“Alternative profit scorecards for revolving credit”

Luis Javier Sánchez Barrios

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ABSTRACT

The aim of this PhD project is to design profit scorecards for a revolving credit using alternative measures of profit that have not been considered in previous research. The data set consists of customers from a lending institution that grants credit to those that are usually financially excluded due to the lack of previous credit records.

The study presents for the first time a relative profit measure (i.e.: returns) for scoring purposes and compares results with those obtained from usual monetary profit scores both in cumulative and average terms. Such relative measure can be interpreted as the productivity per customer in generating cash flows per monetary unit invested in receivables. Alternatively, it is the coverage against default if the lender discontinues operations at time t.

At an exploratory level, results show that granting credit to financially excluded customers is a profitable business. Moreover, defaulters are not necessarily unprofitable; in average the profits generated by profitable defaulters exceed the losses generated by certain non-defaulters. Therefore, it makes sense to design profit (return) scorecards. It is shown through different methods that it makes a difference to use alternative profit measures for scoring purposes. At a customer level, using either profits or returns alters the chances of being accepted for credit. At a portfolio level, in the long term, productivity (coverage against default) is traded off if profits are used instead of returns. Additionally, using cumulative or average measures implies a trade off between the scope of the credit programme and customer productivity (coverage against default).

The study also contributes to the ongoing debate of using direct and indirect prediction methods to produce not only profit but also return scorecards. Direct

scores were obtained from borrower attributes, whilst indirect scores were predicted using the estimated probabilities of default and repurchase; OLS was used in both cases. Direct models outperformed indirect models. Results show that it is possible to identify customers that are profitable both in monetary and relative terms. The best performing indirect model used the probabilities of default at t=12 months and of repurchase in t=12, 30 months as predictors. This agrees with banking practices and confirms the significance of the long term perspective for revolving credit. Return scores would be preferred under more conservative standpoints towards default because of unstable conditions and if the aim is to penetrate relatively unknown segments. Further ethical considerations justify their use in an inclusive lending context. Qualitative data was used to contextualise results from quantitative models, where appropriate. This is particularly important in the microlending industry, where analysts' market knowledge is important to complement results from scorecards for credit granting purposes.

Finally, this is the first study that formally defines time-to-profit and uses it for scoring purposes. Such event occurs when the cumulative return exceeds one. It is the point in time when customers are exceedingly productive or alternatively when they are completely covered against default, regardless of future payments. A generic time-to-profit application scorecard was obtained by applying the discrete version of Cox model to borrowers' attributes. Compared with OLS results, portfolio coverage against default was improved. A set of segmented models predicted time-to-profit for different loan durations. Results show that loan duration has a major effect on time-to-profit. Furthermore, inclusive lending programmes can generate internal funds to foster their growth. This provides useful insight for investment planning objectives in inclusive lending programmes such as the one under analysis.

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INTRODUCTION

Traditionally, lending institutions have used default scorecards to manage credit risk. The objective has been to design scorecards to grant credit to customers based on their predicted probability of default (Thomas, 2000). Default status can be measured once a definition is agreed regarding missed payments; banking standards usually define it as three missed consecutive payments (Thomas, 2009). Academic research has extended the design of scorecards from default to profit scoring since the 1990's; scoring customers according to their profit profiles has gained more relevance (Hopper and Lewis, 1992; Thomas et al., 2005).

There is no consensus on the measure to use to design profit scorecards. Various monetary measures have been used in previous studies (Stepanova and Thomas, 2001; Andreeva et al., 2007; Finlay, 2008; Banasik and Crook, 2009; Ma et al. 2009; Finlay, 2010; Stewart, 2011). All of these measures quantify profits only in monetary terms, whilst the performance of lending institutions is assessed not only with monetary but also with relative profit measures (Rasiah, 2010). This was the initial motivation for conducting this research project. By definition, profits and profitability ratios are not the same; the former quantifies the total profit yielded per customer whereas the latter accounts for the investment per customer and hence expresses monetary profits in relative terms (i.e.: as a ratio). This required defining and implementing a measure of customer returns and comparing it with traditionally used profits. Therefore, the first aim of this study is to define and implement return scores for the first time in consumer revolving credit.

Regarding the design of profit scorecards, direct methods (Finlay, 2008; Finlay, 2010; Stewart, 2011) and indirect methods (Andreeva et al, 2007) have been used to design monetary profit scorecards. Under direct methods, profits are predicted directly from customer attributes. Indirect methods require an additional step where intermediate variables such as probabilities of default and repurchase are predicted; these predicted values are then used as predictors of profits. This follows a similar rationale to that suggested for default scoring (Li and Hand, 2002). These methods have been used separately in profit scoring; their performance has not been compared for monetary profit scorecards. As expected, direct and indirect return scorecards have not been designed yet. Consequently, the second aim of this study is to design and compare direct and indirect profit (return) scorecards as of portfolio results for revolving credit. Additional insight could be gained from the use of both types of scorecards.

A topic suggested previously is the design of time-to-profitability scorecards (Finlay, 2008), so far this does not seem to have been tackled. Building on the use of return scorecards for the first time, the third aim of this study is to define and implement time-to-profit scorecards for revolving credit. This required defining a return-based event, which does not necessarily agree with profit thresholds used previously (Finlay, 2008). The usefulness of time-to-profit scorecards was assessed through their performance at a portfolio level, compared with profit and return scorecards. A distinctive feature of time-to-profit scorecards is that they facilitate the planning of investment schemes of credit programmes; this is presented for the first time in this study.

In order to address the research aims presented above, qualitative and quantitative methods were used. Specifically, qualitative data was collected through interviews administered to 10 credit managers from various utility, lending and education institutions. Such data were analysed through thematic analysis. Where appropriate, findings from qualitative data were used to contextualise some of the findings from quantitative methods. This is particularly useful in microcredit programmes, where not only scorecards but also qualitative data are used by analysts for credit granting (Van Gool et al., 2009).

The first research aim was addressed through the exploratory analysis of alternative profit and return measures that could be used for scoring purposes. Cumulative profits are the accumulated cash flows generated per customer at t=12, 24 and 30 months. Cumulative returns are the accumulated cash flows scaled by the outstanding balance per customer. Such returns are defined for the first time as the productivity per customer. Alternatively, it can be defined as the coverage against default if the lending institution discontinues operations at each point of time. Average profits and returns were calculated accordingly for comparison purposes.

Results show that not all defaulters are loss-makers. Moreover, in average the profits generated by profitable defaulters are exceedingly greater than the losses generated by certain non-defaulters. Therefore, it makes sense to score customers according to their profits (returns). Regarding the use of profit or return measures to score customers, the ranks analysis and Chi-Square tests showed that each measure leads to different results at a customer level. This was further confirmed at a portfolio level as portfolio profits (returns) are improved when profits (return) scores are used. An opportunity cost analysis was useful to choose between cumulative and average measures for scoring purposes. Cumulative profits and returns are preferred to average measures as they provide opportunities to improve a portfolio's coverage against default. Such analysis also shed light on the importance of monetary profits in the short term (t=12 months) and coverage against default in the mid and long term (t=24, 30 months).

In order to tackle the second research aim, direct and indirect cumulative profit and return scorecards were produced through the use of OLS (Ordinary Least Squares) (Panik, 2009). Direct scorecards were predicted directly from customer attributes, whereas indirect scorecards had as predictors the probabilities of default and repurchase at t=12 and 30 months. Results from direct models show that even though the dilemma between improving portfolio profits or returns can not be solved through a single profit or return scorecard, customers with certain attributes can improve profits and returns simultaneously. Models were compared in terms of the error rate and according to their impact on portfolio results. Direct models outperformed indirect models according to both criteria. Indirect models were useful, however, to understand the impact that the probabilities of default and repurchase have on profits and returns for a revolving credit as the one under analysis. Furthermore, the joint use of direct, default and repurchase scorecards shed light on the significance of some attributes on profits and returns, in connection with default and repurchase.

Finally, the third research aim was addressed through the definition of time-to-profit as the moment when a customer is covered against default for the first time (i.e.: when cumulative returns exceed one); that is when the accumulated cash flows are enough to cover the outstanding balance for the first time. The initial exploratory analysis was conducted through the analysis of survivor and hazard functions (Hosmer et al, 2008; Allison, 2010). As time went on, the hazard of being covered against default for the first time increased. The discrete version of the Cox model (1972) was used to produce application scorecards. It was shown that survival time-to-profit scorecards outperformed OLS cumulative profits and returns scorecards in terms of their impact on portfolio coverage against default. An alternative use of predicting time-to-profit was to plan investment activities. Results show that segmented models by loan duration outperform a generic model in terms of classification accuracy and monetary impact on the investment scheme. Such models identified internal funding opportunities from the profits generated by existing customers of the credit programme under analysis.

The following two sections aim at providing the reader with an initial understanding of the credit programme under analysis. Background information and further profitability considerations are presented to achieve such objective.

a) The credit programme under analysis

The data set used in this research project was extracted from a credit programme in Colombia offered by a utility company. The programme operates within a business unit that is independently accountable for financial results.

The programme was launched in 2007 and offers a pre-approved revolving credit to customers that have not been at arrears in the payment of utility bills and/or connection charges during the previous two years; this is the sole criterion considered when deciding if to offer customers this product. Some of these customers cannot access traditional lending institutions given that they lack a previous record with credit bureaus.

The salesforce pays a visit to inform customers about their credit limit, which is based on the customer's socio-economic stratum. Customers can not withdraw cash and can only purchase products from partner retail shops. The credit limit can only be used to buy products that improve the quality of life of individuals (e.g.: television/audio sets, desktops, building materials, furniture, home appliances, among others).

Lending rates charged to customers are regulated by the Colombian Financial Superintendent. Specific legislation prevents lending institutions in Colombia from charging usury rates (Prior and Argandoña, 2009). A single rate is used for all customers. Customers decide on the duration of their loans, which range from 12 to 61 months. Therefore, longer term loans should be more profitable as total paid interests are greater in the long term. No credit limit usage restrictions exist unless customers are in arrears in the payment of current loans.

Loans are paid through monthly instalments together with the utility bill. Customers can pay the full amount of the instalment in various collection points that include supermarkets, banks and customer service facilities. Utility supply is suspended after two missed consecutive payments; therefore being at arrears for two months before suspension is a possibility. Furthermore, some customers prefer to make partial payments to cover first the utility bill and then the credit instalment. They are entitled to do this by law. This can only be done, however, in person at the lender's headquarters. Additional interests are charged to customers that are in arrears, following traditional lending practices. No additional charges result from early repayment.

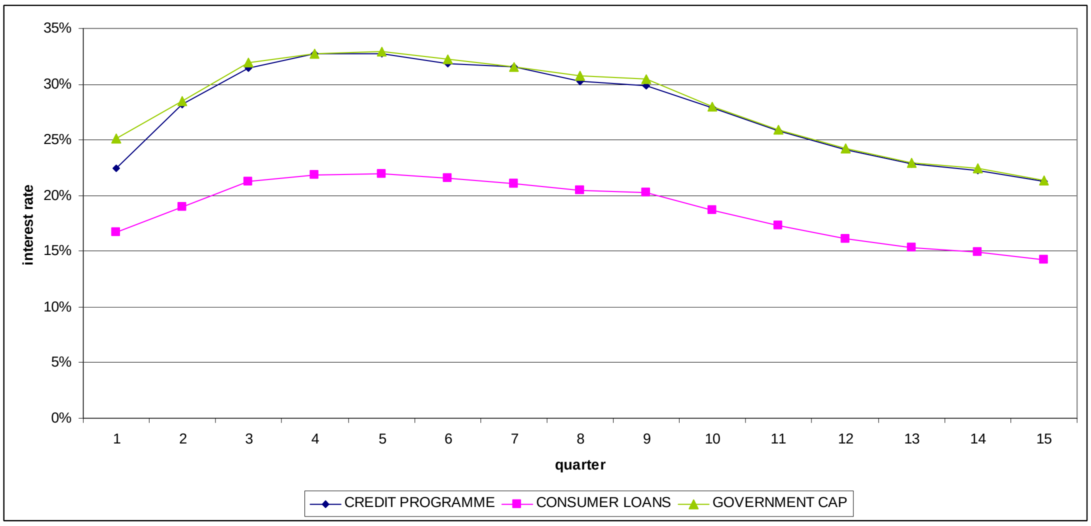
b) Profitability considerations

In order to be financially sustainable, some microlending institutions may decide to serve the marginally-poor and non-poor individuals to achieve financial self-sufficiency (Brau and Woller, 2004). The credit programme under analysis is considered a microcredit initiative; it reaches customers who do not meet usual credit granting requirements but who can actually access the utility service provided by the lender. It relies on external funding (e.g. loans) and shareholders’ equity to fund its operation. The credit programme should be profitable to contribute towards its self-sustainability and therefore to its continuity in the long term.

The earnings potential from customers that take micro credits derives from the interest rates charged to them. They exceed the usual consumer lending rates but are significantly lower than those charged by informal lenders. Solo and Manroth (2006) found rates of 150% charged by such informal lenders. A survey of a sample of Colombian households from low income socioeconomic stratums (e.g. 1 to 3) showed that 79% of them have used at least once informal credit services provided by pawn shops, cash lenders, friends and relatives (Econometria, 2008 cited in Colombian Treasury et al., 2010).

Figure I1.1 shows that interest rates of the credit programme under analysis are greater than those usually charged for consumer loans. Apart from the first quarter, they are usually set at the legal cap defined by the Government. This is a result of the higher risk associated with the served segment, as they would normally not meet the credit requirements to access traditional commercial banks.

Figure I1.1: Comparison of interest rates of the credit programme versus consumer loans and maximum Government rates



Source: Official figures (Superintendence, 2012)

The facts mentioned above suggest that microcredit programmes can be profitable, provided that their cost structures are appropriate (Terberger, 2003). In the case under analysis, important cost savings are obtained from the existing infrastructure of the lender, which is also used to provide administrative support to the utility business unit.

Previous scoring studies for consumer loans in a microcredit context have focused on credit scoring (Schreiner, 2000; Forster and Wilkinson,2010). Results show, however, that in general default rates in microcredit programmes are low (Brau and Woller, 2004); this is also the case in Colombia (Serrano, 2009). This contrasts the view of traditional commercial banks that classify them as high risks (Prior and Argandoña, 2009). Furthermore, given the previous positive payment record on utility bills, one should be aware of default but priority should be given to profit scoring.

A profit scorecard is therefore useful in identifying customers that contribute towards the financial sustainability of the microcredit programme, given that they have not defaulted in the payment of utility bills. This is equally applicable to credit programmes from traditional commercial banks.

The thesis is organised as follows: Chapter 1 presents the literature review conducted to identify the research gaps and the research questions defined in Chapter 2. Chapter 3 introduces the suggested measures and approaches to tackle the research questions. Chapter 4 presents the methodology used to collect and analyse qualitative data; it also describes how quantitative data were prepared and analysed, per research topic. Chapter 5 presents the analysis of results for the chosen dataset. Chapter 6 presents the conclusions per research topic. Chapter 7 includes the limitations of this study; it also includes extensions that would further expand research on return scoring. An appendix and references are presented at the end of the document.

1. LITERATURE REVIEW

1.1 Introduction

The objective of this chapter is to critically review the existing literature on profit measures (Section 1.2), predictive methods (Section 1.3) and survival techniques (Section 1.4) used for scoring purposes. This review includes elements from financial accounting, marketing and statistics that are essential to identify potential gaps in the profit scoring literature.

1.2 Profit measures

Since the 1990's, the initial objective of scoring models, predicting the default of customers, has been extended to the optimization of other business objectives: response, attrition, and particularly profits (Thomas et al., 2005).

A major challenge in the design of profit scorecards is the identification of revenues and expenses at a customer level, as figures are usually presented at a portfolio level and approximations are required. For instance, if some expenses are omitted due to lack of information, they are considered relative and decisions among accounts should be regarded as relative as well (Hopper and Lewis, 1992). The advance in information systems has facilitated the measurement of profits per customer even though some assumptions and approximations are usually made. Once a profit measure is selected, it can be predicted through explanatory variables to produce scorecards.

This section critically reviews previous measures that have been suggested and used for profit scoring purposes. It also presents alternative profit measures that could be used for scoring purposes.

1.2.1 Monetary measures

1.2.1.1 Customer Lifetime Value measures

These measures quantify profits as the discounted cash flows (anticipated or actual) per customer and are usually expressed in monetary units at the application time. They are closely related to the concept of customer lifetime value (CLV).

CLV is defined as the net present value of the anticipated cash flows per customer over time (Berger and Nasr 1998; Collings and Baxter 2005; Pfeifer et al., 2005). Customers can be considered the most valuable asset of a Company and hence, CLV is useful to value companies (Gupta and Lehmann, 2003).

In the simplest scenario, CLV is quantified (Berger and Nasr, 1998) as:

$$CLV = GC \times \sum_{i=0}^{n} \left[\frac{r^{i}}{(1+d)^{i}} \right] - M \times \sum_{i=1}^{n} \left[\frac{r^{i-1}}{(1+d)^{i-0.5}} \right] \qquad (1.2.1),$$

where:

GC= Expected annual gross contribution margin per customer;

M= Relevant annual promotion costs per customer;

n= Projected cash flows period;

r= Annual retention rate;

d= Annual discount rate;

i= Year

n= Observation period, in years

In this particular case it is assumed that promotion expenses approximately occur at the middle of the purchase cycle and n depends on the type of industry. This is not always the case.

In a scoring context, the aim is to design a scorecard to select customers that will generate more value to the Company at an individual level. This requires defining an outcome period to assess a customer's contribution to future profits (Lucas, 2001). This is different to valuing the lifetime relationship with a lender, where time horizon can be infinite.

An approach suggested initially was to quantify profit at application time as the difference between the cumulative discounted installments adjusted by the survival probability at time t and the initial amount of the loan (Stepanova and Thomas, 2001) as

$$\text{Profit} = \sum_{i=3}^{T+2} S_i \frac{a}{(1+r)^{i-2}} - L \qquad (1.2.2),$$

where:

S_i= Survival probability that the customer has not fully repaid the loan and has not defaulted at month i;

a= Monthly instalment;

L= Loan amount;

T= Loan term;

r= Monthly lending rate.

Alternatively, expected profits result from deducting expected losses from default and early repayment from potential inflows from the loan (Banasik and Crook, 2009):

E (Profits) = Potential profits – E (Lost potential from default) – E (Lost potential from early repayment) (1.2.3).

The conditional expected profit for a fixed term loan has been quantified as a result of four income sources (Ma et al., 2009), as presented below.

The summation of expected monthly payments in the absence of default and early repayment is

$$E_{t=c}(\pi) = \sum_{t=1}^{T} S_t^b \times S_t^d \frac{M}{(1+i)^t} \qquad (1.2.4);$$

the expected balance repaid early, given that default had not occurred before that date is

$$\sum_{t=1}^{T} S_t^d \left(S_{t-1}^b - S_t^b\right) \times B_t \times \frac{(1+2j)}{(1+i)^t} \qquad (1.2.5);$$

the expected recovery amount, given that the customer defaults and has not repaid early before that date is

$$\sum_{t=1}^{T} (1 - \text{LGD}) \times S_t^b \times \left(S_{t-1}^d - S_t^d\right) \times \frac{(B_{t-1})}{(1+i)^t} \qquad (1.2.6);$$

and the expected inflows from insurance premia

$$I \times p(I) \times p(U) \qquad (1.2.7),$$

where:

S_t^b = Probability that the loan has not been totally repaid early on or before t;
S_t^d = Probability that default has not occurred on or before t;
i = Interbank monthly rate;
j = Monthly interest rate associated with early repayment;
M = Contractual fixed monthly payment;
T = Terminal loan period set to 24 months;
B_t = Expected balance to repay early at end of t;
LGD = Loss given default;
I = Insurance income if it is taken and in the absence of claims;
p(I) = Probability of taking insurance;
p(U) = Probability of not claiming insurance.

The measures presented above are based on anticipated cash flows and therefore require adjustments for default and repayment. Alternatively, actual payments during the observation period can be used to calculate the dependent variable to be predicted for scoring purposes.

The net revenue of a revolving German store card account has been calculated as the difference between the net present value of the actual discounted total payments and the amount written off from accounts at default (Andreeva et al., 2007):

$$vr_i = \sum_{t=1}^{T} \frac{r_{it}}{(1+\theta_t)^t} - l_i \, , \qquad \text{(1.2.8), with}$$

$r_{it}=b_{it}-b_{it+1}$ if $r_{it}>0$ and $r_{it}=0$ if $r_{tj} \leq 0$,

where:

b_{it}= Outstanding balance at the end of month t, customer i;

vr_i= Present value of net revenue at the end of month 0, customer i;

l_i= Amount written off during period T for each customer;

Θ_t= Bundesbank monthly base rate;

T= Month of account closure/end of observation period.

Data availability has a major role on decision between using anticipated or actual figures. If only the payment plan agreed at the application time is available, instead of actual payments per customer, anticipated values should be used. This assumes that behavioural data on default and early repayment are available as well. In the case of revolving credit, the probability of repurchase needs to be considered to reflect properly sources of additional income.

On the other hand, if actual payments per customer are available, these figures should be used instead. An advantage is that measures reflect directly the actual profits generated per customer (Hopper and Lewis, 1992). Additionally, actual payments reflect the overall payment behaviour resulting from default, repayment and repurchase (where applicable).

1.2.1.2 Customer profitability measures

A second group of measures that have been used for profit scoring purposes are related to customer profitability (CP). Customer profitability is the difference between revenues and accrued costs resulting from the relationship with customers during a specific period. Profits do not need to be discounted and include accrued expenses that not necessarily imply cash outflows (Pfeifer et al., 2005).

A measure that has been used to score customers is their worth. It is the profit per customer net of bad debt provisions (only for accounts in arrears) and average fixed costs of managing each account (Finlay, 2008). It is a cumulative figure that includes the effect of previous payments and arrears status:

$$Y_i^{'} = \alpha Y_{1i} + \sum_{k=0} (\alpha Y_{2ik}(1-\beta_{kt}) - \beta_{kt} Y_{2ik}) - \delta \quad (1.2.9),$$

where:

Y_{1i}= Payments made over the outcome period to account i;

Y_{2ik}= Balance at arrears status k; k=0 to n at the outcome point for account i;

α= Average profit proportion of payments;

β_{kt}= Provision percentage for account balances of accounts at arrears status k;

δ= Average fixed cost of managing each account during the outcome period.

A similar measure (i.e.: contribution per customer) quantifies the worth per customer as the profits after deducting losses for bad accounts (Finlay, 2010):

$$C_i = \alpha N_i - \beta K_i = R_i - L_i \qquad (1.2.10),$$

where:

αN_i = Fixed proportion of N (gross payments received from customer i over the outcome period) ;

βK_i = Fixed proportion of outstanding balance account K.

More recently, spend and charge-offs, were used as proxies for revenues and costs, respectively. Instead of producing a single profit measure, each component was modeled and used in conjunction for strategic decision making (Stewart, 2011).

1.2.2 Relative measures

The monetary measures presented above are useful to assess business units as profit centres accountable for generating revenues and covering costs. Alternatively, they could be considered investment centres that should maximize profits considering the investment base (Ezzamel, 1992; Drury, 2000). Relative measures (ratios) are used instead of monetary measures to scale profits or cash flows by the investment made.

1.2.2.1 Profit-based ratios

Usual return measures include return on equity capital employed (ROE) and return on total assets (ROTA). ROE is the return to shareholders; ROTA quantifies the profit before interest and tax generated per monetary unit invested in assets (Ryan, 2004) and are obtained as

$$\text{ROE} = \left(\frac{\text{Profit attributable to shareholders}}{\text{Equity capital employed}} \right) \times 100 \qquad (1.2.11);$$

$$\text{ROTA} = \left(\frac{\text{Profit before interest and tax}}{\text{Fixed assets + current assets}} \right) \times 100 \qquad (1.2.12).$$

Several variations of these ratios exist, depending on the accounts used for calculation. Both of them are useful to assess the productivity of resources invested in a business unit. These relative measures are widely used by commercial banks (Rasiah, 2010) and microlending institutions to assess their profitability (CGAP, 2009; SEEP, 2010).

It has been suggested that ROE can be calculated at a customer relationship level for pricing decisions (Komar, 1997). The rationale behind assessing customers' performance through the relative measures explained above is that profit generation occurs at a customer level. Likewise, resources are allocated at a customer level to generate profits. Consequently, return measures are a natural alternative to monetary profits.

1.2.2.2 Cash -flow-based ratios

Various cash-based ratios have been suggested to assess the performance of companies: Cash ROCE, portfolio yield and operating cash flow ratio.

The cash return on capital employed (cash ROCE) measures the net cash flow from operations generated per monetary unit invested in the capital employed, which include the operational assets used to generate such cash flows (Davies and Pain, 2002) as:

$$\text{Cash ROCE} = \left(\frac{\text{Net cash flow from operations}}{\text{Average capital employed}} \right) \quad (1.2.13).$$

The portfolio yield is a cash-based measure, gross of interests and expenses. It has been defined in a microlending context for standardized reporting purposes. It measures the ability of a microfinance institution to generate cash from financing activities per monetary unit invested in the gross loan portfolio (SEEP, 2010):

$$\text{Portfolio yield} = \left(\frac{\text{Interests, fees and commissions in loan portfolio}}{\text{Average gross loan portfolio}} \right) \quad (1.2.14).$$

Another measure used to assess the liquidity of a Company is the operating cash flow ratio. It compares the cash flow from operations with current liabilities. It quantifies the ability of a Company's operations to repay short term liabilities (Palepu et al., 2010) as:

$$\text{Operating cash flow ratio} = \left(\frac{\text{Cash flow from operations}}{\text{Current liabilities}} \right) \quad (1.2.15).$$

The measures explained above or similar metrics could be used at a customer level for profit scoring purposes.

A cash-flow based ratio has been suggested to assess the creditworthiness of applicants of fixed loans and revolving credits. The rationale behind it differs from return ratios (i.e.: scaled profits), as it compares actual and expected cash flows. Results from this study are solely based on simulated data (Quirini and Vannucci, 2009).

Until now, only monetary measures (either cash flow or profit-based) have been used for profit scoring purposes. Ratios that scale monetary results by the investment per customer have not been suggested. This presents a research opportunity to explore alternative measures that could provide useful insight for profit scoring purposes.

1.3 Profit scorecard prediction methods

Once a proxy measure of profit is obtained, different methods can be used to predict it through explanatory variables.

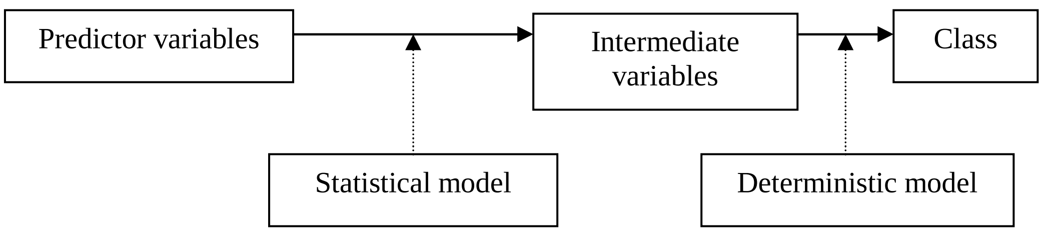
Default models are constructed by using binary measures as the predicted variable. Direct or indirect methods that use predictor variables can be used to produce scorecards. Within each category, specific statistical and/or heuristic techniques can be used for predictive purposes (Li and Hand, 2002). Statistical and non-statistical techniques have been used in a binary context (Hand and Henley 1997; Baesens et al., 2003; Thomas et al., 2005).

A similar rationale can be used in the case of non-classification contexts (Li and Hand, 2002). In particular, profit scoring predictive methods can be broadly classified as direct or indirect, depending on the steps used to generate predicted values. The following section presents the methods that have been used to produce profit scores.

1.3.1 Indirect methods

Under this approach, intermediate variables are predicted from individual attributes through statistical models. These variables are then used to predict classes deterministically. That is, the bank characterises good customers in terms of intermediate variables such as balance, excess and credit turnover and then classifies customers as goods or bads based on predicted values of intermediate variables. The underlying principle of these methods is that intermediate variables capture valuable additional information from the data that are related to default (e.g.: balance). An advantage of these methods is that they are flexible as a classification threshold is not required. Such threshold might be changed throughout time. This allows redefining classes without changing the model (Li and Hand, 2002). Figure 1.3.1 depicts the process followed when indirect predictive methods are used.

