A model to improve management of banking customers

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Antonia Estrella-Ramón[a]
Manuel Sánchez-Pérez[a]
Gilbert Swinnen[b]
Koen Vanhoof[b]
[a] *Department of Economics and Business, University of Almeria, Almeria, Spain*
[b] *Department of Business Economics, University of Hasselt, Hasselt, Belgium*

Abstract

Purpose – The purpose of this study is to provide a model to assess and classify banking customers based on the concept of Customer Lifetime Value (CLV) in order to determine which kind of customers creates more value to the bank.

Design/methodology/approach – The proposed model comprises two sub-models: (sub-model 1) modelling and prediction of CLV in a multiproduct context using Hierarchical Bayesian models as input to (sub-model 2) a value-based segmentation specially designed to manage customers and products using the Latent Class regression. The model is tested using real transaction data of 1,357 randomly-selected customers of a bank.

Findings – This research demonstrates which drivers of customer value better predict the contribution margin and product usage for each of the products considered in order to get the CLV measure. Using this measure, the model implements a value-based segmentation, which helps banks to facilitate the process of customer management.

Originality/value – Previous CLV models are mostly conceptual, generalization is one of their main concerns, are usually focused on single product categories, and they are not design with a special emphasis on their application as support for managerial decisions. In response to these drawbacks, the proposed model will enable decision-makers to improve the understanding of the value of each customer and their behaviour towards different financial products.

Keywords Customer Lifetime Value, Customer Value Management, Customer Relationship Management, Product Portfolio Management, Hierarchical Bayesian model, Latent Class Regression model.

Paper type Research paper

1. Introduction

Due to the inherent complexities of the financial sector industry related to the high level of competition (Worthington and Welch, 2011), the comparatively long duration of many relationships with customers (Leverin and Liljander, 2006), and the fact that it can take several years for customers to become profitable (Reichheld, 1996), nowadays financial service providers realise the importance of an effective Customer Relationship Management (CRM) (Öztaysi *et al*., 2011). Within this industry, decisions about customers are crucial, but complex, because companies have to recognise hazardous customers' relationships in order to be avoided, which will ensure the survival. In this regard, CRM has potential to help financial services providers to acquire new customers, retain existing ones, and maximize their lifetime value through a more efficient provision of financial products (Krasnikov *et al*., 2009; Xu and Walton, 2005). Consequently, given the existence of vast amounts of customer's data recorded in customer databases, the phenomenon known as marketing accountability has grown in importance to manage customer base by taking into account its value to the firm (Customer Value Management, CVM) (Verhoef and Lemon, 2013). Therefore, careful assessment and segmentation of customers offer benefits in the decision making process related to customer management to this industry.

Undoubtedly, one of the main tools for identifying the value of customers is the Customer Lifetime Value (CLV) measure (Kumar and Shah, 2015). CLV is the present value of the future cash flows associated with each customer (Romero *et al*., 2013). CLV includes all the elements of customer profitability (i.e., revenues and costs) and it is a forward-looking measure (i.e., predictive) (Holm *et al*., 2012). In general, CLV provides a good basis to assess the market value of a firm, and it has been proven that marketing decisions based on this measure improve the financial performance of firms (Gupta and Zeithaml, 2006).

Previous CLV models are unconvincing in their ability to manage customers in a banking context because, in general, they have been mostly conceptual and have focused on the impact of a limited set of predictors on CLV (e.g., Fader *et al*., 2005; Park *et al*., 2014), without a special emphasis on their application as support for managerial decisions. Additionally, whereas the early CLV contributions mainly discuss how to develop a CLV model that can be generalized (e.g., Berger and Nasr, 1998), later CLV applications have demonstrated that these models differ substantially across industries and countries (Chuang *et al*., 2013; Haenlein *et al*., 2007). Moreover, despite the fact that most previous research has used aggregated customer data (Fader and Hardie, 2009) in order to measure and predict CLV directly for different customer segments (e.g., Haenlein *et al*., 2007; Hwang *et al*., 2004), the individual or disaggregated approach is able to capture customer heterogeneity and can be considered as more sophisticated and accurate than aggregate approaches (Holm *et al*., 2012). More related to the financial services sector, prior research on CLV is primarily focused on analysing transaction patterns associated with only one product category (e.g., Klein and Kolb, 2015). However, customers' shopping behaviour usually comprises the purchase of multiple product categories. CLV models that cover customers' relationships with a portfolio of products of the company offer a more comprehensive and realistic understanding of the customer base (Park *et al*., 2014).

In response to these drawbacks, the objective of this study is to propose a new and comprehensive model designed to assess and classify banking customers based on the CLV concept in order to determine which kind of customers creates more value to the bank. The proposed model comprises two sub-models. The first sub-model is designed to get a complete assessment of customers predicting the components of CLV using a set of drivers through Hierarchical Bayesian (HB) models. Therefore, the main contribution arising from this work is derived from the use of panel data that provides individual behavioural measures of 1,357 banking customers throughout 24 months of activity with the bank. More specifically, we analyse whether the length of the relationship with the bank, purchase and cancellation recency, cross-buying behaviour, average monthly assets and liabilities and adoption of online banking create customer value to the bank. In the second sub-model the estimated individual CLV (resulting from the first sub-model) is related to demographic variables and customers' portfolio of financial products in order to carry on a value-based segmentation using the Latent Class (LC) Regression methodology. Using the customer segments provided by the model, CVM strategies are proposed.

2. Literature review

2.1. Approaches to model Customer Lifetime Value

Past research has provided numerous definitions of CLV. Examples include the combination of customer value (past contribution), potential value (potential contributions), and customer loyalty (churn probability) (Hwang *et al*., 2004; Kim *et al*., 2006); the compilation of purchase frequency, recency regarding transactions, and monetary value spent per transaction (Donkers *et al*., 2007); the use of aggregate or general measures of customer acquisition, retention, general profits and costs to serve customers (e.g., Libai *et al*., 2009); and the application of the Customer Asset Management of Services (CUSAMS) framework (Bolton *et al*., 2004). The CUSAMS is an integrated theoretical framework to make an assessment of customers as assets of a company, offering a wide scope to study CLV. CUSAMS characterises each customer-company relationship using three dimensions (i.e., length, breadth, depth). Previous authors have made use of this framework by means of unsophisticated CLV models and not adapted to the financial services industry (e.g., Venkatesan and Kumar, 2004). However, because of a multiproduct or multiservice provider generally depends on these three core variables to increase the value of its customers (Verhoef, 2004), these dimensions are used in this research to complement the classification of components and drivers of CLV identified by Persson and Ryals (2010) (for more details see Section 3).

