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Modeling Customer Lifetime Value

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As modern economies become predominantly service-based, companies increasingly derive revenue from the creation and sustenance of long-term relationships with their customers. In such an environment, marketing serves the purpose of maximizing customer lifetime value (CLV) and customer equity, which is the sum of the lifetime values of the company's customers. This article reviews a number of implementable CLV models that are useful for market segmentation and the allocation of marketing resources for acquisition, retention, and cross-selling. The authors review several empirical insights that were obtained from these models and conclude with an agenda of areas that are in need of further research.

Keywords: *customer lifetime value; customer equity; customer retention; probability models; persistence models*

Customer lifetime value (CLV) is gaining increasing importance as a marketing metric in both academia and practice. Companies such as Harrah's, IBM, Capital One,

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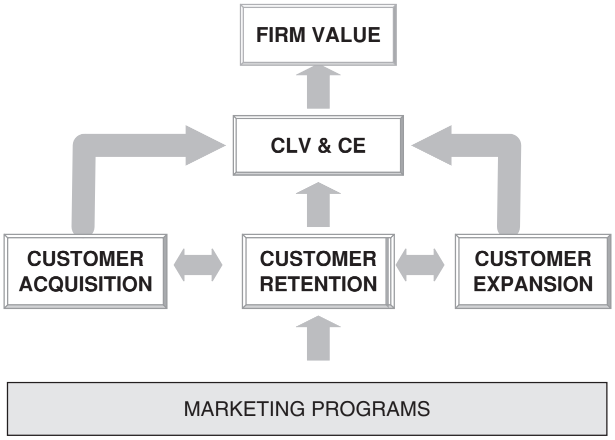
FIGURE 1
Conceptual Framework for Modeling Customer Lifetime Value



NOTE: CLV = customer lifetime value; CE = customer equity.

LL Bean, ING, and others are routinely using CLV as a tool to manage and measure the success of their business. Academics have written scores of articles and dozens of books on this topic in the past decade. There are several factors that account for the growing interest in this concept.

First, there is an increasing pressure in companies to make marketing accountable. Traditional marketing metrics such as brand awareness, attitudes, or even sales and share are not enough to show a return on marketing investment. In fact, marketing actions that improve sales or share may actually harm the long-run profitability of a brand. This is precisely what Yoo and Hanssens (2005) found when they examined the luxury automobile market.

Second, financial metrics such as stock price and aggregate profit of the firm or a business unit do not solve the problem either. Although these measures are useful, they have limited diagnostic capability. Recent studies have found that not all customers are equally profitable. Therefore, it may be desirable to "fire" some customers or allocate different resources to different group of customers (Blattberg, Getz, and Thomas 2001; Gupta and Lehmann 2005; Rust, Lemon, and Zeithaml 2004). Such diagnostics are not possible from aggregate financial measures. In contrast, CLV is a disaggregate metric that can be used to identify profitable customers and allocate resources accordingly (Kumar and Reinartz 2006). At the same time, CLV of current and future customers (also called customer equity or CE) is a good proxy of overall firm value (Gupta, Lehmann, and Stuart 2004).

Third, improvements in information technology have made it easy for firms to collect enormous amount of customer transaction data. This allows firms to use data on revealed preferences rather than intentions. Furthermore, sampling is no longer necessary when you have the entire customer base available. At the same time, sophistication in modeling has enabled marketers to convert these data into insights. Current technology makes it possible to leverage these insights and customize marketing programs for individual customers.

The purpose of this article is to take stock of the advances in CLV modeling and identify areas for future research. This article is the outcome of intensive 2-day discussions during the "Thought Leadership Conference" organized by the University of Connecticut. The discussion groups consisted of a mix of academics and practitioners.

The plan for the article is as follows. We first present a conceptual framework that shows how CLV fits in the value chain and what are its key drivers. Next, we present several modeling approaches that have been adopted to address CLV. These approaches vary from econometric models to computer science modeling techniques. This is followed by a detailed discussion of areas for future research. We end the article with concluding remarks.

CONCEPTUAL FRAMEWORK

We will use the simple framework shown in Figure 1 to motivate our discussion of CLV models. This framework is intuitive and its variations have been used by many researchers (Gupta and Lehmann 2005; Gupta and Zeithaml 2006; Kumar and Petersen 2005; Rust et al. 2004). It shows that what a firm does (its marketing actions) influences customer behavior (acquisition, retention, cross-selling), which in turn affects customers' CLV or their profitability to the firm.[1] CLV of current and future customers, often called CE, eventually forms a proxy for firm value or its stock price.

This framework highlights the various links that researchers in the area of CLV have attempted to model. Broadly speaking, they fall into the following categories. The first category of models consists of those that attempt to find the impact of marketing programs on customer acquisition, retention and/or expansion (or cross-selling) (Kumar, Venkatesan, and Reinartz 2006). For example, several researchers have examined customer churn and the factors that influence churn (Lemmens and Croux in press; Neslin et al. in press). The second category of models examines the relationship between various components of CLV. For example, Thomas (2001) showed the link between customer acquisition and retention. Both these groups of models generally provide a link to CLV or CE. Some focus more on identifying the relative importance of the various components. For example, Reichheld (1996) suggested that retention is the most critical component that influences CLV. In contrast, Reinartz and Kumar (2000) showed that customers with longer duration may not be necessarily the most profitable. The final group of models link CLV or CE to firm value. Whereas Gupta, Lehmann, and Stuart (2004) used data from five companies to show that CLV may provide a good proxy for firm value, Kumar (2006c) showed that CLV is highly correlated with firm value using a longitudinal analysis of a firm's data.

We should also note what we are not covering in this framework and article. Many studies have shown a direct link between marketing programs and firm value. For example, Joshi and Hanssens (2005) showed that advertising not only affects sales but influences stock price over and beyond its impact through sales. Given our focus on CLV, we exclude these studies from this article. We also omit studies that use attitudinal measures (e.g., customer satisfaction) and attempt to find their impact on stock price (e.g., Fornell et al. 2006). Finally, there are several studies that examine the link between attitudinal measures (e.g., satisfaction) and CLV or its components. For example, Kumar and Luo (2006) showed how an individual's brand value affects his or her CLV. Bolton (1998) found that satisfaction is positively related to duration of relationship. We exclude these studies for three reasons. First, many of these studies use purchase *intent* (e.g., intention to repurchase) rather than actual behavior (e.g., Anderson and Sullivan 1993; Rust, Zahorik, and Keiningham 1995). Using a survey to measure both satisfaction and purchase intent creates strong method bias. In an interesting study, Mazursky and Geva (1989) found that whereas satisfaction and intentions were highly correlated when measured in the same survey, they had no correlations when intentions were measured 2 weeks after measuring satisfaction of the same subjects. Second, although the CLV models that are built using transaction data can be applied to the entire customer base, attitudinal measures can usually be obtained for only a sample of customers. Third, given the vast literature in this area, it is impossible for any single article to cover all themes.

MODELING APPROACHES

In this section we discuss six modeling approaches typically used by researchers to examine one or more of the links indicated in Figure 1. Although the key substantive questions are generally the same (e.g., which customers are more valuable, how to allocate resources, etc.) and in some cases the underlying methodology may also be similar (e.g., hazard models of customer retention and negative binomial distribution [NBD]/Pareto models), these approaches highlight the differences in perspectives of different researchers. Before discussing the specific approaches, we briefly lay out the basics of CLV.

