

ESTIMATING CUSTOMER POTENTIAL VALUE USING PANEL DATA OF A SPANISH BANK

Antonia ESTRELLA-RAMÓN¹, Manuel SÁNCHEZ-PÉREZ²,
Gilbert SWINNEN³, Koen VANHOOF⁴

^{1,2}*University of Almeria, Cañada de San Urbano, Ctra. Sacramento, s/n,
Almeria 04120, Spain*

^{3,4}*Hasselt University, Agoralaan – Building D,
Diepenbeek 3590, Belgium*

*E-mails: ¹aer510@ual.es (corresponding author); ²msanchez@ual.es;
³gilbert.swinnen@uhasselt.be; ⁴koen.vanhoof@uhasselt.be*

Received 08 August 2013; accepted 25 September 2014

Abstract. The main goal of this paper is the calculation of a multi-product model of Customer Potential Value using the Probit method. The results of this first analysis are used to perform an ex-post segmentation of customers, whose output can be employed to improve Customer Relationship Management strategies of the companies. Our research contributes to the consumer behaviour literature insofar as, according to our knowledge, no previous work has examined collectively the proposed drivers of Customer Potential Value in a multi-services retailer. To achieve these objectives, we use a panel data of a Spanish bank. The results allow us to confirm the influence of a set of behavioural variables on the ownership of different banking products and identify those customers whose value is higher and lower through the calculation of Customer Potential Value.

Keywords: customer potential value, customer relationship management, customer value management, product ownership, Probit model, ex-post segmentation.

JEL Classification: C51, D12, M31.

Introduction

Due to the rise of the new concept of Customer Relationship Management (CRM) a new age for companies began in the eighties in which making a sale was just the beginning of a relationship with a customer, not the end. CRM emphasizes the establishment, development and maintenance of long-term exchanges (Morgan, Hunt 1994) because such relationships are more profitable than short-term ones as a result of exchange efficiencies between company and customer (Reichheld, Sasser 1990). An increasing number of companies have realized that their most valuable asset is its customer base (Schulze *et al.* 2012) and these customer relationships have been termed relational market-based assets of companies for decades (Srivastava *et al.* 1998, 2001). This fact has further increased the focus on managing relationships with customers (CRM) and led to the

implementation of a Customer Relationship approach (Reinartz *et al.* 2004), using customer data not only for the benefit of the company, but also for the benefit of the customer (Saarijärvi *et al.* 2013). Customer relationships can lead to significant advantages for firms because customers tend to generate higher profits the longer they stay with the company (Reichheld, Sasser 1990). Indeed, customers play a key role in the creation of value for the firm and, consequently, the process of identification of the most profitable/valuable customers is essential to secure an effective competitive advantage for the firm.

Such is the importance of the customer relationships as asset of the company (Srivastava *et al.* 1998, 2001) that the financial community calls for the inclusion of a set of customer measures in financial reports (Persson, Ryals 2010). In this regard, customer value measures are critical to assess the performance of business operations, considered as a good approximation of firm value (Gupta *et al.* 2004). These measures justify the work of the marketing managers to make marketing activities more accountable (Holm *et al.* 2012) and offer valuable information that should be given to investors (Wiesel *et al.* 2008). Nowadays Customer Lifetime Value (CLV) is the most popular customer value measure (Verhoef, Lemon 2013). As Gupta and Zeithaml (2006) determined, CLV provides a good basis on which to assess the market value of a firm. Indeed, marketing decisions based on this measure improve the financial performance of firms (Gupta, Zeithaml 2006; Pepe 2012).

Therefore, based on the preliminaries of CLV models, the main goal of this research implies to get an approximation of CLV called *Customer Potential Value (CPV)*. In particular, we develop a multi-product model of CPV combined with an ex-post segmentation analysis of customers, whose output can be used to improve CRM strategies of the companies (i.e., identifying customers with high and low potential value). According to our knowledge, the predictors used for our model have not been studied together in other previous customer value models. We select the following predictors that define product ownership (the main component of CPV): retention or length of the relationship, cross-buying, product usage (length, breadth and depth dimensions respectively; for more details see Bolton *et al.* 2004), purchase and cancellation recency (from the famous RFM triad), adoption of online banking and balance or intensity of products ownership (measured by average monthly assets and average monthly liabilities). The results of the model are combined with a measure of profitability of each customer to get the CPV. Finally, to develop the ex-post segmentation we consider this CPV and several socio-demographic variables (i.e., age, gender and income) in order to produce customer profiles considering their CPV.

To meet our goals, we use a panel data of a Spanish bank that provide individual behavioural measures of 2,187 customers. The observed time period comprises 24 months, from December 2010 to November 2012. The results allow us to confirm the influence of several variables on the ownership of different banking products and identify those customers whose value is higher and lower through the calculation of CPV measure.

1. Theoretical framework

1.1. Valuing customers

Many models have been proposed for measuring customer value since the articles by Dwyer (1989) and Berger and Nasr (1998). Examples of these are the well-known RFM models (e.g., Pfeifer, Carraway 2000) or more recently, the Weighted RFM models (e.g., Liu *et al.* 2011). Undoubtedly, the contribution of these models is unquestionable and decisive in the field of customer valuation techniques. However, these simple approaches have some serious drawbacks (Kumar *et al.* 2008) and RFM variables were used in more complex models as part of the system (e.g., Fader *et al.* 2007; Glady *et al.* 2009).

