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A Customer Lifetime Value Framework for Customer Selection and Resource Allocation Strategy

The authors evaluate the usefulness of customer lifetime value (CLV) as a metric for customer selection and marketing resource allocation by developing a dynamic framework that enables managers to maintain or improve customer relationships proactively through marketing contacts across various channels and to maximize CLV simultaneously. The authors show that marketing contacts across various channels influence CLV nonlinearly. Customers who are selected on the basis of their lifetime value provide higher profits in future periods than do customers selected on the basis of several other customer-based metrics. The analyses suggest that there is potential for improved profits when managers design resource allocation rules that maximize CLV. Managers can use the authors' framework to allocate marketing resources efficiently across customers and channels of communication.

Customer lifetime value (CLV) is rapidly gaining acceptance as a metric to acquire, grow, and retain the "right" customers in customer relationship management (CRM). However, many companies do not use CLV measurements judiciously. Either they work with undesirable customers to begin with, or they do not know how to customize the customer's experience to create the highest value (Thompson 2001). The challenge that most marketing managers currently face is to achieve convergence between marketing actions (e.g., contacts across various channels) and CRM. Specifically, they need to take all the data they have collected about customers and integrate them with how the firm interacts with its customers. In the academic literature, Berger and colleagues (2002) support the allocation of resources to maximize the value of the customer base, and they strongly argue that such resource allocation models are needed.

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Maximizing CLV

Some researchers have recommended CLV as a metric for selecting customers and designing marketing programs (Reinartz and Kumar 2003; Rust, Zeithaml, and Lemon 2004). However, there is no empirical evidence as to the usefulness of CLV compared with that of other customer-based metrics. Table 1 compares the CLV framework proposed in this study with the existing literature on CLV and database marketing. A comparison of the studies listed in Table 1 shows that most of the previous studies provide guidelines for calculating CLV and return on investment at the aggregate level. Some recent studies (Reinartz and Kumar 2003; Rust, Zeithaml, and Lemon 2004) provide empirical evidence for the existence of a relationship between marketing actions and CLV at the aggregate level. However, as Berger and colleagues (2002) state, none of the studies has proposed and tested a framework that provides rules for resource allocation across various channels of communication for each individual customer and across customers.

On the basis of the comparisons in Table 1, we summarize the significant contributions of our study as follows: We provide a framework for measuring CLV that links the influence of communications across various channels on CLV. We also evaluate the usefulness of CLV as a metric for customer selection and develop a framework for marketing resource allocation that maximizes CLV. Given the assumed link between CLV and firm profitability (Hogan et al. 2002), these are important issues.

In this study, we use customer data from a large business-to-business (B2B) manufacturer to illustrate the proposed framework empirically. The customer database of the organization focuses on B2B customers. Our analyses show that marketing communications across various channels influence CLV nonlinearly. The results from our analyses suggest that customers selected on the basis of CLV provide higher profits than do customers selected on the basis

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TABLE 1
Comparing the Proposed CLV Framework with Existing Models

Type of Model	Representative Research	Return on Investment Modeled and Calculated	CLV Calculation	How Marketing Communication Affects CLV	CLV-Based Resource Allocation	Resource Allocation for Each Customer	Resource Allocation Across Channels	Comparison of Customer-Based Metrics	Statistical Details
CLV	Berger and Nasr (1998)	No	Yes	Yes	No	No	No	No	Yes
	Berger et al. (2002)	Yes	Yes	Yes	Yes	No	Yes	No	No
Customer equity	Blattberg and Deighton (1996)	Yes	Yes	No	Yes	No	No	No	Yes
	Libai, Narayandas, and Humby (2002)	Yes	Yes	Yes	No	No	No	No	No
Database marketing	Reinartz and Kumar (2000)	Yes	Yes	No	No	No	No	No	Yes
	Bolton, Lemon, and Verhoef (2004)	Yes	Yes	Yes	No	No	No	No	Yes
CLV antecedents	Reinartz and Kumar (2003)	Yes	Yes	Yes	No	No	No	Yes	Yes
	Rust, Zeithaml, and Lemon (2004)	Yes	Yes	Yes	No	No	No	Yes	Yes
CLV-based resource allocation	Berger and Bechwati (2001)	Yes	Yes	Yes	Yes	No	No	No	No
	Present Study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

of other widely used CRM metrics. In addition, there is the potential for substantial improvement in profits when managers design resource allocation rules that maximize CLV.

In the next section, we develop the framework for the measurement and maximization of CLV. We then propose hypotheses about the influence of supplier-specific factors and customer characteristics on the various CLV components. In the subsequent section, we explain the models and data we used to estimate CLV. We then discuss the results from our analyses and explain the comparison of CLV with other metrics for customer selection. Specifically, we compare the aggregate profits provided by high-CLV customers with those of customers who score high on several other customer-based metrics. In the section "Resource Allocation Strategy," we provide details on allocating resources that maximize CLV. Our objective there is to evaluate the extent to which CLV, and thus profits, can be increased by allocating marketing resources across channels of contact for each customer so as to maximize his or her respective CLVs. Finally, we derive implications based on the results, discuss the limitations of our study, and identify areas for further research.

CLV Measurement and Maximization

The various components of CLV include purchase frequency, contribution margin, and marketing costs (however, the various CLV components can vary depending on the industry). Some of the antecedents of purchase frequency and contribution margin (e.g., marketing communications) are under management's control and affect the variable costs of managing customers. We use these antecedents to maximize CLV.

Objective Function: CLV

Typically, CLV is a function of the predicted contribution margin, the propensity for a customer to continue in a relationship (customer retention), and the marketing resources allocated to the customer. In general, CLV can be calculated as follows:

$$(1)\quad CLV_i = \sum_{t=1}^{n} \frac{(\text{Future contribution margin}_{it} - \text{Future cost}_{it})}{(1+r)^t},$$

where

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

In contractual settings, managers are interested in predicting customer retention, or the likelihood of a customer staying in or terminating a relationship. However, in noncontractual settings, the focus is more on predicting future customer activity because there is always a chance that the customer will purchase in the future. Therefore, managers who calculate CLV in noncontractual settings are interested in predicting future customer activity and the predicted contribution margin from each customer. Previous researchers have used the variable P(Alive), which represents the probability that a customer is alive (and thus exhibits purchase activity) given his or her previous purchase behavior (Reinartz and Kumar 2000), to predict future customer activity in noncontractual settings. However, the measure assumes that when a customer terminates a relationship, he or she does not return to the supplier. This is also called the "lost-for-good" scenario (Rust, Zeithaml, and Lemon 2004). If a customer is won back after termination, the company treats the customer as a new customer and ignores its history with the customer.

Another method for predicting future customer activity is to predict the frequency of a customer's purchases given his or her previous purchases. The assumption underlying this framework is that customers are most likely to reduce their frequency of purchase before terminating a relationship. This assumption is in accordance with theories about the different phases in a relationship and relationship life cycles (Dwyer, Schurr, and Oh 1987; Jap 2001). In addition, such a methodology enables a customer to return to the supplier after a temporary dormancy in a relationship. Thus, in this framework, we measure CLV by predicting the purchase pattern (purchase frequency or interpurchase times) over a reasonable period. This is also called the "always-a-share" scenario. The lost-for-good approach is questionable because it systematically understates CLV (Rust, Zeithaml, and Lemon 2004). Thus, we use the always-a-share approach in this study. Given predictions of contribution margin, purchase frequency, and variable costs, the CLV function we use can be represented as follows:

$$(2)\quad CLV_i = \sum_{y=1}^{T_i} \frac{CM_{i,y}}{(1+r)^{y/\text{frequency}_i}} - \sum_{l=1}^{n} \frac{\sum_m c_{i,m,l} \times x_{i,m,l}}{(1+r)^{l-1}},$$

where

CLV_i = lifetime value of customer i;
$CM_{i,y}$ = predicted contribution margin from customer i (computed from a contribution margin model) in purchase occasion y, measured in dollars;
r = discount rate for money (set at 15% annual rate in our study);
$c_{i,m,l}$ = unit marketing cost for customer i in channel m in year l (the formulation of CLV does not change if l is used to represent periods other than one year);
$x_{i,m,l}$ = number of contacts to customer i in channel m in year l;
frequency_i = predicted purchase frequency for customer i;
n = number of years to forecast; and
T_i = predicted number of purchases made by customer i until the end of the planning period.