Figure 1.3.1: Indirect methods



Source: Li and Hand (2002)

In a non-classification context, instead of using indirect models as defined above, models that include an intermediate structure are used to separate processes that explain predicted variables. Individual attributes are used to predict intermediate variables. Intermediate variables are then used to predict the final measure per individual (Li and Hand, 2002).

Indirect methods have not been used widely in a profit scoring context because of the continuous nature of the predicted variable. It is natural to think in terms of predicting profit, which is a continuous variable, instead of defining binary models based on profit classes. Even though it is possible to define goods and bads in terms of profits, it is not a straightforward task. Lending institutions may define profitable and unprofitable customers in alternative ways; therefore they are more likely to be inclined towards using direct models to predict profit as a continuous measure.

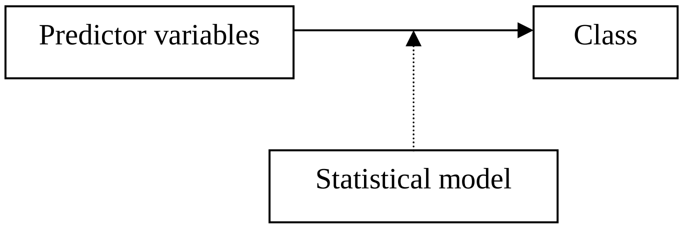
Until now, intermediate structures have only been used once for profit scoring purposes of a revolving credit in Germany (Andreeva et al., 2007). Profit scores were regressed on the probabilities of default and second purchase and amount borrowed. A previous step was completed to predict time to second purchase and time to default through survival models. Time to second purchase and time to default were modelled with an exponential model, using application and first purchase data (Andreeva et al., 2007). This study built on previous research where purchase propensity was modelled through survival techniques (Andreeva et al., 2005).

The "survival combination score" yielded higher values of mean and total net revenue than those obtained with a typical logistic regression model. However, the bad rate among accepts and the total amount written off were higher.

1.3.2 Direct methods

Predicted values are obtained by using observed variables per customer directly. Techniques include logistic regression and discriminant analysis, among others (Li and Hand, 2002). Figure 1.3.2 shows the process followed when direct predictive methods are used.

Figure 1.3.2: Direct methods



Source: Li and Hand (2002)

Within this category of methods, profits are modeled directly (Finlay, 2008). Alternatively, profit components are modeled and subsequently used to obtain an expected profit value (Finlay, 2010; Stewart, 2011).

In the case of a revolving credit in the United Kingdom where customers are charged higher prices for products instead of an explicit interest charge, binary and continuous models were produced to score customers. Logistic regression was used to produce two binary scores: one that defined goods as nondefaulters and another in which goods were customers with a positive worth. Continuous models predicted directly profit per customer (Finlay, 2008).

Binary models outperformed continuous models in terms of classification accuracy (i.e.: identifying goods from bads). The contrary occurs in terms of impact on corporate profits. It should be noted, however, that this was not the case for all acceptance deciles (Finlay, 2008). These results were expected, since binary and continuous models are designed using different types of measures and hence should be assessed according to the appropriate criteria.

In a different study, alternative profit scores were obtained for the product described above. The first approach was modelling the probability of default through logistic regression and assuming a single value for losses and profits. The second approach was to model separately the probability of default and profits and losses for defaulters and non-defaulters through Ordinary Least Squares (OLS) and neural networks. An expected value of profit per customer was then used as profit score in both cases. The third approach was to model directly the expected profit per customer through OLS and neural networks (Finlay, 2010).

Models were assessed through the ratio between the profit captured by the model and the maximum profit if the model was perfect, for different acceptance deciles. Results showed that approaches 2 and 3 should be preferred to approach 1. Overall, approach 2 should be preferred (Finlay, 2010). These results confirm the general rationale that using traditional default scorecards does not benefit portfolio profits; two different objectives are being pursued through default and profit scorecards.

Regarding the better performance of models that predict profit components compared with those that produce a single profit prediction, it could be partly due to the benefits obtained from segmenting the sample into defaulters and non-defaulters. Separate models were obtained for the expected profits from non-defaulters and for the expected profits and losses from defaulters. This contrasts with the use of a generic model to produce alternative scores.

More recently, revenue scores based on spend were produced through a general linear model in which the error term was assumed to follow a Gumbel distribution. Hence spend was assumed to follow an exponential distribution. In order to reduce correlation effects between default and revenue, segments were built according to a default score. Revenue scores were then produced, excluding those variables that were correlated with default. Even though results varied across segments, the bad rate was not constant within the same default segment; a limited correlation between default and revenue was evident (Stewart, 2011).

These results show that even though variables were selected with the aim to reduce correlation between default and revenue, still it is not possible to avoid it. Predictor variables continue to be correlated perhaps by other variables that are not readily distinguishable in a scoring model.

Further research is required regarding the use of continuous modelling or binary classification for profit scoring purposes of interest accruing products such as revolving credit (Finlay, 2008). Results from direct and indirect methods have not been compared until now.

1.4 Survival techniques for scoring purposes

A central concept in survival techniques is the hazard function. Given that the observed individual has survived until time t, it is the instantaneous potential per unit time that the event will occur (Kleinbaum and Klein, 2012). This "time-to-event" concept can be applied in a credit scoring context to forecast default levels depending on time and hence to provision bad debts. Other uses are predicting repayment time and the inclusion of changes in economic conditions in predictive models (Banasik et al., 1999).

The most common survival model used in a scoring context is the proportional hazard model (Cox, 1972). This model assumes that the hazard function, $h(t, \mathbf{x})$ can be split into two components: a baseline hazard function, ($h_0(t)$) and a term that contains covariates, $g(\beta, \mathbf{x})$ in form

$h(t, \mathbf{x}) = h_0(t)\, g(\beta, \mathbf{x})$ (1.4.1),

where:

$\mathbf{x}$= vector of characteristics of individuals and β is a set of coefficients.

Often $g(\beta,\mathbf{x})$ is expressed as $\exp\{\beta' x\}$. This latter function can have time varying covariates.

The aim is to find the weights of the attributes that maximize the partial likelihood function L (β):

$$L(\beta) = \prod_{i:D_{i=1}} \frac{\exp\{\beta x_i\}}{\sum_{j \in R\{i\}} \exp\{\beta x_j\}} \qquad (1.4.2),$$

where:

β= covariate weights

x_i= characteristics of borrower i

x_j= characteristics of borrower j

D_i= binary censoring variable

$R\{i\}$= set of customers in the sample just before time t_i (time at which a default occurs).

These weights are then used to calculate survival scores (Thomas, 2009). The likelihood function presented above applies to continuous time events, which is not always the case in a scoring context. This requires either approximations to handle ties (Stepanova and Thomas, 2002) or the use of the discrete version of the proportional hazard model (Cox, 1972).

Survival techniques have been used in previous studies initially for default scoring purposes (Banasik et al, 1999; Stepanova and Thomas, 2002). In terms of default scoring, results for logistic regression were similar to those of proportional hazard models during the first year; this was not the case for the second year. Proportional hazard models outperformed those obtained from logistic regression for early repayment models (Banasik et al., 1999). Default models based on survival techniques were later improved by including time-by-characteristic interactions to allow for time dependency of covariates (Stepanova and Thomas, 2002).

As a consequence of the growing interest towards profit scoring, survival techniques have also been used to design profit scorecards (Stepanova and Thomas, 2001; Andreeva et al., 2007; Ma et al., 2009). The survival probability of repaying a loan was initially included as a component of expected profits; it has been suggested that expected profits increase as default risk decreases at different points of time (Stepanova and Thomas, 2001); see (1.2.2). These components were further expanded to allow for competing risks of default and/or early repayment in expected profit calculations (Ma et al, 2009); see (1.2.4 to 1.2.6). An alternative approach was to use the probabilities of surviving default and second purchase as predictors of actual profits. It was demonstrated that actual profits and times to default/repurchase are related; profits can be improved if survival probabilities are used instead of a static default probability obtained from logistic regression. It was found, however, that additional risk has to be taken if profits are to be increased (Andreeva et al, 2007). This was explained in Section 1.3.1.

2. RESEARCH QUESTIONS

2.1 Introduction

This chapter presents the gaps identified in the literature review conducted in Chapter 1 and the corresponding research questions of this research project.

2.2 Gaps in the literature

The discussion presented in the previous chapter is useful to identify research challenges related to profit scoring regarding profit measures, predictive methods and time-to-profit, as explained below.

First, there is no consensus on the adoption of a single metric to quantify profit per customer for scoring purposes. Cash flows and profits are indistinctively used to design monetary profit scorecards. In some cases proxies are mixed measures that include accrual and cash-based figures.

Regardless of the underlying accounting principles, profit proxies are useful to rank customers and therefore are useful to design scorecards that aim to maximise portfolio results. Special caution is required for interpretation purposes, as each measure represents a different concept that is not necessarily comparable with alternative metrics. Accrual and cash accounting lead to profit and cash flow measures respectively, which do not necessarily coincide.

The lack of relative measures (in particular, return measures) for profit scoring purposes is evident in the existing literature. This implies that the required investment per customer to achieve certain profits or cash flows is being

overlooked. Alternative measures should therefore be explored to tackle this gap in the profit scoring literature.
Second, it is clear that Ordinary Least Squares (OLS) and other regression techniques are the most commonly used to produce profit scorecards. This is a natural course of action, given the continuous nature of profit measures. Results of previous studies are not conclusive as of the use of direct or indirect predictive methods; the debate is still open.

Previous studies have not compared direct and indirect methods to produce both profit and return scores for revolving credit that accrues interests and other revenue income sources. This offers the opportunity to expand the literature on predictive methods for profit scoring purposes and to gain additional insight from the joint use of methods that predict profit measures directly from borrowers' attributes and those that contain intermediate structures that account for profit drivers of a revolving credit.

Third, the use of scorecards based on predictions of binary or continuous profit measures is a topic under development too. Profit-based categories need to be identified in alternative ways to formally define time-to-profit for the first time in a scoring context.

Indirect OLS models and those that use survival probability components are based on a binary rationale resulting from default, repurchase and/or early repayment. Time-to-profit scorecards based on a profit-related binary event have not been implemented and compared against other regression techniques.
Furthermore, lending institutions could use time-to-profit predictions to schedule investment activities in credit units through the liberation of internal funds from existing customers at different points of time.

2.3 Research questions

In order to address the academic gaps presented above, the following research questions were identified:

- What are return scores and what additional insight do they offer compared with traditional profit scores? This question is addressed in Sections 3.2, 4.3.3.1 and 5.3.
- How can direct and/or indirect methods be used to model profit and return scores for revolving credit? Sections 3.3, 4.3.3.2 and 5.4 address this question.
- What is time to profit in a scoring context and how can it be modelled? This question is addressed in Sections 3.4, 4.3.3.3 and 5.5.

3. SUGGESTED MEASURES AND APPROACHES

3.1 Introduction

This chapter presents the suggested profit and return measures (Section 3.2) and predictive approaches to produce monetary and relative scorecards (Section 3.3). It also defines time-to-profit (Section 3.4). This provides a starting point to tackle the research questions stated in the previous chapter.

3.2 Alternative profit measures

Some of the measures presented in this section could be predicted by using borrowers' attributes. These predicted values can then be used as profit (return) scores.

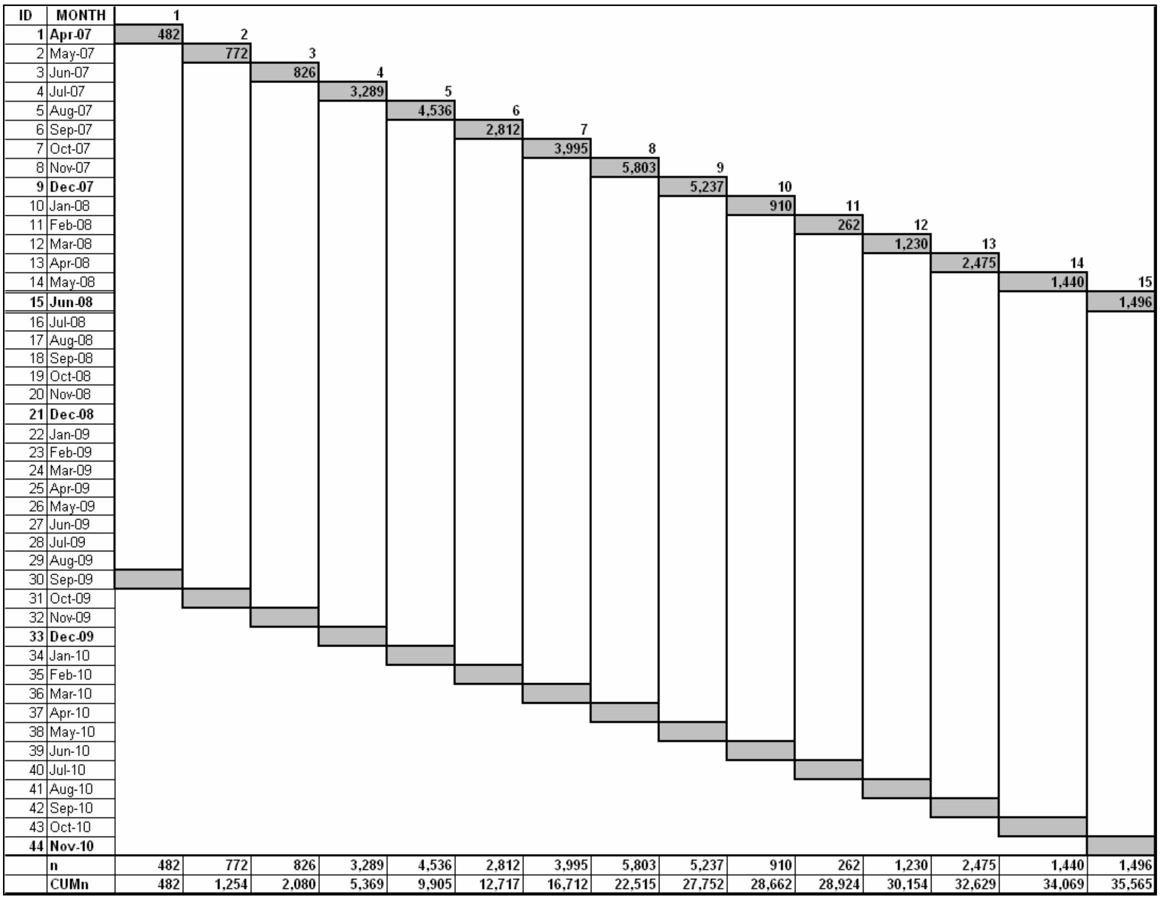
3.2.1 Basic measures

Figure 3.2.1 shows that from the inception of the programme the lender expanded the programme gradually. New customers per month, n, were accumulated into CUM_n, which gradually increased to 35,565 customers. This resulted in 15 monthly consecutive cohorts of accepted applications: $y=0$ *to* 14.

As of the observation period per customer, profit scoring usually requires longer observation periods (i.e.: more than two years), compared with default scoring (Finlay, 2008; Stewart, 2011). A long term stance has also been taken to project customer lifetime duration (Reinartz and Kumar, 2003). In total, data was obtained for 44 months. However, all customers could not be observed during that period of time since they joined the credit programme in different points of time.

In order to exceed the minimum observation period suggested above, each customer was followed during 2.5 years (30 months): t=*1 to 30*; the first purchase occurred in month 1. An alternative observation period would have been 36 months, but this would have resulted in the exclusion of 20% of the customers from the sample.

Figure 3.2.1: Cohorts of borrowers



A performance measure was calculated per period: *z=t+y* month; z Є [1, 44]. In order to address the research questions stated in Section 2.3, two monthly performance measures are suggested per customer: *OPCASH* and *CASHROA.*

OPCASH is the operational cash flow generated per month, after deducting operational expenses in cash from cash inflows per customer. It measures the potential that a customer has to generate operational liquidity to the lender. It does not take into account financing decisions and country tax regimes.

In the case under analysis, payments received from sales and insurance net commissions and interests were added; only cash fixed overheads were subtracted. This was done to produce a cash-flow based measure, which is not based on accrual accounting (Lee, 1984; Lee, 1986; Elliot and Elliot, 2006). Hence, non-cash expenses such as depreciations and amortizations were excluded to calculate $OPCASH$:

$$\boldsymbol{OPCASH_z = Netcommission_z + Interests_z - Overheads_z} \qquad (3.2.1).$$

Net commissions include payments received from partner retailers and those made to the sales force per closed deal. It also includes commissions from insurance payments made by customers. Contractual and/or additional interests because of arrears are charged to customers.

Given the level of detail of the information received from the Company, fixed overheads in cash were included in the calculations. These expenses were allocated based on the total customers with credit records per month. The management team agreed that it was reasonable to assume that all customers demand the same effort to be served. Customer service is considered to start from the first purchase throughout the collection process. Consequently, overheads were allocated from month 1 onwards.

$CASHROA_z$ is the relative cash return generated per monetary unit of receivables at the end of each month. It measures the monthly productivity of the funds invested in the outstanding balance in terms of operational cash flow generation:

$$\boldsymbol{CASHROA_z = {}^{OPCASH_z}\!/_{finalbalance_z}} \qquad (3.2.2),$$

where:

$finalbalance_z$= Outstanding balance at month z

This measure scales operational cash flows to account for the investment per customer. This was the only asset considered to calculate this measure given that the credit programme shares premises with the Utility Company and hence specific fixed assets used by the credit programme are not identified as such by their information systems.

The two basic measures presented above provide a monthly snapshot that does not reflect borrowers' behaviour throughout the observation period. Four measures were obtained from them to reflect borrowers' behaviour throughout time in cumulative (*OPCASHcum* and *CASHROAcum)* and average terms *(OPCASHav* and *CASHROAav)*.

3.2.2 Cumulative measures

The total operational cash flow generated per customer by month *t* will be referred as $OPCASHcum_t$. It quantifies the cumulative operational liquidity per customer as time goes on. Various steps were completed to calculate this measure, as explained below.

First, the month in which the credit programme was launched was chosen as the base period. Apart from $OPCASH_z$ for that month, the rest were adjusted by a deflation factor to express figures in real terms and relative to the base month:

$$\boldsymbol{OPCASHdef_z = OPCASH_z \times df_z} \qquad (3.2.3),$$

where df_z=monthly deflation factor obtained from the monthly inflation rate.

Second, in order to define a single starting point for the observation period, monthly deflated figures of each *y* cohort were discounted during *y* periods using *r,* a real discount rate. This discounted measure accounts for the time value of money and is useful to tackle with customers joining the sample in different cohorts:

$$OPCASHdisc_t = OPCASHdef_z /(1+r)^y ; \; t \in [1, 30] \tag{3.2.4}$$

Finally, the total (i.e.: cumulative) operational cash flow was obtained by compounding and subsequently adding discounted figures:

$$OPCASHcum_t = \sum_{k=1}^{t} OPCASHdisc_k \times (1+r)^{(t-k)} \tag{3.2.5}$$

The monthly cumulative return per customer was then obtained by scaling cumulative operational cash flow in (3.2.5) by the outstanding balance at time *t*:

$$\boldsymbol{CASHROAcum_t = {}^{OPCASHcum_t}\!\big/_{finalbalancedef_t}} \tag{3.2.6}$$

where $finalbalancedef_t$= deflated and discounted final balance at time t.

$CASHROAcum_t$ is the cumulative operational cash flow until month *t*, relative to the outstanding balance at month t. The outstanding balance at month *t* was used instead of average balances to properly reflect the cumulative nature of cash flows and the updated book value of receivables as time went on. This measure can be interpreted as the productivity per customer in terms of the cumulative cash flow generated until month *t*, given that by that month, funds were still invested in receivables. This is a similar rationale to that adopted for ROE, ROTA, Cash ROCE and the portfolio yield, explained in Sections 1.2.2.1 and 1.2.2.2.

Alternatively, it can be interpreted in a similar way to the operating cash flow ratio explained in Section 1.2.2.2. By time *t*, the outstanding balance is an asset for the Company but a liability for the customer. Consequently, this ratio is the number of times that the cumulative operational cash flow covers the outstanding receivables per customer. It is the coverage against default if the Company discontinues operations at time *t*.

3.2.3 Average measures

Average measures are a natural alternative to benchmark results from cumulative measures per customer. They are usually easy to interpret and are stable throughout time. They are also useful to compare results from longer and shorter observation periods, which in the case of cumulative figures, increase throughout time. Average measures could smooth extreme values as time goes on, though.

OPCASHav and *CASHROAav* (average cash flows and returns, respectively) were obtained at time *t* per customer:

$$\overline{X}_t = \left(\sum_{k=1}^{t} X_k\right)/k \qquad (3.2.7),$$

where X= *OPCASHdisc* or *CASHROA.*

Given that in the scoring context it is acceptable to use the term "profit" regardless of the fact that either profits or cash flows are used (Stepanova and Thomas 2001; Andreeva et al., 2007; Finlay 2008; Banasik and Crook 2009; Ma et al., 2009; Finlay 2010), $OPCASHcum_t$ and $OPCASHav_t$ will be referred from here onwards as the "cumulative profits" and "average profits", respectively. Likewise, the terms: "cumulative returns" and "average returns" will be used to refer to $CASHROAcum_t$ and $CASHROAav_t$, respectively. This does not change the interpretation of these measures, which are completely cash-based.

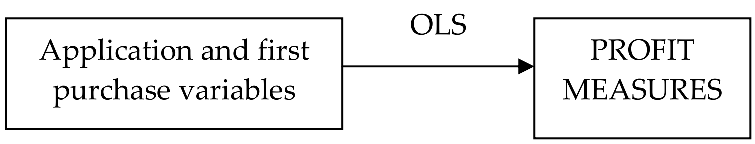
3.3 Direct vs. Indirect predictive approaches

3.3.1 Suggested approach

Direct and indirect approaches are suggested to predict monetary and relative profit measures.

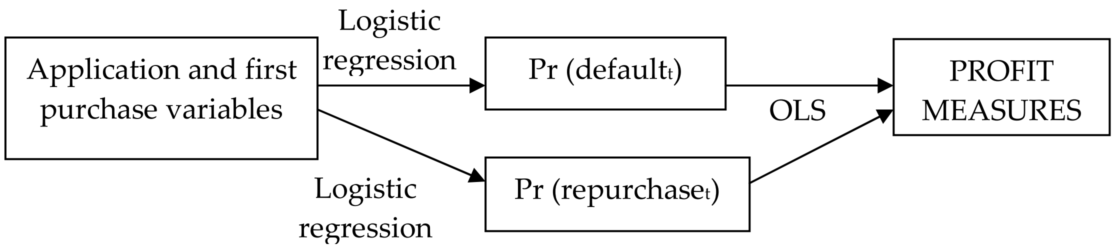
Under the direct approach, profit measures are regressed on application and first purchase variables from borrowers through OLS. This is the usual practice in profit scoring. Figure 3.3.1 shows the suggested prediction scheme.

Figure 3.3.1: Suggested direct approach



Regarding the indirect approach, it is important to note that the term "indirect" actually refers to "intermediate" models in which the probabilities of default and of repurchase are first predicted by using application and first purchase variables through logistic regression. Predicted values of such intermediate variables are then used to predict profit measures through OLS. Figure 3.3.2 shows the suggested prediction scheme. A novel feature of the suggested indirect approach is that the probabilities of default and of repurchase in the short and long term (t=12 and 30, respectively) can be used to predict monetary and relative measures to account for the effect of changing behaviour of customers over time. This has not been done before for revolving credit.

Figure 3.3.2: Suggested indirect method

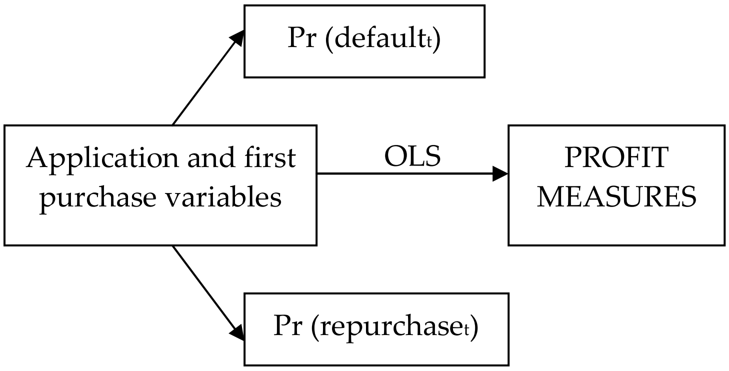


t=12 or 30

On the other hand, instead of predicting these probabilities for specific segments (e.g.: based on default) to calculate an expected profit value (Finlay, 2010), they are used as predictors of profit measures for the complete sample (Andreeva et al., 2007). This approach does not require the definition of segments in a unique way. A single indirect model can be then compared with other direct generic models.

Finally, Figure 3.3.3 shows schematically the joint use of direct scorecards and default (repurchase) scorecards. The models used to predict probabilities of default and repurchase could be further used to understand results from direct models via the joint analysis of significant variables in both direct and default (repurchase) models. This could provide additional insight to the profit score obtained per customer. As expected, this requires a predictor to be significant in both direct scorecards and default (repurchase) models.

Figure 3.3.3: Joint use of direct scorecards and default (repurchase) scorecards



t=12 or 30

3.4 Time-to-profit

In the previous sections, scores were based on profits or returns. An alternative approach for profit scoring purposes is to rank customers according to their probability of experiencing a profit-related event clearly defined within time period *t*:

$$\Pr\,(CASHROAcum_t \geq 1) \approx \Pr\,(OPCASHcum_t \geq Final\ balancedef_t) \qquad (3.4.1).$$

The probability of reaching the event shown in (3.4.1) implies that a customer is profitable (i.e.: he/she has exceeded the threshold) defined in a microlending context (Sinha, 2011). This can be defined as the probability that a customer breaks even (i.e.: cumulative profits completely cover the outstanding balance; the customer is completely covered against default). In the event of future default, the outstanding debt is already covered by cumulative profits.

It is important to note that a *ROA*-based measure (return on assets) is suggested instead of *ROI* (return on initial investment) as the initial investment can change throughout time given the revolving nature of the product under analysis. *ROI* would be more convenient in a fixed loan context. An advantage of using $CASHROAcum_t$ is that when the event occurs, the initial investment is already covered, together with any other outstanding charges.

The suggested threshold takes into account the high risk associated with customers excluded from traditional financial services. This is a more conservative standpoint than that taken to define goods (i.e.: those that exceeded the natural threshold of profits=0) in a previous study (Finlay, 2008). The event shown in (3.4.1) not only scales monetary profits by the outstanding balance through a return measure; it also redefines good customers as those that are completely covered against default, with returns of at least 1. As explained below, such event can be used to design application scorecards or for investment planning objectives.

3.4.1 Time-to-profit application scorecards

Time-to-profit is defined as the time required for a customer to be covered against default. It makes sense to use a survival model to predict the probability that a customer is covered against default and use this as a score for credit granting purposes. In contrast with a binary model, survival techniques are useful to produce time-to-profit application scorecards, based on *when* a customer will be covered against default rather than *if* the event will occur at all. This is a similar rationale to that presented by Banasik et al. (1999) for default purposes.

Knowing *when* a customer reaches the event can be useful to identify customers that require less time than others to be covered against default. This is particularly important in high risk credit programmes as the one under analysis if the objective is to recover the initial investment as soon as possible. Application scorecards can be designed for such purpose. These scorecards should be assessed in terms of classification accuracy and impact on portfolio profits (returns). The former is consistent with usually implemented practices in credit scoring; goods and bads are clearly defined. The latter aims to improve portfolio returns through the use of application scorecards; this is a benchmark to compare results of time-to-profit scorecards with those obtained when using an OLS model.

3.4.2 Time-to-profit prediction for investment planning objectives

When cumulative profits cover the outstanding balance the initial investment (i.e.: principal, initial loan resulting from first purchase) has already been recovered via the payment of instalments and the cumulative cash flows generated by customers. This means that the initial working capital already invested in these customers via receivables has already been recovered. The lending institution has already received these payments and needs to decide how these funds will be allocated. It would not make sense to hold cash flows generated by these customers just in case they default and hence incur in opportunity costs. This rationale is based on managing efficiently the liquidity generated by customers of the credit programme.

