MARKETING SCIENCE INSTITUTE

MSI Reports

2005

WORKING PAPER SERIES

ISSUE FOUR

NO. 05-004

M A R K E T I N G   S C I E N C E   I N S T I T U T E

MSI Reports

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Marketing Science Institute
1000 Massachusetts Avenue
Cambridge, MA
02138-5396

Phone: 617.491.2060
Fax: 617.491.2065
www.msi.org

MSI Reports (ISSN 1545-5041) is published quarterly by the Marketing Science Institute.

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Selecting Valuable Customers Using a Customer Lifetime Value Framework

Rajkumar Venkatesan, V. Kumar, and Timothy Bohling

Customer lifetime value is widely used to customize marketing communications and target customers, despite little research on ROI implications. This study compares CLV to other metrics, and develops a methodology for maximizing return on marketing actions.

Rajkumar Venkatesan is Assistant Professor in Marketing, and **V. Kumar (VK)** is the ING Chair Professor in Marketing and Executive Director, ING Center for Financial Services, both at the University of Connecticut. **Timothy Bohling** is Director, Worldwide Market Intelligence at IBM Corporation.

Report Summary

What are the ROI implications of using customer lifetime value (CLV) to customize marketing actions and target customers? Given the uncertainty of predicting customer behavior, how can managers optimize individual marketing communications to maximize return?

To answer these questions, authors Venkatesan, Kumar, and Bohling propose a customer selection framework that explicitly accounts for uncertainty in predicting customer behavior over the long term by using a Bayesian approach. Further they develop a model for estimating CLV that accounts for the dependence between purchase timing and contribution margin and that can be applied in a Bayesian framework. Using customer data from a large multinational firm that sells high technology products and services in a business-to-business (B2B) context, they examine the ROI implications of using CLV for customer selection as compared to other commonly used metrics.

Among their findings:

- Accounting for the dependence between purchase timing and contribution margin improves accuracy in predicting CLV.
- Irrespective of the metric, selecting customers using a full-Bayesian approach—which offers a distribution of response parameters—leads to better identification of valuable customers.
- When selecting customers, in addition to contribution margin, managers should focus on the expected costs of serving a customer. The optimal costs derived based on estimates of customer's historic responsiveness to marketing communication provide a good estimate of the expected costs of serving a customer.
- The optimal level of investment that maximizes CLV does not necessarily maximize current period customer value (CPCV), share of wallet (SOW), or recency, frequency, and monetary value (RFM).
- Using a CLV measure for customer selection provides a better ROI and value than other metrics such as CPCV, SOW, RFM, and expected spending potential (ESP).

Overall, the study suggests, managers can attain the best accuracy in targeting valuable customers by using (1) a Bayesian approach, (2) optimal marketing costs as an estimate of expected costs, and (3) the customer lifetime value metric. ■

Introduction

Across industries, marketing practitioners are under pressure to measure and maximize return on marketing actions in order to improve the value of the firm. They must identify marketing assets in which to invest and be able to justify how these assets provide the potential for sustained value[1] in the long run (Rust et al. 2004). Customers are considered a critical element of the firm's marketing assets and effective management of customer assets is expected to directly impact firm profits (Bolton, Lemon, and Verhoef 2004). Thus, managers are increasingly focused on measuring the value of customer assets, understanding the impact of marketing expenditures on these metrics, and actively utilizing marketing actions to maximize customer metrics and hence firm value (Webster 1992).

A number of customer performance metrics have been proposed to measure the value of customer assets, to guide the selection of customers to target for marketing communications, and to allocate marketing resources. These include customer lifetime value (CLV), past customer value (PCV), share of wallet (SOW), customer lifetime duration (CLD), and recency, frequency, and monetary value (RFM) (Kumar and Reinartz 2006; Venkatesan and Kumar 2004; Reinartz and Kumar 2003).

Among these metrics, CLV has been recommended (Hanssens 2003; Venkatesan and Kumar 2004) and is being widely adopted across industries—direct marketing, financial services, and business-to-business, among others—to prioritize marketing actions and target customers (Rust et al. 2004). Among retained customers[2] those selected for marketing expenditure based on CLV are shown to provide more future value than customers selected based on customer lifetime duration (Reinartz and Kumar 2003), past customer value, past period revenue, and share of wallet (Venkatesan and Kumar 2004). However, these studies do not consider the resources required to improve the contribution margin obtained from customers selected based on CLV relative to those selected based on the other metrics.

In fact, current evidence indicates that the top 15% of the customers selected based on CLV require more resources for providing revenue relative to customers selected based on other metrics (Venkatesan and Kumar 2004). When faced with a budget constraint, does the higher per-customer value from those customers selected based on CLV outweigh the lesser number of customers that can be selected based on CLV? The answer is not clear.

Consider a scenario where a marketing manager has a budget of $100 to spend on communicating with customers. If each customer selected based on CLV requires $20 in communication costs to obtain a contribution margin of $80, then the manager can only select the top 5 customers rank-ordered based on CLV and obtains a total value of $400. However, if each customer selected based on SOW requires $10 to obtain a contribution margin of $50, the manager can select the top 10 customers rank-ordered based on SOW and obtain a total value of $500. Under this scenario, it seems beneficial for a manager to select customers based on SOW.

Managers recognize that channels of marketing communications and levels of communication need to be customized to individual customer preferences (Schultz 2003). Studies have indicated that value can be substantially improved when resources are allocated so that a long-term oriented and forward-looking metric such as CLV is maximized (Venkatesan and Kumar 2004). However, marketing practitioners and scholars face uncertainty when adopting customized optimal marketing investment guidelines for maximizing return. Specifically, there may be high opportunity costs for not contacting a nonresponsive customer beyond the optimal level that was derived based on expectations of the customer's behavior. While a field experiment can establish the causal link between using optimal marketing costs and higher returns, they are also very expensive.

An alternative approach to establish the benefits of customizing the marketing communications for individual customers when selecting and managing customers would be to conduct an empirical comparison of the total value obtained from customers selected based on the maximized measure of a metric (say CLV) versus those selected based on current or status quo measures of the metric. In this report, we therefore,

1. Provide a methodology that accommodates the uncertainty inherent in predicting customer behavior over the long term and provides a distribution of optimal contact levels that are expected to maximize a customer metric.

2. Suggest a proactive strategy that selects customers based on their maximized measure of a customer metric and the optimal resources required to maximize the metric.

3. Evaluate the ROI implications of selecting customers based on CLV as compared to the other metrics using both the proposed proactive strategy and the status-quo strategy.

A number of empirical studies have modeled customer/prospect response to marketing communications, however, they have not accounted for heterogeneity in customer revenues and marketing costs. Thus, a further aim of this study is to account for heterogeneity in customer revenues and marketing costs in our framework.

To illustrate our proposed framework, we use customer data from a large multinational firm that sells high technology products and services in a business-to-business (B2B) context. Each year, the firm contacts its customers through multiple channels: salesperson, direct mail (including promotional catalogs and e-mail), and telephone. With a limited annual marketing budget, the firm can contact only a fraction of current customers. To select customers for marketing communications, the firm uses the Heckman Two-Stage model (see Krishnamurthi and Raj 1988 for more details) as one of the key inputs and segments customers as "high," "medium," and "lowest" potential. The size of the segments is determined based on the current budget constraints for marketing communication.

With respect to proactive contacts, customers in the "high potential" segment are prioritized over the customers in the "medium potential" segment and so forth until all the resources allocated for the year are used. Customers are contacted through the multiple channels to encourage them to make purchases. The level of contacts in each channel is inversely proportional to the unit cost of communication in each channel. Thus, the highest number of contacts is through direct mail (the least expensive channel), followed by telephone and salesperson (the most expensive channel). Under the firm's current strategy, customers in all segments receive a similar proportion of the different types of communications.

The firm recognizes that there is a large variation across customers, even within the "highest potential" segment, in the number of contacts required for obtaining a response. Further, the firm wants to design marketing communication strategies that recognize the customer's lifetime value and maximize each customer's share of category requirements with its offerings. A key objective of the firm hence is to improve its forward-looking perspective in managing customers through optimization of its marketing resource allocation strategy for each customer.

Customer Selection Framework

In our context, the manager must adopt a metric for selecting customers to contact, and determine the level of resources to allocate in each communication channel, so as to maximize future value. He or she must make these decisions using predictions on how the customers would perform in the future on the metric. The predictions differ on their level of uncertainty; for example, CLV, which forecasts customer behavior over the long term (three years), is associated with higher levels of uncertainty than ESP, which predicts customer behavior over the short term.

