Predicting Customer Lifetime Value in Multi-Service Industries

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Predicting Customer Lifetime Value in Multi-Service Industries[1]

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Predicting Customer Lifetime Value in Multi-Service Industries

Abstract

Customer lifetime value (CLV) is a key-metric within CRM. Although, a large number of marketing scientists and practitioners argue in favor of this metric, there are only a few studies that consider the predictive modeling of CLV. In this study we focus on the prediction of CLV in multi-service industries. In these industries customer behavior is rather complex, because customers can purchase more than one service, and these purchases are often not independent from each other. We compare the predictive performance of different models, which vary in complexity and realism. Our results show that for our application simple models assuming constant profits over time have the best predictive performance at the individual customer level. At the customer base level more complicated models have the best performance. At the aggregate level, forecasting errors are rather small, which emphasizes the usability of CLV predictions for customer base valuation purposes. This might especially be interesting for accountants and financial analysts.

Key-words: Database Marketing, Interactive Marketing, Forecasting, Customer Lifetime Value

INTRODUCTION

Customer lifetime value (CLV) has become an important metric within marketing and CRM (Blattberg and Deighton 1996; Blattberg, Getz and Thomas 2001; Winer 2001; Rust, Zeithaml and Lemon 2000). Usually CLV is defined as the net present value of future earnings or profit of an individual customer (Berger and Nasr 1998; Dwyer 1989). One key-issue when using CLV is whether the firm can assess the value of the future earnings of each individual customer. In this respect Reinartz and Kumar (2000, p. 32) state that firms should try to predict the lifetime characteristics of a customer as early as possible and then act accordingly. The latter refers to the fact that assessment of the future value can be used in determining the marketing investments (e.g. retention budgets) for each individual customer. However, in the case of incorrect assessments of the value of individual customers, there could be a severe mismatch between the assigned customer budget and the true delivered value of an individual customer. As CLV predictions can also be used for segmentation purposes, for example by classification of customers in the well-known and often applied customer pyramid segmentation (Zeithaml, Rust and Lemon 2001), wrong predictions will lead to customers being assigned to the wrong value-segment. In that case, customers might receive special treatments (e.g. being invited for an event for most profitable customers) based on their expected value, while they are actually far less profitable. Again, marketing budgets are wasted by targeting the wrong customers.

Despite the importance of individual CLV predictions, there have been only a few attempts to model CLV and to assess the predictive performance of these models. Originating in the direct marketing literature, mainstream research on CLV proposes rather simple models that use aggregated data on retention- and growth rates to predict the value of (new) customers (e.g., Berger and Nasr 1998; Dwyer 1989; Keane and Wang 1995). Recently, Gupta, Lehman and

Stuart (2001) showed that this type of models works pretty well in predicting customer lifetime value at the aggregated (or customer base) level. Schmittlein and Peterson (1995) developed a model that uses individual customer data to forecast purchase timing and quantity, which subsequently is used to assess the future customer profitability, while Malthouse and Blattberg (2003) use a regression modeling approach to predict CLV. Also, there are a number of studies that solely focus on explaining and/or predicting underlying purchase behaviors, such as relationship duration and purchase quantity (e.g., Bolton 1998; Reinartz and Kumar 2000, 2003).

However, there are no studies available that address the intriguing question, whether firms will be able to predict the CLV of each individual customer using the available data from a customer database. Moreover, there are also no studies that have compared the performance of competing models, which can vary in their complexity and realism. Considering the fact that managers are usually hesitant to adopt complex modeling strategies (Leeflang et al., 2000), a comparison of the performance of the various types of models is very important. Depending on the results of the comparison, the results can either be used to convince the managers that the additional complexity pays off in terms of better predictive performance, or they can lead to the comforting idea that not much is lost by avoiding the use of advanced models.

Especially in modeling CLV, there is a large variation in the complexity of the models that can be used. Particularly in multi-service industries, models for CLV can be very complex, as in these industries customer purchase behavior is multi-dimensional (Bolton, Lemon and Verhoef 2002). Not only customer retention, but also cross-buying and service usage are important drivers of customer value. Although models have been developed to assess cross-buying probabilities (Kamakura, Ramaswami and Srivastava 1991; Knott, Hayes and Neslin 2002; Li, Sun and Wilcox 2002), none of them have yet been incorporated in CLV-models.

In this paper we aim to fill some of these research gaps. Our first objective is to investigate whether CLV can be accurately predicted at the individual customer level. Besides looking at predictions at the customer level, we also consider whether CLV can be predicted at the aggregated or customer base level. Second, we compare the performance of CLV-models that vary in complexity and realism to facilitate a cost-benefit analysis of additional modeling efforts.

The structure of this paper is as follows. In the next section we provide a short review of the literature on customer lifetime value. Next, we describe in detail different models that can be used to predict CLV with varying degrees of complexity. Then we describe our data and analysis and present a comparison of the predictive performance of the different models in the context of an insurance company. We end with a discussion, managerial implications, research limitations, and issues for further research.

LITERATURE REVIEW CLV MODELS

In the direct marketing literature, CLV has been of interest since the end of the 1980's and applications of the CLV-concept in business practice have been reported (e.g., Dwyer, 1989; Keane and Wang, 1995; Mulhern, 1998). Jain and Singh (2002) provide an overview of research in the context of CLV. They distinguish three categories of models for CLV prediction: (1) models for calculation of CLV, (2) models of customer base analysis and (3) normative models for CLV. The latter category concerns studies that have been proposed and used to understand the issues concerning CLV and how managers can impact CLV. Examples of these studies are Blattberg and Deighton (1996), Blattberg and Thomas (2000), Bolton, Lemon and Verhoef (2002) and Rust, Zeithaml and Lemon (2000). The first two categories concern studies that specifically focus on the assessment of CLV. In the first category the models are particularly formulated for managers to calculate CLV and to be used in marketing decision marking (e.g. Berger and Nasr, 1998). The second type of studies uses information on past purchase behavior available from the entire customer database to develop stochastic models to calculate CLV (e.g., Schmittlein and Peterson, 1995; Schmittlein, Morrison and Colombo, 1987; Malthouse and Blattberg, 2003). This study contributes to the latter two categories of CLV research as follows. First, no models have yet been developed that are particularly suited for prediction of CLV in multi-service industries in which customer behavior is more complex than in single-service or single-product industries. We particularly propose a multivariate probit model that accounts for interdependencies between the purchases of different services to forecast service purchase. The estimation results of this model are then used to predict CLV using a Markov-chain approach. Second, we assess and compare the predictive performance of some of the proposed models in the CLV-literature at the individual and customer base level.

