) earned from referrals in a given year

Customer Heterogeneity Variables

Firm-related Variables from Data Set 1	Demographic Variables from Data Set 2
Industry type	Age and gender
Number of years since incorporation	Marital status
Domestic or multinational	Type of dwelling
Number of employees	Household income
Average annual revenue	Distance between residence and store
Segment type (based on company size)	Number of channels used for shopping
Number of branch offices	Loyalty card membership information

corresponding to equations 11 and 12). The estimation procedure is carried out in a sequential manner as follows.

First, we divide the firms' customers from the period January 2000 to December 2003 into two samples, as described above and shown in Figure 3. We use Sample 1 to estimate Θ_1 , and then we apply the set of parameters represented by Θ_1 to estimate the CLV of the customers in Sample 2, the validation sample. The validation sample results in a mean absolute percentage error of 17%, which we deemed reasonable.

To estimate Θ_2 , we use Θ_1 to compute the CLV for all customers (the CE) as of month t and then measure the MC (based on the observed stock price) as of end of month t . This process is repeated for every month, moving forward one month at a time for the period from January 2004 to July 2006. By July 31, 2006, we have 31 values of CE (as predicted by the parameters Θ_1) and 31 values of MC as computed from the observed value of average stock price. We then use these 31 data points to regress MC on CE and variables representing cash flow risk and unobserved factors. The outcome of the regression is parameter estimates for Θ_2 .

Table 2
Parameter Estimates for the CLV Model (B2C firm)

Independent Variables	Coefficients*	
	Mean	Variance
Level of Marketing Contacts		
Relationship duration indicator	3.868	.0471
Lagged level of market communication	.682	.0212
Lagged average number of purchases	.393	.0176
Lagged spending level	.427	.0274
Loyalty program member	2.187	.0262
Lagged level of cross-buying	.312	.0481
Recency of purchase	-.162	.0168
Square of recency of purchase	.009	.0014
Lagged average contribution margin	.582	.0467
Purchase Incidence		
Relationship duration indicator	.412	.0386
Lagged indicator of purchase	.676	.0526
Lagged spending level	.008	.0012
Lagged average contribution margin	.101	.0267
Log of lagged level of contacts	.007	.0014
Lagged level of cross-buying	.281	.0646
Recency of purchase	-.052	.0087
Lag of multichannel behavior	.386	.0375
Contribution Margin		
Relationship duration indicator	.091	.0122
Lagged contribution margin	.729	.0395
Lagged average contribution margin	.686	.0267
Lagged level of cross-buying	.391	.0291
Loyalty program member	.137	.0156
Log of lagged level of marketing communication	.146	.0217
Lag of multichannel behavior	.426	.0428
Lag of product returns	.153	.0354
Lag of square of product returns	-.0621	.0196

*Mean and variance are computed using the 5th through 95th percentiles of the posterior sample.

For Part 2 of this study, we use Θ_1 and Θ_2 to compute CE and predict MC respectively for each month from August 2006 to April 2007. Figure 3 provides a quick overview of various timelines used for model estimation, validation, prediction, and tracking.

Results and discussion for part 1

For the B2C firm, the coefficient estimates of the drivers of CLV are reported in Table 2. The reported values are the posterior means and variances. In the interest of space, we only present the parameter estimates for the B2C firm. For the B2B firm, the results obtained are similar, with all coefficient estimates having identical sign but differing in magnitude. A parameter is considered not significant if a zero exists within the 2.5th percentile and 97.5th percentile values of the posterior distribution for that parameter. Note that the inclusion of lagged values of covariates facilitates prediction and interpretation of causality. Furthermore, we include a relationship duration indicator as a binary variable in all three models. The value of this binary variable is 1 for a customer who began to patronize the firm before January 2000 (i.e., before the observation window used for analysis) and 0 for a customer who began to patronize the firm on or after January 2000 (i.e., within the observation window used for analysis). The results for all parameter estimates are shown in Table 2. The direction of the sign for all variables is consistent with findings from previous studies pertaining to CLV computation at the level of the individual customer (e.g., Kumar, Shah, and Venkatesan 2006; Venkatesan and Kumar 2004).

The results relating to marketing contacts show that the firm tends to contact a customer more frequently if that customer has been contacted frequently in the past, has made more purchases, spent more dollars with the firm, been a member of the loyalty program, or purchased a relatively large number of products. The results on recency of purchase show an inverted U relationship with marketing contacts, indicating that the firm tends to contact a customer who has not made a purchase in the recent past. However, the firm's tendency to contact a person diminishes if the customer fails to make any purchases beyond a threshold point.

The results on purchase incidence indicate that a customer is more likely to purchase if that customer has made a purchase in the past, has spent more dollars with the firm, has been contacted by the firm through marketing initiatives, has purchased a relatively large number of products in the past, transacted through multiple channels, or not made any purchases in the recent past.

The results relating to contribution margin indicate that the expected contribution margin of the customer is high if the customer has spent relatively more in the past, has purchased relatively more products, has been enrolled in a loyalty program, has been contacted by the firm through direct marketing, or has shopped for the firm's products through multiple channels. The contribution margin has an inverted-U relationship with product returns. This is consistent with past findings (see Venkatesan and Kumar 2004, or Kumar, Shah, and Venkatesan 2006).

We use the coefficient estimates to calculate the CLV score for each customer as expressed by Equation 1. To get an idea of the distribution of CLV scores, we first rank-order all customers in descending order. Then, we aggregate customers into deciles so that each decile represents 10% of the customer base and the CLV corresponding to each decile will be the average CLV of customers within the decile. Such a transformation helps in displaying the distribution of CLV scores across customers in a diagrammatic form (as shown in Figures 4A and 4B). The distribution of CLV for both firms is heavily skewed. For the B2B firm (Figure 4A) the top 20% of the customers account for 91% of total profits while the bottom 20% of customers have negative lifetime value. For the B2C firm (Figure 4B), the top 20% of the customers account for 93% of firm's profits while the bottom 30% are a drain on the company's resources with negative lifetime value. For ease of explanation and further analysis, we divide the customer base of both firms into three discrete segments:

high CLV (corresponding to the top 20% of customers for both firms), medium/low CLV (corresponding to the middle 60% and the middle 50% of customers for the B2B and B2C firms, respectively), and negative CLV (corresponding to the bottom 20% and the bottom 30% of customers for the B2B and B2C firms, respectively).

Do customers who differ on lifetime value have any distinguishing demographic or firm-related characteristics? The answer lies in the results of the profile analyses. Tables 3A and 3B contrast the distinguishing characteristics of a typical high-CLV and a typical negative-CLV customer for the B2B firm and the B2C firm, respectively. The results indicate that for the B2B firm, a typical high-CLV customer is a well-established multinational business organization from the high-technology, aerospace, or financial services industry that employs more than 500 people and has been in business for 15 to 25 years, with average annual revenue in excess of \$50 million. In contrast, a typical negative-CLV customer for the B2B firm is a domestic business organization in the chemicals or plastics industry that employs about 100-300 people and has been in business for 5 to 10 years, with average annual revenue in the range of \$5-\$10 million.

For the B2C firm, a typical high-CLV customer is a married female who is 30-40 years old and lives in a house that is relatively close to the store, is a member of the store's loyalty program and has a household income in excess of \$95,000. A typical negative-CLV customer for the B2C firm is a single male who is 20-30 years old and lives in a rented apartment that is relatively far from the store, is not a member of the store's loyalty program and has a household income of less than \$60,000.

