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Practice Prize Report

The Power of CLV: Managing Customer
Lifetime Value at IBM

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Customer management activities at firms involve making consistent decisions over time, about: (a) which customers to select for targeting, (b) determining the level of resources to be allocated to the selected customers, and (c) selecting customers to be nurtured to increase future profitability. Measurement of customer profitability and a deep understanding of the link between firm actions and customer profitability are critical for ensuring the success of the above decisions. We present the case study of how IBM used customer lifetime value (CLV) as an indicator of customer profitability and allocated marketing resources based on CLV. CLV was used as a criterion for determining the level of marketing contacts through direct mail, telesales, e-mail, and catalogs for each customer. In a pilot study implemented for about 35,000 customers, this approach led to reallocation of resources for about 14% of the customers as compared to the allocation rules used previously (which were based on past spending history). The CLV-based resource reallocation led to an increase in revenue of about \$20 million (a tenfold increase) without any changes in the level of marketing investment. Overall, the successful implementation of the CLV-based approach resulted in increased productivity from marketing investments. We also discuss the organizational and implementation challenges that surrounded the adoption of CLV in this firm.

Key words: customer relationship management; customer lifetime value; field experiment; return on marketing contacts; missing value imputation

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1. IBM Background

IBM is one of the leading multinational high-technology firms that markets hardware, software, and services to B2B customers. IBM intends to proactively manage individual customer relationships to maximize overall firm profitability. A variety of marketing factors including product/service innovation, product/service pricing, transaction channel, mass market advertising, and individual customer contacts are expected to impact customer profitability. Among these factors, the level of customer contacts is most applicable for customization across customers, and is the focus of differential resource allocation for managing customer profitability at IBM. Customers are contacted through several channels, such as salesperson, direct mail, telesales, e-mail, and catalogs. At the

time of this study, the channels used for contacting a customer depended largely on the past relationship with a customer. For example, customers who have employees ranging from 100 to 999 (the midmarket) are contacted primarily through direct mail, telesales, e-mails, and catalogs.

Each year, IBM sorts customers based on their score on a customer-level metric and prioritizes marketing contacts to customers based on this score. The choice of the metric (used to score customers) is considered as one of the primary factors that determines the return on marketing and is constantly refined by IBM with the objective of maximizing potential value from customers. Through the 1990s, a customer spending score (CSS) was used to score customers. CSS was defined as the total revenue that can be expected from

a customer in the next year. Customers from the top one or two CSS deciles, depending on the customer segments (small to medium businesses or large companies), are selected for future targeting.

Over the years, additional components were added to augment CSS. Ultimately, the CSS score was abandoned because it focused primarily on customer revenues (i.e., the top line) and largely ignored the variable cost of serving a customer—and therefore, the bottom line. Trials of customer profitability and customer lifetime value (CLV) were proposed as an alternative for scoring customers. In this study, we present the case study of how CLV was measured, evaluated, and implemented in IBM for prioritizing marketing resources among customers in the midmarket.

The objectives of the customer selection process at IBM are summarized by the following questions:

- “Which customers should be selected for targeting?”
- “Is there a way to determine the level of resources to be allocated to those customers?”
- “How can the selected customers be nurtured in order to increase future profitability?”

In trials we tested a simple management belief: “Can an increase in contacts to the right customers create high value from low-value customers when all other drivers are similar?” To accomplish these objectives, IBM adopted the following CLV management framework. The CLV management framework is intended to guide the marketing activity directed towards customers each year.

2. Customer Lifetime Value Management Framework and Impact

The measurement of CLV and the alignment of marketing resources to customers with the highest potential value are at the core of the proposed CLV management framework illustrated in Table 1.

Although the components of this framework have been proposed separately in past literature (Gupta and Zeithaml 2006), this is the first study to provide an integrated framework that is also suitable for field implementation. In this paper, we discuss implementation, through a field study, of the CLV management framework for a sample of IBM’s customers (the midmarket), and the impact of this implementation on marketing productivity. Although field studies are relatively scarce in the literature, they are essential for establishing the external validity of marketing strategies and vastly improve the adoption of the proposed strategy by firms across industries. The field study that we report here also illustrates the interplay

Table 1 Customer Lifetime Value Management Framework

Process	Purpose
Measure customer lifetime value (CLV)	To obtain a measure of the potential value of IBM customers.
Identify the drivers of CLV	So that managers can influence the CLV
Determine optimal level of contacts for each customer that would maximize their respective CLV	To guide managers on the level of investment required for each customer
Develop propensity models to predict what product(s) a customer is likely to purchase	To develop a product message when contacting a customer
Reallocate marketing contacts from low CLV customers to high CLV customers.	To maximize marketing productivity

between the short-term tactical decisions such as marketing contacts and the long-term strategic focus on CLV. In addition, this paper discusses some initiatives at IBM that further expand upon the foundations of the field study reported here.

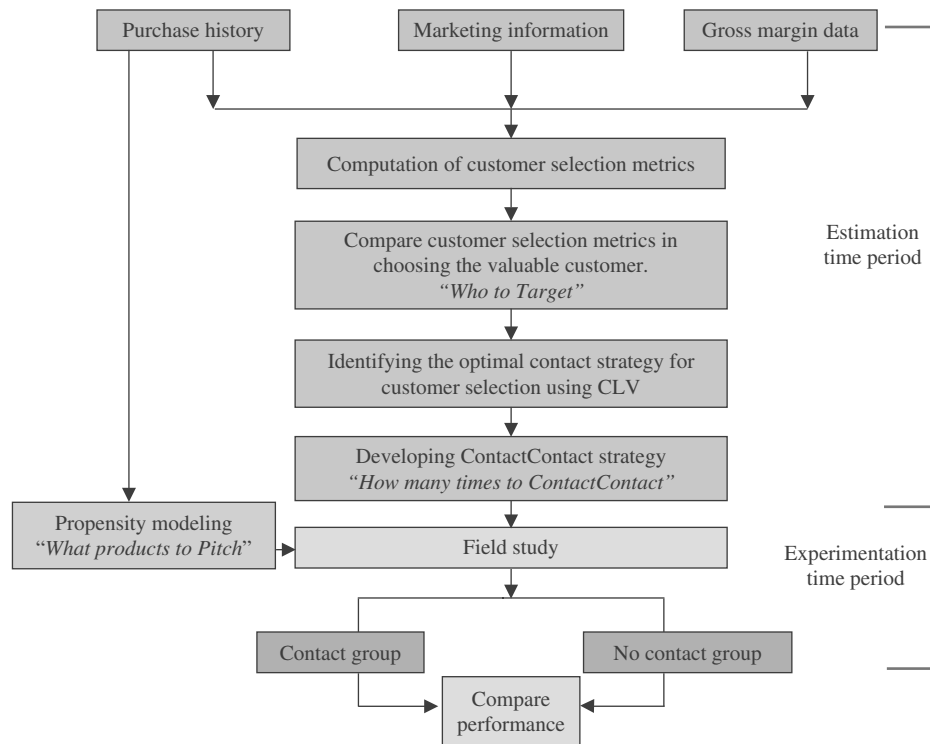
The results from the field study are encouraging. Marketing resources were reallocated based on CLV calculations for 14% of the customers. The resource reallocation involved contacting a certain set of customers in 2005 who were not contacted until 2004, but who are predicted to have high CLV. On average, the revenue from these customers increased tenfold. The total increase in revenues in the test sample for the midmarket customers, as compared to previous years, is about \$20 million dollars. This increase in revenue is obtained without any changes in the level of marketing investment.

