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A Model to Determine Customer Lifetime Value in a Retail Banking Context

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During the past decade, the retail banking industry started to face a set of radically new challenges that had an overall negative impact on industry margin and profitability. In response to these challenges, more and more retail banks have focused on increasing the scale of their operations, which has led to a rising importance of mergers and acquisitions (M&A). From a Marketing perspective, M&A transactions are nothing other than the acquisition of the customer base of one company by another one, usually based on the assumption that the acquiring bank can manage this customer base more profitably than the selling bank was able to. It is therefore not surprising that questions about the valuation of customers have become more important than ever in the retail banking industry.

Our article provides a contribution in this area by presenting a customer valuation model that we developed in cooperation with a leading German retail bank, which takes account of the specific requirements of this industry. Our model is based on a combination of first-order Markov chain modeling and CART (classification and regression tree) and can deal equally well with discrete one-time transactions as with continuous revenue streams. Furthermore, it is based on the analysis of homogeneous groups instead of individual customers and is easy to understand and parsimonious in nature. In our article we provide proof of the practical value of our approach by validating our model using 6.2 million datasets. This validation shows how our model can be applied in day-to-day business life.

Keywords: Customer Relationship Management, Customer Lifetime Value, Retail Banking, Markov Chains, CART Analysis

Introduction

During the past decade, the retail banking industry started to face a set of radically new challenges that had an overall negative impact on industry margins and profitability. For the major part, these challenges have been caused by advances in modern information and telecommunication technologies, which ultimately have resulted in higher cost transparency and brand switching behavior. The resulting increase in competitive intensity has led to a commoditization of basic banking products, such as deposit taking, mortgages and credit extensions. This has further been fueled by an ever rising number of new entrants in the retail banking sector coming from industries as diverse as insurance and automobile production. The acquisition of the German Allbank by General Electric to create the GE Money Bank in 2004 as well as the increasing number of cars sold in a credit vs. cash mode are omnipresent witnesses of this evolution.

In response to these challenges, more and more retail banks have focused on increasing the scale of their operations, which has led to a rising importance of mergers and acquisitions (M&A). Particularly in the European retail banking environment, which has historically always been more fragmented than, for example, its North American counterpart, this trend is obvious. Prominent examples include the 1999 merger of BNP and Paribas in France, the acquisition of the German HypoVereinsbank by the Italian UniCredit Group in 2005 and the merger between Banca Intesa and Sanpaolo in 2006. There are at least four reasons that give room for the assumption that this trend towards increasing M&A in the European retail banking industry is likely to continue in the future. First, in many European countries retail banking is still very fragmented. For example in Italy, the five largest banks own less than half of the banking market. Second, the introduction of the Euro has led to further margin pressure due to an increase in cross-border competition among retail banks. This has resulted, among others, in a decreasing cost of borrowing and the loss of certain revenue streams such as commission fees on currency exchanges. Third, the Basel II framework, which sets new standards in risk management and capital adequacy, is associated with various changes in operations, the implementation of which create a significant cost burden that causes additional worry in this already tortured industry. Finally, mergers and acquisitions can be an appropriate strategy for banks to hedge macroeconomic risks, especially in Europe where loan portfolios are often severely home-biased.

From a Marketing perspective, M&A transactions are nothing other than the acquisition of the customer base of one company by another one, usually based on the assumption that the acquiring bank can manage this customer base more profitably than the selling bank was able to (Selden and Colvin, 2003). It is, therefore, not surprising that questions around the valuation of customers have become more important than ever in the retail banking industry. At the center of this interest lies the concept of customer lifetime value (CLV), which was defined more than 30 years ago by Kotler as ''the present value of the future profit stream expected over a given time horizon of transacting with the customer'' (Kotler, 1974, p. 24). The interest the Marketing discipline has recently been paying to CLV and the related subject of customer relationship management (CRM, e.g. Payne and Frow, 2005) has its roots in an evolution that started in the mid 1980 s. During that time, Dwyer *et al.* (1987) were among the first to highlight that Marketing, which has historically focused on the analysis of single transactions, should start paying attention to the relationship aspect of buyer–seller behavior. Only three years later, Reichheld and Sasser (1990) were able to show empirically that such a relationship-focus can lead to significant advantages since customers tend to generate higher profits the longer they stay with the company. Although Reinartz and Kumar showed that the relationship between lifetime and profitability may be more complex than Reichheld and Sasser assumed, especially in non-contractual relationships (Reinartz and Kumar, 2002; Reinartz and Kumar, 2000), it has nourished the idea that market-based assets, such as customer relationships, can lead to superior market performance and shareholder value (Srivastava *et al.*, 1998; Srivastava *et al.*, 1999).

Central to the idea of CRM is the assumption that customers differ in their needs and the value they generate for the firm, and that the way customers are managed should reflect these differences. CRM is therefore not about offering every single customer the best possible service, but about treating customers differently depending on their CLV. Such appropriate treatment can have many faces, starting with offering loyalty programs to retain the most profitable customers (Shugan, 2005) through to the abandonment of unprofitable customer relationships (Haenlein *et al.*, 2006). Yet, selecting between these strategies requires that the company knows the value its different customers generate. Consequently many papers have been published dealing with customer valuation as well as conceptual and practical challenges associated with it (e.g. Berger and Nasr, 1998; Jain and Singh, 2002; Rust *et al.*, 2004). However, only a few of them (e.g. Berger *et al.*, 2003; Keane and Wang, 1995) are tailored to specific industries and, hence, take account of sector-specific challenges associated with the implementation of those approaches. This is rather surprising as it has long been highlighted that customers may differ substantially across industries and that such differences should translate to the models used to value them. For example Jackson (1985) stressed that customers can be grouped into different categories, depending on the level of commitment they show to a particular seller. On one end of the spectrum is the ''always-a-share'' model, which assumes that customers can easily switch part or all of their spending from one vendor to another. The opposite end of the behavior spectrum assumes that, due to high switching costs, the buyer is committed to only one vendor to satisfy his or her needs. Once the customer stops purchasing from this vendor and changes to another one s/he is ''lost-for-good'' and cannot return to the vendor easily. Although the category every customer can be allocated to depends to a certain extent on this specific customer's preferences, it is also heavily influenced by the type of product sold and, hence, the industry. Building on this categorization, Dwyer (1989) showed that models used to value customers in these two settings differ substantially and proposed two approaches to determining CLV: a customer migration model and a customer retention model. It therefore makes intuitive sense that models to determine CLV should, at least to a certain extent, be adapted to specific industry characteristics.