Time-to-profit could be used to identify the minimum point in time in which existing customers should be contacted to make further purchases. This builds on previous studies related to time-to-repurchase models (Andreeva et al, 2005). In contrast, time-to-profit could be useful to identify internal funding growth opportunities of credit programmes. That is, *when* is it safe to grant further credit to new customers with the profits generated by existing customers? Given the inclusive lending nature of the credit programme under analysis, it makes sense to adopt this stance. If more customers are served, the impact of the credit programme improves and more customers could benefit from it.

Therefore, predicting time-to-profit could be useful for lending institutions to plan the expansion of the credit programme (the monetary value of the initial loan is known at the application time when the first purchase occurs). Accordingly, periods where internal or external funding is expected to occur can be planned ahead. At the moment, 90% of receivables from the credit programme are being funded by bank loans; internal funding opportunities are not being identified at a customer level. A time-to-profit model promotes an ordered growth strategy and sheds light on particular features of inclusive lending programmes as the case under analysis.

Predicting time-to-profit is therefore useful to plan sales campaigns to target new customers. Moreover, since the objective of the credit programme is to assist customers to purchase products that improve their quality of life, accurately predicting time-to-profit makes a difference in social terms.

Models that predict time-to-profit for investment planning objectives should be assessed in terms of the mean absolute error (Wooldridge, 2009; Zhang and Thomas, 2012) as well as classification errors (in customer and monetary terms). This is explained in more detail in Section 4.3.3.3.6.

It is important to note that it would be unrealistic to assume that being covered against default leads to potential time savings from bad debt provisions, as banking practices require them. Moreover, given the high risk nature of the inclusive lending programme under analysis, it is more likely that lending institutions are willing to provision against default. Such provisions will continue to be made and are saved as a “cushion” against default.

4. METHODOLOGY

4.1 Introduction

This chapter presents the qualitative (Section 4.2) and quantitative methods (Section 4.3) used in combination to collect and analyse the data in order to address the research questions. Qualitative methods provide context to some of the results and are useful to explain some of the relationships between variables from quantitative models (Bryman, 2012). Qualitative data provides additional insights in interpreting profit scores obtained through statistical techniques. This is a common practice within microlending institutions, which continue to use jointly general market knowledge and statistical scorecards (Schreiner, 2000; Van Gool et al., 2009).

4.2 Qualitative methods

4.2.1 Data collection

Qualitative data were collected through interviews as they are useful to gather information regarding a person's values, attitudes (Cohen and Manion, 2000; Gray, 2009), which are not captured by quantitative data.

Purposive sampling (Gray, 2009) was used, because the aim was to obtain context information of the credit programme under analysis through a meaningful comparison with other institutions that offer similar services in the Region. In total, ten managers from various companies that provide financing services in the Region were interviewed. Table 4.2.1 outlines the companies included in the sample in terms of the industry, a brief description, the acronym used per company and informant position.

Various reasons justify the chosen sample. Firstly, the manager of the credit programme was interviewed to gain a closer insight of the case under analysis. Secondly, the direct competitor (i.e.: a credit programme offered by another utility Company) and managers from other utility companies were interviewed as well given the similarities and close relationship with credit programmes such as the one under analysis. Thirdly, managers from traditional commercial banks were included in the sample to contrast their practices with those of alternative credit programmes. These Companies are major actors at the national and local levels. This is particularly important, given the heterogeneity between regions in Colombia.

Semi-structured interviews were used to collect the data (Gray, 2009). The objectives of the interview were to:

- Explore the reasons that make customers choose a specific credit supplier.
- Understand the criteria used by credit suppliers to grant credit or to offer additional financing services to customers.
- Explore the reasons behind default.
- Understand the policies related to payments and explore the reaction of customers towards them.
- Explore the measures used to assess the financial performance of customers.

Table 4.2.1: Interviewed Companies

<table>
<tr><th>Industry</th><th>Description</th><th>Company (Acronym)</th><th>Informant position</th></tr>
<tr><td rowspan="2">Credit programme within a utility company</td><td rowspan="2">A utility company grants credit limits to customers with a positive credit history. Credit limit can only be used to purchase specific products or services. Customers pay monthly instalments through the utility bill.</td><td>Credit programme (CP)</td><td>Manager</td></tr>
<tr><td>Competitor (CO)</td><td>Manager</td></tr>
<tr><td rowspan="4">Service provider</td><td rowspan="4">These companies first provide the service and then customers make monthly payments. Utility companies may finance as well the payment of minor hardware associated with the service.</td><td>Education (ED)</td><td>Credit Manager</td></tr>
<tr><td>Utility 1 (U1)</td><td>Collections manager</td></tr>
<tr><td>Utility 2 (U2)</td><td>Collections manager</td></tr>
<tr><td>Utility 3 (U3)</td><td>Collections manager</td></tr>
<tr><td rowspan="4">Financial institution</td><td rowspan="4">This group includes traditional commercial banks that offer saving products and/or credits.</td><td>Lending 1 (L1)</td><td>Regional manager</td></tr>
<tr><td>Lending 2 (L2)</td><td>Regional manager</td></tr>
<tr><td>Lending 3 (L3)</td><td>Regional manager</td></tr>
<tr><td>Lending 4 (L4)</td><td>Regional manager</td></tr>
</table>

4.2.2 Data analysis methods and techniques

Data was analysed through thematic analysis. This was done in two stages: Analysis and interpretation. The analysis phase included inductive and deductive categorisation (i.e.: identifying themes based on previous themes and others emerging from the interviews), abstraction (defining broader categories) and dimensionalisation, which was useful to cross-compare companies. Each category or central theme was then interpreted (Spiggle, 1994). Special emphasis was given to the credit programme under analysis.

A first step was transcribing the interviews. Coding was initially done directly on printed transcripts and then by using specialised software NVivo. Codes were redefined if required as the coding process went on. This was done to guarantee the use of standardised codes for analysis purposes; categories were then used to group codes. Companies were compared by using dimensions across categories. Further code reclassifications were conducted if required.

4.3 Quantitative methods

4.3.1 Data preparation

4.3.1.1 Borrower records

Various raw files were provided by the lender to build the data set. Each borrower was assigned a single ID to facilitate tracking.

A single file containing borrower attributes was provided, as this data was collected by the sales force once the first purchase occurred. The lender generated monthly files for purchase and payment behaviour from the first time that borrowers were included in the accounting books onwards (i.e.: from April 2007 to November 2010). The first purchase could include more than one product; therefore the same ID could have more than one purchase and credit record. Multiple records per customer were concatenated and arranged to obtain a single longitudinal string per month, per borrower. This facilitated the longitudinal tracking of borrowers from the first purchase onwards and calculating totalised figures per customer.

4.3.1.2 Sociodemographic attributes and purchase characteristics

Table 4.3.1a shows explanatory variables 1 through 15 which were requested from the lender. These variables are sociodemographic attributes and first purchase characteristics that are commonly used in default and profit scoring models (Andreeva et al., 2005; Andreeva et al., 2007; Finlay 2008; Ma et al., 2009; Finlay 2010).

An initial step was to transform existing categories for *location* and *activity* into a more manageable and stable number of categories for subsequent treatment. Borrowers living in the state capital city were classified as "urban" and the rest were considered to live in "rural" areas. This was done based on the clear differences that exist between urban and rural areas in sociodemographic terms in the Colombian region under analysis. More than 100 different types of activities were reported in the original data set; the universal industry classification defined by the Colombian Government (DANE, 2006) was used to reduce categories to a more manageable level. *Age* in years and *years at address* were obtained from *date of birth* and *months at address*, respectively.

A second step was handling missing values and outliers, where applicable. The aim was to preserve all cases instead of deleting them for modelling purposes. A "missing" category was created to identify missing values of categorical variables (i.e.: *studies, job, contract, marital status, type of first product purchased* and *first loan duration*).

Given that the data set was entered manually, outliers were identified for *age, years at address* and *dependants.* This occurred most likely because of typing errors from the sales force at time of the first purchase. Specifically, borrowers with more than 12 dependants, younger than 18 years (lending to young people is illegal in Colombia) or with years at home exceeding age fell in this category.

Months at address had missing values as well. In both cases, values were replaced by the mean. This was done to preserve the average performance of individuals that is aimed with a scoring model. It is worthy noting that the participation of outliers varied between 0 and 1.8% of the total sample; therefore this decision should not have a major impact on the models.

Missing values of *loan duration* accounted for 14% of the total sample. No imputation was conducted given its relevance on profits. Accrued and actual payments directly depend on this feature and therefore can not be assumed to take a mean value. These customers also had missing values in the *value of loan*. Instead of imputing the mean, missing values were replaced for the outstanding balance after the first purchase was entered in accounting books. C*redit limit usage* was then calculated as the ratio between *value of first loan* and *approved credit limit as* it provides a relative comparison among borrowers, regardless of their socioeconomic stratum.

4.3.1.3 Borrowers' repurchase and payment behaviour variables

Table 4.3.1b shows the set of interval variables that provided the basic figures to calculate cumulative (average) profits and returns. It also includes indicator variables of default and repurchase. See variables 16 to 22.

Net sales commission was the only variable with missing values; this is related to missing values in some first purchase characteristics. This figure was calculated by using the average net sales commission provided by the Company (5%) and *value of loan*.

Default status was defined as three missed consecutive payments. A repurchase indicator was activated with each additional purchase.

Table 4.3.1a: Borrowers' attributes and first purchase variables

VARIABLE #	ORIGINAL VARIABLE	TYPE	TRANSFORMED VARIABLE (IF APPLICABLE)	DESCRIPTION	Missing values	% sample	Outliers	% sample	DUMMY VARIABLES
	BORROWERS' ATTRIBUTES								
1	ID	Categorical		Individual ID per customer	0	0.00%	N.A.	N.A.	
2	Location	Categorical	Urban or rural	If customer lives in capital city then urban. Otherwise, rural	0	0.00%	N.A.	N.A.	
3	Stratum	Categorical		Socioeconomic segmentation assigned by law to borrowers' address	0	0.00%	N.A.	N.A.	
4	Studies	Categorical		Education level	2,825	7.95%	N.A.	N.A.	
5	Job	Categorical		Occupation	929	2.61%	N.A.	N.A.	
6	Activity	Categorical	Industry	Economic activity according to colombian standards	0	0.00%	N.A.	N.A.	
7	Contract	Categorical		Type of contract related with job	29,930	84.24%	N.A.	N.A.	
8	Marital status	Categorical		Marital status	1,892	5.33%	N.A.	N.A.	
9	Date of birth	Interval	Age= Date of first purchase- Date of birth	Age in years	0	0.00%	646	1.8%	
10	Months at address	Interval	Years at address=(Months at address/12)	Years at address	2,111	5.94%	75	0.2%	
11	Dependants	Interval		Number of dependants	0	0.00%	15	0.0%	
	FIRST PURCHASE CHARACTERISTICS								
12	Type1 to Type4	Categorical		Type of first product purchased	4,936	13.89%	0	0.0%	
13	Approved credit limit (in COP)	Interval	Credit limit usage=Value of loan/Approved credit limit	Percentage of the approved credit limit used for the first purchase	0	0.00%	0	0.0%	
14	Value of loan (in COP)	Interval			4,936	13.89%	0	0.0%	
15	Loan duration (in months)	Categorical		Duration of loan taken to purchase first product	4,936	13.89%	0	0.0%	

Table 4.3.1b: Repurchase and payment behaviour variables

VARIABLE #	ORIGINAL VARIABLE	TYPE	TRANSFORMED VARIABLE (IF APPLICABLE)	DESCRIPTION	Missing values	% sample	Outliers	% sample
16	Net sales commission (in COP)	Interval		Sales commission paid by retailer shops-Sales commission paid to sales force	4,936	13.89%	0	0.0%
17	Paid interests (in COP)	Interval		Total payments=Paid interests+Paid moratory interests+Insurance net commission	0	0.00%	0	0.0%
18	Paid moratory interests (in COP)	Interval			0	0.00%	0	0.0%
19	Received insurance net commission (in COP)	Interval			0	0.00%	0	0.0%
20	Outstanding balance (in COP)	Interval		Total outstanding balance including principal, interests (contractual and moratory) and insurance	0	0.00%	0	0.0%
21	Days at arrears	Interval	Default=1 if days at arrears ≥ 90 otherwise, default=0	Defaulters= Customers with at least three missed consecutive payments	0	0.00%	0	0.0%
22	Repurchase indicator	Categorical		Repurchase=1 if further purchases were made during observation period. Otherwise, 0.	0	0.00%	0	0.0%

4.3.1.4 Fixed overheads

A two-step fixed overhead allocation was conducted. A proportion of central overheads from the utility Company were first allocated to the credit programme based on the proportion of receivables that it is accountable for (i.e.: other credit programme units coexist within the same Company). These overheads, together with own fixed overheads of the credit programme, were totalised to produce a single figure per year. This value was then allocated per month among all active customers.

Cumulative and average profits and returns were then calculated per customers as explained in Chapter 3.

4.3.1.5 Sample considerations

Figure 3.2.1 shows that 35,565 customers gathered in 15 monthly cohorts. A total of 35 frauds were excluded from that sample (i.e.: customers that disappeared permanently from the data set without fully paying the outstanding balance). Table 4.3.2 is a frequency table per loan duration of the portfolio of loans in the data set; 96% of loan durations were 60 months or less. Therefore, 35,530 customers were observed during t=30 months, as explained in Section 3.2.1 allowed for tracking the behaviour of profits for at least half of the duration of almost all loans in the portfolio.

Table 4.3.2: Loan duration frequencies

Loan duration	Frequency	Percent	Cumulative Frequency	Cumulative Percent
12	158	0.52	158	0.52
13	1	0.00	159	0.52
18	298	0.97	457	1.49
19	1	0.00	458	1.50
24	1987	6.49	2445	7.99
25	67	0.22	2512	8.21
30	974	3.18	3486	11.39
31	46	0.15	3532	11.54
36	4924	16.09	8456	27.64
37	395	1.29	8851	28.93
42	1752	5.73	10603	34.66
43	208	0.68	10811	35.34
48	1896	6.20	12707	41.53
49	169	0.55	12876	42.09
54	204	0.67	13080	42.75
55	22	0.07	13102	42.83
60	16223	53.03	29325	95.85
61	1269	4.15	30594	100.00

Frequency Missing = 4936

Cumulative and average profits and returns were then calculated according to the deflating/discounting/compounding rationale explained in Chapter 3. This allows all customers to start at the same point of time (i.e.: month in which the credit programme was launched).

An additional consideration was to test the hypothesis that mean profits and returns (in cumulative and average terms) of the two most distant cohorts (i.e.: 1 and 15) at t=30 were equal. It was assumed that if any, major differences between individuals would happen between these cohorts:

$$Ho: \mu_1 - \mu_{15} = 0 \qquad (4.3.1);$$

$$Ha: \mu_1 - \mu_{15} \neq 0 \qquad (4.3.2).$$

Table 4.3.3 shows the p-values obtained per hypothesis test. It can be inferred at a 5% significance level that mean cumulative and average profits and returns of cohorts 1 and 15 are not different in the long term. Consequently, 35,530 customers from cohorts 1 through 15 were gathered in a single cohort for subsequent analyses.

Table 4.3.3: P-values, hypotheses tests for equality of mean profit measures

NULL HYPOTHESIS	P-VALUE
$\mu OPCASH_{cum1}-\mu OPCASH_{cum15} = 0$	0.13
$\mu OPCASHav_{1}-\mu OPCASHav_{15} = 0$	0.12
$\mu CASHROA_{cum1}-\mu CASHROA_{cum15} = 0$	0.29
$\mu CASHROAav_{1}-\mu CASHROAav_{15} = 0$	0.14

4.3.2 Coarse classification

Explanatory variables were coarse-classified using dummy coding (Anderson, 2007) before producing predictive models. Separate bins were initially created per categorical variable and per decile of interval variables. The overall criterion was that at least 5% of the observations should be included per bin in order to produce stable results (Thomas, 2009). Categories of interval variables were collapsed based on their inherent order; categorical variables were collapsed according to general knowledge of the market. Table 4.3.4 shows the explanatory variables, the reference category and dummy variables created per explanatory variable.

This binning alternative was preferred to using weights of evidence (WOE) as it provided single categories that could be used for direct and indirect models, regardless of default and repurchase classes. It is also useful to represent non-linear relationships and to provide appropriate decision making for high volume portfolios (Anderson, 2007).

Table 4.3.4: Dummy coding, explanatory variables

VARIABLE	REFERENCE CATEGORY	DUMMY VARIABLES
AGE	18<Age ≤ 35 years	dumAGE3: 35< Age ≤ 43.5 years dumAGE4: 43.5< Age ≤ 52 years dumAGE5: 52< Age ≤ 60.5 years dumAGE6: 60.5< Age ≤ 69 years dumAGE7: 69< Age ≤ 103 years
LOCATION	rural (different to the capital city)	dumCITUR : urban (capital city)
CONTRACT	missing, other, or not applicable	dumCONTCON : Any type of contract (permanent, temporary)
JOB	employed	dumJOBRET : retired dumJOBSELF: self-employed dumJOBNOIN : housewife, student, unemployed, missing
MARITAL STATUS	single	dumMARMAR : married dumMARCOH : cohabitators dumMARWID : widow(er) dumMARDIV: divorced dumMARMIS: missing
STRATUM	stratum 1 (poor segments)	dumSTRA35: stratum>1
EDUCATION	missing	dumSTUPRI : primary dumSTUSEC: secondary dumSTUCOL : college dumSTUHIG: higher

Table 4.3.4: Dummy coding, explanatory variables

VARIABLE	REFERENCE CATEGORY	DUMMY VARIABLES
DURATION FIRST LOAN	durloan ≤ 31 months	dumLOAN3637: duration=36 or 37 months dumLOAN4243: duration=42 or 43 months dumLOAN4855: 48≤ duration ≤55 months dumLOAN6061: duration=60 or 61 months dumLOANMIS : missing loan duration
YEARS AT ADDRESS	YAH ≤ 8.5 years	dumYAH2 : 8.5< YAH ≤ 18 years dumYAH3 : 18< YAH≤ 27.5 years dumYAH4 : 27.5< YAH ≤ 37 years dumYAH510 : 37< YAH ≤ 94 years
DEPENDANTS	No dependants	dumDEP1 : 1 dependants dumDEP2 : 2 dependants dumDEP3 : 3 dependants dumDEP4 : 4 dependants dumDEP510 : 5 or more dependants
CREDIT LIMIT USAGE	Low	dumLOANPR2 : intermediate dumLOANPR310 : high
ACTIVITY	Services	dumactNA : Not applicable dumactOTH : Other industries dumactPROD : Manufacturing
FIRST PRODUCT PURCHASED	traditional products	dumprod1 : Non-traditional category 1 dumprod2 : Non-traditional category 2 dumprod3 : Non-traditional category 3

4.3.3 Data analysis methods and techniques

4.3.3.1 Profit and return measures

The first part of this section presents the exploratory framework to justify the use of profit (return) measures versus the traditional default criterion to rank customers. Various methods are then presented to assess the impact of using profit and return measures at customer and portfolio levels.

4.3.3.1.1 Profit and return measures versus default criterion

4.3.3.1.1.1 Characterization of portfolio results

Prior to characterising portfolio profits and returns, borrowers' profits and returns were ranked in ascending order. Cumulative portfolio measures were then produced as customers joined the sample according to their ranks. This was done for the complete sample, defaulters and non-defaulters:

$$Portfolio\ profit_t = \sum_{i=1}^{n_i} C_{i,t} \qquad (4.3.3),$$

where:

$C_{i,t}$ = *OPCASHcum* or *OPCASHav* for borrower *i* at t=12, 24 or 30;

n= total number of customers;

n_i= total customers until customer i;

$n_i \leq n$

$$Portfolio\ return_t = \sum_{i=1}^{n_i} R_{i,t} \times w_{i,t} \qquad (4.3.4),$$

where:

$R_{i,t}$ = *CASHROAcum* or *CASHROAav* for borrower *i* at t=12,24 or 30;

$$w_{i,t} = \frac{\text{final balancedef}_{\text{i,t}}}{\sum_{i=1}^{n} final\,balancedef_{i,t}}\ ;$$

$Finalbalancedef_{i,t}$= deflated and discounted final balance of customer *i* at time *t.*

A weighed portfolio return was preferred to a crude average return to reflect the contribution of each borrower to portfolio results.

A first approach used to characterise portfolio profits and returns of the complete sample, defaulters and non-defaulters was to calculate and analyse two ratios suggested in the marketing literature: the Stobachoff coefficient (STC) and vulnerability factor (VF) (Storbacka, 1995; Helgesen, 2007).

STC quantifies the dependence of portfolio results on a group of customers. Low STC values imply less dependence (i.e.: close to 0). Figure 4.3.1 depicts portfolio profits (returns) vs. cumulative customers. This graph is useful to calculate STC as:

$$STC = \frac{A}{(A+B)} \quad (4.3.5);$$

(A+B) was calculated through the graphical (rectangle) method to approximate the area under a curve. The height of each rectangle corresponds to portfolio profits (returns) until customer *i.* Each rectangle has unitary width as the marginal change of portfolio profits (returns) *Y* occurs per customer. Therefore:

$$(A+B) = \sum_{i=1}^{n_i} Y_i \quad (4.3.6),$$

where:

Y_i= Portfolio profits or weighed returns

B was calculated using the triangle area formula:

$$B = \frac{n \times Y_n}{2} \quad (4.3.7);$$

from (4.3.6) and (4.3.7) it follows that:

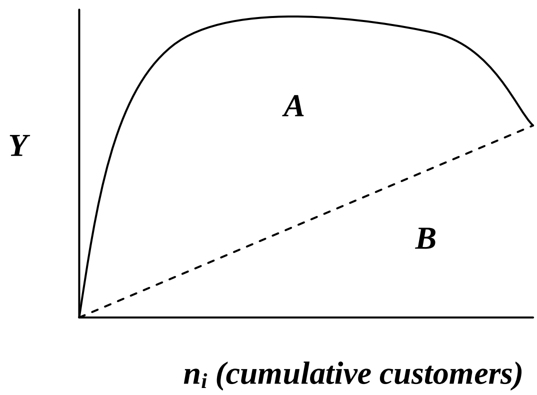
$$A = \left(\sum_{i=1}^{n_i} Y_i \right) - \left(\frac{n \times Y_n}{2} \right) \qquad (4.3.8).$$

On the other hand, VF measures loss subsidisation between segments of customers. Ideally it should be close to zero. It is calculated as:

$$VF = \left(\frac{Loss\ making\ customers}{Total\ customers} \right) \times 100\% \qquad (4.3.9).$$

STC and VF are used for risk assessment purposes in terms of profit dependence and to make various decisions related to specific segments (Van Raaij, 2005; Helgesen, 2007). They are useful to shed light on the profitability features of defaulters and non-defaulters.

Figure 4.3.1: The Stobachoff Curve



Adapted Figure (Helgesen, 2007)

4.3.3.1.1.2 Opportunity cost analysis

A second approach to highlight the additional information profit scoring can provide was to conduct an opportunity cost analysis. This is a common practice in management accounting (Williamson, 1996; Drury, 2000).

An impact ratio was used to compare the mean profits (returns) from profitable defaulters with mean losses from unprofitable non-defaulters. It is useful to assess the relative impact of profitable defaulters versus unprofitable non-defaulters. Defaulters were identified as customers that were at arrears during at least 90 consecutive days:

$$IMPACT_t = \frac{\overline{X}_d}{\left|\overline{Y}_{nd}\right|} \qquad (4.3.10),$$

where:

$\overline{X}_d$ = Mean profits (returns) of defaulters;

$\overline{Y}_{nd}$ = Mean losses (returns) of non-defaulters at

t=12, 24 and 30 months.

This measure was calculated for cumulative and average measures.

4.3.3.1.2 Profit versus return measures

Prior to producing profit and return scores through predictive models, various methods were used to explore the effect of using either profits or returns to rank customers. Spearman correlations and Chi Square tests were used at a customer level. Acceptance rate and opportunity cost analyses were conducted at a portfolio level.

4.3.3.1.2.1 Ranks analysis

A closer comparison between profit and return measures for credit scoring purposes was conducted through the use of customer ranks according to these measures. The aim was to verify whether a borrower's rank changed depending on what measure was used. Relative attractiveness of a borrower to the lender depends on the rank provided by profits (returns).

Spearman's rank-order correlation test was used to compare different scores obtained per customer. A perfect correlation between scores indicates that no additional value is provided by an alternative scorecard versus the original one (Anderson, 2007). Results obtained from this measure were complemented with those from the Chi Square Test (Freund, 1992; Freedman and Pisani, 1998) of scores' independence:

H_o: $Score_x$ and $Score_y$ are independent

H_a: $Score_x$ and $Score_y$ are not independent (4.3.11),

where:

$Score_x$	$Score_y$
$OPCASHcum_t$	$CASHROAcum_t$
$OPCASHav_t$	$CASHROAav_t$
$CASHROAav_t$	$CASHROAcum_t$
$OPCASHav_t$	$OPCASHcum_t$

This test was applied to rank decile bands per month.

4.3.3.1.2.2 Acceptance rate analysis

The impact of using profit (return) ranks on portfolio results was also assessed at various acceptance rates (between 50 and 95). Customers were initially ranked according to cumulative or average profits (returns). Then it was assumed that customers up to each acceptance rate were accepted for credit. Portfolio profits and returns were calculated according to (4.3.3) and (4.3.4), respectively for "accepted" customers. This was useful to analyse the behaviour of portfolio measures across a range of acceptance rates.

4.3.3.1.2.3 Opportunity cost analysis

Finally, an opportunity cost analysis was used to quantify the marginal effect of using profit or return measures on portfolio results at t=12, 24 and 30 months.

This was done solely to choose between cumulative and average measures. A predefined acceptance rate defined n (i.e.: cumulative accepted customers).

Let:

c=cumulative (OPCASHcum) or average (OPCASHav) profits

C= Portfolio profits

r=cumulative (CASHROAcum) or average (CASHROAav) returns

R= Portfolio returns

Ranking customers based on profits would yield the following portfolio profits:

$$C_c = \sum_{i=1}^{n} c_{c\,i,t} \qquad (4.3.12),$$

where:

$c_{c_{i,t}}$ is the profit of customer i at time t if cumulative or average profits are used for credit granting purposes.

Alternatively, if customers were ranked according to their returns, portfolio profits would be:

$$C_r = \sum_{i=1}^{n} c_{r\,i,t} \qquad (4.3.13),$$

where:

$c_{r_{i,t}}$ is the profit of customer i at time t if cumulative or average returns are used instead of profits.

Additional (foregone) portfolio profits may result from ranking customers based on profits instead of returns:

$$OC_{C,t} = C_c - C_r \qquad (4.3.14).$$

A similar rationale was used to assess the impact of using return scoring on portfolio returns:

$$R_c = \sum_{i=1}^{n} R_{c_{i,t}} \times w_{i,t} \quad (4.3.15) \qquad \text{and} \qquad R_r = \sum_{i=1}^{n} R_{r\,i,t} \times w_{i,t} \quad (4.3.16),$$

where:

$w_{i,t} = finalbalance_{i,t} / (\sum_{i=1}^{n} finalbalance_{i,t})$.

Using profits instead of returns may lead to additional (foregone) portfolio returns:

$$OC_{R,t} = (R_c - R_r) \times finalbalance_{c,t} \qquad (4.3.17),$$

where:

$finalbalance_{c,t}$ is the outstanding debt of customers accepted according to profits. This product was calculated to obtain monetary results comparable to (4.3.14).

In total, if profits are used instead of returns to rank customers, the opportunity cost would be:

$$OC_t = OC_{C,t} + OC_{R,t} \qquad (4.3.18);$$

if $OC_{C,t} > OC_{R,t}$ then OC_t = additional portfolio profits (4.3.18a);

If $OC_{C,t} < OC_{R,t}$ then OC_t = foregone portfolio coverage against default (4.3.18b);

otherwise, it would not make a difference to use either profits or returns to rank customers. This analysis can be done for different acceptance rates and can be useful to choose between cumulative and average measures.

4.3.3.2 Predictive methods

This section first presents the effective data set used to produce direct and indirect models. This descriptive analysis was used to define training and holdout samples. Modelling techniques used to predict the probabilities of default at t=12, 30 and of repurchase in t=12, 30 are then presented. Modelling techniques used to produce direct and indirect profit and return scorecards are then explained.

