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Using Customer Lifetime Value in Customer Selection and Resource Allocation

Rajkumar Venkatesan and V. Kumar

Are managers spending their marketing dollars with the wrong customers? These researchers use customer lifetime value to select profitable customers, and compare choices to those selected by other metrics, such as share of wallet. Customer lifetime value surpasses the other measures—by as much as $60,000 in profits for a top customer.

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Report Summary

What is the critical measure to evaluate the value of customers? In this study, authors Venkatesan and Kumar find that customer lifetime value (CLV) is the key. They analyze CLV as a metric for identifying the most profitable customers, and propose a framework for managers to maximize the value of their customer base across individual customers and across different channels of communication.

Using data from a large multinational computer hardware and software company, they first develop a model that calculates the lifetime value for each individual customer as a function of cash flows, interpurchase times, and variable marketing costs. They evaluate CLV capability compared with other commonly used metrics—share of wallet, and recency, frequency, and monetary value (RFM)—and find that CLV is more effective at identifying the most profitable customers. Further, the benefits of CLV over other measures hold for both the short term (an 18-month prediction window) and the long term (a 30-month prediction window).

In the second phase of their study, Venkatesan and Kumar develop a model to optimize the design of marketing communication strategies by maximizing CLV based on cash flows, interpurchase times, and variable marketing costs. They compare the CLV-based algorithm with resource allocation rules that reward primarily share of wallet or RFM. Overall, they find that managers are currently spending their marketing dollars either with the wrong customers or in the wrong channels of communication.

The authors' optimization strategy suggests removing resources from customers who are low on backward-looking metrics (such as share of wallet and RFM) and allocating resources towards customers who are high on both backward-looking and forward-looking metrics. In addition, the strategy suggests allocating more resources towards customers who are high on CLV but low on the backward-looking measures compared with customers who are high on the backward-looking measure but low on CLV. ■

Introduction

Customer relationship management (CRM) systems have enabled managers to accumulate vast amounts of information about the behavior of individual customers on both the supply side (marketing expenditures) and the demand side (past purchase behavior and demographics). This has led to the incorporation of customer lifetime value (CLV) as a CRM tool used to acquire, grow, and retain the right customers. Many companies, however, are not successful at utilizing CLV measurements judiciously. They either work with undesirable customers to begin with or do not know how to tailor the customer's experience to create the highest value (Thompson 2001). Although investments in CRM promise to improve the efficiency of customer management, there is scarce evidence for such an advantage (Rigby, Reichheld, and Schefter 2002). The challenge most marketing managers currently face is to achieve a convergence between marketing and CRM. Specifically, they need to take all the insights they have collected about customers and integrate those insights with how firms interact with their customers.

Let us consider the following scenarios, which managers in most direct marketing positions face. Joe has been using his American Express credit card consistently over the past four years. However, over the last two months, his activity with the credit card has been declining. Jack, a marketing manager at American Express, is exploring his options to proactively intervene and reactivate Joe. While deploying marketing instruments to do so, Jack should be cautious and ensure that the cost of reactivating Joe does not exceed Joe's future revenue potential. In a similar scenario, consider two customers, A and B. A has been a customer for the last 10 years and has spent x dollars. B has been a customer for only 5 years but has already spent more than x dollars. Most marketing managers are faced with the dilemma of which to reward: longer *customer lifetime duration* or higher *customer lifetime value*. In each case, the manager needs to allocate marketing resources to the individual customer.

The above examples provide a representative sample of the problems faced by managers while managing customer equity. A paradigm shift in managerial strategy is currently underway as managers begin to focus on customer lifetime *value* instead of focusing only on customer lifetime *duration*. For example, several major airlines have recently proposed plans to revamp their frequency programs to reward the value of purchases rather than number of miles. CLV, which is the core of managerial decisionmaking, can be improved through increasing revenues from a customer, decreasing the cost of serving that customer, or both. Rust, Moorman, and Dickson (2002) argue that it is usually possible to pursue only one of these two strategies. In this research, we plan to demonstrate that if costs are allocated in some optimal fashion, profits can be improved through both increased revenues and reduced costs. (Recently, for instance, both Dell and AOL announced such strategies.) Furthermore, Berger et al. (2002) clearly suggest the benefit of allocating resources to maximize the value of the customer base and strongly argue for the need for such optimal resource-allocation models.

Two factors motivated us to conduct this research study. First, although researchers have developed theories aimed at improving the lifetime duration of current customers (Bolton 1998; Bolton and Lemon 1999), there is a dearth of information about factors affecting CLV (Reinartz and Kumar 2003; Rust, Zeithaml, and Lemon 2001) and the cost aspect of maximizing customer equity (Niraj, Gupta, and Narasimhan 2001; Blattberg and Deighton 1996). The calls for research assessing the returns on marketing strategies that maximize profitable customer relationships (Reinartz and Kumar 2000; Mulhern 1999) add credence to our objective to explore the influence of marketing strategies in maximizing customer lifetime value. Measuring CLV is therefore necessary, but certainly not sufficient. Marketing researchers have also recognized that managers need to implement marketing initiatives (such as loyalty programs, customer reactivations, cross-selling, and programs to anticipate and forestall defection) that maximize the value of the customer franchise (Bell et al. 2002).

Second, a linear association between customer lifetime duration and profitability would suggest allocating all marketing resources to longer-duration customers (a corner solution in mathematical terms). Even then the question still remains as to the optimal allocation of resources among potential prospects and best customers. However, the assumed linear relationship itself has been shown to be invalid in noncontractual settings (Reinartz and Kumar 2000; Reinartz and Kumar 2002). Thus, there is a need to develop a solution for optimal allocation of marketing resources across customers, irrespective of the relationship between lifetime duration and lifetime value.

Managers are frequently advised to recognize the differences in efficiency across various channels, and the potential benefits of synchronizing communications to customers across these channels (Sawhney 2001). Hence, managers need to know the optimal levels of marketing expenditures in each channel (given expected revenues from the customer and compared with expenditures in other channels) that would maximize future profitability. Literature on marketing resource allocation (Mantrala, Sinha, and Zoltners 1992; Gopalakrishna and Chatterjee 1992) suggests that (1) marketing managers need to optimize not only investment-level decisions but also the allocation of resources across submarkets or customer segments in order to maximize profitability and (2) the interaction among different marketing-mix instruments could lead to different allocation of resources across marketing channels. These findings motivated us to develop a framework for the optimal allocation of marketing resources across individual customers and for each customer across different channels of communication.

Our study addresses the above issues in two phases. In Phase I, we develop an objective function that calculates the lifetime value for each individual customer that is a function of cash flows, interpurchase times, and variable marketing costs. The computation of CLV in Phase I can aid managers in selecting customers for marketing communications. We evaluate the capability of selecting customers compared with other commonly used metrics: share of wallet and recency, frequency, and monetary value (RFM). While the objective in Phase I is the optimal selection of customers for marketing communications, in Phase II we are concerned with the optimal design of the communication strategy itself. Our optimization algorithm focuses on developing resource allocation strategies that would maximize CLV based on the objective function developed in Phase I. We contrast the optimal allocation rules suggested by the CLV-based algorithm with allocation rules that reward primarily share of wallet or RFM.

CLV Framework and Data

In order to measure CLV and simultaneously derive guidelines for optimal resource allocation levels that would maximize CLV, we need the following components in our framework:

- An objective function based on predicted cash flows, interpurchase times, and cost of communications that also incorporates the time value of money (e.g., the inflation rate)

The objective function is then based on:

- A stochastic model that predicts the interpurchase time of each customer, which is influenced by supplier-specific (marketing communications and relationship benefits) and buyer-specific (customers' past purchase behavior) time-varying covariates
- A panel data model that predicts the cash flows from each individual customer, given his or her past purchase behavior, quantity

per purchase, and a set of marketing mix covariates
- An optimization algorithm that maximizes the profits from each individual customer by judiciously allocating marketing resources

(For more details on how we developed the concept of CLV measurement and the components associated with it—as well as the necessary theoretical and conceptual underpinnings for the entire framework, its components, and their respective determinants—see Appendix 1.)

Figure 1 below shows the various components of CLV—interpurchase time, cash flows, and marketing costs, and how they integrate in the computation of CLV. Based on the commitment-trust theory of relationship marketing (Morgan and Hunt 1994) and past literature on customer equity (Rust, Zeithaml, and Lemon 2001), we develop determinants of interpurchase time and cash flows. Some of these determinants are under management control and also affect the variable costs of managing customers. The optimization framework concentrates on utilizing these determinants that are under management control to maximize CLV.