2.2. Approaches to develop a value-based segmentation

Despite the fact that the process of delineating customer segments provides a basis for an effective CRM management (Öztaysi *et al*., 2011), it remains one of the most difficult goals for organizations to achieve in practice (Quinn and Dibb, 2010). Traditional segmentation is focused on identifying customer groups only based on geographic, demographics and attributes such as attitudes and psychological profiles (Foedermayr and Diamantopoulos, 2008). These criteria are helpful to define the customer's needs and wants, and therefore customer's purchasing behaviour (Aeron *et al*., 2012). However, segmentation focused on the basis of profitability (e.g., CLV) is helpful not only to satisfy customers' needs, but also to satisfy the needs of the business, because it enables the company to decide more effectively on the allocation of resources to each customer segment (Kumar *et al*., 2009).

Customer segmentation methods using CLV can be classified into three categories as follows (Kim *et al*., 2006): (i) segmentation by using only CLV values (e.g., Zeithaml *et al*., 2001), (ii) segmentation by using only CLV components, for example, current value, potential value and loyalty (Hwang *et al*., 2004), and (iii) segmentation by considering CLV values and other information, for example, demographic or transaction history (Aeron *et al*., 2012). However, most previous customer value models, with a segmentation proposal, do not calculate CLV using stochastic and disaggregated formulation (e.g., Haenlein *et al*., 2007; Kim *et al*., 2006). This research aims to overcome this drawback through the first sub-model in order to obtain a more accurate individual CLV measure.

3. Research framework

The proposed model is based on the CUSAMS theoretical framework, used to complement the classification of components and drivers of CLV identified by Persson and Ryals (2010). In line with the traditional customer value literature (e.g., Berger and Nasr, 1998; Kumar and Shah, 2009), we include past behavioural data available from the customer database (customer transaction behaviour). According to our knowledge, this set of variables has not been studied together in other previous CLV models.

Persson and Ryals (2010) make an important distinction between components and drivers of CLV. The components of CLV are retention rate, cash flows (or alternatively profits) the firm expects to receive from the customer in each future period and the discount rate. The proposed model complements these components with (i) the level of cross-buying of each customer by considering the portfolio of banking products that each customer chooses and purchases (breadth dimension of the CUSAMS framework), and (ii) the level of usage of each banking product (depth dimension of the CUSAMS framework), which includes the retention rate. From the usual distinction between contractual (when the firm observes customer defection) and non-contractual contexts (in which defection is unobserved and it is necessary to predict whether an individual is active or alive for the company (P (Alive)), CLV models were traditionally focused on retention as the main source of customer value (e.g., Fader *et al*., 2005; Romero *et al*., 2013). However, focusing only on customer retention is not enough, and cross-buying (i.e., breadth dimension) needs to be accounted for (Donkers *et al*., 2007), as customers' shopping behaviour usually comprises the purchase of multiple product categories (Park *et al*., 2014).

Persson and Ryals (2010) complement the CLV concept with its drivers, which depend to a great extent on the availability of data. In particular, as the first group of drivers of product usage we have included loyalty variables, such as length of the relationship between the customer and the bank and recency variables. They are usually included in less sophisticated usage models (Venkatesan *et al*., 2007). Dynamic cross-buying is also a selected driver of product usage, mainly because product usage is a clear consequence of cross-buying (i.e., customers uses more products) (Kumar *et al*., 2008). In addition, Reinartz *et al*. (2008) analyse the dispersion of spending (spread or concentration) across different product categories in the relationship between cross-buying and loyalty. Consequently, it is also interesting to analyse whether the dispersion of spending (i.e., average monthly assets and liabilities) is a driver of product usage within this research. Moreover, as PC banking customers uses more products that the traditional customer population (Hitt and Frei, 2002), adoption of the online banking is also included as a driver of product usage in the proposed model. Finally, we have also included a one-period lagged of product usage, mainly because previous authors suggest that customers decide how much to use the service in the future by considering how resources currently are exchanged within the provider (Villas-Boas and Winer, 1999).

On the other hand, as the first group of drivers of contribution margin we have also included loyalty variables (i.e., length of the relationship and recency variables). They are usually included in less sophisticated contribution margin models (Kumar and Shah, 2009; Kumar *et al*., 2006). We have also included dynamic cross-buying as driver of contribution margin, mainly because previous authors state that cross-selling contributes to customer profitability (Prinzie and Van den Poel, 2008). In addition, Haenlein *et al*. (2007) explain that intensity of product usage (in terms of average monthly assets and liabilities) is also a good driver of contribution margin. Moreover, as some controversy exits around the effect of the adoption of online banking on the contribution margin, it is also configured as an interesting driver of this component. More specifically, some authors point out that PC banking customers, on average, offer a higher contribution margin that the traditional customers (Hitt and Frei, 2002), whereas other authors state the contrary (Campbell and Frei, 2010). We have also included a one lagged variable of contribution margin, following the example of the usage model. Finally, we have included total quantity of purchases as driver of contribution margin following the suggestions of Venkatesan and Kumar (2004).

To summarise, the complete model is shown in Figure 1.

[**Figure 1**. Framework for the proposed model]

In the first sub-model, the components of CLV (i.e., product usage, contribution margin and discount rate) are predicted using a set of HB models. By combining the usage and contribution margin predictions, as well as a discount rate, the system provides individual measures of CLV (using formulas (1) and (2)). CLV for customer *i* is given by:

$$CLV_i = \sum_{t=1}^{T} \frac{Profit_{i,t}}{(1+d)^t} \quad (1)$$

Where: CLV_i = lifetime value for customer *i*, *i* = index for customers ($1 \leq i \leq I$, *I* is the total sample size), t = index for periods of time or months ($1 \leq t \leq T$, *T* is the end of the observation time frame), $Profit_{i,t}$ = current and future (predicted) profit from the customers of the company, and *d* = monthly discount factor.