CLV IN MULTI-SERVICE INDUSTRIES

The basic formula for calculating CLV is (Berger and Nasr 1998):

$$CLV_{i,t} = \sum_{t=0}^{\infty} \frac{\text{Profit}_{\text{i,t}}}{(1+d)^t} \tag{1}$$

So, CLV is the net present value of the future profit of customer i, discounted with a discount rate d. With a fixed discount rate, the key-issue for the prediction of CLV is how the profit of each customer in the years ahead can be assessed. In multi-service industries, a customer's profitability depends on the number of services purchased, the usage of each service and the profit margin of these services. Hence, profitability of customer i at time t of a firm offering J services can then be calculated as follows

$$\text{Profit}_{i,t} = \sum_{j=1}^{J} \text{Serv}_{\text{ij,t}} * \text{Usage}_{\text{ij,t}} * \text{Margin}_{\text{ij,t}} \tag{2}$$

With $\text{Serv}_{ij,t}$ a dummy indicating whether customer i purchases service j at time t and $\text{Usage}_{ij,t}$ the amount of that service purchased. Thus, for the calculation of future annual profits, firms need predictions for future purchase behavior, usage and the profit margin for each service. For simplicity we will assume that the margin of a service is constant over time. Another simplifying assumption, which holds well in our application, is the assumption that the service usage level does not vary among customers. As service usage is especially important in markets such as telecommunications (e.g. the number of minutes called), entertainment and credit cards (e.g., Bolton and Lemon, 2000; Bolton, Kannan and Bramlett, 2000), service usage should be modeled in detail in these industries. In the insurance market there is only little variation in usage levels and this variation only occurs in typical categories, such as car insurances and health insurances. Ignoring the small differences in service usage levels, equation (2) translates into

$$\text{Profit}_{i,t} = \sum_{j=1}^{J} \text{Serv}_{\text{ij,t}} * \text{Margin}_{\text{ij,t}} \tag{3}$$

To predict CLV, changes in customer behavior over time are important. Without variation in service usage rates, two important elements should be accounted for in a CLV-model in multi-service industries. First, customers may defect (e.g., Blattberg, Getz and Thomas, 2001; Bolton, Kannan and Bramlett, 2000). Second, the number of services purchased may change over time (Verhoef, Franses and Hoekstra, 2001). An increase in the number of services purchased is often referred to as cross-buying, add-on selling, or cross-selling (Blattberg, Getz and Thomas, 2001; Knott, Hayes and Neslin, 2002; Li, Sun and Wilcox, 2002). The inclusion of this aspect of customer behavior increases the descriptive realism of the model, but it also enhances the complexity of the model. From the perspective of the database-marketing managers, it is to be expected that they will be reluctant to adopt the more complicated models. Verhoef et al. (2002) show that these managers still use relatively simple models for customer selection and segmentation, although more advanced models and tools are available. The adoption of more complicated CLV-models will perhaps only happen when the more complicated models will substantially outperform simple models (Leeflang et al., 2000). Thus, it is crucial to compare the predictive performance of different models.

BEHAVIORAL MODELS FOR ANNUAL PROFITS

In this section we describe a number of models that can be used to predict the development of annual profits over time that serve as inputs in CLV calculations. Building on prior literature on CLV, we start with a description of simple, but less realistic models. Subsequently, we propose more complex and realistic models for customer behavior that account for retention and/or cross-buying. The next section discusses how to compute CLV from the various models for annual profits.

Status Quo Model

The simplest model for CLV is the status quo model. In this model it is assumed that the current customer profitability is a good predictor of the future customer profitability. Hence, one does not account for the possibility of defection or cross-buying. This model is in line with the customer pyramid segmentation scheme, which also implicitly assumes that customer profitability's are stable over time (Zeithaml, Rust and Lemon 2001). Mathematically, the status quo model assumes

$$\text{Profit}_{i,t+1} = \text{Profit}_{i,t} \tag{4}$$

Regression Based Model

A first extension of the status quo model could be a regression-based approach as is used by Malthouse and Blattberg (2003). In this model the profit in the current year is used as predictor for next years profit. Thus, an autoregressive type of regression model is used. The mathematical representation of the model is given by

$$\text{Profit}_{i,t+1} = a_0 + a_1 \text{Profit}_{i,t} \tag{5}$$

Malthouse and Blattberg (2003) also include other predictors, such as recency of purchase and type of service purchased, in their regression models. However, when modeling profits over time, the regression model does not provide input on whether these predictors indeed change over time. As a consequence, we only chose to incorporate an autoregressive profit term in our model for which a yearly estimate is provided. The study of Malthouse and Blattberg (2003) shows that the autoregressive term explains by far the largest part of the variance in CLV, justifying the inclusion of only an autoregressive profit term.

Modeling customer retention

The above models do not explicitly account for customer retention. A behavior-based extension of the status quo model can account for customer retention, as is proposed by Berger and Nasr (1998). In their model, predicted future profits are either equal to profits in the previous period, as in the status quo model, but when defection occurs, profits are zero. Profit in a future period now is a stochastic process and therefore we focus on the expected value of future profits of a customer, so

$$E_t\{\text{Profit}_{i,t+1}\} = P_t(ret_{i,t+1})\text{Profit}_{i,t} \tag{6}$$

Here E_t denotes the expectation at time t, and $P_t(ret_{i,t+1})$ is the probability that customer i is retained for the company from time t to t+1, given the information at time t. The simplest version of this model assumes that the retention probability is the same for all customers and constant over time. In that case, the average retention rate is used. However, retention probabilities may also vary across segments. For example, for each segment in the customer pyramid a different retention rate can be used. These retention probabilities can subsequently be used as input in equation (6). Finally, one can use probit or logit type of models to calculate an individual-specific retention probability (e.g., Bolton, Kannan and Bramlett, 2000; Bolton, Lemon and Verhoef, 2002). Customer behavior available from the customer database (e.g. relationship age or purchase quantity) can be used as predictor of customer retention (Bolton, 1998).

Modeling Cross-Buying Behavior

A further extension of the behavioral models underlying CLV calculations could account for changes in the number of services purchased. Berger and Nasr (1998) and Gupta, Lehman and Stuart (2001) describe aggregate CLV-models in which a growth rate in the revenues or profits of each customer is assumed. These models, however, cannot be translated directly into a model for multi-service industries, where profit growth consists of the combination of the growth of profits per product and the growth in the number of products purchased. In general, profit-growth will depend on what types of service are purchased, because margins and their growth rate differ across services. Concerning the growth of the number of products purchased, a positive growth rate will be a plausible assumption for new customers, but after some time customers have reached a saturation level resulting in a zero growth rate. We therefore prefer not to use a model with a single growth rate. Instead, as the largest changes in profitability will result from changes in the number of products purchased, we propose a model that focuses on the prediction of the purchase of services over time. For current purchasers of a service this concerns a contract renewal decision, while for non-purchasers it concerns a purchase decision.

The purchase decision of individual services has a binary nature, i.e. it is a decision with only two possible outcomes, yes or no. Suitable econometric model for the analysis of such behavior are binary choice models, such as the well-known logit and probit model. The purchase behavior we consider, however, can be interpreted as a single simultaneous purchase decision of multiple products in every period. This is likely to result in dependencies between the purchase decisions for the individual services. The univariate probit model has been frequently used to model single purchase decisions. The generalization to multiple dependent purchases is the multivariate probit model. We will start with a discussion on the possible dependencies and then we introduce both the univariate and the multivariate probit model.