Fundamentals of CLV Modeling

CLV is generally defined as the present value of all future profits obtained from a customer over his or her life of relationship with a firm.[2] CLV is similar to the discounted cash flow approach used in finance. However, there are two key differences. First, CLV is typically defined and estimated at an individual customer or segment level. This allows us to differentiate between customers who are more profitable than others rather than simply examining average profitability. Second, unlike finance, CLV explicitly incorporates the possibility that a customer may defect to competitors in the future.

CLV for a customer (omitting customer subscript) is (Gupta, Lehmann, and Stuart 2004; Reinartz and Kumar 2003)[3]

$$CLV = \sum_{t=0}^{T} \frac{(p_t - c_t)r_t}{(1+i)^t} - AC \tag{1}$$

where

p_t = price paid by a consumer at time t,
c_t = direct cost of servicing the customer at time t,
i = discount rate or cost of capital for the firm,
r_t = probability of customer repeat buying or being "alive" at time t,
AC = acquisition cost, and
T = time horizon for estimating CLV.

In spite of this simple formulation, researchers have used different variations in modeling and estimating CLV. Some researchers have used an arbitrary time horizon or *expected* customer lifetime (Reinartz and Kumar 2000; Thomas 2001),[4] whereas others have used an infinite time horizon (e.g., Fader, Hardie, and Lee 2005; Gupta, Lehmann, and Stuart 2004). Gupta and Lehmann (2005) showed that using an expected customer lifetime generally overestimates CLV, sometimes quite substantially.

Gupta and Lehmann (2003, 2005) also showed that if margins ($p - c$) and retention rates are constant over time and we use an infinite time horizon, then CLV simplifies to the following expression:[5]

$$CLV = \sum_{t=0}^{\infty} \frac{(p-c)r^t}{(1+i)^t} = m\frac{r}{(1+i-r)}. \tag{2}$$

In other words, CLV simply becomes margin (m) times a *margin multiple* ($r/1 + i - r$). When retention rate is 90% and discount rate is 12%, the margin multiple is about four.[6] Gupta and Lehmann (2005) showed that when margins grow at a constant rate "g," the margin multiple becomes $r/[1 + i - r(1 + g)]$.

It is also important to point out that most modeling approaches ignore competition because of the lack of competitive data. Finally, how frequently we update CLV depends on the dynamics of a particular market. For example, in markets where margins and retention may change dramatically over a short period of time (e.g., due to competitive activity), it may be appropriate to reestimate CLV more frequently.

Researchers either build separate models for customer acquisition, retention, and margin or sometimes combine two of these components. For example, Thomas (2001) and Reinartz, Thomas, and Kumar (2005) simultaneously captured customer acquisition and retention. Fader, Hardie, and Lee (2005) captured recency and frequency in one model and built a separate model for monetary value. However, the approaches for modeling these components or CLV differ across researchers. We now describe the various modeling approaches in detail.

1. RFM Models

RFM models have been used in direct marketing for more than 30 years. Given the low response rates in this industry (typically 2% or less), these models were developed to target marketing programs (e.g., direct mail) at specific customers with the objective to improve response rates. Prior to these models, companies typically used demographic profiles of customers for targeting purposes. However, research strongly suggests that past purchases of consumers are better predictors of their future purchase behavior than demographics.

RFM models create "cells" or groups of customers based on three variables—*R*ecency, *F*requency, and *M*onetary value of their prior purchases. The simplest models classify customers into five groups based on each of these three variables. This gives $5 \times 5 \times 5$ or 125 cells. Studies show that customers' response rates vary the most by their recency, followed by their purchase frequency and monetary value (Hughes 2005). It is also common to use weights for these cells to create "scores" for each group. Mailing or other marketing communication programs are then prioritized based on the scores of different RFM groups.

Whereas RFM or other scoring models attempt to predict customers' behavior in the future and are therefore implicitly linked to CLV, they have several limitations (Fader, Hardie, and Lee 2005; Kumar 2006a). First, these models predict behavior in the next period only. However, to estimate CLV, we need to estimate customers' purchase behavior not only in Period 2 but also in Periods 3, 4, 5, and so on. Second, RFM variables are imperfect indicators of true underlying behavior, that is, they are drawn from a true distribution. This aspect is completely ignored in RFM models. Third, these models ignore the fact that consumers' past behavior may be a result of firm's past marketing activities. Despite these limitations, RFM models remain a mainstay of the industry because of their ease of implementation in practice.

How Well Do RFM Models Do?

Several recent studies have compared CLV models (discussed later) with RFM models and found CLV models to be superior. Reinartz and Kumar (2003) used a catalog retailer's data of almost 12,000 customers over 3 years to compare CLV and RFM models. They found that the revenue from the top 30% of customers based on the CLV model was 33% higher than the top 30% selected based on the RFM model. Venkatesan and Kumar (2004) also compared several competing models for customer selection. Using data on almost 2,000 customers from a business-to-business (B2B) manufacturer, they found that the profit generated from the top 5% customers as selected by the CLV model was 10% to 50% higher than the profit generated from the top 5% customers from other models (e.g., RFM, past value, etc.).

Incorporating RFM in CLV Models

One key limitation of RFM models is that they are scoring models and do not explicitly provide a dollar number for customer value. However, RFM are important past purchase variables that should be good predictors of future purchase behavior of customers. Fader, Hardie, and Lee (2005) showed how RFM variables can be used to build a CLV model that overcomes many of its limitations. They also showed that RFM are sufficient statistics for their CLV model. One interesting result of their approach is the iso-CLV curves, which show different values of R, F, or M that produce the same CLV of a customer.

2. Probability Models

A probability model is a representation of the world in which observed behavior is viewed as the realization of an underlying stochastic process governed by latent (unobserved) behavioral characteristics, which in turn vary across individuals. The focus of the model-building effort is on telling a simple paramorphic story that describes (and predicts) the observed behavior instead of trying to explain differences in observed behavior as a function of covariates (as is the case with any regression model). The modeler is typically quite happy to assume that consumers' behavior varies across the population according to some probability distribution.

For the purposes of computing CLV, we wish to be able to make predictions about whether an individual will still be an active customer in the future and, if so, what his or her purchasing behavior will be. One of the first models to explicitly address these issues is the Pareto/NBD model developed by Schmittlein, Morrison, and Colombo (1987), which describes the flow of transactions in noncontractual setting. Underlying this model is the following set of assumptions:

- A customer's relationship with the firm has two phases: He or she is "alive" for an unobserved period of time, and then becomes permanently inactive.
- While "alive," the number of transactions made by a customer can be characterized by a Poisson process.
- Heterogeneity in the transaction rate across customers follows a gamma distribution.
- Each customer's unobserved "lifetime" is distributed exponential.
- Heterogeneity in dropout rates across customers follows a gamma distribution.
- The transaction rates and the dropout rates vary independently across customers.