The rest of the article is organized as follows. In §3, we provide an overview of how the customer profitability management framework was implemented in IBM. Section 4 explains the context in which the study was conducted, and §5 provides details on the first stage, model development and measurement. The successful application of the customer profitability management framework to IBM’s customer base has been remarkable, and has been described, along with some extensions, in §6. In §7, we discuss the organizational challenges most companies would face when implementing the framework. The paper concludes with a summary in which further issues such as transferability to other industries and the limitation of the customer profitability management framework are discussed.

3. Assessing the Impact of the Customer Lifetime Value Management Framework

We now describe the two-stage process used to determine whether the CLV management framework

Figure 1 Implementing Customer Lifetime Value Management Framework



achieved its objectives. In the first stage, several models were developed to generate inputs for implementation. In the second stage, a field study was conducted based on recommendations from the models developed in the first stage. In the field experiment, we tested an initial theoretical assumption within IBM that, *an increase in contacts to the right customer creates high value from low value customers when all other drivers are similar*.

3.1. First Stage: Model Development

IBM used CLV, coupled with other qualitative inputs from the sales team, to base their marketing decisions for a sample of midmarket customers. Figure 1 illustrates the phased approach that was implemented, and the various steps that were executed in order are explained below:

Phase I: Defined and developed a model to measure CLV for each customer.

Phase II: Conducted a prediction exercise to compare the performance of customers rank ordered based on the traditionally used metrics with that of CLV.

Phase III: To maximize CLV, we developed an optimal contact strategy to allocate contact resources to each customer. Once the guidelines for the optimal number of contacts (in different channels of communication—telephone, catalog, e-mail, and direct mail) with the customers are established, we then observed the performance in the marketplace based on our recommendations.

Phase IV: Propensity models were built for each product category to identify the product to feature in addition to the CLV measure, which helps to select the customers for targeting; and the optimization process, which suggests the contact strategy.

3.2. Second Stage: Implementation

Phase V: Customers were split into two groups—(1) not contacted so far (*Not Contacted Until 2004* group), and (2) previously contacted (*Contacted by 2004* group). Marketing contacts were then reallocated to align resources to the high CLV customers.

Phase VI: Customers with potential for higher CLV, but not contacted so far—i.e., the *Not Contacted until 2004* group—were contacted in 2005 as per the recommendations of the CLV-based approach. The performance of this group of customers was compared between the years 2004 and 2005 to illustrate the impact of the model recommendations. Further, the model recommendations were evaluated even for the intersection of the *Contacted by 2004* group and the *Contacted in 2005* group to see if we missed out on existing source of revenues. In other words, if we recommended that someone be contacted in 2005, did the customers provide higher revenue than the customers who were not contacted?

4. Study Context—Data

Data on midmarket companies were used to evaluate the impact of the CLV-based framework. The midmarket customers represent companies with number

of employees in the range 100–999 at the enterprise level and with total enterprise revenues to IBM in the last three years (2001–2003) that were greater than \$25,000. The total number of enterprises in the data set was greater than 20,000. Because some enterprises can have more than one establishment (e.g., different locations making independent decisions), we conduct our analysis at the establishment level. We aggregate all the customer transactions over a month and conduct our analyses at the monthly level because at least a month is required to sort out the complexities involved in selling to other businesses, and most of the transactions registered within a certain month in the customer database correspond to the same customer order. We have a total of 2.5 million observations (72 months each for the 35,131 establishments) in the analysis group.

5. First-Stage Model Development and Measurement

5.1. Phase I: Measurement of CLV

We adopt the *always-a-share* approach for measuring CLV because it is more appropriate for the noncontractual setting of IBM (Reinartz and Kumar 2000, Rust et al. 2004, Venkatesan and Kumar 2004). The always-a-share approach assumes that there is only dormancy in a customer-firm relationship and that customers never terminate their relationship with a firm. This assumption allows for a customer to return to purchasing from a firm after a temporary dormancy, and when the customer returns to the relationship they retain the memory about their prior relationship with the firm.

We define the lifetime value for customer i as the net present value of cash flows they provide over a three-year period (36 months). Theoretically, CLV models should estimate the value of a customer over the customer's lifetime. However, in many firms, including IBM, three years is considered to be a good estimate for the horizon over which the current business environment (with regard to technology, competition, etc.) would not change substantially. Hence, most customer relationship management (CRM) decisions are made based on CLV estimates over a rolling three-year window. Further, in most cases the majority of a customer's lifetime value is captured within the first three years (Gupta and Lehmann 2005). For example, if the retention rate is equal to 75%, and the discount rate is equal to 20%, then three years accounts for about 86% of the CLV.¹ We therefore measure CLV as,

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

¹ We thank the area editor for providing us with this example.

where,

CLV_i = Lifetime value for customer i ,

$p(Buy_{ij})$ = 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 contacts (or touches) directed towards customer i in time period j ,

\overline{MC} = Average cost for a single marketing contact, this is assumed to be \$7 in the study,

j = Index for time periods; months in this case,

T = Marks the end of the calibration or observation time frame, and

r = Monthly discount factor; 0.0125 in this case (amounts to a 15% annual rate).

Computation of CLV requires predictions on three aspects: (a) the level of marketing contacts directed towards customer i in time period j ("MT" in Equation (1)), (b) the probability that a customer would purchase in each time period (" $p(Buy)$ " in Equation (1)), and (c) the contribution (in \$) provided by the customer in each time period ("CM" in Equation (1)).

Model Likelihood. The three aspects involved in the computation of CLV are inherently correlated. The level of marketing contacts directed towards a customer depends on customer characteristics, past customer behavior, and the past level of marketing resources allocated towards the customer. The probability that a customer would purchase is likely to be dependent on the level of marketing resources directed towards the customer, and finally, the customer provides profits to the firm only if they purchase. In our model framework we allow for correlations among these aspects of firm and customer behavior. We model marketing contacts, probability of purchase, and contribution margin jointly through a "seemingly unrelated regression"-based model structure. The likelihood that summarizes our model structure is provided below,

$$L(MT, Buy, CM)$$

$$\propto \prod_{i=1}^N \prod_{j=1}^T \Pr(Buy_{ij}^* \leq 0, MT_{ij})^{1-Buy_{ij}} \cdot \Pr(CM_{ij}^* = CM_{ij}, Buy_{ij}^* > 0, MT_{ij})^{Buy_{ij}} \quad (2)$$

where

Buy_{ij}^* = customer i 's latent utility for purchasing in time period j .

Please refer to Appendix A for further details on the likelihood. As indicated in Table 2 and explained in Appendix A, the proposed framework extends the

Table 2 Comparison of Model Contributions

Studies	Imputing missing values in contribution margin	Joint estimation of CLV components	Modeling firm's decisions	Field experiment	Forward-looking cost allocation strategy
Reinartz et al. (2005)	No	No	No	No	No
Venkatesan and Kumar (2004)	No	No	No	No	No
Lewis (2004)	No	No	Yes	No	No
Fader et al. (2005)	No	Yes	No	No	No
Donkers et al. (2007)	No	Yes	No	No	No
Current study	Yes	Yes	Yes	Yes	Yes

previous individual level, and always-a-share-based CLV models along four critical dimensions: (a) modeling firm decisions, (b) providing a forward-looking cost allocation strategy, (c) imputing missing contribution margin, and (d) accommodating for unobserved dependence among levels of marketing contacts, purchase incidence, and contribution margin.