The interdependencies between the purchase decisions on multiple products might arise because there might be a hierarchy in the decisions to add a new service to the currently purchased portfolio (e.g., Kamakura, Ramaswami and Srivastava, 1991). Interdependencies might also be due to cross-category promotions or the sale of package deals, which is the case in our application. Also coincidence effects (Manchanda, Ansari and Gupta, 1999, and Liu, Sun and Wilcox, 2002) might play a role, but we do not expect these to be important for the sales of insurances, as these products have a low purchase frequency and reasonably high levels of involvement.

To account for these interdependencies between the ownership of services, the multivariate-probit model can be used to predict the purchase probabilities (Chib and Greenberg, 1998, Manchanda, Ansari and Gupta, 1999). To understand this model we first show the mathematical formulation of the univariate probit model (Franses and Paap, 2001). This model is assumed to hold for each of the J services sold by the company.

$$\begin{aligned} y^*_{ij,t} &= bX_{i,t} + e_{ij,t} \\ y_{ij,t} &= 1 \text{ if } y^*_{ij,t} > 0 \\ y_{ij,t} &= 0 \text{ if } y^*_{ij,t} \leq 0 \end{aligned} \tag{7}$$

where

$y^*_{ij,t}$ = unobserved latent variable;

$X_{i,t}$ = vector of explanatory variables;

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

$y_{ij,t}$ = ownership/purchase of service j by customer i at time t.

This univariate probit model can be used to independently predict the purchase of each individual service. In that case, separate probit models are estimated for every service. In practice, these purchase decisions are unlikely to be independent. We therefore continue with a description of the multivariate probit model to model the purchase decisions more realistically.

The multivariate probit model incorporates interdependencies between service purchases by allowing for dependence of the error terms of the separate probit models. The vector of errors $(e_{ij,t},....,e_{iJ,t})$ is assumed to follow a multivariate normal distribution with unit variances (for identification) and an unrestricted correlation pattern. Hence, the multivariate probit model accounts for possible correlations between the errors that might result from the interdependencies between the purchase decisions. Instead of purchase predictions for a single product, the multivariate probit model yields probabilities with which a certain portfolio of services is purchased. Let $y_{i,t} = (y_{ij,t},....,y_{iJ,t})$ denote such a portfolio of products purchased, where $y_{ij,t}$ indicates whether product j is in this portfolio or not. The probability of purchasing the portfolio of products $y_{ij,t}$ is given by

$$\Pr(Y_{i,t} = y_{i,t} \mid X) = \int_{Bi,J} \ldots \int_{Bi,1} f_J(Y^*_{i,t} \mid X_{i,t} b, \Omega) dY^*_{i,t} \qquad (8)$$

where $B_{i,j}$ is the interval $(0,\infty)$ if $y_{ij,t}=1$ and the interval $(-\infty,0]$ if $y_{ij,t}=0$. Computation of this multi dimensional integral can be performed using the Geweke-Hajivassilou-Keane (GHK) simulator (Hajivassiliou, McFadden and Ruud, 1996).

The models for customer purchase behavior of the service level so far have resulted in ownership probabilities for each service, when the univariate probit models are used, and for every possible portfolio of insurances, when the multivariate probit model is used. Given information on the contribution margins of every product, it is straightforward to compute the profitability of a portfolio of services. Computation of the expected level of annual profits is now obtained by adding up the profits corresponding to each possible outcome, weighted by the probability of occurrence. For the univariate probit model, with $y_{ij,t} = 1$ indicating the purchase of service j by customer i at time t, this leads to the following expression for expected profits

$$\mathrm{E}_{\mathrm{t}}\{\mathrm{Profit}_{i,t+1}\} = \sum_{j=1}^{J} P_t\{y_{ij,t+1} = 1\} * \mathrm{Margin}_{\mathrm{ij,t+1}} \tag{9}$$

A similar expression holds for the expected future profits based on the multivariate probit model, where the summation is over all possible portfolios of insurances and the probabilities of ownership of each portfolio that result from (8).

FROM YEARLY ESTIMATES TO CLV PREDICTION

The above models provide estimates for next year's profits. However, within a CLV-framework estimates for longer time periods are need. In the section we describe how the models in the previous section can be used to predict profits multiple periods ahead. The underlying assumption is that behavior is stable over time, such that a first order Markov chain can be used to predict profits in future periods. For the status quo model, this assumption is not even needed, as the assumption that profits are constant is sufficient. For the regression based profit model we can predict two periods ahead by inserting the predicted profit for the next period into the prediction equation (5). From this it is clear why including other explanatory variables will be difficult. For the profit models that account for customer defection, predicting multiple periods ahead is also rather straightforward. The probability of retaining a customer for two periods is the square of the one period retention probability.

Predicting profits multiple periods ahead is a bit more complicated for the purchase behavior based models. In these models we have used information on the purchased portfolio as explanatory variables and we also model the behavior of these variables. In the simple models, customer profits and implicitly also the purchases were assumed constant. This assumption can be alleviated for the purchase behavior based models by defining an extensive state space for a detailed Markov model of customer behavior, which is the most important element of a Markov chain.

In defining the state space, the most important question is which variables can change and are important in the prediction of the future state. Obviously, the state variables should include information on the services purchased. Other elements can also be incorporated, for example, relationship length (which is deterministic and increases by one every year) or demographics (how likely is it that this household will have a baby, buy a house, etc.). In our application we will use indicators for the services purchased and relationship age as the state variables. With J services and relationship age truncated at age L, there are 2^J possible portfolios of services purchased. The total number of states, K, equals 2^J*L, which is the number of portfolios times the number of possible relationship age levels.

With the Markov chain approach, state probabilities for future states are computed based on a transition matrix between the states. This Markov chain transition matrix P(t) contains the probabilities, p_{ij}, with which a household goes from state s_i to s_j in one period and is given by

$$\begin{array}{lcc} & & \text{State at time } t+1 \\ & \begin{array}{c} s_1 \\ \cdot \\ \cdot \\ s_K \end{array} & \begin{pmatrix} p_{11} & \cdot & \cdot & p_{1K} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ p_{K1} & \cdot & \cdot & p_{KK} \end{pmatrix} = P(t) \\ \text{State at time t} & & \end{array} \tag{10}$$

When all explanatory variables are included in the state space, the univariate or multivariate probit model can be used to predict the transition probabilities for each state. Notice here that a large number of these transition probabilities will be zero, as relationship age is included in the state space. Consequently, one cannot go from a state with relationship age m to a state with a relationship age m-1.

Once the transition probabilities in the transition matrix are computed, either from the set of univariate or the multivariate probit model estimates, one can use the transition matrix to compute future profitability and CLV. Given a customers state in the current period, say j, the probability distribution for next periods states is given by the j^{th} row of P, which can be written as e_jP, with e_j a vector of zeroes with a 1 at the j^{th} place. Now e_jP is a vector with the state probabilities in period t+1. These can be used to compute the state probabilities in period t+2, which are given by e_jP^2. More general, one can show that the state probabilities in year t+k are given by e_jP^k. Let $Statemargins_t$ denote a vector stacking the annual customer profitabilities of each state in period t, and $s_{i,t}$ the state vector for customer i at time t, which is a vector of zeros with a 1 at the position of the state for customer i at time t. With this notation, expected customer profitability in period t+k is given by

$$\mathrm{E}_t\{\text{Profit}_{i,t+k}\} = s_{i,t}P^k Statemargins_{t+k} \tag{11}$$

For each model in the previous section, we have discussed prediction of annual profits in future periods. Predicted values of CLV now follow straightforward from the definition of CLV in equation (1).