Note that the results from the profile analyses do not necessarily indicate that all customers having the profile of a high-CLV customer will have high CLV and vice versa for negative-CLV customers. The profile analyses

Figure 4A
Distribution of CLV Scores for the B2B Firm

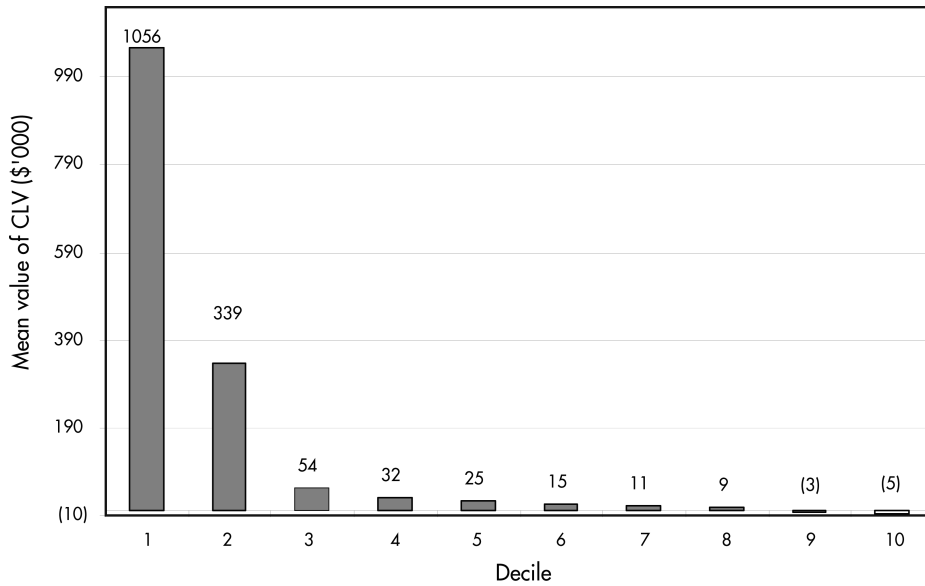
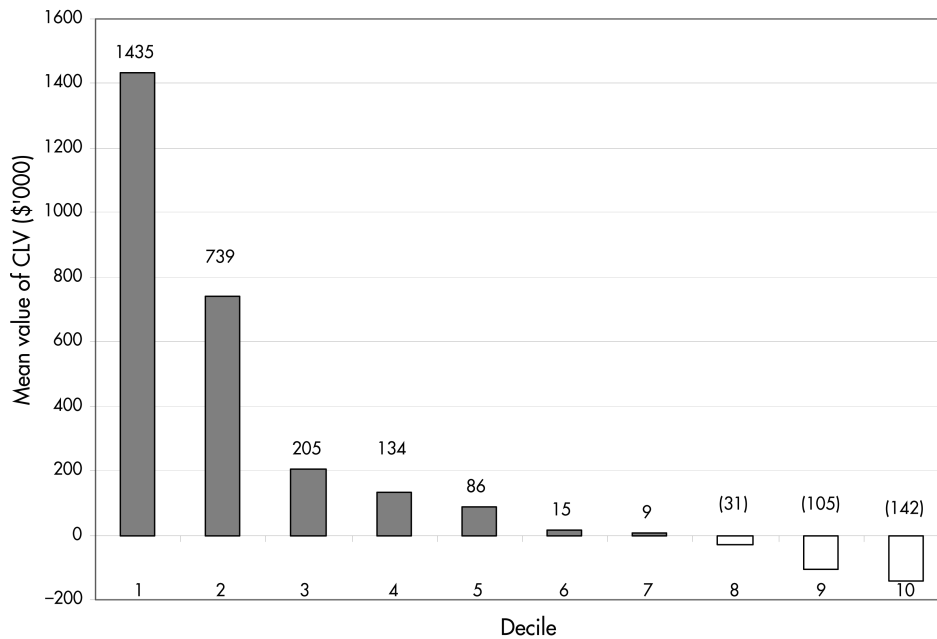


Figure 4B
Distribution of CLV Scores for the B2C Firm



merely indicate that on an average, there is a relatively high probability of high- and negative-CLV customers with the profile descriptions presented in Tables 3A and 3B.

After conducting profile analyses, we test the relationship of CE to MC for different time horizons of CLV computation—a one-year, two-year and three-year time horizon—and evaluate the fit between CE and the MC of

Table 3A
Profile of Typical High- and Negative-CLV Customers for the B2B Firm

Firm-related Variables	Typical High-CLV Customer	Typical Negative-CLV Customer
Industry type	High-tech, aerospace, financial services	Chemicals and plastics
Number of years since incorporation	15–25 years	5–10 years
Domestic or multinational	Multinational	Domestic
Number of employees	> 500 employees	100–300 employees
Average annual revenue	> 50 million	5-10 million

Table 3B
Profile of Typical High- and Negative-CLV Customers for the B2C Firm

Demographic Variables	Typical High-CLV Customer	Typical Negative-CLV Customer
Age	30–40 years	20–30 years
Gender	Female	Male
Marital status	Married	Unmarried
Type of dwelling	Own	Rent
Household income	More than \$95,000	Less than \$60,000
Distance between residence and store	Less than 10 miles	More than 10 miles
Number of channels used for shopping	2 or 3	1 or 2
Loyalty card membership	Enrolled	Not enrolled

the firm. The results in Table 4 indicate that the CLV prediction in the three-year time frame results in the best fit between CE and MC for both the B2B and B2C firm.³ Also, Table 4 shows the extent of improvement in relationship between CE and MC when measures of risk (i.e., *SOW* and *VAR_CE*) are included in the analysis. The R^2 for the model improves by 15% for the B2B firm and by 8% for the B2C firm when measures of risk are added. There is a further improvement of R^2 ($R^2 = 77\%$ for B2B firm and 79% for B2C firm) when the lag of MC is included in the model to account for the impact of omitted variables. The improvement in R^2 is statistically significant for all cases (after accounting for the changes in degrees of freedom).

Next, we evaluate whether measures of volatility, vulnerability, and past MC values are significant predictors of MC (as specified in Equation 12). The results are shown in

Table 5. As expected (and discussed earlier), share of wallet and past MC have a positive impact on MC, while variance in CE prediction has a negative relationship with MC. All hypothesized relationships are statistically significant.

In sum, the best linkage between CE and MC is obtained when we predict CLV for a three-year time horizon, include measures of volatility and vulnerability, and account for the effect of unobserved factors. The results obtained so far help establish the fact that the MC of the firm as determined by the company's stock price is closely tied to the CE of the firm, which is driven by customer-specific drivers and the firm's marketing interventions. Armed with these results, can the firm deploy marketing initiatives to increase the stock price of the firm?