Data for the study come from a large multinational computer hardware (servers, workstations, and PCs) and software (integration and application) manufacturer. The company's database focuses on business customers. The product categories in the database represent different spectrums among high technology products. In addition, when it comes to these product categories, both the buyer and seller choose to develop their relationships and there are significant benefits to maintaining a longstanding relationship for both buyers and sellers. Moreover, the choice of vendors for these products is usually made after much deliberation by the buyer firm. Even though these products are durable goods, they require constant maintenance and frequent upgrades; this provides the variance required in modeling the customer response. For our analyses we use two cohorts of customers. Customers were assigned to Cohort 1 if their first purchase with the manufacturer was made in the first quarter of 1997, to Cohort 2 if their first purchase was made in the first quarter of 1998. This resulted in an effective sample size[1] of 1,316 and 873 observations for customers in Cohort 1 and 2, respectively. The average interpurchase time for customers in Cohort 1 was between −1.5 months and 23 months and for Cohort 2 between 1 month and 20 months.

Managers had the following information about each customer in order to help them make a decision: date of each purchase, number of proactive manufacturer-initiated marketing

Figure 1
CLV Components

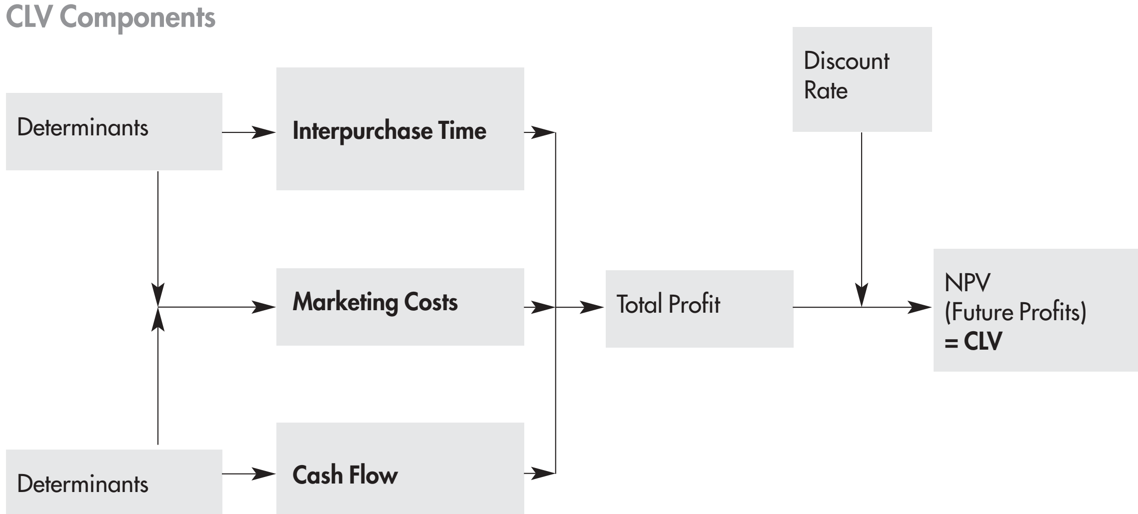


Table 1
Covariates and Expected Effects

Variable	Operationalization	Expected Effect
Interpurchase Time Model *(Dependent Variable: Interpurchase Time)*		
Upgrading	Number of upgrades in product purchases until a purchase occasion	–
Cross-buying	Number of different product categories that a customer has made a purchase with the focal firm until a purchase occasion	–
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 purchase occasions	–
Returns	Number of products returned by the customer between two purchase occasions	"U"
Relationship benefits	Indicator variable of whether a customer is a gold service member or not. A customer qualifies for the gold service in the current year depending on his or her revenue contribution in the past year.	–
Product category	Two indicator variables—one that indicates if a purchase was hardware, another that indicates if a purchase was software	
Frequency of sales-person contacts	Number of contacts made to the customer by the supplier firm in a month through sales personnel between two purchase occasions	"U"
Frequency of standardized modes of communication	Number of contacts made to the customer by the supplier firm in a month through telephone or direct mail between two purchase occasions	"U"
Intercontact time	Average time between two contacts made to the customer by the supplier across all channels of communication between two purchase occasions	–
Frequency online modes of communication	Number of times the customer contacts the supplier through the Internet in a month between two purchase occasions	–

Table 1, *continued*
Covariates and Expected Effects

Variable	Operationalization	Expected Effect
Cash Flow Model *(Dependent Variable: Cash Flows)*		
Lagged contribution margin	Contribution margin from the customer in the past year	+
Size of the establishment	Number of employees in the customer firm	+
Industry category	SIC-based industry category that the customer firm belongs to	
Total marketing efforts	Percentage of rich modes of communication made to the supplier firm compared with the total number of contacts	+
Total quantity purchased	Total quantity of products purchased by the customer firm across all product categories	+

campaigns until that date, the type of campaign (face-to-face, telesales, direct mail, or trading event), number of customer-initiated contacts with the supplier firm, the level of cross-buying within the firm, the number of returns made by the customer, and the amount spent by each individual customer at each purchase occasion. The unique strength of the dataset lies in the availability of individual-level marketing mix contacts/communications, costs associated with the channel contacts, and profile data. This allows us to use individual-level models and derive optimal marketing guidelines for each individual customer or segment.

Interpurchase time model

We model customer retention by predicting the interpurchase time of customers. This prediction of interpurchase times is dependent on the supplier- and customer-specific factors identified in Table 1. The assumption underlying this alternative framework to modeling customer retention is that customers are most likely to reduce their frequency of purchase before exiting a relationship and is in accordance with the theories related to relationship life cycles (Jap 2001; Dwyer, Schurr, and Oh 1987). Table 1 provides a description of the factors used, the operationalization of these factors in the database, and the expected effect of the factors. It is important to note here that a lower interpurchase time represents a higher probability of customer retention. Hence, the antecedents that have a positive influence on customer retention have a negative influence on interpurchase time.

Each purchase occasion for a customer forms an observation in the interpurchase time model.[2] For Cohort 1, we pick customers who made their first purchase in the first quarter of 1997. For each customer, we omit the first purchase occasion in our analysis sample because the first purchase occasion is restricted to be within three months for all customers in the cohort and, theoretically, the retention phase of a customer starts after their first purchase with an organization. Each interpurchase time observation for a customer is explained using covariates

Table 2
Descriptive Statistics for Covariates

Variable	Variable Type	Mean	Standard Deviation	Minimum	Maximum
Interpurchase Time Model					
Interpurchase time	Continuous	5 (4.5)	8.4 (6.8)	1 (1)	34 (26)
Upgrading	Continuous	1.5 (1.1)	.9 (.8)	0 (0)	6 (6)
Cross-buying	Continuous	2.58 (3.13)	1.7 (1.5)	1 (1)	13 (13)
Level of salesperson contacts	Continuous	1.79[a] (1.52)	5.69 (5.84)	.28 (.25)	139 (142)
Level of standard modes	Continuous	20.74 (22.81)	47.75 (45.81)	.15 (.10)	851 (792)
Level of online modes	Continuous	3.88 (4.37)	25.81 (24.94)	.62 (.75)	767 (813)
Bidirectional communication	Continuous	.84 (.62)	2.41 (3.52)	0 (0)	51 (48)
Returns	Continuous	.91 (.86)	3.7 (2.81)	0 (0)	20 (15)
Premium service level	Categorical (1/0)	.09 (.12)	.29 (.25)	0 (0)	1 (1)
Product category:					
Hardware	Categorical (1/0)	.7 (.68)	.25 (.35)	0 (0)	1 (1)
Software	Categorical (1/0)	.75 (.62)	.21 (.30)	0 (0)	1 (1)
Cash Flow Model					
ΔCM_i	Continuous	4,955 (4,827)	417,270 (381,297)	–201,049 (–190,582)	4,525,566 (3,892,168)
Size	Continuous	1.26[b] (1.29)	2.41 (2.37)	.32 (.21)	12 (12)
Aerospace	Categorical (1/0)	.005 (.003)	.07 (.08)	0 (0)	1 (1)
Financial services	Categorical (1/0)	.14 (.15)	.35 (.36)	0 (0)	1 (1)
Manufacturing	Categorical (1/0)	.09 (.10)	.29 (.28)	0 (0)	1 (1)
Technology	Categorical (1/0)	.11 (.08)	.32 (.41)	0 (0)	1 (1)
Consumer packaged goods	Categorical (1/0)	.35 (.29)	.47 (.42)	0 (0)	1 (1)
Education	Categorical (1/0)	.04 (.05)	.19 (.18)	0 (0)	1 (1)
Travel	Categorical (1/0)	.05 (.07)	.23 (.20)	0 (0)	1 (1)
Government	Categorical (1/0)	.06 (.07)	.24 (.30)	0 (0)	1 (1)
Total marketing efforts	Continuous	3.49 (4.5)	17.26 (16.24)	0	350 (402)
Total quantity purchased	Continuous	1.89 (2.01)	13.40 (14.02)	2 (1)	610 (590)