In addition to accurate measurement of CLV for each customer, our objective is to allocate resources so as to maximize CLV. Thus, we model the purchase frequency and contribution margin of customers as a function of marketing resource variables such as channel contact. We then use the customer responsiveness to marketing actions, obtained from the purchase frequency and contribution margin models, to develop resource allocation strategies that maximize CLV. In summary, the objective is to identify the resource allocation rules across various channels of communication for each individual customer such that the respective CLVs (as provided in Equation 2) are maximized.[1] Our objective function is subject to the following constraints: frequency > $0 \; \forall$ i, t, and $x_{i,m,l} \geq 0 \; \forall$ i, m, l.

Discounting contribution margin. We first focus on the discounting of contribution margin over a period of time. Assume that it is currently year $l = 1$ and that we need to forecast the contribution margin from each customer for the next n years (i.e., until l + n). It is possible that a customer makes several purchases in a given year. Berger and Nasr (1998, Equation 2) and Rust, Zeithaml, and Lemon (2004) provide guidelines for discounting contribution margin from customers when there is more than one purchase occasion (y) per year. In this approach, the discount rate from a customer is scaled according to his or her frequency of purchase (as is shown in Equation 2). For example, consider when the planning horizon is one year and the frequency of purchases is two times (frequency = 2). The first purchase occasion (y = 1) occurs after 6 months; therefore, y/frequency = .5 (in other words, we use the square root of the discount rate). The second purchase occasion (y = 2) occurs after 12 months; therefore, y/frequency = 1.

Discounting cost allocations. The discounting of cost allocations is straightforward if we assume that there is a yearly allocation of resources (as is the case in most organizations) and that the cost allocation occurs at the beginning of the year (the present period). Thus, the cost allocation in the first year need not be discounted, the cost allocation in the second year needs to be discounted for one year, and so on. Thus, we raise the denominator in the cost function calculation to current year – 1 (i.e., $l - 1$).

Discussion of model constraints. The constraints ensure the nonnegativity of the predicted purchase frequency and communication levels for each customer i during period l.

Antecedents of Purchase Frequency and Contribution Margin

Purchase Frequency

An objective of relationship marketing is to ensure future purchase activity. Purchase frequency is also a component of our CLV calculation. Therefore, as the basis for selecting antecedents to predict purchase frequency, we use the commitment–trust theory of relationship marketing (Morgan and Hunt 1994) as well as previous research in customer equity and CLV (Bolton, Lemon, and Verhoef 2004; Bowman and Narayandas 2001; Reinartz and Kumar 2003; Rust, Zeithaml, and Lemon 2004) and channel communications (Grewal, Corner, and Mehta 2001; Mohr and Nevin 1990; Morgan and Hunt 1994; Rindfleisch and Heide 1997).

The overall theoretical framework that we used is provided in Figure 1. We summarize the antecedents of purchase frequency, their operationalization, expected effects, and the rationale for our expectations in Table 2. Next, we provide a detailed discussion for a few of the hypotheses that are unique to our study.

Supplier-Specific Factors: Channel Communications

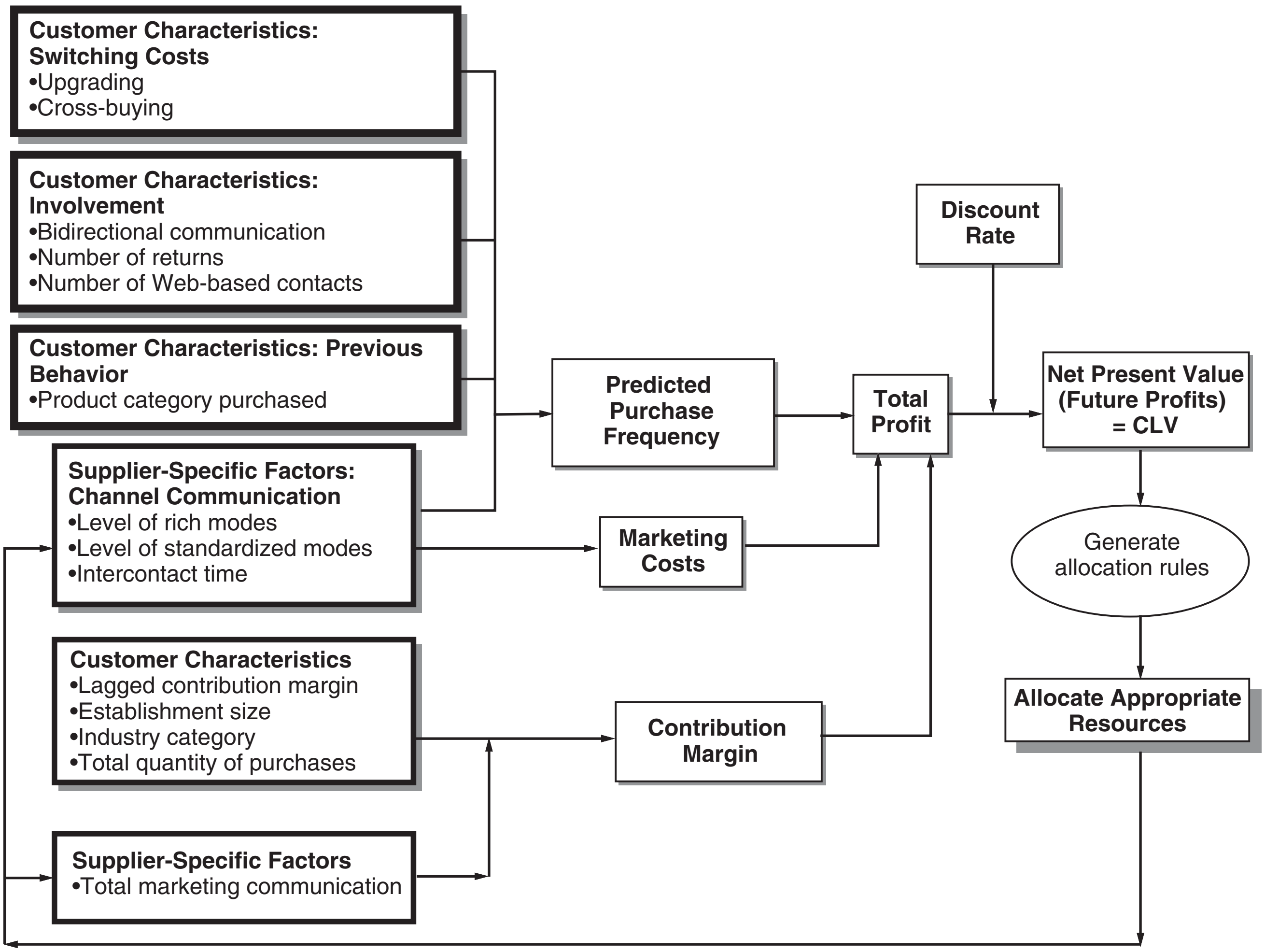
In this study, we classify channels of communication into the following contact modes: rich (e.g., face-to-face, trading event meetings), standardized (e.g., direct mail, telephone), and Web based (Mohr and Nevin 1990). Although we expect the relationships between different channels of communication and predicted customer activity to be similar, we need to analyze customer responses separately across different channels because the costs of serving customers across different channels are different, and customers might exhibit different responsiveness across the various channels. The costs of communication in each channel can influence managers' frequency of communication in each channel.

Frequency of rich and standardized modes. Face-to-face communications and trading event meetings are the richest and most direct mode of communication possible among channel members (Mohr and Nevin 1990). Relational customers tend to have high commitment and trust with their suppliers, which results in less uncertainty, more cooperation, and less complexity in their relationships than in those of transactional customers (Morgan and Hunt 1994). Rich modes of communication are preferred to standardized modes when issues in the channel structure are complex and when there is a high degree of uncertainty in the relationship. Rich modes of communication are also effective in converting transactional customers to relational ones (Ganesan 1994).

Direct mail and telephone communication are the most standardized and cost-effective modes of individual-level communication available to an organization. Standardized modes are also the most cost-effective method for identifying customers who are interested in an organization's current promotion (Shepard 2001). For transactional customers, direct mail can be used in combination with telephone sales to generate interest in products while simultaneously improving the return on investment (Nash 1993). For relational customers, direct mail serves to maintain commitment and trust by communicating relationship benefits (Morgan and Hunt 1994) and to inform the best customers about new product offerings. Therefore, although the purpose of standardized communication may be different for transactional customers than for relational ones, we expect that the marginal response for increased frequency is the same across segments.

[1]In this study, we do not use a budget constraint on the total resources available for contacting customers. Therefore, we are interested only in allocating resources across channels for each individual customer (i.e., within each customer across channels). However, our framework can be applied to allocate resources across channels with each individual customer and across customers in the presence of a budget constraint.