Earlier, we saw a heavily skewed distribution of customer profitability (see Figures 4A and

Table 4
Comparison of Model Performance

Measurement Condition for CE–MC Equation	Model Performance (R^2)	
	B2B firm	B2C firm
CLV computed with one-year time horizon	.26	.28
CLV computed with two-year time horizon	.30	.34
CLV computed with three-year time horizon	.33	.38

Measurement Condition for CE–MC Equation with CLV computed over a three-year time horizon	Model Performance (R^2)	
	B2B firm	B2C firm
After adding measures of volatility and vulnerability	.48	.46
After adding past shareholder value	.77	.79

Table 5
Results for Linking CE to MC

Variable	Parameter Estimate (standard error)*	
	B2B firm	B2C firm
Intercept	16.21 (2.96)	9.62 (1.81)
CE	3.47 (.68)	1.86 (.42)
SOW	1.55 (.27)	.90 (.18)
VAR_CE	-5.96 (1.33)	-3.04 (.76)
CE * SOW	.836 (.317)	.561 (.186)
CE * VAR_CE	-1.142 (.393)	-1.06 (.329)
Lag of MC	.49 (.06)	.45 (.07)

*The standard error values are provided in parentheses.

4B). This implies that different customers have different impact on the firm's bottom line. To quantify the differential impact, we perform a simulation to compute the change in CE supposing an increase of 1% in the firm's rate of acquiring customers and an increase of one product in cross-buying

(applicable for the firms' retained customers). Next, we apply the CE–MC relationship to calculate the corresponding change in MC. Our results indicate that a 1% increase in the customer acquisition rate could translate into a 1.4% and 1.9% increase in MC for the B2B and B2C firms, respectively. Similarly, an increase in cross-buying by one product across all retained customers could translate into a 5.3% and 7.5% increase in MC for the B2B and B2C firms, respectively, as shown in Table 6A. We repeat the simulation, applying the 1% increase in acquisition rate and the increase in cross-buy (by one product) for the high-CLV, medium/low-CLV, and negative-CLV customers separately. The results indicate that the lift in MC (in percentage terms) is more than threefold when acquisition and cross-selling efforts are targeted to only high-CLV customers rather than all customers of the firm. Furthermore, the MC of the firm drops if the firm acquires the wrong customers (i.e., customers who subsequently end up with negative CLV), while the MC of the firm increases only marginally when negative-CLV customers buy an additional product, as shown in Table 6A.

The results in Table 6A underscore the importance of customer heterogeneity in driving firm value. In other words, it is more impactful

Table 6A
Expected Impact of Increase in Acquisition Rate and Cross-Sell on MC

Increasing Acquisition Rate by 1%	Impact on MC	
	B2B firm	B2C firm
For all customers	↑1.4%	↑1.9%
For high-CLV customers	↑7.9%	↑9.2%
For medium/low-CLV customers	↑.8%	↑2.0%
For negative-CLV customers	↓3.0%	↓3.1%

Increasing Cross-Buy by One Product	Impact on MC	
	B2B firm	B2C firm
For all customers	↑7.2%	↑8.3%
For high-CLV customers	↑18.1%	↑21.6%
For medium/low-CLV customers	↑5.1%	↑6.8%
For negative-CLV customers	↑2.1%	↑1.8%

Table 6B
Actual Impact of Implementation of CRM Strategies on MC

B2B Firm		B2C Firm	
Customer Segment	Effect of CRM Strategies (Lift in CE)	Customer Segment	Effect of CRM Strategies (Lift in CE)
All segments	19.4%	All segments	23.3%
High CLV	44%	High CLV	41%
Medium/low CLV	20%	Medium/low CLV	18%
Negative CLV	8%	Negative CLV	7%

when the firm improves acquisition and cross-sell for High CLV customers rather than improving the acquisition and retention rates across all customers of the firm. Marketing resources are potentially wasted when allocated to the wrong customers such as customers with negative lifetime value.

In Part 2 of our study, we advance the results and discussion of Part 1 to demonstrate how two real-world firms deploy CLV-based differentiated customer management tactics and strategies. We track the outcome with respect to the actual movement of the firm's stock price.

Part 2: Lifting the Stock Price of the Firm

In our earlier discussion, we showed the conceptual link between marketing interventions as the key input and the stock price of the firm as the key outcome. To put that concept into practice using the proposed framework, a marketing manager would need to deploy marketing initiatives that are directed at increasing the customer equity of the firm. We refer to these marketing initiatives as customer relationship management (CRM) strategies. We presented different CRM strategy options to the B2B and B2C firms used in this study and sought their cooperation in implementing one or more of these strategies to allow us to track the outcome in terms of the firms' stock value.

Strategy implementation

The B2B firm implemented the following CRM strategies: (a) resource reallocation, (b) selective acquisition, and (c) multichannel behavior. The B2C firm implemented the following strategies: (a) customer selection, (b) cross-selling, and (c) multichannel behavior.

The B2B firm implemented the resource reallocation strategy by moving a portion of marketing resources from the medium/low-CLV and negative-CLV customers to high-CLV customers. It implemented the selective acquisition strategy by focusing customer acquisition resources on prospective customers who matched the profile of high-CLV customers. The multichannel behavior strategy entailed offering special incentives to high-CLV and medium/low-CLV customers to shop from more than one channel, while negative-CLV customers were directed to conduct their transaction (including customer service) only through the online channel.

The B2C firm implemented the cross-selling strategy by sending promotion incentives (through direct marketing) to relevant customers to induce cross-buying. It used proprietary cross-sell models to determine what

product to offer to which customer, and it varied the type of promotion incentives it offered to correspond with the type and lifetime value of each customer. High-CLV customers, for example, were offered unconditional incentives to purchase from a new product category, while some medium/low-CLV customers and all negative-CLV customers were offered cross-buy incentives contingent on minimum spending (\$30 on average).

Implementation of these CRM strategies had a direct influence on the principal drivers of CLV (contribution margin, number of purchases, recency of purchase, cross-buying, and so on), which in turn increased the overall CE of the firm. As shown in Table 6B, the various CRM strategies resulted in an average CE lift of 19.4% for the B2B firm and 23.3% for the B2C firm during the observation period.

Table 6B also summarizes the contribution to lift in CE made by high-CLV, medium/low-CLV, and negative-CLV customers. As expected, the high-CLV customers offer the highest lift in CE on application of relevant CRM strategies.

Evaluating the impact on stock price

The marketing and sales teams of the two firms do a fine job of successfully implementing CLV-based CRM strategies to lift the CE of the firm, as Table 6B shows. However, does this translate into any positive impact on the stock value of the firm? To find out, we compare the movement in stock price of the two firms nine months before and after the implementation of the CLV-based CRM strategies (i.e., nine months before and after July 2006),⁴ as shown in figures 5A and 5B. We find that the percentage of stock price increases (relative to July 2006 stock price) for the B2B firm and B2C firm are about 32.8% and 57.6%, respectively, at the end of the observation window (i.e., nine months following the CLV-based strategy implementations). However, to what extent can we predict such an increase in stock price on the basis of changes in CE?

We apply the CE–MC relationship developed in Part 1 to predict the MC of the firm for each future month t and repeat this procedure (i.e., update the CE and MC prediction for each month as new information becomes available) between the observation period August 2006 to April 2007. This means we compute nine monthly values of MC based on CE predictions. We then divide MC by the number of outstanding shares of the firm to arrive at nine monthly average values of the stock price of the firm. We plot these values over time and compare them with the actual average values of the stock price of the two firms, as shown in Figures 6A and 6B. The results indicate that we are able to track the actual movement of stock prices within a maximum deviation range of 12–13%.