Thinking about the retail banking environment, a model to determine CLV should satisfy at least three conditions: First, it needs to be able to handle discrete one-off transactions, which occur either only once in a lifetime or in very long purchasing cycles (e.g. mortgages), and continuous revenue streams (e.g. regular account maintenance charges) equally well. This is due to the fact that retail banks generate revenue in two main ways: by gaining a margin on lending and investment activities and by receiving transaction fees for transactions, credit cards, etc. (Garland, 2002). Second, in order to be easily implementable, it should focus on the valuation of homogeneous segments of customers instead of individual clients (Libai *et al.*, 2002). This requires a trade-off between reflecting individual client characteristics, such as product usage or lifetime phase, while at the same time taking account of the sheer size of an average retail bank's customer base, where individual valuation would result in disproportionate effort and unmanageable complexity. Finally, it needs to be easy to understand and parsimonious in nature to ensure its applicability in many business contexts. This specifically implies limiting data requirements to the information available in an average bank's information system.

In this article we present a customer valuation model, which we developed in cooperation with a leading German retail bank and which takes account of these specific requirements. This model is based on a combination of first-order Markov chain modeling and CART (classification and regression tree) analysis and has been validated using a sample of roughly 6.2 million datasets. In the next section we will discuss in more detail which type of data is needed as an input for our model. We will then develop our model conceptually and subsequently validate it to show how it has been implemented at our cooperating retail bank. The article finishes with a discussion of the limitations of our approach and areas of future research.

Data Requirements

Our model is based on four different groups of profitability drivers: age, demographics/ lifestyle data, product ownership (type and intensity) and activity level. These profitability drivers have been defined in collaboration with the management of the collaborating retail bank to ensure that all of them fulfill the aforementioned condition of being easily operationalizable using data available in the bank's information system.

Age

The work of Garland gives an indication that customer contribution (defined as relationship revenue minus relationship cost) is significantly influenced by the customer's age. Garland (2002, 2004) analyzed 1,100 personal retail customers of a New Zealand regional bank. Using a stepwise regression analysis, he showed that out of 26 non-financial profitability drivers representing perceived service quality, customer satisfaction, customer loyalty and customer demographics, only four had significant explanatory power for customer contribution. These were age, share-of-wallet, household income and joint accounts, with age being the most important one. Also Campbell and Frei (2004) stress that in a retail banking context age can be assumed to influence profitability by its impact on consumption patterns. For example middle-aged customers tend to be more profitable than younger ones because they tend to maintain higher balances and are more likely to have mortgages.

Demographics/Lifestyle

Before and immediately after acquisition, a company has only very limited data at its disposal which can be used to determine customer value. Hence, it is a common approach to use census and overlay data on demographics and lifestyle as a proxy for other unknown customer characteristics in early relationship stages. As noted by Campbell and Frei (2004) a typical retail bank spends between \$1 million and \$2 million annually to procure demographic data from outside vendors. This highlights the strong importance this type of data has in the day-to-day reality of many retail banks. Although demographic variables often tend to be only weak predictors of future behavior, we opted for their inclusion as profitability drivers due to their high relevance in business life.

Type and Intensity of Product Ownership

Several studies in the area of Direct Marketing and Customer Relationship Management have shown a strong relationship between future and past purchase behavior. For example, Venkatesan and Kumar (2004) provided an indication that past interpurchase time (i.e. the time period between two consecutive purchases) is a good predictor of future interpurchase time. This implies that the number of transactions in the previous period (which is, essentially, nothing other than the reverse of the interpurchase time) can serve as a predictor of the transaction volume in the current period. Similarly, Fader *et al.* (2005b) predicted future customer value based on information on past customer recency, frequency and monetary value with high accuracy. Among others, such findings can be explained by the existence of consumer inertia and switching cost which often result in customers sticking with a certain choice although changing would be preferable from a utility-maximization perspective. Many models used in Marketing literature, such as the NBD-Pareto (Schmittlein *et al.*, 1987) and BG-Pareto model (Fader *et al.*, 2005a) rely on this assumption and have proven to be very successful in modeling future transaction behavior. Since past and current purchase behavior are reflected by (current) type and intensity of product ownership, we decided on the inclusion of these variables as potential profitability drivers.

Activity Level

In every type of database analysis it is crucial to differentiate between contractual and non-contractual settings (Schmittlein *et al.*, 1987). In a contractual setting, such as magazine subscriptions or health club memberships, the company can easily observe whether a customer is still active, i.e. whether the customer is still doing business with the company, or not. In a non-contractual setting, such as catalog retailing or retail banking, where there may not be a steady revenue stream to be expected from the customer, the question of distinguishing between active and inactive clients is far from trivial. In the retail banking industry, for example, a client may no longer be active, but still own an account. One potential reason for this could be that in the absence of regular account maintenance charges, this ownership is not associated with any costs. Hence, there is only limited motivation for the customer to formally end the business relationship with his/her bank. However, inactive customers carry a higher risk of being unprofitable, because they no longer generate any revenue, while the client relationship may still lead to costs, for example due to direct marketing campaigns or regular mailing of account statements. It can therefore be assumed that customer value and profitability are heavily influenced by the activity level of the customer, speaking for the inclusion of this variable in our model.

With regard to the operationalization of these four potential profitability drivers, we measured the first one (age) by one indicator, the second one (demographics/lifestyle) by four indicators (marital status, sex, income, region type) and the third one (type and intensity of product ownership) using 11 and 15 items respectively (see details in Table 1). Concerning the last profitability driver (activity level), we defined two conditions under which the client was to be considered as active (vs. inactive), based on discussions with the management of the collaborating retail bank: First, all clients owning either a savings product, a home financing product, a loan or an insurance product were defined as being active due to the regular revenue streams (savings, interest payments, insurance fees) resulting from any of these products. Second, all clients owning transaction accounts, custody accounts and savings deposits were defined as being active when these accounts either showed a positive balance of at least 100 Euros and/or at least one transaction had been carried out during the last three months (for transaction accounts) or twelve months (for custody accounts and savings deposits).

Model Development

Our modeling approach consists of three steps: First, we use the aforementioned profitability drivers as predictor variables together with the target variable ''profit contribution'' in a CART analysis to build a regression tree. This tree helps us to cluster the customer base into a set of homogeneous sub-groups. Second, using these sub-groups as discrete states, we subsequently estimate a transition matrix which describes movements between them. In a final step this transition matrix is then used to calculate CLV for each of the homogeneous sub-groups using backward induction. We will now describe each of these three steps in more detail.