We used the first 54 months of data to estimate model parameters, and the CLV score was computed for each customer over the next 36 months (2002 through 2004), as described in Equation (1). Further details on model estimation and model comparisons are provided in the Technical Appendix, which is available at <http://mktsci.journal.informs.org>.

5.1.1. Drivers of CLV. Although firms are interested in knowing the lifetime value of their customers, they are also keen on identifying the factors that are in their control that could increase the value of their customers. Reinartz and Kumar (2003) identified the factors that explain the variation in the profitable lifetime duration among customers. The antecedents of profitable lifetime duration are grouped as exchange characteristics and customer heterogeneity. The exchange characteristics define and describe the nature of the customer-firm exchange, whereas firmographic variables capture customer heterogeneity. Different exchange characteristics that we include as drivers of purchase propensity and contribution margin include past customer-spending level, cross-buying behavior, purchase frequency, recency of purchase, past purchase activity, and the marketing contacts by the firm. We also evaluated interactions between the drivers to accommodate for nonlinearity in the influence of the drivers on purchase incidence and contribution margin. To accommodate for the diminishing returns to marketing efforts (Venkatesan and Kumar 2004), we use the logarithm of the marketing contacts variables as predictors in the purchase incidence and contribution margin equations.²

² We also evaluated both a linear and a quadratic term of marketing contacts as independent variables in the model. We found that the in-sample fit and predictive accuracy were better when log of marketing contacts was used, given the range of marketing contacts in our data.

Drivers of marketing contacts were based both on theory and discussions about how marketing contacts are executed at IBM. The drivers of contact history include past customer spending, past levels of marketing contacts, customer relationship (or exchange) characteristics such as cross buying and recency, and past purchase activity. The past levels of marketing contacts were by definition equal to zero for establishment without contact history. Similar to the purchase propensity and contribution margin equations, we included interactions between the drivers in the marketing contacts equation. When assigning predictors, we ensured that there is at least one unique predictor for each dependent variable, i.e., marketing contacts, purchase propensity, and contribution margin, to ensure model identification (Greene 1993).

Customer firmographics were included as drivers of a customer-specific intercept (α in Equation (A7) in Appendix A) in all three components of our model framework: marketing contacts, purchase propensity, and contribution margin. The various firmographics included were the sales of an establishment (a measure of the size of the establishment), an indicator for whether the establishment belonged to the B2B or B2C industry category, and the installed level of PCs in the establishment (PcQ), a measure of the level of demand for IT products in the establishment.

The coefficient estimates of the drivers of CLV are reported in Table 3. The reported values are the posterior means and variances. 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.

Regarding the level of marketing contacts, the results reflect IBM practices related to contacting customers. The level of marketing contacts for a customer depends on the recent purchase behavior of the customer, which is captured through the covariates—lagged indicators of purchase incidence, lagged contribution margin, and the lagged number of purchases made by a customer so far. Whereas a customer's past purchase behavior in general determines whether a customer is contacted, the specific level of marketing contacts directed towards a customer in a particular month is influenced to a large extent by the level contacts for the customer in the two prior months. Finally,

Table 3 Estimation Results

Independent variables	Coefficients*	
	Mean	Variance
Level of marketing contacts		
Lagged level of contacts	0.7366	0.0316
Two-period lagged level of contacts	0.3239	0.0333
Lagged average number of purchases	0.5836	0.2158
Two-period lagged indicator of purchase	4.7114	1.4023
Interaction of cross buying and recency	-0.0149	0.0035
Lagged contribution margin	0.6016	0.1128
Purchase incidence		
Lagged indicator of purchase	0.6573	0.0902
Two-period lagged indicator of purchase	0.2172	0.0891
Lagged average level of contribution margin	0.0056	0.0026
Log of lagged level of contacts	0.0041	0.0012
Interaction of cross buying and recency	-0.0047	0.0074
Interaction of log of lagged level of contacts and lagged indicator of purchase	0.0004	0.0002
Contribution margin		
Lagged contribution margin	0.8612	0.0247
Lagged average contribution margin	0.7442	0.0325
Cross buying	0.2858	0.1075
Frequency of purchases	7.3692	1.887
Log of lagged level of contacts	0.079	0.0105
Interaction of cross buying and recency	-0.038	0.0565

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

the interaction of cross buying and recency of purchase reflects IBM's strategy of focusing marketing activities on customers who have been actively purchasing products across several categories.

The significant positive influence of the two lagged indicators of purchase indicates the existence of stationarity in customer purchase incidence. Also, customers who have spent more (as captured by the average level of contribution margin), and customers who have made a recent purchase (indicating that the customer is active) and have purchased across a wider range of product categories (as captured by cross buying) are more likely to purchase in the current month. Finally, marketing contacts have a significant positive influence on customer purchase incidence, and the influence of marketing contacts is enhanced for customers who have made a recent purchase.

Similar to purchase incidence, past customer spending seems to have a positive reinforcing effect on spending in the future. Over and beyond the lagged effects of customer spending, customers who have a greater breadth of relationship (i.e., cross buying) and customers who have purchased frequently in the past provide a higher contribution margin. Also, the contribution margin potential is further enhanced for customers who have both a greater relationship breadth and have made a recent purchase.

The heterogeneity distribution for the customer-specific intercepts (provided in Technical Appendix

W1) indicate that although IBM allocates more marketing contacts for customers who have a higher sales, the purchase incidence and contribution margin is lower for these customers. This is possible because customers who have higher sales (or larger companies) in general split their purchases across several vendors (Bowman and Narayandas 2004). Similarly, customers in the B2B industry are allocated more marketing contacts, but these customers have a lower purchase incidence and lower contribution margin than customers in the B2C industries. The coefficients for customer sales and industry category imply that IBM may benefit from reallocating the marketing contacts. Finally, customers who have a large installed base of PCs (an indicator of the demand for IT-related products) have a higher purchase incidence and contribution margin and are contacted more by IBM.

5.2. Phase II: Comparing Traditional Customer Selection Metrics with CLV

Difference Between CLV and the Traditionally Used Metrics. Although recency-frequency-monetary value (RFM), past customer value (PCV), and CSS are commonly used for computing the customer's future value, they suffer from the following drawbacks.³ RFM and PCV are not forward looking and do not consider whether a customer is going to be active in the future. These measures consider only the observed purchase behavior and assume that past behavior reflects future behavior. RFM assumes that the recency, frequency, and monetary value of a customer's purchase explain the future value of the customer. It fails to account for other factors (e.g., marketing actions) that help to predict the customer's future purchase behavior and the customer's worth to the firm. Also, the weights given for R, F, and M greatly influence the computation of a customer's worth. PCV fails to account for factors (e.g., cross buying) influencing future purchase behavior of customers. It also does not incorporate the expected cost of maintaining the customer in the future. This limits its use as a valuable input in designing customer-level marketing strategies. As mentioned before, CSS focuses only on customer revenue and ignores the cost of serving a customer. On the other hand, the CLV measure incorporates the probability of a customer being active in the future, the future contribution margin, and the marketing costs to be spent to retain the customer. All these factors used to measure CLV are essential for designing customer-level marketing strategies that maximize firm value.