It is evident that implementation of CLV-based marketing strategies does increase the stock price of the firm in a way that can be reasonably predicted with customer-level measures of the CE of the firm. In such a scenario, of interest to the CEO would be whether such an increase in stock price can beat market expectations. In other words, can the increase in the stock prices of the two firms be attributed to shareholder value creation? To answer this question, we compare the stock price movement of the two firms with the S&P 500 index during the observation period, as shown in figures 7A and 7B. The S&P 500 index is commonly used by financial analysts to benchmark the stock performance of a firm (especially for large firms such as the two firms used in this study). To adjust for differences in scale, we normalize the stock price and the index value movements to percentage changes with respect to a reference value. The average value of the stock price of the two firms and the S&P 500 index on July 2006 are chosen as the reference values. This date corresponds to the time point immediately preceding the CRM strategy implementation, and hence is an appropriate reference point. Figures 7A and 7B show that the stock prices of both firms consistently outperform the S&P 500 during the observation window. The

Figure 5A
Actual Stock Price Movement of the B2B Firm

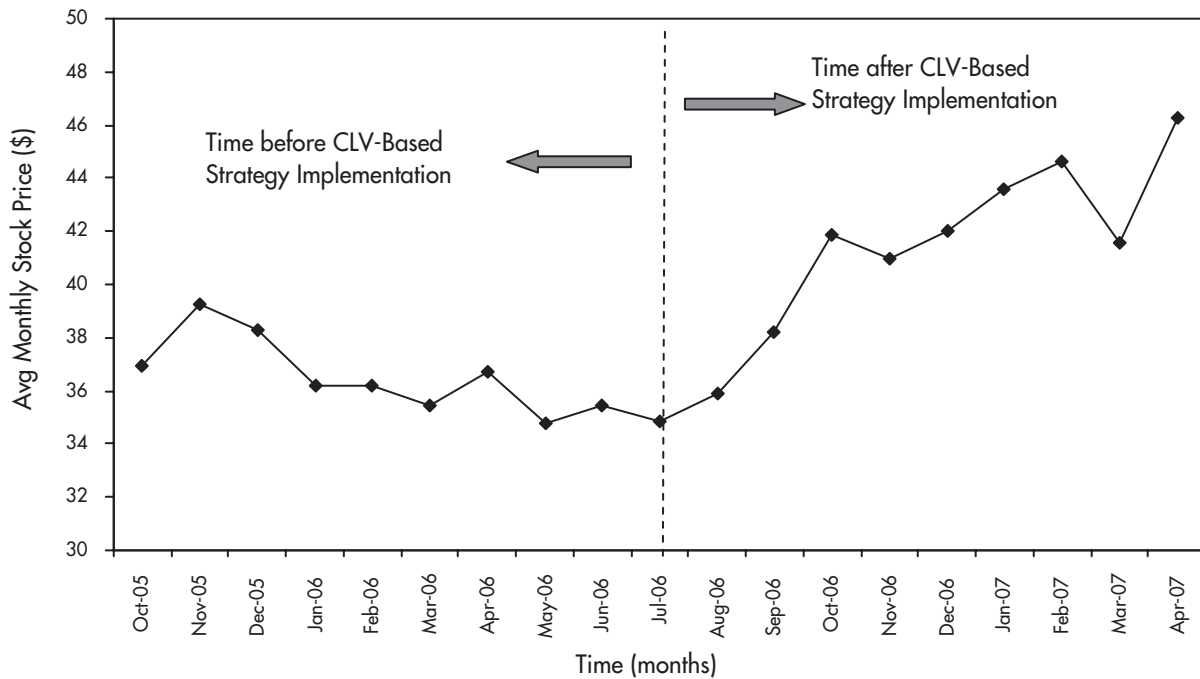
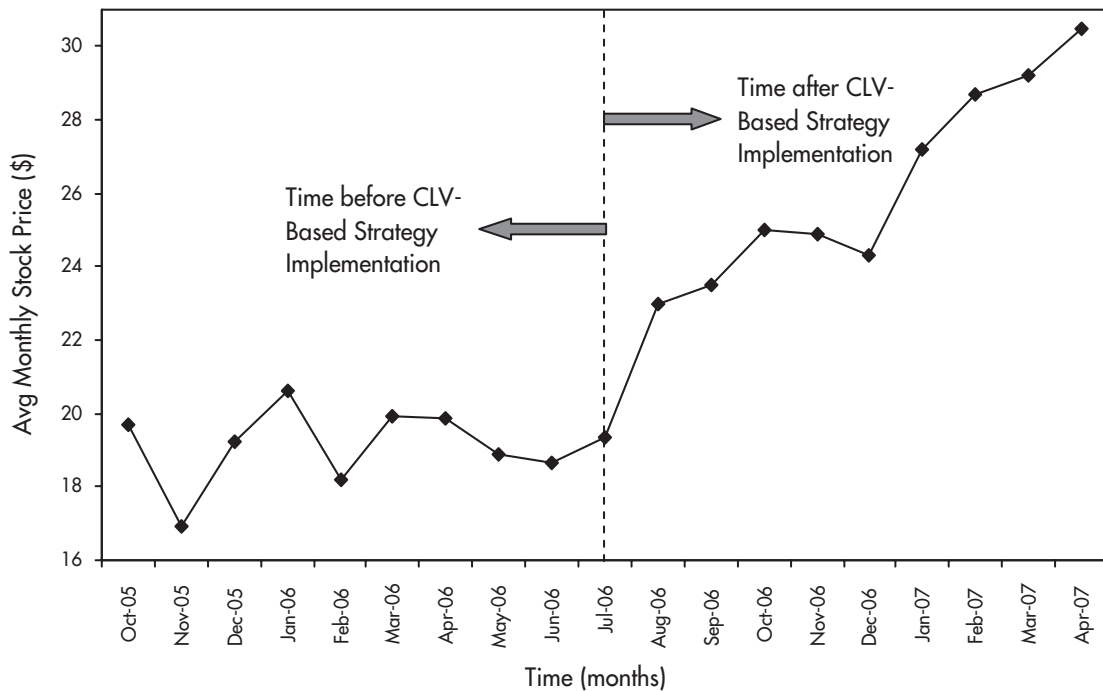


Figure 5B
Actual Stock Price Movement of the B2C Firm



B2B firm outperforms the S&P 500 by two times as much, while the B2C firm outperforms the S&P 500 by 3.6 times as much.