DATA DESCRIPTION

We obtained data from an insurance company in the Netherlands. This company is a large direct writer, which does not use agents and sells 18 insurance types. We provide the number of records in the database we received from this firm. The database consisted of 1.304.206 records, with each record corresponding to an insurance policy that has been purchased. It contains information on the relationship number, the insurance type, the commencing date and end date of the particular insurance and this information has been aggregated to the customer level. In the database we have 3-year data on the purchase of the offered insurances for each individual customer, starting from January 1st 1998 until January 1st 2001. All customers are active on January 1st 1998, so no newly acquired customers are incorporated. This does not harm our analysis, as one usually would use available information on existing customers to estimate models for prediction.

The database not only consists of information on the purchase behavior of customer, but also whether the customer is member of the reward program. Customers are allowed to become member when they purchase two or more insurances. Our analysis of the longitudinal changes of reward program membership shows that this membership is rather stable and that only few customers join this program over time.

On average the 1998 customers have a relationship age of 11.7 years, while the average purchase rate of insurances per customer is approximately 2.29 insurances. As noted this firm offers 18 different insurance types. However, for some types of insurance the percentage of people purchasing this insurance is rather low (see Table 1). As a consequence we decided to focus on the five most frequently purchased insurances (purchase rates above 10%). These insurance types are liability, car, furniture, house and legal aid insurances. One additional insurance type that has been included is health insurance with a purchase incidence rate of 8%, but with a relatively high contribution margin, which makes it important for the CLV calculations. Limiting the number of insurances leads to a less extended multivariate probit model, which facilitates estimation. It is also assumed that the usage level of a type of insurance is one. Thus, customers cannot have two or more policies of the same insurance type.

In Table 1 we provide an overview of the purchase rates of all insurances and their development over time. As can be seen from these data most purchase rates decrease over time (see the paired sample t-tests). This can be largely explained by the effects of customer defection. Between 1998 and 2001 approximately 4.07% of the customers defected. Considering both this low defection rate and the relatively small changes in purchase rates over time, purchase behavior in this market is rather stable. This stability may be explained by factors, such as inertia, switching costs and contracting (Klemperer, 1995; Rust, Zeithaml and Lemon, 2000).

The limited time frame of our data has an important implication for the time horizon of CLV-predictions. In principle one would like to make predictions for an infinite time horizon. However, our data only covers a time period of three years. Hence, we set our time horizon (m) to 3 years. Note, however that this period can already give a good indication of our CLV-predictions. Moreover, the discounting of CLV causes that predictions for the revenues or profit in later time periods add less to the CLV-prediction.

-- Insert Table 1 about here --

ANALYSIS

Model Comparison

In line with our discussion in the section on CLV-models we compare the predictive performance of the following CLV-models:

1. Status Quo Model (eq. 4)
2. Regression Model (eq. 5)
3. Retention model: (eq. 6)
    - with fixed retention rate;
    - retention rates varying per segment;
    - retention rates predicted with probit model.
4. Service Purchase Model:
    - purchase probabilities modeled with univariate probit model (eq. 7, 10 and 11);
    - purchase probabilities modeled with multivariate probit model (eq. 8, 10 and 11).

As noted we have three year of data. The behavior in the first year is used to provide aggregate retention rates and retention rates per segment. It is also used to estimate the regression-model, the probit retention model and the (multivariate) probit model for service purchase. The resulting model parameters are subsequently used for prediction purposes in the following years. Based on these predictions CLV-estimates are provided.

In our assessment of the predictive performance of CLV for our models we consider both the accuracy of the individual level predictions as well as the aggregate level (that is customer base) predictions. Thereby we use the well-known Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) as forecasting criteria (see, e.g., Leeflang et al., 2000). Note, that the MAPE cannot be cannot be calculated, because for some cases actual CLV is zero. As CLV predictions can also be used for segmentation purposes we also investigate whether the individuals are correctly classified in a tier of the customer pyramid (Zeithaml, Rust and Lemon, 2001). To compare the predictive performance at the aggregate level we calculate the percentage deviation from the true value of the customer base.

Estimation results

We will now briefly discuss the estimation results of the econometric models that underlie the CLV models. The input for model 1 is rather straightforward and does not need any further clarification. In model 2 we estimate a regression model. The parameters in equation (5) are as follows: α_0 =7.735 ($p<0.00$) and α_1 = 0.927 ($p<0.00$). Thus, over time profits decreases ($\alpha_1 = 1$ constant profits; $\alpha_1 > 1$ growing profits). The R^2 of this model is 0.92.

Model 3a represents the model with a fixed retention rate for each customer. Based on observed customer retention between t_0 and t_1, this rate is set to 0.9586. In model 3b we assume that retention rates vary between segments of customers. Based on our discussions with the management of the firm and insights from CRM-theory we consider three possible segmentation schemes. First, we use a customer pyramid type of segmentation grouping customers based on their current profitability (model 3b.1). Based on a median split we divide customers into two profitability groups (Verhoef and Donkers, 2001). Second, we group customers based on the number of insurances (#Ins) purchased from the supplier (Model 3b.2). We consider three segments: #Ins =1; #Ins =2 and #Ins >2. Third, we consider a segmentation scheme based on a combination of two variables: relationship length and reward program membership (Model 3b.3). In the CRM literature both variables are considered as antecedents of retention (e.g., Bolton, 1998; Bolton, Lemon and Verhoef, 2002; Leenheer et al., 2002; Reinartz and Kumar 2003). The respective retention rates for each segmentation scheme are provided in Table 2. As can be seen from these schemes the segments within each segmentation scheme differ substantially with respect to their retention rate.

In model 3c we use a univariate probit model to provide a prediction for the retention probability for each individual customer. The estimation results of this probit model on customer defection (0= stay, 1= defect) are given in Table 3. In this model we use purchase behavior data at t_0 as an explanatory variable of retention between t_0 and t_1. After stepwise deletion of all non-significant predictors a model remains that includes a number of dummies for different insurance types, a dummy for a relationship of less than a year and dummies indicating ownership of 2, 3, 4, or 5 or more insurances as explanatory variables. The estimation results show that customers are more likely to stay when they purchase more products. Moreover, customers purchasing health insurances or house insurances are less likely to defect. Remarkably, no significant effect for reward program membership is found.