³ Details on the measurement of the traditional metrics are provided in the Technical Appendix at <http://mktsci.journal.informs.org>.

Table 4 A Comparison of Metrics for Customer Selection

		Using the first 54 months of data to predict the next 18 months of purchase behavior			
Percent of cohort (selected from top)		Customer lifetime value	CSS	RFM	Past customer value
15	Average revenue	30,427	21,789	22,622	23,542
	Gross value	9,184	6,659	6,966	7,185
	Variable costs	107	114	110	104
	Net value	9,077	6,544	6,856	7,081

Notes. The reported values are in dollars (expressed as a multiple of the actual numbers) per customer and are cell medians. The net result was identifying the top customers who provided the best customer value.

Metrics Evaluation. The CLV score for each customer was computed using information from the predictions of marketing contacts, purchase incidence, and contribution margin (obtained from the proposed modeling framework illustrated in Appendix A), as well as the unit marketing costs for each channel. Seventy-two months of historical data were available for model development. Traditional metrics were also computed using the first 54 months of data. Customers were then rank ordered based on the CLV measure as well as on the traditionally used metrics. The comparative performance of the customers (i.e., the observed profits provided by the customers in the last 18 months) in the top 15% of each metrics' list clearly shows the power of CLV to identify the best customers for future targeting (see Table 4). Previous research in contractual settings has found that current profit is a good indicator of future profitability (Donkers et al. 2007). In contrast, our results indicate that in noncontractual settings, at least with regard to selecting high-potential customers for future targeting, current profit performs worse than estimates of future profitability.

5.3. Phase III: Optimal Contact Strategy

Forward-Looking Cost Allocation Strategy. In Phase III, we use a genetic algorithm to obtain the "optimal contact strategy" for each customer (Venkatesan et al. 2007). Once the posterior distribution of the parameter estimates of the model used to measure CLV (Phase I) are obtained, we vary the frequency of marketing contacts for each customer and then calculate the sum of the expected CLV of all the customers in the sample. For each customer, we calculate a CLV corresponding to each sampled value of the posterior distribution of the parameter estimates for that customer, and the average of the CLVs across the posterior distribution for the customer provides the expected CLV. The optimization algorithm maximizes the sum of expected CLVs for all the customers.

To compute the optimal contact strategy, we assume that IBM would make the same number of contacts to a particular customer every month over the three-year prediction horizon. IBM contacts its midmarket

customers through direct mail, telesales, and e-mail. Within IBM, the implementation of marketing contacts within each channel is managed by separate groups. Obtaining the support and participation of each marketing channel group would have significantly delayed the implementation of the field experiment. Also, the field experiment was intended to illustrate the usefulness of the CLV management framework within the organization. We expected the success of the field experiment to improve the chances of organization-wide adoption of this framework and also to help us obtain the participation of all the marketing channel groups in future campaigns. Therefore, we identify the optimal level of marketing contacts across all channels, and not the optimal level for each channel.

Given the posterior sample of model coefficients, the optimization algorithm is implemented by varying the level of lagged marketing contacts and two-period lagged marketing contacts for each customer. For the first time period in the prediction horizon ($j = T + 1$, in Equation (1)), we first compute the level of marketing contacts (Equation (A1) in Appendix A). Given the predicted level of marketing contacts, we then predict purchase incidence (Equations (A2) and (A3) in Appendix A), and predict contribution margin (Equation (A4) in Appendix A) given the level of marketing contacts and purchase incidence. The predicted quantities for the first time period are then substituted back as independent variables to predict the values in the second time period and so forth. These predictions are carried forward to 36 months to calculate CLV from Equation (1). This process is repeated for each sampled value in the posterior distribution of the parameters to compute the expected CLV for each customer for a given level of marketing contacts.

Different values of lagged marketing contacts and two-period lagged marketing contacts that are simulated from the optimization algorithm will lead to different predictions of marketing contacts, purchase incidence, and contribution margin, and hence expected CLV. The objective of the optimization algorithm is to find the optimal level of marketing contacts for each customer that would maximize the

sum of expected CLVs of all the customers. The optimization algorithm therefore maximizes the sum of expected CLVs by varying 10,000 parameters (i.e., varying the lagged and two-period lagged levels of marketing contacts for the 5,000 customers in the estimation sample). We set the parameters in the genetic algorithm as follows: population size = 200, probability of crossover = 0.8, probability of mutation = 0.25, and convergence criteria = difference in optimal solution over the last 10,000 iterations is less than 0.1%. Further details on the genetic algorithm used in this study are provided in online Appendix W3. Note that even though we estimate a single marketing contact response parameter for all the customers, the optimal level of marketing contacts that would maximize a customer's expected CLV is different because the values of the other covariates in the model vary by each customer.

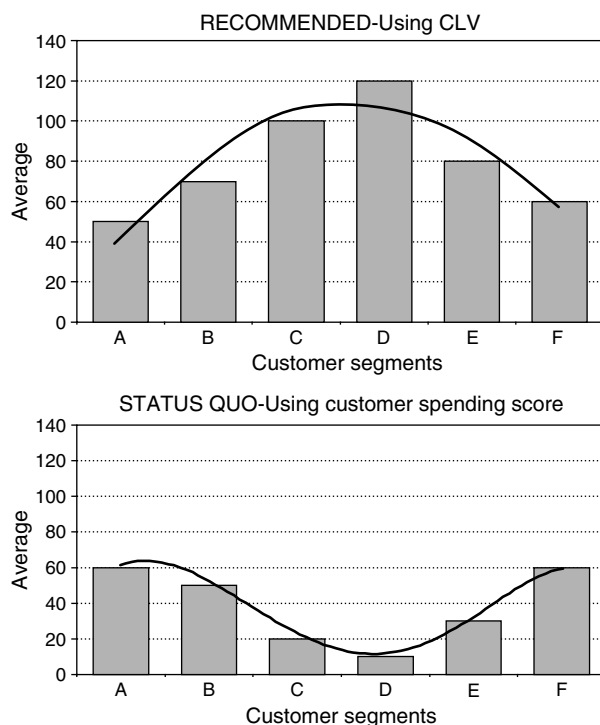
The output from the optimal resource allocation model produced input into the decision-making process about the number of contacts in each channel for each customer in various customer segments described below. The differences in suggested optimal contact frequencies across various customer segments are shown below. At the time of the study, the firm was using CSS as a key metric for targeting customers and allocation of contact resources. The segments themselves are fixed. For example, one segment could be recently acquired customers, and the other segment could be dormant customers, and so on. Figure 2 shows the contact frequencies for each of these

segments (whose names are not revealed due to confidentiality reasons). However, as shown in Table 5, when we used the CLV metric, the contact frequencies changed (as a result of maximizing CLV) for these segments (quite the contrary to the CSS metric). CLV, coupled with other techniques, provided further insights for IBM to redistribute marketing contacts by customer segments.

For example, some customers in Segment D are not being contacted at all, and some other customers in that segment are contacted at a very low frequency. The proposed framework recommends that customers in Segment D be contacted more so that the resulting CLV is higher. This exercise indicates that the resource allocation strategy suggested by CLV is different from that suggested by a CSS metric. However, we would be able to assess whether the different resource allocation strategy suggested translates into higher profits for the firm only through a field experiment.