Our proposed customer selection procedure consists of seven phases that are described below:

1. For each customer metric (m_l), we specify a model that links the customer metric to past marketing decision variables such as standard and rich contacts through salesperson, direct mail, and telephone; customer characteristics such as breadth of purchases, past contribution margin, transaction purchase frequency; firmographics such as the number of employees in the customer firm, size, and industry category; and customer-specific response parameters (B_i).

2. Using data estimated above, we estimate a distribution (or range) of most likely values for the response parameters for each customer that provides the best explanation of the variation in the customer metric. For example, the range of the response parameter for the variable breadth of purchases for a customer could be from .4 to .8.

3. We predict a distribution of the most likely values of the customer metric in future time periods ($\hat{m}_l$). The length of prediction interval varies for each metric. For example, using the response parameter range .4 to .8, for the variable breadth of purchases, the range of CLV for a customer, provided other factors are held constant, could be from $2,028 to $2,420.

4. We determine the optimal distribution of the marketing decision variables and the corresponding distribution of the maximized customer metric ($\hat{m}^*_l$). For example, if the CLV range for a customer is from $2,028 to $2,420, the range of maximized CLV could be from $3,107 to $3,946. We also compute the average of the optimal level of marketing decision variables from the distribution of optimal marketing decisions.

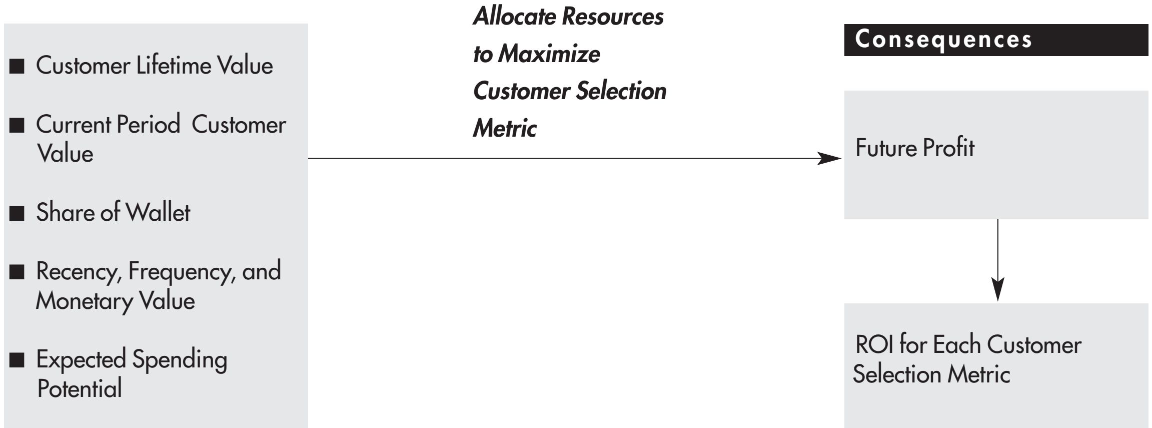
5. Picking a random sample of the maximized customer metric, we rank-order the customers in descending order of their maximized metric ($\hat{m}^*_{lj}$). The optimal marketing cost corresponding to the optimal level of the marketing decision variables obtained in phase 3 is used as an estimate of the marketing cost for the customer in the future time periods. Beginning from the top, we assign customers to a selection set until the sum of the estimated marketing costs for the selected customers equals the budget constraint (BC). This process is repeated for all the sampled values of the maximized metric resulting in multiple overlapping selection sets. For example, if we sample three maximized metrics each for customers C1, C2, C3, and C4 from their respective distributions, we would obtain three selection sets that could look like: S1 = {C1, C2, C4}, S2 = {C1, C3}, and S3 = {C3, C4, C2}.

6. For each customer, we count the number of times a customer is featured in the selection sets obtained in phase 5. We divide this number by the total number of selection sets to obtain the customer's selection probability. For example, given three selection sets such as S1 = {C1, C2, C4}, S2 = {C1, C3}, and S3 = {C1, C4, C2}, the selection probabilities for C1, C2, C3, and C4 are 1, .7, .3, and .7 respectively.

7. We rank-order customers in descending order of their selection probability obtained in phase 6. Beginning from the top, we assign customers to the final selection set until the sum of the average optimal marketing cost (obtained in phase 4) for the selected customers equals the budget constraint (BC). For example, if the selection probabilities for four customers C1, C2, C3, and C4 are 1, .7, .3, and .7 respectively, the final selection set would be S = {C1, C2, C4}.

A metric "m_l" is considered to have better selection capabilities if the customers in the final selection set for that metric provided higher value in the future time periods (π_{obs}) as compared to the customers in the final selection set of the other metrics. Figure 1 provides a graphic illustration of the objectives and design of our study.

Figure 1
A Conceptual Framework for Comparison of Customer Selection Metrics



We term the proposed customer selection strategy, a full-Bayesian approach. In contrast to this full-Bayesian approach to customer selection, traditional customer selection approaches use a single estimate of the response parameters (B_i) to obtain a single measure of the maximized customer metric in order to rank-order customers for customer selection (Kumar and Reinartz 2006). We term this approach as "selection using a plug-in estimate." Such a method depends heavily on the ability of the single response parameter estimate to accurately predict future customer behavior. However, the full-Bayesian approach allows managers to obtain a range (in other words, a distribution) of most likely values of the response parameters (B_i) and as a consequence the manager can also obtain a range for the maximized customer metric. This range (or distribution) of response parameters and of the maximized metric represent the uncertainty inherent in predicting future customer behavior. Finally, phases 5-7 allow managers to utilize the information on the range of response parameters and the maximized metric to obtain higher accuracy in their customer selection decisions.

Comparing Customer Metrics

Here, we compare the selection capabilities of CLV, CPCV, SOW, RFM, and expected spending potential (ESP). We develop the model specifications that predict the value of each customer metric and link the metric to marketing decision variables (i.e., the number of contacts in rich and standard modes), and customer characteristics (both past purchase behavior and firmographics) as described above.

Customer lifetime value

In general, CLV can be calculated as

$$CLV_i = \sum_{t=1}^{n} \frac{(Future\ contribution\ margin_{it} - Future\ cost_{it})}{(1+r)^t} \quad (1)$$

where
i = customer index,
t = time index,
n = forecast horizon, and
r = discount rate.

In our B2B study context this framework must incorporate the following factors: (1) that customers make several purchases within a single year, (2) that marketing costs are typically allocated at the beginning of a year, and (3) that marketing cost varies by the channel of communication. Accommodating for these factors, the CLV for a customer i, is measured as

$$CLV_i = \sum_{y=1}^{Ti} \frac{CM_{i,y}}{(1+r)^{t_{i,y}}} - \sum_{t=1}^{n} \frac{\sum_q c_{i,q,t} * x_{i,q,t}}{(1+r)^{t-1}} \quad (2)$$

where,

CLV_i = lifetime value of customer i

$CM_{i,y}$ = predicted contribution margin (contribution margin) from customer i in purchase occasion y, measured in dollars

r = discount rate for money (set at 1.25% monthly rate in our study)

$c_{i,q,t}$ = unit marketing cost, for customer i in channel q in year t

$x_{i,q,t}$ = number of contacts to customer i in channel q in year t

$t_{i,y}$ = predicted time period of purchase for customer i for the y^{th} purchase

n = number of years to forecast, and

T_i = predicted number of purchases made by customer i, until the end of the planning period.

In Venkatesan and Kumar (2004), the computation of CLV is based on predictions from a contribution margin model and a purchase frequency model that are estimated separately because they assume that contribution margin and purchase frequency are independent. Recent research in a B2C setting (for online grocery retailers) has shown that purchase frequency[3] and customer spending are in fact dependent on each other (Boatwright, Borle, and Kadane 2003). We therefore extend the framework proposed by Venkatesan and Kumar (2004) for predicting a customer's CLV by explicitly accommodating for the dependence between contribution margin and purchase timing.[4] This enables us to estimate both the contribution margin and purchase timing models in a single step and use the full-Bayesian approach proposed in this study. The joint contribution margin-purchase timing model consists of three components: segment membership, purchase timing, and contribution margin.

Segment Membership. We assume that the customers fall into K segments, and that purchase frequency and contribution margin are independent given membership in segment k. For example, say there are two segments ($K = 2$) of customers, active ($k = 1$) and inactive ($k = 2$). Customers that belong to segment 1 are expected to purchase more frequently and provide higher contribution margin than customers in segment 2. However, given that a customer belongs to segment 1, their level of purchase frequency does not determine their level of contribution margin or vice-versa.