The second and third assumptions result in the NBD, whereas the next two assumptions yield the Pareto (of the second kind) distribution. This model requires only two pieces of information about each customer's past purchasing history: his or her "recency" (when his or her last transaction occurred) and "frequency" (how many transactions he or she made in a specified time period). The notation used to represent this information is (x, t_x, T), where x is the number of transactions observed in the time period $(0, T]$ and $t_x (0 < t_x \leq T)$ is the time of the last transaction. Using these two key summary statistics, Schmittlein, Morrison, and Colombo (1987) derived expressions for a number of managerially relevant quantities, including (a) $P(\text{alive} \mid x, t_x, T)$, the probability that an individual with observed behavior (x, t_x, T) is still an active customer at time T, and (b) $E[Y(t) \mid x, t_x, T]$, the expected number of transactions in the period $(T, T + t]$ for an individual with observed behavior (x, t_x, T).

This basic model has been used by Reinartz and Kumar (2000, 2003) as an input into their lifetime value calculations. However, rather than simply using it as an input to a CLV calculation, it is possible to derive an *expression* for CLV directly from this model. As an intermediate step, it is necessary to augment this model for the flow of transactions with a model for the value of each transaction. Schmittlein and Peterson (1994), Colombo and Jiang (1999), and Fader, Hardie, and Berger (2004) have all proposed models based on the following story for the spend process:

- The dollar value of a customer's given transaction varies randomly around his mean transaction value.
- Mean transaction values vary across customers but do not vary over time for any given individual.

Fader, Hardie, and Berger (2004) are able to derive the following explicit formula for the expected lifetime revenue stream associated with a customer (in a noncontractual setting) with "recency" t_x, "frequency" x (in a time period of length T), and an average transaction value of m_x, with continuous compounding at rate of interest δ:

$$\begin{aligned} CLV(\delta|r, \alpha, s, \beta, p, q, \gamma, x, t_x, T) \\ = \frac{\alpha^r \beta^s \delta^{s-1} \Gamma(r + x\_1) \Psi(s, s; \delta(\beta + T))}{\Gamma(r)(\alpha + T)^{r+x+1} L(r, \alpha, s, \beta|x, t_x, T)} \\ \times \frac{(\gamma + m_x x) p}{px + q - 1} \end{aligned} \quad (3)$$

where (r, α, s, β) are the Pareto/NBD parameters, (p, q, γ) are the parameters of the transaction value model, $\psi(\cdot)$ is the confluent hypergeometric function of the second kind, and $L(\cdot)$ is the Pareto/NBD likelihood function.

The Pareto/NBD model is a good benchmark model when considering noncontractual settings where transaction can occur at any point in time. It is not an appropriate model for any contractual business settings. Nor is it an appropriate model for noncontractual settings where transactions can only occur at fixed (discrete) points in time, such as attendance at annual academic conferences, arts festivals, and so on, as in such settings, the assumption of Poisson purchasing is not relevant. Thus, models such as Fader, Hardie, and Berger's (2004) beta-binominal/beta-geometric (BG/BB) model or Morrison et al.'s (1982) brand loyal with exit model would be appropriate alternatives.

Several researchers have also created models of buyer behavior using Markov chains. Although these models, which we discuss in the next section, are probability models (in that they are based on basic stochastic modeling tools), they differ from the models discussed here in that they are not based on hierarchical model structure (i.e., there is no modeling of heterogeneity in individual customer characteristics).

3. Econometric Models

Many econometric models share the underlying philosophy of the probability models. Specifically, studies that use hazard models to estimate customer retention are similar to the NBD/Pareto models except for the fact that the former may use more general hazard functions and typically incorporate covariates. Generally these studies model customer acquisition, retention, and expansion (cross-selling or margin) and then combine them to estimate CLV.

Customer Acquisition

Customer acquisition refers to the first-time purchase by new or lapsed customers. Research in this area focuses on the factors that influence buying decisions of these new customers. It also attempts to link acquisition with customers' retention behavior as well as CLV and CE. The basic model for customer acquisition is a logit or a probit (Gensch 1984; Thomas 2001; Thomas, Blattberg, and Fox 2004). Specifically, customer j at time t (i.e., $Z_{jt} = 1$) is modeled as follows:

$$\begin{aligned} Z^*_{jt} &= \alpha_j X_{jt} + \varepsilon_{jt} \\ Z_{jt} &= 1 \text{ if } Z^*_{jt} > 0 \\ Z_{jt} &= 0 \text{ if } Z^*_{jt} \leq 0, \end{aligned} \tag{4}$$

where X_{jt} are the covariates and α_j are consumer-specific response parameters. Depending on the assumption of the error term, one can obtain a logit or a probit model (Lewis 2005b; Thomas 2001).

Although intuition and some case studies suggest that acquisition and retention should be linked (Reichheld 1996), early work in this area assumed these two outcomes to be independent (Blattberg and Deighton 1996). Later, Hansotia and Wang (1997) indirectly linked acquisition and retention by using a logit model for acquisition and a right-censored Tobit model for CLV. More recently, several authors have explicitly linked acquisition and retention (Thomas 2001; Thomas, Blattberg, and Fox 2004).

Using data for airline pilots' membership, Thomas (2001) showed the importance of linking acquisition and retention decisions. She found that ignoring this link can lead to CLV estimates that are 6% to 52% different from her model. Thomas, Blattberg, and Fox (2004) found that whereas low price increased the probability of acquisition, it reduced the relationship duration. Therefore, customers who may be inclined to restart a relationship may not be the best customers in terms of retention. Thomas, Reinartz, and Kumar (2004) empirically validated this across two industries. They also found that customers should be acquired based on their profitability rather than on the basis of the cost to acquire and retain them.

Lewis (2003) showed how promotions that enhance customer acquisition may be detrimental in the long run. He found that if new customers for a newspaper subscription were offered regular price, their renewal probability was 70%. However, this dropped to 35% for customers who were acquired through a $1 weekly discount. Similar effects were found in the context of Internet grocery where renewal probabilities declined from 40% for regular-priced acquisitions to 25% for customers acquired through a $10 discount. On average, a 35% acquisition discount resulted in customers with about half the CLV of regularly acquired customers. In other words, unless these acquisition discounts double the baseline acquisition rate of customers, they would be detrimental to the CE of a firm. These results are consistent with the long-term promotion effects found in the scanner data (Jedidi, Mela, and Gupta 1999).

In contrast, Anderson and Simester (2004) conducted three field studies and found that deep price discounts have a positive impact on the long-run profitability of first-time buyers but negative long-term impact on established customers. The dynamics of pricing was also examined by Lewis (2005a) using a dynamic programming approach. He found that for new customers, price sensitivity increases with time lapsed, whereas for current customers, it decreases with time. Therefore, the optimal pricing involves offering a series of diminishing discounts (e.g., $1.70 per week for new newspaper subscribers, $2.20 at first renewal, $2.60 at second renewal, and full price of $2.80 later) rather than a single deep discount.

Customer Retention

Customer retention is the probability of a customer being "alive" or repeat buying from a firm. In contractual settings (e.g., cellular phones, magazine subscriptions), customers inform the firm when they terminate their relationship. However, in noncontractual settings (e.g., buying books from Amazon), a firm has to infer whether a customer is still active. For example, as of October 2005, eBay reported 168 million registered customers but only 68 million active customers. Most companies define a customer as active based on simple rules of thumb. For example, eBay defines a customer to be active if she or he has bid, bought, or listed on its site during the past 12 months. In contrast, researchers rely on statistical models to assess the probability of retention.