In the first step, the four potential profitability drivers and their associated items were used as predictor variables in a CART analysis with contribution margin as the target variable. CART analysis (classification and regression trees), first introduced by Breiman *et al.* (1984), is a technique for determining membership of a set of classes as a function of certain predictor variables. In this sense, it is comparable to traditional discriminant or regression analysis (see Armstrong and Andress, 1970; Armstrong, 1971; Crocker, 1971 for a discussion of similarities and differences). CART analysis assumes that the researcher identifies a target (response) variable, which is used to define the set of classes, and one or more predictor variables, both of which can be either discrete or continuous. For our analysis, we relied on 'contribution margin' as the target variable, which we defined as revenue resulting from interest payments and commission fees less liquidity cost, equity cost, risk cost and transaction cost covering the bank's cost of holding cash, maintaining a certain credit risk-dependent equity ratio, accepting the risk of credit loss and carrying out customer-related transactions respectively. With respect to predictor variables, using variables with different scales (nominal for type of product ownership vs. continuous for intensity of product ownership and contribution margin) was possible without running the risk of inconsistent results, due to the soft statistical assumptions underlying CART analysis. However, we faced the potential problem that client age can be assumed to heavily influence the other potential profitability drivers. With regard to demographics/lifestyle, marital status and income can be expected to be life cycle- and, therefore, age-dependent. Also type and intensity of product ownership are likely to depend on age, as discussed previously. Although correlations (even high ones) between different predictor variables are not a problem in CART analysis, we decided to carry out separate CART analyses for different age groups to appropriately take account of these effects.

In the second step, each of the resulting homogeneous groups was considered as one state of nature, between which we allowed the customers to flow

Table 1 Operationalization of Potential Profitability Drivers: Type and Intensity of Product Ownership

Type of product ownership		
TP-01	Client owns transaction account	(0 = no, 1 = yes)
TP-02	Client owns custody account	(0 = no, 1 = yes)
TP-03	Client owns savings deposits	(0 = no, 1 = yes)
TP-04	Client owns savings plan	(0 = no, 1 = yes)
TP-05	Client owns home savings agreement	(0 = no, 1 = yes)
TP-06	Client owns own home financing	(0 = no, 1 = yes)
TP-07	Client owns complex home financing	(0 = no, 1 = yes)
TP-08	Client owns personal loan	(0 = no, 1 = yes)
TP-09	Client owns arranged credit product	(0 = no, 1 = yes)
TP-10	Client owns life insurance	(0 = no, 1 = yes)
TP-11	Client owns other insurance products	(0 = no, 1 = yes)
Intensity of product ownership		
IP-01	Positive balance transaction account	(in EURO)
IP-02	Negative balance transaction account	(in EURO)
IP-03	Positive balance custody account	(in EURO)
IP-04	Negative balance custody account	(in EURO)
IP-05	Market value custody account	(in EURO)
IP-06	Turnover custody account during last 12 months	(in EURO)
IP-07	Balance savings deposits	(in EURO)
IP-08	Balance of savings plans	(in EURO)
IP-09	Balance home savings agreement	(in EURO)
IP-10	Balance own home financing	(in EURO)
IP-11	Balance complex home financing	(in EURO)
IP-12	Balance personal loan	(in EURO)
IP-13	# cash payments and withdrawals during last 3 months	(number of transactions)
IP-14	# form-based fund transfers during last 3 months	(number of transactions)
IP-15	# transactions custody account during last 12 months	(number of transactions)

following a first-order Markov process. A first-order Markov process is a stochastic process in which the transition probability between two discrete states of nature depends only on the properties of the immediate preceding state, independent of the path by which this state was reached – a condition also referred to as Markov property. The combination of different Markov processes in a row is called a Markov chain and the respective transition probabilities are usually summarized in a transition matrix. Markov chains have a long history in marketing in general (Styan and Smith, 1964; Thompson and McNeal, 1967), as well as customer lifetime valuation in particular (Morrison *et al.*, 1982; Pfeifer and Carraway, 2000; Rust *et al.*, 2004). Due to the fact that the different groups resulting from the CART analysis were defined as being age-dependent (although, as will be seen later, there is no one-to-one relationship between states of nature and age groups), the state each customer belongs to can change due to increasing age, even if all other factors remain constant. To estimate the corresponding transition probabilities, we determined the state of nature each customer belonged to at the beginning and end of a predefined time interval T by using the decision rules resulting from the aforementioned CART analysis. By counting the number of customers who moved between two states and dividing this number by the total number of customers, we were able to estimate transition frequencies that served as proxies for the underlying transition probabilities.

In the final step, we determined the CLV for each customer group as the discounted sum of state-dependent contribution margins, weighted with their corresponding transition probabilities. This calculation was carried out using backward induction. We started with calculating the value of a group of customers in the second-to-last age group $G-1$ and state of nature k. This value can be determined by multiplying the contribution margin to be expected from a client in age group G and state of nature j with the probability that a customer will transit from state k in $G-1$ into state j in G. Summing these products over all potential states of nature for age group $G(j = 1,2, \ldots n)$ and discounting them back one period using a pre-defined discount rate, results in an estimate for the value of a group of customers in the second-to-last age group $G-1$ and state of nature k. Based on the same logic we then determined customer values for all periods $G-1$, $G-2, \ldots ,2$ and associated states of nature, which finally helped us to calculate the CLV of a client in state of nature k at the beginning of the analysis period.[1]

Model Validation

To carry out validation, we took two random samples from the customer base of our cooperating retail bank, the first one consisting of 687,000 and the second one of 5.5 million datasets. To ensure confidentiality of this data we multiplied all monetary values (such as, for example, contribution margin) in the following output with an arbitrary factor, which we chose small enough not to distort key patterns in the data. They are, therefore, no longer expressed in Euros, but in currency units (CU).

In order to reflect the latent nature of the predictor variables' type and intensity of product ownership without loosing the detailed information provided by their respective items, we calculated additional predictor variables for the CART analysis by summing up all or sub-sets of their formative indicators. This approach is in line with the basic philosophy behind this type of measurement (see Jarvis *et al.*, 2003 for more details). Regarding type of product ownership, we defined the variable ''*usage intensity*'' as measuring the number of products owned and calculated it by summing up all items TP-01 to TP-11. With regard to intensity of product ownership, we calculated three additional variables: First, ''*total savings*'' were defined as the sum of positive balances of transaction (IP-01) and custody accounts (IP-03) plus the balances of savings deposits (IP-07) and savings plans (IP-08). Second, ''*total liabilities*'' were determined as the sum of negative balances of transaction (IP-02) and custody account (IP-04) plus the balances from home savings agreements (IP-09), as well as own (IP-10) and complex home financing (IP-11) and personal loans (IP-12). Finally, ''*client's net wealth*'' (CNW) was calculated as the sum of total savings and total liabilities.