-- Insert Table 2 and Table 3 about here ---

The final CLV models are based on the predictions for the purchase decisions for individual insurances. For the purchase decision of the individual services we have estimated both a set of univariate probit models and the multivariate probit model. The parameter estimates for the univariate probit models are not very different from the ones obtained for the multivariate probit model, except for the correlations between the errors, which are only available for the multivariate probit model. We therefore only present the parameter estimates of the multivariate probit model. The resulting parameter estimates are presented in Table 4. The data that is used are the situations at January 1st 1999 (t_1) for the dependent variables and the situation at January 1st 1998 (t_0) for the explanatory variables. In this model we included the ownership of insurance types at t_0, reward program membership at t_0 and relationship age at t_0. With respect to relationship age we included two dummies: relationship age smaller than one year and relationship age between 1 and 2 years. We did so on instigation of the insurance company that argued that relationships take-off in the first two years, while they are rather stable afterwards. Moreover, customers in the beginning of their relationship are probably more inclined to switch. As can be seen from the estimation results, the ownership of an insurance type in the previous period is the most important predictor of future ownership for this type of insurance. However, the purchase of other insurances also has some predictive power. For example, the purchase of health insurance is a significant predictor for all other types of insurance. Another effect that is visible in the estimation result is the fact that the company sells an insurance package that includes liability, house and furniture insurance. These insurances therefore affect the probability of owning one of the other insurances in the package deal. This package deal is also sold to customers not owning any of these insurances, resulting in large correlations, which we present below, between the errors in the equations for these insurance types. Notice also that this set of insurances seems to be negatively related to car insurance ownership.

Besides the effect of insurance ownership, also reward program membership has a significant effect on the purchase of all insurances. Finally, our results also indicate a positive effect of the relationship age dummies. Note, that the coefficients are almost all positive and generally larger for the dummy indicating the shortest relationship age than for the intermediate relationship age. This clearly supports the idea of a take-off in the first two years of the relationship. In order to assess the stability of our model over time, we have also estimated the model for the next time period (1999-2000). The estimation results do not significantly differ from each other. When estimation results are used in a Markov chain model, stability of the parameters certainly is a desirable feature. At least, application of Markov chain models with unstable parameters cannot be recommended.

-- Insert Table 4 about here --

An essential element in the multivariate probit model is the correlation between the error terms. This correlation matrix is provided in Table 5. As can be seen from the correlation matrix there exist significant correlations between the error terms. Hence, using the multivariate probit model is a useful modeling strategy. To assess this further, compare the fit of the set of univariate probit models with the fit of the multivariate probit model using a likelihood-ratio test. The log-likelihood of the multivariate probit model is –25026.0 with 98 free parameters, while the log-likelihood of the separate probit models is –29294.9 with 77 free parameters. The value of the likelihood-ratio test statistic 6537.8 with 21 degrees of freedom is highly significant, indicating a substantial increase in the model fit. We also assessed whether this improved model fit also leads to better out-of-sample predictions of service purchase. Our results indicate that the hit rates in both modeling approaches are similar. Hence, the improved model fit does not lead to better predictions. Note, however that the predictions of CLV might be better for the multivariate-probit model, because the estimated probabilities and not predicted ownership is used in the CLV calculations.

-- Insert Table 5 about here --

PREDICTIVE PERFORMANCE

In the first four columns of Table 6 we report the predictive performance of the different models. The MAE varies between 30.37 and 38.19. Considering a median total CLV of approximately 202, the predicted errors are not that large. The MAE heavily favors model 1 and the profit regression performs moderately well with respect to MAE. The service purchase models (4a and 4b) perform badly on the MAE criterion. However, they have the best performance with respect to the RMSE criterion. With respect to this criterion model 1 has the worst performance. Because the RMSE punishes large forecast errors much heavier than MAE, these results suggest that the forecasting errors of model 4a and 4b are most of the time relatively small, but not very small. For the other models, there are more often very small deviations, but also more large observations. Consider, for example, the prediction errors of the status quo model. Many customers will not change their portfolio, which results in a zero prediction error. For the customers that defect, however, the prediction error is large. A more detailed model will make a larger error for the customers that do not change and a smaller error for the customers that do change, which leads to the opposing patterns for MAE and RMSE.

-- Insert Table 6 about here --

To assess the predictive performance from a segmentation perspective, we segmented customers based on their achieved CLV in the considered 3-year period. Four quartiles were distinguished: (1) CLV < 118, (2) 118 ≤ CLV < 202, (3) 202 ≤ CLV < 295 and (4) CLV > 295. In the fourth column of Table 5 we report the percentage of correctly classified customers for each method. The status quo model has the highest hit rate of 81.38%. The second best hit rate (81.18%) is achieved by model 2 (profit regression). The multivariate probit model has a hit rate of only 78.24%. To understand the hit rates of the considered models, we also consider the hit rates at the segment level. That is, we investigate the percentage of customers of a value segment that are classified correctly. The results are shown in Table 7, where each of the six rows in a cell represents the results for one of the six models. Our results show that all models achieve high hit rates in segment (2) with hit rates varying from 85.74% to 90.90%. This basically stems from the fact that many customers are predicted to be in segment 2 by the models. However, for all models the hit rates in segment (3) are rather low with values varying from 52.13% to 67.34%. In this category especially the status quo model performs poorly. In segment (1) and segment (4) the hit rates are somewhat below the overall hit rates. Note, however that the status quo model has very good predictive performance in segment (4) with a hit rate of almost 90%. Thus, this model does especially a good job in the high value segment. An explanation for this result might be, that these customers have a rather stable purchase pattern, because there are not much growth possibilities and they have high switching costs.

-- Insert Table 7 about here --

The percentage deviations of the predicted value of the customer base from its true value are shown in the second column of Table 8. According to these results the status quo model has the largest deviation from the true value, while the probit retention model has the smallest absolute deviation (0.27%). The profit regression model (2) has a relatively small deviation of 0.94%. The model with a fixed retention rate for the total customer base has a relative large negative deviation from the true value. This negative deviation can be explained by the high retention rate of the profitable customers, which is underestimated by the fixed retention rate. Consequently, the model where the retention rate is measured conditional on profitability performs much better. Note, that the model 3a.1, 3a.2 and 3c have relative small absolute deviations. Finally, the deviations of the service purchase models are also much better than the deviations of the status quo model, but not as good as the models that only use retention rates based on simple segmentations.

-- Insert Table 8 about here --

It might come as a surprise that the complicated models perform relatively poor. One of the reasons could be that there are only very few changes in the composition of the insurance portfolios purchased by the households. To investigate whether the more advanced models perform better when more changes occur, we repeat the profit predictions, but now we focus on the prediction of a customer's profitability three years ahead. In the first year(s) customer behavior might be rather stable, which favors the models that assume stability, such as the status quo model. In later years, purchase behavior will have changed for more customers, so methods that allow for such changes are expected to perform better.

In the last three columns of Table 6 we describe the predictive performance on the individual customer level. Again the MAE favors the status quo model. The RMSE is again minimal for the service purchase models and the segment hit rates again favor the status quo model. Note, however that for all models the hit rates for the third year are substantially lower than the hit rates for the total period. Overall these results are pretty much alike with the Total CLV results.

In Table 9 we show the exact segment predictions per model. Again, the more advanced models seem not to be doing better than the simplest status quo model in segmenting the existing customer base. The status quo model does a poor job in segmenting the least profitable customers, but handles all other segments well. The retention-based models perform well for the least profitable customers, but they do not as well for most of the other situations. More changes in the insurance portfolios seem not to harm the performance of the simple models disproportionately more than the other models in segmenting the customer base.

The last column of Table 8 presents the deviations from actual profitability for the whole customer base. Confirming our expectations, here the more advanced model performs best with a deviation of only 0.6%, while the status quo model overvalues the profits by about 10%. Note, that the profit regression model performs not that good in the third year.