Modeling segment membership provides an early warning indication of whether a customer is about to enter into an inactive state, and also accounts for the large abrupt changes in interpurchase times and contribution margins for a customer. The membership to segment k, for the j^{th} purchase occasion of customer i, is obtained from a function, $f_{w,k}(.)$, whose value is determined from marketing decision variables, customer characteristics, and customer-specific response parameters for the segment membership function (BW_i). The value of function, $f_{w,k}(.)$, can be interpreted as the segment membership probability ($w_{i,j,k}$) for segment k, and the sum of the segment membership probabilities are restricted to be equal to 1.

Purchase Timing. For customer i, the j^{th} interpurchase time is assumed to be a weighted sum of K generalized gamma (GG) distributions (corresponding to each segment k). The weights for each segment k is provided by the probability of segment membership ($w_{i,j,k}$). If the j^{th} purchase occasion for customer i is observed, then the function, $f_t(t_{i,j}|BT_{i,k})$, which is assumed to be distributed generalized gamma, provides the probability that the j^{th} purchase for customer i occurs at time period t, and is determined based on the response parameters $BT_{i,k}$. However, if the j^{th} purchase occasion for customer i is not observed (this can occur because the end of the data observation period need not coincide with a purchase made by a customer), then the function, $S_t(t_{i,j}|BT_{i,k})$, which is also assumed to be distributed generalized gamma, provides the probability of the j^{th} purchase occurring at a time

Table 1
Measuring CPCV, SOW, and RFM

Metric	Measurement
CPCV	The current period customer value (CPCV) is measured as the present value (at time period t) of the profits provided by a customer between time periods $t-1$ and t, and is represented as; $CPCV_{i,t} = \sum_{j=t-1}^{t} (CM_{i,j} - MC_{i,j})*(1+r)^{T-t^{*}_{ij}}$. Where, j is an index for purchase occasion and t^{*}_{ij} is the time period for purchase occasion j between time periods $t-1$ and t. For example, if 't' represents a quarter then t^{*}_{ij}s represent the purchase occasion within during quarter t.
SOW	Share of wallet (SOW) of a customer is measured as the ratio of the customer spending with the focal firm to the total customer spending in the entire product category in a given time period. By definition SOW is a proportion and is always between 0 and 1.* We use a logistic transformation of SOW as the customer metric in equation 9. The logistic transformation is represented as, $Log\left\{\frac{SOW_{it}}{1-SOW_{it}}\right\}$
RFM	RFM is measured as the composite score of the factor analysis of recency, frequency, and monetary value (as suggested by Venkatesan and Kumar 2004).

* In the case we observed zero revenues from a customer for a quarter, we added an arbitrarily small number (ξ= .001) to avoid taking the logarithm of zero. We varied ξ from .01 to .0001 and found no significant differences in the model estimates.

period greater than t and which is also determined based on the response parameters $BT_{i,k}$. Both $f_t(.)$ and $S_t(.)$ are determined by the same set of parameters $BT_{i,k}$ because for each customer at least one purchase occasion is observed and some purchase occasions are not observed.

Contribution Margin. The difference in contribution margin provided by a customer i, in between purchase occasions j and $j-1$ ($\Delta CM_{i,j}$), is assumed to be a weighted sum of K normal distributions. Similar to the interpurchase time distribution, the weights for each segment k is provided by the probability of segment membership ($w_{i,j,k}$). The mean, $M_{cm,i,j,k}$, of the normal distribution for the contribution margin model for k^{th} segment is given by the following relationship:

$$M_{cm,i,j,k} = f_{cm,k}(\text{lagged contribution margins, lagged interpurchase time intervals, industry category, } BC_{i,k}) \quad (3)$$

where $BC_{i,k}$ is the individual-specific response parameter corresponding to the drivers of contribution margin such as lagged contribution margins, lagged interpurchase time intervals, and industry category.

The set of parameters $\{BW_i, BT_{i,k}, BC_{i,k}\}$ represent the unknown customer-specific response parameters for the metric CLV. Once the updated response parameters ($B_{i,clv}$) are estimated, the predictions from the purchase timing and contribution margin models can be used to compute a customer's CLV using Equation 2.[5]

CPCV, SOW, and RFM

Table 1 illustrates how we measure CPCV, SOW, and RFM. For each of these metrics, we assume that the difference in the customer metric between time periods t and $t-1$ follows a normal distribution. Similar to the contribution margin component for CLV, the means of the normal distributions for CPCV, SOW, and RFM are given by the following relationships;

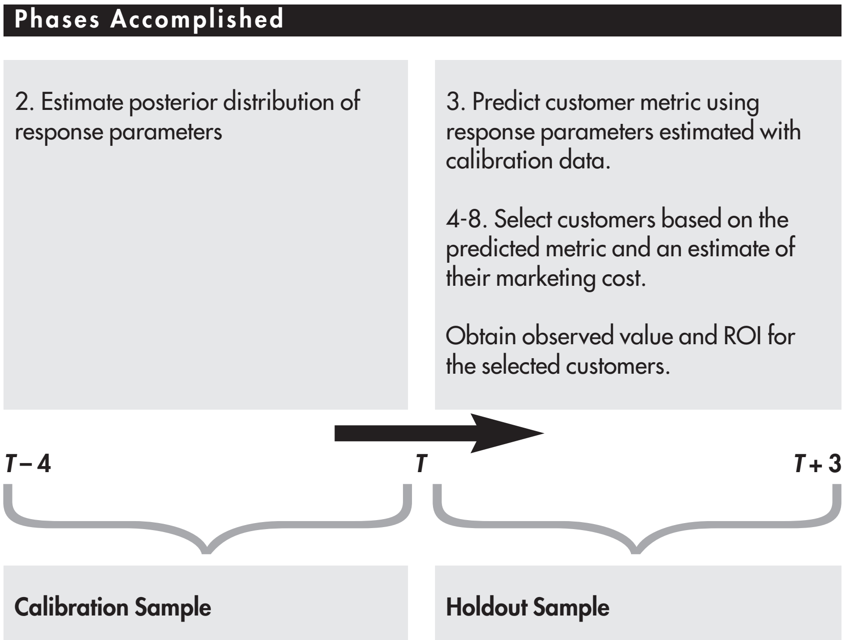
$$M_{cpcv,i,t} = f_{cpcv}(\text{marketing decision variables } (x_{d,i}), \text{ customer characteristics } (x_{cust,i}), B_{i,cpcv}) \quad (4a)$$

$$M_{sow,i,t} = f_{lsowv}(\text{marketing decision variables } (x_{d,i}), \text{ customer characteristics } (x_{cust,i}), B_{i,sow}) \quad (4b)$$

$$M_{rfm,i,t} = f_{rfm}(\text{marketing decision variables } (x_{d,i}), \text{ customer characteristics } (x_{cust,i}), B_{i,rfm}) \quad (4c)$$

$B_{i,cpcv}$, $B_{i,sow}$, and $B_{i,rfm}$ represent the customer-specific response parameters for the metrics CPCV, SOW and RFM respectively.[6]

Figure 2
Customer Selection Phases Performed in Calibration and Holdout Sample



Expected spending potential

The collaborating firm uses ESP as one of the key criteria to sort customers. ESP is computed from a Heckman Two-Stage Model (Krishnamurthi and Raj 1988). In this model, a logistic regression is used to predict whether a customer would purchase from the firm in time period t. Given purchase in time period t, a linear regression (ad-justed for the selectivity bias) is used to predict the revenue that is expected from the customer in time period t. The factors used to predict ESP are similar to CLV, CPCV, SOW, and RFM, and include the marketing decision variables and the customer characteristics. As part of this study, the collaborating firm used this procedure to provide us with the ESP score for each customer. However, under the current procedure the firm only computes response parameters that are common for all customers, that is, it does not account for heterogeneity in customer-specific parameters.

Data

We use data from a large multinational firm that sells a number of high technology products and services. The company's database focuses on business customers. The firm's products typically require maintenance and frequent upgrades. These factors result in variation in the interpurchase times and the number of purchases both within and across customers and provide justification for building a model to predict CLV, CPCV, SOW, RFM, and ESP. For our analyses we use two cohorts of customers. Customers were assigned to Cohort 1 (Cohort 2) if their first purchase with the manufacturer was made in the first quarter of 1997 (first quarter of 1998). For Cohort 1 (Cohort 2) we use the first 48 months (36 months) of data as the calibration sample to estimate the CLV, CPCV, SOW, RFM, and ESP models. We use the next 36 months of data for both Cohort 1 and Cohort 2 as the holdout sample to evaluate the effectiveness of the customer selection strategies. Figure 2 illustrates the phases in the proposed customer selection procedure that are accomplished using the calibration and holdout sample.