[a] Levels of rich, standardized, and online modes of communication represent the number of the respective mode of communication in a month.
[b] The size values are in 100,000s. Values in parentheses represent Cohort 2.

listed in Table 2. The covariates used in the model can be classified as cumulative and each-period effects. All the covariates used in our model are lagged one time period. The cumulative covariates include cross-selling and upgrading. The current effects covariates include bidirectional communication, returns, type of product purchased, relationship benefits, intercontact time, and frequency of rich, standardized, and online communications. In order to assess U-shaped relationships, we use a quadratic conversion (including the squared covariate term also in the equation) of the respective independent variables. For all the customers, we use the interpurchase times until the end of 2000 as our calibration sample. We use the data in 2001 as a holdout sample and for comparison of strategies.

Cash flow model

In order to model cash flows from a customer, we use the annual sales from various product and software purchases for each customer. For customers in Cohort 1, we have the annual sales from each customer between 1997 and 2000. We have two observations per customer in our analysis sample. Specifically, in observation 1 for each customer, the dependent variable is the difference in annual sales between 2000 and 1999, and the independent variables include the annual sales in 1998, firm size in 1999, the industry category of the customer, the total number of contacts made to the customer in 1999, and the total quantity of products purchased in 1999. Similarly, for observation 2, the dependent variable is the difference in annual sales between 1999 and 1998, and the independent variables are defined in a similar fashion to the dependent variable. As stated earlier, the data in 2001 are used as a holdout sample and for comparison of strategies. Also, we use the cash flows in 1998 to predict growth in cash flows from 1999 to 2000 in order to accommodate endogeneity issues in cross-section time-series variables that use lagged dependent variables. Similarly, we use lagged values of the other independent variables in order to accommodate endogeneity issues. The descriptive statistics for the data used in the study are provided in Table 2.

Customer selection strategy

Organizations in direct marketing situations in general rank-order their customers based on a particular metric and prioritize their resources from their best customers to their worst customers based on that rank order. Such a strategy is similar to the customer pyramid advocated by Zeithaml, Rust, and Lemon (2001). In this study, we compare the customer selection capabilities of the following metrics: customer lifetime value (CLV), our proposed metric; share of wallet (SOW), the metric currently employed by the organization that provided the database as a proxy for loyalty; and recency, frequency, and monetary value (RFM), a commonly used metric in the industry.

Customer Lifetime Value. Predictions from the interpurchase time model and the cash flows model are plugged into an equation to obtain the net present value of future profits (time period t+1) from each customer. (See Equation A1.2 in Appendix 1.) The interpurchase time model predicts the expected time until the next purchase for each customer in months. The ratio of 12 (because we use months as the unit of analysis) to the prediction from the interpurchase time model provides the frequency of purchases for a customer in a year. The cash flow model predicts the annual cash flow from each customer. The cash flow from a customer for a purchase occasion is obtained by dividing the predicted annual revenue from the cash flow model by the predicted frequency of purchases from the interpurchase time model. We assign a margin of 30% after accounting for cost of goods sold, and the variable costs are computed using the costs of communication. (The managers who provided the database informed us that 30% was a nominal margin for a majority of the products and services they provided.) The mean unit cost of standardized modes of communication is approximately $6.50 ($3 for direct mail and $10 for telesales) and the mean unit cost of rich modes of communication is $300. We compute the unit cost of communication for each customer as the ratio between the total contacts to the total cost of contact for a given channel in a given year. We use an annual discount rate of 15% for each customer. The discount rate we use is based on the lending rate that is appropriate for the time the data are available.

Share of Wallet. Relationship-marketing theory proposes concentrating a supplier's marketing expenses on improving customer retention—in other words, concentrating marketing efforts on increasing loyalty and hence retention rates. Reichheld (1998) proposes that an organization can attain better performance by concentrating its efforts on developing loyalty. However, recent findings (Reinartz and Kumar 2000; Reinartz and Kumar 2002) show that high loyalty, measured in terms of retention rates, need not always lead to higher profits. Although the strategy proposed in Reichheld (1998) is intuitively appealing, the empirical results of Reinartz and Kumar (2000) show that high loyalty need not always lead to high profits. Researchers have proposed using share of wallet (Bowman and Narayandas 2001) and customer lifetime duration (Reinartz and Kumar 2000) as proxies for measuring loyalty from behavioral data.

Share of wallet is defined as the ratio of customers' spending with a particular supplier to their spending in the whole category. The category spending for the customers is obtained from third-party data sources, such as Harte-Hanks and Dun and Bradstreet. The current strategy of the organization is to use share of wallet to segment customers and allocate the maximum resources to the high share of wallet customers. In addition, several firms use share of wallet as an objective for customer management efforts. For example, Merrill Lynch and Wells Fargo are adding new services to their current portfolios in order to attain a higher share of customer spending (Thornton 2003).

Recency, Frequency, and Monetary Value (RFM). The RFM methodology is a commonly used industrywide scoring method for customer selection. We use the RFM methodology used in Reinartz and Kumar (2003) for our purposes. Specifically, the RFM score is a weighted sum of each dimension, with the weights obtained from the coefficients of a regression analysis of lagged RFM on current cash flows. We also included the average values for supplier- and customer-specific factors used to model CLV in order to predict cash flows but did not attain significant improvements in predictive power. This could be because the CLV models allow the incorporation of time-varying covariates, whereas the regression model here allows us to use only annual average values for the supplier- and customer-specific factors.

In the above regression, recency is defined as the time elapsed since most recent purchase, frequency is defined as the number of months between two consecutive purchases, and monetary value is defined as the average value of purchases until the last purchase period. We obtained weights close to 60% for recency, 25% for frequency, and 15% for monetary value. However, unlike Reinartz and Kumar (2003), we do not use customer heterogeneity variables, such as cross-buying, in our RFM framework, because it does not reflect common industry practices.

Phase I Results and Discussion

In this study, we assume that the amount a customer spends is independent of the timing of the purchase. This is a rather restrictive assumption in the case of frequently bought consumer goods (Tellis and Zufryden 1995). However, given the product category we are dealing with in our dataset—high tech computer hardware and software—we believe that the purchase quantity is mainly driven by customer-specific variables and that the purchase timing is determined by the customer's needs and marketing contacts. In addition, the correlation between interpurchase times and the contribution margin is not significant in the time period used for the analyses.

Predicting expected interpurchase time

The results from the interpurchase time model are provided in Table 3. For both Cohort 1 and Cohort 2, the results are based on sampling 2,000 values from the conditional distribution of the parameter estimates of the interpurchase time model. The sampling of the parameter estimates was performed using a Markov Chain Monte Carlo algorithm. (For more details, see Allenby, Leone, and Jen 1999.)

Table 3

Coefficients for Generalized Gamma Interpurchase Time Models [a]

Variable	Generalized Gamma Model (with mixture components and temporal variation)
Component I	
α_1	1.5 ***
ν_1	45.53 ***
θ_1	.03 ***
γ_1	1.3
Mass point	.42
Component II	
α_2	1.90 ***
ν_2	30.70 ***
θ_2	.004 ***
γ_1	.9
Mass point	.58
Coefficients	
β_{01}	2.64 **
Lagged log interpurchase time	2.92 ***
Termination consequences	
Upgrading	–5.57 ***
Cross-buying	–6.12 ***
Bidirectional communication	–2.39 ***
Returns	–14.08 ***
Square of returns	5.64 **
Relationship benefits	–10.08 ***
Facets of communication	
Frequency of salesperson contacts	–6.23 ***
Square of frequency of sales person contacts	3.98 ***
Frequency of standardized modes of communication	–6.85 ***
Square of frequency of standardized modes of communication	.68 ***
Frequency of online communications	–4.52 ***
Intercontact time	–5.78 ***
Log likelihood	–2 777.57
RAE-I[b]	.52

[a] Similar results were obtained for Cohort 2 and are available from the authors upon request (vk@sba.uconn.edu). The product category variable was not significant in our analysis and is hence not included in the table.
[b] Relative absolute error with respect to a moving average model.
*Significant at $\alpha = 10\%$; ** significant at $\alpha = 5\%$; *** significant at $\alpha < 1\%$.