If we take the performance of the S&P 500 index as the baseline expected performance of the two firms, then the area between the curves

Figure 6A
Actual versus Predicted Stock Price of the B2B Firm

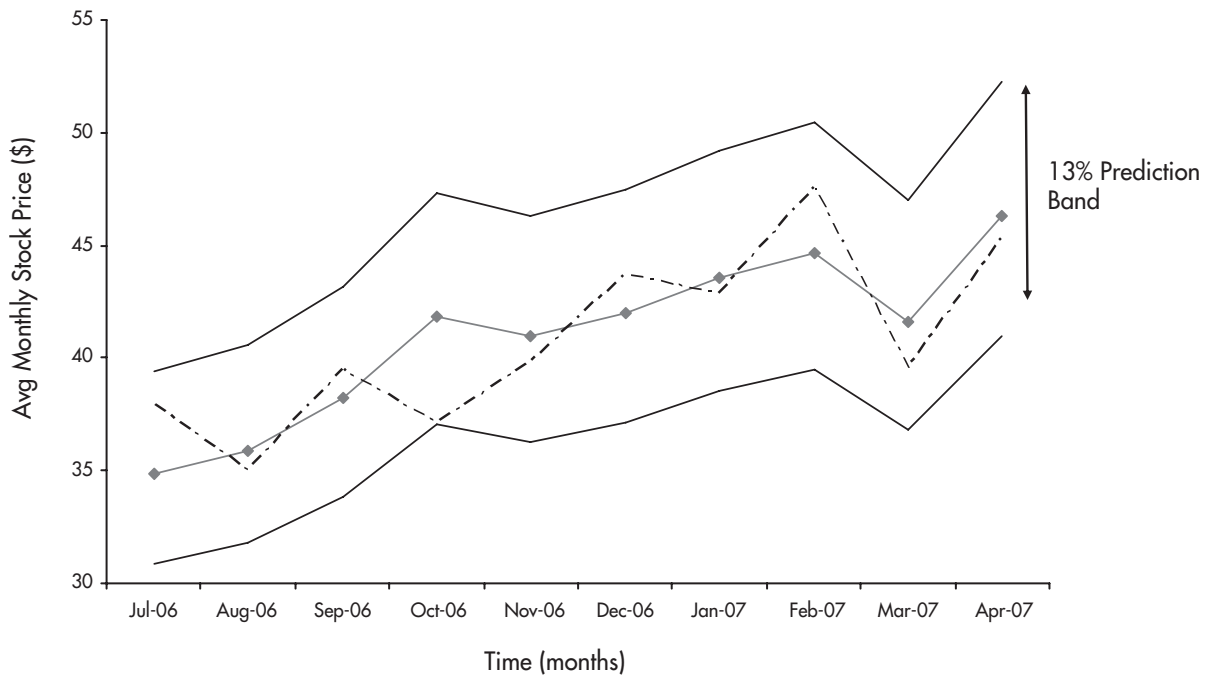
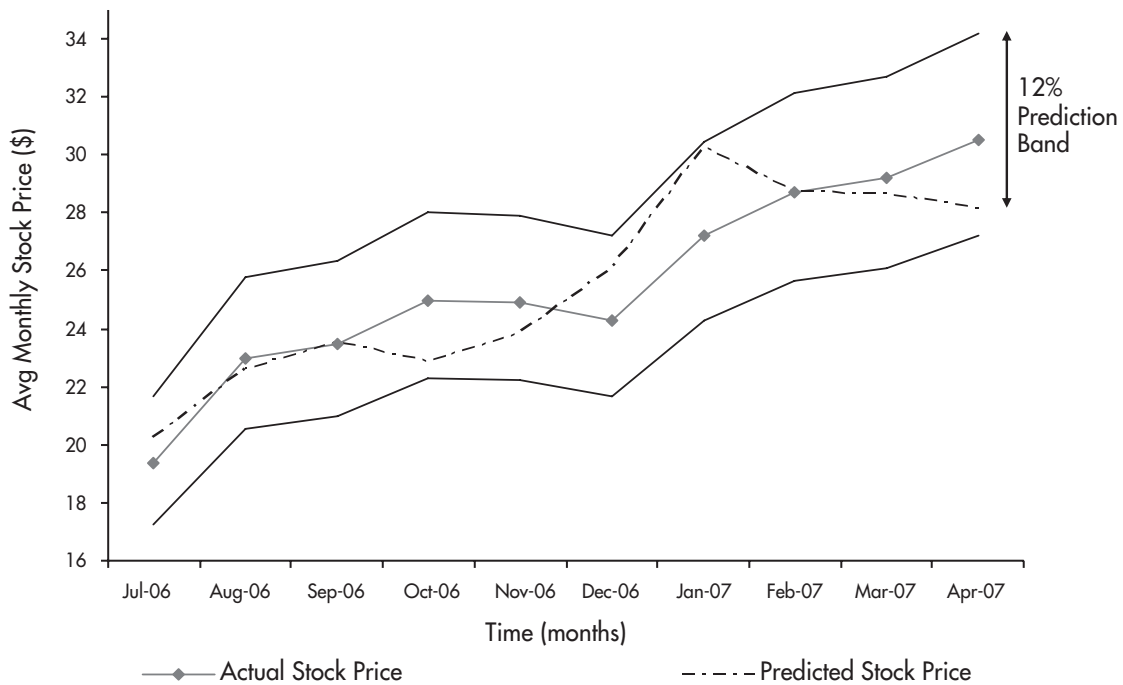


Figure 6B
Actual versus Predicted Stock Price of the B2C Firm



(denoted by A and B in Figures 7A and 7B, respectively) can be attributed to shareholder value creation due to CLV-based marketing

strategies implemented by the two firms' marketing and sales teams. Note that the area between the two curves increases over time.