$Profit_{i,t}$, the main input to get CLV_i, is calculated using the following equation (it makes use of the predicted components of CLV for each customer (estimated in the sub-model 1)):

$$Profit_{i,t} = \sum_{j=1}^{J} \begin{matrix} PRODUCT\ USAGE_{ij,t} \\ * \ CONTRIBUTION\ MARGIN_{i,t} \end{matrix} \qquad (2)$$

Where: *j* = index for banking products ($1 \leq j \leq J$, *J* is the total number of products).

In the second sub-model, the estimated CLV_i resulting from the first sub-model is related to customers' portfolio of financial products and demographic variables (i.e., age, gender and income) in order to carry on a value-based segmentation using LC regression methodology.

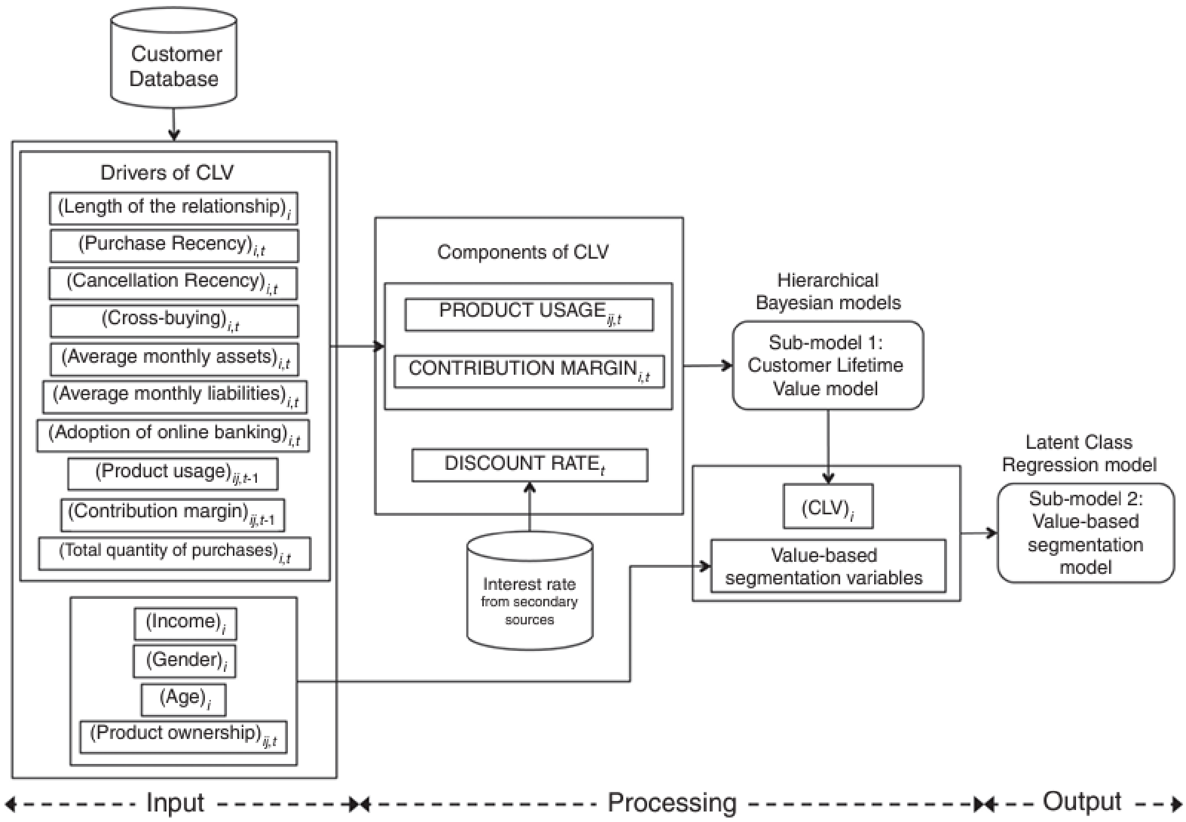
4. Methodology

4.1. Data

For the empirical analysis, we use panel data collected by Cajamar, a large Spanish bank that operates at the national level. Cajamar is a cooperative group that has arisen out of the mergers of several banks during recent years. Therefore, this bank has an extensive physical branch network, as well as an online banking offering the same product assortment, maintaining an important database of customers. All these characteristics make it suitable to test the proposed model. Cajamar provided transaction data of 1,357 randomly-selected new customers[1] during 24 months (from December 2010 to November 2012; the total number of observations is 32,568). The set of variables used in the model are described in Table 1, where *i* refers to customers, *j* refers to products, and *t* refers to periods of time (months). Right-censoring is presented when a customer *i* leaves the company (t_{death}) before the end of the observation period *t* (i.e., $t_{death} < t$). The rows without observations are converted to null vectors according to the observed pattern of death and censoring (except in case of non-time variables) (Mau, 1986). From the sample, the 51.5% of customers are males, and the remaining 48.5% are females. On average, the selected customers have an age of 39.57 years, and an income of 15,836.58€.

The product portfolio considered for this research consists of (1) stock capital, (2) credit card, (3) debit card, (4) saving insurance, (5) home insurance, (6) not linked life insurance, (7) linked life insurance, (8) other insurances, (9) account, (10) home loan, (11) deposit, (12) investment fund, (13) pension plan, (14) securities, (15) consumer loan, (16) micro consumer loan, (17) mortgage, and (18) credit. Therefore, the selected product portfolio is consistent with the financial products available to a standard individual customer (not including companies) of any bank.

[1] Customers who started the relationship with the bank in December 2012 to avoid the possible bias generated by left censoring (Baesens *et al*., 2004 p. 515).



Notes: (*) Where i is the customer index, t is the time period, (t-1) refers to the previous period of data, and j is the banking product index

Table 1. Model variables measures

4.2. Sub-model 1: Prediction of individual CLVs

CLV has been predicted using individual information for the observation period of 24 months, of which the first 12 months (analysis sample) are used for model estimation and the last 12 months (hold-out sample) for the evaluation of the predictive quality (Rust and Schmittlein, 1985). For the prediction of CLV, a set of HB models are used as implemented in WinBUGS 1.4.3 software (Lunn *et al*., 2000).

The proposed HB model is a mixture of Poisson and normal distributions, which are used to jointly estimate the usage of banking products and the contribution margin. The hierarchical nature of the model is reflected by the fact that the parameters (the priors) of the two distributions are expressed as a function of the available covariates of the customer (i.e., drivers of CLV).