In our samples, we removed customers who had missing values for contacts through any of the communication modes, i.e., salesperson, direct mail, or telephone. We also restricted our sample to customers who had made at least five purchases. Overall, we had to remove 20% of the original cohort of customers for our analyses. We then randomly sampled 238 customers from Cohort 1 and 210 customers from Cohort 2 which resulted in 4,326 and 3,521 purchase occasions in cohorts 1 and 2, respectively. Each purchase occasion is used as an observation (j) for the joint purchase frequency-contribution margin model used to predict CLV. However, the purchase occasions are aggregated to the quarterly level for the models used to predict CPCV, RFM, and SOW. In other words, the time period, t, in equations 4a-4c represents a quarter. As a result, there are 16 (12) observations per customer resulting in a total sample

Table 2

Operationalization of Marketing Decision Variables, Customer Characteristics, and Control Variables[a]

Variable	Operationalization
Marketing Decision Variables	
Frequency of rich modes	Number of contacts made to the customer by the supplier firm in a month through sales personnel between two observed purchases
Frequency of standard modes	Number of contacts made by the supplier firm to the customer in a month through telephone direct mail between two observed purchases
Customer Characteristics	
Upgrading	Number of upgrades in product purchases until an observed purchase
Cross-buying	Number of different product categories that a customer has purchased
Bidirectional communication	Ratio of number of customer-initiated contacts to total number of contacts made to the customer (both customer initiated and supplier initiated) between two observed purchases
Returns	Number of products returned by the customer between two observed purchases
Frequency of Web contacts	Number of times the customer contacts the supplier through the Internet in a month between two observed purchases
Control Variables	
Size of the establishment	Number of employees in the customer firm
Industry category	SIC-based industry category that the customer firm belongs to

[a] The rationale and expected effects of these variables are provided in previous research (Bolton, Lemon, and Verhoef 2004; Reinartz and Kumar 2003; Venkatesan and Kumar 2004).

size of 3,808 (2,520) in Cohort 1(2) for the models used to predict CPCV, RFM, and SOW. Table 2 provides a description and the operationalization of the marketing decision variables (x_d) and customer characteristics (x_{cust}) used in our study to predict the various customer metrics. We recognize the fact that all the contact information for each customer may not be recorded in the data. However, we believe that the extent of missing information is not expected to vary systematically from one customer to another. Since our focus is on relative value across customers and across metrics, the missing information is not expected to substantially influence the conclusions.

As described earlier, we use two marketing decision variables—frequency of rich modes of contact and frequency of standard modes of contact—in this study. Similar to previous research (Reinartz, Thomas, and Kumar 2005; Venkatesan and Kumar 2004), we categorize rich modes as contacts through sales personnel and standard modes as contacts through either telephone or direct mail. Given previous empirical evidence that marketing contacts have a non-linear, inverted-U-shaped influence on customer behavior, we use a quadratic conversion (including both the linear and squared term) of the marketing decision variables in all the models. The marketing decision variables

(x_d) are measured as the number of contacts made through the rich and standardized modes in a month between two observed purchases (j and $j-1$) for the joint purchase frequency-contribution margin model. For the other models, the marketing decision variables are measured as the number of contacts made through the rich and standard modes in a given quarter (t).

The antecedents of customer value identified in previous literature (Reinartz, Thomas, and Kumar 2005; Venkatesan and Kumar 2004) form the basis for the selection of the covariates (x_{cust}) and include upgrading, cross-buying, returns, bidirectional communication,[7] and frequency of Web contacts. These customer characteristics (x_{cust}) can be classified as cumulative- and current-effects variables. The cumulative-effects variables include cross-buying and upgrading, and their values represent the total number of different products (for cross-buying) or upgrades that the customer has purchased until the current observation since birth. (As described earlier, the current observation represents a purchase occasion in the joint purchase frequency-contribution model and the current quarter in the models for CPCV, RFM, and SOW.) The current-effects variables include returns, bidirectional communication, and frequency of Web contacts. These are calculated based on the activities of the customer between the previous observation and the current observed purchase. In the joint purchase frequency-contribution margin model, the current-effects variables are calculated based on customer activities between the previous purchase occasion ($j-1$) and the current purchase occasion (j) and in the models for CPCV, RFM, and SOW they are calculated based on customer activities between the previous quarter ($t-1$) and the current quarter (t).

All the marketing decision variables and customer characteristics used in our analyses are *lagged* variables in order to address the possibility for endogeneity. Specifically, for observed purchase j, the cumulative-effects variables will represent activity of the customer since birth until observed purchase $j-1$. Similarly, for observed purchase j, the current-effects variables will represent activity of the customer (or supplier) between observed purchase $j-2$ and $j-1$. In addition to addressing the potential endogeneity issues, lagged variables are appropriate because, when selecting customers for targeting, the manager would need to predict the performance of a customer on each metric based on knowledge about customer activities until the current time period. Therefore, a customer metric model that uses lagged values of the marketing decision variables and the customer characteristics allows the manager to use the estimated parameters to directly predict future values of the corresponding metric.[8]

We included the two- and three-period lagged values of contribution margin and one-period and two-period lagged interpurchase time intervals as drivers for the joint purchase frequency-contribution margin model used to predict CLV. Similarly, we included the two-period lagged dependent variables as drivers in the models for each metric. For example, the two-period lagged CPCV was included as a driver in the model for CPCV, and the two-period lagged SOW was included as a driver in the model for SOW, and so forth. We also included firm size and industry category as control variables in all the models. In the next section, we present the results from the estimation of the models for the customer metrics.

Model Comparison

The explanatory power of the models, for the calibration sample, is computed using the log-marginal density measure (Newton and Raferty 1994, p. 21). In order to evaluate the predictive accuracy of the models, we re-estimate the model using all but the last observation in the calibration sample for each customer. We then use the model estimates to predict the customer metric for the last observation. The Mean Absolute Deviation (MAD) between the predicted value of the customer metric and the

Table 3a
Determination of Number of Segments for CLV Model[a]

Number of Segments	CLV Model
1	–6,560
2	–6,432
3	–6,493
4	–6,529

[a] Reported values are the log marginal densities (LMDs) for Model II

observed value of the customer metric provides us an estimate of the predictive accuracy of the model. We also compare the predictive accuracy of each model with the accuracy of a naïve estimate which is defined as the average of customer metric in the calibration sample (excluding the last observation). The Relative Absolute Error (RAE) of a model is then computed as the ratio of the MAD of the model to the MAD of the naïve estimate (Armstrong, Morwitz, and Kumar 2000). We provide the results of the comparison of explanatory power and the predictive accuracy over the different models in tables 3a and 3b.

Table 3b
Comparison of Model Performance

	CLV[a]	CPCV[b]	SOW	RFM
Log Marginal Density (LMD)				
Model I[c]	–6,786	–5,571	–5,685	–5,382
Model II[d]	–6,432	–4,964	–5,126	–4,721
Mean Absolute Deviation (MAD)				
Model I	Purchase time = 2.8 Contribution margin = 8.3	3.2	.52	1.62
Model II	Purchase time = 2.3 Contribution margin = 6.2	2.3	.46	1.28
Naïve estimate	Purchase time = 4.5 Contribution margin = 15.5	5.6	.75	1.86
Relative Absolute Error (RAE)				
Model I	Purchase time = .62 Contribution margin = .54	.57	.69	.87
Model II	Purchase time = .50 Contribution margin = .40	.41	.61	.69

[a] Contribution margin is measured in $1,000s and purchase time is measured in months.
[b] CPCV is measured in $1,000s.
[c] For CLV, Model I is the framework proposed in Venkatesan and Kumar (2004); for CPCV, SOW and RFM, Model I is the proposed model with homogenous parameters.
[d] Model II is the proposed model for CLV, CPCV, SOW, and RFM.

CLV

We estimated four versions of the CLV model by varying the number of segments (k); the results are provided in Table 3a. We compared the log marginal density (LMD) of the four versions. From Table 3a, we see that the log marginal density is the lowest for the model with two segments, and therefore use the model version with two segments for further analyses.