The insights that can be derived based on the results reported from Table 3 are as follows:

- The results indicate that upgrading and cross-buying positively influence a customer's interpurchase time. This is in line with the findings of Reinartz and Kumar (2003), who also find that breadth of purchase positively affects the duration a customer stays in a relationship. Overall these results indicate that up-selling and cross-selling are good strategies for improving customer purchase frequency.

- We also find that the higher the bidirectional communication between the customer and supplier, the higher the customer's propensity to be active in the future. This result supports the recent initiatives by organizations to improve the management of customer-initiated contacts (Bowman and Narayandas 2001). Our results also indicate that organizations should take appropriate steps to increase communication initiated by a customer. Incentives for providing suggestions that could improve the performance of a supplier's product or service could be one such initiative.
- Regarding returns from a customer, our analysis suggests that managers need to exercise caution. We see that whenever customers return a product, this process presents an opportunity for the supplier to understand the causes for dissatisfaction. However, we also find that a higher number of returns negatively influence the propensity of a customer to stay in a relationship.
- Our analyses indicate that a supplier's contact strategy and propensity to provide relationship benefits significantly affect a customer's predicted interpurchase time.
- We find that frequency of contacts affects customer interpurchase time in a nonlinear fashion, given the support for a U-shaped relationship. This lends support to the notion that too much communication between a customer and a supplier could turn out to be disruptive, hence suggesting a nonlinear relationship (Fournier, Dobscha, and Mick 1997). It also provides the reasoning for the optimization framework in Phase II.
- The results highlight the importance of incorporating the online mode of communication in a supplier's marketing strategy. The online channel provides an ideal setting for organizations in the B2B space to enhance their relationships with their customers. However, the online contact strategy of an organization needs to be integrated across different channels of communication—face to face, direct mail, and telesales. Organizations like IBM and Charles Schwab now integrate the online medium with telesales in such a way that customers can search for information on websites and can place an order either online or by calling on a direct phone number to place the order with a live person.

Predicting cash flows

Table 4 shows the results from our cash flow model.

The insights derived from tables 4 and 5 can be summarized as follows:

- The cash flow model provides an adjusted R^2 of .68 and is hence able to explain significant variation in cash flows from customers.
- The two-period lagged contribution margin provides the highest contribution towards explaining current period cash flows. In addition, total lagged marketing effort and total lagged purchase quantity also contribute towards explaining variations in current cash flows.
- Among customer characteristics, firm size and industry category explain variation in current period cash flows. Among the various industry categories, firms in financial services, technology, consumer packaged goods, and the government industry categories on average provide higher cash flows compared with firms in other industry categories. Firms in the education industry category provide lower cash flows compared with firms in other industry categories.

Performance of customer selection metrics

In order to compare the performance of the customer-selection metrics, we rank-order customers from best to worst according to each metric and then compare the sales, costs, and profits from the top 5%, 10%, and 15% of customers. Our analysis here is similar to Reinartz and Kumar (2003) where we compare the predictive capabilities of the four metrics at

Table 4

Regression Results from Cash Flows Model[a]

Independent Variable	Parameter Estimate
Contribution in *t* - 2	.83***
Size	.02**
Aerospace	n.s.
Financial services	.02*
Manufacturing	n.s.
Technology	.03**
Consumer packaged goods	.03***
Education, K-12	–.03***
Travel	n.s.
Government	.02*
Lagged total level of marketing effort	.04***
Lagged total quantity purchased	.02**

[a]The reported coefficients are standardized estimates; similar results were obtained for Cohort 2.
n.s. = not significant; * significant at α = 10%; ** significant at α = 5%;
*** significant at α < 1%

two time periods—18 months and 30 months. We use the data from the first 18 months and 30 months to score and sort the customers on each metric. We then compare the actual sales, variable costs of communication, and profits for the top 5%, 10%, and 15% of the customers from the censoring time period (18 months and 30 months) until the end of the observation window. In order to select customers for contact, organizations in general pick the top 15–20% of their customers rank-ordered based on a scoring metric. Selecting more customers for contact may not be feasible given limited time and resources. Hence, in order to reflect industry practice, we compare the performance of our metric among the top 5%, 10%, and 15% of customers. The values reported in Table 5 are cell means.

The results from our comparison can be summarized as follows:

- Overall, CLV is better at identifying profitable customers than share of wallet and RFM.
- Based on the 30-month prediction window, the average net profits (revenues after removing cost of goods sold—70%—and variable costs of communication) of customers selected from the top 5% using the proposed CLV metric is expected to be $148,749, whereas the average net profits are $83,630 and $93,303 for the top 5% of the customers selected based on share of wallet and RFM respectively.
- The net profits obtained from the top 5% of the customers selected based on CLV are about 1.8 times the net profits obtained from the top 5% of the customers selected based on share of wallet. Similarly the net profits obtained from the top 5% of the customers selected based on CLV are about 1.6 times the net profits obtained from the top 5% of the customers selected based on RFM.
- The above findings hold across all the percentage subgroups (top 5%, 10%, and 15%) and across different points in time (18-month and 30-month prediction window). The results provide substantial support to incorporating the responsiveness of each individual customer across various communication channels and the utility of CLV as a metric for customer scoring and customer selection.
- Whereas the difference in profits between employing either share of wallet or RFM and CLV is on average about $60,000 for a customer in the top 5%, the total profit across the top 5% to 15% of the entire customer base can easily yield profits in the multimillions of dollars.

Phase II Results and Discussion

Having evaluated the utility of using a forward-looking measure such as CLV for customer selection, we now discuss the results from Phase II of our study: designing optimal resource reallocation strategies in order to maximize the customer equity of an organization. The optimization framework provides managers with a tool to assess return on marketing investments

Table 5

Comparing CLV, SOW, and RFM for Customer Selection*

Percentage of cohort (Selected from top)		Customer Lifetime Value: Evaluation at 18 months (30-month prediction window)	Customer Lifetime Value: Evaluation at 30 months (18-month prediction window)	Share of Wallet: Evaluation at 18 months (30-month prediction window)	Share of Wallet: Evaluation at 30 months (18-month prediction window)	RFM: Evaluation at 18 months (30-month prediction window)	RFM: Evaluation at 30 months (18-month prediction window)
5	Average revenue	500,630	489,541	281,265	255,885	313,645	308,698
	Net profit	148,749	145,592	83,630	76,146	93,303	91,558
10	Average revenue	289,892	265,664	108,468	105,394	159,287	185,557
	Net profit	86,007	78,948	31,790	31,030	46,815	54,892
15	Average revenue	215,515	194,566	75,429	59,377	136,673	121,234
	Net profit	63,745	57,680	22,529	17,301	40,241	35,738
50	Average revenue	64,973	58,357	62,357	60,889	61,832	57,328
	Net profit	19,587	17,983	19,328	17,301	15,387	15,097

* Cohort 2 provides similar results. The reported values are in U.S. dollars and are cell medians. Gross profit is residual revenue after removing cost of goods sold. In general, for the firm that provided the database, the cost of goods sold is around 70%. Hence gross profit is equal to revenue * .3.

by identifying avenues for optimal resource allocation across channels of communication—and hence to maximize profits.

A genetic algorithm is used to develop optimal levels of communication strategies for each individual customer based on their CLV. The genetic algorithm proceeds by searching for the optimal level of contact for each individual customer that would maximize the total net present value of profits from all the customers. In other words, the sum of the CLV (provided in Equation A1.2) for all the customers is used as the objective function and the level of contacts for each individual customer is varied so as to maximize the objective function. Following research in customer equity (Rust, Zeithaml, and Lemon 2001), we set the time frame for our optimization framework as three years.[3] We set the parameters in the genetic algorithm as follows: population size = 200, probability of crossover = .8, probability of mutation = .25, and convergence criteria = difference in solution in the last 10,000 iterations should be less than .01%. The genetic algorithm is run at least 50 times, and the mean of the optimal values from each run of the algorithm is used as the optimal resource reallocation rule for each customer. The total net present value of future profits after our optimization phase (using the predicted contribution margin) is approximately $47 million. The total net present value of future profits before optimization is approximately $28 million. We find that the optimization of contact strategy results in an increase in profits by approximately 67%. The increase in profits is realized through the appropriate identification of customers for cost-cutting and resource reallocation. The total cost of communication after the optimization is approximately $314,000. The total cost of communication in the organization's current strategy is approximately $233,000. We find that the organization is improving profits by increasing costs of serving customers (compared with the cost of communication in the previous year) by 34%.