We then defined the indicators of the variables demographics/lifestyle, type and intensity of product ownership, as well as the activity level and the four newly created composite variables (i.e. usage intensity, total savings, total liabilities, client's net wealth) as predictor variables. Together with contribution margin as target variable, we carried out a CART analysis based on the first sample consisting of 687,000 datasets. Hereby, we split the sample into a training sample (172,000 datasets, ~25%) and a testing sample (515,000 datasets, ~75%). This analysis was carried out using the ALICE software tool, Version 6.5. To reduce the complexity of our analysis, we started with the hypothesis of profitability drivers being equal across different age groups and used the training sample to estimate a regression tree for all age groups simultaneously. In a second step we split the testing sample into six different sub-samples according to client's age (<19 years, 19–29 years, 30–39 years, 40–49 years, 50–65 years, >65 years) and tested whether this (pooled) tree was able to classify datasets in each of these sub-samples correctly. While this was the case for five sub-samples (significance of all nodes above 0.9981), the tree was not able to classify the <19 years age-group correctly (three out of eleven p-values insignificant). We therefore carried out a second CART analysis using the training sample to estimate a separate regression tree for clients <19 years. These two regression trees (one for clients <19 years and one for clients of age 19 and above) then helped to split customers in the different age-bands into 10 and 22 different homogeneous sub-groups respectively. Finally, we defined one additional segment to cover clients who terminated the relationship with the bank, whether due to brand switching or death.

Figure 1 shows the resulting regression tree for clients of age 19 and above.[2] As can be seen, contribution margin is primarily influenced by client net wealth with higher net wealth leading to higher average contribution margins. For clients with negative net wealth (debtors), profitability is subsequently dependent on the size of personal loans while for high net wealth clients (CNW > 7,500) it is a function of custody account turnover (IP-06). For customers with medium net wealth ($350 < \text{CNW} \leqslant 7{,}500$), which represent roughly 45% of the total client base (see Table 2), the main driver of higher contribution margins is type and intensity of product ownership (personal loans, savings products, custody accounts), as well as their activity status and usage intensity. Finally, clients with low net wealth ($0 < \text{CNW} \leqslant 350$), accounting for about 16% of the client base, are primarily characterized by negative contribution margins due to low usage intensity.

Subsequently, we used the second sample consisting of 5.5 million datasets to estimate the transition probabilities between these different states by assuming an arbitrarily chosen time interval T of 2 years. We first split the client base into 39 different age-bands covering two years each, from clients 1–2 years old up to clients aged 77–78 years. Using the decision rules resulting rules from the aforementioned CART analysis (see Figure 1 and Table 2), we then determined the segment each client belonged to at the beginning and end of this 2-year timeframe. The transition probabilities were subsequently approximated by the transition frequencies calculated as the number of clients either staying in one segment or moving between two divided by the number of all clients in the respective segment.[3]

Table 3 shows one exemplary transition matrix for the 19*th* age-band (clients aged 37/38 years). As can be seen in Table 2, *Segment 1* primarily consists of customers holding small- to medium-sized personal loans. Since these loans are usually not paid back within one period, the majority of customers stay within this segment in the next period (41%). However, some customers also increase the size of their loans and move to Segment 2 (12%), while others pay their loans back and decide to terminate their relationship with the bank (12%). Users of large personal loans and mortgages are within *Segment 2* (total liabilities > 5,250 CU). Due to the long life of such loans, 66% of these customers stay within Segment 2 and only a small fraction (2%) pays them back within the same period and leaves the bank. *Segment 3* is also composed of debtors. However, unlike

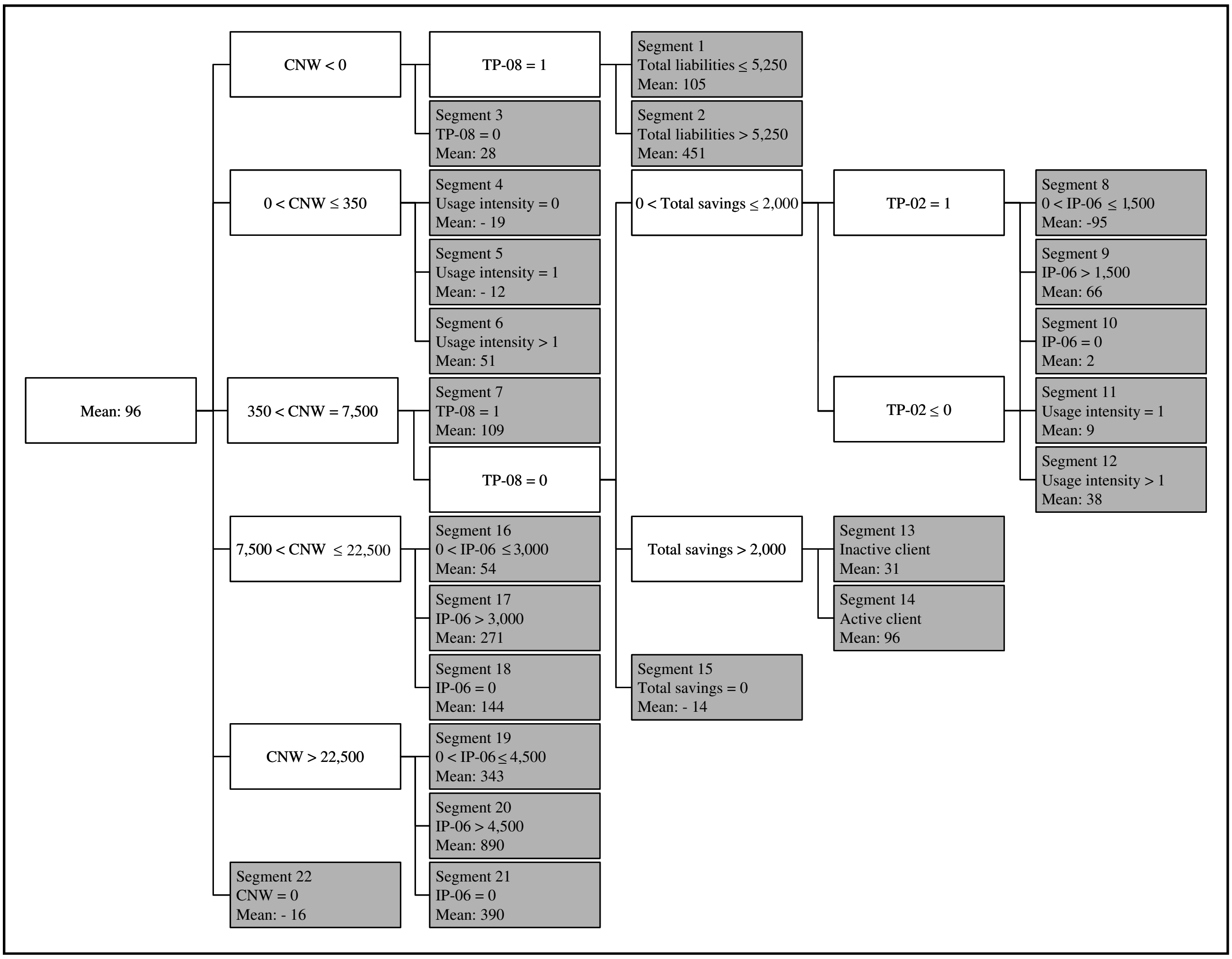

Figure 1 Regression Tree for Clients of Age 19 and Above (Mean = Average Contribution Margin of Segment in CU)