4.3.3.2.1 Effective data set

As explained in Section 4.3.1.5, the original dataset consisted of 35,530 customers. In total, 4% of the customers were missing at t=12, 24 or 30 months; these were not considered for modelling purposes. Intuitively, this was based on the fact that the objective of the models is to predict cumulative profits (returns) of customers that had an ongoing relationship with the lender, during the observation period. This was preferred to compounding figures from the last month a customer was in the sample to t=30 to calculate $OPCASHcum_{30}$ and $CASHROAcum_{30}$, and therefore assuming that these customers remained in the data set without generating additional profits during the missing months. Another complication would have been the treatment of fixed overheads during missing periods; it would not make sense to charge them to these customers as they were "inactive". As of $CASHROAcum_{30}$, further assumptions would have to be made regarding the outstanding balance during the rest of the observation period. This would not correspond to reality as those customers did not have an outstanding balance during that period and hence it would not be possible to calculate cumulative returns at t=30.

The aim was to produce the best possible model through OLS without making any assumptions regarding cumulative profits of missing observations. Excluding missing customers allowed as well the comparison of indirect models with probabilities of default and repurchase in the short and long term: t=12 and t=30, respectively. The dataset after exclusions consisted of 33,964 customers split randomly as 80/20 to configure $training_1$ and $holdout_1$ samples, as shown on Table 4.3.5.

Table 4.3.5: $Training_1$ and $Holdout_1$ sample sizes

	$Training_1$	$Holdout_1$	Total
n	27,157	6,807	33,964

Prior to the modelling phase, descriptive measures of location and dispersion (Freedman and Pisani, 1998; Der and Everitt, 2009) and graphs were used to analyse the behaviour of $OPCASHcum_{30}$ and $CASHROAcum_{30}$ per customer. This provided a starting point to gain a better insight of the measures to predict and hence to define the effective data set to be used for modelling purposes.

Table 4.3.6 includes the following descriptive statistics for each measure in $training_1$ (label=1) and $holdout_1$ (label=0) samples: number of observations, standard deviation, minimum, maximum, skewness and kurtosis. Standard deviations, minimum and maximum values are relative to the mean value of each measure due to confidentiality reasons.

Minimum and maximum values in Table 4.3.6 show that both measures have extreme observations that result in high values of standard deviation and skewness in $training_1$ (label=1) and $holdout_1$ (label=0) samples. Some customers are substantially more profitable than the rest; this results in heavy tails in the distributions of both measures. Loss makers are unusual but still present. Neither of the two measures follows a normal distribution.

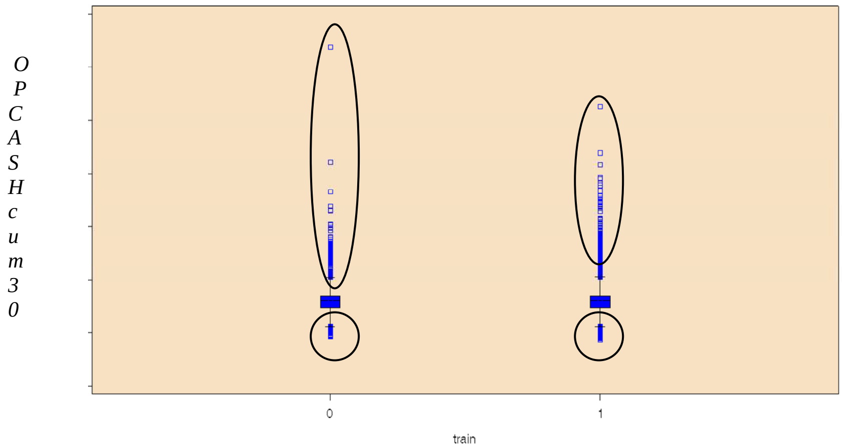
Figures 4.3.2 and 4.3.3 are box plots of $OPCASHcum_{30}$ and $CASHROAcum_{30}$, respectively. Values are not displayed for confidentiality reasons. It is evident that extreme values affect more substantially the distribution of $CASHROAcum_{30}$; they are more dispersed and distant from the mean. Thirty (seven) customers from $training_1$ ($holdout_1$) sample had an outstanding balance less than £1.3 (£1). These values are not significant in monetary terms. They may result from the payment of instalments greater than those agreed or because of system errors. Given the responsiveness of relative measures to small values in the denominator, losses or profits can be magnified and hence affect the distributions. Other outliers may arise from less critical cases that still affect the distributions of profits and returns.

Table 4.3.6: Descriptive statistics, training$_1$ and holdout$_1$ samples

LABEL	N	VARIABLE	STD DEV	MIN	MAX	SKEWNESS	KURTOSIS
0	6,807	*OPCASHCUM $_{30}$*	0.39	-0.10	9.11	2.42	35.99
		CASHROACUM $_{30}$	12.71	-1.46	1,024.44	77.16	6,181.44
1	27,157	*OPCASHCUM $_{30}$*	0.38	-0.20	7.24	1.21	11.41
		CASHROACUM $_{30}$	59.69	-97.38	7,879.36	110.61	13,299.75

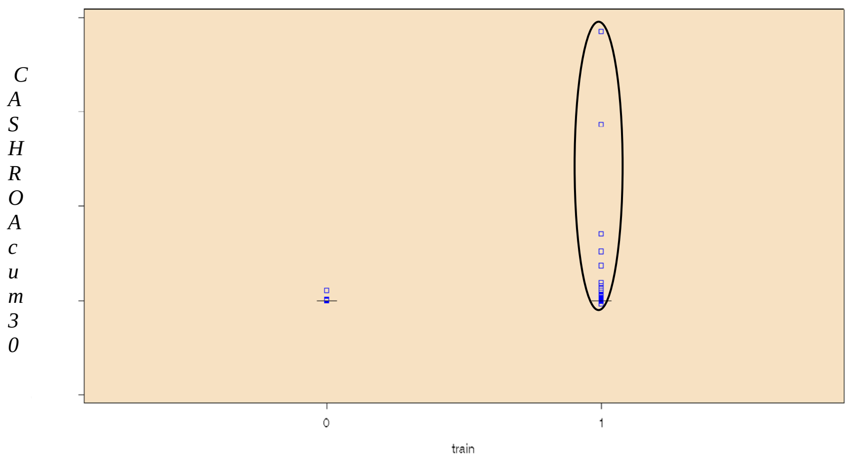
0= Holdout$_1$ 1= Training$_1$ samples

Figure 4.3.2: *OPCASHcum$_{30}$* box plots, training$_1$ and holdout$_1$ samples



0= Holdout$_1$ 1= Training$_1$ samples

Figure 4.3.3: *CASHROAcum$_{30}$* box plots, training$_1$ and holdout$_1$ samples



0= Holdout$_1$ 1= Training$_1$ samples

Consequently, outliers from each measure were trimmed to visualise better the distributions. Initially, values that exceeded 1.5 times the interquartile range were considered outliers. This resulted in outliers that account for 5% and 16% of the observations for *OPCASHcum*$_{30}$ and *CASHROAcum*$_{30}$, respectively. The proportion is acceptable for the former but not for the latter.

Alternatively, outliers were observations where *CASHROAcum*$_{30}$ $\in (-\infty, -0.5]$ or $[1.5, \infty)$. These are considered extreme outliers by the management team. Training$_1$ and holdout$_1$ samples were therefore trimmed by 5% according to cumulative profits and returns to configure training$_2$ and holdout$_2$ samples, as shown on Table 4.3.7.

Table 4.3.7: Training$_2$ and Holdout$_2$ sample sizes

	Training$_2$	Holdout$_2$	Total
n	24,617	6,186	30,803

Table 4.3.8 includes descriptive statistics for training$_2$ and holdout$_2$ samples. Again, standard deviations, minimum and maximum values are relative to the mean value of each measure due to confidentiality reasons. As expected, training$_2$ and holdout$_2$ samples are less dispersed than training$_1$ and holdout$_1$ samples, respectively.

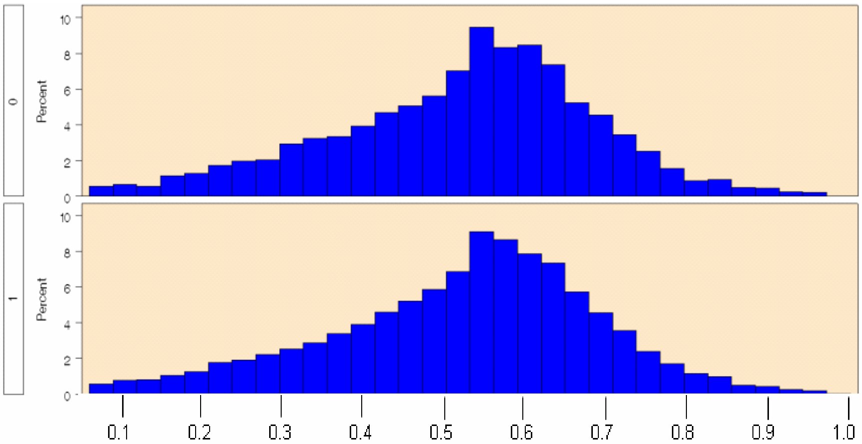
Figures 4.3.4 and 4.3.5 depict the distributions of *OPCASHcum*$_{30}$ and *CASHROAcum*$_{30}$, respectively. Values are not displayed for confidentiality reasons. *OPCASHcum*$_{30}$ (*CASHROAcum*$_{30}$) is left (right) skewed. Negative (positive) skewness values in Table 4.3.8 confirm this. Furthermore, *CASHROAcum*$_{30}$ has a greater kurtosis than that of OPCASH*cum*$_{30}$. This highlights the differences between both measures: More customers may yield higher profits whereas this may not be the case in terms of returns due to the scaling of profits by the outstanding balance.

Table 4.3.8: Descriptive statistics, training$_2$ and holdout$_2$ samples

LABEL	N	VARIABLE	STD DEV	MIN	MAX	SKEWNESS	KURTOSIS
0	6,186	*OPCASHCUM$_{30}$*	0.28	0.21	1.77	-0.37	-0.001
		CASHROACUM$_{30}$	0.32	0.11	2.01	0.71	1.19
1	24,617	*OPCASHCUM$_{30}$*	0.28	0.21	1.77	-0.39	0.02
		CASHROACUM$_{30}$	0.33	0.09	2.01	0.66	1.08

0= Holdout$_2$ 1= Training$_2$ samples

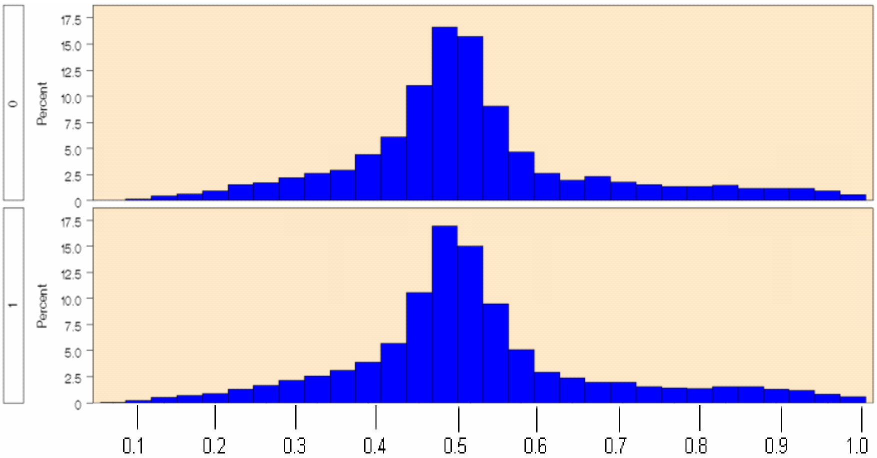
Figure 4.3.4: *OPCASHcum$_{30}$* histograms, training$_2$ and holdout$_2$ samples



OPCASHcum$_{30}$

0= Holdout$_2$ 1= Training$_2$ samples

Figure 4.3.5: *CASHROAcum$_{30}$* histograms, training$_2$ and holdout$_2$ samples



CASHROAcum$_{30}$

0= Holdout$_2$ 1= Training$_2$ samples

Finally, Figures 4.3.6 and 4.3.7 display the joint behaviour of *OPCASHcum*$_{30}$ and *CASHROAcum*$_{30}$ for training$_2$ and holdout$_2$ samples, respectively. Values are not displayed for confidentiality reasons. The plots suggest that in general, as cumulative profits increase, cumulative returns increase as well. However, the relationship is not linear as different customers with the same profits (returns) may have different returns (profits). This suggests that using return measures to rank customers can offer additional insight to that offered by profits. This justifies the separate modelling of each measure for scoring purposes.

Figure 4.3.6: *CASHROAcum*$_{30}$ vs. *OPCASHcum*$_{30}$ (training$_2$ sample)

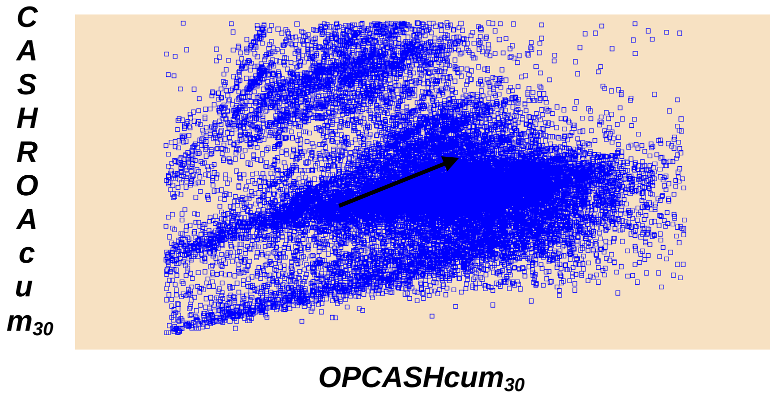
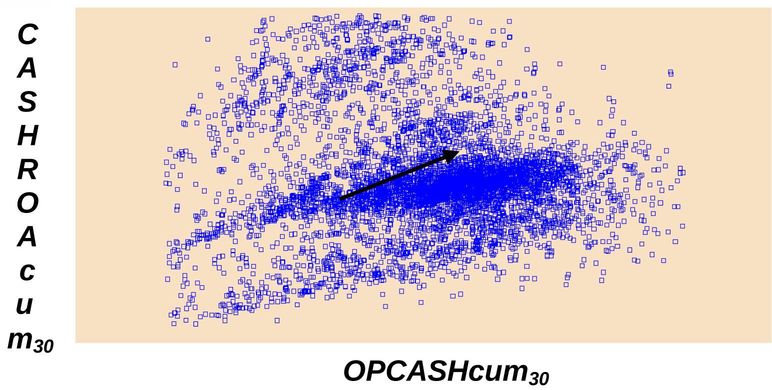


Figure 4.3.7: *CASHROAcum30* vs. *OPCASHcum*$_{30}$ (holdout$_2$ sample)



4.3.3.2.2 Probabilities of default and repurchase

Probabilities of default and repurchase were predicted from borrowers' attributes in $training_1$ sample; models were tested in $holdout_1$ sample. A logit model (Loffler and Posch, 2007) was used:

$$\Pr(Y_i) = \frac{1}{1 + \exp(\alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_k x_{ik})} \qquad (4.3.19),$$

where:

Y_i = Default at t=12, 30; repurchase in t=12, 30;

$\beta_{m=1\ to\ k}$ = Coefficients of significant attributes at a 1% significance level, estimated through the maximum likelihood method with a stepwise variable selection software;

$x_{im=1\ to\ k}$ = Actual attributes of borrower *i*.

A maximum variance inflation factor VIF of 5 was taken as a threshold to avoid near multicollinearity issues:

$$VIF = \frac{1}{1 - R_j^2}, \quad j = 1,...,k \qquad (4.3.20);$$

R_j^2 represents the coefficient of multiple determination resulting from regressing each attribute on the remaining *(k-1)* attributes. This was done to better identify the effects of each significant attribute on the predicted variable, as other unobserved variables may be affecting results. Furthermore, high multicollinearity leads to regression coefficients that lack precision (i.e.: their variance is artificially inflated).

Results were interpreted through the odds ratio, which quantifies how much more likely the event is to occur, when the attribute takes values different to the reference category (Panik, 2009) as

$$\varphi(X_a, X_r) = \frac{O(X_a)}{O(X_r)} = \exp(\beta_a) \qquad (4.3.21).$$

This method is widely used in the banking industry and academia (Hand and Henley, 1997; Baesens et al., 2003; Anderson, 2007). Discrimination accuracy is tested through the area under the ROC curve (AUC), which compares (1-specificity) (i.e.: false positive rate) against sensitivity (i.e.: true positive rate) for different cut-offs. Such area should be greater than 50% to perform better than a random guess (Anderson, 2007).

4.3.3.2.3 Direct methods

Prior to modelling profits and returns, extreme outliers discussed in Section 4.3.3.2.1 had to be dealt with. Winsorizing or trimming (Barnett and Lewis 1994) those observations were initial alternatives. This was avoided, as the former requires assuming specific values for extreme observations, whereas the latter ignores cases that are still feasible to occur. Another option was using the natural logarithm of returns; this would require setting an arbitrary minimum value close to zero for negative returns and consequently different significant positions could be obtained, affecting the overall model.

The approach taken was to exclude from training_1 sample observations with outliers in either $OPCASHcum_{30}$ or $CASHROAcum_{30}$. These observations were then included in holdout_1 sample to use original values and test models under extreme conditions. Consequently, models were developed using training_2

sample; holdout_3 sample was used to test such models. Table 4.3.9 shows sample sizes.

Table 4.3.9: Training_2 and Holdout_3 sample sizes

	Training_2	Holdout_3	Total
n	24,617	9,347	33,964

A multiple linear regression was used to produce direct profit (return) scores, $\gamma_{i,}$ from borrowers' attributes in Table 4.3.4:

$$\gamma_i = \sum_{n=1}^{k} \beta_n x_{in} + e_i \qquad (4.3.22),$$

where:

$\beta_{n=1\ to\ k}$ = Coefficients of significant attributes at a 1% significance level, estimated through OLS (Ordinary Least Squares) with a stepwise variable selection. Attributes with a VIF >5 were excluded from the models to avoid multicollinearity issues;

$x_{in=1\ to\ k}$ = Application attributes of borrower *i*.

This method has been used in previous studies (Andreeva et al., 2007; Finlay, 2008; Finlay, 2010). No intercept was included in the models (Panik, 2009), as no profits or losses are generated by customers that have not taken loans through the credit programme. Fixed overheads can only be charged to existing customers; likewise, there are no a priori profits or returns when attributes=0. Coefficients are interpreted as the increase (decrease) in average profits or returns, compared with the reference group.

Results from OLS regression can not be assessed in terms of classification accuracy, given that the predicted measure is continuous by definition (i.e.:

profits or returns). An error measure similar to the mean absolute error (MAE) (Wooldridge, 2009) was used to assess the predictive accuracy of models:

$$Error\ rate = \frac{\sum_{i=1}^{n} | Y_i - \hat{Y}_i |}{FB_{def}} \times 100\% \qquad (4.3.23),$$

where:

Y_i ($\hat{Y}_i$) = actual (predicted) score for customer *i*.

FB_{def} = Portfolio deflated and discounted outstanding balance at t=30.

This overall measure compares the accuracy of prediction in relative terms to portfolio receivables, which is useful to scale and compare results in training and holdout samples. Ideally this measure should be 0% (i.e.: predicted and actual values coincide). In the case of $CASHROAcum_{30}$, prior to calculating the error rate, absolute differences in returns were multiplied by the outstanding balance per customer. This is consistent with error rate calculations of $OPCASHcum_{30}$.

4.3.3.2.4 Indirect methods

Predicted probabilities of default and repurchase were used as predictors to generate indirect profit (return scores), Ψ_i, per customer through OLS:

$$\Psi_i = \sum_{j=1}^{2} \beta_j x_{ij} + e_i \qquad (4.3.24),$$

where:

β_j= Coefficients of significant attributes at a 1% significance level, estimated through OLS (Ordinary Least Squares) with a stepwise variable selection;

x_{i1}= Pr (default at t=12 or t=30) and x_{i2}=Pr (repurchase in t=12 or t=30). Training[2] and holdout[3] samples were used to develop and test indirect models respectively, in order to be consistent with the data set used to produce direct models. The predictive accuracy of indirect models was assessed through the error rate according to (4.3.23).

4.3.3.2.5 Scorecard comparison

Since predicted values should be considered scores (Anderson, 2007) instead of predicted profits or returns, two additional criteria were used to compare models. First, the usefulness of models was assessed according to their impact on portfolio results. Portfolio profits and returns resulting from direct and indirect scorecards were compared for different acceptance rates, as explained in Section 4.3.3.1.2.2. This is the usual assessment criterion in profit scoring (Andreeva et al., 2007; Finlay 2008; Finlay 2010). Second, the best performing profit (return) model was assessed in terms of its marginal effect on portfolio profits (returns), per acceptance rate.

4.3.3.3 Time-to-profit

Time-to-profit was previously defined in Section 3.4 as the moment when a customer is totally covered against default. This is the event of interest, before clearing the outstanding balance; once the loan is paid off, it is pointless to analyse coverage against default. Since the response variable is “time to”, this section presents various considerations regarding the survival techniques that were used for descriptive and predictive purposes (Hosmer et al., 2008).

4.3.3.3.1 Discrete time

Even though payments can occur at any time during each month, the event can only be recorded at the end of the month. This is because accounting records from paid interests and net commissions are produced monthly. Income is matched accordingly with fixed overheads, which require the completion of each observation period (i.e.: month). Furthermore, the resulting outstanding balance can only be obtained once all the monthly payments have been made. These financial accounting considerations define the discrete nature of time-to-profit, as it can only occur once each month has been completed and not at any point of time (i.e.: continuous case). This is a similar situation to that presented in a previous study where time was discrete due to the record of data from mortgage products on a monthly basis (Mc Donald et al., 2010).

4.3.3.3.2 Sampling and time-to-first event

All 35,530 customers were taken regardless if customers had left the sample at t=12, 24 and 30 because survival models allow for censoring. Table 4.3.10 shows the composition of the total sample of customers in terms of the frequency and cumulative frequency (number of customers and as a percentage of the total sample) of customers which were covered or not against default during the observation period. Only the first event was considered because 77% of the customers had not experienced it by t=30 mostly because they took longer term loans (between 55 and 60 months). Furthermore, given the cumulative nature of $CASHROAcum_t$, some customers could experience the event during various consecutive months. This is mostly a consequence of magnified ratios resulting from both a decreasing outstanding balance and marginally increasing cumulative profits, rather than as a result of further purchases. Customers were observed until they censored from the sample or up to t=30 months, as explained previously.

Table 4.3.10: Frequencies of customers with event

Status	Frequency	%	Cumulative Frequency	Cumulative %
0	27,495	77%	27,495	77%
1	8,035	23%	35,530	100%

0=not covered against default by t=30; 1, otherwise.

An 80/20 split in the complete data set was used to obtain training_3 and holdout_4 samples, as shown in Table 4.3.11.

Table 4.3.11: Training_3 and Holdout_4 sample sizes

	Training_3	Holdout_4	Total
n	28,424	7,106	35,530

4.3.3.3.3 Descriptive analysis

A descriptive analysis was completed to gain an initial understanding of the event in terms of survivor and hazard functions (Jenkins, 2005; Hosmer et al., 2008; Allison, 2010).

T is the random variable that represents the event time. The survivor function, $S(t)$, is defined as the probability of not being covered against default beyond *t*. If *T* is a continuous variable, then:

$$S(t) = \Pr(T > t) = 1 - F(t) \qquad (4.3.25),$$

where:

$F(t) = \Pr\,(T \leq t)$ is the cumulative distribution function of *T*.

On the other hand, the hazard function for continuous survival data is defined as the instantaneous risk that the event will occur at time *t*:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \le T < t + \Delta t / T \ge t)}{\Delta t} \qquad (4.3.26).$$

The life-table method was used to estimate survivor and hazard functions in order to gain an initial understanding of the data set. This method is useful for large data sets and when measures of event times are crude. Under this method, event times are grouped into intervals rather than presenting results per individual. It is assumed that censored cases occur at the midpoint of the interval (Allison, 2010).

For interval *i* with starting time t_i and q_i conditional failure probability, then the survival estimate, $\hat{S}(t)$, the probability of surviving to t_i or beyond was calculated as:

$$\hat{S}(t) = \prod_{j=1}^{i-1} (1 - q_j) \qquad (4.3.27),$$

where:

$$q_j = \frac{number\ failed}{effective\ sample\,size} \qquad (4.3.28).$$

On the other hand, the estimate of the hazard function evaluated at the midpoint of each interval *i* was calculated as:

$$h(t_{im}) = \frac{d_i}{b_i\left(n_i - \frac{w_i}{2} - \frac{d_i}{2}\right)} \qquad (4.3.29),$$

where:

t_{im}= midpoint of interval *i*

d_i= number of events

b_i= width of interval *i*

n_i= number of customers still at risk at the beginning of interval *i*

w_i= number of censored cases within interval *i* (Allison, 2010).

4.3.3.3.4 Time-to-profit application scorecards

The same covariates and coarse classifications used to produce profit and return scores were used to generate time-to-profit scorecards. Given the discrete nature of the event under analysis, the discrete version of semi parametric survival regression (Cox, 1972) was accordingly used to predict $Pr\ (CASHROACUM_t \geq 1)$. This was preferred to choose an approximation method from the continuous to the discrete case.

An initial step was to generate an observation per customer per month until censoring (Allison, 1982; Allison, 2010). Thus training[3] and holdout[4] samples resulted in 824,994 and 206,418 customer-months, respectively.

Given that there were no time dependant covariates, each observation generated per customer had the same attributes at the time of the first purchase. The following logistic regression model was used for modelling purposes:

$$Log\ [P_{it} / (1-P_{it})] = \alpha_t + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} \qquad (4.3.30),$$

where:

P_{it} = Conditional probability that customer *i* is covered against default at time *t* given that this has not occurred in the previous month.

$\beta_{s=1 \text{ to } k}$ = Coefficients of significant covariates at a 1% significance level, estimated through the maximum likelihood method by using a stepwise procedure. Again, a maximum VIF of 5 was defined to avoid multicollinearity issues.

$x_{is=1 \text{ to } k}$ = Application attributes of borrower *i*.

Different alternatives to include the effect of time on hazard α_t were explored:

- **Constant hazard**

This model assumes that time does not have an effect on the hazard of occurrence of the event:

$$\boldsymbol{\alpha_t = \alpha} \qquad (4.3.31).$$

Intuitively, this rationale does not correspond to reality, as it is clear that as time goes on, the hazard of coverage against default either increases or decreases; it is not expected to remain constant throughout the observation period. This alternative was explored as a starting point as it is the most parsimonious option for modelling purposes. Additionally, it was useful to validate if time has an effect on the hazard of event through the model's fit when compared against those that account for the effect of time.

- **Time dependent hazard**

The following alternatives account for the effect of time on hazard in different ways:

$$\alpha_t = \alpha + \beta_1 t \qquad (4.3.32);$$

this model assumes that the hazard changes at a constant rate β_1. It is the most basic model to include the effect of time directly.

$$\alpha_t = \alpha + \beta_1 t + \beta_2 t^2 \qquad (4.3.33) \text{ and}$$

$$\alpha_t = \alpha + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 \qquad (4.3.34) ;$$

the quadratic and cubic models assume that the hazard changes at rates:

$\beta_1 + 2\beta_2 t$ and $\beta_1 + 2\beta_2 t + 3\beta_3 t^2$, respectively. The aim was to explore other alternatives to the shape of the hazard function throughout time.

$$\alpha_t = \alpha + \beta_1 \ln(t) \qquad (4.3.35);$$

this alternative aims to smooth the effect of time in the long term by using its logarithmic transformation.

Two final alternatives that used categorical (dummy variables for (n-1) months or quarters) were included, following the rationale of using solely dummy variables, in line with that used to produce profit and return scores:

$$\alpha_t = \alpha + \beta_t \qquad (4.3.36),$$

where: t=1 to 29 months or t=1 to 9 quarters.

Various methods were used to compare models. Models were assessed in terms of their fit and considering multicollinearity issues. The former was assessed according to Akaike's information criterion (AIC):

$$AIC = -2\log L + 2k \qquad (4.3.37),$$

where:

log L= log-likelihood

k= number of estimated parameters (Panik, 2009).