Despite the fact that other authors have developed different formulas to measure customer value, there is no consensus about the best method for their calculation (Holm *et al.* 2012; Singh, Jain 2010: 39). In this regard, some authors have given detailed overviews and comparisons of the wide range of different approaches that have been used for customer value modelling (e.g., Holm *et al.* 2012; Ngai *et al.* 2009). Despite the fact that more complex methodologies has been proposed, which supposedly provides more accurate estimates of customer value (e.g., Bayesian models were developed by Abe 2009 or Borle *et al.* 2008), other studies have compared the performance of complex versus noncomplex models for customer purchase behaviour and customer value prediction (e.g., Donkers *et al.* 2007; Zhang *et al.* 2010). These studies show that a model does not necessarily have to be sophisticated in order to accurately forecast a customer value, especially with respect to managerial relevance and applicability. In our case, where we have to develop a model that covers a significant number of heterogeneous products (i.e., assets and liabilities) and predictors of CPV in an extremely complex context, the Probit model is the key to solving our problem.

1.2. Customer Potential Value

An interesting body of research about Customer Potential Value has been identified and classified for this research into two related groups:

- The first group, headed by Donkers *et al.* (2003, 2007), and later followed, for example, by Benoit and Van den Poel (2009).
- The second group, headed by Hwang *et al.* (2004) and Kim *et al.* (2006), and later followed, for example, by Han *et al.* (2012).

The first group uses the terms length, depth and breadth of the relationship to refer to the three dimensions of customer-company relationships (i.e., CUSAM framework) in order to get a measure of customer value for each customer. More specifically, Verhoef and Donkers started to model customer value with the concept of Potential Value of current customers (Verhoef, Donkers 2001). They define Customer Potential Value as the profit or value delivered by a customer if this customer behaves ideally, i.e., the customer purchases all products or services he or she currently buy in the market at full prices at the local company (Verhoef, Donkers 2001: 190). The formula to obtain CPV is:

$$CPV_i = \sum_{k=1}^K Prob(customer_i_owns_portfolio_k) * Profit_k, \quad (1)$$

where $Prob(\text{customer } i \text{ owns portfolio } k)$ is the probability of customer i purchasing portfolio k (calculated with Probit model) and $Profit_k$ is the profit margin of all services in portfolio k .

On the other hand, the second group uses three components to define customer value in order to segment customers. These three components are: (i) current value, (ii) potential value, and (iii) customer loyalty. With respect to potential value, it is defined as the expected profits that can be obtained from a certain customer when he/she uses additional services of the company. It can be calculated using the following formula:

$$Potential_Value_i = \sum_{j=1}^n Prob_{ij} * Profit_{it}, \quad (2)$$

where $Prob_{ij}$ is the probability that customer i would use service j among n -optional services and $Profit_{it}$ is the profit that a company can get from customer i , who uses optional services provided by the company (Hwang *et al.* 2004: 185).

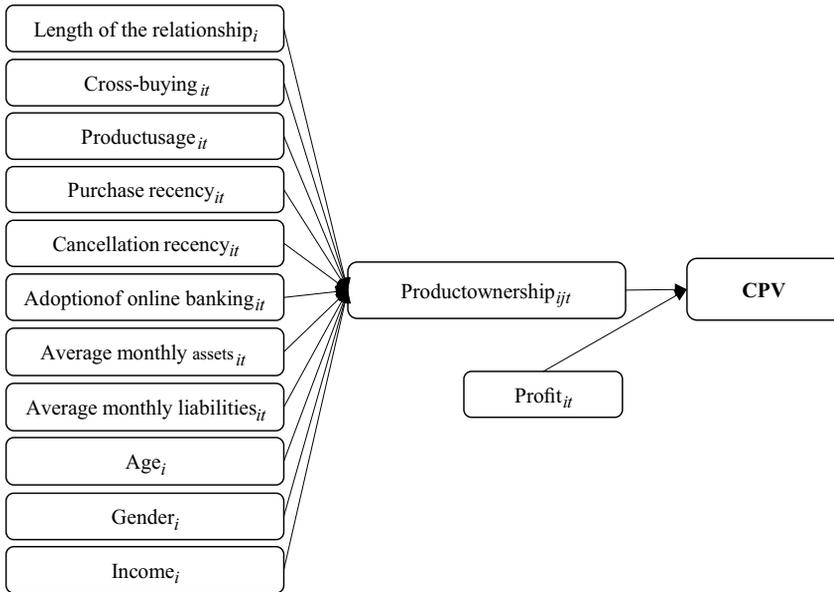
This second group of researchers estimate this potential value from measures solely related to socio-demographic information of customers and transaction data (usage information). They do not make a clear distinction between the three components of the CUSAMS framework in their model.