-- Insert Table 8 about here --

DISCUSSION

In this paper we focused on the prediction of CLV in multi-service industries. These industries are characterized by complex multidimensional buying behavior. Our research objectives were twofold. First, we addressed the question whether CLV can be accurately predicted at the individual level. Second, we aimed to compare the predictive performance of different models, which vary in complexity and realism.

Prediction of CLV

One of the crucial questions is whether a firm can predict CLV at the individual customer level. To date there is no research that has addressed this issue. We examined this issue with an empirical study for an insurance provider. Our results indicate that the different proposed methods vary with respect to their predictive accuracy with an average MAE of 35.05. Given the median CLV of 202, this difference is not that large (17%). However, there are some cases when these differences occur to be pretty large. This especially holds for methods that do not account for defection and/or cross-buying. From a customer segmentation-perspective most CLV models classify approximately 80% of the customers in the right segment. However, it should be noted that the performance varies over the different segments, where especially the third segment is poorly predicted. One of the issues that is more prevalent in the insurance industry than in most other industries is the fact that customer behavior is 'discrete'. Customers either purchase or do not purchase an insurance, leading to substantial misclassifications when the decision is not predicted correctly. In industries where purchases are more `continuous', such as credit card or mobile telephone usage, one has to predict total sales or total number of minutes called. Here predicting exactly the right sales volume is far more difficult, whereas deviations will in general be much smaller.

Although the models perform relatively well with respect to the classification of customers in the right segment, our results also show that there can be systematic deviations. Moreover, our results also show that for later-year profits the performance of the CLV models deteriorates. Of course, this could be expected, as our models do not account for changing conditions in the market environment and changes in the customer's circumstances. This problem becomes more prevalent in later time periods, as our models are based on today's customer data. Based on these observations, we conclude that CLV can be predicted rather well at the individual level. However, with about 20% of the customers classified incorrectly, one might still aim at better prediction methods, as misclassification-errors can lead to substantial wastes in customer budgets.

We also considered the predictive performance at the aggregated level. The percentage deviations from the true value are rather low. Compared with the predictive performance of the CLV-models at the individual level, the performance at the aggregate level is much better. The errors at the individual level average out at the aggregated level. This especially holds for the more complicated models.

Comparison of Models

We initially expected that the more realistic models would have a better predictive performance at both the individual customer level and the customer base level. However, our results are not in line with this expectation. At the individual, level the simplest model that assumes no changes in profits has the best predictive performance. There are two explanations for this result. First, in this industry there is not that much variation in profits over time. Defection- and purchase rates of new services are rather low. As a result, this model is not far from the truth. However, once there occur changes in purchase behavior, this model has a large forecasting error. The other models are better in capturing the changes in customer behavior. However, they have a poorer performance in predicting stable profits over time. As a result, they have larger average absolute errors, while the status quo model in general has larger errors when its prediction is incorrect. Thus, the overall conclusion of our application is that firms can rely on simple models to predict CLV at the individual level. This especially holds for markets with relatively stable purchase behavior.

At the aggregate level, the more complicated models that account for retention and/or cross-buying perform much better. Thus, for customer base valuation purposes firms should rely on these methods. In our example, especially the retention models have a good performance. In later years the proposed multivariate-probit model has the best performance.

MANAGERIAL IMPLICATIONS

The managerial implications of our results are as follows. First, many firms using customer pyramid type of segmentations assume constant profits over time. This might be questioned from a theoretical viewpoint, as customers will change their behavior over time. However, our results indicate that for predicting the value of customers at the individual level, the constant profit assumption is often the best prediction strategy. More realistic complicated models are not able to outperform this very simple approach to valuing customers. Thus, firms using the customer pyramid way of thinking when valuing customers can continue doing this. At the customer base level the use of this method causes larger deviations from the true value. This especially holds for profit predictions further ahead in the future.

For customer base valuation purposes more complicated models should be used. Our forecasting results on the customer base level provide very useful results for accountants and financial analysts (Hogan et al. 2002; Srivastava, Shervani and Fahey 1998), who try to value the customer base of a company operating in a stable market. In some cases our deviation are as small as 0.2%. Thus, accurate predictions of the total value of the customer base can be made using some of our CLV models. These accurate predictions can perhaps be incorporated in the firms' balance sheet or can be used by companies when negotiating on takeovers.

RESEARCH LIMITATIONS AND FURTHER RESEARCH

This research has several research limitations. First, our study is conducted in one single industry. This industry is characterized by relatively stable customer behavior, resulting in low defection and cross-buying rates. As a result models assuming no variation in profits can perform rather well. We expect that in industries with less stable behavior, empirical comparisons will not favor the status quo model. Future research should investigate the predictive performance of CLV in these types of markets. Second, we assumed constant usage rates. In the insurance industry this is a reasonable assumption. However, in some industries (e.g. telecom) usage is key-behavior. Models should be developed and tested that also account for this behavior. Third, although we studied CLV, our time frame is still limited due to the available data. Future research could aim to predict CLV for longer time periods. We expect no strong differences, as longer-term forecasts are discounted more heavily.

Besides the research issues arising from our limitations, there are also some additional avenues for further research. First, this research focused on prediction of CLV, but did not consider the impact of CRM-variables and how firms may optimize their CRM-interventions in such a way that CLV is optimized. Future research could focus on this issue. Second, although CLV is claimed to be able to bridge the gap between finance and marketing, no research has established the link between CLV and financial indicators. Third, CLV calculations are based on straightforward financial calculations (NPV). However, new financial methods, such as real options, are proposed to evaluate assets. Hogan and Hibbard (2001) propose a methodology to incorporate real-option thinking in customer valuations. However, more efforts should be focused on incorporating new financial valuation methods when calculating the value of a customer (base).

Table 1:

Purchase Rates of Insurance Types over Time

	OWNERSHIP RATES (%)				PAIRED SAMPLE T-TEST 1998-2001	
	1998	1999	2000	2001	t-value	p-value
Liability	43.29 %	43.95 %	43.18 %	39.88 %	-23.71	0.000
Car	55.21 %	52.59 %	49.69 %	47.18 %	-48.77	0.000
Investment	0.83 %	0.87 %	0.91 %	0.91 %	3.68	0.000
Boat	4.59 %	4.38 %	4.22 %	4.05 %	-10.31	0.000
Moped	1.27 %	1.20 %	1.11 %	0.00 %	-26.15	0.000
Caravan	7.77 %	7.36 %	7.01 %	6.60 %	-14.71	0.000
Continuous travel	3.89 %	4.74 %	6.27 %	7.65 %	39.19	0.000
Mortgage	0.20 %	0.15 %	0.07 %	0.02 %	-9.30	0.000
Furniture	43.07 %	43.41 %	43.18 %	41.22 %	-14.72	0.000
Credit	2.36 %	2.85 %	3.10 %	3.26 %	14.36	0.000
Annuity	0.39 %	0.35 %	0.31 %	0.15 %	-11.16	0.000
Motor	1.10 %	1.14 %	1.18 %	1.21 %	2.95	0.003
Disability	2.32 %	2.38 %	2.43 %	2.14 %	-4.74	0.000
House	30.90 %	31.33 %	31.41 %	30.75 %	-1.43	0.15
Legal aid	11.49 %	13.09 %	13.89 %	14.18 %	29.47	0.000
Rest	3.73 %	3.59 %	3.40 %	2.77 %	-14.92	0.000
Risk	2.00 %	1.53 %	1.15 %	0.75 %	-24.73	0.000
Savings account	3.11 %	2.93 %	2.84 %	2.75 %	-10.86	0.000
Savings insurance	0.28 %	0.21 %	0.10 %	0.00 %	-12.10	0.000
Funeral	2.87 %	2.97 %	3.07 %	3.10 %	7.80	0.000
Compulsory health	0.00 %	0.42 %	0.88 %	0.87 %	21.61	0.000
Health	8.59 %	8.69 %	8.42 %	7.97 %	-7.90	0.000
Health for students	0.16 %	0.11 %	0.08 %	0.05 %	-6.89	0.000