The latter was assessed according to a model's variance inflation factor (VIF), as shown in (4.3.20).

The predictive accuracy of models was assessed in terms of their ability to discriminate goods from bads, mainly through the AUC. The H measure was also calculated to compare models using a different criterion. Compared with

AUC, this measure does not depend on the distribution of scores itself. It ranges from 0 to 1 and large values are preferred (Hand, 2009).

Various approaches were taken to calculate AUC and H measure. Approach 1 assessed the predictive accuracy at the last month when a customer either was covered against default (status=1) or was censored without experiencing such event (status=0). The status of a customer was taken as it was in the original data set. Table 4.3.12 shows the number of customers, n, per status for training_3 and holdout_4 samples, under approach 1. Predicted probabilities by each model at time to event were used to calculate the accuracy measures.

Table 4.3.12: Customers per sample, approach 1

SAMPLE	n	status=0	status=1
TRAINING_3	28,424	21,980	6,444
HOLDOUT_4	7,106	5,515	1,591

0= customer is not covered against default; 1, otherwise.

Approaches 2a, 2b and 2c assumed that customers stayed in the sample until t_c=12, 24 and 30 months, respectively. Probabilities of the event at t_c were predicted accordingly, using each of the models. This was based on the fact that at the application time one cannot know when customers will be censored until they actually do so. Regarding the status of a customer, the following criteria were applied:

- If status=1 and $t>t_c$, then status at t_c =0 (i.e.: the event had not occurred until t_c)
- If status=1 and $t\leq t_c$, then status at t_c = 1 (terminal state)
- If status=0 and $t\leq t_c$, then status at t_c=0 (i.e.: the event never occurred until t_c)

Table 4.3.13 shows the number of customers, n, per status for training$_3$ and holdout$_4$ samples, under approaches 2a, 2b and 2c.

Table 4.3.13: Customers per sample, approach 2

Approach 2a: t_c=12 months

SAMPLE	n	status=0	status=1
TRAINING$_3$	28,424	28,402	22
HOLDOUT$_4$	7,106	7,095	11

Approach 2b: t_c=24 months

SAMPLE	n	status=0	status=1
TRAINING$_3$	28,424	26,845	1,579
HOLDOUT$_4$	7,106	6,696	410

Approach 2c: t_c=30 months

SAMPLE	n	status=0	status=1
TRAINING$_3$	28,424	21,980	6,444
HOLDOUT$_4$	7,106	5,515	1,591

0= customer is not covered against default; 1, otherwise.

Under approach 3, an observation was generated per customer per month until they were either covered against default or left the sample; a customer-month had status=0 until coverage against default (status=1). Otherwise, status=0 throughout the observation period. See Table 4.3.14 for details on the composition of training$_3$ and holdout$_4$ samples under approach 3.

Table 4.3.14: Customer-months per sample, approach 3

SAMPLE	n	status=0	status=1
$TRAINING_3$	824,994	818,550	6,444
$HOLDOUT_4$	206,418	204,827	1,591

0= customer is not covered against default; 1, otherwise.

AUC results were complemented with a hypothesis test of difference between ROC curves (De Long et al., 1988) of the chosen model and some alternative models that yielded similar graphical results for the hazard function.

Finally, accuracy of prediction of the chosen model was tested per ranks and deciles instead of using a sole measure of accuracy. It was calculated as a percentage of the customers that actually experienced the event and were identified per rank (decile). The majority of these customers should be included in top ranks (deciles). This approach has been used previously for discrete survival models (Schumway, 2001; Nam et al., 2008).

Accuracy was assessed per rank and decile by calculating the probabilities of experiencing the event in t=12, 24 and 30. This assumes that customers survived until those points of time since at application time it is uncertain when a customer will censor from the sample. The accuracy per rank and decile was then calculated as a proportion out of the total customers that actually experienced the event at t $\leq$ 12, 24 and 30.

4.3.3.3.5 Comparison of profit, return and time-to-profit application scorecards

OLS models only considered customers with a continuing relationship with the lender at t=12, 24 and 30 months (i.e.: $Training_2$, n=24,617). On the other hand, the complete sample of customers was used to develop time-to-profit application scorecards (i.e.: $Training_3$=28,424). In order to fairly compare results from both techniques, only customers used to develop OLS, those in $Training_2$ sample, were considered to produce another survival model. Portfolio profits and returns were then compared across various acceptance rates, as explained in Section 4.3.3.2.5.

4.3.3.3.6 Predicting time-to-profit for investment planning objectives

Another use of survival models is that they allow predicting time-to-profit, which is useful for investment planning purposes as explained in Section 3.4.2. Time-to-profit can be obtained through the use of (4.3.30) and one of the hazard formulae (4.3.31 to 4.3.36), depending on the chosen model. It follows from (4.3.30) that instead of a single value for time-to-profit, a distribution of months when a customer might be covered against default given that this had not occurred previously, results from the probability distribution of occurrence of such event.

In order to assess the predictive accuracy of the model, a choice was made regarding the optimal percentile to minimize the prediction error (Zhang and Thomas, 2012). The optimal percentile that minimises the mean absolute error (MAE) is:

$$MAE_p = \frac{\sum_{i=1}^{n} \left| \hat{M} - M \right|}{n} \tag{4.3.39}$$,

where:

p=1,…, 100

$\hat{M}\,(M)$= predicted (actual) month and

n = customers that were predicted to experience the event and either experienced it or not.

In particular: If status=1 then $error_p = \left|\hat{M} - M\right|$; if status=0 and $\hat{M} > 30$ then $error_p = 0$; if status=0 and $\hat{M} \le 30$ then $error_p = \left|31 - \hat{M}\right|$; in this case, $\hat{M}$=31 was taken as a common reference point for all customers, as it is outside of the observation period. The optimal percentile was then used to obtain a predicted value of time-to-profit in months, per borrower. This value was rounded to integer due to the discrete nature of time.

4.3.3.3.6.1 Segmented models

Intuitively, it made sense to segment borrowers according to *loan duration*. It is clear that there are different types of loan durations ranging from the shortest to the longest term: 12 and 61 months, respectively. By definition, the former are allowed to roll over faster than the latter in the short term. Given that the observation period was 30 months after the first purchase, customers with longer term loans still require a longer period of time to be covered against default.

A decision tree was used, however, to gain a better insight of the data structure of $training_3$ sample. It was useful to identify potential segments arising from subpopulations of customers. Customers that were covered against default were classified as goods. Figure 4.3.8 is a decision tree based on the event: Pr ($CASHROAcum_{30} \ge 1$). It was confirmed that *loan duration* is a strong predictor, as it determines first level segments. Five segments of customers were identified: [12, 37], [42, 48], [55], [60, 61] and missing. These segments correspond to categories "≤37", "(37, 48]", "(48, 55]", ">55" and "missing", respectively in Figure 4.3.8. In segment [12, 37], 68% of the customers were covered against default; in the other segments, they are a minority instead. At time t=30 months, customers with longer loan durations are less likely to experience the event, compared with those with shorter loan durations. The majority of customers have loan durations of at least 55 months. Furthermore, some customers with loan duration=37 months accumulate enough profits as to be covered against default by month 30.

A second variable that discriminates well goods from bads is *credit limit usage*. Three categories of customers were differentiated within segment [12, 37]: Those with low, medium, and high credit limit usage. Within those with low and medium *credit limit usage*, sub segments [12, 30] and [36, 37] were identified.

The proportion of goods in the first sub segment was greater than that of the second sub segment. This was expected, as customers with shorter loan durations that coincide with the observation period are more likely to be covered against default. *Location* and *dependants* discriminate goods from bads in the high usage range. In segment [42, 48], product discriminates goods from bads, followed by credit limit usage.

Customers with missing *loan durations* exhibit a different behaviour, as it is a mixed group that may include customers with varied loan durations.

Additional to the decision tree, other criteria were used to identify segments: The observations and events per segment and the definitions used in accounting for the short and long term.

In accounting terms, the short term is usually understood as periods of at most 12 months. Given that loan durations of less than 19 months were a minority, this category was collapsed with the following (i.e.: 24 and 25 months) to form the first segment. From the second segment onwards, different categories were built based on semi-annual increases of loan durations; if customers were to pay on time their loans, this would match with accounting performance measurement periods prior to the end of each year. There is a clear long term oriented segment of customers: [48, 61], which are expected to take longer to be covered against default. Customers with missing loan durations were left in a separate segment given their mixed nature, as explained before. Tables 4.3.15 and 4.3.16 show the composition of training[3] and holdout[4] samples, respectively in terms of loan-duration based segments. The number of customers per segment, n, the events per segment and the percentage of customers that were covered against default characterise each segment.

Figure 4.3.8: Decision tree, event Pr (*$CASHROAcum_{30}$* ≥ 1), training$_3$ sample

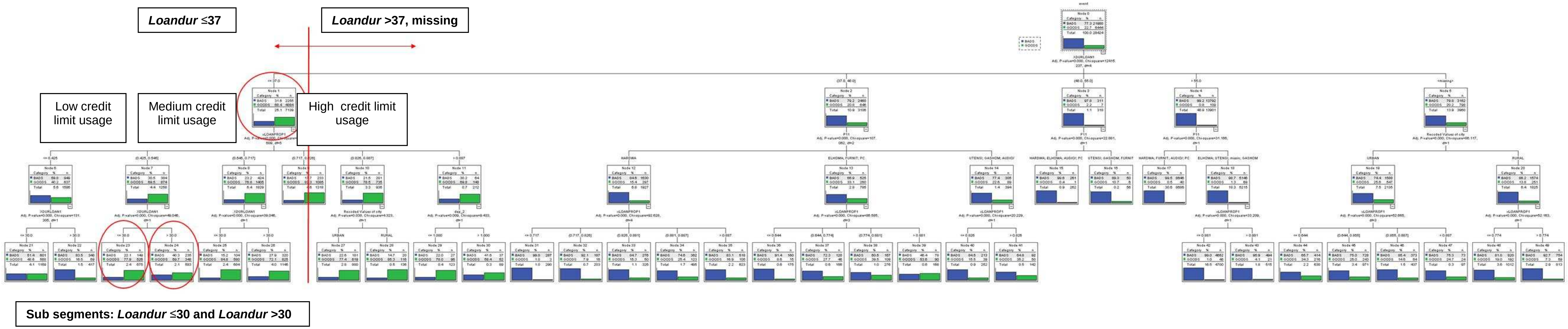


Table 4.3.15: Segments, training$_3$ sample

ID	SEGMENT	n	%/TOTAL	events	% within segment
1	**[12,25]**	2,029	7%	1,303	64%
2	**[30,31]**	817	3%	640	78%
3	**[36,37]**	4,293	15%	2,941	69%
4	**[42,43]**	1,581	6%	582	37%
5	**[48,61]**	15,744	55%	180	1%
6	**missing**	3,960	14%	798	20%
	TOTAL	**28,424**	100%	**6,444**	**23%**

Table 4.3.16: Segments, holdout$_4$ sample

ID	SEGMENT	n	%/TOTAL	events	% within segment
1	**[12,25]**	483	7%	334	69%
2	**[30,31]**	203	3%	162	80%
3	**[36,37]**	1,026	14%	701	68%
4	**[42,43]**	379	5%	144	38%
5	**[48,61]**	4,039	57%	61	2%
6	**missing**	976	14%	189	19%
	TOTAL	**7,106**	100%	**1,591**	**22%**

Since observation period=30 months and given that for the majority of customers in segments 1 to 3 were covered against default by t=30 months, only these customers were considered to produce segmented models. Furthermore, it would not be possible to test the models' predictive accuracy of the remaining segments as this would require a longer observation period. This data are not available at the moment. Customers with missing loan durations were not considered, as it was not possible to identify the required observation period to assess the model classification accuracy.

Customer-month observations were generated per customer in segments 1 to 3 until they were either covered against default or censored from the sample. A logistic regression model as shown in (4.3.30) was run using stepwise selection and 1% significance level (S.L.) and allowing for a maximum VIF of 5.

4.3.3.3.6.2 Generic model

A generic model was also produced to predict time-to-profit, following a similar process to that explained for segmented models. This was done to compare results from a single model with those of specific models that capture the specificity of each segment. Only customers from segments 1 to 3 in training$_3$ sample were considered to produce the generic model in order to use the same data set in both generic and segmented models.

4.3.3.3.6.3 Model classification accuracy

Generic and segmented models were compared per segment in terms of classification accuracy. Cumulative confusion matrices were used to compare actual versus predicted number of goods and bads (Thomas, 2009) for specific points of time (i.e.: investment periods). It made sense to use longer periods than months because strategic decisions usually require longer intervals. Such periods were defined after considering *loan duration* and median time-to-profit or censoring: t_{median}=23, 25 and 29 for segments [12, 25], [30, 31] and [36, 37], respectively. Therefore:

$t_{investment}$=24 months if segment= [12, 25] and

$t_{investment}$ =30 months if segment= [30, 31] or [36, 37]. In the specific case of segment [12, 25] t=12 months was not considered because loan durations ≤ 12 months are a minority in this segment and there were not enough events.

Table 4.3.17 shows the six categories of customers resulting from the classification accuracy of models per investment period. For illustration purposes, consider 6 customers. Customer 1 was predicted to be covered against default in t=29 and this actually occurred in t=27; therefore by t=30 she was correctly predicted. Customer 2 was predicted to be covered against default in t=27; however this actually occurred in t=21; therefore by t=24 she was incorrectly predicted. Customer 3 was covered against default in t=22 but according to the model, this did not occur by t=30 (end of observation period). Customer 4 was covered against default in t=25, but by t=24 she was incorrectly predicted earlier (t=22). Customer 5 was incorrectly predicted as being covered against default in t=22 even though this did not occur during the whole observation period. Customer 6 was not covered against default during the observation period; predicted month (t=39) is outside of the observation period accordingly.

Usual classification accuracy measures were obtained per segment, per investment period. Categories 1 and 6 contribute to an increased accuracy of classification per period. One would expect to obtain high accuracy values for a model to be useful in an investment planning setting. Table 4.3.18 shows the confusion matrix resulting from the categories of customers explained above.

Table 4.3.17: Customer categories

CATEGORY	DESCRIPTION	M	$\hat{M}$	COVERED AGAINST DEFAULT?
1	Correctly predicted within investment period	27	29	YES
2	Incorrectly predicted later in another investment period	21	27	YES
3	Not predicted at all	22	31	YES
4	Incorrectly predicted earlier in another investment period	25	22	YES
5	Incorrectly predicted	-	22	NO
6	Correctly predicted within investment period	-	39	NO

Table 4.3.18: Confusion matrix, time-to-profit models

	Actual goods	**Actual bads**	**Totals (predicted)**
Predicted goods	*1*	*4,5*	G
Predicted bads	*2,3*	*6*	B
Totals (actual)	n_G	n_B	

Adapted table (Thomas, 2009)

4.3.3.3.6.4 Impact on investment scheme

Monetary matrices were built per segment to quantify the impact of a model's classification accuracy on the investment scheme of the credit programme. This is directly related to each of the six categories, as explained below.

Profits generated by customers in Category 1 can be allocated on time to new customers and hence provide further opportunities for the organic growth of the credit programme per investment period. Conversely, customers in Category 6 impose constraints to organic growth and set up the minimum investment in the credit programme if the strategy is to continue growing at the current level.

Profits from customers in Categories 2 and 4 would be misallocated in specific investment periods even though they contribute as a whole to budgeting in the overall planning horizon.

The foregone profits from customers in Category 3 result in a social opportunity cost attached to depriving other potential customers of being granted credit through funds that will actually be available. These customers would have to access informal lending sources that are ultimately more costly and hence deteriorate their wellbeing. From the Company's perspective, this cost is relevant as the Company's funding policies are more internally oriented or under external funding constraints.

Finally, artificial profits from customers in Category 5 imply that a less conservative stance is adopted regarding coverage against default. The credit programme would continue to grow regardless of the complete coverage against default during the observation period. One would expect fewer customers within this category. As the Company's strategy is more growth-oriented, given that it has and will continue to provision for bad debt, this type of error becomes less relevant.

Various steps were completed to obtain monetary matrices. First, the value of the initial loan (i.e.: at time of the first purchase) was obtained. The Company expects to recover this value at some point of time to further reinvest it in new customers. Second, the identification of recovered funds (i.e.: profits) per investment period will depend on a model's classification accuracy. Therefore, profits were totalised per category and then accumulated sequentially throughout the investment periods previously defined. Third, total profits per category were divided by the total initial investment of the segment under analysis (i.e.: total value of the initial loans). This was done to compare results against the initial value invested per segment after the first purchase took place. It also facilitated the comparison of results across segments and models. Finally, the net organic funding per period was calculated as the difference between results from category 1 and other categories related to incorrect predictions (i.e.: 2, 3, 4 and 5).

5. ANALYSIS OF RESULTS

5.1 Introduction

This chapter presents the analysis of results from qualitative and quantitative research methods. Section 5.2 presents the data collection questionnaire and general results from the qualitative data analysis.

Sections 5.3, 5.4 and 5.5 present results obtained from quantitative methods to address the research questions stated in Chapter 2. Relevant results from qualitative data analysis were included to contextualise some of the findings obtained from quantitative methods, where applicable.

5.2 Qualitative data

5.2.1 Data collection questionnaire

This section presents the protocol and questionnaire used to conduct semi-structured interviews to collect qualitative data as explained in Section 4.2.1. The interviewees were asked additional questions if required.

“Good morning (afternoon), many thanks for accepting being interviewed. I would be more than grateful if you could answer each of the questions I will ask you in the next hour or so. Please feel free to add as much detail as you need.

1. Before granting the loan or offering additional services
   - Is the service you offer equally accessible by potential customers from all socio-economic levels?
   - What other options are available in the market?

- Mention the main three reasons that customers give for using your Company instead of other alternatives existing in the market.
- If any, what criteria are being used to accept new customers?

2. During the loan period
    - How does the Company define default?
    - Is the company aware of early signals of default? If applicable, what policies are defined? How do customers react to them?
    - Please mention at most 5 reasons that customers mention as being the main drivers for defaulting in their payments.
    - If any, what policies exist for:
        - Grace periods? How do customers react to them?
        - Prepayment or additional payments? How do customers react to them?
        - Non-default? How do customers react to them?
        - Refinancing? How do customers react to them?
    - If any, what measures are being used to assess the financial performance of customers?
    - In financial terms, how would you define an ideal customer?
    - If applicable, what policies exist in line with the financial performance of customers? How do customers react to them?"

5.2.2 Data analysis

A total of 53 codes (themes and subthemes) were initially defined. Five categories were identified: offer, customers' preferences, competition, default and collection. Each category included themes and dimensions (i.e.: values depending on the Company under analysis) and was analysed as explained in Section 4.2.2.

Table A1.1 in the Appendix shows the final version of the themes and subthemes included in each category, after further reclassification of the original codes. The overall relevance of the categories was verified via the references per informant; no informant had categories in blank. The nomenclature used to identify each Company was as follows: CP=Credit programme under analysis, CO=Competitor, ED=Education, U(1,2,3) =Utility Company(1,2,3) and L(1,2,3,4)= Lending institution(1,2,3,4).

Table A1.2 presents the definitions of dimensions 1 to 3 per category. Table A1.3 is a graphical comparison of the credit programme under analysis with other Companies. Only relevant results are presented in Sections 5.2.2.1 to 5.2.2.4. Detailed results are presented in Appendix 1.

5.2.2.1 Inclusiveness of the programme

Compared with traditional lending institutions and similar programmes such as CO, CP is more inclusive; credit limit is defined per stratum and is restricted to buy specific products considered to improve customers' quality of life. Ease of access (no previous credit history or evidence of income sources) and favourable credit conditions (i.e.: interest rates and long term loan duration, payment of the first instalment usually two months after the first purchase) are key features considered by customers to take the credit.

Customers are accessed on a one-to-one basis, leveraging on the know-how of a market that is usually unexplored by other lending institutions. This is useful to verify *in situm* some of the customers' characteristics and hence confirm their validity to design scoring models. It also facilitates the customised treatment of customers from application time throughout the collection process. This is a distinctive feature among microlending institutions that rely both on scorecards and personal observation of customers to grant credit (Van Gool et al., 2009).

5.2.2.2 Programme results

The bad rate of CP was considered low by the manager. An important reason for this is that only customers with a clean credit history in utility payment were granted credit.

Permanent collection and refinancing strategies if full instalment payment is not possible contribute to reduce the bad rate. Penalties related to partial payments are also useful as customers can only do this at the central headquarters to "open" a consolidated bill (i.e.: partially paying the loan and/or instalment). This requires an additional effort from them, which is not usually embraced by locals in the Region.

Finally, informal lending sources may also explain these results. They are readily accessible to customers but at lending rates that are extremely higher than those of CP. Customers are willing to start a formal credit history; therefore it is expected that they look after their payments.

5.2.2.3 Default risk factors

Customers served by CP are considered high risks by traditional lending institutions, regardless of the positive results explained above. This follows from the lack of previous credit history. Other factors such as: the lack of personal collaterals, a "pay until the end" culture, and overindebtness related to informal lending and lifestyle may account as well for defaulting.

A downside of CP is that using a single bill to pay both the utility and loan results in more permissiveness that may foster delayed payments from customers. Suspension of the service only occurs after two missed consecutive payments. This is used by some customers that might find it difficult to repay their loans on time.

Finally, financial illiteracy was also mentioned as a reason behind default. Customers may not be fully aware of the duties deriving from taking credit since they do not have a basic knowledge of financial terms; they may lack as well financial planning skills (Colombian Treasury et al., 2010).

5.2.2.4 Profitability assessment

Customers are assessed solely in terms of default. Profits are measured in monetary terms at a portfolio level.

The benefits of using profit scorecards have been discussed in previous chapters. Return scorecards could be particularly useful as they provide an alternative perspective for profit scoring purposes in high risk cases such as CP, where all loans are unsecured. The only guarantee that the borrower has in case of default is the cumulative profit that can be used to breakeven in case of default. This is even more critical when borrowers are untraceable after they leave their tenancy.

The features presented above confirm that using profit and return scorecards is relevant for the case under analysis. It should be noted, however, that it can be equally applied in different lending contexts and to fixed loans as well as to revolving credits.

5.3 Profit and return measures

5.3.1 Profit and return measures versus default criterion

5.3.1.1 Characterization of portfolio results

Table 5.3.1 presents results of Stobachoff coefficient (STC) and vulnerability factor (VF) explained in section 4.3.3.1.1.1. These coefficients were calculated at t=12, 24 and 30 for each profit (i.e.: *OPCASHcum* and *OPCASHav*) and return measure (i.e.: *CASHROAcum* and *CASHROAav*). Each column presents results for the complete sample, non-defaulters and defaulters.

STC results in Table 5.3.1 show that *OPCASHcum* at t=12 is more concentrated in defaulters than in non-defaulters (22.4% vs. 16.9%, respectively). A similar situation occurs at t=24 and 30 and for *OPCASHav* and *CASHROAcum* at all points of time. This is a result of a low bad rate, since few customers are defaulters and hence results for this segment depend more on few profitable customers. These customers have made partial payments but are still considered defaulters until they do not clear their outstanding balances.

It is important to note that STC results for *CASHROAav* differ significantly from the rest. STC for non-defaulters is significantly greater than that of defaulters (e.g.: 90.7% vs. 19.3% at t=12, respectively). This is a result of a sharp decrease in portfolio returns because of the magnifying effect of losses compared with very low outstanding balances; this is a weakness of average measures with extreme values that cannot be diluted over the observation period. This is not the case for cumulative measures.

Cumulative returns are less concentrated than cumulative profits in defaulters and non-defaulters. For instance, at t=12 $STC_{non\text{-}defaulters}$=9.4% and 16.9% for *CASHROAcum* and *OPCASHcum*, respectively. This occurs because return measures scale profits by the investment made on receivables per customers. If the aim is to maximise portfolio profits, these would be more concentrated on specific customers than if the objective was to maximise portfolio returns. These results offer an initial insight to the implications of using each measure for scoring purposes. There is a greater difference in values of STC for *OPCASHcum* and *CASHROAcum* for non-defaulters (e.g.: 16.4% vs. 1.7% at t=30, respectively) compared with that of defaulters (e.g.: 24.6% vs. 17.1% at t=30, respectively). This suggests that there is a greater discordance between profit and return measures in the former segment.

On the other hand, VF results for all four measures show that more loss subsidisation occurs within defaulters, compared with non-defaulters at each point of time. For instance, at t=12 $VF_{defaulters}$=3.7% and $VF_{non-defaulters}$=0.2% for *OPCASHcum.* That is, profitable defaulters outperform unprofitable defaulters more noticeably compared with non-defaulters.

Table 5.3.1: Profit concentration and loss subsidisation: complete sample, non-defaulters and defaulters

MEASURE	T	COMPLETE SAMPLE		NON-DEFAULTERS		DEFAULTERS	
		STC	VF	STC	VF	STC	VF
OPCASHcum	12	17.1%	0.3%	16.9%	0.2%	22.4%	3.7%
	24	17.1%	0.6%	17.0%	0.6%	26.6%	4.3%
	30	16.5%	0.3%	16.4%	0.2%	24.6%	3.8%
OPCASHav	12	17.1%	0.3%	16.8%	0.2%	22.4%	3.7%
	24	17.1%	0.6%	16.9%	0.6%	26.6%	4.3%
	30	16.5%	0.3%	16.3%	0.2%	24.6%	3.8%
CASHROAcum	12	9.8%	0.3%	9.4%	0.2%	19.3%	3.7%
	24	2.7%	0.6%	2.3%	0.6%	20.4%	4.3%
	30	1.9%	0.3%	1.7%	0.2%	17.1%	3.8%
CASHROAav	12	89.6%	0.4%	90.7%	0.4%	19.3%	3.3%
	24	58.5%	1.6%	59.0%	1.5%	24.4%	4.7%
	30	69.1%	1.3%	69.6%	1.2%	21.1%	4.0%

5.3.1.2 Opportunity cost analysis

Table 5.3.2 shows the impact ratio explained in Section 4.3.3.1.1.2. This ratio was calculated per profit (return) measure at t=12, 24 and 30.

Table 5.3.2: Opportunity cost analysis: Impact ratio

MEASURE	t	IMPACT
OPCASHcum	12	22.20
	24	18.86
	30	21.22
AVOPCASH	12	22.19
	24	18.81
	30	21.15
CROAcum	12	21.63
	24	18.53
	30	20.84
AVCROA	12	0.00
	24	0.03
	30	0.02

At t=12, in average the cumulative profit, *OPCASHcum*, yielded by some defaulters is 22 times greater than the losses yielded by some non-defaulters. This applies to cumulative (average) profits and cumulative returns, with slightly lower values in the latter as a result of the scaling effect of ratios. Receivables from profitable defaulters are high risk assets for the Company which yield better results than those of certain non-defaulters. The contrary occurs in terms of average returns. This is directly related to the magnified values of negative returns of loss making non-defaulters. This confirms the instability of average returns.

These results confirm that defaulters are not always loss-makers and suggest that profit maximisation opportunities exist in that segment. Cumulative profits and returns could be maximised if customers are assessed according to their profit profiles. This has been discussed in previous studies by using solely profit measures and risk bands (Andreeva et al., 2007; Finlay,2008).

5.3.2 Profit versus return measures

5.3.2.1 Ranks analysis

This section presents results from Spearman correlations and Chi-Square tests, as explained in Section 4.3.3.1.2.1.

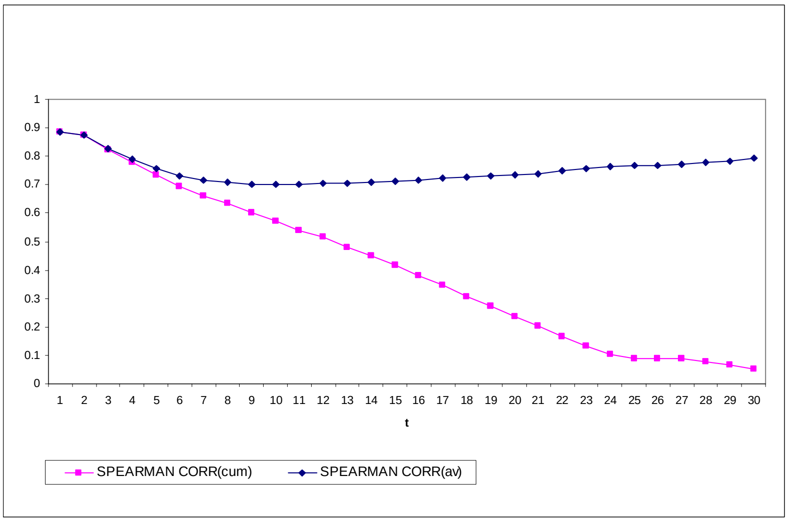
5.3.2.1.1 Chi square tests

As explained in Section 4.3.3.1.2.1, the independence of distributions of monthly scores based on $OPCASHcum_t$, $OPCASHav_t$, $CASHROAcum_t$ and $CASHROAav_t$ was assessed through various hypotheses tests. At a 0.01% S.L., profit and return scores are not independent.