From this theoretical review, we have found a common suggestion for further research, i.e., apply the different models in other types of business relationships, especially in the financial services context (Lewis 2006). Equally necessary are models that cover the customer's relationships with a portfolio of the company's products (Rust, Chung 2006; Singh, Jain 2010). This task constitutes a challenge for this research because despite the apparent theoretical simplicity of CPV concept, it is fraught with difficulty when applied in practice. This task is even more difficult particularly in the chosen banking context, where purchase behaviour is rather complex: (i) customers can purchase more than one service or banking product (there are a large number of (heterogeneous) services/products at their disposal (i.e., assets and liabilities)), (ii) there are different types of transactions and channels available to customers, and (iii) it is difficult to assign an amount of profits or contribution margin to each transaction because of the complex finances in this sector (some products are considered assets and others liabilities).

1.3. Predictors of CPV

The variables that can be used to predict the CPV in a marketing decision support system depend to a great extent on the availability of data. In line with the traditional customer value literature (e.g. Berger, Nasr 1998) we only include past behavioural data available from the customer database (see Fig. 1).

To make an assessment of customers as assets of a company, Bolton *et al.* (2004) propose an integrated framework, called CUSAMS (CUSomer Asset Management of Services) that enables service organizations to make a comprehensive assessment of the value of their customer assets through three dimensions, called (1) length (duration), (2) depth (increased usage/upgrading) and (3) breadth (cross-buying). It is well known



Where i is the customer index, t is the time period index, and j – banking product index

Fig. 1. Conceptual model

that a multi-services provider generally depends on these three core variables to increase the value of its customers (Wu *et al.* 2005). Therefore, to measure customers as assess of the company in this research, these three variables are included as predictors of CPV, in particular: (1) *length of the relationship*, (2) *product usage* and (3) *cross-buying*.

Retention and acquisition rates are important factors in customer value estimation (e.g., Rust *et al.* 2000 2004). However, both factors are not the only relevant sources of value (e.g., Gupta *et al.* 2004; Singh, Jain 2010). Many studies have ignored the contribution of other behaviours, such as service/product usage and cross-buying, to business performance (e.g., Blattberg *et al.* 2001), especially for different product categories (Jain, Singh 2002). The dynamic nature of the customer relationship is especially important in service firms, such as financial services retailers, because customers’ service usage levels have a substantial impact on the long-term profitability of the organization (Livne *et al.* 2011), and also on customer value (Chang, Weng 2012).

With respect to cross-buying, Kamarura *et al.* (2003: 47) and later Prinzie and Van den Poel (2008: 714) study the cross-buying of products to discover the hierarchical process of their acquisition. They encourage us to choose cross-buying in our CPV model from the following statement (an idea which they did not prove): “*cross-selling is effective for customer retention by increasing switching costs and enhancing customer loyalty, thus directly contributing to customer profitability and customer value*” (Kamarura *et al.* 2003: 47; Prinzie, Van den Poel 2008: 714). More recently, other authors have also recognised the importance of cross-buying to customer value (Singh, Jain 2010).

We have also included two recency variables (called *purchase recency* and *cancellation recency*). They have been previously used by other authors as predictors of product choice (Donkers *et al.* 2007). In a similar vein, the *adoption of online banking* clearly influences the product choice. The opportunities to use online capabilities to increase sales through add-on sales are enormous (Sarel, Marmorstein 2003). Internet banking is easier, more convenient and offers more features with lower cost than banking in the eighties or nineties (Han, Baek 2004). Additionally, there has been limited attention to how much such technologies alter actual customer demand for services and/or the financial performance of individual relationships (Campbell, Frei 2010).

Furthermore, following the suggestions of Prinzie and Van den Poel (2006), we have also included intensity of product ownership as a driver of CPV (herein called *average monthly assets* and *average monthly liabilities*). Past and current purchase behaviours are reflected by the (current) intensity of product ownership, and therefore this information is a good predictor of product choice and also of customer value (Haenlein *et al.* 2007; Reinartz *et al.* 2008). Haenlein *et al.* (2007) define two conditions under which the customer is considered as active (versus inactive) in a banking context. These conditions are also applicable in our context, although we have adapted them according to the specific characteristics of our collaborating retail bank. In particular, these conditions are:

- Condition 1: All clients owning either a savings product, a home financing product, a loan or an insurance product are defined as being active.
- Condition 2: All customers owning transaction accounts, custody accounts and savings deposits are defined as active customers when these accounts either showed a positive balance of at least 50 euros.

To check these two conditions, two pieces of information are used: type of product ownership (condition 1) and intensity of product ownership (measured by average monthly assets and average monthly liabilities) (condition 2).

2. Empirical modelling

2.1. Data set and variables

We have 24 months of behavioural data for 2,187 customers of a Spanish bank (a multi-services retailer). The time period considered in this database begins in December 2010 and ends in November 2012. All customers started their relationships with the bank during this period. Data pre-processing was required to ensure data field consistency. Missing data in the sample are generated by expectation maximization (in case of the variable profit) and multiple imputation (in case of income, average monthly assets and average monthly liabilities) using missing data module in SPSS v. 20. The missing data are presented in the following variables (where i is the customer index): $income_i$, with 2,764 missing observations (6.74% over the total number of observations); $average\ monthly\ assets_i$, with 171 missing observations (0.42%); $average\ monthly\ liabilities_i$, with 171 monthly observations (0.42%); and $profit_i$, with 14 missing observations (0.03%).