The optimal level of marketing contacts is used to guide the determination and budgeting of customer-level marketing resources. However, recognizing the fact that the optimization framework does not consider competitive reactions and changes in the product/service space, the optimal level of contacts served only as a planning tool. During implementation, a customer was contacted until a purchase, or when an additional contact would result in negative profitability. Because the customer responses in the current period are augmented to the customer database, repetition of the CLV measurements and the determination of the corresponding optimal level of contacts over time are expected to reduce the discrepancy between the planned optimal level of resources and the realized level of resources.

Figure 2 A Comparison of Contact Strategies



5.4. Phase IV: Prediction of Purchase Probabilities for Each Product Category

The CLV ranking determines which customers to target; the propensity model determines which products to pitch to the targeted customers. In Phase IV we estimated a customer's propensity to purchase in each of the product categories. A series of binomial logit models are estimated (one for each product category) to predict customer purchase propensity. The use of sophisticated modeling approaches that accommodate for coincidence of product category purchases such as the multivariate probit model (Seetharaman et al. 2006) are also being evaluated currently for predicting purchase propensity. However, the simple binary logistic model approach was used in this study because it was the primary methodology used in the organization at the time, and we wanted to clearly evaluate the benefits from implementing the CLV approach first.

Propensity models were built to predict the propensity of buying products within the following

Table 5 Optimization Strategies

Customer lifetime value	Customer spending score (CSS)	
	Low	High
High	Direct mail/Telesales/Catalog/Email: Current interval is 4.82 days Optimal interval is 1.9 days Gross value: Current value is \$10,936 Optimal value is \$17,809	Direct mail/Telesales/Catalog/Email: Current interval is 6.3 days Optimal interval is 5.3 days Gross value: Current value is \$53,488 Optimal value is \$90,522
Low	Direct mail/Telesales/Catalog/Email: Current interval is 9.7 days Optimal interval is 12.6 days Gross value: Current value is \$743 Optimal value is \$1,203	Direct mail/Telesales/Catalog/Email: Current interval is 8.4 days Optimal interval is 8.3 days Gross value: Current value is \$1,091 Optimal value is \$2,835

categories—hardware, software, and services. Our assumption is that the customer's need for certain product types as well as familiarity with the focal categories are the key drivers of product category choice. The drivers of product category choice that have a significant influence include (1) the proportion of same-category purchases, i.e., the *dominance* of a category over others; (2) the depth of same-category purchases measured as the number of products purchased within the focal category, i.e., the *knowledge* of the focal category; and (3) the breadth of same-category purchases measured as the number of different product types purchased within the focal category. Marketing contacts are not included as a predictor in the logistic regressions because the customer database currently does not register the product message in a marketing contact. The percentage of correct classifications for the propensity models were 88%, 84%, and 89% for the hardware, software, and services categories, respectively. A product message was used in a marketing contact to a customer if the predicted purchase propensity for the category was greater than 0.5 for that customer. The predictions from the propensity models were used to provide *further insight on the right product/service message* to convey when contacting the selected customers.

6. Second Stage—Implementation

The second stage involves the field implementation of the models developed and validated for measuring CLV, and the selection of the product message in the first stage. The general guidelines for the second stage, which involves the implementation of the CLV management framework, are provided below:

1. Assess the distribution of customer value.
2. Identify customers with high potential value that have been ignored in the past.

3. Select customers for contacting in the next year by dropping customers that were targeted in the past but are predicted to have low CLV, and picking customers who are identified in Step 2.

4. Provide the new customer list to the salespeople. Make them aware of the optimal level of resources and the product message identified for each customer in Phase III (in the first stage) as a guideline.

5. Record the revenue obtained from each customer and the resources that were required to obtain the revenues.⁴

6. Going forward to the subsequent year, reestimate the CLV and propensity models developed in the first stage with the new data obtained the prior year.

We now provide details about the implementation of the above implementation guidelines in our study.

6.1. Phase V: Resource Reallocation

In Phase V, the marketing resources are aligned with customers who have the highest potential. The customers are first divided into two groups—customers who have not been contacted at all (the *Not Contacted Until 2004* group), and customers who were contacted previously (the *Contacted by 2004* group). In each group, the customers were further divided into deciles, and the mean CLV in each decile is provided in Table 6.

Table 6 shows that customers in Decile 10 for the *Contacted by 2004* group have a negative mean CLV, and the customers in Decile 1 for the *Not Contacted Until 2004* group have a higher CLV than Decile 2 (and onwards) of the *Contacted by 2004* group.

⁴ Salespeople also use their judgment and intuition when deciding on the resources required for each customer. Further, salespeople from the multiple product groups coordinate their sales calls as deemed appropriate.

Table 6 Resource Reallocation Based on CLV*

Decile	Not contacted until 2004 (\$)	Contacted by 2004 (\$)	Customer segment
1	350,471	2,124,483	Super high CLV
2	993	125,460	High CLV
3	669	43,681	Medium CLV
4	638	23,624	
5	623	17,499	
6	611	13,675	
7	534	10,513	Low CLV
8	444	8,051	
9	369	5,023	
10	80	(35)	

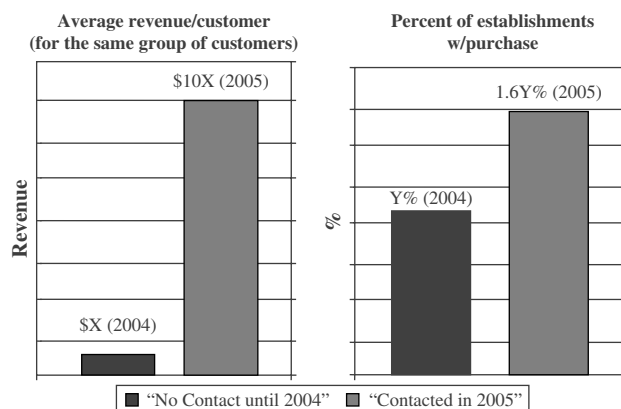
*The values reported here have been adjusted by a constant factor of the actual figures.

Based on the distribution of CLVs across the deciles, it was recommended that marketing contacts be reallocated from customers in Decile 10 in the *Contacted by 2004* group to customers in the top three deciles of the *Not Contacted Until 2004* group. For the customers in the top three deciles of the *Not Contacted Until 2004* group, we then obtained the predictions for purchase probability for the three product categories from Phase IV. Customers who had a high purchase propensity for at least one of the three product categories were selected as candidates for resource reallocation. The candidate customers were then rank ordered based on their CLV (provided in Table 6). Marketing resources were allocated based on this rank order (i.e., higher CLV candidate customers were first allocated resources) until all the resources that were available from Decile 10 of the *Contacted by 2004* group were exhausted. The level of resources allocated to each candidate customer was determined based on the optimal contact strategy described in Phase III. This process for resource reallocation resulted in some customers in Deciles 1 and all the customers in Deciles 2 and 3 in the *Not Contacted Until 2004* group being allocated marketing resources for 2005.