Comparison of communication strategies

We compare the allocation rules based on CLV to allocation rules that reward primarily share of wallet or RFM.

CLV and Share of Wallet. We perform a median split of the customers with respect to CLV and their share of wallet. This results in four segments (two levels each for CLV and share of wallet). We then contrast the customer management strategy across these individual cells and also highlight the insight that CLV provides in addition to using just share of wallet. Table 6 provides a matrix of resource reduction versus escalation across low share of wallet customers versus high share of wallet customers, and low CLV customers versus high CLV customers. The values in the cells represent the optimal levels of communication as suggested by the optimization routine computed in Phase II and the values in parentheses represent the current levels of communication in the organization (and are cell means).

The results on CLV and share of wallet reported in Table 6 can be summarized as follows:

- Overall, the results indicate that the organization is clearly not allocating resources to the most valuable customers, and there is scope for improvement in their communication strategy.
- The customers in Cell 1 have low share of wallet and low CLV. One would expect these customers to provide the worst value. The optimal strategy in this case is to consider low investment (disinvestment or outsourcing) in both rich modes of communication and standardized modes of communication. The net effect of decreased frequency of communication across channels is a decrease in average resource allocation (compared with the previous year) of approximately $150 (720–570)[4] in Cell 1.
- The customers in Cell 4 have high share of wallet and high CLV. They represent the best customers in the database. The optimal strategy suggests decreasing the time between contacts through rich modes of communication and through standardized modes. The net effect of increased frequency of communication across channels is an increase in average resource allocation (compared with the previous year) of approximately $350 (2,690–2,340) in Cell 4.
- Cell 2 represents the low share of wallet/high CLV segment. The customers in this segment are profitable but are simultaneously restricting their breadth of purchases. The optimal strategy suggests decreasing the time between contacts through rich modes of communication and through standardized modes. The net effect of increased frequency of communication across channels is an increase in average resource allocation of approximately $1,260 (2,220–960) in Cell 2 (low share of wallet/high CLV). Overall, the optimization suggests a heavy conversion strategy to motivate the customers to buy across categories and move them to the high share of wallet and high CLV segment.
- Customers in Cell 3 have high share of wallet but low CLV. The customers in this segment in general could represent either heavy expenses or the best opportunity for growth. However, in the current scenario they are more likely to be a high expense. The optimal strategy suggests increasing the time between contacts through rich modes of communication and slightly decreasing the time between contacts through standardized modes. The net effect of the optimal communication strategy is a decrease of approximately $300 (1,770–1,470) in Cell 3 (high share of wallet/low CLV).
- In summary, the increase in profits ranges from 160% for Cell 3 to 62% for Cell 1.

Customer Lifetime Value and RFM. Similar to the share of wallet analyses, we perform a median split of the customers with respect to

Table 6

Comparison of Customer Management Techniques*

		Share of Wallet		RFM	
		Low	High	Low	High
CLV	Low	**Cost ($):** 570 (720) **Rich modes[a]:** 12.5 (4.5) **Standard modes:** 12.6 (9.7) **Profits ($):** 12,030 (7,435) *n* = 84 **Cell 1**	**Cost ($):** 1,470 (1,770) **Rich modes:** 10 (2.4) **Standard modes:** 8.3 (8.4) **Profits ($):** 28,354 (10,913) *n* = 15 **Cell 3**	**Cost ($):** 750 (620) **Rich modes:** 12.5 (5.0) **Standard modes:** 18.9 (7.2) **Profits ($):** 15,157 (8,715) *n* = 58 **Cell 1**	**Cost ($):** 658 (783) **Rich modes:** 12.5 (5.8) **Standard modes:** 8.2 (9.1) **Profits ($):** 13,574 (5,314) *n* = 58 **Cell 3**
	High	**Cost ($):** 2,220 (960) **Rich modes:** 2.2 (6.6) **Standard modes:** 1.9 (4.82) **Profits ($):** 178,092 (109,364) *n* = 68 **Cell 2**	**Cost ($):** 2,690 (2,340) **Rich modes:** 1.5 (2.5) **Standard modes:** 2.3 (6.3) **Profits ($):** 905,224 (534,888) *n* = 37 **Cell 4**	**Cost ($):** 2,480 (1,260) **Rich modes:** 1.9 (7.1) **Standard modes:** 3.2 (6.9) **Profits ($):** 324,231 (127,124) *n* = 45 **Cell 2**	**Cost ($):** 2,203 (1,743) **Rich modes:** 1.2 (2.7) **Standard modes:** 2.9 (4.1) **Profits ($):** 565,615 (395,051) *n* = 55 **Cell 4**

**n* represents sample size in Cohort 1. We could not compute share of wallet for 11 customers because of missing values. Values in the cells represent the optimal value proposed by the integrated strategy analyses. Cohort 2 provided similar results, which can be obtained from the authors.

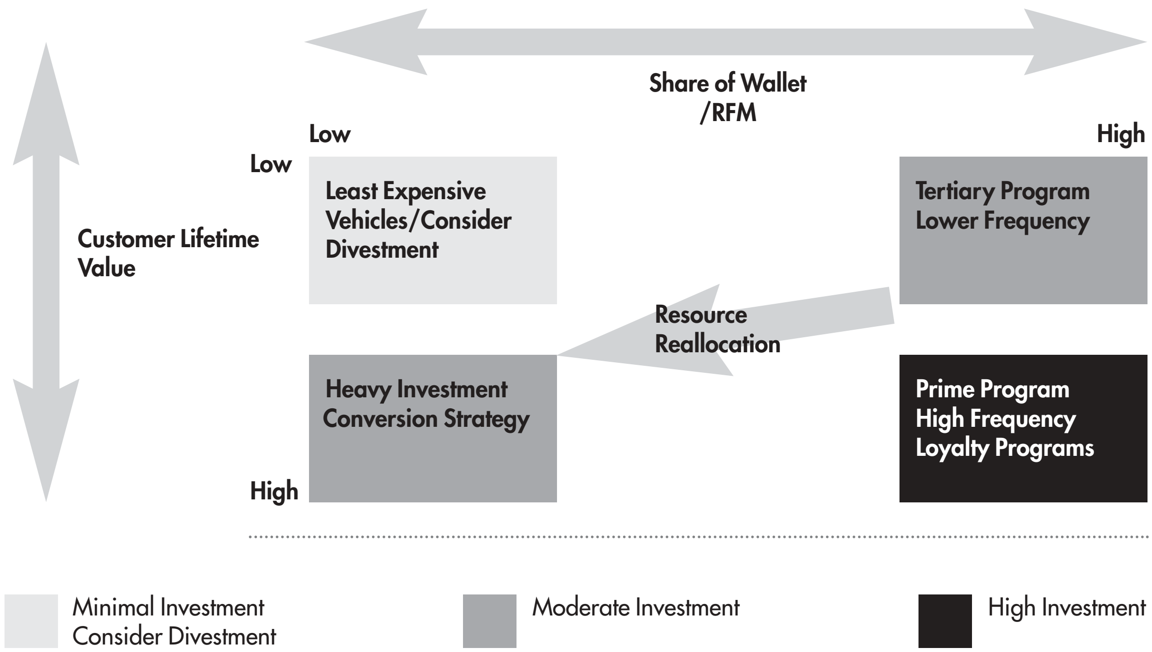
[a] At present, the organization on average contacts customers (by rich modes of communication) in Cell 1 once every 4.5 months. However, the optimal strategy suggests contacting customers in Cell 1 only once every 12.5 months. Values in the parentheses represent current strategies, costs, and profits. The standardized modes can be interpreted in a similar fashion.

CLV and their RFM score. This results in four segments of Cohort 1 customers (two levels each for value and RFM). We then contrast the customer management strategy across these individual cells and also highlight the insight that CLV provides in addition to using just RFM. Table 6 provides the resource reduction versus escalation across RFM and CLV segments.