After the data are filtered, for each month t the following variables are observed, where i refers to customers, j refers to products and t refers to periods of time (months):

- *Product ownership* $_{ijt}$, measured using binary variables indicating with a 1 the ownership (or the opposite with a 0) of each banking product (Donkers et al. 2003, 2007). To be more exact, the bank sells different types of products, some of them with very low ownership rates or percentage of people purchasing this product. For this reason, we have decided to include in our model only those products with ownership rates above 5%, or owned by more than 109 customers in the sample (Donkers et al. 2003; Verhoef, Donkers 2001). This decision is justified as it fixes a certain threshold of customers that own each of the products in order to obtain convergence in Probit models. The selected banking products are: stock capital, credit card, debit card, linked life insurance, account and deposit.
- *Length of the relationship* $_i$, measured as continuous variable indicating the length of the relationship between the customer and the company (Donkers et al. 2007).
- *Cross-buying* $_{it}$, measured as the difference in the number of products purchased/cancelled across all product categories between t_{n+1} and t_n (Verhoef et al. 2001).
- *Product usage* $_{it}$, measured as the total quantity of purchases made by customer i (Venkatesan et al. 2007: 585).
- *Purchase recency* $_{it}$, measured as a binary variable indicating whether the customer purchased a new product in the last period and *cancellation recency* $_{it}$, measured as a binary variable indicating whether the customer cancelled a product in the last period (Donkers et al. 2007).
- *Adoption of online banking* $_{it}$, measured using a binary variable which takes a value of 1 if customer i adopts the online channel and 0 for all non-adoption months (Campbell, Frei 2010).
- *Average monthly assets* $_{it}$, measured as the sum of monthly positive balances and *average monthly liabilities* $_{it}$, measured as the sum of monthly negative balances (Prinzie, Van den Poel 2006).
- *Profit* $_{it}$ (monetary value) measures each customer specific margin. In more precise terms, this variable is measured as the difference between interest and fees charged to the customer minus the cost or income for the bank (of investments funds or collected from the customer) at the *Interbank Lending Market* (a market where banks extend loans to one another for a specified term; low transaction volume in this market was a major contributing factor to the financial crisis of 2007).
- Socio-demographic information of each customer is observed: *age* $_i$ (continuous variable), *gender* $_i$ (“1” = male, “2” = female) and *income* $_i$ (continuous variable).

2.2. Specification of the model

The estimation of CPV can be carried out with models at different levels of aggregation of behaviour. We have the lowest level of aggregation in the data with individual information. Following Verhoef and Donkers (2001) suggestions and Donkers et al. (2003, 2007), we have estimated univariate Probit models and a multivariate Probit model to obtain predictions of the product ownership as a first step to calculate CPV using the predictors previously mentioned.

In the situation without dependence across different services (i.e., the errors are independent across individuals), a (univariate) Probit model for purchases of product $j, j = 1, \dots, J$, by customer i during t months of relationship with the bank is adequate. Thus, using information of the profitability of each customer, potential value of each customer can be predicted with the estimation results of the binary choice models. The following formula is used to calculate each customer potential value:

$$Potential_Value_i = \sum_{j=1, t=1}^{J, T} Prob(y_{ij} = 1) * Profit_{i,t}. \tag{3}$$

In many cases, purchase decisions are made simultaneously, or they are related. Multivariate Probit model allows for correlations between the errors terms in the Probit equations for each service. Therefore, in the situation with dependence across different services a multivariate Probit model for purchases of product $j, j = 1, \dots, J$, by customer i during t months of relationship with the bank is adequate. They obtain the following equation to compute the potential value of customer i :

$$Potential_Value_i = \sum_{j=1, t=1}^{J, T} Prob(customer_i_owns_portfolio_k) * Profit_{i,t}, \tag{4}$$

where $Prob(customer\ i\ owns\ portfolio\ k)$ is the probability of customer i during t months purchasing portfolio k and $Profit_{i,t}$ is the Profit margin of each customer during his/her relationship with the bank

3. Results

3.1. Checking multicollinearity

Descriptive statistics are shown in Table 1. To check the existence of multicollinearity, we examine bivariate correlation values and the Variance Inflation Factor (VIF) criterion (correlations and VIFs were calculated for the independent variables). Correlations with

Table 1. Descriptive statistics

	Mean	S.D.	Median	Minimum	Maximum
1. Length of the relationship	21	4,99	24	1	24
2. Cross-buying	n.a.	n.a.	0	-4	5
3. Product usage	2,30	1,52	2	0	12
4. Purchase recency	n.a.	n.a.	0	0	24
5. Cancellation recency	n.a.	n.a.	0	0	24
6. Adoption online banking	n.a.	n.a.	0	0	1
7. Average monthly assets	6,363.09	39,304.89	0	0	813,905.5
8. Average monthly liabilities	6,862.70	21,753.92	406.01	0	446,715.5
9. Age	38.42	19.72	36	1	100
10. Gender	n.a.	n.a.	1	1	2
11. Income	15,168.24	21,598.06	9.894.02	0	643,298.1

values above 0.8 indicate multicollinearity. In our case, all correlations are below this value (see Table 2). All VIF values were below 2, which is the cut-off value recommended by Neter *et al.* (1990). Accordingly, we can conclude that multicollinearity is not a problem in this study.