Figure 7A
Comparison of B2B Firm's Stock Price Movement with the S&P 500 Index

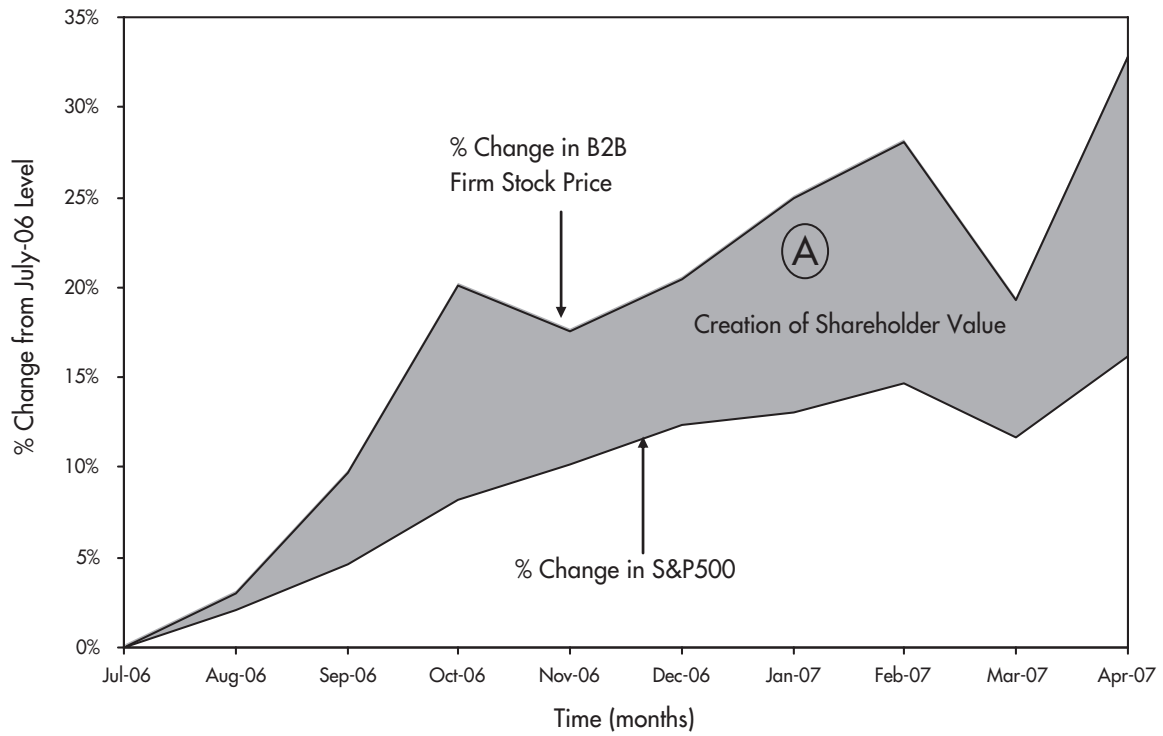
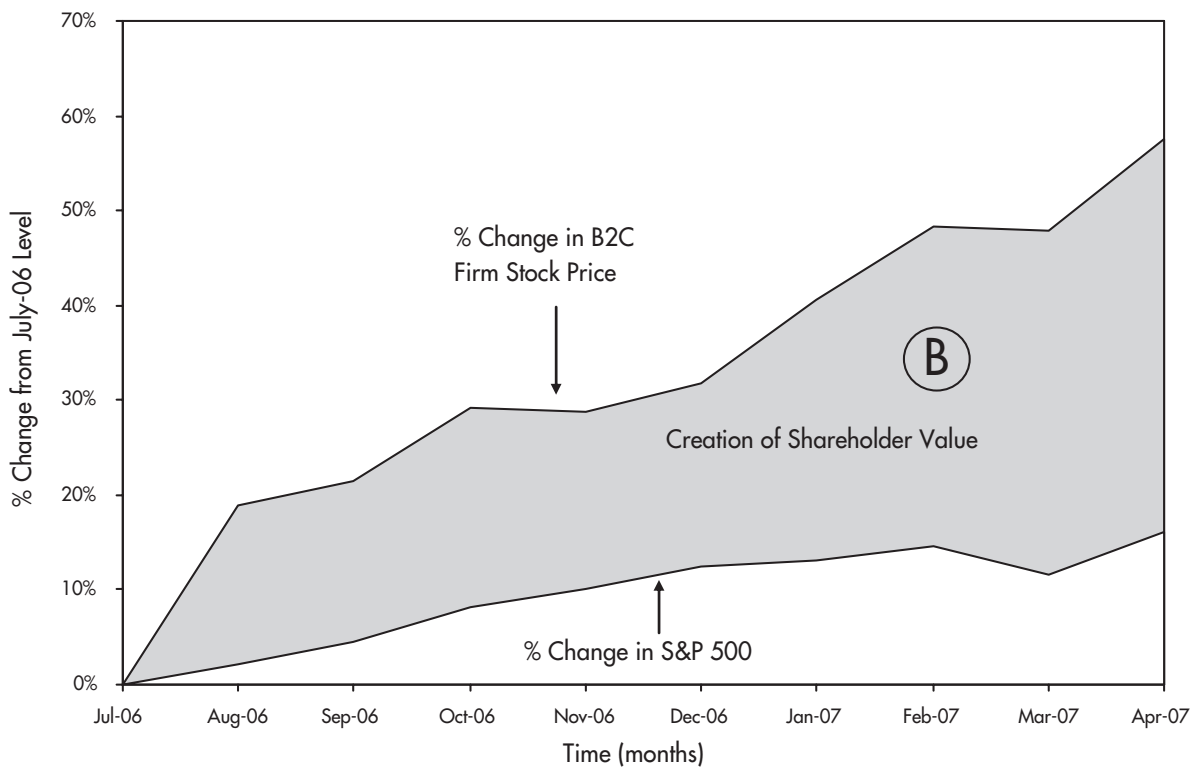


Figure 7B
Comparison of B2C Firm's Stock Price Movement with the S&P 500 Index



This is to be expected, given that some lead time is necessary before the tactics and strategies deployed by the two firms can be expected to start producing concrete results in the form of dollar increases in revenue and stock price. Because the purchase cycle of B2B firms' customers is longer than the purchase cycle of B2C firms' customers, the B2C firm shows a faster rise in stock price than the B2B firm.

We also benchmark the stock performance of the two firms against the average stock performance of three of their closest competitors (as identified by the two firms and leading stock analysis portals). We find that the B2B firm's stock increases by 32.8% during the observation period, while its competitors' stock goes up by 12.1% (on average) over the same period. Similarly, the B2C firm's stock increases by 57.6%, while its competitors' stock goes up by only 15.3% (on average) over the same period.

Managerial Implications

Expanding the role of marketing and the marketer

One of the biggest challenges facing marketers today is their marginalization in the firm (Nath and Mahajan 2008). Possible reasons are marketers' failure to persuasively and precisely prove their worth and their inability to relate marketing performance to reliable financial metrics (Rust, Lemon, and Zeithaml 2004). The proposed framework in this study enables marketing managers to deploy marketing initiatives at the customer level and to measure their outcome in the form of market capitalization, or the firm's market value. In other words, marketers can quantify the impact of the marketing organization toward the boardroom's primary agenda of increasing the market capitalization value of the firm. Consequently, implementation of the proposed framework bears the promise of augmenting both the scope and the importance of the marketer and the marketing function in virtu-

ally any organization. One direct benefit of this might be the marketing function's being allocated more of the firm's resources relative to competing functions such as manufacturing and R&D.

Aligning the CMO's objectives with the CFO's agenda

Our study offers a means of demonstrating how marketing strategies and tactics affect financial measures. By doing so, we hope to bridge the gap between the CMO's objectives and the CFO's agenda. This is important because more often than not the performance metrics used by marketing (such as advertisement recall, brand awareness, customer satisfaction scores, net promoter score) are not well appreciated by the CFO, who prefers to see the performance impact in a more familiar, financial language. The performance metric of market capitalization proposed in our study is not only well understood by the CFO but also by the CEO and other important stakeholders of the firm, such as the shareholders.

Managing customers' profits and cash flow risks

Past research has clearly showed the benefits of customer-centricity (e.g., Shah et al. 2006) and how CLV- or CE-based strategies can increase a firm's profitability (e.g., Kumar et al. 2008; Rust, Lemon, and Zeithaml 2004). This study goes a step further to empirically demonstrate the effects of different customer-specific measures (e.g., cross-buying, spending level, purchase frequency, relationship duration and demographic/firmographic variables) directed at different customers (due to customer heterogeneity) on future profits. Furthermore, our framework recognizes that future profit streams are susceptible to risks that can be quantified through customer-centric measures such as share of wallet and variance in CLV computation. Consequently, our framework can help marketers to manage profit and risk simultaneously through specific marketing interventions directed at specific customers.

Limitations and Future Directions

This study addresses the substantive topic of how marketers can increase the market capitalization of the firm. While our findings have significant managerial implications, we hope to motivate researchers to continue to advance this exciting stream of research. Important issues that future studies might address include:

Sustainability of stock price gains

Our study shows how increase in customer equity can be linked to increase in stock price. We show that the relationship exists for at least nine months after implementation of the relevant customer management strategies. However, it would be interesting to test empirically whether this holds true for longer time horizons. Furthermore, it would be interesting to see whether stock price gains are sustained when competitive actions and reactions are factored in. For example, what would have happened if the marketing tactics of the two firms used in the study were imitated by their competitors? Would the stock price have risen by the same level? What happens if competitors adopt a CLV-based framework of their own, replicating the strategic actions of the two firms? Would this reduce the firms' gain in market value? These are certainly exciting avenues for future research.