The results on CLV and RFM can be summarized as follows:

- Overall, the results from the RFM comparison are similar to the share of wallet comparison. The optimal strategy suggests a reduction in communication to customers in Cell 1 (low RFM/low CLV) and an escalation in communication to customers in Cell 2 (low RFM/high CLV) and Cell 4 (high RFM/high CLV). Similar to the share of wallet scenario in Cell 3 (high RFM/low CLV), the optimal strategy suggests a heavy reduction in rich modes of communication and a slight escala-

Figure 2
Maximizing Customer Lifetime Value



tion in standardized modes of communication.

- In summary, the increase in profits ranges from 155% for Cell 3 to 73% for Cell 1.

Implications, Limitations, and Future Research

The objective of our study was to analyze the utility of CLV as a metric for optimal marketing resource allocation and, in the process, propose a framework for managers to maximize the value of their customer base. First, we developed a generalized individual customer-level objective function in order to measure the lifetime value of a customer in a noncontractual setting and provide a basis for optimal resource allocation. Second, we demonstrated the superiority of selecting customers for contact on the basis of lifetime value as compared with commonly used metrics such as share of wallet and RFM. Third, we evaluated the benefits that managers can derive from optimizing their marketing communications based on the lifetime value of a customer. We then provided guidelines for managing customers who are neither the best nor the worst. We did this by contrasting allocation rules based on CLV with allocation rules that reward backward-looking metrics, such as share of wallet and RFM. Here we would like to discuss how managers can use this knowledge to design efficient marketing programs and provide an outline for future researchers to develop the framework proposed here.

Managerial implications

A CLV metric is able to accurately identify customers that would provide higher profits in the future than share of wallet and RFM. Our analyses indicate that it is preferable to incorporate the dynamics of customer purchase behavior into the customer selection process. Given a fixed budget, managers can substantially improve their profits by using a dynamic, individual customer-level measure of lifetime value for scoring and prioritizing contact programs compared with the other metrics suggested in the literature. In addition, the benefits of the proposed metric over share of wallet and RFM hold for both the short term

(18-month prediction window) and long term (30-month prediction window).

The optimization phase highlights the importance of considering each individual customer's responsiveness to marketing communication, along with the costs involved across various channels of communication, while making resource allocation decisions. Our analyses suggest that managers are currently myopic in their identification of valuable customers and are spending their marketing dollars either with the wrong customers or in the wrong channels of communication. In addition, managers can substantially improve their profits by adopting a strategy of optimal resource allocation and maintaining the strategy over the long term. An increase in profits is realized by judicious matching of customer value and communication channels, without any major cost cutting or cost escalation programs. The proposed optimal resource allocation strategy can act as a basis for evaluating the potential benefits of CRM implementation in organizations and provide accountability for strategies geared towards managing customer assets.

Figure 2 provides a summary of the strategies proposed by the optimization phase. The optimal strategies in our analyses are derived based on the determinants of interpurchase time and cash flows (e.g., marketing efforts) identified in Phase I. Our framework allows managers to use these determinants in an optimal fashion in order to maximize CLV. The results from our analyses suggest recognizing the responsiveness of customers to rich and standardized modes of communication while designing their communication strategies. Overall, our analyses suggest making the least investments with the worst customers—i.e., customers who are neither high on the commonly used metrics (share of wallet and RFM) nor on customer lifetime value. Loyalty programs and high frequency contacts need to be geared towards the best customers—i.e., customers who are high on both the commonly used metrics and on customer lifetime value.

The above findings provide face validity to the optimization framework. However, as Dhar and Glazer (2003) note, the challenge in customer management is deciding on the appropriate strategies for erratic big spenders and consistent low spenders. Our framework can act as a guideline for optimal management of these customers. Given that a substantial portion of customers are low on the backward-looking metrics (share of wallet and RFM) but high on customer lifetime value, they need to be targeted with a heavy conversion strategy that focuses on assessing the needs of these customers with the objective of increasing the profits derived from them over the long term. Customers who are high on the backward-looking metrics but low on customer lifetime value need to be provided with incentives to move to the online channel, and management needs to consider a reduction in investment given their low predicted value.

We find that this comparison of allocation rules provides guidelines for better management of customers who are neither the best nor the worst (in other words customers who represent either high potential for growth or decline) in addition to the best and worst customers. Our results provide managers with a strategic framework to maximize the value of their customer base. The study also provides managers with a framework for proactively intervening and reactivating dormant customers.

Limitations and future research

The study has limitations that can be addressed by future studies. The results of this study are from a customer database in the high technology industry. Future research studies need to investigate if the results are generalizable to other industries and settings. In addition, competitive pressures in the marketplace largely determine strategies of organizations. Future research studies need to develop models that combine forecasts of aggregate competitive responses to marketing actions, and customer brand switching with individual-level models of direct marketing. The results from such studies have immense potential to influence the acceptance of direct marketing strategies in different industrial settings.

In addition, including share of wallet as an independent variable in the interpurchase time and cash flow models can help account for competition and brand switching. Although we do not analyze the difference in purchase pattern across different product categories that a firm may provide in this study, it is quite possible that the purchase patterns might be interlinked across different product categories. An understanding of the purchase patterns across different product categories could lead to effective cross-marketing strategies. Consequently, future research studies need to model cross-buying as a dependent variable and not just use it as a covariate in the customer value computation. Also, in this study we only consider the average levels of optimal communication strategy in channel. However, organizations can improve their efficiency of communication strategy even further by appropriately sequencing their customer contacts across different channels. For example, contacting a customer first through rich modes followed by standardized modes could yield the best results for a customer, while alternating between rich and standardized models could yield the best results for another customer.

In this research, we concentrated on evaluating the effects of "hard" economic measures of customer and exchange variables. Several "soft" measures of relationship quality (Crosby, Evans, and Cowles 1990) have also been found to be an important determinant of relationship duration. Future researchers should combine both these measures in a single model to identify behavioral indicators of changes in customer attitudes towards a relationship and its effects on customer profitability. Also, in our study we did not have any data on the content of communication. The substantive implications of adding content information into the analyses are tremendous. Once communications are coded for, say, loyalty building, information provision, and reminders, the interaction of type of message on customer response and relationship lifecycle stage can provide valuable insights to both researchers and practitioners.

The current model can be extended to predict customer momentum (Seybold 2001)—the rate at which new customers are going to be acquired—and measure their respective predicted profitability. The combination of both future customer retention and acquisition costs/profits would allow organizations to have a comprehensive measure of the health/wealth of their customer database. In this study, our objective was to maximize the value of the customer base and the objective function was the total NPV of all the customers, which is also termed the loss function for managerial decision-making. Future researchers can assess the differential strategies that could evolve based on various loss functions that need to be minimized. In our analyses we use the means of the posterior samples to compute the NPV for each customer. This strategy reflects the method that would normally be used in any industrial setting. However, the theoretically sound method is to use predictive distributions to forecast the probability of future customer activity given past activity. Studies that would assess the tradeoff between the ease of using posterior means and the theoretical sophistication of using predictive distributions would have high managerial relevance.

The customer- and supplier-specific covariates used in the customer response model can also directly affect costs, and hence margins. However, since we estimate the customer response model in a single step, which is then included in an NPV function, we assess the indirect effect of these covariates on both costs and margins. Future studies can develop and test hypotheses that directly relate customer management efforts to costs and margins. Additionally, it can be expected that the margins used in Equation A1.1 may change over time. (See Appendix 1.) In this case, the value that a customer provides to an organization is a function of both the expected time until the next purchase and the contribution margin at that particular time period. It is very simple to integrate this into our model; the results from such a modification may be of interest to future researchers. However, the interesting question that arises from our analyses is whether the recommendations from an optimization framework span out when implemented in the real market. What are the effects of missing variables that may or may not be under the control of management, such as content of communication and satisfaction with service encounters, on the profits for an organization? 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. ■

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Appendix 1: CLV Measurement and Associated Components

Phase I

Blattberg and Deighton (1996) used a decision calculus approach to suggest a way to optimally decide on customer acquisition and retention investments. Blattberg, Getz, and Thomas (2001) suggested a methodology for planning customer acquisition, relationship development, and customer retention strategies. Berger and Nasr (1998) and Berger and Bechwati (2001) demonstrated how the basic CLV model could be relaxed—for example, to allow the incorporation of different promotion expenditures. Recently, Rust, Zeithaml, and Lemon (2001) offered a decision support system that takes into account future brand switching (i.e., the customer can leave and come back) and ties marketing actions and perceptions (based on a sampling technique) into CLV calculations. These calculations are an important input to the firm's strategic marketing decisions dealing with issues such as the effects of changes in retention rate on expected CLV (Reichheld 1998) or understanding how different marketing mix actions affect firm profitability (Rust, Zeithaml, and Lemon 2001). Clearly, they represent a significant step toward incorporating long-term customer profitability effects into firm-level managerial decisionmaking.