Table 2. Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11
1. Length of the relationship	1										
2. Cross-buying	-0.04**	1									
3. Product usage	0.20**	0.12**	1								
4. Purchase recency	-0.13**	0.43**	0.04**	1							
5. Cancellation recency	0.04**	-0.54**	0.04**	-0.04**	1						
6. Adoption online Banking	0.02**	0.02**	0.31**	0.01*	0.05**	1					
7. Average monthly Assets	0.06**	0.01	0.36**	0.01	0.02**	0.10**	1				
8. Average monthly liabilities	0.12**	0.001	0.22**	0.01	0.05**	-0.03**	0.03**	1			
9. Age	0.12**	0.004	0.15**	0.004	0.04**	0.002	0.03**	0.27**	1		
10. Gender	0.02**	-0.01	-0.06**	-0.01**	-0.01**	-0.03**	-0.04**	-0.02**	-0.04**	1	
11. Income	0.10**	0.002	0.30**	0.01	0.05**	0.12**	0.22**	0.42**	0.19**	-0.06**	1

Notes: *p < 0.05, **p < 0.01; n.a. = not applicable.

3.2. Prediction of purchases

The parameter estimates for the models are presented in Table 3 for univariate Probits and in Table 4 for multivariate Probit. The variables average monthly assets, average monthly liabilities, age and income have been standardized. As can be seen in said Tables, many functions are significant (p < 0.05), and product usage is configured as a predictor of product ownership for all the products considered. Despite the fact that the values of these coefficients are not directly interpretable (because of the nonlinear nature of the Probit model), the significant probabilities that result from these Probit models explain the ownership of these banking products.

We have also noted pseudo R² measures to compare models (McFadden 1974). At first sight, it seems remarkable that the more complicated model (i.e., multivariate Probit model) does not perform better than the univariate Probit model. Therefore, to obtain CPV, we are going to use the results of univariate Probit models (marginal effects are reported in Table 5). A common way of estimating the predictive power of a model

is to look at the area under the Receiver Operating Characteristics curves or AUROC (Thomas *et al.* 2005). A ROC curve represents the relationship between the “true positive fraction” (the fraction of actually positive cases correctly classified as positive) and the “false positive fraction” (the fraction of actually negative cases incorrectly classified as positive) (Metz *et al.* 1998). Ideally, a model that differentiates the two classes very effectively has an AUC with a value close to 1. Figure 2 shows the results for the models proposed.

Table 3. Parameter estimates for univariate Probit models (Coefficient (standard error))

	Stock capital	Credit card	Debit card	Linked life insurance	Account	Deposit
Length of the relationship	0.17 (0.02)*	0.01 (0.03)	0.13 (0.01)	0.02 (0.03)	0.10 (0.02)*	0.07 (0.03)**
Cross-buying	0.11 (0.13)	-0.06 (0.13)	-0.10 (0.12)	-0.33 (0.14)**	-0.66 (0.19)*	-0.11 (0.15)
Product usage	3.68 (0.07)*	1.44 (0.07)*	3.97 (0.07)*	2.55 (0.10)*	1.85 (0.10)*	1.65 (0.07)*
Purchase Recency	-0.40 (0.13)*	-0.18 (0.16)	-0.29 (0.09)*	0.40 (0.19)**	0.64 (0.18)*	0.31 (0.14)**
Cancellation Recency	1.10 (0.25)*	-0.34 (0.24)	-1.28 (0.18)*	0.34 (0.28)	-0.63 (0.32)***	-0.78 (0.23)*
Adoption online Banking	-0.13 (0.14)	1.03 (0.22)*	1.31 (0.12)*	-0.80 (0.26)*	-0.15 (0.19)	-1.19 (0.19)*
Average monthly assets	1.24 (0.17)*	-3.34e ⁻⁴ (0.07)	-1.42 (0.06)*	0.46 (0.07)*	-2.35 (0.09)*	-1.48 (0.21)*
Average monthly liabilities	-0.66 (0.09)*	-0.79 (0.16)*	-1.62 (0.10)*	-3.31 (0.38)*	-0.01 (0.09)	1.41 (0.09)*
Age	1.60 (0.09)*	0.57 (0.18)*	-0.46 (0.08)*	-0.34 (0.20)***	-1.34 (0.11)*	2.55 (0.12)*
Gender	-0.42 (0.16)*	1.46 (0.35)*	0.89 (0.13)*	0.35 (0.29)	-1.14 (0.22)*	-1.04 (0.27)*
Income	0.05 (0.06)	0.06 (0.05)	0.14 (0.06)**	-0.16 (0.08)*	0.23 (0.15)	-0.07 (0.05)
Pseudo R ²	0.56	0.37	0.56	0.47	0.33	0.39

Notes: * Significant at the 0.01 level, ** at the 0.05 level, *** at the 0.1 level.