5.3.2.1.2 Spearman correlations: Profits versus returns in cumulative and average terms

Figure 5.3.1 depicts Spearman correlations between ranks of ($OPCASHcum_t$, $CASHROAcum_t$) and ($OPCASHav_t$,$CASHROAav_t$) during the observation period. See graphs with labels: “SPEARMANCORR(cum)” and “SPEARMANCORR(av)”, respectively.

Figure 5.3.1: Spearman Correlations, Profits versus returns (in cumulative and average terms)



Correlations between profits and returns ranks (in cumulative and average terms) are very similar during the first five months of the observation period. Therefore, it would not make a difference for scoring purposes to choose between both sets of measures.

As time goes on the correlation between $OPCASHav_t$ and $CASHROAav_t$ stabilises at values close to 0.8. This suggests that minor differences may arise if customers were scored according to these measures; correlation is still high as both measures have a smoothing effect that results in similar ranks. Some of the differences could be due to values that were magnified after scaling profits by the outstanding balance.

On the other hand, $OPCASHcum_t$ and $CASHROAcum_t$ are less correlated as time goes on. Values start at 0.7 at t=6 and decrease to 0.1 by t=30. This is a result of the cumulative nature of these measures. As time goes on, cumulative profits and returns do not necessarily change in the same proportion. $CASHROAcum_t$

depends not only on cumulative profits, but also on the outstanding balance which does not change in the same proportion throughout time. Consequently, customers well ranked according to profits are not necessarily ranked equally in terms of returns. Likewise, high coverage against default (i.e.: cumulative returns) does not imply that customers will be ranked equally in terms of cumulative profits.

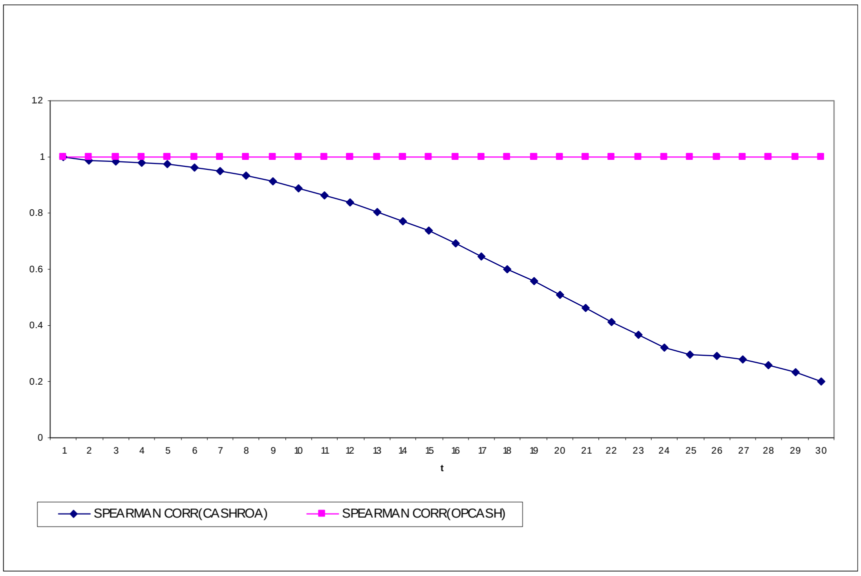
5.3.2.1.3 Spearman correlations: Cumulative versus average profits and cumulative versus average returns

Figure 5.3.2 shows Spearman correlations between ranks of ($OPCASHcum_t$, $OPCASHav_t$) and ($CASHROAcum_t$,$CASHROAav_t$) during the observation period. See graphs with labels: “SPEARMANCORR(OPCASH)” and “SPEARMANCORR(CASHROA)”, respectively.

$OPCASHcum_t$ and $OPCASHav_t$ are almost perfectly correlated throughout the observation period. An increase (decrease) in profits results in higher (lower) cumulative profits; changes in the same direction occur in average profits. Apart from the interpretation that might be given to each measure, either could be used for scoring purposes.

The correlation between $CASHROAcum_t$ and $CASHROAav_t$ decreases as time goes on. At t=1 both measures are perfectly correlated; by month 30, it is as low as 0.2. This is a result of the definitions of these measures. Cumulative returns depend on cumulative profits and final balance, whereas average returns are a simple mean of returns. In cumulative terms a customer may yield high (low) returns but lower (higher) average returns if results from particular months are deficient (good). It has been shown that average returns can be substantially affected by extreme negative values; this is not the case for cumulative returns; any losses from a particular month can be covered by cumulative profits from previous months.

Figure 5.3.2: Spearman Correlations, Cumulative versus average profits, cumulative versus average returns



Results show that at a customer level it makes a difference to use alternative profit measures for scoring purposes. Average measures should be taken, however, as a benchmark to compare results from cumulative profits and returns, considering that average returns are particularly sensitive to extreme values. Furthermore, cumulative profits are more readily interpretable and have been used in previous studies. Cumulative returns offer an additional insight to cumulative profits, depending on the aim of the scorecard.

Difference in results throughout time indicates that time has an essential role on cumulative profits and returns. This confirms the relevance of the variable loan duration to build scorecards for certain types of revolving credit with defined loan duration as the case under analysis. Such loan duration can extend beyond the original loan duration if further purchases occur.

5.3.2.2 Acceptance rate analysis

Portfolio results were analysed through the acceptance rate analysis explained in Section 4.3.3.1.2.2.

Figures 5.3.3 and 5.3.4 show portfolio $OPCASHcum_t$ and $CASHROAcum_t$ respectively, for different acceptance rates, when customers are ranked according to $OPCASHcum_t$ and $CASHROAcum_t$ at t=12,24 and 30 months. Portfolio $OPCASHcum_{30}$ dominates $OPCASHcum_{24}$ and $OPCASHcum_{12}$ when customers are ranked using either cumulative profits or returns. This is a result of the cumulative nature of these measures. The same applies to $CASHROAcum_t$.

The increasing trend of each curve in Figure 5.3.3 shows that portfolio $OPCASHcum_t$ increases as the acceptance rate increases. This occurs because figures are accumulated in monetary terms. In contrast, Figure 5.3.4 shows that when customers are ranked according to $CASHROAcum_t$, portfolio $CASHROAcum_t$ decreases as the acceptance rate increases because customers with the highest returns are accepted first. The weight of returns from these customers decreases as more customers are accepted; portfolio returns decrease accordingly.

At all points of time portfolio profits (returns) obtained from ranking customers according to $OPCASHcum_t$ ($CASHROAcum_t$) were greater than results obtained from using $CASHROAcum_t$ ($OPCASHcum_t$). This was the case for all acceptance rates. The difference between portfolio profits and returns decreases as more customers are accepted (i.e.: curves coincide at acceptance rate=95). Therefore, if the policy is to accept almost everyone, there is no major difference between using profit or return measures for scoring purposes. This would be equivalent to continue using the current criterion of granting credit to all customers that qualify based on non-default in the payment of utility bills.

Figures 5.3.5 and 5.3.6 show portfolio $OPCASHav_t$ and $CASHROAav_t$ respectively, for different acceptance rates, when customers are ranked according to $OPCASHav_t$ and $CASHROAav_t$ at t=12, 24 and 30 months. Figure 5.3.5 shows that portfolio $OPCASHcum_{12}$ dominates $OPCASHcum_{24}$ and $OPCASHcum_{30}$ because in the long term monthly average profits are more diluted compared with the short term.

The sharp decrease in portfolio returns in Figure 5.3.6 when *OPCASHav* is used instead of *CASHROAav* at t=12, 24 and 30 months occurs because the marginal average return forgone increases at acceptance rate=95 when customers are scored through profits instead of returns.

When customers are scored according to average profits (returns), portfolio profits (returns) are improved accordingly. This is similar to results obtained if cumulative measures are used instead to rank customers. Portfolio profits and returns can therefore be improved if cumulative or average profits and cumulative or average returns are used as scores, respectively. However, it is not possible to improve both portfolio measures simultaneously with a single profit or return scorecard. This result highlights the fact that each measure offers a different insight for scoring purposes.

Figure 5.3.3: Portfolio *OPCASHcum$_t$* per acceptance rate, scores based on cumulative measures

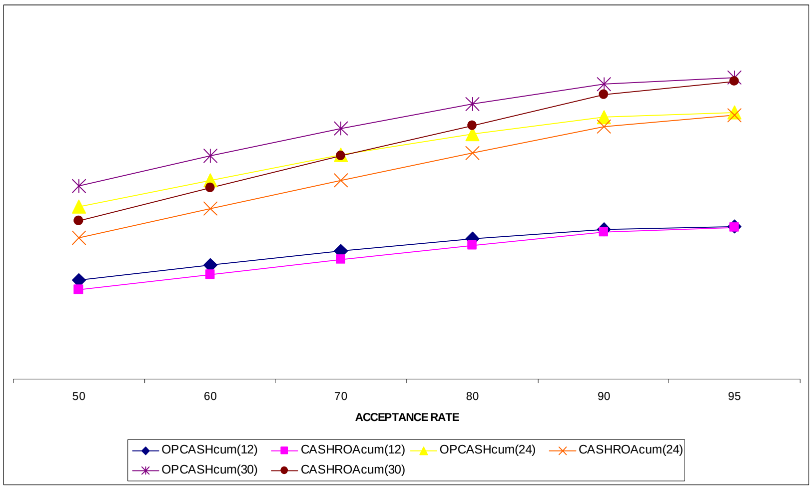
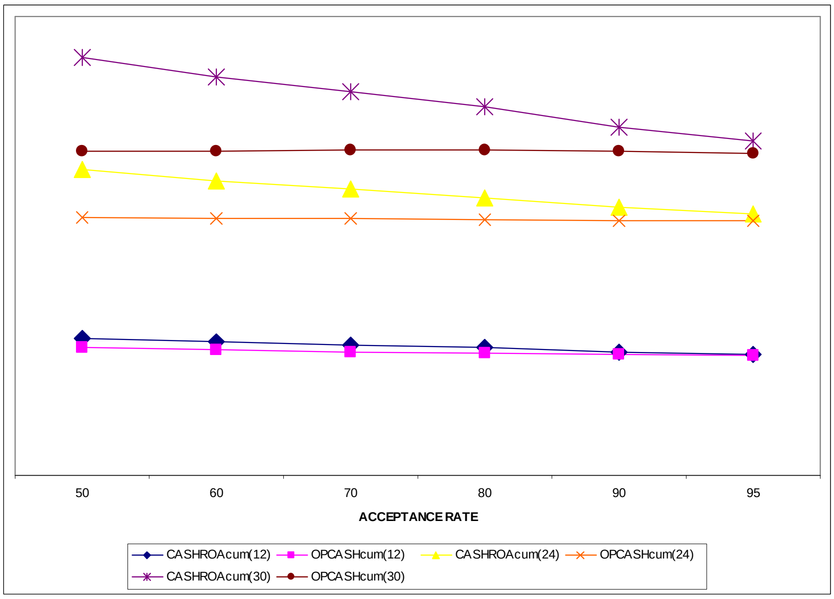
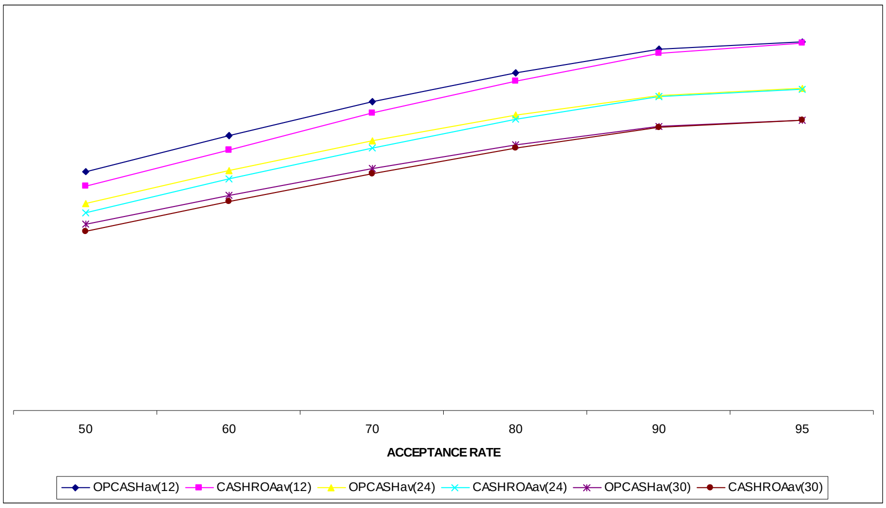


Figure 5.3.4: Portfolio *CASHROAcum$_t$* per acceptance rate, scores based on cumulative measures



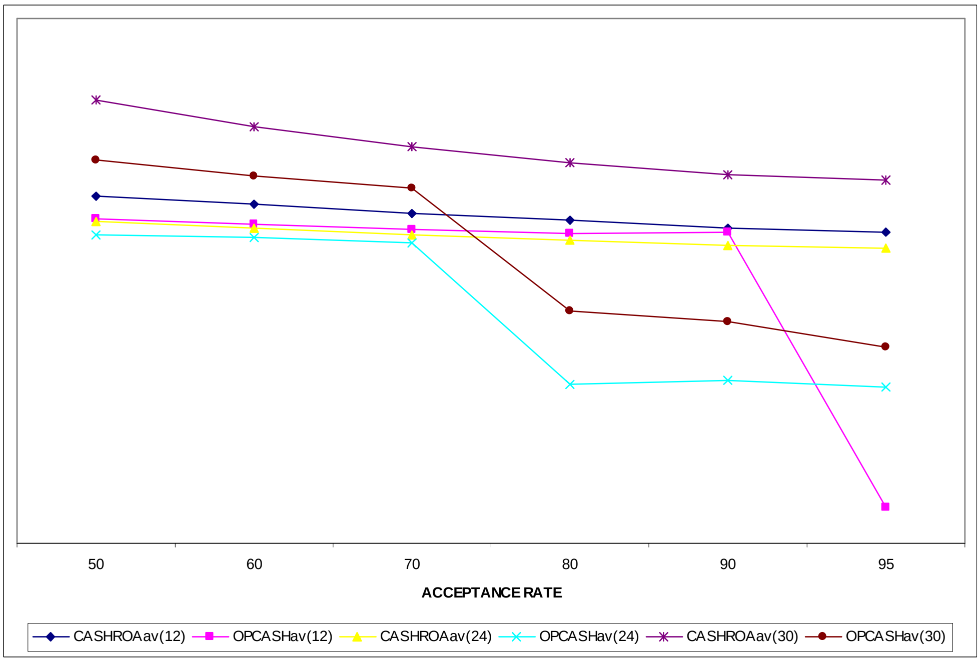
Values are not displayed for confidentiality reasons

Figure 5.3.5: Portfolio *OPCASHav$_t$* per acceptance rate, scores based on average measures



Values are not displayed for confidentiality reasons

Figure 5.3.6: Portfolio *CASHROAav$_t$* per acceptance rate, scores based on average measures



Values are not displayed for confidentiality reasons

5.3.2.3 Opportunity cost analysis

The opportunity cost, OC_t in (4.3.18), of using profits instead of returns for scoring purposes was calculated as explained in Section 4.3.3.1.2.3. The aim was to choose between cumulative and average measures.

5.3.2.3.1 *$OPCASHcum_t$* vs. *$CASHROAcum_t$*

Table 5.3.3 shows OC_t per acceptance rate (from 50 to 95) of using *$OPCASHcum_t$* instead of *$CASHROAcum_t$* at t=12, 24 and 30. OC_t values are relative to those of band 50 because of confidentiality reasons. This provides a meaningful comparison of figures. Bold cells stand for acceptance rates that maximise OC_t. Yellow-coloured cells represent acceptance rates in which additional portfolio profits exceed the foregone coverage against default if customers are scored according to profit instead of return measures (i.e.: according to (4.3.18a)). The opposite situation (i.e. according to (4.3.18b)) occurs otherwise.

At t=12 the optimal acceptance rate is 50, which was obtained by scoring customers according to *$OPCASHcum_{12}$*. Additional portfolio profits would be foregone if *$CASHROAcum_{12}$* was used instead. Consequently, in the short term monetary profits are more significant than coverage against default. This makes sense, as *loan duration* of more than half of the customers is between 48 and 61 months and hence coverage against default is not feasible for the bulk of the portfolio in the short term. See Table 4.3.2.

At t=24, the situation is different. The optimal acceptance rate is 90. This resulted from scoring customers according to *$CASHROAcum_{24}$*. The foregone coverage against default would exceed additional portfolio profits if OP*$CASHcum_{24}$* was used instead. This implies that a major proportion of current customers should continue to be accepted according to the sole criterion of not defaulting during the previous two years of utility payment. Using such criterion would be almost as useful as using return measures for scoring purposes. This might be the result of positive payment habits for an equal period of time in the past, which increases reliance on the current credit granting system.

At t=30, the optimal acceptance rate is 50, which resulted from using *CASHROAcum30* to score customers. Consequently, the acceptance criterion should be stricter compared with a mid term standpoint. These results confirm that in the long term, profits should be scaled by the outstanding balance to account for the investment in receivables that are still at risk given that the portfolio is mainly composed of loans in the long term. Furthermore, at t=30 not all customers with *loan duration* ≤ 30 had censored from the sample, which suggests that additional purchases took place. This increases the portfolio's outstanding balance and consequently the risk of not being covered against default.

These results suggest that in the mid and long term coverage against default is more relevant than profits, especially taking into account that at those points of time most of the customers still have an outstanding balance to pay.

Table 5.3.3: Opportunity cost of using (cumulative) profits instead of returns

OPCASHcum vs CASHROAcum	t		
	12	24	30
50	**1.0**	1.0	**1.0**
60	0.8	1.0	0.9
70	0.4	2.0	0.8
80	0.0	3.9	0.7
90	0.2	**7.6**	0.6
95	0.4	6.8	0.4

Values are relative to opportunity cost of acceptance rate 50

5.3.2.3.2 *OPCASHav$_t$* vs. *CASHROAav$_t$*

Table 5.3.4 presents OC_t per acceptance rate (from 50 to 95) of using *OPCASHav$_t$* instead of *CASHROAav$_t$* at t=12, 24 and 30. Conventions are the same as those explained in the previous section.

At t=12, 24 and 30 the optimal acceptance band is 95, which resulted from using *CASHROAav$_t$* to score customers. This means that almost every current customer should be accepted by using return measures. Furthermore, it would almost not make a difference if return scorecards were used instead of the current default-based acceptance criterion. If average figures are used instead of cumulative values, more customers (i.e.: higher acceptance rates) are accepted.

Table 5.3.4: Opportunity cost of using (average) profits instead of returns

OPCASHav vs CASHROAav	t		
	12	24	30
50	1.0	1.0	1.0
60	0.8	2.1	1.0
70	2.8	0.1	0.9
80	3.5	89.9	4.4
90	0.2	92.4	4.8
95	**236.7**	**97.2**	**5.6**

Values are relative to opportunity cost of acceptance rate 50

5.3.2.4 Implications for scorecard design

It was confirmed that it is useful to consider other alternatives to the traditional default criterion to score customers when the aim is to improve portfolio profits (returns). Defaulters should not be stereotyped as loss makers; this is particularly relevant in contexts were there is an ongoing relationship between the lender and borrowers.

Financially excluded segments can be profitable as well. An important feature of the credit programme under analysis is that borrowers have already been granted credit because of previous good performance in the payment of utility bills. However, this does not guarantee that they will not default in their loans.

Profits and return scorecards aim to improve two conflicting objectives at a portfolio level. Rather than reconciling them through a single scorecard, decisions should be guided by the strategic priorities of the lender and its risk perception of the targeted customers.

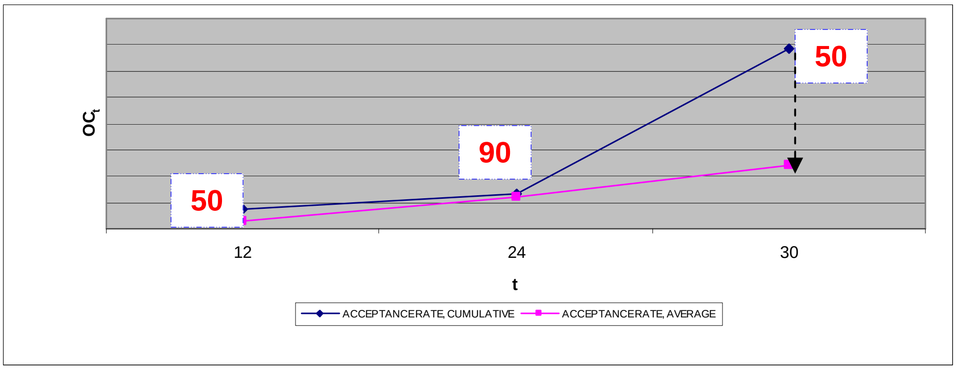
The opportunity cost analysis presented was useful to choose between cumulative and average profits (returns). Average measures failed to detect opportunities to improve portfolio results compared with cumulative measures. This validates using cumulative measures instead of averages to design scorecards. For illustration purposes, refer to Figure 5.3.7, which depicts OC_t at t=12, 24 and 30. At t=30, portfolio coverage against default would be traded off if the acceptance rate changed from 50 (according to $CASHROAcum_{30}$ scores) to 95 (based on $CASHROAav_{30}$ scores). The vertical distance between the curves is the cost that the lender would assume if the aim is to serve more customers, almost regardless of their return profiles.

The differences obtained at a customer and portfolio levels when using $CASHROAcum_t$ show that it can be used as an alternative to usual profit scores. Conceptually, it goes beyond the traditional criterion of assigning higher ranks to customers based solely on their cumulative profits. It facilitates a fair comparison within customers for scoring purposes, as results are relative to their outstanding balance and hence to credit limit usage, payment behaviour, and ultimately to their socioeconomic stratum.

It offers a novel way of implicitly considering default through the inclusion of the outstanding balance, which is at risk of default until full repayment occurs. This measure is particularly important for revolving credit, where monetary profits change throughout time and the scaling effect gains further relevance.

Results indicate that time may have an important role in the design of profit scorecards. The selected observation period (t=30 months) not only agrees with the long term perspective suggested to design profit scorecards but also takes into account the revolving nature of the product under analysis.

Figure 5.3.7: Traded-off profits (t=12) and coverage against default (t=24, 30)



Values are not displayed for confidentiality reasons

5.4 Predictive methods

This section includes results from the predictive methods explained in Section 4.3.3.2. Results from models used to predict probabilities of default and repurchase are presented first. Results for direct and indirect profit and return models are then explained. Fonts in *italics* represent findings from the qualitative data analysis that is relevant to understand some of the results in quantitative models. Where applicable, results from default and repurchase models are used to provide further insight to results from direct models, as shown in Figure 3.3.3. Table 5.4.1 shows the variables considered to predict the various models presented in this section. These are the same variables presented in Table 4.3.4.

Table 5.4.1: Reference categories and dummies per predictor variable

VARIABLE	REFERENCE CATEGORY	DUMMY VARIABLES
AGE	18<Age ≤ 35 years	dumAGE3: 35< Age ≤ 43.5 years dumAGE4: 43.5< Age ≤ 52 years dumAGE5: 52< Age ≤ 60.5 years dumAGE6: 60.5< Age ≤ 69 years dumAGE7: 69< Age ≤ 103 years
LOCATION	rural (different to the capital city)	dumCITUR : urban (capital city)
CONTRACT	missing, other, or not applicable	dumCONTCON : Any type of contract (permanent, temporary)
JOB	employed	dumJOBRET : retired dumJOBSELF: self-employed dumJOBNOIN : housewife, student, unemployed, missing
MARITAL STATUS	single	dumMARMAR : married dumMARCOH : cohabitators dumMARWID : widow(er) dumMARDIV: divorced dumMARMIS: missing
STRATUM	stratum 1 (poor segments)	dumSTRA35: stratum>1
EDUCATION	missing	dumSTUPRI : primary dumSTUSEC: secondary dumSTUCOL : college dumSTUHIG: higher
DURATION FIRST LOAN	durloan ≤ 31 months	dumLOAN3637: duration=36 or 37 months dumLOAN4243: duration=42 or 43 months dumLOAN4855: 48≤ duration ≤55 months dumLOAN6061: duration=60 or 61 months dumLOANMIS : missing loan duration
YEARS AT ADDRESS	YAH ≤ 8.5 years	dumYAH2 : 8.5< YAH ≤ 18 years dumYAH3 : 18< YAH≤ 27.5 years dumYAH4 : 27.5< YAH ≤ 37 years dumYAH510 : 37< YAH ≤ 94 years
DEPENDANTS	No dependants	dumDEP1 : 1 dependants dumDEP2 : 2 dependants dumDEP3 : 3 dependants dumDEP4 : 4 dependants dumDEP510 : 5 or more dependants
CREDIT LIMIT USAGE	Low	dumLOANPR2 : intermediate dumLOANPR310 : high
ACTIVITY	Services	dumactNA : Not applicable dumactOTH : Other industries dumactPROD : Manufacturing
FIRST PRODUCT PURCHASED	traditional products	dumprod1 : Non-traditional category 1 dumprod2 : Non-traditional category 2 dumprod3 : Non-traditional category 3

5.4.1 Probabilities of default and repurchase

Training$_1$ sample (n=27,157) was used to model probabilities of default and repurchase; models were tested in holdout$_1$ (n=6,807) sample. This was explained in Section 4.3.3.2.2.

5.4.1.1 Default probability

Defaulters were borrowers with three missed consecutive payments by the end of month. Prior to modelling the probability of default, it is important to understand the behaviour of the bad rate (i.e.: defaulters/active customers) during the observation period.

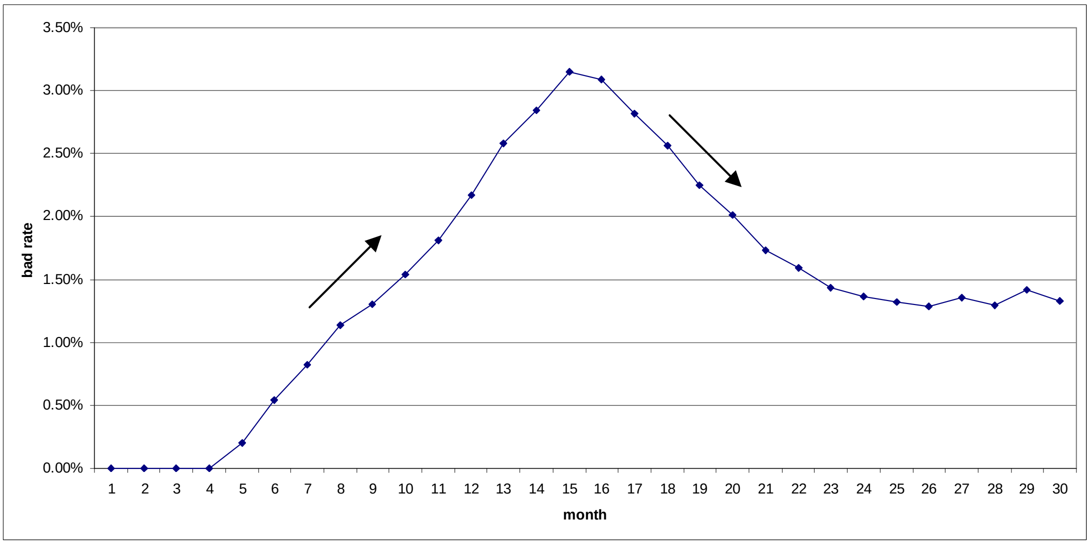
Figure 5.4.1 shows the monthly bad rate for active customers from training$_1$ sample. The increasing trend until month 15 was a consequence of the lack of a collections department. The management team considered that given the positive utility payment record of customers, they would replicate such behaviour and pay on time their loans. Once the credit programme was launched, customers were given the option of paying the utility bill and/or the loan instalment. *A good proportion of customers knew that missing the utility payment would lead to a service suspension, whereas missing the payment of the credit programme would not have major implications*.