Applicability of framework

Our study is more suitable for relatively large and mature publicly traded firms whose primary source of revenue is from doing business with its customers. Some firms may have other sources of sizeable income, such as investments, rental fees, licensing fees, and so on. In such cases, Equation 11 should be modified to include more terms (in addition to the CLV) to acknowledge the additional sources of cash flow that could significantly impact the MC of the firm. Furthermore, in our study, CLV is estimated over a future time horizon of three years. During this time period, both firms used in the study anticipated continuous

growth and non-saturation of their market. However, this may not hold true for firms in industries such as telecommunications that are experiencing market saturation. Also, our assumptions may not be valid over longer time horizons, as firms may experience increasing difficulty acquiring profitable customers and hence diminishing contribution margins over time. Future studies can look into these issues by extending the framework to different industry settings and time horizons.

Efficient-market hypothesis

Our framework is based on the assumptions of the efficient-market hypothesis, which means we expect the stock market to correctly respond to changes in the customer equity of the firm. However, if the efficient-market theory hypothesis is challenged, our assumptions may be proved incorrect. For example, research in behavioral finance has shown that investors tend to react more strongly (and often irrationally) to bad news as compared to good news (Kahneman and Tversky 1979). Similarly, in emerging markets, stock prices are often influenced by investor sentiments rather than economic fundamentals (Barberis, Shleifer, and Vishny 1998). In such a market, the relationship between customer equity and market capitalization will be weaker than what we found in this study.

Investing in customers versus investing in brands

Our study gives examples of how investment in customer-based initiatives (such as cross-buy and optimal resource allocation) can increase the customer equity and hence the market capitalization of the firm. What about investing in brands? Our contention is that firms should continue to invest in brands as long as that investment helps to increase customer equity and lower cash flow risk. For example, investment in brand-related initiatives such as advertisements can increase the share of wallet customers give to the firm or increase their purchase probability by increasing their brand awareness. Rust, Zeithaml, and

Lemon (2004) offer a compelling discussion on how investment in brands should be governed by customer equity. Kumar, Luo, and Rao (2008) present an empirical framework to link brand value to customer lifetime value.

Conclusion

In conclusion, our findings are intended to demonstrate empirically the power of marketing to shape firm value. Our ulterior goal is to equip the marketer with the means to broaden the scope and importance of marketing. Will the CMO rise to the challenge? Will the CMO be able to justify his or her role and

turn around the lamentable trend of being the most frequently fired executive, becoming instead a highly valued executive of the organization? The answer has far-reaching implications for the future of marketing and how the function is perceived within firms.

Acknowledgments

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Appendix: Technical Details

The formulation of equations 2, 3, and 4 is similar to the structure of the "seemingly unrelated regression" model, in which the predictor variables in the equations need not be the same. We assume the covariance structure of the errors in equations 2, 3, and 4 to be:

$$\begin{bmatrix} u_{1ij} \\ u_{2ij} \\ u_{3ij} \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_{22} & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_{33} \end{bmatrix} \right) = N_3(0, \Sigma_y) \quad (A1)$$

Such a covariance structure allows correlation across the residual terms. We fix σ_{11} to be equal to 1 to ensure model identification. The covariance structure of the errors accounts for any unobserved dependence between MT_{ij} , Buy_{ij} , and CM_{ij} . By letting $\beta = [\beta_1, \beta_2, \beta_3]$, and $\alpha = [\alpha_1, \alpha_2, \alpha_3]$, the system-of-equations model gives rise to the likelihood specified in Equation 5.

The customer-specific intercept terms for equations 2, 3, and 4 are obtained from a multivariate normal distribution:

$$\alpha_i \sim MVN(\emptyset Z_i, \Sigma_\alpha) \quad (A2)$$

where Z_i is a $p * 1$ vector of customer characteristics; \emptyset is a $3 * p$ matrix of coefficients for the customer characteristics; Σ_α is a $3 * 3$ variance-covariance matrix; p = number of customer characteristics that are used to capture heterogeneity.

The customer-specific coefficients for equations 2, 3, and 4 are obtained from a multivariate normal distribution:

$$\beta_i \sim MVN(\Psi Z_i, \Sigma_\beta) \quad (A3)$$

where Z_i is a $p * 1$ vector of customer characteristics; Ψ is a $3 * p$ matrix of coefficients for the customer characteristics; Σ_β is a $3 * 3$ variance-covariance matrix; p = number of customer characteristics that are used to capture heterogeneity.

For both the B2B firm and the B2C firm, $p = 3$. For estimation, we assume diffuse and conjugate priors for the model parameters. We assume multivariate normal priors for Ψ and \emptyset . Let d_Ψ denote the dimension of the Ψ vector, then the prior specification of Ψ is given as $\Psi \sim MVN(\alpha_\Psi, \Sigma_\Psi)$, where α_Ψ is a d_Ψ -dimensional column vector of zeros, and $\Sigma_\Psi = 100I_{d_\Psi}$; I_{d_Ψ} is a $d_\Psi * d_\Psi$ -dimensional identity matrix. Similarly, let d_\emptyset denote the dimension of \emptyset , then the prior specification of \emptyset is given as $\emptyset \sim MVN(\alpha_\emptyset, \Sigma_\emptyset)$, where α_\emptyset is a d_\emptyset -dimensional column vector of zeros, and $\Sigma_\emptyset = I_{d_\emptyset}$; I_{d_\emptyset} is a $d_\emptyset * d_\emptyset$ -dimensional identity matrix.

Inverse Wishart priors are assumed for the variance parameters. The prior specification for Σ_β is given as $\Sigma_\beta = IW(\rho I_{d_\Psi}, \rho)$, where $\rho = 15$ and I_{d_Ψ} is a $d_\Psi * d_\Psi$ -dimensional identity matrix. Similarly, the prior specification for Σ_α is given as $\Sigma_\alpha = IW(\rho I_{d_\emptyset}, \rho)$, where $\rho = 15$ and I_{d_\emptyset} is a $d_\emptyset * d_\emptyset$ -dimensional identity matrix. The prior specification for Σ_y is given as $\Sigma_y = IW(15I_3, NT)$, where I_3 is a $3 * 3$ -dimensional identity matrix. For details on data augmentation, please refer Cowles, Carlin, and Connett (1996).

Notes

1. We also tried alternative functions of CLV_T , such as $\text{Log}(CLV_T)$ and CLV_T^2 . However, the linear form of CLV_T as specified in Equation 11 provided the best fit.
2. We tested for issues related to autocorrelation of error terms using standard diagnostic tests and found that autocorrelation does not significantly impact our results.
3. CLV prediction beyond three years deteriorated the relationship between CE and MC. This could be due to loss of prediction efficiency (at the individual customer level) beyond three years.
4. Note that the firms actually rolled out the strategies over a period of three months from June to August 2006. Consequently, we would expect to begin seeing the full benefits of the strategies after August 2006.