Table 4. Parameter estimates for multivariate Probit model (Coefficient (standard error))

	Stock capital	Credit card	Debit card	Linked life insurance	Account	Deposit
Length of the relationship	0.01 (0.002)*	-0.01 (0.003)**	0.01 (0.001)*	0.005 (0.003)**	-0.005 (0.002)*	0.02 (0.003)*
Cross-buying	0.04 (0.04)	0.09 (0.05)**	0.005 (0.04)	-0.04 (0.04)	-0.20 (0.04)*	-0.003 (0.04)
Product usage	0.68 (0.01)*	0.41 (0.01)*	0.53 (0.007)*	0.57 (0.01)*	0.26 (0.01)*	0.26 (0.008)*

End of Table 4

	Stock capital	Credit card	Debit card	Linked life insurance	Account	Deposit
Purchase recency	-0.19 (0.03)*	-0.1 (0.05)***	-0.13 (0.03)*	0.01 (0.05)	0.07 (0.03)**	0.17 (0.04)*
Cancellation recency	0.26 (0.07)*	0.06 (0.1)	-0.59 (0.07)*	0.16 (0.09)**	-0.27 (0.07)*	0.08 (0.09)
Adoption online banking	-0.31 (0.02)*	0.31 (0.03)*	0.59 (0.01)*	-0.38 (0.03)*	0.03 (0.02)	-0.33 (0.03)*
Average monthly assets	0.10 (0.01)*	-0.04 (0.01)*	-0.24 (0.01)*	0.06 (0.01)*	-0.16 (0.01)*	-0.84 (0.03)*
Average monthly liabilities	-0.12 (0.01)*	-0.13 (0.01)*	-0.40 (0.01)*	-0.98 (0.04)*	0.03 (0.01)*	1.11 (0.02)*
Age	0.23 (0.01)*	0.15 (0.02)*	0.02 (0.01)**	-0.04 (0.01)**	-0.29 (0.01)*	0.19 (0.01)*
Gender	-0.08 (0.02)*	0.08 (0.03)*	0.19 (0.01)*	0.18 (0.02)*	-0.37 (0.02)*	0.03 (0.02)
Income	-0.03 (0.01)*	0.04 (0.01)*	-0.01 (0.01)***	-0.04 (0.01)*	0.10 (0.01)*	-0.12 (0.01)*
Pseudo R ²	0.06					

Notes: * Significant at the 0.01 level, ** at the 0.05 level, *** at the 0.1 level.

Table 5. Marginal effects for univariate Probit models (Coefficient (standard error))

	Stock capital	Credit card	Debit card	Linked life Insurance	Account	Deposit
Length of the relationship	4.30e ⁻⁸ (0.00)**	7.14e ⁻³² (0.00)	0.005 (0.004)	6.35e ⁻²² (0.00)	0.00 (0.00)	9.54e ⁻²² (0.00)**
Cross-buying	2.92e ⁻⁸ (0.00)	-3.60e ⁻³¹ (0.00)	-0.04 (0.05)	-9.73e ⁻²¹ (0.00)**	0.00 (0.00)	-1.54e ⁻²¹ (0.00)
Product usage	9.57e ⁻⁷ (0.00)**	8.39e ⁻³⁰ (0.00)*	1.53 (0.03)*	7.58e ⁻²⁰ (0.00)*	0.00 (0.00)	2.26e ⁻²⁰ (0.00)*
Purchase recency	-5.20e ⁻⁸ (0.00)**	-1.77e ⁻⁴⁹ (0.00)	-0.12 (0.04)*	3.22e ⁻²⁵ (0.00)	0.00 (0.00)	8.99e ⁻²⁶ (0.00)
Cancellation recency	1.03e ⁻⁵ (0.00)	-1.63e ⁻⁴⁹ (0.00)	-0.45 (0.05)*	2.54e ⁻²⁵ (0.00)	0.00 (0.00)	-5.78e ⁻²⁷ (0.00)
Adoption online banking	-3.14e ⁻⁸ (0.00)	1.60e ⁻⁴⁵ (0.00)	0.46 (0.04)*	-1.83e ⁻²⁵ (0.00)	0.00 (0.00)	-6.00e ⁻²⁵ (0.00)
Average monthly assets	3.22e ⁻⁷ (0.00)**	-1.94e ⁻³³ (0.00)	-0.55 (0.03)*	1.36e ⁻²⁰ (0.00)*	0.00 (0.00)	-2.02e ⁻²⁰ (0.00)*
Average monthly liabilities	-1.77e ⁻⁷ (0.00)**	-4.59e ⁻³⁰ (0.00)*	-0.63 (0.04)*	-9.84e ⁻²⁰ (0.00)*	0.00 (0.00)	1.93e ⁻²⁰ (0.00)*
Age	4.17e ⁻⁷ (0.00)**	3.33e ⁻³⁰ (0.00)*	-0.18 (0.03)*	-1.03e ⁻²⁰ (0.00)***	0.00 (0.00)	3.48e ⁻²⁰ (0.00)*
Gender	-1.09e ⁻⁷ (0.00)***	8.50e ⁻³⁰ (0.00)*	0.35 (0.05)*	1.05e ⁻²⁰ (0.00)	0.00 (0.00)	-1.42e ⁻²⁰ (0.00)*
Income	1.36e ⁻⁸ (0.00)	3.26e ⁻³¹ (0.00)	0.05 (0.02)**	-4.79e ⁻²¹ (0.00)***	0.00 (0.00)	-1.03e ⁻²¹ (0.00)

Notes: *Significant at the 0.01 level, **at the 0.05 level, ***at the 0.1 level.