Segments 1 and 2, these customers are not subject to contractual credit periods but consume bank overdrafts. Due to the high interest rate associated with these products, the majority decide to switch to a (cheaper) personal loan in the next period and move to Segment 2 (80%). *Segment 4* consists of inactive customer relationships with small net wealth, the majority of which (87%) are not activated within the next period. In most cases, these clients are not interested in actively managing their account. In cases where they decide to do so, 7% terminate their relationship with the bank. Although active, clients in *Segment 5* are also characterized by low net wealth. Except for the rare cases in which these clients decide either to increase their net wealth (8% move to Segment 11) or to raise a personal loan (5% move to Segment 1), the majority remain within the same segment (46%), become inactive (22% move to Segment 4) or terminate the client relationship (10%). Clients in *Segment 6* have a higher usage intensity than those in Segment 5. Consequently, the share that decides to increase its net wealth (14% move to Segment 12) or to raise a personal loan (23% move to Segment 1 or 2) is substantially higher and only 3% close their account.

Clients who at the same time hold savings with the bank and consume a personal loan, are within *Segment 7*. While 21% of these clients remain within the same segment during the next period, an equally large group pays their loans back (20% move to Segment 12 or 14) or increases total liabilities (17% move to Segment 1). Customers in *Segment 8* have small to medium net wealth (⩽ 7,500 CU) and small custody account turnover that is often below break-even point. Nearly half of these clients (48%) stay within the same segment, while the others either reduce their net wealth even further (20% move to Segments 4, 5 and 6) or close their account (9%). Clients in *Segment 9* also have small to medium net wealth and limited custody account turnover (yet above that of Segment 8). During the next period 10% reduce their net wealth and move to Segments 5 or 6. Roughly one third remain in the same segment (34%) and another third increase net wealth and custody account turnover (30% move to Segment 17). Clients in *Segment 10* are comparable to the ones in Segments 8 and 9 with respect to net wealth, but do not perform any share trading. In the next period 24% do not change this, 10% start using a custody account, but with limited turnover (Segment 8), while another

Table 2 Overview of Segmentation Criteria and Segment Description

Segment #	Average Contribution Margin (Segment size)	Segmentation Criteria	Description
20	890 (2.1%)	CNW > 22,500 IP-06 > 4,500	Clients with high net wealth and high custody account turnover
2	451 (4.7%)	CNW < 0 Liabilities > 5,250 TP-08 = 1	Clients with mortgages and large personal loans
21	390 (2.2%)	CNW > 22,500 IP-06 = 0	Clients with high net wealth, focused on traditional investment strategies
19	343 (2.2%)	CNW > 22,500 0 < IP-06 ⩽ 4,500	Clients with high net wealth and low to medium custody account turnover
17	271 (4.2%)	CNW > 7,500 CNW ⩽ 22,500 IP-06 > 3,000	Clients with medium net wealth and medium to high custody account turnover
18	144 (4.8%)	CNW > 7,500 CNW ⩽ 22,500 IP-06 = 0	Clients with medium net wealth, focused on traditional investment strategies
7	109 (2.3%)	CNW > 350 CNW ⩽ 7,500 TP-08 = 1	Clients simultaneously consuming investment and financing products
1	105 (4.1%)	CNW < 0 Liabilities ⩽ 5,250 TP-08 = 1	Clients owning small to medium personal loans
14	96 (10.1%)	CNW > 350 CNW ⩽ 7,500 Savings > 2,000 TP-08 = 0 Active client	Clients with small to medium net wealth, focused on payment transactions and savings products
9	66 (1.7%)	CNW > 350 CNW ⩽ 7,500 0 < Savings ⩽ 2,000 TP-08 = 0 TP-02 = 1 IP-06 > 1,500	Clients with small to medium net wealth, focused on using custody accounts; only limited use of other services
16	54 (5.3%)	CNW > 7,500 CNW ⩽ 22,500 0 < IP-06 ⩽ 3,000	Clients with medium net wealth and low custody account turnover
6	51 (0.9%)	CNW > 0 CNW ⩽ 350 Usage intensity > 1	(Often relatively young) clients with very low net wealth, focused on payment transactions and short-term savings products
12	38 (4.7%)	CNW > 350 CNW ⩽ 7,500 0 < Savings ⩽ 2,000 TP-08 = 0 TP-02 = 0 Usage intensity > 1	Clients with low net wealth, focused on payment transactions and a limited amount of savings products
13	31 (5.5%)	CNW > 350 CNW ⩽ 7,500 Savings > 2,000 TP-08 = 0 Inactive client	Clients with low to medium net wealth, focused on investment; payment transactions conducted using alternative bank accounts
3	28 (4.0%)	CNW < 0 TP-08 = 0	Clients with overdrafts
11	9 (12.4%)	CNW > 350 CNW ⩽ 7,500 0 < Savings ⩽ 2,000 TP-08 = 0 TP-02 = 0 Usage intensity = 1	Clients with low net wealth, focused on savings products

Table 2 (*continued*)

Segment #	Average Contribution Margin (Segment size)	Segmentation Criteria	Description
10	2 (1.7%)	CNW > 350 CNW ⩽ 7,500 0 < Savings ⩽ 2,000 TP-08 = 0 IP-06 = 0 TP-02 = 1	Clients with low net wealth and (probably inactive) custody accounts without turnover
5	−12 (7.1%)	CNW > 0 CNW ⩽ 350 Usage intensity = 1	Clients with very low net wealth (i.e. often clients without assets or using the bank as secondary correspondent bank)
15	−14 (4.7%)	CNW > 350 CNW ⩽ 7,500 Savings = 0 TP-08 = 0	Clients focused on stock trading, small custody account turnover and small to medium custody account volume
22	−16 (5.6%)	CNW = 0	Clients without assets and liabilities, often using only specific services (e.g. credit cards, safe-deposit boxes)
4	−19 (7.7%)	CNW > 0 CNW ⩽ 350 Usage intensity = 0	Inactive accounts with 'dead' savings books or unused custody accounts
8	−95 (1.7%)	CNW > 350 CNW ⩽ 7,500 0 < Savings ⩽ 2,000 0 < IP-06 ⩽ 1,500 TP-08 = 0 TP-02 = 1	Clients focused on stock trading with small turnover
0	0		Terminated client relationships (due to brand switching or death)