There are two broad classes of retention models. The first class considers customer defection as permanent or "lost for good" and typically uses hazard models to predict probability of customer defection. The second class considers customer switching to competitors as transient or "always a share" and typically uses migration or Markov models. We briefly discuss each class of models.

Hazard models fall into two broad groups—accelerated failure time (AFT) or proportional hazard (PH) models. The AFT models have the following form (Kalbfleisch and Prentice 1980):

$$\ln(t_j) = \beta_j X_j + \sigma \mu_j, \tag{5}$$

where t is the purchase duration for customer j and X are the covariates. If $\sigma = 1$ and μ has an extreme value distribution, then we get an exponential duration model with constant hazard rate. Different specifications of σ and μ lead to different models such as Weibull or generalized gamma. Allenby, Leone, and Jen (1999), Lewis (2003), and Venkatesan and Kumar (2004) used a generalized gamma for modeling relationship duration. For the kth interpurchase time for customer j, this model can be represented as follows:

$$f(t_{jk}) = \frac{\gamma}{\Gamma(\alpha)\lambda_j^{\alpha\gamma}} t_{jk}^{\alpha\gamma-1} e^{-(t_{jj}/\lambda_j)^{\gamma}} \tag{6}$$

where α and γ are the shape parameters of the distribution and λ_j is the scale parameter for customer j. Customer heterogeneity is incorporated by allowing λ_j to vary across consumers according to an inverse generalized gamma distribution.

Proportional hazard models are another group of commonly used duration models. These models specify the hazard rate (λ) as a function of baseline hazard rate (λ_0) and covariates (X),

$$\lambda(t; X) = \lambda_0(t)\exp(\beta X). \tag{7}$$

Different specifications for the baseline hazard rate provide different duration models such as exponential, Weibull, or Gompertz. This approach was used by Bolton (1998), Gonul, Kim, and Shi (2000), Knott, Hayes, and Neslin (2002), and Levinthal and Fichman (1988).

Instead of modeling time duration, we can model customer retention or churn as a binary outcome (e.g., the probability of a wireless customer defecting in the next month). This is a form of discrete-time hazard model. Typically the model takes the form of a logit or probit. Due to its simplicity and ease of estimation, this approach is commonly used in the industry. Neslin et al. (in press) described these models which were submitted by academics and practitioners as part of a "churn tournament."

In the second class of models, customers are allowed to switch among competitors and this is generally modeled using a Markov model. These models estimate transition probabilities of a customer being in a certain state. Using these transition probabilities, CLV can be estimated as follows (Pfeifer and Carraway 2000):

$$\mathbf{V}' = \sum_{t=0}^{T} [(1+i)^{-1}\mathbf{P}]^t \mathbf{R} \tag{8}$$

where $\mathbf{V}'$ is the vector of expected present value or CLV over the various transition states; $\mathbf{P}$ is the transition probability matrix, which is assumed to be constant over time; and $\mathbf{R}$ is the reward or margin vector, which is also assumed to be constant over time. Bitran and Mondschein (1996) defined transition states based on RFM measures. Pfeifer and Carraway (2000) defined them based on customers' recency of purchases as well as an additional state for new or former customers. Rust, Lemon, and Zeithaml (2004) defined $\mathbf{P}$ as brand switching probabilities that vary over time as per a logit model. Furthermore, they broke $\mathbf{R}$ into two components—customer's expected purchase volume of a brand and his or her probability of buying a brand at time t.

Rust et al. (2004) argued that the "lost for good" approach understates CLV because it does not allow a defected customer to return. Others have argued that this is not a serious problem because customers can be treated as renewable resource (Dréze and Bonfrer 2005) and lapsed customers can be reacquired (Thomas, Blattberg, and Fox 2004). It is possible that the choice of the modeling approach depends on the context. For example, in many industries (e.g., cellular phone, cable, and banks), customers are usually monogamous and maintain their relationship with only one company. In other contexts (e.g., consumer goods, airlines, and business-to-business relationship), consumers simultaneously conduct business with multiple companies, and the "always a share" approach may be more suitable.

The interest in customer retention and customer loyalty increased significantly with the work of Reichheld and Sasser (1990), who found that a 5% increase in customer retention could increase firm profitability from 25% to 85%. Reichheld (1996) also emphasized the importance of customer retention. However, Reinartz and Kumar (2000) argued against this result and suggested that "it is the revenue that drives the lifetime value of a customer and not the duration of a customer's tenure" (p. 32). Reinartz and Kumar (2002) further contradicted Reichheld based on their research findings of weak to moderate correlation (.2 to .45) between customer tenure and profitability across four data sets. However, a low correlation can occur if the relationship between loyalty and profitability is nonlinear (Bowman and Narayandas 2004).

What drives customer retention? In the context of cellular phones, Bolton (1998) found that customers' satisfaction with the firm had a significant and positive impact on duration of relationship. She further found that customers who have many months of experience with the firm weigh prior cumulative satisfaction more heavily and new information relatively less heavily. After examining a large set of published studies, Gupta and Zeithaml (2006) concluded that there is a strong correlation between customer satisfaction and customer retention.

In their study of the luxury car market, Yoo and Hanssens (2005) found that discounting increased acquisition rate for the Japanese cars but increased retention rate for the American brands. They also found product quality and customer satisfaction to be highly related with acquisition and retention effectiveness of various brands. Based on these results, they concluded that if customers are satisfied with a high-quality product, their repeat purchase is less likely to be affected by that brand's discounting. They also found that advertising did not have any direct significant impact on retention rates in the short term.

Venkatesan and Kumar (2004) found that frequency of customer contacts had a positive but nonlinear impact on customers' purchase frequency. Reinartz, Thomas, and Kumar (2005) found that face-to-face interactions had a greater impact on duration, followed by telephones and e-mails. Reinartz and Kumar (2003) found that duration was positively affected by customers' spending level, cross-buying, number of contacts by the firm, and ownership of firm's loyalty instrument.

Customer Margin and Expansion

The third component of CLV is the margin generated by a customer in each time period t. This margin depends on a customer's past purchase behavior as well as a firm's efforts in cross-selling and up-selling products to the customer. There are two broad approaches used in the literature to capture margin. One set of studies model margin directly while the other set of studies explicitly model cross-selling. We briefly discuss both approaches.

Several authors have made the assumption that margins for a customer remain constant over the future time horizon. Reinartz and Kumar (2003) used average contribution margin of a customer based on his or her prior purchase behavior to project CLV. Gupta, Lehmann, and Stuart (2004) also used constant margin based on history. Gupta and Lehmann (2005) showed that in many industries this may be a reasonable assumption.

Venkatesan and Kumar (2004) used a simple regression model to capture changes in contribution margin over time. Specifically, they suggested that change in contribution margin for customer j at time t is

$$\Delta CM_{jt} = \beta X_{jt} + e_{jt}. \tag{9}$$

Covariates for their B2B application included lagged contribution margin, lagged quantity purchased, lagged firm size, lagged marketing efforts, and industry category. This simple model had an R^2 of .68 with several significant variables.