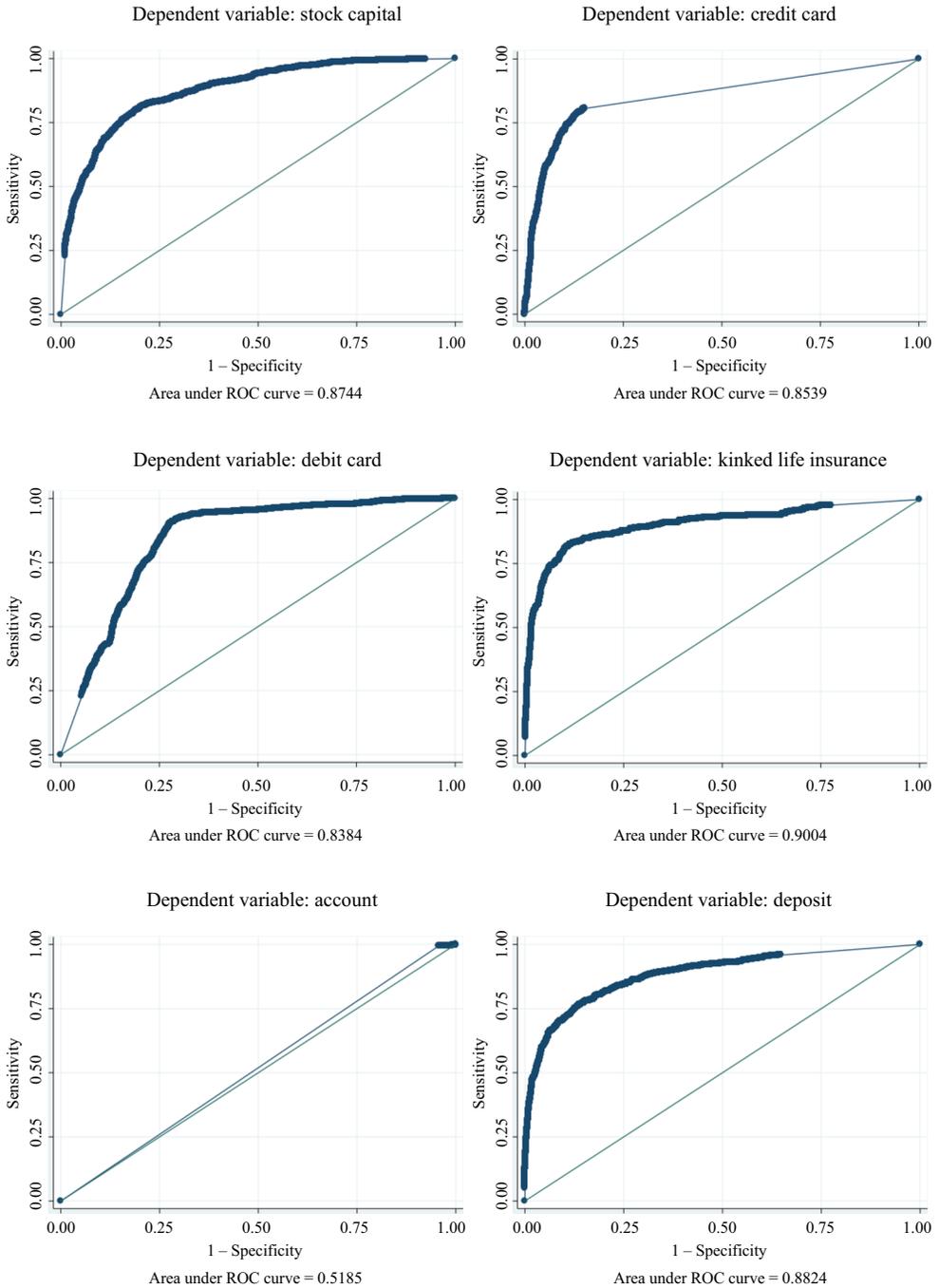


Fig. 2. ROC curves for univariate Probit models

3.3. Prediction of customer potential value

The aim of this paper is not to predict ownership rates only, but to estimate CPV that helps to develop CRM strategies, based on these estimates. We have information from the bank about the contribution margin of each customer during his/her relationship with the bank (called profit). Combining this information with the predicted ownership probabilities of the choice models that better predicts ownership rates (i.e., univariate Probit models), the potential value of each customer can be predicted. We have also performed a simple segmentation of customers according to their potential value (Table 6 presents descriptive statistics (about CPV) about high and low potential value segments). We have distinguished customers with a high and a low potential value using a median split in the estimation sample. This simple segmentation has often used in marketing practice (Rust, Verhoef 2005; Verhoef, Donkers 2001).