However, these models provide less insight into decisions about how to manage individual customers in a way that accounts for heterogeneity and provides a mechanism for dynamic updating of profitability assessment (Libai, Narayandas, and Humby 2002). Libai, Narayandas, and Humby (2002) provide a general guideline for modeling customer segment level resource allocations based on CLV calculations. In this study, we build on existing research to first develop an individual customer level resource allocation framework that is based on CLV (see figure A1) and also provide an empirical demonstration of our proposed framework. We now specify the formulation for calculating CLV for each individual customer.

Typically, CLV is a function of the predicted cash flows, the propensity for a customer to continue in a relationship (customer retention), and the marketing resources allocated to the customer. The marketing mix variables are expected to affect all three components of the CLV function, and hence the objective of our study is to find the optimal levels of marketing mix elements that would maximize the profits from each individual customer over the planning horizon. In general, CLV can be calculated as *CLV = (Future Cash Flows – Future Cost) / Discount Factor*

$$= \sum_{i=1}^{n} (Future\ \ cash\ \ flows - Future\ \ Cost)_i \Big/ (1+r)^i \qquad \text{(A1.1a)}$$

where, i = time index, n = forecast horizon (in years), and r = discount rate.

Managers calculating CLV in noncontractual settings are interested in predicting (1) customer retention, which is a function of a customer's lifetime duration, and (2) the predicted cash flows from each individual customer. Following Rust et al. (2001), we use the "*always a share*" approach to model CLV. Given predictions of cash flows, interpurchase times, and variable costs the CLV function can be represented as

$$NPV_i = \sum_{t=1}^{T_i} \frac{CM_{i,t}}{(1+r)^{t/frequency_i}} - \sum_{l=1}^{n} \frac{\sum_m c_{i,m,l} * x_{i,m,l}}{(1+r)^{l-1}} \qquad \text{(A1.2)}$$

Our objective function is subject to the following constraints

$$expint > 0 \; \forall \; i,t, \qquad \text{(A1.2a)}$$

$X_{i,m,l} \geq 0 \; \forall \; i,m,l,$ and the budget constraint, (A1.2b)

$$\sum_{i=1}^{n} c_{i,m,l} * x_{i,m,l} \leq AVG(TOTCOST)^{l}; \; n = 3 \text{ in this case} \qquad \text{(A1.2c)}$$

where

NPV_i = net present value of future profits from customer i

$CM_{i,t}$ = \$ amount of contribution margin from customer i (computed from a cash flow model) in purchase occasion t

r = discount rate for money (set at 15% annual rate in our study or $r/12$ for the monthly rate)

$c_{i,m,l}$ = unit marketing cost, for customer i in channel m in time period 1

$X_{i,m,l}$ = number of contacts to customer i in channel m in time period 1

$Frequency_i = 12/expint_i$, where, $expint_i$ = expected interpurchase time for customer i (computed from an interpurchase time model)

$AVG(TOTCOST)$ = average of the annual cost of communication across all channels over the previous three years

n = number of years to forecast

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

Discounting Cash Flows

Let us first focus on the discounting of cash flows over a period of time. Assume that we are currently in year 1 = 1 and we need to forecast the cash flows from each customer for the next n years; i.e., until $1 + n$. It is also possible that a customer makes several purchases within a given year. Berger and Nasr (1998, Equation A1.2) and Rust, Lemon, and Zeithaml (2000) provide guidelines for discounting cash flows from customers when there is more than one purchase occasion (t) per year. Specifically, the discount rate from a customer is scaled according to their respective frequency of purchase (as shown in Equation A1.2), which is 12 divided by the cycle time (predictions from the stochastic interpurchase time model). For example, if a customer is expected to purchase once every six months, then the frequency of purchases in a year is two ($f = 2$). In the case where the planning horizon is equal to a year and frequency equals two ($f = 2$), the first purchase occasion ($t = 1$) occurs after six months, therefore "*t/frequency*" is equal to "1/2 = .5" (in other words, the square root of the discount rate is used); and the second purchase occasion ($t = 2$) occurs after twelve months; therefore, "*t/frequency*" is equal to "2/2=1".

Discounting Cost Allocations

The discounting of cost allocations is straightforward if one assumes a yearly allocation of resources (as is the case in most organizations) and that the cost allocation is made at the start of the year (the present time period). Hence, the cost allocation in the first year need not be discounted, and the cost allocation in the second year needs to be discounted for one year, and so on. Hence, we raise the denominator in the cost function calculation to current year minus one (1 – 1).

Discussion of Model Constraints

Constraints (A1.2a and A1.2b) ensure the nonnegativity of the cash flows and communication levels for each customer i during period l. Constraint A1.2c sets the budget constraint for our optimization framework. We use the average cost allocation over the last three years as a guideline for the total resource allocation limit for the current year. The managers of the database also use an identical guideline.

Interpurchase Time

In order to model interpurchase times, we use the generalized gamma model of interpurchase timing developed by Allenby, Leone, and Jen (1999). The generalized gamma model also accommodates the commonly used exponential distribution for interpurchase times (Reinartz and Kumar 2003; Schmittlein, Morrison, and Colombo 1987). For a given customer (i), the j^{th} interpurchase time is assumed to be distributed generalized gamma (GG), i.e.,

$$t_{ij} \sim GG(\alpha, \lambda_i, \gamma) = \frac{\gamma}{\Gamma(\alpha)\lambda_i^{\alpha\gamma}} t_{ij}^{\alpha\gamma - 1} e^{-(t_{ij}/\lambda_i)^{\gamma}} \qquad \text{(A1.3)}$$

The parameters α and γ establish the shape of the distribution and λ_i is the individual specific purchase rate parameter. In addition to the distribution of interpurchase times, we also assume that the customers have a distinct probability of belonging to two subgroups, which we term as *active* and *inactive* subgroups. For each customer, the expected time until purchase based on Equation A.1.3 is then a weighted sum (the weights are stochastically determined by a probit function of the supplier- and customer-specific factors) of their predictions of expected time to next purchase from each subgroup.[2] Given that a customer *i* has a probability ϕ_{ijk} of belonging to one of the *k* states at each interpurchase occasion *j*, the expected time until next purchase is then

$$\sum \Phi_{ik} * \left\{ \left[\Gamma\left(\alpha_k + \frac{1}{\gamma_k}\right) \right] \Big/ \Gamma(\alpha_k) \right\} * \lambda_{ik} \qquad \text{(A1.4)}$$

In addition to a reasonable assumption of interpurchase times, the above framework allows us to model the expected time until next purchase, the propensity that a customer would be active, and the influence of customer- and supplier-specific covariates in a single step. This property is very suitable for developing optimal resource allocation rules in the second phase of our analyses. To address the issue of endogeneity, we use lagged values of the variables in our analysis (Villas-Boas and Winer 1999). However, to account for any extraneous factors not accounted for by the proposed variables we also use the log of the lagged interpurchase time in the covariate set.[3] The specification of the model also allows us to estimate individual customer-level coefficients for the influence of the various supplier- and customer-specific factors on the probability of a customer belonging to a particular subgroup and hence interpurchase times. Out of sample predictive accuracy of our model is also good. Our model has 52% lower prediction errors as compared to a naïve moving average model.

Predicting Cash Flows

The cash flows[4] from a customer are modeled using panel data regression methodologies. The independent variables used in the model include lagged contribution margin, firm size, industry category, lagged total marketing efforts,[5] and lagged total quantity purchased. We need to address endogeneity issues while using lagged contribution margin as an independent variable in our model. In panel data models with lagged dependent variables, the endogeneity in formulation can be alleviated by using a one-period difference in the dependent variable and a two-period lagged dependent variable as an independent variable (Baltagi 1998). Specific to our case, we use the growth in contribution margin from time period *t* -1 to *t* as the dependent variable and use the contribution margin in *t* -2 as the independent variable. The other independent variables used in the model are specific to time period *t* -1. The cash flow model is hence given by

$$\Delta CM_{it} = \beta_1 CM_{i,t-2} + \beta_2 Size_{it} + \sum_j \delta_j Industry_{j} + \beta_3 Totmark_{i,t-1} + \beta_4 Quantity_{i,t-1} + e \qquad \text{(A1.5)}$$

where

ΔCMi = difference in Contribution Margin from time period *t* -1 to time period *t* for customer *i* measured in $

$Size_{it}$ = firm size for customer *i* in time period *t*, measured as the number of employees

Industry = indicator variable for industry category of the customer firm

$Totmark_{i,t-1}$ = total number of contacts made to customer *i* in time period *t* -1

$Quantity_{i,t-1}$ = Total quantity of products bought by customer *i* in time period *t* -1

e_i = error, *i* = index for the customer, *t* = index for time.