Thomas, Blattberg, and Fox (2004) modeled the probability of reacquiring a lapsed newspaper customer. One of the key covariates in their model was price, which had a significant impact on customers' reacquisition probability as well as their relationship duration. Price also has a direct impact on the contribution margin of a customer. This allowed Thomas, Blattberg, and Fox to estimate the expected CLV for a customer at various price points.

The second group of studies has explicitly modeled cross-selling, which in turn improves customer margin over time. With the rising cost of customer acquisition, firms are increasingly interested in cross-selling more products and services to their existing customers. This requires a better understanding of which products to cross-sell, to whom, and at what time.

In many product categories, such as books, music, entertainment, and sports, it is common for firms to use recommendation systems. A good example of this is the recommendation system used by Amazon. Earlier recommendation systems were built on the concept of collaborative filtering. Recently, some researchers have used Bayesian approach for creating more powerful recommendation systems (Ansari, Essegaier, and Kohli 2000).

In some other product categories, such as financial services, customers acquire products in a natural sequence. For example, a customer may start her or his relationship with a bank with a checking and/or savings account and over time buy more complex products such as mortgage and brokerage service. Kamakura, Ramaswami, and Srivastava (1991) argued that customers are likely to buy products when they reach a "financial maturity" commensurate with the complexity of the product. Recently, Li, Sun, and Wilcox (2005) used a similar conceptualization for cross-selling sequentially ordered financial products. Specifically, they used a multivariate probit model where consumer i makes binary purchase decision (buy or not buy) on each of the j products. The utility for consumer i for product j at time t is given as

$$U_{ijt} + \beta_i \mid O_j - DM_{it-1} \mid + \gamma_{ij} X_{it} + \varepsilon_{ijt}, \tag{10}$$

where O_j is the position of product j on the same continuum as demand maturity DM_{it-1} of consumer i. X includes other covariates that may influence consumers' utility to buy a product. They further model demand or latent financial maturity as a function of cumulative ownership, monthly balances, and the holding time of all available J accounts (covariates Z), weighted by the importance of each product (parameters λ):

$$DM_{it-1} = \sum_{j=1}^{J} [O_j D_{ijt-1} (\lambda_k Z_{ijk-1})]. \tag{11}$$

Verhoef, Franses, and Hoekstra (2001) used an ordered probit to model consumers' cross-buying. Knott, Hayes, and Neslin (2002) used logit, discriminant analysis, and neural networks models to predict the next product to buy and found that all models performed roughly the same and significantly better (predictive accuracy of 40% to 45%)

than random guessing (accuracy of 11% to 15%). In a field test, they further established that their model had a return on investment (ROI) of 530% compared to the negative ROI from the heuristic used by the bank that provided the data. Knott, Hayes, and Neslin complemented their logit model, which addresses what product a customer is likely to buy next, with a hazard model, which addresses the question of when customers are likely to buy this product. They found that adding the hazard model improves profits by 25%. Finally, Kumar, Venkatesan, and Reinartz (2006) showed that cross-selling efforts produced a significant increase in profits per customer when using a model that accounts for dependence in choice and timing of purchases.

4. Persistence Models

Like econometric models of CLV, persistence models focus on modeling the behavior of its components, that is, acquisition, retention, and cross-selling. When sufficiently long-time series are available, it is possible to treat these components as part of a *dynamic system*. Advances in multivariate time-series analysis, in particular vector-autoregressive (VAR) models, unit roots, and cointegration, may then be used to study how a movement in one variable (say, an acquisition campaign or a customer service improvement) impacts other system variables over time. To date, this approach, known as persistence modeling, has been used in a CLV context to study the impact of advertising, discounting, and product quality on customer equity (Yoo and Hanssens 2005) and to examine differences in CLV resulting from different customer acquisition methods (Villanueva, Yoo, and Hanssens 2006).

The major contribution of persistence modeling is that it projects the long-run or equilibrium behavior of a variable or a group of variables of interest. In the present context, we may model several known marketing influence mechanisms jointly; that is, each variable is treated as potentially endogenous. For example, a firm's acquisition campaign may be successful and bring in new customers (consumer response). That success may prompt the firm to invest in additional campaigns (performance feedback) and possibly finance these campaigns by diverting funds from other parts of its marketing mix (decision rules). At the same time, the firm's competitors, fearful of a decline in market share, may counter with their own acquisition campaigns (competitive reaction). Depending on the relative strength of these influence mechanisms, a *long-run* outcome will emerge that may or may not be favorable to the initiating firm. Similar dynamic systems may be developed to study, for example, the long-run impact of improved customer retention on customer acquisition levels, and many other dynamic relationships among the components of customer equity.

The technical details of persistence modeling are beyond the scope of this article and may be found, for example, in Dekimpe and Hanssens (2004). Broadly speaking, persistence modeling consists of three separate steps:

1. Examine the evolution of each system's variable over time. This step distinguishes between temporary and permanent movements in that variable. For example, are the firm's retention rates stable over time, are they improving or deteriorating? Similarly, is advertising spending stable, growing, or decreasing? Formally, this step involves a series of *unit-root tests* and results in a VAR model specification in levels (temporary movements only) or changes (permanent or persistent movements). If there is evidence in favor of a long-run equilibrium between evolving variables *(cointegration test)*, then the resulting system's model will be of the vector-error correction type, which combined movements in levels and changes.
2. Estimate the VAR model, typically with least-squares methods. As an illustration, consider the customer-acquisition model in Villanueva, Yoo, and Hanssens (2006):

$$\begin{pmatrix} AM_t \\ AW_t \\ V_t \end{pmatrix} = \begin{pmatrix} a_{10} \\ a_{20} \\ a_{30} \end{pmatrix} + \sum_{l=1}^{p} \begin{pmatrix} a_{11}^l & a_{12}^l & a_{13}^l \\ a_{21}^l & a_{22}^l & a_{23}^l \\ a_{31}^l & a_{32}^l & a_{33}^l \end{pmatrix} \begin{pmatrix} AM_{t-l} \\ AW_{t-l} \\ V_{t-l} \end{pmatrix} + \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} \tag{11}$$

   where *AM* stands for the number of customers acquired through the firm's marketing actions, *AW* stands for the number of customers acquired from word of mouth, and *V* is the firm's performance. The subscript t stands for time, and p is the lag order of the model. In this VAR model, $(e_{1t}, e_{2t}, e_{3t})'$ are white-noise disturbances distributed as $N(0, \Sigma)$. The direct effects of acquisition on firm performance are captured by a_{31}, a_{32}. The cross effects among acquisition methods are estimated by a_{12}, a_{21}; performance feedback effects by a_{13}, a_{23}; and finally, reinforcement effects by a_{11}, a_{22}, a_{33}. Note that, as with all VAR models, instantaneous effects are reflected in the variance-covariance matrix of the residuals (Σ).
3. Derive the impulse response functions. The parameter estimates of VAR models are rarely interpreted directly. Instead, they are used in obtaining estimates of short- and long-run impact of a single shock in one of the variables on the system. These "impulse response" estimates and their standard errors are often displayed visually, so that one can infer the anticipated short-term and long-run impact of the shock. In the illustration

> above, Villanueva, Yoo, and Hanssens (2006) found that marketing-induced customer acquisitions are more profitable in the short run, whereas word-of-mouth acquisitions generate performance more slowly but eventually become twice as valuable to the firm.