FIGURE 1
A Conceptual Framework for Measuring and Using CLV



However, it has been proposed that too much communication causes a relationship to be dysfunctional (Fournier, Dobscha, and Mick 1997). In addition, the marginal response to a higher level of rich modes of communication need not always be higher; sometimes, it even can be negative. Although the utility of marketing contacts is not questioned, too much contact can overload buyers and have dysfunctional consequences (e.g., ubiquitous junk mail). Thus:

H_1: An inverted U-shaped relationship exists between the frequency of rich and standardized modes of communication and a customer's predicted purchase frequency.

Intercontact time. Following the theory that leads to H_1, we expect that there exists an optimal level of intercontact time between suppliers and buyers. Higher levels of previous communications lead to trust with the supplier and act as glue that holds together a communication channel (Morgan and Hunt 1994). However, too much communication may be dysfunctional. In addition, the marginal utility of an additional piece of information from a supplier firm in a short period is low. To maximize the effect of each contact, supplier firms need to pace their communication schedule to suit customer needs. Thus:

H_2: An inverted U-shaped relationship exists between intercontact time and a customer's predicted purchase frequency.

Customer Characteristics: Customer Involvement

Bidirectional communication. Research on channel communications shows that highly relational channel structures are associated with large bidirectional communications among channel members (Mohr and Nevin 1990). Although customer-initiated contacts are associated primarily with complaints in business-to-consumer settings, the same is not necessarily true for B2B settings. In a B2B setting, customers can initiate contacts with suppliers for several reasons, such as if they have new needs that the supplier may be able to fulfill, if they want the supplier to conduct training programs at the customer's site (Cannon and Homburg 2001), or if the supplier invites the customer to participate in new product development sessions. On most occasions, bidirectional communication in channels strengthens a relationship, indicates customer involvement,

TABLE 2
Antecedents, Covariates, and Expected Effects

Variable	Operationalization	Expected Effect	Rationale
Purchase Frequency Model			
Antecedents			
Upgrading	Number of product purchase upgrades until an observed purchase	+	Customers who upgrade have higher switching costs with each upgrade, which can lead to lower propensity to leave and higher recurrent needs (Bolton, Lemon, and Verhoef 2004).
Cross-buying	Number of different product categories a customer has purchased	+	Customers who purchase across several product categories have higher switching costs and recurrent needs (Bowman and Narayandas 2001; Reinartz and Kumar 2003).
Bidirectional communication	Ratio of number of customer-initiated contacts to total number of customer contacts (customer initiated and supplier initiated) between two observed purchases	+	Two-way communication between parties strengthens the relationship and ensures that the focal firm is recalled when a need arises (Morgan and Hunt 1994).
Returns	Number of products the customer returns between two observed purchases	∩	Returns provide an opportunity for firms to satisfy customers and ensure repeat purchases (Reinartz and Kumar 2003), but too many purchases can be detrimental to the relationship and can indicate that the firm has not used the return opportunities appropriately.
Frequency of Web-based contacts	Number of times in a month the customer contacts the supplier through the Internet between two observed purchases	+	Customers who use online communication want transaction efficiencies, and customers who want to create efficiencies are highly relational and have recurring needs (Grewal, Corner, and Mehta 2001; Rindfleisch and Heide 1997).
Relationship benefits	Indicator variable of whether a customer is a premium service member (based on revenue contribution in the previous year)	+	Acknowledgment of customers with relationship benefits reduces the propensity of customers to quit and increases the probability that the focal firm is recalled when a need arises (Morgan and Hunt 1994).
Frequency of rich modes of communication	Number of customer contacts by the supplier in a month (through sales personnel) between two observed purchases	∩	Timely communication between parties reduces the propensity of a customer to quit a relationship (Mohr and Nevin 1990; Morgan and Hunt 1994), but too much communication can be detrimental to the relationship (Fournier, Dobscha, and Mick 1997; Nash 1993); thus, there is an optimal communication level.
Frequency of standardized modes of communication	Number of customer contacts by the supplier in a month (through telephone or direct mail) between two observed purchases	∩	
Intercontact time	Average time between two customer contacts by the supplier across all channels of communication between two observed purchases	∩	A long time between contacts can lead to forgetfulness, but contacts that are too soon can cause dysfunction.

TABLE 2
Continued

Variable	Operationalization	Expected Effect	Rationale
Covariate			
Product category	Two indicator variables: one indicates a hardware purchase; the other indicates a software purchase		A customer's purchase patterns may depend on the product category purchased.
Contribution Margin Model			
Antecedents			
Lagged contribution margin	Customer's contribution margin from the previous year	+	Previous revenue is a good predictor of current revenue and accounts for any model misspecification (Niraj, Gupta, and Narasimhan 2001).
Total marketing efforts	Total number of customer contacts across all channels	+	Previous marketing communications and depth (quantity) of purchases positively affect contribution margin (Gupta 1988; Tellis and Zufryden 1995).
Total quantity purchased	Total quantity of products the customer purchased across all product categories	+	
Covariates			
Size of firm	Number of employees in the customer firm	+	Control variables that accommodate for customer heterogeneity (Niraj, Gupta, and Narasimhan 2001).
Industry category	Standard industrial classification–based industry category to which the customer firm belongs		

Notes: For the purchase frequency model, the dependent variable is purchase frequency; for the contribution margin model, the dependent variable is contribution margin.

and increases interdependence among channel members (Ganesan 1994; Mohr and Nevin 1990). Thus:

> H_3: The higher the level of bidirectional communication, the higher is a customer's predicted purchase frequency.

Frequency of Web-based contacts. In this study, we analyze Web-based contacts separately from other channels of communication because Web-based communication is customer initiated (i.e., a passive mode of operation for the supplier). However, there are several advantages to tracking Web-based contacts in a B2B setting. First, Web-based communication between buyers and suppliers is the most cost-effective method of communication. Second, Web-based contacts from the buyers provide some important signals to the supplier about the buyer's relationship orientation. Grewal, Corner, and Mehta (2001) find that organizations enter and actively participate in electronic markets if their motivation is to improve efficiency in transactions. In addition, participation in electronic markets (or use of Web-based initiatives) improves transaction effectiveness and efficiency (Rindfleisch and Heide 1997). Efficiency of communication and transactions among channel members is associated with a relational structure and higher customer involvement (Mohr and Nevin 1990; Sheth and Parvatiyar 1995). Thus:

> H_4: The higher the number of Web-based contacts from a customer, the higher is the customer's predicted frequency of purchase.

Contribution Margin

The antecedents that we adopt to predict contribution margin are based on findings from previous research on antecedents of customer revenue (Niraj, Gupta, and Narasimhan 2001) and purchase quantity (Gupta 1988; Tellis and Zufryden 1995). As with purchase frequency, we classify the antecedents of contribution margin as supplier-specific factors (total marketing efforts) and customer characteristics (lagged contribution margin and purchase quantity). We use size of an establishment and industry category as covariates in our model. In Table 2, we provide a description of the antecedents that we propose influence customer purchase frequency and contribution margin. In the database, we also provide the operationalization of the antecedents, their expected effects, and the rationale for our expectations based on previous research. Because all the antecedents we use in our contribution margin model are based on previous research and findings, we do not discuss the hypotheses in detail. In Table 2, we provide a description of the covariates we use as control variables in the purchase frequency and contribution margin models.

Modeling CLV and Data

Model Development

To predict CLV, we need a stochastic model to predict each customer's purchase frequency and a panel-data model that predicts contribution margin. In this study, we assume that the amount a customer spends is independent of purchase timing. This is a rather restrictive assumption for frequently bought consumer goods (Tellis and Zufryden 1995). However, in our product category, we find that the correlation between purchase frequency and contribution margin is not significant.

Purchase Frequency

We model a customer's purchase frequency using the generalized gamma model of interpurchase timing that Allenby, Leone, and Jen (1999) developed. The generalized gamma model also accommodates the commonly used exponential distribution for interpurchase times (Reinartz and Kumar 2003). The likelihood function for the purchase frequency model is given as follows:

$$(3)\qquad L = \prod_{i=1}^{n}\prod_{j=1}^{J_i}\sum_{k=1}^{K}\Phi_{ijk} f_k\left(t_{ij}|\alpha_k, \lambda_{ik}, \gamma_k\right)^{c_{ij}} S_k(t_{ij}|\alpha_k, \lambda_{ik}, \gamma_k)^{(1-c_{ij})},$$

where

$f(t_{ij}|\alpha, \lambda_i, \gamma)$ = the density function for the generalized gamma distribution (i.e., the probability of the jth purchase for customer i occurring at period t, given α, λ_i, γ);
$S(t_{ij}|\alpha, \lambda_i, \gamma)$ = the survival function for the generalized gamma distribution (i.e., the probability of the jth purchase for customer i occurring at a given period is greater than t, given that the jth purchase has not occurred until time t, given α, λ_i, γ);
c_{ij} = the censoring indicator, where $c_{ij} = 1$ if the jth interpurchase time for the ith customer is not right-censored, and $c_{ij} = 0$ if the jth interpurchase time for the ith customer is right-censored;
Φ_{ijk} = the probability of observation j for the ith customer belonging to subgroup k; and
$\alpha, \lambda_i, \gamma$ = the parameters of the generalized gamma distribution.