Table 2:

Retention Rates per Segment for Different Segmentation Schemes (3b.1, 3b.2, 3b.3)

Model 3b.1	
Profit ≤ 60 Euro	0.942
Profit > 60 Euro	0.986

Model 3b.2	
#Ins = 1	0.916
#Ins = 2	0.979
#Ins > 2	0.993

Model 3b.3		
Relationship Length (l)	Reward Program Member	
	Yes	No
l ≤ 1	0.992	0.952
1 < l ≤ 2	0.995	0.935
l > 2	0.984	0.945

Table 3:

Probit Model Results for Retention '98-'99 (N=30.000)

Variable	Coefficient
Constant	-1.365**
Boat '98	-0.189**
Motor '98	0-.417**
Caravan '98	0.153**
Furniture '98	0.010**
House '98	-0.168**
Obsequies '98	-0.876**
Health '98	-0.245**
Health Student '98	0.696**
Save '98	0.740**
Other Insurances '98	0.286**
Relationship Length ≤ 1 year	-0.179**
Two Insurances	-0.695**
Three Insurances	-0.951**
Four Insurances	-1.136**
Five Insurances	-1.500**

Model Statistics:
McFadden R^2 = 0.113;
LR Statistic = 1172.98 (p =0.00); AIC = 0.307

Notes: *** Significant at the 0.01 level, ** at the 0.05 level, * at the 0.10 level

Table 4:

Multivariate probit maximum likelihood estimation results '98-'99; (N=30,000)

	Liability '99	Car '99	Furniture '99	House '99	Legal aid '99	Health '99	Other '99
Intercept	-2.230***	-1.852***	-1.943***	-2.015***	-1.922***	-2.658***	-2.115***
	(0.033)	(0.026)	(0.033)	(0.040)	(0.041)	(0.061)	(0.037)
Liability '98	3.567***	-0.058*	0.282***	0.111***	0.095**	0.011	0.040
	(0.035)	(0.037)	(0.027)	(0.039)	(0.041)	(0.056)	(0.034)
Car '98	0.061**	3.038***	0.036	-0.070**	0.030	0.039	0.053**
	(0.031)	(0.027)	(0.029)	(0.031)	(0.030)	(0.043)	(0.026)
Furniture '98	0.312***	-0.040	3.244***	0.299***	0.270***	-0.014	0.025
	(0.033)	(0.039)	(0.033)	(0.039)	(0.044)	(0.060)	(0.036)
House '98	0.324***	-0.134***	0.366***	3.231***	0.139***	0.020	-0.048*
	(0.035)	(0.037)	(0.030)	(0.045)	(0.032)	(0.056)	(0.033)
Legal aid '98	0.177***	0.096**	0.134***	0.219***	3.384***	0.125**	0.075**
	(0.062)	(0.044)	(0.050)	(0.053)	(0.062)	(0.060)	(0.039)
Health '98	0.122**	0.097**	0.061*	0.064*	0.107***	3.799***	0.327***
	(0.054)	(0.044)	(0.045)	(0.049)	(0.046)	(0.053)	(0.040)
Other insurances in '98	0.051*	0.019	0.048**	0.021	0.033	0.011	3.060***
	(0.035)	(0.028)	(0.028)	(0.033)	(0.031)	(0.046)	(0.028)
Loy. Rew. program '98	0.385***	0.260***	0.271***	0.259***	0.202***	0.272***	0.281***
	(0.032)	(0.029)	(0.029)	(0.033)	(0.031)	(0.052)	(0.029)
Relation length ≤ 1 year	0.396***	0.271***	0.255***	0.137**	0.160**	0.282***	0.130***
	(0.075)	(0.045)	(0.058)	(0.084)	(0.073)	(0.079)	(0.053)
1 < Relation length ≤ 2	0.325***	0.047	0.172***	0.125**	0.164**	0.024	-0.031
	(0.071)	(0.048)	(0.060)	(0.078)	(0.074)	(0.098)	(0.064)

Notes: *** Significant at the 0.01 level, ** at the 0.05 level, * at the 0.10 level

Table 5:

Correlation Matrix Error Terms Multivariate Probit Model

$$\hat{W}_{'98\rightarrow'99} = \begin{pmatrix} 1 & . & . & . & . & . & . \\ \underset{(0.021)}{0.341^{***}} & 1 & . & . & . & . & . \\ \underset{(0.005)}{0.911^{***}} & \underset{(0.023)}{0.285^{***}} & 1 & . & . & . & . \\ \underset{(0.012)}{0.675^{***}} & \underset{(0.028)}{0.194^{***}} & \underset{(0.008)}{0.784^{***}} & 1 & . & . & . \\ \underset{(0.011)}{0.732^{***}} & \underset{(0.026)}{0.253^{***}} & \underset{(0.011)}{0.782^{***}} & \underset{(0.008)}{0.799^{***}} & 1 & . & . \\ \underset{(0.041)}{0.025} & \underset{(0.032)}{0.106^{***}} & \underset{(0.047)}{-0.018} & \underset{(0.044)}{-0.035} & \underset{(0.049)}{0.042} & 1 & . \\ \underset{(0.023)}{0.225^{***}} & \underset{(0.018)}{0.046^{***}} & \underset{(0.027)}{0.211^{***}} & \underset{(0.028)}{0.044^{*}} & \underset{(0.029)}{0.138^{***}} & \underset{(0.031)}{0.043^{*}} & 1 \end{pmatrix}$$

Notes: *** Significant at the 0.01 level, ** at the 0.05 level, * at the 0.10 level

<u>Table 6:</u>

Predictive Performance of CLV Models

	Total CLV			Value 3rd year		
	MAE	**RMSE**	**Hit Rate**	**MAE**	**RMSE**	**Hit Rate**
1: Status Quo Model	30.37	62.14	81.38%	13.25	25.27	71.13%
2: Profit regression	34.74	60.19	81.18%	15.23	24.30	70.35%
3.: Retention Models						
a. Fixed Retention Rate	36.01	60.48	78.49%	15.85	24.33	64.69%
b.1: profit segmentation	34.95	61.48	80.47%	15.36	24.87	65.66%
b.2: purchase volume segmentation	34.69	61.15	79.07%	15.25	24.71	64.92%
b.3: relationship length – reward program segmentation	35.22	61.00	78.73%	15.49	24.18	65.00%
c: probit model retention	34.35	61.05	78.59%	15.10	24.71	64.89%
4: Service Purchase Model						
a: probit model	36.93	59.07	77.71%	15.26	23.85	66.28%
b: multivariate probit model	38.19	59.32	78.24%	16.75	23.93	65.68%