References

- ANA-Booz Allen Hamilton (2004), *Are CMOs Irrelevant? Organization, Value, Accountability, and the New Marketing Agenda*. New York, N.Y.: Booz Allen Hamilton.
- Anderson, Eugene W., Claes Fornell, and Sanal K. Mazvancheryl (2004), "Customer Satisfaction and Shareholder Value." *Journal of Marketing* 68 (4), 172–85.
- Barberis, Nicholas, Andrei Shleifer, and Robert Vishny (1998). "A Model of Investor Sentiment." *Journal of Financial Economics* 49, 307–43.
- Bauer Hans H., Maik Hammerschmidt, and Matthias Braehler (2003), "The Customer Lifetime Value Concept and Its Contribution to Corporate Valuation." *Yearbook of Marketing and Consumer Research*, 1, 47–66.
- Berger, Paul D., Naras Eechambadi, Morris George, Donald R. Lehmann, Ross Rizley, and Rajkumar Venkatesan (2006), "From Customer Lifetime Value to Shareholder Value." *Journal of Service Research* 9 (2), 156–67.
- , and Nadal I. Nasr (1998), "Customer Lifetime Value: Marketing Models and Applications." *Journal of Interactive Marketing* 12 (1), 17–29.
- CMO Council (2007), *Define and Align the CMO*. Palo Alto, Calif.: CMO Council.
- Cowles, Mary K., Bradley P. Carlin, and John E. Connett (1996), "Bayesian Tobit Modeling of Longitudinal Ordinal Clinical Trial Compliance Data with Nonignorable Missingness." *Journal of American Statistics Association* 91(433), 86–98.
- Doyle, Peter (2000), *Value-based Marketing*. Chichester, U.K.: John Wiley & Sons.
- Fader, Peter, Bruce Hardie, and Ka Lok Lee (2005), "RFM and CLV: Using Iso-CLV Curves for Customer Base Analysis." *Journal of Marketing Research* 42 (November), 415–30.
- Fama, Eugene F. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25 (2), 383–417.
- Fleener, Wadne (2006), "Managing the Risky Business of Marketing." Available to subscribers at https://www.marketingprofs.com/premium_preview.asp?adref=&file=%2F6%2Ffleener1%2Easp.
- Fornell, Claes, Sunil Mithas, Forrest Morgeson, and M. S. Krishnan (2006), "Customer Satisfaction and Stock Prices: High Returns, Low Risk." *Journal of Marketing* 70 (1), 3–14.
- Gupta, Sunil, and Donald R. Lehmann (2005), *Managing Customers as Investments: The Strategic Value of Customers in the Long Run*. Upper Saddle River, N.J.: Wharton School Publishing.
- , ———, and Jennifer Stuart (2004), "Valuing Customers." *Journal of Marketing Research* 41 (February), 7–18.
- Joshi, Amit M., and Dominique M. Hanssens (in press), "Movie Advertising and the Stock Market Valuation of Studios." *Marketing Science*.
- Kahneman, Daniel, and Amos Tversky (1979), "Prospect Theory: An Analysis of Decision under Risk." *Econometrica* 47 (2), 263–91.
- Kerin, Roger A., and Raj Sethuraman (1998), "Exploring the Brand Value-Shareholder Value Nexus for Consumer Goods Companies." *Journal of the Academy of Marketing Science* 26 (4), 260–73.
- Kim, Namwoom, Vijay Mahajan, and Rajendra K. Srivastava (1995), "Determining the Going Market Value of a Business in an Emerging Information Technology Industry: The Case of the Cellular Communication Industry." *Technological Forecasting and Social Changes* 49 (3), 257–79.

- Kumar, Nirmalya (2004), *Marketing as Strategy: Understanding the CEO's Agenda for Driving Growth and Innovation*. Boston, Mass.: Harvard Business School Press.
- Kumar, V., Man Luo, and Vithala Rao (2008), "Linking an Individual's Brand Value to Customer Lifetime Value." Atlanta, Ga.: Georgia State University, Atlanta, Working Paper.
- , Denish Shah, and Rajkumar Venkatesan (2006), "Managing Retailer Profitability—One Customer at a Time." *Journal of Retailing* 82 (4), 277–94.
- , Rajkumar Venkatesan, Timothy Bohling, and Denise Beckmann (2008), "The Power of CLV: Managing Customer Value at IBM." *Marketing Science* 27 (4), 585–99.
- Lewis, Michael (2004), "The Influence of Loyalty Programs and Short-term Promotions on Customer Retention." *Journal of Marketing Research* 41 (August) 281–92.
- (2005), "A Dynamic Programming Approach to Customer Relationship Pricing." *Management Science* 51(6), 986–94.
- Libai, Barak, Eitan Muller, and Renana Peres (2006), "The Diffusion of Services." Tel Aviv, Israel: Tel Aviv University, Working Paper.
- Mizik, Natalie, and Robert Jacobson (2008), "The Financial Value Impact of Perceptual Brand Attributes." *Journal of Marketing Research* 45 (February), 15–32.
- Nath, Pravin, and Vijay Mahajan (2008), "Chief Marketing Officers: A Study of Their Presence in Firms' Top Management Teams." *Journal of Marketing* 72 (1), 65–81.
- New York Stock Exchange Group (2007), *NYSE CEO Report 2007: Planning for Growth, Valuing People*. New York, N.Y.: Opinion Research Corporation.
- Perkins-Munn, Tiffany, Lerzan Aksoy, Timothy L. Keiningham, and Demitry Estrin (2005), "Actual Purchase as a Proxy for Share of Wallet." *Journal of Service Research* 7 (3), 245–56.
- Reinartz, Werner J., and V. Kumar (2000), "On the Profitability of Long-Life Customers in a Noncontractual Setting: An Empirical Investigation and Implications for Marketing." *Journal of Marketing* 64 (4), 17–35.
- , and ——— (2003), "The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration." *Journal of Marketing* 67 (1), 77–99.
- 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 (2004), "Customer-Centered Brand Management." *Harvard Business Review* 82 (9), 110–8.
- Shah, Denish, Roland T. Rust, A. Parasuraman, Richard Staelin, and George S. Day (2006), "The Path to Customer Centricity." *Journal of Service Research* 9 (2), 113–24.
- Sorescu, Alina, Venkatesh Shankar, and Tarun Kushwaha (2007), "New Product Preannouncements and Shareholder Value: Don't Make Promises You Can't Keep." *Journal of Marketing Research* 44 (August), 468–89.
- Srinivasan, Shuba, and Dominique M. Hanssens (in press), "Marketing and Firm Value." *Journal of Marketing Research*.
- Srivastava, Rejendra K., Tasadduq A. Shervani, and Liam Fahey (1998), "Market-based Assets and Shareholder Value: A Framework for Analysis." *Journal of Marketing* 62 (1), 2–18.
- Tobin, J. (1969), "A General Equilibrium Approach to Monetary Theory." *Journal of Money, Credit and Banking* 1 (January), 15–29.
- Venkatesan, Rajkumar, and V. Kumar (2004), "A Customer Lifetime Value Framework for Customer Selection and Optimal Resource Allocation Strategy." *Journal of Marketing* 68 (4), 106–25.
- , V. Kumar, and Timothy Bohling (2007), "Optimal Customer Relationship Management Using Bayesian Decision Theory: An Application for Customer Selection." *Journal of Marketing Research* (November), 579–94.
- Villanueva, Julian, and Dominique M. Hanssens (2007), "Customer Equity: Measurement, Management and Research Opportunities." *Foundation and Trends in Marketing* 1 (1), 1–95.
- Webster, Frederick E., Alan J. Malter, and Shankar Ganesan (2003), "Can Marketing Regain a Seat at the Table?" Cambridge, Mass.: Marketing Science Institute, Report No. 03-113.

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