Because we use a generalized gamma distribution to model interpurchase time and the likelihood function in Equation 3, the expected time until next purchase is given as follows:

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

The ratio of 12 (because we use months as the unit of analysis) to the expected time until next purchase (which we obtain by modeling a generalized gamma distribution on the interpurchase times, as is shown in the work of Allenby, Leone, and Jen [1999]) gives the predicted purchase frequency. The parameters α and γ establish the shape of the interpurchase time distribution, and λ_i is the individual-specific purchase rate parameter. We assume that the population consists of k subgroups, and Φ_{ik} provides the mass point (i.e., weight) for each subgroup. We model the probability of a customer belonging to each subgroup Φ_{ik} as a probit function of the antecedents and covariates of purchase frequency. Specifically, we represent the link function as $\Phi_{ik} = f(x_{ij}\beta_i)$, where x_{ij} represents the antecedents and covariates of purchase frequency for customer i in purchase occasion j, and β_i represents the customer-specific response coefficients.

Our model framework, as presented in Equation 3, resembles a hierarchical Bayes formulation of the concomitant continuous mixture model. To address the issue of endogeneity, we use the one-period lagged value for all the antecedents and covariates in our analysis (Villas-Boas and Winer 1999). However, to account for any extraneous factors, we also use the log of the lagged interpurchase.[2] The specification of the model enables us to estimate individual customer-level coefficients for the influence of the covariates on the probability of a customer belonging to a particular subgroup and thus interpurchase times.

Contribution Margin

We model the contribution margin from a customer using panel-data regression methodologies. We needed 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 with a one-period difference in the dependent variable and a two-period lagged dependent variable as an independent variable (Baltagi 1998). We use the growth in contribution margin from period t – 1 to t as the dependent variable and the contribution margin in period t – 2 as an independent variable. The other independent variables we used are specific to period t – 1 (this also accommodates the issue of endogeneity). The independent variables in the contribution margin model are thus lagged contribution margin, lagged total quantity purchased, lagged firm size, industry category, and lagged total marketing efforts. Thus, the contribution margin model is

$$(5)\quad \Delta CM_{i,t} = \beta_0 + \beta_1 CM_{i,t-2} + \beta_2 Quantity_{i,t-1} + \beta_3 Size_{i,t-1} + \Sigma_j\beta_j Industry_j + \beta_4 Totmark_{i,t-1} + e_{i,t},$$

where

$\Delta CM_{i,t}$ = difference in contribution margin from period t – 1 to period t for customer i, measured in dollars;
$Size_{i,t-1}$ = firm size for customer i in period t – 1, measured as 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 period t – 1;

[2]We also used lagged interpurchase time instead of the log of the lagged interpurchase time, and we did not find any difference in the substantive conclusions. We used log of the lagged interpurchase times because lagged interpurchase times can have a threshold effect on the influence of current interpurchase times (Allenby, Leone, and Jen 1999). The log of the lagged interpurchase time achieved this objective in scaling the tail of the lagged interpurchase time distribution.

$\text{Quantity}_{i,t-1}$ = total quantity of products bought by customer i in period t – 1;

$e_{i,t}$ = error term;

i = index for the customer; and

t = index for time.

Data

We used data from a large multinational computer hardware (servers, workstations, and personal computers) and software (integration and application) manufacturer for the empirical application of our framework. The company's database focuses on business customers. The product categories in the database represent different areas of high-technology products. In addition, for these product categories, it is the choice of the buyer and seller to develop their relationships, and there are significant benefits for both parties to maintain a long-standing relationship. The choice of vendors for the products is normally made after much deliberation by the buyer firm. Even though the firm's products are durable goods, they require constant maintenance and frequent upgrades, which provides the variance required in modeling customer response. For our analyses, we used two cohorts of customers: Cohorts 1 and 2. We assigned customers to Cohort 1 (Cohort 2) if their first purchase with the manufacturer occurred in the first quarter of 1997 (first quarter of 1998). In our samples, we removed customers who had missing values for either rich or standardized modes of communication. We also restricted our sample to customers who had made at least five purchases. Overall, we removed 20% of the original cohort of customers for our analyses, which resulted in an effective sample size of 1316 and 873 observations for customers in Cohorts 1 and 2, respectively. The interpurchase time for customers in Cohort 1 ranges from 1.5 to 23 months; for Cohort 2, it ranges from 1 month to 20 months.

Purchase frequency model. We used each observed purchase for a customer as an observation in the purchase frequency model. For Cohort 1, we selected customers who made their first purchase in the first quarter of 1997. For each customer, we omitted the first observed purchase in our analysis sample because the first observed purchase is restricted to be within three months for all customers in the cohort, and theoretically the customer retention phase begins after the first purchase. The antecedents and covariates we used can be classified as cumulative and current effects. The cumulative effects antecedents include cross-buying and upgrading, and their values represent the total number of different products (for cross-buying) or upgrades that the customer has purchased since the first purchase until the current observed purchase.

The current-effects antecedents include bidirectional communication; returns; relationship benefits; frequency of rich, standardized, and Web-based contacts; and intercontact time. The covariates in the purchase frequency model (type of product purchased) can be classified as current effects. We calculated the current-effects antecedents and covariates on the basis of the activities of the customer or the supplier (in the case of channel communications) between the previous observed purchase (j – 1) and the current observed purchase (j). To assess the inverted U-shaped relationships, we used a quadratic conversion (including the square covariate term in Equation 3) of the respective antecedent. For all customers, we used the interpurchase times until the end of 2000 as our calibration sample. We used the 2001 data as a holdout sample and to compare strategies. All the antecedents and covariates we used in our analyses are lagged variables. Specifically, for observed purchase j, the cumulative-effects antecedents represent the customer's activity since relationship initiation until observed purchase j – 1. Similarly, for observed purchase j, the current effects antecedents and covariates represent the customer's (or supplier's) activity between observed purchases j – 2 and j – 1.

Contribution margin model. To model contribution margin from a customer, we used the annual sales from various purchases of each customer. For customers in Cohort 1, we used the annual sales from each customer from 1997 to 2000. Given our model structure in Equation 5, there are two observations per customer in our analysis sample. Specifically, for each customer, for Observation 1 the dependent variable is the difference in contribution margin between 2000 and 1999, and the independent variables include the contribution in 1998, the 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 contribution margin between 1999 and 1998, and the independent variables include the contribution margin in 1997. As we stated previously, we used the 2001 data as a holdout sample and to compare strategies. The descriptive statistics for the data and the correlation matrix of the antecedents are provided in Table 3.

Results from Estimation of CLV

Purchase Frequency Model

As we discussed previously, we used an effective sample size of 1316 and 873 observations that belong to Cohort 1 (first purchase in 1997) and Cohort 2 (first purchase in 1998), respectively, for our analyses. We discuss the results from Cohort 1 in detail in the text. The results from Cohort 2 are quite similar to those of Cohort 1 and are provided along with the results for Cohort 1 in the corresponding tables. We censored our data set in 2000 and used the 2001 data as our validation (or holdout) sample in both cohorts. We estimated the purchase frequency model in Equation 3 using Markov chain Monte Carlo (MCMC) methods. The results from the purchase frequency model for Cohorts 1 and 2 are provided in Table 4 (for details on the model estimation, model selection, model performance, and support for hypotheses, see Appendix A). The coefficients of the antecedents reported in Table 4 are the means from the posterior samples of β_i, and the signs for the coefficients represent their influence on a customer's purchase frequency. There are several insights that we derive from Table 4, which we discuss subsequently.