For product usage, the random variable U_i follows a Poisson distribution with parameter λ_i, where λ_i is the expected number of products used by customer *i* (Ascarza and Hardie, 2013):

$$P(U_i = u) = \frac{e^{-\lambda}}{x!}\lambda^u, with\ i = 1,2, \ldots, n \quad (3)$$

$$E(U_i) = Var(U_i) = \lambda_i \quad (4)$$

Heterogeneity between customers can be accommodated into the model by assuming λ_i to be a random variable that is influenced by covariates of a particular customer (X_k is a vector of *k* specific covariates, and $\beta = (\beta_0, \beta_1, \beta_2, \ldots \beta_k)$ are the regression coefficients). The Poisson log-linear model is summarised by the following expression:

$$U_i \sim Poisson(\lambda_i),$$

$$log\lambda_i = \beta_0 + \sum_{k=1}^{K} \beta_k x_k = X_k \beta \qquad (5)$$

We specify product usage for each customer *i*, each product *j* and each month *t* as follows:

$$U_{ij,t} = f\left(L_i, PR_{i,t}, CR_{i,t}, CB_{i,t}, AMA_{i,t}, AML_{i,t}, OL_{i,t}\right), if\ t = 1$$

$$U_{ij,t} = f\left(L_i, PR_{i,t}, CR_{i,t}, CB_{i,t}, AMA_{i,t}, AML_{i,t}, OL_{i,t}, U_{ij,t-1}\right), if\ t > 1 \qquad (6)$$

For contribution margin, we use a normal distribution (Borle *et al*., 2008):

$$CM \sim normal(\mu_i, \tau_i)\ ,$$

$$\mu_i = \rho_0 + \sum_{k=1}^{K} \rho_k x_k = X_k \rho \qquad (7)$$

We use varying μ_i's for each customer to emphasize the differences between customers due to different characteristics, i.e., where *i = 1,…, n*, X_k is a vector of *k* covariates for customer *i*, and $\rho = (\rho_0, \rho_1, \rho_2, \dots \rho_k)$ are the regression coefficients. We specify contribution margin for customer *i* and period (month) *t* as follows:

$$CM_{i,t} = f\left(L_i, PR_{i,t}, CR_{i,t}, CB_{i,t}, AMA_{i,t}, AML_{i,t}, OL_{i,t}, Q_{i,t}\right), if\ t = 1$$

$$CM_{i,t} = f\left(L_i, PR_{i,t}, CR_{i,t}, CB_{i,t}, AMA_{i,t}, AML_{i,t}, OL_{i,t}, Q_{i,t}, CM_{i,t-1}\right), if\ t > 1 \qquad (8)$$

4.3. Sub-model 2: Value-based segmentation

A customer classification is obtained based on CLV_i as dependent variable, certain demographic variables as independent variables (age_i, $gender_i$ and $income_i$, where *i* represents each customer) and customers' portfolio of financial products as covariates ($O_{ij,t}$) using LC regression methodology as implemented in the Latent Gold 4.5 software.

LC regression analysis is a powerful technique for marketing segmentation that has demonstrated its superior performance over other traditional methods (DeSarbo and Wedel, 1994). LC regression provides a powerful probabilistic analysis especially flexible to deal with dependent and independent variables of mixed types (Kamakura and Wedel, 1995; Magidson and Vermunt, 2004).

5. Results

5.1. Predictions of product usage and contribution margin

The parameter estimates for the models are presented in Table 2 for Poisson models (usage models) and in Table 3 for the normal model (contribution margin model). Both tables show that many functions are significant ($p < 0.05$).

Table 2. Parameter estimates for Poisson models (Coefficient (Monte Carlo error))

Parameter	Stock capital	Credit card	Debit card	Saving insurance	Home insurance	Not linked life insurance	Linked life insurance	Other insurances	Account
β_0	-4.81 (0.04)*	-8.28 (0.14)*	-0.63 ($7.04e^{-3}$)*	-13.42 (0.21)*	-14.67 (0.23)*	-14.17 (0.22)*	-8.88 (0.12)*	-7.41 (0.12)*	-12.37 (0.13)*
β_1 (L_i)	0.13 ($1.76e^{-3}$)	0.18 ($5.91e^{-3}$)	$-8.00e^{-3}$ ($3.06e^{-4}$)	0.37 ($8.96e^{-3}$)*	0.45 ($9.42e^{-3}$)*	0.41 ($9.12e^{-3}$)	0.26 ($5.07e^{-3}$)*	0.10 ($5.22e^{-3}$)	16.71 (0.14)*
β_2 $(PR_{i,t})$	-1.63 ($3.96e^{-4}$)*	-1.36 ($1.19e^{-3}$)*	-1.69 ($8.50e^{-4}$)	-1.33 ($1.47e^{-3}$)*	-1.44 ($8.36e^{-4}$)*	-1.20 ($1.83e^{-3}$)*	-1.42 ($1.05e^{-3}$)*	-1.21 ($1.85e^{-3}$)*	-16.41 (0.14)
β_3 $(CR_{i,t})$	$-4.27e^{-3}$ ($3.28e^{-4}$)	-0.08 ($8.15e^{-4}$)	-0.03 ($7.23e^{-4}$)	0.02 ($7.60e^{-4}$)	-0.03 ($6.82e^{-4}$)	-0.06 ($1.17e^{-3}$)	-0.10 ($8.38e^{-4}$)*	$4.53e^{-3}$ ($9.31e^{-4}$)	-0.59 (0.04)
β_4 $(CB_{i,t})$	0.35 ($1.04e^{-3}$)*	0.61 ($1.77e^{-3}$)	-0.19 ($2.13e^{-3}$)	0.46 ($2.20e^{-3}$)	0.48 ($1.56e^{-3}$)*	0.59 ($2.23e^{-3}$)*	0.57 ($1.55e^{-3}$)*	0.74 ($1.94e^{-3}$)*	-1.52 (0.07)
β_5 $(AMA_{i,t})$	$2.14e^{-5}$ ($4.15e^{-6}$)*	$3.9e^{-8}$ ($8.82e^{-9}$)	$-1.01e^{-6}$ ($5.03e^{-6}$)	$-2.82e^{-7}$ ($1.58e^{-8}$)	$1.88e^{-5}$ ($1.43e^{-6}$)*	$-2.72e^{-6}$ ($2.71e^{-5}$)	$1.41e^{-5}$ ($1.44e^{-8}$)*	$2.96e^{-6}$ ($1.21e^{-8}$)	6.06 (0.29)
β_6 $(AML_{i,t})$	$2.39e^{-6}$ ($1.04e^{-8}$)	$-5.12e^{-7}$ ($2.58e^{-8}$)	$-9.15e^{-6}$ ($1.46e^{-6}$)*	$1.91e^{-6}$ ($2.52e^{-8}$)	$-1.79e^{-5}$ ($6.67e^{-6}$)*	$-4.65e^{-5}$ ($1.50e^{-7}$)*	$-5.23e^{-5}$ ($7.88e^{-8}$)*	$-4.17e^{-5}$ ($1.70e^{-7}$)*	7.25 (0.23)*
β_7 $(OL_{i,t})$	0.10 ($7.63e^{-4}$)	1.16 ($2.81e^{-3}$)*	0.68 ($5.88e^{-4}$)*	0.23 ($2.94e^{-3}$)	0.66 ($2.33e^{-3}$)*	0.61 ($3.52e^{-3}$)	0.21 ($1.55e^{-3}$)	0.55 ($3.80e^{-3}$)	7.67 (0.08)
β_8 $(U_{ij,t-1})$	19.83 ($1.39e^{-3}$)*	19.50 ($4.04e^{-3}$)*	19.86 ($1.31e^{-3}$)*	18.96 ($7.90e^{-3}$)*	19.58 ($3.35e^{-3}$)*	18.97 ($7.87e^{-3}$)*	19.65 ($2.91e^{-3}$)*	18.69 (0.01)*	3.58 (0.09)