We now compare the proposed joint model of purchase frequency and contribution margin for predicting CLV with the model framework proposed by Venkatesan and Kumar (2004). The results are provided in Table 3b. We obtained similar results for both Cohort 1 and Cohort 2, and we report the results from Cohort 1 for simplicity. At least in our study, we see that the log marginal density values indicate that accommodating for the dependence between purchase frequency and contribution margin leads to better in-sample fit to the data (LMD for Model II = –6,432) as compared to a model which assumes that purchase frequency and contribution margin are independent (LMD for Model I = –6,786). The better in-sample fit also seems to translate into better predictive accuracy. The MAD for predicting purchase time is equal to 2.8 months for Model I versus 2.3 for Model II. Similarly, the MAD for predicting contribution margin is equal to approximately $8,300 for Model I and $6,200 for Model II. For each model, we also compared the predictive accuracy with a naïve estimate. The naïve estimate was the average, calculated over the time period of the calibration sample, of the interpurchase times and contribution margin for purchase timing and contribution margin, respectively. The RAE for Model I is equal to .62 for purchase time and .54 for contribution margin. The RAE for Model II is equal to .50 for purchase time and .40 for contribution margin. Therefore, the RAE measures indicate that both Model I and Model II provide better predictive accuracy than simple heuristics in addition to providing a framework for linking CLV to marketing actions.

We also compared the predictive accuracy of CLV with a naïve estimate. The naïve estimate was the average, calculated over the time period of the calibration sample, of the interpurchase times and contribution margin for purchase timing and contribution margin, respectively. The RAE measures indicate that the CLV model provides better predictive accuracy than simple heuristics in addition to providing a framework for linking CLV to marketing actions.

CPCV, SOW, and RFM

In order to evaluate the benefit from using customer response parameters, we evaluated two versions of each metric's proposed model: (1) with common parameters for all customers—homogenous parameters, and (2) with customer-specific response parameters—heterogeneous parameters. Comparing the log-marginal density values we find that the model with heterogeneous parameters provides a better fit over the model that has homogenous parameters for all the three metrics. This implies that, similar to several other studies (Venkatesan and Kumar 2004; Reinartz and Kumar 2003; Bolton, Lemon, and Verhoef 2004; Rust et al. 2004), in our study we find that customers exhibit significant heterogeneity with regard to their value and accounting for this heterogeneity in response models provides a better fit to the data. Allowing for *heterogeneous* parameters also translates into better predictive accuracy. Further we find that the model with heterogeneous parameters provides better predictive accuracy over naïve estimates of the future values of the metric (computed as the moving average of historic values of the metric).

In addition to linking the customer metrics to marketing actions, the models provide better predictive accuracy, thereby justifying the

Table 4
Results from Estimate of CLV

4a. Segment Membership[b]

Intercept	3.8	(.98)
Marketing Decision Variables		
Frequency of rich modes	3.8	(.26)
(Frequency of rich modes)^2	−1.6	(.18)
Frequency of standard modes	5.2	(1.01)
(Frequency of standard modes)^2	−.8	(.92)
Covariates		
Upgrading	2.2	(.56)
Cross-buying	3.6	(.30)
Bidirectional communication	1.7	(.52)
Returns	2.2	(.38)
(Returns)^2	−4.2	(.22)
Frequency of Web contacts	2.8	(.92)
Lagged interpurchase time	−.62	(.16)
% in active segment	64	(.10)

4b. Contribution Margin

First Segment		
Intercept[c]	−.21	(.01)
Two-period lagged contribution margin	.79	(.09)
Three-period lagged contribution margin	.35	(.07)
Lagged interpurchase time	−2.90	(.08)
Two-period lagged interpurchase time	−2.40	(.09)
Size	.15	(.01)
Aerospace	.26	(.08)
Financial services	n.s.	
Manufacturing	n.s.	
Technology	.41	(.07)
Consumer packaged goods	n.s.	
Travel	.27	(.07)
Government	n.s.	
Error variance	.32	(.02)
Second Segment		
Intercept	.04	(.01)
Two-period lagged contribution margin	.35	(.18)
Three-period lagged contribution margin	n.s.	
Lagged interpurchase time	−2.20	(.06)
Two-period lagged interpurchase time	n.s.	
Size	n.s.	
Aerospace	.13	(.02)
Financial services	n.s.	
Manufacturing	n.s.	

Technology	.08	(.01)
Consumer packaged goods	.44	(.07)
Travel	n.s.	
Government	n.s.	
Error variance (V)	10.30	(3.71)

4c. Purchase Timing—Generalized Gamma Distribution

First Segment		
α_1	8.14	(.53)
ν_1	1.00	(.03)
θ_1	58.40	(1.00)
γ_1	1.1	
Second Segment		
α_2	3.42	(.12)
ν_2	1.66	(.03)
θ_2	49.43	(.55)
γ_2	1	

[a] Values in parentheses are standard deviations of the parameter distribution
[b] Values reported are means of the parameter distribution.
[c] Values reported are the means of the customer specific intercept term and the standard deviation across customers is reported in parentheses.

n.s.= not significant; i.e., a zero exists between the 2.5th percentile and 97.5th percentile values of the parameter distribution.

investment in building a model to predict customer performance along a metric.

Influence of Marketing Decision Variables and Customer Characteristics

We report the results from estimation of the proposed CLV model in Table 4 and the results from estimation of the proposed models for CPCV, SOW, and RFM in Table 5. The reported values are the means and standard deviations (within parentheses) of the distribution of the response parameters. 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.

CLV

The average interpurchase time and contribution margin for customers who belong to Segment 1 is 2 months and $42,000 respectively. The average interpurchase time and contribution margin for customers who belong to Segment 2 is equal to 5 months and $15,000 respectively. We therefore name Segment 1 as the "active segment" (low interpurchase time and high contribution margin) and Segment 2 as the "inactive segment" (high interpurchase time and low contribution margin). The parameters reported in Table 5a determine the probability that an observation would belong to the "active" segment. The results indicate that approximately 64% of the observations belong to the "active" segment.

The main insights from Table 4 are as follows:

- Similar to previous research (Venkatesan and Kumar 2004; Reinartz, Thomas, and Kumar 2005) we find that marketing decision variables have a non-linear, inverted-U-shaped influence on customer behavior. The linear terms for both rich and standardized modes are positive and significant (frequency of rich modes = 3.8 and frequency of standard modes = 5.2), whereas the quadratic term for both rich and standard modes are negative and significant (square of frequency of rich modes = –1.6 and square of frequency of standard modes = –0.8). For both rich and standard modes, the parameter estimates indicate that until a certain threshold, an increase in the frequency of touches would increase the probability that an observation would belong to the "active" segment. However, beyond the threshold, increasing the frequency of touches would decrease the probability that an observation belongs to the "active" segment. See Table 4a.
- Similar to the expectations in the customer management literature (Bolton, Lemon, and Verhoef 2004), we find that an increase in upgrading, cross-buying, bidirectional communication, and frequency of Web contacts leads to an increase in the probability that an observation would belong to the "active" segment. We also find that returns have a non-linear, inverted-U-shaped influ-

ence on the likelihood that an observation belongs to the "active" segment. Finally, our results indicate that the longer the customer's lagged inter-purchase time, the lower the probability that the customer's current observation would belong to the "active" segment. See Table 4a.

- The parameters of the generalized gamma distribution (used to model interpurchase times), and contribution margin for each segment are substantially different from each other. This implies that the model is able to accommodate for differences in interpurchase times and contribution margin between observations that belong to the "active" and "inactive" segments, and also substantiates the choice of a concomitant mixture framework for joint modeling of interpurchase times and contribution margin in a B2B setting. See Table 4c.
- All the lagged effects have a significant influence on contribution margin in the current time period for observations that belong to the "active" segment, whereas only the two-period lagged contribution margin and lagged interpurchase time have a significant influence on contribution margin for observations that belong to the "inactive" segment. See Table 4b.
- In our sample, among observations pertaining to the "active" segment, larger customers (firm size), and customers that belong to industry categories 1, 4, and 6 provide higher contribution margin than other customers. Among observations pertaining to the "inactive" segment, customers that belong to industry categories 1, 4, and 5 provide higher contribution margin than other customers. See Table 4b.