Model fit. The results show that the generalized gamma model with two subgroups provides a good fit to the data

TABLE 3
Descriptive Statistics and Correlation Matrix

Variable	Mean	Standard Deviation	Purchase Frequency	Upgrading	Cross-Buying	Bidirectional Communication	Returns	Frequency of Web-Based Contacts	Relationship Benefit–Premium Service Level	Frequency of Rich Modes	Frequency of Standardized Modes	Intercontact Time (Days)
Purchase Frequency Model												
Purchase frequency	5 (4.5)	8.4 (6.8)	1									
Upgrading	1.32 (1.16)	.89 (.91)	.62***	1								
Cross-buying	2.58 (3.13)	1.7 (1.5)	.53***	.39*	1							
Bidirectional communication	.84 (.62)	2.41 (3.52)	.68***	.51*	.48*	1						
Returns	.91 (.86)	3.7 (2.81)	.36***	.09	.13	.11*	1					
Frequency of Web-based contacts	3.88 (4.37)	25.81 (24.94)	.40***	.21	.15	.17**	.06	1				
Relationship benefit–premium service level	.09 (.12)	.29 (.25)	.41***	.31**	.36**	.22	–.21*	.25	1			
Frequency of rich modes	1.79 (1.52)	5.69 (5.84)	.45***	.15**	.29**	.32*	.05	.34*	.07	1		
Frequency of standardized modes	20.74 (22.81)	47.75 (45.81)	.44***	.22*	.34*	.24**	.07	.32*	.19*	.30**	1	
Intercontact time (days)	15.3 (16.1)	13.8 (14.2)	.51***	–.08	.06	–.01	–.01	–.04	–.03	–.11	.06	1

TABLE 3
Continued

Variable	Mean	Standard Deviation	Growth in Contribution Margin	Lagged Contribution Margin	Total Marketing Efforts	Total QuantityPurchase
Contribution Margin Model						
Growth in contribution margin	4955	417,270	1			
	(4827)	(381,297)				
Lagged contribution margin	31,143	323,139	–.78***	1		
	(32,825)	(318,867)				
Total marketing efforts	3.49	17.26	.61***	.08*	1	
	(4.5)	(16.24)				
Total quantity purchased	1.89	13.40	.71***	.05**	.07	1
	(2.01)	(14.02)				

*Significant at $\alpha = 10\%$.
**Significant at $\alpha = 5\%$.
***Significant at $\alpha < 1\%$.
Notes: The frequency of rich, standardized, and Web-based contacts represents the frequency of the respective mode of communication between two consecutive purchases. Values in parentheses for the descriptive statistics represent Cohort 2. The correlation matrix for Cohort 2 is similar to that of Cohort 1 and is available on request from the authors. We do not report the correlation matrix of the covariates because it does not have any substantive interpretation.

TABLE 4
Coefficients for the Generalized Gamma Purchase Frequency Models

Variable	Model 1 (Generalized Gamma Without Mixture)		Model 2 (Generalized Gamma with Mixture, Without Temporal Variation)		Model 3 (Generalized Gamma with Mixture and Temporal Variation)	
Component 1						
α_1	3.05	(4.12)**	4.1	(4.2)**	3.27	(3.59)**
υ_1	26.18	(25.08)**	42.97	(43.82)**	47.05	(48.90)**
θ_1	.007	(.002)**	.01	(.08)**	.04	(.02)**
γ_1	1.2		1.2	(1.3)	1.2	(1.5)
Mass point			.54	(.55)	.54	(.56)
Component 2						
α_2			.58	(1.57)**	1.48	(3.61)**
υ_2			38.21	(34.28)**	32.07	(49.02)**
θ_2			.008	(.012)**	.005	(.001)**
γ_2			.9	(.9)	.9	(.9)
Mass point			.46	(.45)	.46	(.44)
Coefficients						
β_{01}			.89	(–1.52)**	–2.05	(–2.51)*
Lagged log interpurchase time					–2.09	(–2.85)**
Antecedents: Customer Characteristics						
Upgrading					5.01	(5.62)**
Cross-buying					6.08	(6.92)**
Bidirectional communication					1.49	(1.01)**
Returns					10.52	(9.98)**
(Returns)^2					–3.84	(–4.01)*
Frequency of Web-based contacts					3.52	(2.38)**
Antecedents: Supplier-Specific Factors						
Relationship benefits					9.78	(7.65)**
Frequency of rich modes of communication					4.50	(5.65)**
(Frequency of rich modes of communication)^2					–1.30	(–1.28)**
Frequency of standardized modes of communication					6.53	(7.02)**
(Frequency of standardized modes of communication)^2					–.28	(–.53)**
Intercontact time					9.64	(8.56)**
(Intercontact time)^2					–3.21	(–4.05)**
Log-likelihood	–3298.91	(–3627.08)	–2908.66	(–3297.04)	–2237.82	(–2437.91)
AIC	–6606	(–7262)	–5825	(–6602)	–4484	(–4884)
BIC	–6639	(–7295)	–5910	(–6687)	–4683	(–5083)
Relative absolute error	.95	(.91)	.84	(.80)	.51	(.53)

*Posterior sample values between the 2.5th and 97.5th percentile do not contain zero.
**Posterior sample values between the .5th percentile and 99.5th percentile do not contain zero.
Notes: Values in parentheses represent Cohort 2. The product category variable was not significant in our analysis, and thus we do not include it here. Relative absolute error is with respect to a moving average model. The significance levels apply to the coefficients of Cohorts 1 and 2.

and is better than other models for modeling purchase frequency (log-likelihood for Model 3 = –2237.82, Akaike information criterion [AIC] = –4484, and Bayesian information criterion [BIC] = –4683). We also used a hazard model with the finite mixture framework (Kamakura and Russell 1989) to model purchase frequency, and we found that our proposed model fits the data better and has better predictive capabilities.

Distribution parameters.[3] The mean expected purchase frequency for Subgroup 1 is 4.2 purchases in a year, and the

[3]The parameter estimates of the purchase frequency model are based on mean values from 50 repeats with random starting values for each repetition. We adopted such a procedure to ensure that the parameter estimates are global optimal values and are not affected by any local maxima.

mean expected purchase frequency for Subgroup 2 is 1.01 purchases in a year. Given the variation in expected purchase frequencies in each subgroup, we term Subgroup 1 the "active state" and Subgroup 2 the "inactive state." The component masses for Subgroup 1 (φ_1) and Subgroup 2 (φ_2) are .54 and .46, respectively. This implies that we expect 54% of the customers to be active in the prediction window and 46% of the customers to be inactive in the prediction window.

Supplier-specific factors. Our analyses indicate that a supplier's contact strategy and provision of relationship benefits significantly affect a customer's predicted purchase frequency. We find that the frequency of contacts affects purchase frequency nonlinearly. Specifically, we find an inverted U-shaped relationship. This leads us to believe that there is an optimal level of marketing communication for each customer. A firm's increasing communication beyond a certain threshold may result in diminishing returns in terms of customer purchase frequency. This finding also provides the reasoning to determine the optimal level of resources that needs to be allocated across channels to maximize CLV in Phase 2.

The coefficients of the marketing contacts reveal a difference in the influence of various channels on customer purchase frequency. The coefficient of the quadratic term for rich modes of communication (–1.30 for Cohort 1) is higher than the coefficient of the quadratic term for standardized modes of communication (–.28 for Cohort 1). Thus, we can infer that the rate of diminishing returns (after exceeding the threshold) is much higher for the rich mode of communications than for standardized modes. Therefore, although the rich mode of communication is interactive and effective, firms should use it with great caution.

Customer characteristics. The results indicate that upgrading and cross-buying positively influence a customer's purchase frequency. This is in line with the findings of Reinartz and Kumar (2003), who also find that breadth of purchase positively affects a customer's duration in a profitable relationship. We also find that the higher the bidirectional communication between the customer and supplier, the higher is the customer's purchase frequency. Thus, in addition to timely communication from the supplier to the customer (Morgan and Hunt 1994), communication from a customer can be a good indicator of a customer's activity.

With respect to returns from a customer, our analysis suggests that managers need to exercise caution. We find support for an inverted U-shaped relationship between purchase frequency and returns. This indicates that customers who return products within a threshold are a good asset to the firm. The results highlight the importance of firms' recognizing the customers who establish contact through the online channel in their CRM strategies.

Contribution Margin Model

We estimated the contribution margin model with annual data from 1997 (t – 4) to 2000 (t) for Cohort 1 and from 1998 to 2000 for Cohort 2.[4] The revenue in 2001 (t + 1) acts as a holdout sample for Cohorts 1 and 2. The coefficients of the contribution margin model are provided in Table 5. The main insight from Table 5 is that the contribution margin model provides an adjusted R^2 of .68 and thus can explain significant variation in contribution margin from customers. We derive several other insights from Table 5, which we discuss subsequently.

Supplier-specific factors. Total lagged marketing efforts contribute significantly to an explanation of variation in current contribution margin, which implies that a supplier's contact strategy affects both purchase frequency and contribution margin.

Customer characteristics. The two-period lagged contribution margin provides the highest contribution to an explanation of current-period contribution margin. In addition, lagged quantity of goods is significant in explaining variation in contribution margin. Firm size and industry category explain variation in current-period contribution margin. Among the various industry categories, firms in the financial services, technology, consumer packaged goods, and government industry categories provide, on average, a higher contribution margin than do firms in other industry categories. However, firms in the education industry provide a lower contribution margin than do firms in other industries.