In conclusion, as customer lifetime value is de facto a long-term performance metric, persistence models are well suited in this context. In particular, they can quantify the *relative importance* of the various influence mechanisms in long-term customer equity development, including customer selection, method of acquisition, word of mouth generation, and competitive reaction. With only two known applications, this approach to CLV modeling is early in its development, in part because the demands on the data are high, for example, long time series equal-interval observations. It would be useful to explore models such as fractionally differenced time series models (Beran 1994) or Markov switching modes (Hamilton 1994) and extensions to duration dependent Markov switching models in CLV analysis.

5. Computer Science Models

The marketing literature has typically favored structured parametric models, such as logit, probit, or hazard models. These models are based on theory (e.g., utility theory) and are easy to interpret. In contrast, the vast computer science literature in data mining, machine learning, and nonparametric statistics has generated many approaches that emphasize predictive ability. These include projection-pursuit models; neural network models; decision tree models; spline-based models such as generalized additive models (GAM), multivariate adaptive regression splines (MARS), classification and regression trees (CART); and support vector machines (SVM).

Many of these approaches may be more suitable to the study of customer churn where we typically have a very large number of variables, which is commonly referred to as the "curse of dimensionality." The sparseness of data in these situations inflates the variance of the estimates, making traditional parametric and nonparametric models less useful. To overcome these difficulties, Hastie and Tibshirani (1990) proposed generalized additive models where the mean of the dependent variable depends on an additive predictor through a nonlinear, nonparametric link function. Another approach to overcome the curse of dimensionality is MARS. This is a nonparametric regression procedure that operates as multiple piecewise linear regression with breakpoints that are estimated from data (Friedman 1991).

More recently, we have seen the use of SVM for classification purposes. Instead of assuming that a linear function or plane can separate the two (or more) classes, this approach can handle situations where a curvilinear function or hyperplane is needed for better classification. Effectively the method transforms the raw data into a "featured space" using a mathematical kernel such that this space can classify objects using linear planes (Friedman 2003; Kecman 2001; Vapnik 1998). In a recent study, Cui and Curry (2005) conducted extensive Monte Carlo simulations to compare predictions based on multinomial logit model and SVM. In all cases, SVM outpredicted the logit model. In their simulation, the overall mean prediction rate of the logit was 72.7%, whereas the hit rate for SVM was 85.9%. Similarly, Giuffrida, Chu, and Hanssens (2000) reported that a multivariate decision tree induction algorithm outperformed a logit model in identifying the best customer targets for cross-selling purposes.

Predictions can also be improved by combining models. The machine learning literature on bagging, the econometric literature on the combination of forecasts, and the statistical literature on model averaging suggest that weighting the predictions from many different models can yield improvements in predictive ability. Neslin et al. (in press) described the approaches submitted by various academics and practitioners for a "churn tournament." The winning entry used the power of combining several trees, each tree typically no larger than two to eight terminal nodes, to improve prediction of customer churn through a gradient tree boosting procedure (Friedman 1991).

Recently, Lemmens and Croux (in press) used bagging and boosting techniques to predict churn for a U.S. wireless customer database. Bagging (*B*ootstrap *AGG*regat*ING*) consists of sequentially estimating a binary choice model, called base classifier in machine learning, from resampled versions of a calibration sample. The obtained classifiers form a group from which a final choice model is derived by aggregation (Breiman 1996). In boosting, the sampling scheme is different from bagging. Boosting essentially consists of sequentially estimating a classifier to adaptively reweighted versions of the initial calibration sample. The weighting scheme gives misclassified customers an increased weight in the next iteration. This forces the classification method to concentrate on hard-to-classify customers. Lemmens and Croux compared the results from these methods with the binary logit model and found the relative gain in prediction of more than 16% for the gini coefficient and 26% for the top-decile lift. Using reasonable assumptions, they showed that these differences can be worth more than $3 million to the company. This is consistent with the results of Neslin et al. (in press), who also found that the prediction methods matter and can change profit by hundreds of thousands of dollars.

These approaches remain little known in the marketing literature, not surprisingly because of the tremendous emphasis that marketing academics place on a parametric setup and interpretability. However, given the importance of prediction in CLV, these approaches need a closer look in the future.

6. Diffusion/Growth Models

CLV is the long-run profitability of an individual customer. This is useful for customer selection, campaign management, customer segmentation, and customer targeting (Kumar 2006b). Whereas these are critical from an operational perspective, CLV should be aggregated to arrive at a strategic metric that can be useful for senior managers. With this in mind, several researchers have suggested that we focus on CE, which is defined as the CLV of current and future customers (Blattberg, Getz, and Thomas 2001; Gupta and Lehmann 2005; Rust, Lemon, and Zeithaml 2004).

Forecasting the acquisition of future customers is typically achieved in two ways. The first approach uses a disaggregate customer data and builds models that predict the probability of acquiring a particular customer. Examples of this approach include Thomas (2001) and Thomas, Blattberg, and Fox (2004). These models were discussed earlier.

An alternative approach is to use aggregate data and use diffusion or growth models to predict the number of customers a firm is likely to acquire in the future. Kim, Mahajan, and Srivastava (1995); Gupta, Lehmann, and Stuart (2004); and Libai, Muller, and Peres (2006) followed this approach. For example, Gupta, Lehmann, and Stuart suggested the following model for forecasting the number of new customers at time t:

$$n_t = \frac{\alpha\gamma \exp(-\beta - \gamma t)}{[1 + \exp(-\beta - \gamma t)]^2} \tag{13}$$

where α, β, and γ are the parameters of the customer growth curve. It is also possible to include marketing mix covariates in this model as suggested in the diffusion literature. Using this forecast of new customers, they estimated the CE of a firm as

$$CE = \int_{k=0}^{\infty} \int_{t=k}^{\infty} n_k m_{t-k} e^{-ik} e^{-\left(\frac{1+i-r}{r}\right)(t-k)} dt\, dk - \int_{k=0}^{\infty} n_k c_k e^{-ik} dk \tag{14}$$

where n_k is the number of newly acquired customers for cohort k, m is the margin, r is the retention rate, i is the discount rate, and c is the acquisition cost per customer. Rust et al. (2004) used a simpler approach where they estimated CLV for an average American Airlines customer and then multiplied it by the number of U.S. airline passengers to arrive at its CE.

Using data for five companies, Gupta, Lehmann, and Stuart (2004) showed that CE approximates firm market value quite well for three of the five companies (exceptions were Amazon and eBay). In addition, they assessed the relative importance of marketing and financial instruments by showing that 1% change in retention affected CE by almost 5%, compared to only a 0.9% impact by a similar change in discount rate. Rust et al. (2004) estimated CE for American Airlines as \$7.3 billion, which compared favorably with its 1999 market capitalization of \$9.7 billion. They also found that if American Airlines could increase its quality by 0.2 rating points on a 5-point scale, it would increase its customer equity by 1.39%. Similarly, a \$45 million expenditure by Puffs facial tissues to increase its ad awareness by 0.3 ratings points would result in an improvement of \$58.1 million in CE.