Table 7:

Classification scores per value segment for each CLV model

True future value v	Future value predictions: Category 1	Category 2	Category 3	Category 4	% in correct category
	Model 1, status quo model without retention prob. Model 2, profit regression Model 3a, fixed retention prob. Model 3b.1, retention prob. based on current profit Model 3b.2, retention prob. based on # insurances Model 3b.3, retention prob. based on rel. length & loy. rew. program Model 3c, retention prob. based on probit model Model 4a, Markov model, univariate probit Model 4b, Markov model, multivariate probit				
Category 1	18.56%	5.97%	0.18%	0.27%	74.31%
($v < 118$)	18.77%	6.24%	0.43%	0.09%	73.51%
	19.39%	5.13%	0.33%	0.12%	77.66%
	19.39%	5.13%	0.33%	0.12%	77.66%
	19.33%	5.20%	0.33%	0.12%	77.40%
	19.22%	5.32%	0.31%	0.12%	76.96%
	19.33%	5.20%	0.33%	0.12%	77.40%
	18.30%	6.04%	0.51%	0.13%	73.28%
	18.30%	6.22%	0.34%	0.11%	73.29%
Category 2	1.87%	33.92%	0.97%	0.80%	90.32%
($v \geq 118$	1.65%	33.64%	1.44%	0.27%	90.90%
$v < 202$)	3.59%	32.20%	1.42%	0.35%	85.74%
	3.59%	32.20%	1.42%	0.35%	85.74%
	3.44%	32.34%	1.42%	0.35%	86.13%
	3.10%	32.67%	1.27%	0.35%	87.00%
	3.44%	32.36%	1.38%	0.37%	86.18%
	1.75%	32.47%	3.03%	0.30%	86.47%
	1.75%	33.83%	1.68%	0.28%	90.10%
Category 3	0.60%	2.97%	6.82%	2.69%	52.13%
($v \geq 202$	0.66%	3.35%	12.12%	1.87%	67.34%
$v < 295$)	0.70%	2.87%	8.17%	1.33%	62.48%
	0.70%	2.87%	8.17%	1.33%	62.48%
	0.67%	2.90%	8.17%	1.33%	62.48%
	0.66%	3.09%	7.99%	1.33%	61.13%
	0.67%	2.90%	8.11%	1.39%	61.99%
	0.55%	2.65%	8.46%	1.41%	64.72%
	0.55%	3.05%	8.08%	1.39%	61.79%
Category 4	0.16%	0.97%	1.33%	21.94%	89.93%
($v \geq 295$)	0.10%	0.59%	2.12%	16.64%	85.55%
	0.20%	0.93%	4.77%	18.51%	75.85%
	0.20%	0.93%	4.77%	18.51%	75.85%
	0.19%	0.93%	4.77%	18.51%	75.85%
	0.18%	0.97%	4.75%	18.51%	75.85%
	0.19%	0.93%	4.48%	18.79%	77.01%
	0.13%	0.87%	5.26%	18.14%	74.36%
	0.13%	0.98%	5.26%	18.03%	73.88%

Table 8:

Predictive Performance of CLV at Aggregate Level

	deviation from true value (total CLV)	**deviation from true value (third year)**
1: Status Quo Model	3.75%	10.08%
2: Profit Regression	0.94%	3.73%
3.: Retention Models		
a. Fixed Retention Rate	-2.88%	-3.05%
b.1: profit segmentation	-0.22%	1.00%
b.2: purchase volume segmentation	-0.38%	0.68%
b.3: relationship length – reward program segmentation	-1.34%	-1.60%
c: probit model retention	0.27%	+1.02%
4: Service Purchase Model		
a: probit model	0.79%	+3.38%
b: multivariate probit model	-1.10%	-0.56%

Table 9:

Classification scores per value segment for each CLV model (third year profits)

	Future value predictions				
	Model 1, status quo model without retention prob. Model 2, Regression model Model 3a, fixed retention prob. Model 3b.1, retention prob. based on current profit Model 3b.2, retention prob. based on # insurances Model 3b.3, retention prob. based on rel. length & loy. rew. program Model 3c, probit model for retention Model 4a, Markov model, univariate probit models Model 4b, Markov model, multivariate probit model				
True future value v	Category 1	Category 2	Category 3	Category 4	% in correct category
Category 1 ($v < 43$)	7.56%	11.06%	1.23%	0.90%	36.43%
	7.56%	11.06%	1.30%	0.83%	36.43%
	10.29%	8.38%	1.29%	0.78%	49.61%
	10.29%	8.32%	1.23%	0.90%	49.61%
	10.29%	8.32%	1.39%	0.74%	49.61%
	10.27%	8.39%	1.27%	0.81%	49.52%
	10.95%	7.68%	1.21%	0.90%	52.80%
	6.80%	11.34%	1.81%	0.80%	54.65%
	8.31%	10.37%	1.45%	0.62%	40.05%
Category 2 ($v \geq 43$ $v < 94$)	1.27%	39.16%	3.17%	2.02%	85.84%
	1.27%	39.16%	3.35%	1.84%	85.84%
	9.48%	31.17%	3.15%	1.84%	68.30%
	9.48%	30.96%	3.17%	2.02%	67.85%
	9.48%	30.96%	3.31%	1.88%	67.85%
	9.46%	31.13%	3.15%	1.89%	68.22%
	10.91%	29.62%	3.08%	2.02%	64.91%
	1.09%	35.51%	7.20%	1.83%	77.82%
	4.24%	35.58%	4.27%	1.54%	77.98%
Category 3 ($v \geq 94$ $v < 138$)	0.30%	3.27%	8.48%	1.46%	62.77%
	0.30%	3.27%	8.60%	1.34%	63.66%
	0.88%	2.98%	8.31%	1.33%	61.56%
	0.88%	2.69%	8.48%	1.46%	62.77%
	0.88%	2.69%	8.50%	1.43%	62.96%
	0.86%	2.95%	8.29%	1.41%	61.36%
	0.93%	2.73%	8.39%	1.46%	62.10%
	0.23%	2.76%	9.03%	1.50%	66.79%
	0.40%	3.59%	8.26%	1.26%	61.14%
Category 4 ($v \geq 138$)	0.21%	2.18%	1.80%	15.93%	79.17%
	0.21%	2.18%	2.70%	15.03%	74.70%
	0.53%	1.91%	2.75%	14.92%	74.19%
	0.53%	1.86%	1.80%	15.93%	79.17%
	0.53%	1.86%	2.56%	15.17%	75.40%
	0.52%	1.92%	2.37%	15.31%	76.09%
	0.62%	1.78%	1.79%	15.93%	79.17%
	0.16%	1.65%	3.36%	14.95%	74.30%
	0.22%	2.07%	4.30%	13.53%	67.25%

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