Table 3 Transition Matrix for 19th Age-Band: Clients Aged 37/38 Years

State of Nature *i*	State of Nature *j* (Transition Probability in %)																						
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**0**
1	**41**	**12**	0	1	5	2	3	0	0	0	4	4	0	3	0	0	0	1	0	0	0	11	**12**
2	**17**	**66**	1	0	1	1	3	0	0	0	1	2	0	1	0	0	0	1	0	0	0	4	**2**
3	1	**80**	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	7
4	0	0	0	**87**	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	3	**7**
5	**5**	0	0	**22**	**46**	1	0	0	0	0	**8**	1	1	1	1	0	0	0	0	0	0	3	**10**
6	**19**	**4**	1	4	12	13	5	1	0	0	5	**14**	0	7	2	0	0	2	0	0	0	6	**3**
7	**17**	7	1	1	2	4	**21**	2	0	1	2	**9**	1	**11**	1	1	1	8	0	0	1	5	3
8	1	1	0	**7**	**10**	**3**	1	**48**	2	1	1	1	3	2	1	2	0	2	0	0	0	5	**9**
9	0	0	0	0	**6**	**4**	3	0	**34**	0	0	4	3	2	0	0	**30**	0	3	6	0	2	4
10	5	2	1	1	2	4	7	**10**	0	**24**	2	5	1	17	0	0	0	**10**	0	0	1	5	3
11	6	1	0	5	11	1	0	1	0	0	43	2	3	6	0	0	0	2	0	0	0	5	**13**
12	10	2	1	1	4	5	5	0	0	0	8	29	1	19	1	0	0	5	0	0	1	5	**3**
13	0	0	0	6	6	1	0	10	1	0	7	1	34	1	0	1	1	8	0	0	1	3	18
14	6	2	0	1	3	2	4	2	0	1	8	9	1	33	0	1	1	14	0	1	2	6	**5**
15	0	1	7	1	3	0	0	2	0	0	0	0	0	0	58	0	0	4	0	0	0	5	19
16	1	2	0	0	1	1	4	10	6	0	0	1	1	4	0	**37**	**14**	0	**11**	3	0	2	1
17	0	1	1	0	1	2	2	0	5	0	0	1	0	3	0	0	**42**	0	0	**39**	0	1	2
18	2	1	1	2	3	1	2	**8**	0	1	3	2	3	**8**	1	0	0	**42**	0	0	7	5	**8**
19	1	2	1	0	0	1	1	1	2	0	0	1	0	1	0	**16**	9	0	44	**19**	0	1	1
20	0	2	0	0	0	2	0	0	1	0	0	0	0	1	0	0	11	0	0	**79**	0	1	**2**
21	1	2	1	1	1	0	1	2	0	1	2	1	1	3	0	0	0	23	0	0	46	5	**8**
22	1	1	2	0	1	0	0	0	0	0	0	0	0	0	8	0	0	1	0	0	0	53	**33**

10% increase their net wealth, but decide to invest in traditional savings products (move to Segment 18).

Segment 11 consists of clients with low usage intensity and strong focus on savings products. These

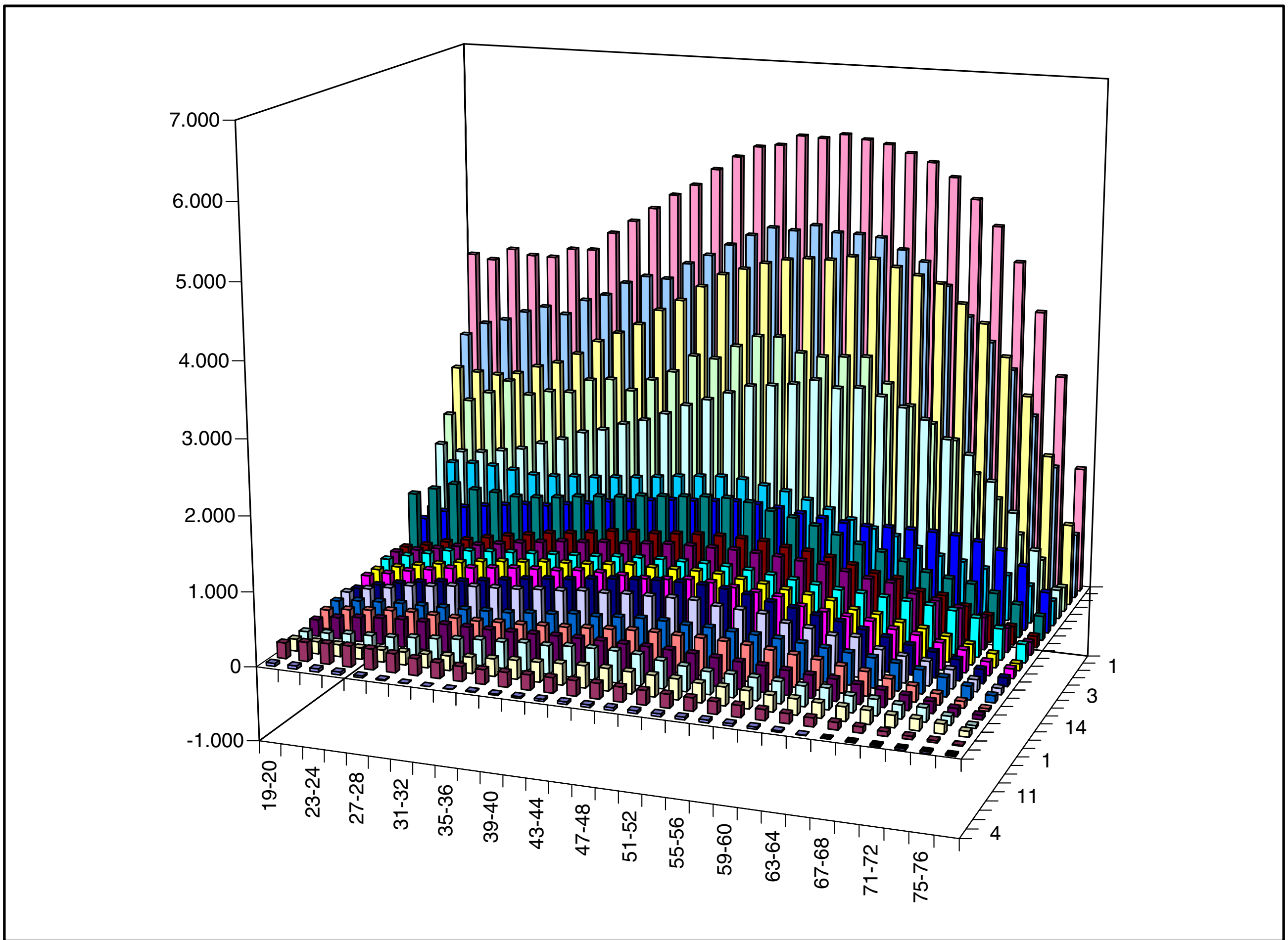

Figure 2 CLV (in Currency Units) for Clients of Age 19 and Above by Segment (State of Nature)