CPCV, SOW, and RFM

The main insights from Table 5 are as follows:

- Similar to the effects observed for CLV, we find that marketing decision variables have a non-linear, inverted-U-shaped influence on CPCV, SOW, and RFM. The linear term for both rich and standard modes are positive and significant (frequency of rich modes = 6.4, 7.4, and 6.4 for CPCV, SOW, and RFM respectively and frequency of standard modes = 1.5, .5, and 2.5 for CPCV, SOW, and RFM respectively). The quadratic term for both rich and standard modes are negative and significant (square of frequency of rich modes = −1.8, −1.7, and −1.5 for CPCV, SOW, and RFM respectively, and square of frequency of standard modes = −.95,–.85, and −1.95 for CPV, SOW, and RFM respectively).
- An increase in upgrading and cross-buying leads to an increase in CPCV, SOW, and RFM. In addition, returns have a non-linear, inverted-U-shaped influence on all the three metrics. However, bidirectional communication has a positive influence on only CPCV and SOW, while frequency of Web contacts has a positive influence on only CPCV and RFM. One reason for these results could be that bidirectional communication between the customer and supplier can strengthen the relationship. Therefore it has a direct impact on customer value (probably through a resultant decrease in marketing costs) and breadth of relationship (i.e., SOW), but not on their revenues or recency of purchase (components of RFM). It is expected that Web contacts indicate an intention to improve efficiency in transactions among customers, therefore an increase in frequency of Web-based contacts can lead to an increase in customer value (CPCV), recency, frequency, and monetary value (RFM) but need not necessarily increase the breadth of the relationship (SOW).
- In our sample, customer size has an influence on CPCV and SOW. Customers that belong to industry categories 1, 4, and 6 have a higher CPCV than others. With regard to SOW, customers that belong to industry categories 5 and 7 have a higher SOW and customers that belong to industry category 1 have a lower SOW than others. Finally, with regard to RFM, customers that belong to industry catagories industry categories 2, 5, 6, and 7 have a higher RFM and customers

Table 5

Results from Estimation of CPCV, SOW, and RFM[a]

Metric	CPCV		SOW		RFM	
Independent Variables						
Intercept	4.4	(.95)	1.2	(.11)	.89	(.25)
Marketing Decision Variables						
Frequency of rich modes	6.4	(1.02)	7.4	(.23)	6.4	(.27)
(Frequency of rich modes)^2	−1.78	(.87)	−1.74	(.26)	−1.45	(.49)
Frequency of standard modes	1.48	(1.01)	.48	(.29)	2.48	(.45)
(Frequency of standard modes)^2	−.95	(.92)	−.95	(.69)	−1.95	(.16)
Covariates						
Upgrading	1.9	(.45)	2.9	(.12)	1.9	.39
Cross-buying	2.35	(.71)	1.35	(.66)	1.35	(.56)
Bidirectional communication	1.62	(.56)	1.62	(.28)	n.s.	
Returns	1.76	(.42)	.76	(.04)	.24	(.10)
(Returns)^2	−.82	(.22)	−.58	.22	−2.82	(.40)
Frequency of Web contacts	1.85	(.81)	n.s.		1.85	(.90)
Two-period lagged dependent variable	.75	(.91)	.25	(.07)	1.75	(.82)
Control Factors						
Size	.03	(.01)	.94	(.49)	n.s.	
Industry Category 1	.41	(.08)	−.43	.23	n.s.	
Industry Category 2	n.s.		n.s.		.83	(.46)
Industry Category 3	n.s.		n.s.		n.s.	
Industry Category 4	.10	(.07)	n.s.		−.87	(.20)
Industry Category 5	n.s.		.75	(.52)	.52	(.30)
Industry Category 6	.22	(.07)			1.25	(.87)
Industry Category 7	n.s.		.52	(.31)	.70	(.35)
Error variance (V)	8.4	(4.29)	5.3	(1.20)	3.7	(1.49)

[a] Values reported are means of the parameter distribution. Values in parentheses are standard deviations of the parameter distribution. n.s.= not significant; i.e., a zero exists between the 2.5th percentile and 97.5th percentile values of the parameter distribution.

that belong to industry category 4 have a lower RFM score than others. Overall, the influence of the control factors indicates that focusing on a single metric can potentially bias the managers to favor customers in one industry over the others.

Comparison of Selection Capability

In this section, we compare the selection capabilities of the various customer metrics, CLV, CPCV, SOW, RFM, and ESP (phases 5-7 of the proposed customer selection procedure). In our selection exercise we manipulated the way in which we score the customers over two levels (1) using the "plug-in estimate" (explained earlier), and (2) using the "full-Bayesian approach." We also manipulated the manner in which we obtain an estimate of the cost of serving each customer over two levels: (1) using the "status-quo" marketing cost (the average cost of serving the customer in the calibration sample), and (2) using the "optimal" marketing cost, (the optimized cost[8] of serving the customer, given the parameter estimates in the calibration sample).

Table 6

Evaluation of Customer Selection Capability

Metric used to select customers	CLV		CPCV		SOW		RFM		ESP
	Status quo marketing costs	Optimal marketing costs	Status quo marketing costs	Optimal marketing costs	Status quo marketing costs	Optimal marketing costs	Status quo marketing costs	Optimal marketing costs	Status quo marketing costs
Plug-in Estimate									
Number of customers	174	176	188	189	185	191	183	182	183
Total net value in $t+1$[a]	912	1,165	890	1,070	846	1,020	782	960	851
Total net value in $t+2$	910	1,118	861	1,070	823	1,028	758	987	845
Total net value in $t+3$	905	1,098	834	1,043	794	1,010	744	956	819
Total costs in $t+1$[b]	170	160	180	160	170	150	180	160	180
Total costs in $t+2$	180	160	220	190	220	190	170	200	210
Total costs in $t+3$	190	170	200	190	190	150	150	210	240
ROI in $t+1$[c]	5	7	5	7	5	7	4	6	5
ROI in $t+2$	5	7	4	6	4	5	4	5	4
ROI in $t+3$	5	6	4	5	4	7	5	5	3
Full-Bayesian[d]									
Number of customers	152	153	167	168	166	167	164	169	n.a.
Total net valuein $t+1$[a]	991	1,286	939	1,095	900	1,048	839	1,035	n.a.
Total net value in $t+2$	972	1,195	908	1,083	888	1,067	807	1,022	n.a.
Total net value in $t+3$	926	1,168	850	1,071	873	1,050	798	1,007	n.a.
Total costs in $t+1$[b]	160	150	180	160	170	170	180	170	n.a.
Total costs in $t+2$	170	150	180	160	190	170	180	180	n.a.
Total costs in $t+3$	180	160	200	170	210	180	190	190	n.a.
ROI in $t+1$[c]	6	9	5	7	5	6	5	6	n.a.
ROI in $t+2$	6	8	5	7	5	6	4	6	n.a.
ROI in $t+3$	5	7	4	6	4	6	4	5	n.a.

[a,b] Net value and costs are in $1,000s. [c] ROI is measured as net value/costs.

We set the budget constraint as 70% of the average of the total annual cost of serving all the customers in the calibration sample over the most recent three years (1999-2001), 2001). The total budget available for serving all the customers in Cohort 1 is therefore equal to approximately $100,000. The results from our selection exercise are presented in Table 6. The important insights from Table 6 are discussed below.

Plug-in estimate versus full-Bayesian approach

- For the four metrics—CLV, CPCV, SOW, and RFM—a lesser number of customers are selected through the full-Bayesian method as compared to the plug-in estimate. For example, in the case of selecting customers using CLV and status quo marketing costs, the full-Bayesian method selects 152 customers whereas the plug-in estimate selects 174 customers. In addition, the total marketing costs for customers selected based on the full-Bayesian method is lesser than the total marketing costs for customers selected based on the plug-in estimate. For example, when customers are selected based on CLV using the full-Bayesian method and status quo marketing costs, the total costs in the first, second, and third years are $160,000, $170,000, and $180,000 respectively. The total costs in the first, second, and third years when customers are selected based on CLV using the plug-in estimate and status quo marketing costs are $170,000, $180,000, and $190,000 respectively. Similar results are observed for CPCV, SOW, and RFM and when optimal marketing costs are used for customer selection.

- For the four metrics—CLV, CPCV, SOW, and RFM—the net value obtained from customers selected based on the full-Bayesian estimates are higher than the value obtained from customers selected based on the plug-in estimate. For example, in the case of selecting customers based on CLV using status quo marketing costs, the value observed in first, second, and third years in the holdout time period when plug-in estimates are used are $912,000, $910,000, and $905,000 respectively. The value observed in the first, second, and third years in the holdout time period when the full-Bayesian method is used are equal to $991,000, $972,000, and $926,000 respectively.
- The return on investments (ROI)[10] obtained from customers selected using the full-Bayesian method is also higher than the customers selected using the plug-in estimates because the customers selected using the full-Bayesian method provide better value and lower costs than those selected using the plug-in estimate. For example, the ROI from customers selected based on CLV using the full-Bayesian method, and status quo marketing costs are equal to 6, 6, and 5 in the first, second and third years respectively. The corresponding ROIs in the first, second, and third years are equal to 5 when plug-in estimates are used.