Parameter	Home loan	Deposit	Investment fund	Pension plan	Securities	Consumer loan	Micro-consumer loan	Mortgage	Credit
β_0	-15.49 (0.14)*	-15.71 (0.21)*	-13.93 (0.19)*	-7.02 (0.10)*	-13.66 (0.22)*	-14.73 (0.20)*	-14.31 (0.21)*	-11.71 (0.24)	-11.44 (0.26)
β_1 (L_i)	0.16 ($6.62e^{-3}$)	0.49 ($8.58\ e^{-3}$)*	0.25 (0.01)	0.10 ($4.37e^{-3}$)	0.31 ($9.34e^{-3}$)	0.44 (0.03)*	0.40 ($8.93e^{-3}$)*	-3.06 (0.40)	-4.23 (0.48)
β_2 $(PR_{i,t})$	-0.80 ($5.80e^{-3}$)*	-1.54 ($8.29e^{-4}$)*	-0.85 ($4.55e^{-3}$)*	-1.03 ($1.88e^{-3}$)*	-1.00 ($2.56e^{-3}$)*	-0.97 ($7.00e^{-3}$)*	-0.90 ($3.92e^{-3}$)*	-4.79 (0.44)*	-4.49 (0.40)*
β_3 $(CR_{i,t})$	-0.32 ($5.24e^{-3}$)	-0.07 ($7.22e^{-4}$)	-0.25 (0.03)	-0.06 ($7.94e^{-4}$)	-0.11 ($1.62e^{-3}$)	-0.23 (0.01)*	-0.16 ($2.96e^{-3}$)	-0.56 (0.30)	-1.29 (0.34)
β_4 $(CB_{i,t})$	-0.08 ($8.64e^{-3}$)	0.77 ($2.41e^{-3}$)*	0.62 (0.03)	0.53 ($1.93e^{-3}$)*	0.58 ($3.22e^{-3}$)	0.75 (0.01)*	1.51 ($6.40e^{-3}$)*	-1.03 (0.25)	0.49 (0.19)
β_5 $(AMA_{i,t})$	-10.18 (0.03)*	$-5.36\ e^{-5}$ ($6.54e^{-8}$)*	-10.21 (0.03)*	$1.49e^{-6}$ ($9.00e^{-9}$)	$-3.62e^{-6}$ ($3.68e^{-5}$)	$1.54e^{-4}$ ($1.27e^{-4}$)	$-6.95e^{-5}$ ($4.15e^{-7}$)*	0.03 ($5.61e^{-3}$)*	1.66 (0.19)
β_6 $(AML_{i,t})$	$-1.58\ e^{-7}$ ($1.02e^{-7}$)	$2.14\ e^{-4}$ ($1.92e^{-7}$)*	$1.91e^{-5}$ ($1.20e^{-5}$)	$6.59e^{-6}$ ($1.57e^{-6}$)*	$7.86e^{-6}$ ($2.88e^{-6}$)	$9.99e^{-3}$ ($9.03e^{-3}$)*	$-4.07e^{-4}$ ($1.30e^{-6}$)*	-0.06 (0.01)*	-2.01 (0.25)*
β_7 $(OL_{i,t})$	7.34 (0.15)*	-0.08 ($1.94e^{-3}$)	3.01 (0.05)*	0.61 ($3.32e^{-3}$)	1.09 ($7.21e^{-3}$)	0.33 (0.07)	-0.07 ($4.15e^{-3}$)	-1.26 (0.29)	0.52 (0.16)
β_8 $(U_{ij,t-1})$	17.86 (0.02)*	19.74 ($2.27e^{-3}$)*	17.60 (0.02)*	18.18 (0.01)*	18.16 (0.01)*	18.61 (0.01)*	18.16 (0.01)*	17.89 (0.18)*	15.80 (0.25)

* $p < 0.05$

Table 2. Parameter estimates for Poisson models (Coefficient (Monte Carlo error))

Parameter	Coefficient (Monte Carlo error)
ρ_0	-7.945 (0.03)
$\rho_1\ (L_i)$	0.29 (0.001)
$\rho_2\ (PR_{i,t})$	-0.93 (0.003)
$\rho_3\ (CR_{i,t})$	-1.29 (0.003)
$\rho_4\ (CB_{i,t})$	-15.68 (0.03)*
$\rho_5\ (AMA_{i,t})$	0.004 ($2.21e^{-7}$)*
$\rho_6\ (AML_{i,t})$	-0.005 ($3.24e^{-7}$)*
$\rho_7\ (OL_{i,t})$	-8.06 (0.01)
$\rho_8\ (Q_{i,t})$	26.69 (0.005)*
$\rho_9\ (CM_{ij,t-1})$	0.73 ($1.32e^{-5}$)*

* $p<0.05$

Table 3. Parameter estimates for normal model (Coefficient (Monte Carlo error))

The measure of predictive accuracy, used to validate the results obtained from product usage models, is the hit ratio or the percentage of cases correctly classified (Hair *et al*., 2009 p. 266). Comparisons between the hit ratio and the proportional chance criterion (a measure of random allocation or classification by chance) are estimated. The model performs significantly better when compared with a classification by chance because the difference between the two percentages is substantial. Using a z-test, we have also checked whether the classification rate for the hold-out sample is significantly larger than the percentage due to chance. The majority of the results are significant (except in case of deposit ($z = 18.90$, $p > 0.05$), investment fund ($z = 1.37$; $p > 0.05$) and micro-consumer loan ($z = 3.05$, $p > 0.05$)).