We evaluated the performance of the cash flow model in the holdout sample based on our estimates from the calibration sample. The mean predicted cash flow in time *t* + 1 in the holdout sample is approximately $67,729, while the mean observed cash flow in time *t* + 1 in the holdout sample is approximately $64,396.

Phase II

The net present value calculated from Equation A1.2 is used as the objective function to calculate optimal resource allocation rules for the customers in the database. In Equation A1.2 the level of rich and standard modes of communication are under the supplier's control and hence can be optimized depending on the cost of each mode of communication and the responsiveness of the customer (in terms of both interpurchase time and cash flows) to each mode of communication. Once the expected interpurchase time and cash flows from a customer, along with the coefficients (β_s) of the covariates (X_s), are obtained, they can be plugged into Equation A1.1 to obtain optimal levels of marketing resources for each customer that maximize their respective CLV and hence consequently the customer equity of the firm. Marketing resources for a firm—in other words, the customer contact levels, across different channels—appear in both the revenue side and the cost side of Equation A1.2, and hence avoid the scope of corner solutions. A genetic algorithm is used to derive the optimal levels of contact desired for each individual customer. Genetic algorithms (Goldberg 1989) are simulation-based, parallel search algorithms that have been used in econometrics (Dorsey and Mayer 1995; Liang and Wong 2001; Venkatesan, Krishnan, and Kumar 2004) to handle optimization problems when the complexity of the optimization function tends to be intractable and multidimensional. In this study, the utility of a genetic algorithm is increased given the need to maximize the response from each individual customer, which is a function of several independent variables, while simultaneously minimizing the cost involved in contacting the customers.

Appendix 1 Notes

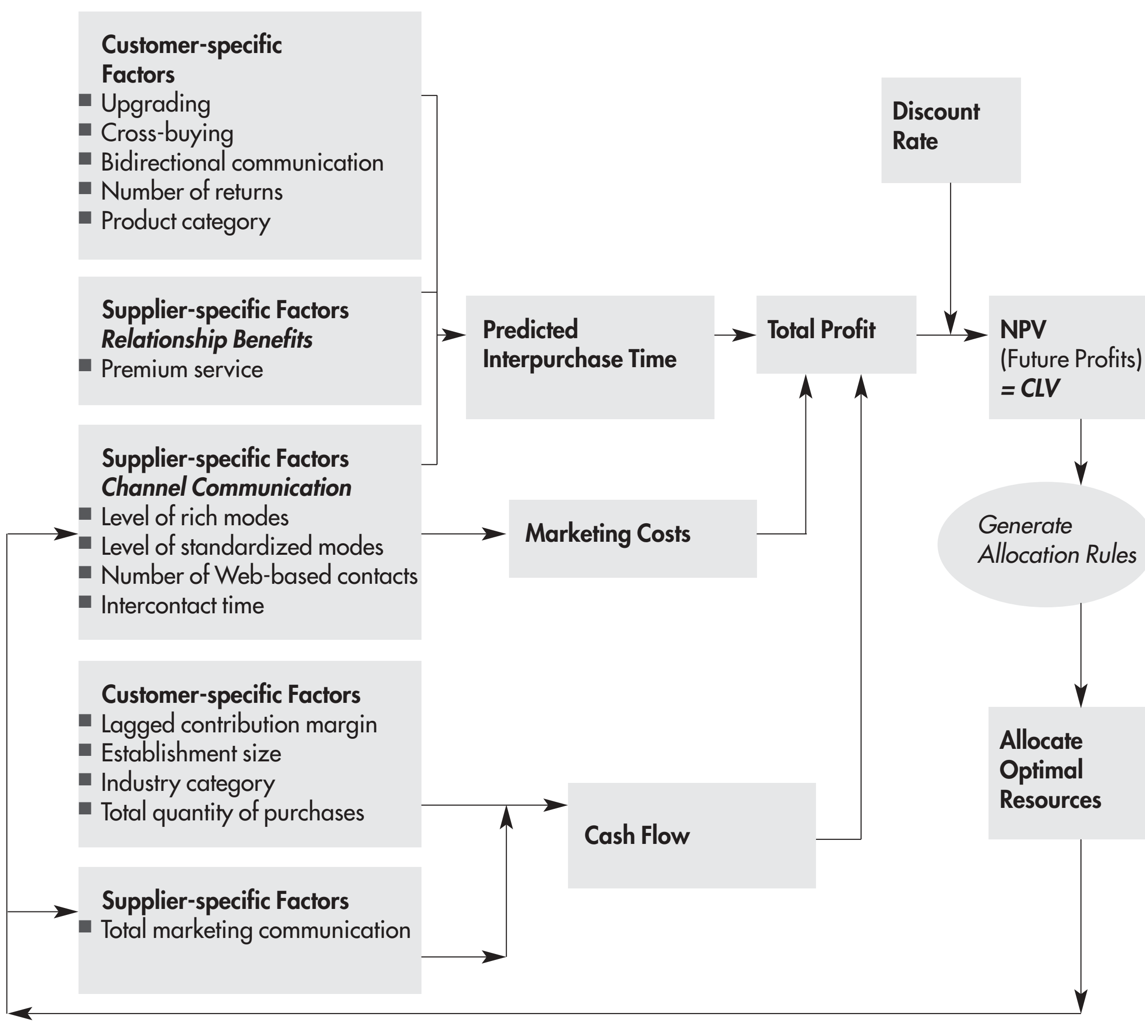
1. In order to have a full dynamic optimization problem we should not have a budget constraint in our problem formulation. A budget constraint in our formulation can be considered as optimizing resource reallocation rather than optimizing resource allocation because the objective is to redistribute resources across customers and not determine the optimal level of resources. However, the budget constraint may not be a factor in the optimization if it is very large. In this case the optimal resource allocation would be within the budget constraint. We find that to be the case in our analyses (explained later), hence we use the term optimal resource allocation even though there is a budget constraint. Also, our methodology reflects

common management practice where the customer management group is normally provided an exogenous budget.
2. The interpretation of subgroups also holds good for propensity of staying active if the hazard function is used as a classification scheme instead of expected time until next purchase. In fact, a high hazard probability represents a low expected time until next purchase.
3. We also used lagged interpurchase time instead of the log of lagged interpurchase time in our analysis and did not find any difference in the substantive conclusions. We use log of the lagged interpurchase time because lagged interpurchase times can have a threshold effect on the influence of current interpurchase times (Allenby et al. 1999). The log of interpurchase time achieves this objective in scaling the tail of the lagged interpurchase time distribution.
4. In our case cash flows represent the contribution in dollars (margin of revenue after removing cost of goods sold). Given our assumption of constant margins across customers and over time the substantive results do not change if we use either revenues or contribution in our model.
5. We use the total lagged marketing effort in the cash flow model because using total level of contacts in the rich, standardized and online modes individually resulted in multicollinearity.

Notes

1. In our samples, we removed customers from the database who had missing values for either rich modes of communication, or standardized modes of communication. We also restricted our sample to customers who have made at least three purchases. Overall, we had to remove 20% of the original cohort customers for our analyses.

Figure A1
A Conceptual Framework for Optimal Resource Allocation



2. If censoring is an issue, the model can be easily updated.

3. When forecasting cash flows for three years ahead, we need to note that we have data on marketing activities from years 1997 until 2001. Our last prediction for the long term analysis is in time period 2003, for which we need marketing variables in 2002, which we do not have. For forecasting the cash flows in 2003 we use the average of marketing mix variables from 1997 until 2001 for imputing the values in 2002. However, for the optimization phase, the optimized marketing mix variables are substituted for the 2002 values. We thank a reviewer for bringing this to our attention.

4. The numbers within the parentheses refer to the difference between cost allocation without optimization and cost allocation after optimization.

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