Customer Selection Strategy

In this section, we compare the customer selection capabilities of the following: CLV, our proposed metric; previous-period customer revenue (PCR), a simple metric; past customer value (PCV), which is widely considered a good

[4]We also estimated the contribution margin model at the monthly, quarterly, and semiannual levels, but we did not find any significant differences in model performance. Thus, to maintain simplicity, we used the contribution margin model with the annual data.

TABLE 5
Regression Results from the Contribution Margin Model

Independent Variable	Parameter Estimate	
Intercept	N.S.	(N.S.)
Contribution in t – 2	.83***	(.85***)
Lagged total quantity purchased	.02**	(.03**)
Size	.02**	(.02**)
Aerospace	N.S.	(N.S.)
Financial services	.02*	(.02**)
Manufacturing	N.S.	(N.S.)
Technology	.03**	(.02**)
Consumer packaged goods	.03***	(.03***)
Education, K–12	–.03***	(–.02***)
Travel	N.S.	(N.S.)
Government	.02*	(.02*)
Lagged total level of marketing effort	.04***	(.06***)

*Significant at α = .10.
**Significant at α = .05.
***Significant at α < .01.
Notes: The reported coefficients are standardized estimates; the values in parentheses represent Cohort 2. N.S. = not significant.

predictor of future customer value; and customer lifetime duration (CLD), a forward-looking metric that is also used as a proxy for loyalty. (We also compared the customer selection capabilities of CLV with other customer-based metrics, such as share of wallet and recency, frequency, and monetary value. The results were similar to the comparison with PCR, PCV, and CLD.) In general, organizations in direct marketing situations rank-order their customers on the basis of a particular metric and prioritize their resources from best customers to worst customers on the basis of the rank order (Roberts and Berger 1999). Descriptions of the various customer-based selection metrics used in our analyses are provided in Appendix B.

Performance of the Customer Selection Metrics

To compare the performance of the four metrics, we rank-ordered customers from best to worst according to each metric and then compared the sales, costs, and profits from the top 5%, 10%, and 15% of customers. We used the data from the first 30 months to score and sort the customers on each metric, as do Reinartz and Kumar (2003). We then compared the actual sales, variable costs of communication, and profits for the top 5%, 10%, and 15% of customers from the censoring period (30 months) until the end of the observation window (48 months).[5] To select customers for contact, in general organizations choose the top 5% to 15% of their customers, rank-ordered on the basis of a scoring metric. Selection of more customers to contact may not be feasible because of limited time and resources. Thus, to reflect industry practice, we compared the performance of our metric among the top 5%, 10%, and 15% of customers. The results are provided in Table 6, and the reported values are cell medians. We subsequently summarize the results from our comparison.

Overall, Table 6 shows that the proposed metric better identifies profitable customers than do other metrics we compared in the study, such as PCR, PCV, and CLD. On the basis of the 18-month prediction window, we expect the average net profits of customers selected from the top 5% using the proposed CLV metric to be $143,295 (after accounting for cost of goods sold [70%] and variable costs of communication), whereas the average net profits are $70,929, $130,785, and $106,389 for the top 5% of the customers selected on the basis of PCR, PCV, and CLD, respectively. These findings hold across all the percentage subgroups. The results provide substantial support for incorporating the responsiveness of each individual customer across various communication channels and for the usefulness of CLV as a metric for customer scoring and customer selection. Although the difference in profits from use of PCR, PCV, CLD, and CLV is, on average, approximately $40,000 for a customer in the top 5% sample, the difference in total profit across the top 5% to 15% of the entire customer base can easily yield more than $1 million.

[5]We also compared the metrics with a censoring time at 18 months and prediction window of 30 months. The substantive results of the study hold even for a 30-month prediction window. The results are available on request from the authors.

Resource Allocation Strategy

Having evaluated the usefulness of using CLV for customer selection, we now describe our methodology for designing resource allocation strategies that maximize CLV. The framework also provides managers a tool for assessing return on marketing investments by identifying avenues for optimal resource allocation across channels of communication for each individual customer (and possibly across customers), so as to maximize CLV. The marketing literature has provided guidelines for optimal resource allocation in acquisition and retention decisions (Blattberg and Deighton 1996; Blattberg, Getz, and Thomas 2001), promotion expenditures (Berger and Bechwati 2001; Berger and Nasr 1998), and marketing actions when future brand switching

TABLE 6
Comparisons of CRM Metrics for Customer Selection

Percentage of Cohort (Selected from Top)	CLV	PCR	PCV	CLD
5%				
Gross profit ($)	144,883	71,908	131,735	107,719
Variable costs ($)	1,588	979	950	790
Net profit ($)	143,295	70,929	130,785	106,389
10%				
Gross profit ($)	78,401	27,981	72,686	55,837
Variable costs ($)	1,245	943	794	610
Net profit ($)	77,156	27,038	71,892	55,227
15%				
Gross profit ($)	56,147	15,114	52,591	44,963
Variable costs ($)	807	944	809	738
Net profit ($)	55,340	14,170	51,782	44,225

Notes: All metrics are evaluated at 30 months, with an 18-month prediction window. Cohort 2 provides similar results. The reported values 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 approximately 70%; thus, gross profit = revenue × .3.

is considered (Rust, Zeithaml, and Lemon 2004). These guidelines represent a significant step toward incorporation of long-term customer profitability effects into firm-level managerial decision making. However, the models provide less insight into decisions about how to manage individual customers in a way that accounts for the heterogeneity, and they do not provide a mechanism for dynamic updating of profitability assessment (Libai, Narayandas, and Humby 2002).

Our resource allocation algorithm uses Equation 2 as the objective function, and the purpose of the optimization is to find the level of contacts across various channels with each individual customer that would maximize CLV. Equation 2 is a function of predicted purchase frequency (based on Equation 4), predicted contribution margin (based on Equation 5), and marketing costs. We first estimated the responsiveness of customers (coefficients, β_s) to marketing contacts from the purchase frequency model and the contribution margin model. To design a CLV-based resource allocation strategy, we held the coefficients constant and identified the level of covariates (i.e., level of channel contacts) for each customer that would maximize CLV. In summary, in Equation 2, the contacts made to a customer across various channels are under the supplier's control and thus can be used to maximize CLV, depending on the cost of each mode of communication and the responsiveness of the customer (in terms of both purchase frequency and contribution margin) to each channel of communication.[6] In other words, with respect to marketing resources for a firm, the customer contact levels across different channels appear in the revenue and cost sides of Equation 2 and thus avoid the scope of corner solutions.

We used a genetic algorithm to derive the levels of contact desired for each individual customer that maximize CLV. Genetic algorithms (Goldberg 1989) are simulation-based, parallel-search algorithms that have been used in econometrics (Dorsey and Mayer 1995; Liang and Wong 2001) to obtain optimal solutions when the complexity of the optimization function tends to be intractable and multidimensional. In our study, support for a purchase frequency distribution with two subgroups led us to believe that the optimization surface is multimodal. In addition, we intended to allocate resources for each customer on the basis of individual responsiveness. These issues made our optimization problem extremely complex and intractable with traditional analytical methods. Thus, we resorted to a search algorithm to find the optimal resource allocation levels. In addition, the multimodal nature of the optimization surface (given the support for a mixture distribution for purchase frequency) motivated us to use a parallel-search technique, which is not susceptible to local minima (common in multimodal distributions) (Venkatesan, Krishnan, and Kumar 2004). Appendix C explains how we used a parallel-search technique for resource allocation purposes.

[6]In Equation 2, the level of contacts in each channel for each customer is varied each year. However, to simplify our optimization routine, we assumed that the level of contacts is equal across the prediction period. Our assumption can be viewed as taking the average level of contacts in the prediction periods.

Aggregate Results

The total net present value of future profits from a resource allocation strategy that maximizes CLV (with the predicted contribution margin) is approximately $44 million. We also computed the total net present value of future profits when the organization uses its current resource allocation strategy. Specifically, for each customer, we maintained the resource allocation levels for the most recent year and calculated CLV over a three-year period. We find that, based on this status quo resource allocation strategy, the total net present value of future profits is approximately $24 million. Therefore, we find that a resource allocation strategy that maximizes CLV results in an increase in profits by approximately 83%. The total cost of communication (over three years), based on the resource allocation strategy that maximizes CLV, is approximately $1 million. The total cost of communication in the organization's current strategy is approximately $716,188. We find that the organization improves profits by increasing costs of serving customers (rather than cost of communication in the previous year) by 48%. The return on marketing communication to the organization, based on its current strategy, is approximately $34 million ($24 million/$716,188). With a communication strategy that maximizes CLV, the return on marketing communication to the organization is approximately $44 million ($44 million/$1 million). Thus, it is possible to improve profits and return on marketing communication by appropriately identifying customers for target communications and by matching the channel of communication with customer preferences. The aggregate results suggest that given the improvement of approximately $20 million among a sample of 216 customers, there is a potential for the firm to increase its revenue by at least $1 billion across its entire customer base. However, such benefits may not be realized immediately because the firm also needs to incur costs to move toward a customer-centric view and to train its employees to manage customers on the basis of CLV.