To validate the results obtained from the contribution margin model Pearson correlation is used ($r = 0.750$, $p < 0.05$), which indicates that a strong positive relationship exists between predicted contribution margin and observed contribution margin, validating our results.

5.2. Predictions of CLV

The predicted CLV_i is obtained using the predicted values (calculated with the analysis sample) for product usage and contribution margin using Equations (1) and (2). We also calculate the observed CLV_i using the observed values for product usage and contribution margin (extracted from the hold-out sample). Predicted and observed CLV_i are compared using Pearson correlation ($r = 0.977$, $p < 0.05$), which indicates a strong positive relationship between both measures, validating our results.

5.3. Value-based segmentation

The segment membership is identified by applying LC regression analysis. Among one to six possible class structures, the four-class solution has the lowest BIC (572,974.20) and CAIC (573,099.20) values (see Table 4), validating model fit and parsimony (Magidson and Vermunt, 2004). The entropy or proportional reduction of errors of a model R^2 (0.53) and the classification error (0.0489) also support the appropriateness of the four-segment solution.

Number of segments	BIC (LL)	Change in BIC[a] (%)	AIC	Change in AIC[a] (%)	AIC3 (LL)	Change in AIC3[a] (%)	CAIC (LL)	Change in CAIC[a] (%)	Classification error	R^2
1. cluster	34,655.56	–	34,556.51	–	34,575.51	–	34,674.56	–	0	0.06
2. clusters	28,701.32	−17.18	28,404.18	−17.80	28,461.18	−17.68	28,758.32	−17.06	0.0114	0.17
3. clusters	28,237.58	−1.62	27,742.35	−2.33	27,837.35	−2.19	28,332.58	−1.48	0.0392	0.31
4. clusters	*28,161.43*	*−0.27*	27,468.10	−0.99	27,601.10	−0.85	*28,294.43*	*−0.13*	*0.0489*	*0.53*
5. clusters	28,227.77	0.24	27,336.34	−0.48	27,507.34	−0.34	28,398.77	0.37	0.0537	0.60
6. clusters	28,324.17	0.58	27,234.64	−0.85	27,443.64	−0.57	28,533.17	0.84	0.0497	0.65

Notes: [a]Changes in BIC, AIC3, and CAIC refer to the previous number of clusters; [b]the values supporting the appropriateness of the four-segment solution are printed in italic

Table 4. Selection criteria for competing LC regression models

As detailed in Table 5, latent class sizes and average value of CLV were unbalanced among the four differentiated segments. From the LC regression results, we are able to rank customers in terms of their mean CLV. Additionally, for each segment the expected CLV will be expressed as a percentage of the overall sample mean CLV.

	Class 1	Class 2	Class 3	Class 4
Class size (% of the sample)	69.59	12.56	12.01	5.83
Class size (number of customers)	944	170	163	79
Mean CLV (dependent variable)	1,654.56	−16,604.73	11,004.35	203,527.78
% CLV of overall sample mean	5.08	−50.98	33.79	624.93
Class order in terms of CLV	3	4	2	1
Class brief description	No ownership pattern identified (low engagement)	The least valuable segment (deposit customers)	Debit card and account customers	The most valuable segment (high engagement)

Table 5. Description of the classes

The regression model suggests the existence of statistically significant influences of age, income, and several ownership variables on the CLV (see Table 6). Age and income, initially measured as a continuous variables, were categorised to facilitate the interpretation of the segments profiles.

Results were validated in a focus group with members of Cajamar, who expressed their agreement with the model and the utility that it reports to the bank.