The design and implementation of formal collection strategies took approximately 4 months. The company decided to consolidate in a single bill the utility and loan instalment charges. Even though by law the Company must receive payments associated with the utility, *this requires an additional effort from the customer*: Approaching the central headquarters of the gas company to open the bill, with additional transportation costs and time. It is evident that collection results improved, as the bad rate decreased until month 25. The pattern was then stable until month 30.

It is remarkable that by t=30 the bad rate reduced in approximately 40% of its value at t=12 months. It was confirmed that customers *need to be penalised or regularly contacted to pay on time their obligations*. This is particularly important in the case under analysis, as customers were not used to take formal loans.

Therefore, it made sense to develop models for Pr (default at t=12 months) as usual banking practices suggest and for Pr (default at t=30 months) to allow for changes in default behaviour. The rationale behind identifying defaulters "at" t=12 and 30 months instead of "in" those periods of time is that borrowers *are also customers of the utility core business provided by the lender*; therefore a long term relationship has been already built with these customers, together with the fact that *the Company is used to wait* if customers recover from default. Defining the event in this way allows waiting for their eventual recovery from default.

Figure 5.4.1: Monthly bad rate, active customers (training$_1$ sample)



5.4.1.1.1 Pr (default at t=12)

Table 5.4.2 shows results of model DEF12 for Pr (default at t=12). It includes estimates of significant variables, odds ratios and the area under the ROC curve (AUC) for $training_1$ and $holdout_1$ samples. The odd ratios presented are relative to the reference category per variable previously presented in Table 5.4.1. Results are discussed per significant variable or group of dummy variables, where possible. Dummy variables are explicitly stated in the latter case.

Cohabitators are more likely to default than singles. These individuals are involved in informal relationships that may affect their partners' commitment towards paying the loans.

Those that completed secondary level studies are more likely to default than customers that did not report their education level because they actually did not complete a basic education level. This suggests that having some level of education does not ensure that default will not occur. It also shows that customers from least favoured segments in terms of education are more committed towards paying their first formal loan. It seems as well that formal education is not necessarily directly associated with *financial literacy.*

Customers that buy products that are not associated with the utility provided by the lender (see results for dumprod3 and dumprod2) are more likely to default than those that do so. This might be related to the fact that the lender considers *these products will improve borrowers' quality of life,* which not necessarily implies that they will actually pay on time the instalments. These products can be still considered luxury goods by them, *hence paying the loan might not be a priority compared with paying the utility bill.* Furthermore, it is an *unsecured loan* and hence the product can not be claimed as collateral.

Those that have an intermediate level of credit limit usage are less likely to default than those that have a lower usage level. These customers might be more committed towards paying their loans because of the greater financial impact that it has on monthly household finance, compared with lower instalments that are easier to ignore.

Table 5.4.2: Results for model DEF12, Pr (default at t=12)

PARAMETER	Estimate	Odds ratio	AUC (T)	AUC(H)
Intercept	-4.2537			
dummarcoh	0.2714	1.312		
dumstusec	0.3208	1.378		
dumloanpr2	-0.3023	0.739		
dumprod3	0.4854	1.625		
dumprod2	0.5594	1.75	0.60	0.59

T=Training$_1$ sample, H=Holdout$_1$ sample

5.4.1.1.2 Pr (default at t=30)

Table 5.4.3 shows results of model DEF30 for Pr (default at t=30).This is presented in the format explained in the previous section.

The informality associated with self-employed customers increases their probability of default, compared with those formally employed. Income sources for these customers are more unstable and so is their repayment capacity. This is associated with the *high risk perception* that traditional lenders have of the credit programme, due to its *ease of access*.

Customers from age group 5 have less financial commitments in their households compared with those in the youngest age group. At that stage of their life cycle, they have already provided education to their children, acquired fixed assets and covered family needs. This increases their payment capacity and hence reduces the probability of default.

Married customers are less likely to default than singles. This might be related to regular payment habits in the household, compared with singles that may continue to live with their parents until they get married and hence are not fully responsible of paying their own bills until they leave the household. Again, this might be associated with *financial illiteracy.*

Living in urban areas reduces the probability of default, compared with rural areas. This might be a consequence of the income disparity between rural and urban areas in Colombia. These customers have more access to traditional financial services and hence may appreciate more *the importance of having a positive credit history.*

Table 5.4.3: Results for model DEF30, Pr (default at t=30)

PARAMETER	Estimate	Odds ratio	AUC (T)	AUC(H)
Intercept	-3.8869			
dumage5	-0.3684	0.692		
dumcitur	-0.5335	0.587		
dumjobself	0.4161	1.516		
dummarmar	-0.3802	0.684	0.61	0.65

T=Training$_1$ sample, H=Holdout$_1$ sample

5.4.1.1.3 Default in the short and long terms

The type of product first purchased does not affect the probability of default in the long term. This suggests that the dual role that the Company has as utility provider and lender is more evident for customers as time goes on.

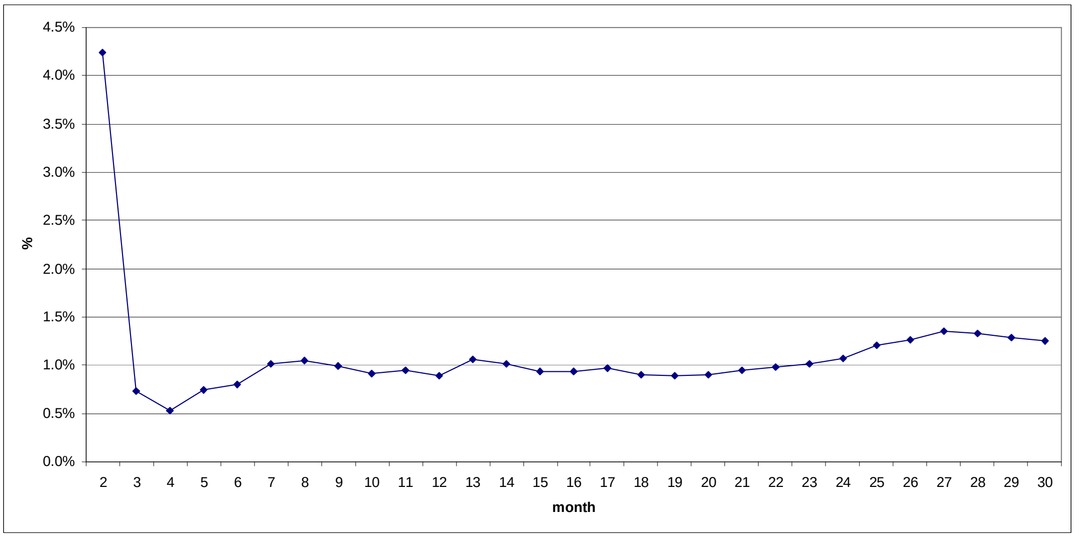
First loan duration is not significant to predict the probability of default. Given that the effective data set included active customers at t=12, 24 and 30 months, it does not make a difference if a loan was taken in the short, mid or long term as they had outstanding balances at those points of time.

It is worthy noting that stratum and non-income generating jobs such as students and housewives were not significant in the short and long terms. This confirms that the *inclusive lending nature of the credit programme* goes beyond usual definitions used in microfinance associated exclusively with the poor (Sinha, 2011). It also shows that other individual features prevail when it comes to predicting default probability.

5.4.1.2 Repurchase probability

Figure 5.4.2 shows the monthly percentage rate of active customers from $training_1$ sample that made further purchases after the first one. Most of the repurchases occur in month 2 (immediately after the first purchase). This is related to the *various billing cycles* of the utility Company, which allow for making further purchases before the first instalment has to be paid. As the second year of the observation period comes to an end, more customers make further purchases. This suggests that short and long term models should be designed, especially because of the revolving nature of the credit product under analysis.

Figure 5.4.2: Monthly percentage rate of customers with repurchases ($training_1$ sample)



Repurchase status was defined "in" t=12 and t=30, instead of "at" those points of time. It would be unrealistic to identify the repurchase event at a particular point of time as it occurs instead during a specific time period. These two points of time were chosen to account for the short and long term as was done for default probability.

5.4.1.2.1 Pr (repurchase in t=12)

Table 5.4.4 shows results of model REP12 for Pr (repurchase in t=12) in the format explained before.

Customers are more likely to repurchase as they belong to more socio economically favoured stratums. This is a consequence of a greater purchase capacity and of *peer pressure expectations associated with life style*. A similar situation occurs with customers that have secondary education compared with those that did not report any education at all.

As customers use more their credit limit (see results for dumloanpr2 and dumloanpr310), the probability of repurchase decreases. It is expected that less available credit limit prevents customers to make further purchases.

Customers with loan duration of 36 months are less likely to repurchase compared with those that take loans of 12 or 31 months. This might be related to a longer term commitment that results in cash outflows for longer periods of time.

The probability of repurchase decreases if the purchased product is a non-traditional product, compared with that of products associated with the utility that the lender provides (see results for dumprod1 and dumprod3). These products are durables and hence do not need to be replaced in the short term; this might hinder customers from taking further credit.

Table 5.4.4: Results for model REP12, Pr (repurchase in t=12)

PARAMETER	Estimate	Odds ratio	AUC (T)	AUC(H)
Intercept	-0.4499			
dumstra35	0.1671	1.182		
dumstusec	0.1111	1.118		
dumloan3637	-0.2798	0.756		
dumloanmis	-0.6622	0.516		
dumloanpr2	-0.5861	0.557		
dumloanpr310	-1.6486	0.192		
dumprod1	-0.5829	0.558		
dumprod3	-0.9249	0.397	0.70	0.70

T=Training$_1$ sample, H=Holdout$_1$ sample

5.4.1.2.2 Pr (repurchase in t=30)

Table 5.4.5 shows results of model REP30 for Pr (repurchase in t=30) in the format explained before.

Customers' aging increases the probability of repurchase perhaps as a result of more awareness of *their perceived needs* and a greater purchase capacity; both are associated with life cycle stages (see results for dumage4 to dumage6). In contrast, as dependants increase, repurchase propensity decreases (see results for dumdep2 to dumdep510). This is a direct consequence of further financial commitments for the household and hence less purchase capacity.

Any loan duration greater than 31 months results in lower probabilities of repurchase (see results for dumloan3637 to dumloan6061). This suggests that the observation period plays an important role in the impact that loan duration has on the probability of repurchase.

Those living in urban areas or from higher socio economic stratums are more likely to repurchase than those in rural areas or from least favoured stratums, respectively. This can be related as well to their purchase capacity. Results for credit limit usage and type of product can be interpreted following a similar rationale to that explained in the previous section.

Finally, customers that work in the production industry are less likely to repurchase compared with those in the services industry. This could be due to different economic conditions within specific sectors.

Table 5.4.5: Results for model REP30, Pr (repurchase in t=30)

PARAMETER	Estimate	Odds ratio	AUC (T)	AUC(H)
Intercept	1.6888			
dumage4	0.154	1.166		
dumage5	0.2221	1.249		
dumage6	0.1963	1.217		
dumcitur	0.2622	1.3		
dummarmis	-0.6178	0.539		
dumstra35	0.1506	1.163		
dumstupri	-0.1644	0.848		
dumloan3637	-1.1711	0.31		
dumloan4243	-1.1049	0.331		
dumloan4855	-1.0531	0.349		
dumloan6061	-1.2021	0.301		
dumloanmis	-1.7369	0.176		
dumdep2	-0.1144	0.892		
dumdep3	-0.2459	0.782		
dumdep4	-0.238	0.788		
dumdep510	-0.2833	0.753		
dumloanpr2	-0.5972	0.55		
dumloanpr310	-1.4466	0.235		
dumactprod	-0.2701	0.763		
dumprod1	-0.8711	0.418		
dumprod3	-1.1008	0.333	0.71	0.71

T=Training$_1$ sample, H=Holdout$_1$ sample

5.4.1.2.3 Repurchase in the short and long terms

In the long term, modelling repurchase is less parsimonious than in the short term. Almost all significant variables in the short term are also significant in the long term. Individuals rarely change their socioeconomic stratum in 18 months. Similarly, durable products are long term investments. First loan duration and credit limit usage depend on the first transaction, regardless of the time horizon.

5.4.1.3 Profit and return scorecards

Table 5.4.6 describes and presents the composition of direct and indirect models used to produce profit and return scores. Training[2] (n=24,617) and holdout[3] (n=9,347) samples were used to produce and test direct and indirect models, respectively. As explained in Section 4.3.3.2.3, two direct models were obtained by using directly individual attributes in Table 5.4.1: P1 for profits and R1 for returns. Indirect models P2 to P5 (R2 to R5) resulted from using probabilities of default and repurchase to predict profits (returns); this was done as explained in Section 4.3.3.2.4. Results are discussed in detail in the following sections.

Table 5.4.6: Direct and indirect models

MODEL	Description	Model composition
P1	**DIRECT, $OPCASHcum_{30}$**	**Age, location, marital status, stratum, education, loan duration, years at address,credit limit usage and product**
P2	INDIRECT, $OPCASHcum_{30}$	Pr(default at t=12), Pr(repurchase in t=12)
P3	INDIRECT, $OPCASHcum_{30}$	Pr(default at t=12), Pr(repurchase in t=30)
P4	INDIRECT, $OPCASHcum_{30}$	Pr(default at t=30), Pr(repurchase in t=12)
P5	INDIRECT, $OPCASHcum_{30}$	Pr(default at t=30), Pr(repurchase in t=30)
R1	**DIRECT, $CASHROAcum_{30}$**	**Location, type of contract, job, marital status, stratum,education, loan duration,dependants, credit limit usage and product**
R2	INDIRECT, $CASHROAcum_{30}$	Pr(default at t=12), Pr(repurchase in t=12)
R3	INDIRECT, $CASHROAcum_{30}$	Pr(default at t=12), Pr(repurchase in t=30)
R4	INDIRECT, $CASHROAcum_{30}$	Pr(default at t=30), Pr(repurchase in t=12)
R5	INDIRECT, $CASHROAcum_{30}$	Pr(default at t=30), Pr(repurchase in t=30)

5.4.1.3.1 Direct scorecard, $\boldsymbol{OPCASHcum_{30}}$

Table 5.4.7 shows significant variables, estimates and p-values of direct model P1 for $OPCASHcum_{30}$.

Older customers are more profitable as they are more likely to repurchase in the long term (see results for dumage3 to dumage7). Profits increase monotonically as loan duration increases (see dumloan4243 to dumloan6061). Even though customers with longer term loan durations are less likely to repurchase in the long term, more interests are accrued compared with shorter term loan durations; this evidently increases profits.

Staying in the same address for more than 8.5 years increases profits (see results for dumyah2 to dumyah510). Even though borrowers are responsible for paying the instalments, loans are registered under the details of the occupied property. *Customers that move less frequently are more stable in their payments than those that can potentially become frauds.*

Wealthier customers are more profitable than those that belong to least favoured socio economic stratums. This is associated with their income level, which allows them to repurchase more in the short and long terms.

Profits decrease as customers have an intermediate credit limit usage, compared with those in the lowest segment. They are less likely to repurchase in the short and long term and to default in the short term; it can be considered a conservative segment from both points of view.

Customers that are not singles are more profitable than singles (see results for dummarmar to dummarmis). There is no clear relationship between this overall pattern and results for default and repurchase.

As customers are more educated, they are more profitable (see results for dumstusec to dumstuhig). In particular, customers with secondary education are more profitable than those with missing education because they are more likely to default and repurchase in the short term. Customers that live in urban areas are more profitable than those located in rural areas even though they are less likely to default in the long term. However, they are more likely to repurchase in the short term.

Finally, non-traditional products are more profitable than traditional products (see results for dumprod1 and dumprod2). In the former case, it may be a question of higher margins and sales commissions of the product per se; in the latter, it is related to a greater probability of default in the short term.

Table 5.4.7: Results for direct model P1

Parameter	Estimate	p-value
dumage3	92,626	0
dumage4	95,637	0
dumage5	100,047	0
dumage6	102,355	0
dumage7	101,205	0
dumcitur	28,593	1.0682E-174
dummarmar	29,490	1.5788E-109
dummarcoh	34,918	3.2135E-124
dummarwid	30,288	5.33976E-50
dummarmis	33,080	7.36133E-40
dumstra35	50,155	0
dumstusec	21,455	4.51336E-85
dumstucol	36,465	3.94541E-64
dumstuhig	41,866	8.752E-100
dumloan4243	82,592	0
dumloan4855	85,004	0
dumloan6061	101,649	0
dumloanmis	103,840	0
dumyah2	45,256	5.7274E-177
dumyah3	43,874	4.0096E-146
dumyah4	46,303	5.0897E-132
dumyah510	44,305	1.1348E-100
dumloanpr2	-59,348	0
dumprod1	34,615	9.9096E-222
dumprod2	10,377	7.59458E-13

5.4.1.3.2 Indirect scorecards, *$OPCASHcum_{30}$*

Table 5.4.8 shows significant variables, estimates and p-values of indirect models P2 to P5 for *$OPCASHcum_{30}$*. In general, an increase in the probabilities of default or repurchase in the short or long term leads to greater profits.

Customers that are more likely to be at default have accumulated contractual and moratory interests calculated on the total outstanding balance. *Permanent collection policies and refinancing strategies to cope with previous payment habits and cultural features* that may be fostering default contribute to reduce default and eventually to recover from it. At the end of the day, *customers have a previous and ongoing relationship with the lender given that it also provides a basic utility* that no other Company can supply. Therefore, the positive sign of this predictor makes sense. Its economic impact is substantially more significant than that of repurchase (between 32 and 69 times). This is understandable, as repurchase results in a one-off sales commission compared with the continuous accrual related to arrears and eventually default.

Table 5.4.8: Results for indirect models P2 to P5

Model	Estimates	
	DEF12*	**REP12***
P2	10,808,596	333,699
	DEF12*	**REP30***
P3	10,469,388	182,917
	DEF30*	**REP12***
P4	17,028,295	284,284
	DEF30*	**REP30***
P5	15,537,087	226,039

*p-value < 0.0001

5.4.1.3.3 Direct scorecard, *CASHROAcum*$_{30}$

Table 5.4.9 shows significant variables, estimates and p-values of direct model R1 for *CASHROAcum*$_{30}$.

Results for loan duration contrast with those of direct profit scorecards; as loan duration increases, cumulative returns decrease sharply. Missing loan duration is the segment with the highest increase in returns; this might be the result of it being a mixed category that includes various loan durations (see results for dumloan3637 to dumloanmis). These results are useful to justify the differences in scoring obtained in Section 5.3.2 when using profits or returns. It is clear that longer term durations result in greater profits; however those profits are balanced off by the outstanding receivable, which results in lower returns. This has implications for scoring purposes depending on the measure used, given that *accessing long term credit is a favourable condition for borrowers.*

Customers with intermediate credit limit usage are marginally less profitable in relative terms compared with those with low credit limit usage. Customers different to singles (see results for dummarmar to dummarmis), living in urban areas, non-traditional products (see results for dumprod1, dumprod3 and dumprod2), customers with secondary education level and wealthier customers are more profitable than those in the reference categories. These results are consistent in sign with those obtained for cumulative profits and can be equally related to default and repurchase, as explained before. It is therefore possible to identify segments that can increase simultaneously profits and returns where the dilemma of choosing between both measures does not exist.

It is important to note, however, that stratum loses economic significance when returns are predicted instead of profits; this might be accounting for the scaling effect of the outstanding balance and the relative consumption within each stratum.

Finally, those that are self-employed are more profitable than those that are formally employed; a similar coefficient was obtained for customers with any type of contract. This justifies bearing a higher risk by granting credit to customers that do not have a stable source of income.

Table 5.4.9: Results for direct model R1

Parameter	Estimate	p-value
dumcitur	0.0729	1.5497E-118
dumcontcon	0.0308	4.84306E-13
dumjobself	0.0345	2.11539E-26
dummarmar	0.1985	0
dummarcoh	0.1940	3.0448E-306
dummarwid	0.2055	1.9122E-216
dummardiv	0.1940	4.2259E-151
dummarmis	0.2309	3.8237E-191
dumstra35	0.0717	3.4287E-126
dumstusec	0.0132	1.84938E-05
dumloan3637	0.3837	0
dumloan4243	0.2505	0
dumloan4855	0.1192	3.79761E-93
dumloanmis	0.4685	0
dumdep510	0.0235	0.000201086
dumloanpr2	-0.0098	0.001563256
dumprod1	0.3557	0
dumprod3	0.3431	0
dumprod2	0.1680	5.4025E-253

5.4.1.3.4 Indirect scorecards, *CASHROAcum*$_{30}$

Table 5.4.10 shows significant variables, estimates and p-values of indirect models R2 to R5 for *CASHROAcum*$_{30}$. Results for indirect models R2 to R5 also show that cumulative returns increase when the probabilities of default or repurchase increase. The economic impact of default is also greater than that of repurchase. These results can be interpreted in a similar way to the analysis presented for indirect profit models; both measures are based on cumulative profits.

Table 5.4.10: Results for indirect models R2 to R5

Model	Estimates	
R2	DEF12*	REP12*
	25.33	1.24
R3	DEF12*	REP30*
	23.84	0.70
R4	DEF30*	REP12*
	40.55	1.07
R5	DEF30*	REP30*
	36.31	0.77

*p-value < 0.0001

5.4.1.3.5 Scorecard comparison

Table 5.4.11 shows the error rates of direct and indirect models for training$_2$ and holdout$_3$ samples, as explained in Section 4.3.3.2.3.

Prior to comparing direct and indirect models for each measure, indirect models were chosen based on the lowest error rate. The best performing indirect models of $OPCASHcum_{30}$ were P2 and P3, with probabilities of default at t=12 and repurchase in t=12 or 30 as predictors. Similarly, indirect models R2 and R3 for $CASHROAcum_{30}$ outperformed other indirect models.

In terms of default, these results agree with usual banking practices of following customers' payment behaviour during the first year of the observation period. Additionally, this suggests that the current credit granting criterion based on utility payment during the previous two years is conservative. Following the payment behaviour of customers during the first year once they take a loan is better for prediction purposes than taking a long term perspective.

Table 5.4.11: Scorecard comparison

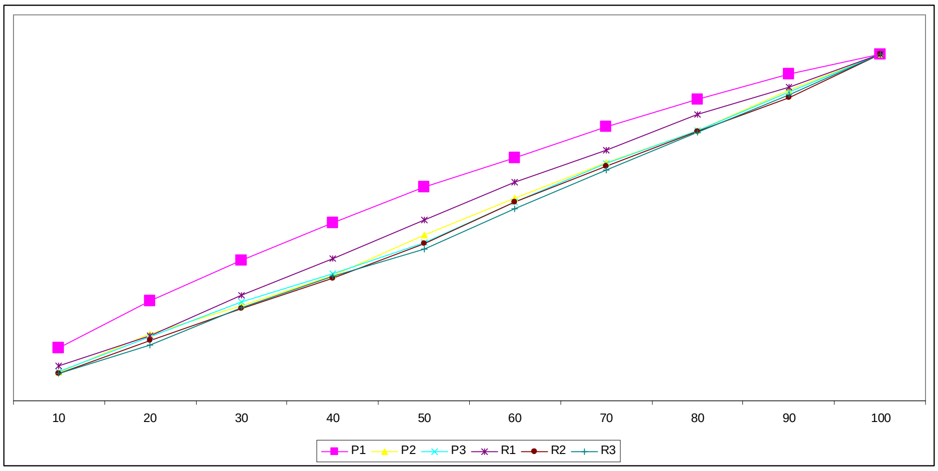
MODEL	Description	Model composition	ERROR RATE TRAINING$_2$	ERROR RATE HOLDOUT$_3$
P1	**DIRECT, OPCASHcum$_{30}$**	**Age, location, marital status, stratum, education, loan duration, years at address,credit limit usage and product**	**12%**	**23%**
P2	INDIRECT, OPCASHcum$_{30}$	Pr(default at t=12), Pr(repurchase in t=12)	21%	35%
P3	INDIRECT, OPCASHcum$_{30}$	Pr(default at t=12), Pr(repurchase in t=30)	21%	35%
P4	INDIRECT, OPCASHcum$_{30}$	Pr(default at t=30), Pr(repurchase in t=12)	26%	40%
P5	INDIRECT, OPCASHcum$_{30}$	Pr(default at t=30), Pr(repurchase in t=30)	25%	40%
R1	**DIRECT, CASHROAcum$_{30}$**	**Location, type of contract, job, marital status, stratum,education, loan duration,dependants, credit limit usage and product**	**17%**	**24%**
R2	INDIRECT, CASHROAcum$_{30}$	Pr(default at t=12), Pr(repurchase in t=12)	24%	31%
R3	INDIRECT, CASHROAcum$_{30}$	Pr(default at t=12), Pr(repurchase in t=30)	24%	31%
R4	INDIRECT, CASHROAcum$_{30}$	Pr(default at t=30), Pr(repurchase in t=12)	27%	34%
R5	INDIRECT, CASHROAcum$_{30}$	Pr(default at t=30), Pr(repurchase in t=30)	26%	33%

Models were assessed also as of their impact on portfolio results, according to the process explained in Section 4.3.3.2.5. Figures 5.4.3 and 5.4.4 depict portfolio profits and returns respectively, per acceptance rate for holdout$_3$ sample.

Portfolio profits (returns) are improved when direct models P1 and R1 are used instead of indirect models per measure. This further confirms that direct models should be preferred to indirect models. Additionally, profit (return) scores improve portfolio profit (return) throughout acceptance rates. This is a result of the design of scorecards using profit (return) at a customer level. It is also consistent with results from Section 5.3.2.2. The difference in shapes of portfolio profits and returns confirms that each scorecard serves different purposes. Since the same number of customers is accepted if the same rate is adopted, choice will depend on corporate objectives (i.e.: profits or coverage against default).

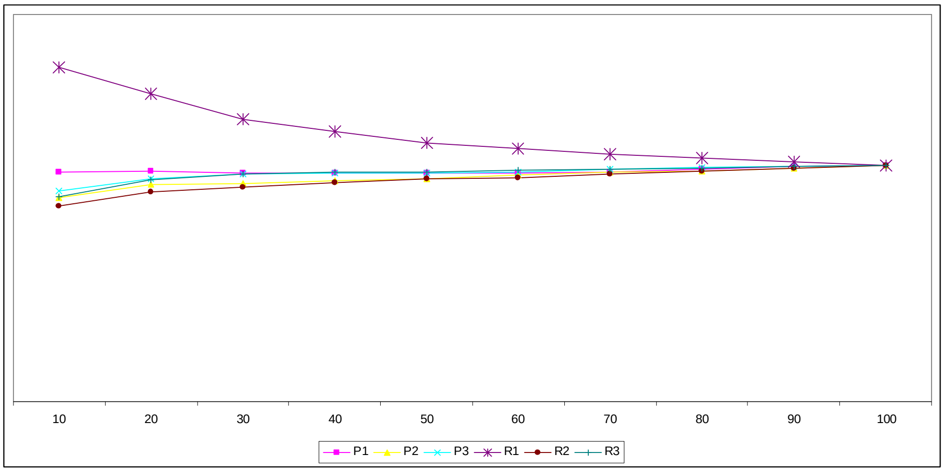
Even though some segments can be profitable in monetary and relative terms, portfolio results show that the dilemma is still present.