are usually clients that use the bank as a secondary correspondent bank for short- and medium term financial investment, leading to a relatively large churn probability for this segment (13%). Clients in *Segments 12*, *13*, *14* and *15* are similar to the ones in Segment 11 with respect to product usage. Segments 12 and 14 do, however, have a higher usage intensity, leading to significantly lower churn probabilities (3% and 5% respectively). Clients in *Segment 16* have medium net wealth (between 7,500 and 22,500 CU), but relatively small custody account turnover (below 3,000 CU). While the majority of these customers stays within the same segment (37%), 14% significantly increase their custody account turnover and move to Segment 17 while another 11% also increase their net wealth and move to Segment 19. Clients in *Segment 17* have larger custody account turnover than the ones in Segment 16. The main share of these clients can be maintained in this attractive state during the next period (42%) and some (39%) even increase their net wealth and profitability from the bank's perspective.

In contrast to clients in Segments 16 and 17, customers in *Segment 18* do not conduct any share trading and are unlikely to change this in the immediate future (42% stay within Segment 18). Of these, 16% decide to reduce their net wealth (moving to Segments 8 and 14) or to close their account (8%). Clients in *Segment 19* have large net wealth (above 22,500 CU) and low to medium custody account turnover (below 4,500 CU). In the next period 19% increase their custody account turnover and move to Segment 20, while an equally large share (16%) reduces turnover, transferring to Segment 16. The bank's most profitable customers are within *Segment 20*. These customers do not only have large net wealth, but also significant custody account turnover and stability (79% stay within Segment 2). The churn probability is only 2% which is remarkable, given that these customers are also likely to be attractive for competing retail banks. While clients in *Segment 21* also have substantial net wealth, they do not conduct any custody account transactions and have a significantly larger probability of closing their account (8%). Finally, customers in *Segment 22* have neither savings nor liabilities with the bank. Many of these clients only use specific services (e.g. safe-deposit boxes) and others have a credit card for which the associated transactions are conducted via an alternative correspondent bank. Very often these clients have already terminated their client relationship and transferred their net wealth to another bank, but not yet officially closed their account. Consequently, 33% are likely to do so in the next period.

Table 4 CLV (in Currency Units) for Clients of Age 19 and Above by Segment (State of Nature)

Age Groups	Segment (State of Nature) #																					
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
19–20	266	1,069	706	40	212	313	390	259	1,896	350	222	345	286	410	161	1,541	2,919	398	2,505	4,027	622	161
21–22	350	1,173	1,386	43	257	392	451	299	2,128	416	288	417	323	472	177	1,462	3,110	483	2,470	3,973	761	162
23–24	409	1,270	1,406	42	275	443	528	329	2,269	487	325	475	345	527	203	1,483	3,185	547	2,456	4,145	852	159
25–26	458	1,223	1,398	38	282	505	591	359	2,466	538	354	527	360	590	217	1,535	3,325	621	2,504	4,077	904	153
27–28	501	1,215	1,367	25	279	535	656	375	2,292	592	371	581	363	642	231	1,590	3,422	653	2,627	4,075	946	163
29–30	541	1,186	1,329	13	253	571	716	368	2,371	633	376	629	373	690	264	1,697	3,338	676	2,710	4,214	991	173
31–32	585	1,203	1,337	5	226	600	763	365	2,385	667	377	662	382	742	285	1,787	3,565	696	2,863	4,225	1,001	180
33–34	630	1,235	1,364	0	209	615	819	360	2,587	697	379	690	397	780	314	1,915	3,666	716	3,069	4,489	1,051	196
35–36	676	1,280	1,381	5	198	634	850	378	2,626	717	379	727	409	825	347	1,982	3,862	740	3,216	4,680	1,094	215
37–38	712	1,313	1,412	12	193	664	892	385	2,492	732	385	745	440	847	354	2,095	3,980	759	3,366	4,881	1,154	232
39–40	739	1,340	1,441	16	196	682	944	406	2,675	768	396	764	463	882	380	2,176	3,968	778	3,590	5,092	1,192	251
41–42	783	1,388	1,478	23	202	717	969	422	2,817	774	406	793	503	896	378	2,299	4,206	807	3,754	5,252	1,236	262
43–44	816	1,412	1,520	28	205	721	979	447	3,067	770	412	823	501	927	406	2,444	4,347	825	3,972	5,490	1,274	283
45–46	842	1,440	1,551	32	205	744	1,007	469	3,051	759	416	817	528	955	417	2,553	4,515	838	4,166	5,685	1,293	293
47–48	865	1,469	1,579	34	207	750	1,031	491	3,253	785	412	827	550	967	421	2,675	4,673	840	4,265	5,843	1,321	296
49–50	874	1,481	1,571	36	196	763	1,044	501	3,418	820	412	839	551	971	412	2,799	4,798	849	4,367	5,886	1,348	289
51–52	874	1,453	1,515	36	192	767	1,043	495	3,436	811	407	833	532	976	368	2,833	4,780	841	4,438	6,031	1,340	282
53–54	856	1,366	1,463	37	181	722	1,036	498	3,240	778	395	795	536	964	334	2,881	4,872	823	4,478	6,017	1,317	274
55–56	814	1,305	1,376	35	174	711	986	494	3,210	751	378	767	518	949	302	2,963	4,795	794	4,481	6,086	1,276	255
57–58	751	1,224	1,277	37	165	692	965	479	3,237	728	362	723	512	925	305	2,876	4,796	761	4,550	6,034	1,241	247
59–60	706	1,132	1,164	32	155	602	915	452	3,260	630	351	689	498	910	299	2,908	4,771	729	4,538	5,989	1,207	238
61–62	643	1,037	1,071	28	142	572	846	427	2,919	595	327	647	476	848	289	2,820	4,626	694	4,449	5,886	1,191	217
63–64	595	964	999	19	129	512	764	399	2,637	567	305	559	448	782	269	2,694	4,482	683	4,359	5,781	1,210	210
65–66	526	866	867	7	115	528	725	354	2,421	540	292	531	424	763	281	2,553	4,176	665	4,272	5,597	1,212	197
67–68	461	751	791	–4	97	402	586	322	2,222	467	259	460	397	651	219	2,314	3,779	646	4,021	5,319	1,210	187
69–70	394	700	743	–11	80	351	566	265	1,782	428	227	413	364	592	214	2,128	3,450	624	3,776	4,972	1,197	181
71–72	342	661	680	–21	60	321	452	212	1,466	364	197	345	316	528	182	1,790	3,097	591	3,344	4,503	1,145	158
73–74	278	567	624	–24	43	251	364	148	1,005	303	158	278	254	436	184	1,394	2,483	527	2,833	3,842	1,059	150
75–76	188	449	514	–24	28	158	249	89	686	185	107	188	179	328	116	902	1,800	419	2,035	2,979	876	128
77–78	113	325	340	–16	9	82	153	33	335	128	58	92	95	175	37	392	883	247	1,108	1,720	551	75