		Parameter estimates – *Z-values*[a]											
		Class 1		Class 2		Class 3		Class 4		Wald	*p*-value	Wald (=)	*p*-value
Independent variables													
Income/person	**up to 5,000**	**−1,414.63**	***−6.88***	**−19,861.52**	***−0.08***	**−8,340.45**	***−2.00***	**−72,714.13**	***−0.04***	**219.64**	**0.00**	**50.37**	**0.01**
	(5,000-6,000)	**−665.92**	***−2.18***	**−11,774.77**	***−0.03***	**−7,516.14**	***−1.28***	**−128,481.11**	***−0.02***				
	(6,000-7,000)	**−736.58**	***−3.41***	**35,330.72**	***0.65***	**−3,057.27**	***−0.90***	**−129,475.00**	***−0.16***				
	(7,000-8,000)	**−684.27**	***−3.89***	**7,335.47**	***0.15***	**−5,281.02**	***−1.85***	**−20,228.46**	***−0.03***				
	(8,000-9,000)	**−448.21**	***−2.23***	**−13,793.96**	***−0.27***	**2,800.80**	***0.80***	**38,348.82**	***0.06***				
	(9,000-10,000)	**80.14**	***0.32***	**−27,292.32**	***−0.57***	**−1,589.36**	***−0.56***	**43,787.58**	***0.06***				
	(10,000-11,000)	**120.55**	***0.47***	**21,108.71**	***0.40***	**5,435.38**	***1.43***	**14,484.45**	***0.02***				
	(11,000-12,000)	**315.53**	***1.21***	**3,271.66**	***0.07***	**1,188.75**	***0.49***	**10,908.27**	***0.01***				
	(12,000-13,000)	**192.28**	***0.53***	**2,811.50**	***0.06***	**5,283.87**	***1.94***	**92,721.66**	***0.14***				
	(13,000-14,000)	**1,060.29**	***2.19***	**32,009.01**	***0.62***	**1,467.22**	***0.41***	**−38,481.59**	***−0.02***				
	more than 14,000	**2,180.82**	***9.48***	**−29,144.50**	***−0.66***	**9,608.23**	***6.10***	**189,129.50**	***0.28***				
age	**up to 15**	**−383.97**	***−2.13***	**−5,704.57**	***−0.17***	**−4,779.55**	***−0.94***	**−13,997.02**	***0.00***	**57.33**	**0.00**	**47.21**	**0.00**
	(15-25)	**166.42**	***0.98***	**21,317.60**	***1.11***	**1,009.02**	***0.42***	**74,776.27**	***0.14***				
	(25-35)	**157.21**	***1.04***	**36,763.74**	***3,14***	**−1,870.22**	***−1.17***	**26,720.73**	***0.05***				
	(35-45)	**10.63**	***0.06***	**16,877.49**	***1,49***	**689.18**	***0.37***	**39,877.60**	***0.08***				
	(45-55)	**−67.40**	***−0.34***	**−28,428.89**	***−2,11***	**−7.36**	***0.00***	**151,652.88**	***0.29***				
	(55-65)	**453.38**	***1.98***	**−9,124.97**	***−0,75***	**3,234.01**	***1.24***	**−193,973.43**	***−0.37***				
	more than 65	**−336.27**	***−1.37***	**−31,700.40**	***−2,96***	**1,724.92**	***0.67***	**−85,057.04**	***−0.16***				
gender	male	58.72	*0.81*	−1,200.06	*−0,25*	228.84	*0.29*	24,085.88	*0.83*	1.45	0.84	0.79	0.85
	female	−58.72	*−0.81*	1,200.06	*0,25*	−228.84	*−0.29*	−24,085.88	*−0.83*				
Covariates													
stock capital	**0**	**0.43**	***3.24***	**0.24**	***1.15***	**−0.32**	***−2.16***	**−0.34**	***−1.18***	**30.31**	**0.00**		
	1	**−0.43**	***−3.24***	**−0.24**	***−1.15***	**0.32**	***2.16***	**0.34**	***1.18***				
credit card	**0**	**1.01**	***3.81***	**0.31**	***0.79***	**−0.02**	***−0.09***	**−1.30**	***−4.21***	**25.97**	**0.00**		
	1	**−1.01**	***−3.81***	**−0.31**	***−0.79***	**0.02**	***0.09***	**1.30**	***4.21***				
debit card	**0**	**0.30**	***2.39***	**0.28**	***1.56***	**−0.32**	***−2.06***	**−0.26**	***−0.94***	**20.37**	**0.00**		
	1	**−0.30**	***−2.39***	**−0.28**	***−1.56***	**0.32**	***2.06***	**0.26**	***0.94***				

(*continued*)

		Parameter estimates – *Z-values*[a]											
		Class 1		Class 2		Class 3		Class 4		Wald	*p*-value	Wald (=)	*p*-value
saving insurance	0	0.53	*1.61*	0.76	*1.66*	−0.32	*−0.78*	−0.98	*−2.07*	7.54	0.06		
	1	−0.53	*−1.61*	−0.76	*−1.66*	0.32	*0.78*	0.98	*2.07*				
home insurance	**0**	**0.73**	***1.23***	**1.48**	***0.88***	**−0.35**	***−0.57***	**−1.86**	***−2.73***	**22.47**	**0.00**		
	1	**−0.73**	***−1.23***	**−1.48**	***−0.88***	**0.35**	***0.57***	**1.86**	***2.73***				
not linked life insurance	0	−0.34	*−0.71*	−0.23	*−0.38*	−0.61	*−1.31*	1.18	*1.15*	2.02	0.57		
	1	0.34	*0.71*	0.23	*0.38*	0.61	*1.31*	−1.18	*−1.15*				
linked life insurance	0	0.30	*1.33*	−0.55	*−1.88*	0.09	*0.34*	0.16	*0.44*	5.25	0.15		
	1	−0.30	*−1.33*	0.55	*1.88*	−0.09	*−0.34*	−0.16	*−0.44*				
other insurances	0	0.41	*0.73*	0.24	*0.42*	−0.54	*−1.20*	−0.12	*−0.20*	2.57	0.46		
	1	−0.41	*−0.73*	−0.24	*−0.42*	0.54	*1.20*	0.12	*0.20*				
account	**0**	**0.60**	***2.20***	**1.03**	***2.66***	**−0.35**	***−1.04***	**−1.29**	***−1.86***	**10.05**	**0.02**		
	1	**−0.60**	***−2.20***	**−1.03**	***−2.66***	**0.35**	***1.04***	**1.29**	***1.86***				
home loan	0	2.55	*0.52*	−1.67	*−0.74*	−1.27	*−0.55*	0.38	*0.08*	0.70	0.87		
	1	−2.55	*−0.52*	1.67	*0.74*	1.27	*0.55*	−0.38	*−0.08*				
deposit	**0**	**0.99**	***3.67***	**−2.01**	***−6.29***	**1.69**	***2.70***	**−0.66**	***−1.51***	**123.00**	**0.00**		
	1	**−0.99**	***−3.67***	**2.01**	***6.29***	**−1.69**	***−2.70***	**0.66**	***1.51***				
investment fund	0	0.49	*0.21*	−2.01	*−0.90*	1.56	*0.32*	−0.05	*−0.01*	7.21	0.07		
	1	−0.49	*−0.21*	2.01	*0.90*	−1.56	*−0.32*	0.05	*0.01*				
pension plan	0	0.43	*1.30*	0.20	*0.37*	0.07	*0.20*	−0.71	*−1.44*	2.73	0.43		
	1	−0.43	*−1.30*	−0.20	*−0.37*	−0.07	*−0.20*	0.71	*1.44*				
securities	0	2.60	*0.59*	−1.76	*−0.87*	1.62	*0.37*	−2.46	*−1.21*	1.79	0.62		
	1	−2.60	*−0.59*	1.76	*0.87*	−1.62	*−0.37*	2.46	*1.21*				
consumer loan	**0**	**2.00**	***2.92***	**−1.44**	***−3.39***	**1.23**	***2.38***	**−1.79**	***−3.67***	**25.72**	**0.00**		
	1	**−2.00**	***−2.92***	**1.44**	***3.39***	**−1.23**	***−2.38***	**1.79**	***3.67***				
micro-consumer loan	0	−0.77	*−0.49*	2.36	*0.71*	−1.93	*−1.23*	0.34	*0.10*	3.28	0.35		
	1	0.77	*0.49*	−2.36	*−0.71*	1.93	*1.23*	−0.34	*−0.10*				
mortgage	**0**	**2.81**	***1.63***	**0.58**	***0.43***	**0.34**	***0.32***	**−3.73**	***−3.90***	**23.88**	**0.00**		
	1	**−2.81**	***−1.63***	**−0.58**	***−0.43***	**−0.34**	***−0.32***	**3.73**	***3.90***				
credit	0	0.96	*0.23*	−0.29	*−0.07*	1.78	*0.42*	−2.45	*−1.03*	1.15	0.76		
	1	−0.96	*−0.23*	0.29	*0.07*	−1.78	*−0.42*	2.45	*1.03*				