Hogan, Lemon, and Libai (2003) also used a diffusion model to assess the value of a lost customer. They argued that when a firm loses a customer it not only loses the profitability linked directly to that customer (his or her CLV) but also the word-of-mouth effect that could have been generated through him or her. Using their approach, they estimated that in the online banking industry the direct effect of losing a customer is about \$208, whereas the indirect effect can be more than \$850.

FUTURE RESEARCH

Based on the state of our modeling tools as reflected in the current academic literature and the needs of the "leading edge" industry practitioners, we have identified the following set of issues that represent opportunities for future research.

1. Moving Beyond the Limits of Transaction Data

As noted in the introduction, one of the drivers of the growing interest in the CLV concept has been the increased amount of customer transaction data that firms are now able to collect. A number of elaborate models have been developed that are both able to extract insights and develop predictions of future behavior using these data.

We must, however, recognize the inherent limitations of transaction databases. In the context of cross-selling, transaction data provide information on the basket of products that customers buy over time. However, we do not know the underlying motives/requirements that may have led to these purchases across categories. To obtain richer insights to facilitate cross-selling, it may be worthwhile to collect information through surveys to understand the needs/requirements of these customers that led to these purchases. A second limitation of transaction data is that although they provide very detailed information about what customers do with the company, they provide virtually no information on what these customers do with the competitors. In other words, there is no information on share of wallet.

One possible option is to augment transaction data with surveys that can provide both attitudinal as well as competitive information. However, these survey data can be collected only for a sample of customers. How do we integrate the survey data from a sample of customers with transaction data from all the customers of a company? A natural starting point is the work of data fusion and list augmentation. Although we have seen some preliminary applications in marketing (e.g., Kamakura et al. 2003; Kamakura and Wedel 2003), this area of research is still in its infancy and we have a lot to learn about the processes and benefits of augmenting transaction data with other customer data.

2. Moving From a Customer to a Portfolio of Customers

Locally optimal decisions regarding the acquisition and development of customers may in some cases be globally suboptimal from the broader business perspective. For example, in some financial services settings (e.g., credit cards), current CLV measurement practices that focus on the expected value of a customer may predict that high-risk customers are more valuable than low-risk ones. Acting on this information, the marketing manager will focus on acquiring these high-risk customers. However, the financial markets expect the firm to have a portfolio of customers that comprises a mix of low- and high-risk customers. “Locally” optimal behavior by the marketing manager may therefore be suboptimal for the firm.

The developers of models used to compute customer lifetime value have focused on deriving expressions for expected lifetime value. To assess the risk of customers, we need to derive expressions for the distribution (or at least the variance) of CLV. We then need to develop models for valuing a portfolio of customers and develop rules that guide the marketing manager to undertake actions that maximize the value of the portfolio rather than the value of the next-acquired customer. Dhar and Glazer (2003) have taken a first step in this direction. The large base of finance literature on portfolio optimization can certainly serve as a source of insights for researchers wishing to explore this topic.

3. Reconciling Top-Down Versus Bottom-Up Measurements

Estimates of CLV are based on a model of buyer behavior that can be used to project future purchasing by a customer. Typically these are micro models that use disaggregate data at an individual customer level. The results from these models are used for customer selection, targeting, campaign management, and so on. At the same time, these results can be aggregated to arrive at the overall demand forecast for a business. Alternatively, one can use an aggregate macro demand model for forecasting purposes. In many firms, marketing managers develop disaggregate or micro models whereas nonmarketing executives (e.g., finance, supply chain) are more comfortable using aggregate macro models of demand forecast.

A major problem is that the demand estimates of micro models do not always agree with the macro model results. There are many possible reasons for this discrepancy. One potential reason is the difference in methodology. However, a more likely cause is the use of different variables in micro versus macro models. For example, a macro demand model for a credit card company may include general economic variables that may influence interest rate, employment rate, and so on, which in turn are likely to influence people’s attitude toward credit card spending. In contrast, micro model of customer purchase behavior or customer acquisition, retention, and cross-selling are less likely to include such macro variables. Even if we include these covariates in the micro model, there is usually little variation in these macro variables in the recent past making them less relevant for the analyst.

Whatever the reason, this is a problem as senior management are communicating to the financial markets on the basis of the top-down numbers, which can lead to a distrust of analyses based on bottom-up analyses that are telling a very different story. It is important that we develop methods that help reconcile these differences.

Perhaps we can learn from advances to hierarchical modeling to develop models that may integrate both micro and macro data. In this connection, we may be able to borrow from wavelet methods (Percival and Walden 2000). Wavelet methods constitute a multiscale analysis tool, enabling us to examine the signal in a possibly nonstationary time series on different scales, that is, either to isolate short-term local singularities in the signal, or to focus on its long-term by filtering out insignificant high-frequency changes, or to detect patterns such as points of discontinuity and local singularities of a signal. In addition, we may also be able to learn from recent research in marketing and economics that have tried to use information from both micro- as well as macro-level data (see, for example, Chintagunta and Dube 2005). For example, in the context of packaged goods, although one can gain a better understanding regarding the distribution of consumer heterogeneity using disaggregate data, aggregate data have some advantages such as being free from sampling error (Bucklin and Gupta 1999).

4. Cost Allocations

In contrast to sales or share models, CLV is an estimate of customer profitability. Therefore, it requires a good estimate of costs. This poses challenges at several fronts. First, most companies have accounting systems that track costs based on functions (e.g., freight) rather than on a per customer basis. Second, in many cases it is not clear how costs can be allocated at a customer level. For example, how should we allocate marketing or distribution costs? How do we allocate the marketing touch costs across different media? One approach is to have an index of the various costs. For example, "one sales call is equivalent in cost to 20 telephone calls." Is this appropriate? Third, this also raises the issue of variable and fixed costs. Consider, for example, the cost of a retail store. Should a company allocate this cost across individual customers, or argue that beyond a certain level, these costs are not variable? Fourth, some costs are more easily quantifiable than others. For example, whereas acquisition costs can be easily quantified, retention costs cannot. Is this one of the reasons why managers overwhelmingly believe that they overspend on acquisition relative to retention?

As marketers, we have a good grasp of the issues surrounding revenue, whereas we frequently ignore the complexities and subtleties of cost side of the equation. Advances in activity-based costing have the potential to allow for more appropriate cost estimates when calculating customer profitability (e.g., Bowman and Narayandas 2004; Niraj, Gupta, and Narasimhan 2001). There is scope to develop a dialogue with our managerial accounting colleagues to explore these issues in greater detail.