These results imply that accommodating for the uncertainty in predicting customer behavior leads to better accuracy and better value when selecting customers for targeting. We note here that our results only imply that a full-Bayesian methodology leads to selection of customers that provide *higher* value and ROI. However, the set of customers that provide the maximum valule need not necessarily provide the maximum ROI.

Status quo versus optimal marketing costs

- For the four metrics—CLV, CPCV, SOW, and RFM—and between plug-in and full-Bayesian methods, the customers selected based on optimal marketing costs provide higher value than customers selected based on status quo marketing costs. For example, in the case of selecting customers based on CLV using full-Bayesian estimates, the value observed in first, second, and third years in the holdout time period when optimal marketing costs are used are $1,286,000, $1,195,000, and $1,168,000 respectively. The value observed in the first, second, and third years in the holdout time period when status quo marketing costs are used are $991,000, $972,000, and $926,000 respectively.
- Across all the scenarios, the observed costs of serving customers are lower and closer to the expected costs (i.e., the budget constraint) when optimal marketing costs are used as compared to the status quo marketing costs. For example, in the case of selecting customers based on CPCV using full-Bayesian estimates, the total costs observed in first, second, and third years in the holdout time period when optimal marketing costs are used are $160,000, $160,000, and $170,000 respectively. The total costs observed in the first, second, and third years in the holdout time period when status quo marketing costs are used are $180,000, $180,000, and $200,000 respectively.
- The higher value and lower costs lead to higher observed ROI for customers selected based on optimal marketing costs as compared to status quo marketing costs. For example, in the case of selecting customers based on CPCV for full-Bayesian estimates, the ROI observed in the holdout time period when optimal marketing costs are used are

equal to 7, 7, and 6 for the first, second, and third years respectively. The ROI observed in the first, second, and third years in the holdout time period when status quo marketing costs are used are equal to 5, 5, and 4 respectively.

These results imply that managers need to take a forward-looking perspective for managing customer costs. Optimal marketing costs seem to act as a good estimate for the costs of serving customers in the future time periods.

Selection capability of CLV, CPCV, SOW, and RFM

Since for CLV, CPCV, SOW, and RFM, customers selected using the full-Bayesian estimates and optimal marketing costs provide higher value, have lower costs, and provide higher ROI we only discuss the comparison of the four metrics for the scenario when full-Bayesian estimates and optimal marketing costs are used. The main insights are as follows:

- CLV selects a lower number of customers (153) than CPCV (168), SOW (167), and RFM (169).
- The total value observed in the first, second, and third years in the holdout time period (*t*,+,1) from customers selected based on CLV are $1,286,000, $1,195,000, and $1,168,000 respectively and are higher than the value observed from customers selected based on CPCV (first year = $1,095,000, second year = $1,083,000, and third year = $1,071,000), SOW (first year = $1,048,000, second year = $1,067,000, and third year = $1,050,000), and RFM (first year = $1,035,000, second year = $1,022,000, and third year = $1,007,000).
- The total costs observed in the first, second, and third years in the holdout time period (*t* + 1) from customers selected based on CLV are equal to $150,000, $150,000, and $160,000 respectively and are lower than the total costs observed from customers selected based on CPCV (first year = $160,000, second year = $160,000, and third year = $170,000), SOW (first year = $170,000, second year = $170,000, and third year = $180,000), and RFM (first year = $170,000, second year = $180,000, and third year = $190,000).
- With regards to the observed costs of the selected customer, given that a lesser number of customers are also selected based on CLV, the cost (after discounting the costs in the first, second, and third year to the current year) over the three years in the holdout period of serving a single customer selected based on CLV is higher ($2,281) than the present value of the unit cost of serving customers selected based on CPCV ($2,213), but lower than the present value of the unit cost of serving customers selected based on SOW ($2,363), and RFM ($2,419).
- With regards to ROI, customers selected based on CLV provide a higher ROI (first year = 9, second year = 8 and third year = 7) than customers selected based on CPCV (first year = 7, second year = 7, and third year = 6), SOW (6 in all three years), and RFM (first year = 6, second year = 6, and third year = 5).
- Finally, the customers selected based on CPCV provide higher value and ROI than those selected based on SOW, and customers selected based on SOW provide higher value and ROI than those selected based on RFM.

Comparison with the selection capability of ESP

- The collaborating firm provided us with the ESP scores for the customers using the calibration sample, which we then used in our selection exercise. Currently, the firm does not estimate customer-specific response parameters, uses a plug-in estimate, and uses status quo marketing costs as an estimate of future costs. We therefore compare CLV, CPCV, SOW, and RFM with ESP when plug-in estimates and status quo marketing costs are used for customer selection. We find that the customers selected based on ESP provide higher value ($851,000 in the first year, $845,000 in the second year, and $819,000 in the third year) than customers selected based on SOW, but lower value than customers selected based on CLV, CPCV, and RFM.

Comparing optimal marketing costs with a regression-based estimate of future costs

Our selection exercise indicated that customers selected using optimal marketing costs as an estimate of future costs provide higher value and actually have observed costs that are closer to the expected costs. We now compare the value obtained from customers selected using optimal marketing costs with the value from customers selected using a weighted sum of the marketing costs in the three most recent three time periods. The weights are determined through regression analysis.

The selection exercise using CLV and full-Bayesian estimates was then repeated using the regression-based cost estimates. The results are provided in Table 7. From Table 7 we see that the observed costs of the customers selected based on CLV using the regression-based estimate ($150,000 in the first year, $160,000 in the second year, and $150,000 in the third year) are similar to the costs of customers selected based on optimal marketing costs, and are lower than the costs of customers selected based on status quo marketing costs. However, the total value obtained from customers using the regression-based estimate ($1,056,000, $998,000, and $976,000 in the first, second, and third years respectively) is lower than the value obtained from customers selected using optimal marketing costs and is higher than the value obtained from customers selected using status-quo marketing costs. These results imply that the rank-ordering of customers based on the maximized CLV (using optimal marketing costs) seems to provide better targeting of valuable customers than the rank-ordering of customers based on CLV estimated using a simple regression-based estimate of future costs. One possible reason for optimal marketing costs providing better targeting is that the optimal marketing costs enable managers to dynamically update their estimates of future customer costs based on customer responsiveness to historic marketing communication, whereas the regression-based estimate simply projects historic marketing costs into the future while accommodating for any general trends that may exist over time. However, we should note here that further research which investigates several possible scenarios (for example, using more sophisticated models to predict future costs) is necessary before any conclusive evidence can be obtained on whether optimal marketing costs provide better targeting over regression-based estimates of marketing costs. Overall, the results from our study indicate that selecting customers based on their expected (future) marketing costs leads to better targeting of valuable customers than selecting customers using their historic marketing costs.

Table 7
Selection Capability of Regression-based Estimate of Future Costs

Metric used to select customers	CLV
Number of customers	153
Total value in $t+1$[a]	1,056
Total value in $t+2$	998
Total value in $t+3$	976
Total costs in $t+1$[b]	150
Total costs in $t+2$	160
Total costs in $t+3$	150
ROI in $t+1$[c]	7
ROI in $t+2$	6
ROI in $t+3$	7

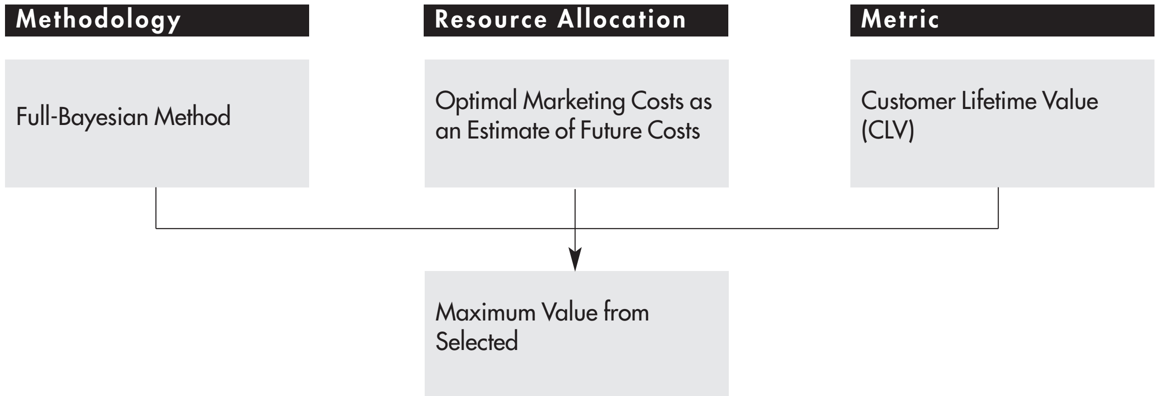
[a,b] Value and costs are in $1,000s. [c] ROI is measured as value/costs.