Notes: [a]Parameter estimates represent class-specific associations, of each independent variable and covariate, with CLV; *Z*-values in italics; [b]The significant values are printed in boldface

Table 6. Financial product portfolio and demographic associations with CLV

6. Discussion

This study is an attempt to provide theoretical contributions to the customer value analysis literature since according to our knowledge no previous work has examined the proposed drivers of CLV together. In this regard, we have extended the classification of components and drivers of CLV proposed by Persson and Ryals (2010) using the CUSAMS framework (Bolton *et al*., 2004). In particular, from the results obtained in the first sub-model related to the usage model, we can observe a large variation among the different banking services considered (all the variables considered as drivers of usage are significant for, at least, one of the products included). In this regard, this model emphasised the importance of considering a wide range of products offered by the company in order to provide a complete picture to determine which customer behaviours better predict the usage of financial services (Park *et al*., 2014). On the other hand, regarding the contribution margin model, dynamic cross-buying, average monthly assets and liabilities, total quantity of purchases and one period lagged of contribution margin are the drivers that better predict contribution margin component of CLV. Therefore, we are in line to previous authors, who state that cross-selling contributes to customer profitability (Prinzie and Van den Poel, 2008). We also get support to the idea that intensity of product usage (in terms of average monthly assets and liabilities) is also a good driver of contribution margin (Haenlein *et al*., 2007). Finally, we also corroborate that total quantity of purchases (Venkatesan and Kumar, 2004) and one period lagged of contribution margin (Villas-Boas and Winer, 1999) are good drivers of contribution margin.

From a managerial point of view, when firms adopt a segmentation approach based on CLV, they are more able to make consistent decisions on how to acquire and retain customers and to identify customers that are not interesting enough in investing in. In other words, it enables the company to decide more effectively on the allocation of resources to each customer segment (Kumar and Rajan, 2009). Therefore, the challenge is how to get customer segments usefully applicable to real settings (Nenonen and Storbacka, 2014). In response to this need, this research combines the value-based segmentation with the ideas emerging from product portfolio optimization (Katsifou *et al*., 2014) and market basket analysis (Brijs *et al*., 2004). In this regard, we use the portfolio of products that each customer owns as segmentation variable in order to not only improve the understanding of the value of each customer, but also their behaviour towards different financial products. Consequently, due to the segmentation results link customer profiles with portfolio of banking products, it has been demonstrated the utility of the system to indirectly design product portfolio management (PPM) strategies. In this regard, the results that emerge from this study allow for managing products appropriately, renewing (i.e., enhancing products related to high value customers), removing obsolete ones (i.e., products related to low value customers), and adding new products (i.e., in order to design cross-buying strategies aimed at increase the value of low value customers).

7. Conclusions

Within the banking industry, an optimal CRM strategy is a key issue under the current growing competitive pressure that encourages banks to increase profits and reduce costs. In this context, the proposed model is a valuable tool to support decisions about customers and products. Using transaction data of banking customers it has been demonstrated which drivers better predict the contribution margin and product usage for each of the products considered (i.e., sub-model 1). In addition, the LC regression analysis provides homogeneous groups of customers using $\boldsymbol{CLV_i}$ as a grouping variable (i.e., a value-based segmentation) (i.e., sub-model 2). Using the segmentation results, companies are able to know which are the most profitable customers in relation to demographic variables and customers' portfolio of financial products. Consequently, the proposed model allows the CVM (Verhoef and Lemon, 2013) (see Figure 2), causing less waste of marketing spending and more effective allocation of marketing resources to customers and marketing instruments.

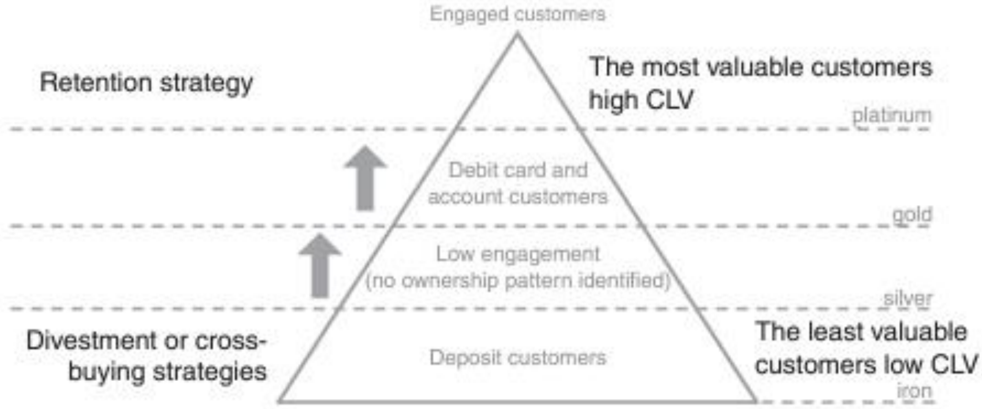


Figure 2. Customer Value Management using the proposed system]

This study suffers from several limitations that suggest avenues for further research. Firstly, the proposed system has been tested using panel data of one bank. It would be desirable to replicate the study using data from other banks in order to analyse the effect of competition. Secondly, the empirical setting for this study is limited to restricted information regarding products, customers, and the period of time for the analysis at our disposal. With respect to the estimation of CLV, this study only considers objective variables as sources of value. It would be of further interest to also consider subjective measures as sources of value (i.e., perceptions of customers, such as satisfaction). This type of information can complete the definition of customer value, integrating the voice of customers and the firm (Larivière *et al.*, 2013). Additionally, more detailed demographic information can also lead to a more sophisticated value-based segmentation. Finally, useful extensions of this work would be to apply the model in other industries and contexts (e.g., different countries and business models).

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