Using these transition probabilities, the customer lifetime values for each customer segment were determined using backward induction as described above. As can be seen in Table 4 and Figure 2, clients with highest CLV can be found in Segment 20 (net wealth above 22,500 and custody account turnover above 4,500), closely followed by Segments 17, 16 and 9. This is especially true for elderly customers, mainly caused by their higher contribution margins and higher probability to stay within these attractive segments. Only for clients of age 60 and above does CLV start to decline due to shorter overall lifetimes. Next to customers with high custody account turnover, users of account overdrafts (Segment 3) and large personal loans or mortgages (Segment 2) are also part of the top quartile with respect to CLV, as long as these customers are in low or medium age segments. The high profitability of users of overdraft facilities can be explained by the high interest rates charged for these products as well as the fact that many of these customers subsequently consume personal loans of significant amounts (transition to Segment 2). However, retired customers within these segments prove to have only medium CLV, due to the fact that the majority of interest payments have already been conducted before this point in time.

The high importance of net wealth and custody account turnover can also be seen when looking at the bottom quartile with respect to CLV as these customers are mainly characterized by low net wealth and the absence of a custody account. Inactive client relationships (Segment 4) as well as customers with very low net wealth and low usage intensity (Segments 5 and 22) fall into this category. Their low CLV is hereby less a function of low current usage but more a consequence of the fact that these customers primarily use alternative correspondent banks to conduct payment transactions and are unlikely to change this in future. With respect to the remaining 50% of clients with medium CLV, customers are characterized by medium net wealth and the absence of a custody account (Segments 11, 12, 13, 14) as well as custody account ownership, but no (Segment 10) or very limited turnover (Segments 8, 15). Additionally, customers with low net wealth but high usage intensity (Segment 6) belong to this category, unlike clients with low net wealth and low usage intensity (Segment 5) who belong to the bottom quartile. After client net wealth and custody account turnover, usage intensity counts among the most important profitability drivers. For example, the differences between Segments 11 and 12 in terms of CLV are only a function of differences in usage intensity.

Limitations and Areas of Further Research

Summarizing our findings, we have highlighted that M&A transactions have become of increasing importance for the European retail banking industry in recent years. Since M&A activities are, at the end, nothing other than the acquisition of the customer base of one company by another one, this trend has resulted in an increasing interest in questions of customer valuation. We therefore proposed a model to value retail banking customers that is based on a combination of first-order Markov chain modeling and CART analysis. Using the profitability driver's age, demographics/lifestyle, type and intensity of product ownership and activity level as predictor variables, we carried out age-dependent CART-analyses to split customers of similar age into homogeneous sub-groups concerning the target variable contribution margin. These groups then served as states of nature between which we allowed customers to flow following a first-order Markov process with corresponding transition probabilities being approximated by estimated transition frequencies. Finally, CLV for each customer was determined as the discounted sum of state-dependent contribution margins, weighted by their corresponding transition probabilities. As can be seen our model can deal equally as well with discrete one-time transactions as with continuous revenue streams, is based on the analysis of homogeneous groups instead of individual customers and is easy to understand and parsimonious in nature. It therefore fulfills the three general conditions for such a model as stated in the introduction. Finally, we validated our model using 6.2 million datasets to show how it can be applied in day-to-day business life and how it has been implemented at our cooperating retail bank.

Due to its simple structure and the fact that it only requires data available in an average bank's IT system, our model can easily be implemented by any retail bank, where it may serve as a tool for customer base analysis. For example, customers could be grouped according to their CLV and, for each of the resulting customer groups, the company could then define a specific customer relationship management strategy. Our model could also serve as a tool to optimize the current client base and focus on unprofitable customers, either by serving them using special business models (Rosenblum *et al.*, 2003) or by abandoning them (Haenlein *et al.*, 2006). Finally, a retail bank could use our model to assign acquisition allowances for new customers by comparing prospects with existing customers and, hence, estimating the lifetime value to be expected from an acquisition prospect beforehand. Beyond the retail banking industry, companies could build on our general approach (i.e. combining CART analysis with Markov chain modeling) to create similar models that take account of the specific requirements to be met in their industries.

Despite its merits and ease-of-use, our approach also encompasses some limitations with respect to model building. First, we assumed client behavior to follow a first-order Markov process, where the transition probabilities depend only on the behavior during the last period. Although this does not mean that behavior of earlier periods has no influence on current behavior, there is no explicit modeling of such effects. Second, our analysis builds on the assumption that the transition matrix will be stable and constant over time, which seems appropriate for medium-term forecasts, as long as there are no obvious and foreseeable reasons for a dramatic shift in customer behavior. It might not, however, be a sensible assumption for long-term forecasting. Regarding areas of further research, we think that combining our approach with the work on customer equity of Rust *et al.* (2004) could be particularly interesting. In our model, we assumed marketing budgets to be constant for all customers. Comparable to the approach of Rust *et al.* (2004), one could relax this assumption and estimate the effect of customer-specific marketing activities on the transition probabilities between the different states of nature. However, unlike their approach, our transition probabilities do not represent (external) brand switching, but (internal) changes in customer behavior. Since the transition probabilities have a direct influence on the CLV of each customer, it would then be possible to determine the potential increase or decrease in individual or aggregated CLV resulting from these marketing activities.

Notes

1. Details on the mathematical computations and formulas used can be obtained from the first author on request.
2. In the following discussion and interpretation we only focus on the results for clients of age 19 and above. The corresponding results for clients younger than 19 years can be obtained from the first author on request.
3. Due to space constraints, we do not show each of the resulting 39 transition matrices in detail. However, detailed results can be obtained from the first author on request.

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