Implications, Limitations, and Further Research

The objective of our study was to analyze the usefulness of CLV as a metric for customer selection and resource allocation strategy. First, we developed and estimated an individual customer-level objective function, the goal of which is to measure CLV. Second, we demonstrated the superiority of selecting customers for contact on the basis of CLV compared with commonly used metrics such as PCR, PCV, and CLD. Third, we evaluated the benefits of designing marketing communications that maximize CLV. We now discuss the implications of our study and how managers can use this knowledge to design efficient marketing programs. We also provide an outline for future researchers to build on the framework proposed herein.

Implications

Antecedents of purchase frequency and contribution margin. The theoretical implications of the purchase frequency model are also related to the CUSAMS customer asset management framework (Bolton, Lemon, and Verhoef 2004). In this study, we tested parts of the CUSAMS framework and found empirical support for the parts we tested. Specifically, the CUSAMS framework proposes that marketing instruments (e.g., direct mailings, reward programs) affect a customer's price perceptions, satisfaction, and commitment. In turn, these affect the length, depth, and breadth of a relationship, which then ultimately influence CLV. We find empirical support for marketing instruments' effects on purchase frequency (rich and standardized modes of communication and relationship benefits) and contribution margin (total marketing efforts), both of which ultimately influence CLV. We also find that breadth of purchases (cross-buying) and depth of buying (upgrading) affect purchase frequency, which ultimately influences CLV. In addition, we find support for a nonlinear relationship between supplier communications and purchase frequency. This supports Fournier, Dobscha, and Mick's (1997) expectations that too much communication between suppliers and customers can be disruptive. Thus, our results indicate that managers need to be cautious when designing marketing communication strategies across different channels and need to be wary of contacting customers too many times, especially through rich modes of communication.

We find an inverted U-shaped relationship between returns and purchase frequency. A possible benefit from customers who return products could be the opportunity to understand the reasons for dissatisfaction. In addition, customers who return products within a certain period may do so because they have inherent trust in the supplier and because they expect future benefits, such as improvements in the quality of the product. However, a customer's returning too many times may indicate erosion of trust with the firm or a lower level of future activity. We also find that customers that establish contact through the online channel of communication exhibit high frequency of purchases and have high involvement. Therefore, the online channel can provide an ideal setting for B2B firms to enhance their customer relationships. We find that in addition to influencing purchase frequency, marketing communications influence the expected contribution margin from a customer. Also in the B2B scenario, industry category and size seem to be important factors that influence the magnitude of contribution margin.

Enhancement of marketing productivity. Rust, Zeithaml, and Lemon (2004) propose that firm strategies and tactical marketing actions affect the marketing productivity chain. Our analyses of customer selection investigate how firms can enhance strategies, and our analysis of optimal resource allocation investigates how firms can improve tactical marketing actions.

Customer selection. A CLV metric better identifies customers that provide higher future profits than do PCR, PCV, and CLD. Our analyses indicate that CLV is preferred to incorporate the dynamics of customer purchase behavior into the customer selection process. Managers can substantially improve their return on marketing investments by using a dynamic, customer-level measure of CLV for scoring rather than using the other metrics suggested in the literature and by prioritizing contact programs.

Resource allocation strategy. The results from our study highlight the importance of firms' considering individual customers' responsiveness to marketing communication as well as the costs involved across various channels of communication when making resource allocation decisions. Our analyses suggest that there is a potential for substantial improvement in CLV through appropriate design of marketing contacts across various channels. When firms design resource allocation rules, they can realize the increase in profits by incorporating the differences in individual customer responsiveness to various channels of communication and the potential value provided by the customer. The proposed resource allocation strategy can be a basis for evaluating the potential benefits of CRM implementations in organizations, and it provides accountability for strategies geared toward managing customer assets.

To summarize, the major conclusions that we derive from our study are the following:

- Marketing communication across various channels affects CLV nonlinearly;
- CLV performs better than other commonly used customer-based metrics for customer selection such as PCR, PCV, and CLD; and
- Managers can improve profits by designing marketing communications that maximize CLV.

Limitations and Further Research

The study has limitations that further studies can address. The results of this study are from a customer database in the high-technology industry. Further studies need to investigate whether the results are generalizable to other industries and settings. In addition, further research needs to develop models that combine forecasts of aggregate competitive responses to marketing actions and customer brand switching with individual-level models of direct marketing. We also consider only the average levels of optimal communication strategy in a channel. However, firms can further improve the efficiency of communication strategy by appropriately sequencing their customer contacts across different channels. In addition, in our study, we provide a framework for maximizing CLV with marketing communications. However, note that we do not compare our proposed resource allocation strategy (that focuses on maximizing CLV) with a strategy that focuses on allocating resources to customers for which the increment in CLV from appropriate design of marketing communication is highest. For example, with an appropriately designed marketing strategy, it is possible that customers that previously had high CLV continue to have high CLV in the future, irrespective of the level of marketing communications, and that some customers that have had low CLV transform to high-CLV customers. Further research can investigate whether the customers selected for high levels of marketing communications are the same when the resource allocation strategy focuses on maximizing CLV or on maximizing incremental CLV. Finally, the sum of optimal CLVs for each individual customer need not lead to the optimal customer equity in the case of a budget constraint. We performed our optimization with a budget constraint, and there were no changes in the substantive results of the study. In addition, our optimization algorithm is flexible enough to allow for inclusion of the budget constraint without any substantial adjustments.

The customer- and supplier-specific antecedents used in the customer response model also can directly affect costs and thus margins. However, because we estimated the customer response model in a single step, which we then included in a net present value function (Equation 1) that includes both costs and margins, we assessed the indirect effect of the covariates on both costs and margins. Further studies can develop and test hypotheses that directly relate CRM efforts to costs and margins. In addition, it can be expected that margins change over time. In this case, the value that a customer provides to a firm is a function of both the expected time frame until the next purchase and the contribution margin at that particular period. We treated several antecedents used in our framework (e.g., upgrading, cross-buying, bidirectional communication, number of returns, number of Web-based contacts) as exogenous variables in our analysis. We used the lagged variables of these to account for potential endogeneity. Further research can investigate more sophisticated techniques that explicitly treat these variables as endogenous. Finally, a notable issue that arises from our analyses is whether the recommendations from an optimization framework pan out when implemented in the real market. Although 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.

Appendix A
Results from Data Analyses

Purchase Frequency Model

Model estimation. For Cohorts 1 and 2, the results are based on 50,000 samples of the MCMC algorithm (for details of the algorithm, see Allenby, Leone, and Jen 1999, Appendix). We simulated the posterior distribution using five parallel chains with overdispersed starting values. In each chain, we used the initial 40,000 iterations as burn-in and used the last 10,000 iterations to obtain posterior statistics. We used "slice-sampling" (Neal 2000) to obtain random samples. We assessed the autocorrelations of the posterior samples to perform thinning. The autocorrelation functions revealed that every fifth sample is unrelated to every other fifth sample. Thus, the posterior statistics are based on 2000 samples (using every fifth sample from 10,000 samples). We assessed the convergence of the algorithm from the line plots of the posterior sample and by evaluating Gelman and Rubin's (1992) $\sqrt{\hat{R}}$ statistic. Values of $\sqrt{R}$ that are closer to 1 reveal that all the chains have converged to true posterior distribution. In our analyses, we found that the value of $\sqrt{R}$ ranged from 1.2 to .9 (in previous research [Cowles and Carlin 1996], these values have been found to indicate convergence of the MCMC chains). Our approach to investigating within-chain autocorrelations, computing Gelman and Rubin's statistic, and visually inspecting the sampling plots has been recommended widely for convergence diagnostics (Cowles and Carlin 1996). We implemented the estimation algorithm using the GAUSS software package, and we performed the convergence diagnostics using CODA. We also used multiple prior values for the estimates and did not find a significant impact on the posterior samples; this is because we used diffuse prior values and because of the large sample size of our data set.