5. Developing Incentive Schemes That Encourage Globally Optimal Behavior

Most firms have two levels of marketing managers. Among the lower level managers, one is in charge of customer acquisition, the other in charge of retention; they both report to the higher level manager. The higher level executive's problem is that of allocating the marketing budget between these two lower level managers. In theory, such allocation is a relatively straightforward exercise, based on distribution of the current and potential customers in the market. However, if the two lower level managers' objective functions are maximizing acquisition and retention, respectively, the resulting outcome may be suboptimal. For example, maximizing acquisition may imply acquiring low CLV customers, which is not congruent with the higher level manager's objective. Hence, the challenge is how to design the correct incentive structures for the lower level managers to ensure that they use their budgets in a manner that is optimal for the firm. The marketing literature on sales force incentives can perhaps serve as a source of insights for researchers wishing to explore this topic (see, for example, Basu et al. 1985; Joseph and Thevarajan 1998; Lal and Srinivasan 1993; Raju and Srinivasan 1996).

6. Understanding the Limits of CLV and CE

A strict adherence to the notion of maximizing ROI and retaining only those customers with high CLV will lead to a shrinking, albeit more profitable, customer base. When this is reflected in a reduction in market share, we can expect an adverse reaction by the financial markets. How do we reconcile these two points of view? Along similar lines, when seeking to maximize CE, is it better to acquire a few large customers or a large number of small customers? One argument in favor of the latter is that acquiring a few large customers may be risky. This brings us to the issue raised earlier—when talking about CLV and CE, we tend to consider the expected values of these measures, which may not always be appropriate. We must almost consider the variance so that we can move toward quantifying the risk associated with any given customer.

Most CLV applications focus on the service industry where customer acquisition and retention are meaningful contexts. However, a vast literature in marketing has examined consumer packaged goods. Most of our modeling sophistication has come from this industry and the use of scanner data. Yet it is not clear if CLV and the accompanying models are relevant in consumer product industry.

7. Understanding the Scope of Application

Building on the previous issue of whether CLV is the correct metric to maximize, we need to consider the market setting in which it is being applied. For example, in a new and growing market, firms are in a "land grab" in which they focus on customer acquisition, which in turn leads to growth in market share. Under these circumstances, is the CLV of acquired customers even a valid performance metric, especially when we lack sufficient longitudinal data (or market knowledge) to reliably estimate CLV? Is CLV only a useful concept when the market matures? Although there is no obvious answer, we need to think through the limits of applicability of the CLV concept, especially for those who develop data-based models.

8. Appreciating the Limits of Our Theory-Based Models

Within the field of marketing, we tend to expect our models to be developed based on sound statistical or economic theory. Is that always the best approach? What is the need for a formal model when we can simply apply algorithms to very large amounts of data? Marketing has largely ignored the body of work on "data mining" developed by computer scientists. We only have to look at the annual ACM SIGKDD Knowledge Discovery and Data Mining conference (e.g., http://www.kdd2005.com/) to appreciate the interesting work performed in the computer sciences, some of which is addressing CLV-related issues. Rather than using the words *data mining* as a pejorative term, we need to develop a dialogue with computer scientists and understand the relative merits and appropriate limits of application for the various models we have developed. Furthermore, can we integrate the best aspects of these two research streams? Only one such integrated approach is known to us in the marketing science literature: the use of data mining techniques on the residuals of large-scale promotion response models to capture patterns for which there are no a priori marketing hypotheses (Cooper and Giuffrida 2000).

9. Understanding How to Model Rare Events

The models developed in marketing are typically applied to situations where the events of interest occur with some frequency (e.g., customer churn, customer purchases). These models can break down when applied to setting where the behavior of interest is rare. For example, when modeling the correlates of customer acquisition in a low-acquisition rate setting, the performance of the familiar logit model is often unacceptable. There may be opportunity to gain valuable insights from the statistics literature on the modeling of rare events (King and Zeng 2001).

10. Recognizing the Dangers of Endogeneity

It is well known that the statistical significance of a model parameter does not necessarily imply that the correct variable was used and that the effects we are measuring are valid. We need to focus on the relevant theory, understand the threats of confounds such as endogeneity, and develop the appropriate modeling methodologies. The issue of endogeneity has received considerable attention in the past decade (e.g., Wittink 2005). There is considerable literature in the field of new empirical industrial organization (I/O) that deals with the issue of endogeneity (e.g., Berry, Levinsohn, and Pakes 1995). However, its proposed solutions (such as instrumental variables and VAR models discussed earlier) put additional demands on the data that are not always within reach of the CLV modeler. In some cases, CLV parameters may have to be estimated from experimental designs in which endogeneity is eliminated. We need to understand to what extent endogeneity is a threat to our models, not only in theory, but also in practice.

11. Accounting for Network Effects

Most of the research on CLV has implicitly assumed that the value of a customer is independent of other customers. In many situations, customer network effects can be strong, and ignoring them may lead to underestimating CLV. Hogan, Lemon, and Libai (2003) showed that word of mouth or direct network effects can be quite substantial for online banking. Villanueva, Yoo, and Hanssens (2006) found that word-of-mouth acquisitions are twice as valuable to the firm as customer acquisitions through traditional marketing instruments. As word of mouth and buzz marketing become more and more important, we need to have a better understanding of these phenomena and how they contribute to the value of a customer over and beyond his or her purchases.

In many situations, there are also strong indirect network effects. Consider the case of Monster.com, an employment marketplace where job seekers post their resumes and firms sign up to find potential employees. Monster provides this service free to job seekers and makes money by charging the employers or the firms. How much should Monster spend to acquire a job seeker? Traditional models of CLV cannot answer this question because job seekers do not provide any direct revenue. This indirect network effect is not limited to employment services only (e.g., Monster, Hotjobs, Craigslist) but also extends to any exchange with multiple buyers and sellers (e.g. real estate, eBay). Research in the social network theory can be very useful for exploring these issues (e.g., Newman 2003; Wasserman and Faust 2005; Watts 2004).

CONCLUSION

As marketing strives to become more accountable, we need metrics and models that help us assess the return on marketing investment. CLV is one such metric. The easy availability of transaction data and increasing sophistication in modeling has made CLV an increasingly important concept in both academia and practice. In this article, we reviewed modeling advances in this area and also highlighted some of the promising directions for future research. We hope our discussion sparks new interest and accelerates the progress in this already exciting area.

NOTES

1. Whereas the customer relationship management (CRM) literature typically takes the firm's perspective and uses the terminology of customer acquisition, retention, and expansion, the choice modeling literature takes the consumers' perspective and uses the terminology of when, what, how much, and where to buy the product. The modeling approaches of both these areas have a large overlap with some models being identical in both domains.

2. It can be argued that the use of the term *value* means we should consider the cash flows associated with a customer, rather than the profits; see Pfeifer, Haskins, and Conroy (2005) for a comprehensive discussion of this issue.

3. As this expression includes the acquisition cost (AC), we are implicitly considering the lifetime value of an as-yet-to-be-acquired customer. If we were computing the expected residual lifetime value of an existing customer, we would not include AC. Furthermore, if a consumer purchases multiple products from a firm, the margin used in Equation 1 is the sum of margins obtained from all products purchased.

4. Expected lifetime of a customer is directly related to the churn rate. Specifically, if churn or retention is exponential distributed then it can be shown that expected lifetime is 1/churn rate. For example, if annual churn rate is 20%, then expected lifetime is 1/0.2 = 5 years.

5. One can subtract the AC from this equation for newly acquired customers.

6. When first-period margin is guaranteed from all customers, for example, through upfront payment, then the margin multiple is $1 + [r/(1 + i - r)]$.

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