Table 6. Ex-post segmentation based on CPV (descriptive statistics calculated for CPV)

High potential value segment	Mean	10,402.55
	Std. dev.	31,609.39
	N	1.094
Low potential value segment	Mean	-2,838.01
	Std. dev.	16,463.04
	N	1.093

Additionally, in Table 7 we reflect the real power of this technique, that is, to relate current profitability with CPV. The objective of this second ex-post segmentation analysis is to know which customers are the most appropriate ones to invest in (e.g., through retention strategies, such as monetary and non-monetary promotions).

Table 7. Ex-post segmentation based on current profit and CPV (descriptive statistics calculated for CPV)

		High current profitability	Low current profitability
High potential value segment	Mean	10,447.86	533.31
	Std. dev.	31,674.84	107.92
	N	1.089	5
Low potential value segment	Mean	349.59	-2.852.66
	Std. dev.	0.74	16.499.43
	N	5	1.088

This will allow companies to invest in those customers (segments) that are (potentially) valuable for the company, but also minimise their investments in non-valuable customers. The following order should guide investment objectives in order to maximise the return of such investment:

1. Invest in customer with high current profitability and high CPV (the most valuable ones).
2. Invest in customers with low current profitability and high CPV.
3. Invest in high current profitability and low CPV. Companies also need to develop strategies to recapture this group of customers and move them to a more profitable segment (e.g., cross-selling strategies).
4. Invest in low current profitability and low CPV customers, the least valuable ones. Companies should minimise their investments in them or apply customer divestment strategies (Mittal, Sarkees 2006).

Conclusions

In this research we have carried out a dynamic analysis, which implies the calculation of CPV of customers of a multi-services retailer estimating a multi-product model. One of the most interesting results from this first part of the model is that those customers, who use more products, have a higher probability choosing more products in the future and consequently, have more potential value. The same occurs with the length of the relationship (in the special cases of stock capital, account and deposit), purchase recency or whether the customer has purchased a product in the previous month (in case of linked life insurance, account and deposit), cancellation recency or whether the customer has cancelled a product in the previous month (for stock capital), adoption of online banking (for credit and debit card), average monthly assets (for stock capital and linked life insurance), average monthly liabilities (in case of deposit), age (in case of stock capital, credit card and deposit), income (for credit card). Finally, with respect to gender, women have a higher probability of choosing products such as credit or debit cards, and men of choosing stock capital, account and deposit (investment products).

Our research contributes to the consumer behaviour literature insofar as, according to our knowledge, no previous work has examined collectively the proposed drivers of CPV in a multi-services retailer. In addition, as we have explained in the previous paragraph, we have generated new insights into the nature of choice behaviour of banking customers, indicating the significant predictors for each product considered. Moreover, for the prediction of potential value, the ownership probabilities that result from the Probit models can also be used to analyse in depth the choice process of each type of services studied and identify those customers who are more likely to buy these services according to the value of his/her predictors. Potential values can represent a measure of individual cross-selling opportunity and it can be used to recommend optional services to customers. In general, potential value is one element of marketing accountability that can be used for decision making purposes, facilitating the allocation of marketing resources.

We have also performed an ex-post segmentation identifying profiles of customers that helps us to explain the usefulness of this kind of models, for example, to guide CRM strategies. Numerous researchers have recommended customer value measures for selecting customers and designing marketing programs because customers selected on the basis of customer value generate more profits than customers selected using other measures, i.e., only socio-demographics variables.

Finally, with regard to the limitations and future research, we must highlight that our model has been tested using panel data of only one bank and it would be desirable to replicate the study using data from other banks, as well as in other locations and industries in order to observe differences or generalise the results. Another interesting future line of research is to develop a more completed model to obtain individual predictions of CLV. Additionally, we propose to design a more complete ex-post segmentation scheme of customers in order to improve CRM strategies of the company.

Acknowledgements

The authors would like to express their gratitude to the reviewers for their valuable guidance and advice throughout this research work.

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Antonia ESTRELLA-RAMÓN, PhD in Economics, Business and Legal sciences from the University of Almeria and PhD in Applied Economics from Hasselt University (Belgium). Assistant professor of Marketing at the University of Almeria (Spain). Her research interests include prediction of time series and data analysis applied to customer value modelling.

Manuel SÁNCHEZ-PÉREZ, PhD in Management from the University of Valencia (Spain). Full professor of Marketing at the University of Almeria (Spain). His major research interests are in the areas of marketing strategy, internationalization and innovation management.

Gilbert SWINNEN, PhD in Applied Economic Sciences at the University of Antwerp. Professor Emeritus of Marketing at the Hasselt University (Belgium). His research interests include retail marketing, customer value measurement and marketing research methods.

Koen VANHOOF, PhD in Computer Science from the Catholic University of Leuven. Full professor of Business Informatics at the Hasselt University (Belgium). His research interests include data mining, knowledge based systems, artificial intelligence and operations research.