6.2. Phase VI: Field Study

Recommendations from Phase V coupled with inputs from other groups, including the sales managers, formed the basis for the marketing contact strategy implemented in 2005.⁵ The process of implementing the strategy involved contacting the customers who were not contacted until 2004 but who exhibit the potential for high CLV in 2005—i.e., Deciles 1 through 3 in the *Not Contacted Until 2004* group.

⁵ 2005 can also be considered as a “true holdout” time period.

Figure 3 Measuring the Impact of the Contact Strategy

6.2.1. Impact. The results reveal that on average the revenue from the customers who were not contacted until 2004, but contacted in 2005 increased by 10 times (across all customers), as shown in Figure 3. To ensure that the increase in revenue is due to contacts and pitching the right products/services, the revenues for the customer group who requested not to be contacted at all—*Do Not Contact* group—were compared for the years 2004 and 2005. The average revenue for this group in both years showed similar revenues (i.e., similar to the revenue provided in 2004 by the “not contacted until 2004 but contacted in 2005” group). We therefore infer that the higher performance in 2005 for the group of customers who were not contacted in 2004 was due to contacting the right customers with the right message. As explained before, the selection of the customers and the corresponding messages were based on the models developed in Phases 1 through 5, thereby illustrating the economic impact of these models. The effectiveness of the propensity models was reflected in the superior performance of the sales revenue metric. In other words, if inappropriate products were pitched, then the firm would not have realized higher revenues. Further, the average number of contacts (8.9) per customer across the customers was close to the predicted number of contacts (8.1) for this group.

The net result was higher revenues (although it is still not the net profit, given that certain selling [general and administration] expenses have to be accounted for, the comparison holds good), and higher value in 2005 versus 2004 for the no contact until 2004 but contacted in 2005 group of customers (Deciles 1 through 3 in the *Not Contacted Until 2004* group). The total increase in revenues for the no contact until 2004 but contacted in 2005 group of customers is about \$19.2 million dollars. We use the increase in revenue among the *Contacted by 2004* group of customers from 2004 (\$751 M) to 2005 (\$793 M), which is about 5%, as the year-to-year growth

Table 7 Further Analysis of the “Not Contacted Until 2004” Group

	Dormant customers reactivated in 2005	Customers active in 2004 and 2005
Number of customers	273	1,827
Change in revenue from 2004 (\$)	11.4 M	7.6 M
Average increase in revenue per customer (\$)	41.76 M	4,160

in revenue from IBM customers. After adjusting for the annual growth in customer revenue, the incremental revenue due to resource reallocation among the *No Contact until 2004* group of customers is about \$19.1 M. The direct marketing contact cost for contacting these establishments is about \$95,200 (given the average unit cost of \$7 per contact). The model development costs for this study are estimated to be about \$25,000. The ROI for IBM in this study is therefore around 160.⁶

Similar to Elsner et al. (2004), we investigate the sources of incremental value. The incremental value in 2005 for the *No Contact Until 2004 but Contacted in 2005* group of customers is derived from two sources. Table 7 shows that \$7.6 million (approximately 40%) is obtained from the increase in purchase amount from customers who were active (or purchased) in 2004 and \$11.4 million (approximately 60%) is obtained from new purchases from customers who did not purchase in 2004, i.e., reactivation of dormant customers. About 273 customers who were dormant in 2004 were reactivated in 2005; therefore, the average increase in revenue from reactivating dormant customers was about \$41,758. One thousand eight hundred twenty-seven customers were active in both 2004 and 2005. Therefore, the average increase in revenue from existing customers was \$4,160. The resource reallocation therefore seems to result in both growing existing customers and reactivating dormant customers, with slightly more emphasis on reactivating dormant customers.

The total revenue from the customers who were contacted in 2004 and 2005 (based on our model recommendations) was over 750 million dollars (after accounting for the direct marketing expenses). Therefore, our model identified both existing and new sources of revenue. The reallocation of marketing resources led to about a 3% increase in profits from 2004 to 2005 for the midmarket customers from contacting only 1% of the IBM customers. The impact of the CLV-based campaign on the profitability of midmarket customers has accelerated the adoption of the CLV management framework for other customer segments in IBM. One such initiative that is

notable is the implementation of the CLV management framework for marketing multiple service solutions to very large customers (i.e., customers with greater than 1,000 employees), the large enterprise segment. Within this initiative, sales team contacts are prioritized based on the potential value of the customers, and predictions from propensity models for the various service options act as inputs for the message of the sales team.

7. Organizational and Implementation Challenges

The reorientation required to implement a CLV management framework has to be carefully managed by the firm. In this section, we outline some of the challenges faced and the steps that are necessary to manage this change successfully. Customers are more central to firms than brands and brand equity, although current management practices in many firms do not reflect this shift (Rust et al. 2004). Traditionally, in many companies, marketing and sales activities for individual product groups are implemented by a product-specific sales team, sometimes with little idea of what activities have been planned by the other product groups targeted at the same customer.

Although many multiproduct firms may strive to coordinate their messaging strategy, they fall short in the customer’s mind when the firm’s various marketing and sales groups set forth group-specific communication goals that often are not in sync with each other or with the overall strategy. Customers often feel they are dealing with multiple companies because they receive uncoordinated communications from both sales and marketing. This is possible because some customers have been observed to have a high affinity for the firm’s products. On the other hand, some potential high-value customers get ignored. Applying the CLV management framework helps a firm to understand which products, specific customers, and/or customer segments are likely to buy at varying time frames. Thus, to reap the benefits of the CLV management framework, a firm should try to develop strategies and tactics from a customer’s perspective rather than from a product perspective. This transformation presents multiple organizational and implementation challenges. We summarize some of these challenges next.

Organizational challenges can be broadly categorized along business and people dimensions. The business dimension requires defining and articulating the business case for change and the desired outcomes of change. Quantification of the projected return on investment is required not just within specific business units but also across multiple key stakeholders and across business units. Cross-organization

⁶ The ROI measure excludes any selling (general and administration) expenses.

collaboration is essential to identify and assess key stakeholders, degree of risk, and cost of change in the planning and implementation phases. As to the human element, managers and professionals who have traditionally been responsible for all aspects of the marketing of a single brand now have to be empowered with the ability and responsibility across brands, products, and units. Thus, the following steps are recommended:

1. Generate awareness of the need to change.
2. Create a desire to participate and support the change through innovative rewards and incentives.
3. Disseminate knowledge of how to change.
4. Empower ability to implement the change on a day-to-day basis.
5. Provide managerial reinforcement to keep the change in place.

Success of campaigns implemented based on the CLV management framework depends largely on understanding customer-level campaign responses and documenting the relationship progression to provide effective feedback to the system. The three critical aspects for campaign implementation are outlined next.

Applying the Time-Based Probability Measure. The measure for the probability to purchase in each product category and customer value for each quarter or any other time frame of interest is provided in the campaign execution output file for each customer. The recommendation from the output file may suggest a significant change in the customer contact pattern. Figure 2, described earlier, illustrates the actual versus recommended contact pattern (aggregated across customers within each segment, over three product categories across four quarters) for each of the six different customer segments. The recommendation runs counter to the current practice. The analysis suggests that customer segments C, D, and E, which were being contacted least frequently, should be contacted most frequently to maximize CLV across various marketing initiatives. If, after several contacts, the customer does not purchase a product in the expected quarter, it is prudent to reevaluate the contact frequency with the customer in the next quarter and onwards for that product category.