Discussion

Implications

Managers are concerned with the ROI implications of selecting customers based on CLV as compared to other traditionally employed metrics. Further, given the uncertainty inherent in predicting customer behavior, managers are wary about taking actions based on the recom-

Figure 3
Conclusions from Selection Exercise



mendations of a metric that is calculated using predictions of customer behavior over the long term. We proposed a customer selection framework which explicitly accounts for uncertainty in predicting customer behavior over the long term. Further we proposed a model for estimating CLV that accounts for the dependence between purchase timing and contribution margin and is amenable for application in a Bayesian framework. Finally, we examined the ROI implications of using CLV for customer selection as compared to other commonly used metrics such as CPCV, SOW, RFM, and ESP.

The major recommendations provided by our study for managers interested in customer selection are as follows:

- The proposed joint model, accounting for the dependence between purchase timing and contribution margin, is more accurate in predicting CLV than other currently available model frameworks.
- Irrespective of the metric, selecting customers using a full-Bayesian approach leads to better identification of valuable customers.
- During the customer selection process, in addition to contribution margin, managers should focus on the expected costs of serving a customer. The optimal costs derived based on estimates of customer's historic responsiveness to marketing communication provides a good estimate of the expected costs of serving a customer and aids in identifying valuable customers.
- The optimal level of investment that maximizes CLV does not necessarily maximize CPCV, SOW, or RFM.
- Using a CLV measure for customer selection provides a better ROI and value than other metrics such as CPCV, SOW, RFM, and ESP.

To summarize, as depicted in Figure 3, managers can attain the best accuracy in targeting valuable customers by combining (1) the right methodology—a full-Bayesian approach, (2) the right resource allocation strategy—using optimal marketing costs as an estimate of expected costs, and (3) the right customer metric—the CLV measure. We now discuss the implications of our recommendations for enhancing marketing productivity and for estimating returns from marketing actions.

Enhancing Marketing Productivity. Several researchers have proposed that customer value can be substantially improved if managers customize marketing contacts to individual customer preferences (Ansari and Mela 2003; Venkatesan and Kumar 2004; Reinartz, Thomas, and Kumar 2005; Kumar and Reinartz 2006). However, previous academic research does not show any causal link between using optimal contact levels and maximized customer value.

Given the huge opportunity costs of conducting a field experiment to establish a causal link between optimal contact levels and maximized customer value, we adopt an alternative approach to establish the benefits from harnessing the power of historic customer information to improve marketing productivity. Our results show that deriving optimal contact levels can lead to improved targeting of valuable customers, and thereby improved marketing productivity. In addition, the optimal contact levels are a better estimate of future costs than historic marketing costs.

Although a causal link between optimal marketing contacts and maximized customer value is still not established, we believe that results from our selection exercise would lead to improved adoption of customization of marketing contacts among practitioners at least for the purposes of customer targeting. The results from our study imply that a proactive customer selection strategy would enable managers to target valuable customers leading to higher value given a fixed marketing budget. By using the customer-specific optimal marketing costs as a guideline for marketing actions, managers can improve the productivity of their tactical actions and by integrating these costs into the customer selection process they can also observe how the improvement in tactical actions leads to better customer management strategies.

Estimating Returns from Marketing Actions. Our proposed strategy enables managers to identify which customers would be more valuable in the future and estimate the expected costs of serving the selected customers. These results and the selection exercise would enable managers to justify investments in customized marketing for retained customers and also provide a better estimate of the budget that would be required for achieving their goals. Managers can use the proposed CLV framework and the corresponding optimal marketing costs that maximize CLV to show a link between marketing investments and the returns expected from each customer. Marketing managers can use the selection exercise proposed in our study to show top management the ROI that can be obtained from a marketing strategy that targets individual customers. In addition, the CLV measure and the corresponding optimal marketing costs can form the basis for discussions regarding marketing budgets over the long term.

Limitations and future research

The study has limitations that can be addressed by future studies. The results of this study are from a sample of customers in the high-technology industry. Further replications are necessary across samples within the sponsoring firm before generalizing the findings to the entire population of customers in this firm. Also, future research studies need to investigate if the results are generalizable to other industries and settings. A fertile area for future research studies would be to evaluate the value of information regarding the competitor's marketing actions on the forecasts of customer value. Also, research is needed on whether managers would be able to improve their targeting capabilities by combining forecasts of aggregate competitive responses to marketing actions and customer brand-switching with forecasts from individual-level models of direct marketing. Also, we only consider the average levels of optimal communication strategy in each channel in this study. However, organizations can further improve the efficiency of their customer selection process by deriving the optimal sequence of customer contacts across different channels. In addition, in our study we provide a framework which evaluated the benefits from selecting customers using the maximized metric. However, one needs to note that we do not compare our proposed proactive customer selection strategy with one that focuses on allocating resources to customers for whom the increment in a customer metric from appropriately designing marketing communication is the highest. For example, it is quite possible that customers who have had high CLV in the past can continue to have high CLV in the future irrespective of the level of marketing communication, while some customers who have been low on CLV in the past can transform to high CLV customers with an appropriately designed marketing strategy, thereby providing higher ROI. Our study indicates that in addition to predicting future customer value, estimating a customer's future costs also contributes to better selection capabilities. Further research is necessary to identify frameworks for planning the future marketing communications for a customer that is dynamically updated based on customer responses.

Additionally, it can be expected that the margins may change over time. In this case, the value that a customer provides to an organization is a function of both the expected time frame until the next purchase and the contribution margin at that particular time period. Finally, the interesting question that arises from our analyses is whether the recommendations from an optimization framework span out when implemented in the real market. While our study is a step in the right direction to assess the accountability of marketing actions, a field experiment that tests the recommendations of such a framework on a test group against a control group that is managed according to existing norms would provide a stronger justification for CRM-based efforts. ■

Acknowledgements

The authors thank a multinational firm for not only providing access to the data used in this study but also for actively participating in the execution of this study. The study benefited from presentations at numerous places including the MSI/Yale conference on Practitioner-Academic collaboration, and the IBM corporation. The authors thank Gary Lilien, Leigh McAlister, Anil Menon, Denise Beckman, and Scott Neslin for their suggestions to improve the contribution of this manuscript. We also thank Renu for copyediting the manuscript.

Notes

1. We define the value provided by a customer in this manuscript as the difference between the gross margin from products purchased by the customer and the variable marketing costs.

2. In this study we focus on retained customers; we do not address list selection for acquiring prospects.

3. Purchase frequency can be obtained as the ratio of 12 to the expected interpurchase time when interpurchase time is measured in months.

4. The concomitant mixture framework (Allenby, Leone, and Jen 1999; Venkatesan and Kumar 2004) is more appropriate to model interpurchase times than the Conway-Maxwell-Poisson distribution used by Boatwright, Borle, and Kadane 2003.

5. Details regarding model specification for CLV, as well as the method used to estimate the updated response parameters ($B_i clv$) and the algorithm used to predict CLV can be obtained from the authors.

6. Details regarding model specification for CPCV, SOW, and RFM, as well as the method used to estimate the updated response parameters and the algorithm used to predict CPCV, SOW, and RFM can be obtained from the authors.

7. Customer contacts through the Web are included in the calculation of frequency of Web contacts, rather than in the calculation of bidirectional communication.

8. Simple descriptive statistics showed that the levels of the marketing decision variables are in fact random, thereby alleviating the need to model the level of marketing communications (Manchanda, Rossi, and Chintagunta 2004). Discussions with the managers in the collaborating firm revealed that while the customers are selected for communication based on their expected spending potential (ESP), there is no standard heuristic for the level of communications used for each individual customer. Also, since we removed customers who were not contacted, we do not expect that directly using the levels of the marketing decision variables would bias our results.

9. Details on identifying the optimal marketing costs can be obtained from the authors.

10. We measure ROI as the ratio of value to marketing costs (i.e., cost of contacts through rich and standard modes).

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