Model selection. Table 4 shows that a simple generalized gamma model without the probit link function or time-varying covariates (Model 1) provides a log-likelihood of –3298.91 (we calculated the log-likelihood using Newton and Raferty's [1994] log marginal density measure). A generalized gamma model with the probit link function (two subgroups) but no time-varying covariates (Model 2) provides a log-likelihood of –2908.66. Finally, the log-likelihood for the generalized gamma model with the probit link function (with two subgroups) and time-varying covariates (Model 3) is –2237.82. Increasing the number of subgroups in Models 2 or 3 did not result in significantly higher log-likelihoods. We also computed the AIC and BIC for model selection. For both measures, a higher value indicates a better model. We find that Model 3 has the highest value for both AIC and BIC (AIC = –4484 for Model 3, –5825 for Model 2, and –6606 for Model 1; BIC = –4683 for Model 3, –5910 for Model 2, and –6639 for Model 1). In addition, a latent-class finite mixture model with two segments provides a likelihood of –2938. Overall, the results show that the generalized gamma model with two subgroups provides a good fit to the data.

Distribution parameters. The values of γ in the generalized gamma model are $\gamma_1 = 1.2$ and $\gamma_2 = .9$ for Subgroups 1 and 2, respectively. The component masses for Subgroup 1 (φ_1) and Subgroup 2 (φ_2) are .54 and .46, respectively. All the distribution parameters (α_k, ν_k, and θ_k) have more than 99% of their samples different from zero. The mean expected interpurchase time for Subgroup 1 is 4.2 purchases in a year, and the mean expected frequency for Subgroup 2 is 1.01 purchases in a year. Given the variation in expected frequencies in each subgroup, we term Subgroup 1 the "active state" and Subgroup 2 the "inactive state."

Influence of antecedents and covariates. Our empirical analyses support all the proposed effects of the antecedents on purchase frequency.

Out-of-sample forecasting accuracy. We used relative absolute error (RAE) to evaluate the forecasting accuracy of the generalized gamma model compared with that of a naive moving average model (the moving average model is implemented as an updated average of every consecutive interpurchase time for a customer). We used all but the last observation for each customer (calibration sample) to estimate the parameters of each model. We then used the mean posterior values to compute the expected time until next purchase from Equation 3. We then compared the forecast time until the next purchase with the holdout sample (formed from the last observation for each customer) to assess the mean absolute deviation (MAD). The RAE is given by the ratio of the model MAD to the MAD based on the moving average measure. Based on the RAE measure, the generalized gamma model with time-varying covariates (Model 3) has an RAE of .51, compared with that of a naive moving average technique. The MAD from Model 3 is 5.21 months, compared with 10.24 months for the moving average measure. Model 3 provides the best improvement in forecasting accuracy compared with Model 2 (RAE = .84) and Model 1(RAE = .95). We also assessed the predictive capability of the purchase frequency model using hit rate. In other words, we assessed the number of purchases in the holdout sample that the model also correctly predicted as a purchase. We observe that among customers who bought within 12 months, the model currently identifies 89% of them, and among customers who did not buy within 12 months, the model currently identifies 90% of them.

Contribution Margin Model

Estimation and influence of antecedents and covariates. We estimated the contribution margin model on annual data from 1997 (t – 4) to 2000 (t) for Cohort 1 and from 1998 to 2000 for Cohort 2. The revenue in 2001 (t + 1) is a holdout sample for Cohorts 1 and 2. The coefficients of the contribution margin model are provided in Table 5. The contribution margin model provides an adjusted R^2 of .68. Overall, the results of the analyses support all the hypothesized relationships.

Out-of-sample forecasting accuracy. As with typical time-series models, we advanced the independent variables by one period to forecast the dependent variable in period t + 1. Specifically, when the contribution margin model is used to predict period t + 3, the contribution margin in period t + 1 is an independent variable and is obtained from the prediction in period t + 1. The contribution margin model predicts the growth in revenue from period t to t + 1. We obtained the magnitude of revenue in period t + 1 by adding the predicted value from the contribution margin model to the base revenue in period t. We evaluated the performance of the contribution margin model in the holdout sample on the basis of our estimates from the calibration sample. Table A1 provides the descriptive statistics of the observed contribution margin and the predicted contribution margin in the holdout sample (period t + 1). In the holdout sample, the mean predicted contribution margin in period t + 1 is approximately $67,729, and the mean observed contribution margin is approximately $64,396.

Appendix B Description of Customer Selection Metrics

CLV

We entered predictions from the purchase frequency (Equation 3) and contribution margin (Equation 4) models into Equation 2 to obtain the net present value of future profits (period t + 1) from each customer. The purchase frequency model predicts the expected time in months until next purchase for each customer. We assigned a 30% margin after accounting for cost of goods sold (the managers who provided the database informed us that 30% was a nominal margin for most of their products), and we computed the variable costs using costs of communication. The mean unit cost of standardized modes of communication is approximately $3, and the mean unit cost of rich modes of communication is $60. We computed the unit cost of communication for each customer as the ratio of the total contacts for a given channel in a given year to the total cost of contact for a given mode in a given year. Finally, we used an annual discount rate of 15% for each customer, which is based on the lending rate that is appropriate for the time of the study.

PCR and PCV

We define PCR as the revenue provided by the customer in the most recent observed purchase. We define PCV as the cumulative profits obtained from a customer until the current period. The cumulative profits are calculated annually from a customer's initiation until the current period. We projected the profit in each year to current terms using a discount factor. The PCV calculation is as follows:

$$\text{(B1)} \qquad PCV_i = \sum_{t=0}^{T} \left(CM_{it} - MC_{it}\right) \times (1 + r)^{T-t},$$

where $CM_{i,t}$ is the contribution margin for customer i in period t; $MC_{i,t}$ denotes marketing costs for customer i in period t; t is an index for time period (t = 0 for the period of customer initiation; for example, t = 0 for 1997 for Cohort 1 customers, and t = 0 for 1998 for Cohort 2 customers); T is

TABLE A1
Comparison of Descriptive Statistics Between Observed Contribution Margin and Predicted Contribution Margin in the Holdout Sample

	Mean	Standard Deviation	Minimum	Maximum
Observed	50,199	23,850	–171	1,010,881
	(49,229)	(24,836)	(–181)	(1,420,981)
Predicted	57,729	24,538	–178	1,897,257
	(74,283)	(22,598)	(–159)	(1,938,458)

Notes: All reported values are in dollars and are rounded to the nearest integer. Values in parentheses represent Cohort 2.

the current period; and r is the discount rate, which we set at 15%.

CLD

In our analysis, we evaluated the probability that a customer is alive or dead in the planning window using the P(Alive) measure that Schmittlein and Peterson (1987) and Reinartz and Kumar (2002) recommend. The P(Alive) measure uses the previous purchase pattern to predict the probability that a customer is still alive at each period in the prediction window. Higher values of P(Alive) indicate longer lifetime duration.

Appendix C
Genetic Algorithms to Develop Resource Allocation Strategies

Researchers in marketing have only recently begun to recognize the potential benefits of using genetic algorithms (Balakrishnan and Jacob 1996; Midley, Marks, and Cooper 1997; Naik, Mantrala, and Sawyer 1998; Venkatesan, Krishnan, and Kumar 2004) in deriving optimal strategies for complex marketing problems. The genetic algorithm proceeds by searching for the optimal level of contact for each customer that maximizes CLV. The sum of the optimal CLVs from each individual customer provides the optimal customer equity of the analysis sample.[7] Specifically, we varied the contact levels for each customer and then calculated the sum of CLV of all customers in the sample. Our objective was to calculate the maximum value for this sum of the CLVs. In this case, our optimization algorithm maximized the objective function by varying 432 parameters in Cohort 1 (216 customers and 2 parameters for each customer [levels of rich and standardized modes]). Following research in customer equity (Rust, Zeithaml, and Lemon 2004), we set the time frame for our optimization framework as three years. Our database provides information on the approximate unit cost of communication through rich modes and standardized modes to each customer. On average, the unit marketing cost through standardized modes (average of direct mail and telephone sales) is $3, and the unit marketing cost through rich modes (salesperson contacts) is $60. Thus, the cost of communication through rich modes is approximately 20 times the cost of communication through standardized modes. Such a cost index is commonly encountered. 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%. We ran the genetic algorithm at least 50 times and used the mean of the resource levels corresponding to the maximum CLV from each run as the resource reallocation rule for each customer.

[7]When forecasting contribution margin for three years ahead, note that we have data on marketing activities from 1997 to 2001. Our last prediction for the long-term analysis is in period 2003, for which we need marketing variables in 2002, which we do not have. For forecasting the contribution margin in 2003, we used the average of marketing-mix variables from 1997 to 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.

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