Documentation of Progress. To effectively assess performance, the purchases made by the customer need to be recorded in real time. For the customers who have already made the purchase, the product category purchased needs to be documented, and further contact efforts need to be tailored based on this information.

Performance Tracking and Monitoring. To provide the inputs into the CLV computation, measures such as marketing communications cost, manufacturing

cost, service delivery cost, retention and acquisition costs, and revenues need to be monitored and reported. Other metrics that guide performance are often reported to the management. Examples of these are cross-sell ratio, win-back ratio, share of wallet, increase in profits, and overall return on investment.

8. Conclusions and Future Steps

The CLV management framework proposed can allow a firm to refine and improve its customer contact strategy. Using the CLV-based approach, firms can:

- Increase the return on their marketing investment by allocating resources towards customers who are most likely to provide value in the next year.
- Identify products to sell as bundles.
- Reallocate the excess resources (after targeting the most likely customers to buy in a given time period) to other prospects (acquiring new customers or reactivating dormant customers).

Plans are in place to measure the CLV for the larger set of customers (greater than 1,000 employees) and focus on even higher marketing productivity to expand this concept to the entire organization. Two major initiatives that are being considered based on the CLV management framework include (a) segmentation and profiling, and (b) understanding customer migration.

Segmenting and Profiling. The segmentation and profiling initiative is intended to guide the acquisition activities. Customers are segmented into distinct groups based on their CLV, share/size of wallet estimates and firmographics-based profiles of these customer segments are built. The expected CLV and the segment affiliation of the CLV deciles for the midmarket customers discussed in this study are presented in Table 6. The customer deciles are grouped to form four segments based on the CLV; Super High CLV, High CLV, Medium CLV, and Low CLV. For these customer segments the firmographics used to build the customer profiles primarily include the industry category, the number of employees, the sales of the establishment, and the installed level of PCs in the establishment. Only those firmographics that had discernible differences across CLV segments are included for profile analyses. The customer acquisition contacts are then directed towards prospects that match the profiles of the Super High CLV and the High CLV segments.

Understand Customer Migration. The customer migration initiative harnesses CLV measurements over time to improve retention activities. Customer migration is defined as the movement of customers from either the high-value segments (Super High CLV and High CLV segments in Table 7) in a year to the low-value segment (Low CLV segment in Table 7) in the

next year, or vice versa. Separate propensity models are built to identify (1) the drivers of customer migration to the low-profitability segments and (2) the drivers of customer migration to high-profitability segments. The various drivers that are considered include the level and change in marketing resource allocation, the rate of acquisition of new products by the customer, the intensity of financing availed by the customer, and the changes in the depth of purchasing exhibited by a customer. The drivers of customer migration are used to guide customer retention strategies.

We expect that the framework presented here has immediate application in industries where a firm has direct contact with its customers, such as online retailing, telecommunications, hospitality, and direct-to-consumer financial services firms. In industries where firms market through resellers or agents, firms may adopt a multistage profitability analysis where the profitability of the intermediary (i.e., the resellers or the agents) is determined by the profitability of the end consumers associated with the intermediaries. Marketing resource allocations can then be determined based on the intermediary's profitability.

Limitations and Future Research. The CLV management framework presented here has limitations that could serve as fruitful avenues for future research. The model does not include the impact of competitive marketing efforts on CLV. Although we did accommodate for competitive effects indirectly by the imputation of unobserved contribution margin values, a richer understanding of customer responsiveness to marketing contacts can be obtained by including the level of marketing contacts initiated by competitors at the same time. Accurate data on competitive initiatives is of course hard to obtain, but the customer transaction information can be augmented with information from periodic surveys of customers on the intensity of competitor actions and the customer's attitudes to IBM's products (Keller and Lehmann 2006). The CLV management framework presented in this study is similar in some aspects to previous research in sales call planning (Lodish 1971, Zoltners and Sinha 2005). For example, both our framework and CALLPLAN (Lodish 1971) consider cost and revenue, as well as customer responsiveness, to optimize across customer allocation of marketing resources. Whereas CALLPLAN estimates customer responsiveness based on salesperson estimates, our model framework estimates them based on historical data on customer revenue and salescall frequency. Also, our framework includes a component on predicting customer's product choices, which is absent in the CALLPLAN framework. Future research should evaluate the relative superiority of the proposed framework with earlier sales-planning frameworks such as CALLPLAN. The design of our field

experiment does not allow us to estimate the contribution of accurately predicting customer's product purchase propensities (Phase IV) towards the growth in profitability for the "Not Contacted in 2004" group. Research indicates that appropriate cross-selling models can improve the profitability of sales campaigns significantly (Kumar et al. 2008). Future research that compares the contribution provided by better models that accurately select profitable customers and models that accurately identify the product message (such as the cross-selling models) would provide a valuable contribution to the marketing productivity literature. Although we measured CLV and determined the customers to target based on CLV at the individual customer level, we did not provide any recommendations about optimal level of marketing resources for each customer. As also suggested by Rust and Chung (2006), studies that document the benefits of customer-level optimal marketing resource allocation based on CLV would provide a good contribution to the literature.

Our framework does not include the impact of macroeconomic trends and new product introductions by competitors on CLV because the current study dealt with a single instance of CLV measurement. These are factors that are important to consider when the CLV measurement is carried over multiple years and would prove especially critical for understanding customer migration. The interaction of customer appreciation initiatives such as loyalty programs, and the frequency of communication in each marketing channel, with customer profitability-based marketing resource allocation, is a fruitful area for future research. Finally, the development of sophisticated models based on the multivariate probit framework for predicting customer's basket choices in the context of the CLV management framework is a good avenue for future research.

In summary, the impact on marketing productivity realized in the field study has been instrumental in the adoption of the customer profitability management as a core framework for IBM's marketing strategies for customer acquisition, retention, growth, and win back.

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Appendix A. Details on Model Framework for Measuring CLV

As mentioned in the text, measurement of CLV requires predictions of (a) marketing contacts (MT) directed towards a customer, (b) the purchase propensity of the customer [$p(\text{Buy})$], and (c) the contribution margin provided by the customer given purchase (CM).

We first model the log of the level of marketing contacts allocated by the firm towards customer i as

$$\log(\text{MT}_{ij}) = \alpha_{1i} + x_{1ij}^T \beta_1 + u_{1ij}, \quad (\text{A1})$$

where x_{1ij} , β_1 , α_{1i} , u_{1ij} are a vector of predictor variables, a vector of corresponding coefficients, an individual-level intercept, and an error term.

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

$$\begin{aligned} (\text{Buy}_{ij}^*) > 0, & \quad \text{if } \text{Buy}_{ij} = 1 \\ (\text{Buy}_{ij}^*) \leq 0, & \quad \text{if } \text{Buy}_{ij} = 0. \end{aligned} \quad (\text{A2})$$

The latent utility, (Buy_{ij}^*), for customer i to purchase from the firm in time period j is then modeled as a function of predictor variables in a linear model

$$\text{Buy}_{ij}^* = \alpha_{2i} + x_{2ij}^T \beta_2 + u_{2ij} \quad (\text{A3})$$

where, similar to Equation (A1), x_{2ij} , β_2 , α_{2i} , u_{2ij} are a vector of predictor variables, a vector of corresponding coefficients, an individual-level intercept, and an error term. Finally, we assume that a latent variable, CM_{ij}^* , represents the amount spent by customer i in time period j , irrespective of whether it is with the firm, as a function of predictor variables with a linear structure

$$\text{CM}_{ij}^* = \alpha_{3i} + x_{3ij}^T \beta_3 + u_{3ij} \quad (\text{A4})$$

where, similar to Equations (A1) and (A3), x_{3ij} , β_3 , α_{3i} , u_{3ij} are a vector of predictor variables, a vector of corresponding coefficients, an individual-level intercept, and an error term. If the customer purchased from the firm in time period j , then the firm observes the contribution margin provided by the customer, i.e.,

$$\begin{aligned} \text{CM}_{ij} &= \text{CM}_{ij}^*, \quad \text{if } \text{Buy}_{ij} = 1 \\ &= \text{unobserved}, \quad \text{if } \text{Buy}_{ij} = 0. \end{aligned} \quad (\text{A5})$$

When data about customer transactions with all the firms in a product category are available (e.g., in scanner panel data), we can treat the contribution margin provided by a customer when there is no-purchase as equal to zero. However, in CRM databases, there is rich information about customer transactions with a single firm, but almost no information about the customer's transactions with other firms. Therefore, when we don't observe a purchase from a customer in time period j , we cannot assume that the customer did not make a purchase at all. A no-purchase in a CRM database would only imply that the customer has not made a purchase with the focal firm, but may have a purchase with a competitor. We therefore treat the time periods when a customer does not provide any revenue to the firm as "missing data." We then impute these missing values based as random realizations from a normally distributed

prior distribution for the missing contribution margins. We assume the mean and variance of the prior distribution to be the empirical mean and variance in the contribution margin provided by a customer to IBM in a calibration sample.

For observations with no purchase incidence (i.e., Buy_{ij} equals zero), there is a possibility that the customer has made a purchase with a competitor. However, the imputation of the missing contribution margins should also take into account a customer's interpurchase time. We therefore compute a customer's average interpurchase time from the calibration sample used to compute the mean and variance for the prior distribution. The imputation of contribution margins is performed only for those observations whose time since last purchase (or recency) is greater than the average interpurchase time calculated in the calibration sample. For example, if a customer's average interpurchase time in the calibration sample is three, then only those missing contribution margin observations whose recency is greater than three are imputed from the prior distribution; the contribution margin is allowed to be zero for the nonpurchase occasions whose recency is less than three. We choose this approach for selecting the nonpurchase occasions that qualify for imputation based on the assumptions about customer purchase patterns in IBM. We specify the following prior for missing CMs in months j , when the recency of purchase exceeds customer i 's average interpurchase time obtained from the calibration sample, $[\text{CM}_{ij}^* | \text{recency}_{ij} > \bar{t}_i] = \text{TN}_{[-\infty, 0]}(\mu_{i, \text{CM}}, \sigma_{i, \text{CM}}^2)$, where \bar{t}_i = average interpurchase time for customer i in the calibration sample, $\mu_{i, \text{CM}}$ = average observed contribution margin provided by customer i in the calibration sample, and $\sigma_{i, \text{CM}}^2$ = variance in the observed contribution margin provided by customer i in the calibration sample.

The imputations are obtained as a random draw from a truncated normal distribution (whose parameters are determined in the calibration sample as explained before) with limits $-\infty$ and 0. In other words, we impute negative contribution margin values (including zero) for the no purchase incidence occasions reflecting the contribution margin lost to competitors on these occasions. The customer-specific mean and variance of the prior distribution accommodates for customer-specific variations in the spending levels. The prior distribution parameters assume that a customer has the same spending level with IBM as well as with the competitors. We adopt this conservative assumption because of a lack of a reliable share of wallet information about the customers. If reliable share of wallet information were available, then the product of a customer's average contribution margin with IBM and the share of the customer's competitor purchases can be used as the mean of the prior distribution. Given that no information is available about customer transactions with competition, the calibration sample provides us with the best estimate (or expectation) of customer interactions with competitors. We expect that by treating a no-purchase occasion in this manner we would obtain better estimates of a customer's value, the opportunity cost of a customer and of the customer's responsiveness to marketing communications. The imputation of missing contribution margin is performed only

in the estimation sample. When calculating CLV, the contribution margin is set to zero for months when the predictions indicate no purchase incidence. The imputation of missing contribution margins in the estimation sample are hence relevant for providing better estimates of a customer's response elasticity, which is critical for accurately calculating CLV. Our approach here is the first step towards accommodating the missing information about customer's transactions with competition. Future research that evaluates other mechanisms for addressing this issue would be very valuable.

The above formulation is similar to the “seemingly unrelated regression” model structure, and the predictor variables in Equations (A1), (A3), and (A4) need not be the same. We assume that the covariance structure of the errors in Equations (A1), (A3), and (A4) may be modeled as,

$$\begin{bmatrix} u_{1ij} \\ u_{2ij} \\ u_{3ij} \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_{22} & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_{33} \end{bmatrix} \right) = N_3(0, \Sigma_y), \quad (\text{A6})$$

affording the possibility of correlations among the three residuals. We fix σ_{11} to be equal to one to ensure model identification. The covariance structure of the errors accounts for any unobserved dependence between a firm's decision to contact a customer (MT), a customer's decision to purchase from the firm (Buy), and the amount the customer spends with the firm (CM). Letting $\beta = [\beta_1, \beta_2, \beta_3]$, and $\alpha = [\alpha_1, \alpha_2, \alpha_3]$, the simultaneous equations model gives rise to the likelihood specified in Equation (2). The customer-specific intercept terms are obtained from a multivariate normal distribution;

$$\alpha_i \sim MVN(\Delta Z_i, \Sigma_\alpha) \quad (\text{A7})$$

where,

Z_i = a $p \times 1$ vector of customer characteristics;

Δ = a $3 \times p$ matrix of coefficients for the customer characteristics;

Σ_α = a 3×3 variance-covariance matrix;

p = number of customer characteristics that are used to capture heterogeneity.

We assume diffuse and conjugate priors for the model parameters. We assume multivariate normal priors for β , and Δ . Let d_β denote the dimension of the β vector; then, the prior specification of β is given as $\beta \sim MVN(\mu_\beta, \Sigma_\beta)$, where μ_β is a d_β dimensional column vector of zeros, and $\Sigma_\beta = 100I_{d_\beta}$; I_{d_β} is a $d_\beta \times d_\beta$ dimensional identity matrix. Similarly, let d_Δ denote the dimension of Δ ; then the prior specification of Δ is given as $\Delta \sim MVN(\mu_\Delta, \Sigma_\Delta)$, where μ_Δ is a d_Δ dimensional column vector of zeros, and $\Sigma_\Delta = I_{d_\Delta}$; I_{d_Δ} is a $d_\Delta \times d_\Delta$ dimensional identity matrix. Inverse Wishart priors are assumed for the variance parameters. The prior specification for Σ_α is given as $\Sigma_\alpha = IW(\rho I_{d_\Delta}, \rho)$, where $\rho = 15$ and I_{d_Δ} is a $d_\Delta \times d_\Delta$ 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.

Further details on the data augmentation, the prior specifications, and the Markov chain Monte Carlo (MCMC) estimation algorithm can be obtained from Cowles et al. (1996).

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