Figure 5.4.3: Impact of direct and indirect models on portfolio *$OPCASHcum_{30}$*, holdout$_3$ sample



Values are not displayed for confidentiality reasons

Figure 5.4.4: Impact of direct and indirect models on portfolio *$CASHROAcum_{30}$*, holdout$_3$ sample

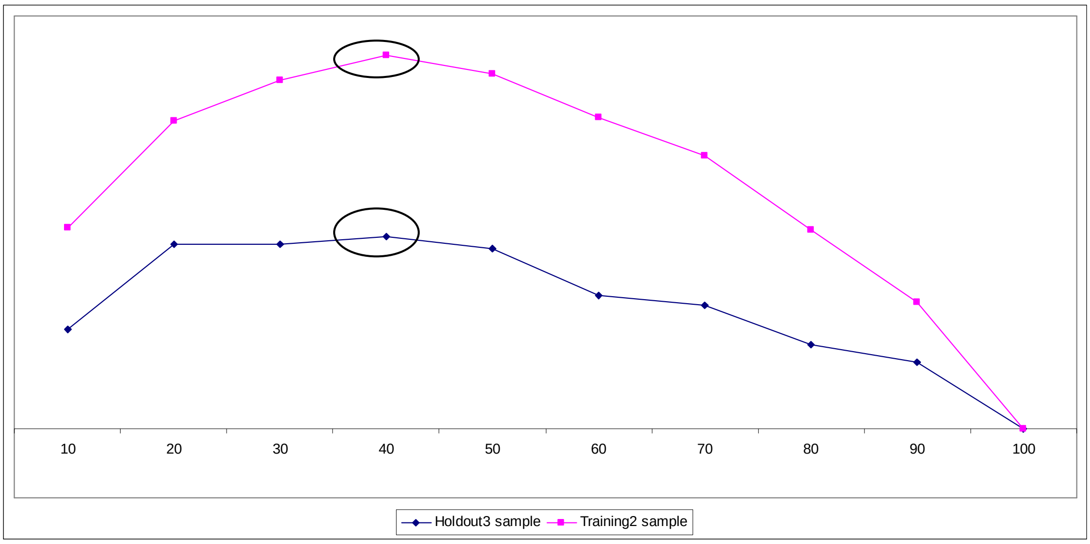


Values are not displayed for confidentiality reasons

Finally, Figures 5.4.5 and 5.4.6 depict marginal portfolio profits and returns respectively per acceptance rate. If the objective is to maximise marginal portfolio profits, then a maximum is obtained at acceptance rate 40; as more customers are accepted, it decreases monotonically until no additional marginal profit is obtained. Alternatively, if the aim is to maximise marginal portfolio returns, acceptance rates 10 ($holdout_3$) and 20 ($training_2$) should be chosen, as it decreases monotonically from there onwards.

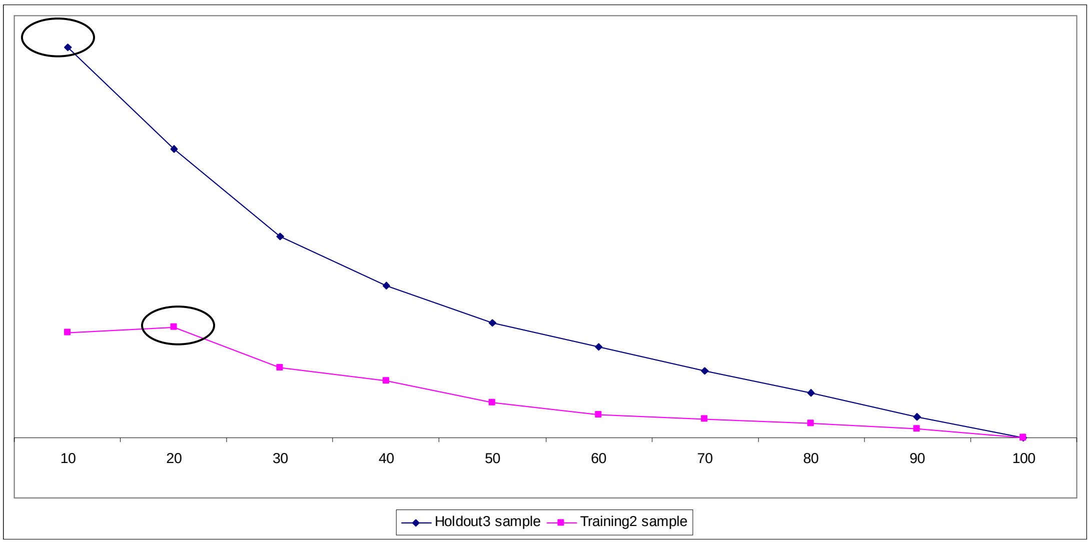
These results show that profit scorecards would tend to accept more customers whereas return scorecards are stricter as the aim is coverage against default. If the former standpoint is adopted, the scope of the credit programme is increased at the expense of taking additional risk by accepting more customers that may be less covered against default. Conversely, fewer customers would be accepted if the latter stance is taken; the credit programme would be more exclusive. These results further confirm that return scores offer additional insight to profit scores.

Figure 5.4.5: Marginal portfolio profits, model P1



Values are not displayed for confidentiality reasons

Figure 5.4.6: Marginal portfolio returns, model R1



Values are not displayed for confidentiality reasons

5.4.1.3.6 Direct vs. indirect methods

Results show that direct methods should be preferred to indirect methods for modelling purposes. This might have occurred because indirect models use predicted probabilities of default and repurchase as predictors of profits and returns. In a scoring context, these values are used for ranking (scoring purposes). Predicted probabilities include error terms that are further included in the prediction of profits and returns.

Another possible reason of such performance is that default probability in the credit programme under analysis depends as well on collection policies, which were unstable during the first year of the observation period. Individual attributes used to predict direct models remain unaltered and could be better proxies of features that affect profits and returns.

These results would discourage the prediction of default and repurchase for profit scoring purposes. This is not the case, as these are the main profit drivers for revolving credit. Instead of using these values as covariates for profit (return) prediction, they could be jointly used to interpret significant variables in default, repurchase and profit scorecards and accordingly to define strategies to target specific segments if the aim is to improve profits or returns.

Indirect models were also useful to highlight the relative economic importance that default has on profits and returns versus that of repurchase. This has major implications for collection policies and is implicitly related to the cross-sale nature of the credit programme, which fosters arrears and eventually default to a certain extent.

5.5 Time-to-profit

This section includes results from the exploratory analysis of survivor and hazard functions, modelling of time-to-profit to produce application scorecards and predicting time-to-profit for investment planning purposes. This was explained in Section 4.3.3.3. The modelled event was:

$$\Pr\left(CASHROAcum_t \geq 1\right) \qquad (5.5.1),$$

which refers to a customer being profitable or being covered against default. Training_3 (n=28,424) and holdout_4 (n=7,106) samples were used to produce and test the models, respectively; see Section 4.3.3.3.2.

5.5.1 Exploratory analysis

This section presents results from the exploratory analysis conducted through survivor and hazard functions, as explained in Section 4.3.3.3.3.

Figure 5.5.1 depicts the survivor function of training_3 sample. The survivor function is stable during the first year of the observation period. Between months 12 and 24, some customers were covered against default. This is related to loan durations and more specifically to the time it took the lender to stabilise its collection process (approximately 18-20 months, as explained in Section 5.4.1.1).

Figure 5.5.2 depicts the hazard function of $training_3$ sample. Consistent with the results explained above, the hazard of $CASHROACUM_t \geq 1$ is very low during the first year. It increases at a faster pace from month 18 onwards. The hazard is monotonically increasing as time goes on. It should be noted that eventually customers should be covered against default for the first time and hence be censored from the sample.

Figure 5.5.1: Survivor function, $training_3$ sample

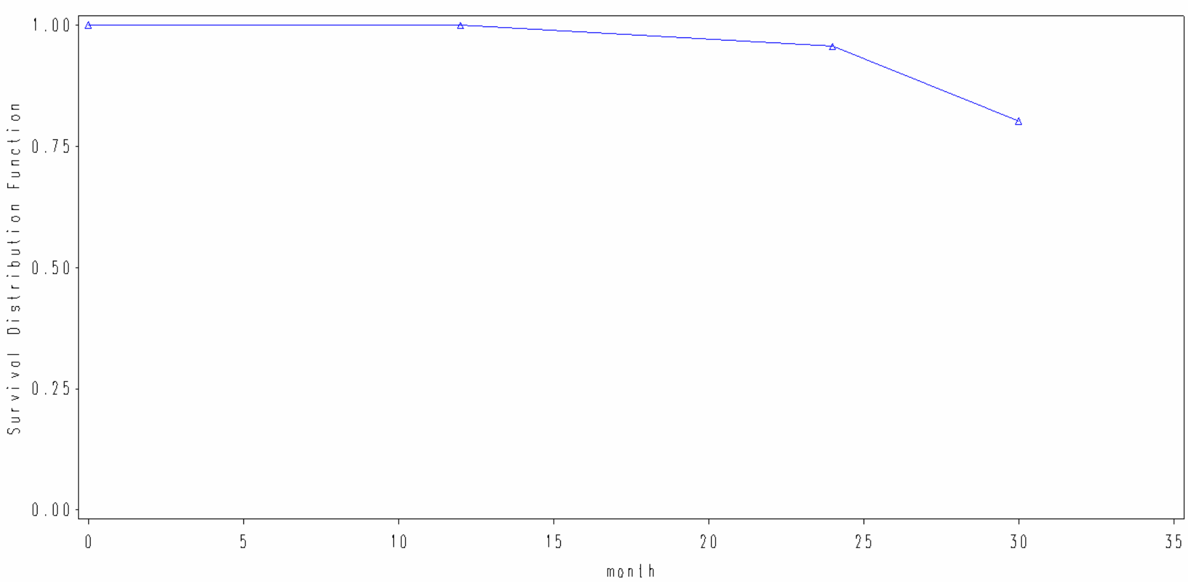
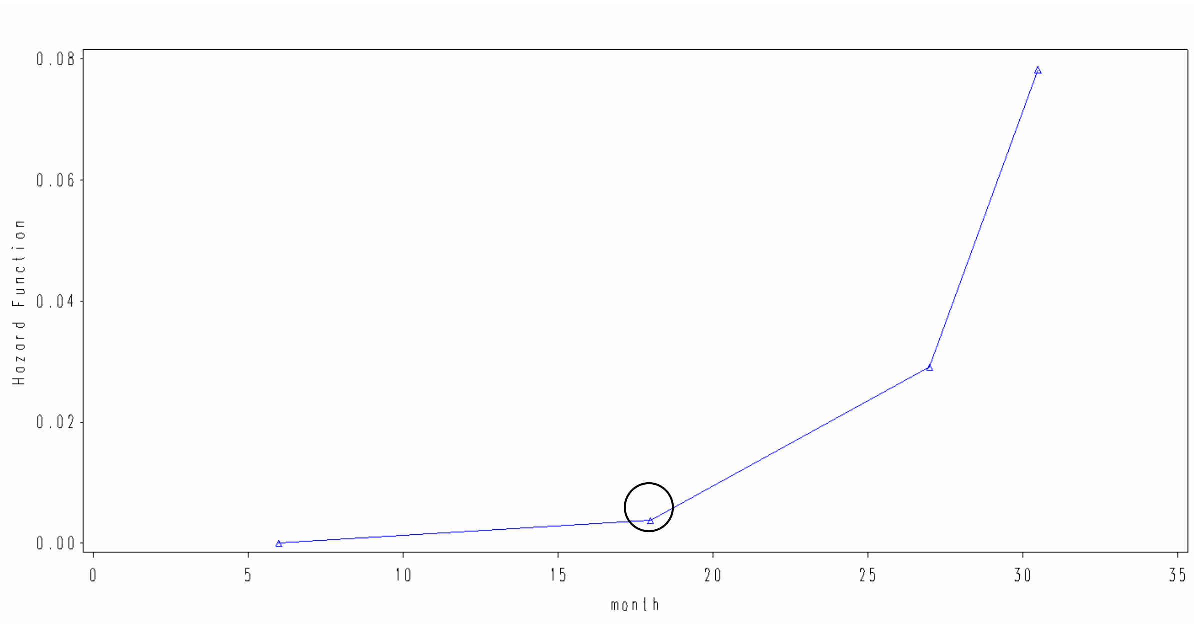


Figure 5.5.2: Hazard function, training$_3$ sample



5.5.2 Time-to-profit application scorecards

This section presents results from models to produce time-to-profit scorecards according to the process presented in Sections 4.3.3.3.4 and 4.3.3.3.5. The covariates used for survival models are the same as those used for models P1 and R1. See Table 5.4.1.

5.5.2.1 Parameter estimates

Seven models were obtained, namely: constant hazard, time direct, quadratic, cubic, logarithmic, monthly and quarterly time dummies. Table 5.5.1 shows the parameter estimates and odds ratios of each model. Given that results for all covariates different to the covariate time are very similar across models in terms of values and signs, a single interpretation is provided per covariate. This was expected, since the only difference among models in terms of variable definition was the treatment of time.

As customers take longer term loans (see results for dumloan3637 to dumloan6061), it is less likely that they will be covered against default compared with those that took shorter term loans. Customers that use more their credit limit (see results for dumloanpr2 and dumloanpr310) in their first purchase are more likely to reach the event. This is consistent with a lower probability of default in the short term, as discussed in Section 5.4.1.1.1. Furthermore, these customers have less available credit limit to repurchase and hence are more likely to be covered against default for the first time.

Customers that live in urban areas, have any type of contract (i.e.: permanent or temporary) and belong to higher socioeconomic stratums are more likely to be completely covered against default than those that live in rural areas, do not have a contract and belong to poor stratums, respectively. Customers that purchase non-traditional products (see results for dumprod1 and dumprod2) are more likely to be covered against default than those that buy traditional products. These results are similar in signs to those obtained for model R1.

As of the effect that time has on hazard, the odds ratios of time-related variables in all models different to the constant hazard model (see results for m, m^2, m^3, Ln (m), dum12 to dum30, dumq4 to dumq10) are greater than one. This confirms the general rationale that time does have an effect on the hazard of being covered against default, as expected.

Table 5.5.2 shows performance measures of each model in terms of AIC and VIF. The constant hazard model was outperformed by time dependent hazard models in terms of the AIC criterion. This further confirms the effect of time on hazard. Therefore, only time-dependent hazard models were considered from here onwards.

Table 5.5.1 shows that parameter estimates of the quadratic and cubic terms are almost negligible numerically (see estimates for m^2 and m^3). Table 5.5.2 shows that a better fit in terms of AIC comes at the expense of an extremely high multicollinearity as more time-related terms are included in the model (see VIF results for quadratic and cubic models). This is a consequence of the high correlation between the various powers of time in these two models.

On the other hand, Table 5.5.2 shows that models with monthly and quarterly dummies have high VIF values and hence multicollinearity issues as well. This might arise because of the interaction of particular months and some explanatory variables and/or as a result of a high correlation between time dummies (i.e.: these dummies can be directly predicted from other time-related dummies). Even though it has been argued that multicollinearity should not be an issue (Allison 1982; Allison 2010), these models may be unstable as time goes on. This is a crucial feature particularly for revolving credits, which are long term oriented.

A graphical comparison of the hazards obtained for the direct, logarithmic, quadratic and cubic models provides further insight to understand the results. Figure 5.5.3 shows that until month 18 (indifference point), model choice does make a difference in terms of the predicted hazard. The hazards predicted by alternative models almost coincide from that point until the end of the observation period. The increasing hazard may be understood as a consequence of censoring. Only the first event is being modelled (i.e.: being covered against default); consequently, the hazard increases until the event is reached and then the customer is censored from the sample.

Table 5.5.1: Parameter estimates and Odds ratios, Cox Discrete Regression

CONSTANT HAZARD

PARAMETER	ESTIMATE	Odds ratio
Intercept	-4.28	
dumcitur	0.13	1.14
dumcontcon	0.08	1.08
dumstra35	0.15	1.16
dumloan3637	-0.34	0.71
dumloan4243	-1.05	0.35
dumloan4855	-3.32	0.04
dumloan6061	-4.90	0.01
dumloanmis	-1.48	0.23
dumloanpr2	0.63	1.88
dumloanpr310	0.69	1.99
dumprod1	0.19	1.21
dumprod2	0.09	1.10

TIME DIRECT

PARAMETER	ESTIMATE	Odds ratio
Intercept	-11.91	
dumcitur	0.17	1.19
dumcontcon	0.14	1.15
dumstra35	0.26	1.30
dumloan3637	-1.15	0.32
dumloan4243	-2.29	0.10
dumloan4855	-4.68	0.01
dumloan6061	-6.26	0.00
dumloanmis	-2.62	0.07
dumloanpr2	1.08	2.95
dumloanpr310	1.22	3.39
dumprod1	0.35	1.41
dumprod2	0.16	1.18
m	0.35	1.42

QUADRATIC

PARAMETER	ESTIMATE	Odds ratio
Intercept	-13.27	
dumcitur	0.17	1.19
dumcontcon	0.14	1.15
dumstra35	0.26	1.30
dumloan3637	-1.15	0.32
dumloan4243	-2.27	0.10
dumloan4855	-4.66	0.01
dumloan6061	-6.24	0.00
dumloanmis	-2.61	0.07
dumloanpr2	1.08	2.93
dumloanpr310	1.21	3.36
dumprod1	0.34	1.41
dumprod2	0.16	1.18
m	0.47	1.60
m^2	0.00	1.00

CUBIC

PARAMETER	ESTIMATE	Odds ratio
Intercept	-11.85	
dumcitur	0.17	1.19
dumcontcon	0.14	1.15
dumstra35	0.26	1.30
dumloan3637	-1.16	0.32
dumloan4243	-2.27	0.10
dumloan4855	-4.66	0.01
dumloan6061	-6.24	0.00
dumloanmis	-2.61	0.07
dumloanpr2	1.08	2.93
dumloanpr310	1.21	3.36
dumprod1	0.34	1.41
dumprod2	0.16	1.18
m	0.25	1.29
m^2	0.01	1.01
m^3	0.00	1.00

LN(M)

PARAMETER	ESTIMATE	Odds ratio
Intercept	-29.00	
dumcitur	0.17	1.19
dumcontcon	0.14	1.15
dumstra35	0.26	1.29
dumloan3637	-1.14	0.32
dumloan4243	-2.24	0.11
dumloan4855	-4.62	0.01
dumloan6061	-6.19	0.00
dumloanmis	-2.57	0.08
dumloanpr2	1.06	2.89
dumloanpr310	1.19	3.29
dumprod1	0.34	1.40
dumprod2	0.16	1.17
Ln(M)	8.06	>999.999

Table 5.5.1: Parameter estimates and Odds ratios, Cox Discrete Regression

MONTHLY DUMMIES

PARAMETER	ESTIMATE	Odds ratio
Intercept	-9.95	
dumcitur	0.17	1.19
dumcontcon	0.14	1.15
dumstra35	0.26	1.30
dumloan3637	-1.16	0.31
dumloan4243	-2.29	0.10
dumloan4855	-4.67	0.01
dumloan6061	-6.24	0.00
dumloanmis	-2.61	0.07
dumloanpr2	1.07	2.92
dumloanpr310	1.21	3.37
dumprod1	0.35	1.42
dumprod2	0.17	1.18
dum12	2.58	13.23
dum13	2.74	15.47
dum14	3.10	22.19
dum15	2.18	8.88
dum16	3.20	24.51
dum17	3.99	54.00
dum18	4.22	68.23
dum19	4.31	74.80
dum20	5.18	177.83
dum21	5.80	329.44
dum22	6.02	410.84
dum23	5.99	400.99
dum24	6.22	502.68
dum25	6.65	776.06
dum26	7.03	>999.999
dum27	7.62	>999.999
dum28	8.11	>999.999
dum29	8.24	>999.999
dum30	8.29	>999.999

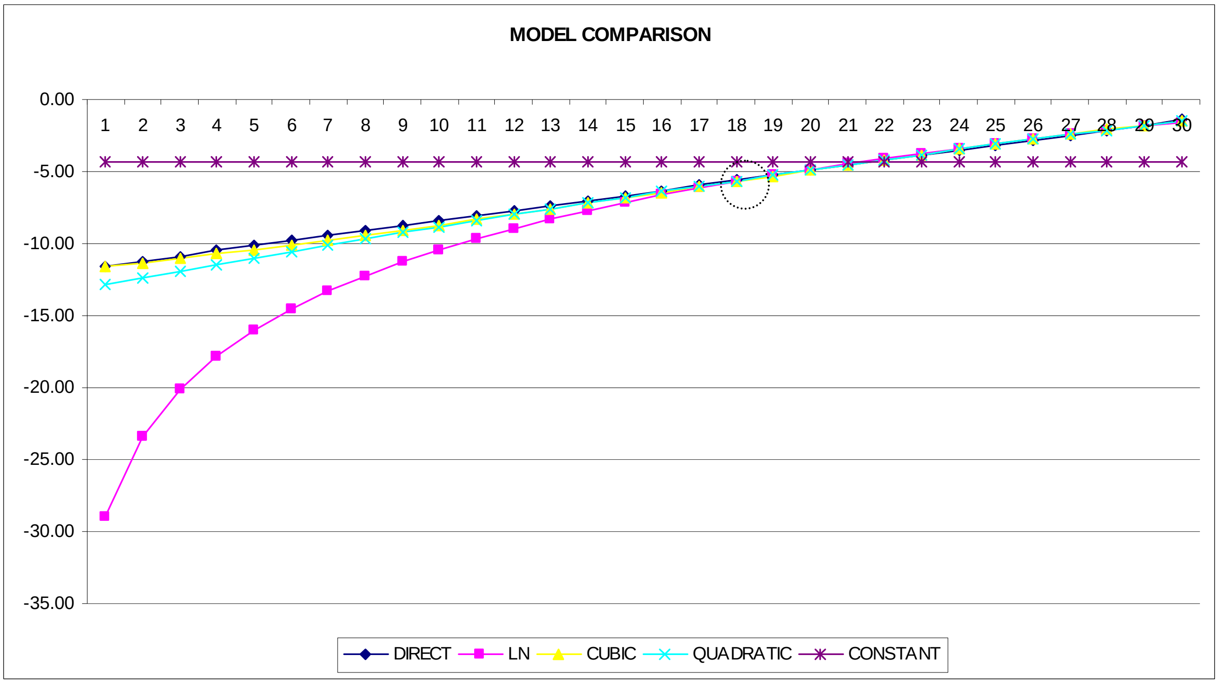
QUARTERLY DUMMIES

PARAMETER	ESTIMATE	Odds ratio
Intercept	-10.10	
dumcitur	0.17	1.19
dumcontcon	0.14	1.15
dumstra35	0.26	1.30
dumloan3637	-1.14	0.32
dumloan4243	-2.24	0.11
dumloan4855	-4.61	0.01
dumloan6061	-6.19	0.00
dumloanmis	-2.57	0.08
dumloanpr2	1.05	2.87
dumloanpr310	1.19	3.28
dumprod1	0.34	1.41
dumprod2	0.16	1.18
dumq4	1.86	6.42
dumq5	2.90	18.10
dumq6	4.04	56.87
dumq7	5.40	221.85
dumq8	6.23	506.45
dumq9	7.28	>999.999
dumq10	8.34	>999.999

Table 5.5.2: Model comparison

MODEL	AIC	VIF
TIME DIRECT	**45,397**	**4**
LN (M)	45,466	4
QUADRATIC	45,385	82
CUBIC	45,385	5337
MONTHLY DUMMIES	45,184	76
QUARTERLY DUMMIES	45,635	196
CONSTANT HAZARD	63,957	4

Figure 5.5.3: Hazard rate throughout time



5.5.2.2 Accuracy of prediction

Table 5.5.3 shows predictive accuracy measures of time-dependent models in terms of AUC and H measure, per approach as explained in Section 4.3.3.3.4.

Predictive accuracy values are very similar across models in terms of either the H measure or AUC, per approach. For instance, under approach 1, H measure varies between 0.31 and 0.35 whereas AUC varies between 0.83 and 0.86 for holdout$_4$ sample.

A cross-approach comparison shows that apart from approach 2a, results are similar in both training$_3$ and holdout$_4$ samples for all models (e.g.: under approach 2b, H measure and AUC were 0.29 and 0.91 , respectively in both training$_3$ and holdout$_4$ samples). Specifically, H measure and AUC of all models decreased sharply under approach 2a when models were tested in holdout$_4$

sample, compared with results for $training_3$ sample. These poor results may be a consequence of the irregular collection process during the first year of the observation period. This resulted in unstable performance in $training_3$ and $holdout_4$ samples. Such differences in results disappear at t=24 and 30 months.

Among the models where hazard varies with time, apart from the logarithmic alternative and the model that uses time directly, all models have multicollinearity issues. Given its slightly better fit in terms of AIC compared with the logarithmic alternative (see Table 5.5.2), the model that uses time directly was preferred to produce time-to-profit scores.

Because of the graphical similarity between the chosen model and the cubic and quadratic alternatives in Figure 5.5.3, the hypothesis of equality of ROC curves of these models was tested. Table 5.5.4 shows the estimates, standard errors and p-values of these tests. Under approach 2a, results are not significantly different between models (p-value=0.1641 for $holdout_4$ sample). This is consistent with the lower predictive accuracy of all models if survival is assumed at t=12 months given the unstable collection process. A similar situation occurs under approach 2c, which corresponds to t=30 (p-values are 0.2026 and 0.2365 for $holdout_4$ sample). This agrees with the convergence of the linear, quadratic and cubic curves at t=30 as shown in Figure 5.5.3. Conversely, results are significantly different under approach 2b (i.e.: at t=24); p-values are 0.0024 and 0.0002 for $holdout_4$ sample. Furthermore, it does make a difference to test the accuracy of prediction if customers are observed until they left the sample (approach 1) or if customer months (approach 3) are used instead. In the former, results are significantly different whereas the contrary occurs in the latter.

Table 5.5.3: Models accuracy of prediction

APPROACH 1: LAST OBSERVATION MONTH PER CUSTOMER

$TRAINING_3$ SAMPLE

MODEL	H	AUC
M	0.30	0.83
LN	0.33	0.84
QUADRATIC	0.31	0.83
CUBIC	0.32	0.84
MONTHLY DUMMIES	0.35	0.85
QUARTERLY DUMMIES	0.35	0.86

$HOLDOUT_4$ SAMPLE

MODEL	H	AUC
M	0.31	0.83
LN	0.34	0.85
QUADRATIC	0.32	0.84
CUBIC	0.32	0.84
MONTHLY DUMMIES	0.35	0.86
QUARTERLY DUMMIES	0.35	0.86

APPROACH 2a: ASSUMING SURVIVAL AT T=12 MONTHS

$TRAINING_3$ SAMPLE

MODEL	H	AUC
M	1.07E-05	0.80
LN	1.09E-05	0.80
QUADRATIC	1.08E-05	0.80
CUBIC	1.08E-05	0.80
MONTHLY DUMMIES	1.09E-05	0.80
QUARTERLY DUMMIES	1.08E-05	0.80

$HOLDOUT_4$ SAMPLE

MODEL	H	AUC
M	5.70E-06	0.56
LN	5.70E-06	0.56
QUADRATIC	5.70E-06	0.56
CUBIC	5.70E-06	0.56
MONTHLY DUMMIES	5.76E-06	0.56
QUARTERLY DUMMIES	5.70E-06	0.56

APPROACH 2b: ASSUMING SURVIVAL AT T=24 MONTHS

$TRAINING_3$ SAMPLE

MODEL	H	AUC
M	0.29	0.91
LN	0.29	0.91
QUADRATIC	0.29	0.91
CUBIC	0.29	0.91
MONTHLY DUMMIES	0.29	0.91
QUARTERLY DUMMIES	0.29	0.91

$HOLDOUT_4$ SAMPLE

MODEL	H	AUC
M	0.29	0.91
LN	0.29	0.91
QUADRATIC	0.29	0.91
CUBIC	0.29	0.91
MONTHLY DUMMIES	0.29	0.91
QUARTERLY DUMMIES	0.29	0.91

APPROACH 2c: ASSUMING SURVIVAL AT T=30 MONTHS

$TRAINING_3$ SAMPLE

MODEL	H	AUC
M	0.49	0.92
LN	0.49	0.92
QUADRATIC	0.49	0.92
CUBIC	0.49	0.92
MONTHLY DUMMIES	0.49	0.92
QUARTERLY DUMMIES	0.49	0.92

$HOLDOUT_4$ SAMPLE

MODEL	H	AUC
M	0.51	0.93
LN	0.51	0.93
QUADRATIC	0.51	0.93
CUBIC	0.51	0.93
MONTHLY DUMMIES	0.51	0.93
QUARTERLY DUMMIES	0.51	0.93

APPROACH 3: CUSTOMER-MONTHS

$TRAINING_3$ SAMPLE

MODEL	H	AUC
M	0.05	0.96
LN	0.05	0.96
QUADRATIC	0.05	0.96
CUBIC	0.05	0.96
MONTHLY DUMMIES	0.05	0.97
QUARTERLY DUMMIES	0.05	0.96

$HOLDOUT_4$ SAMPLE

MODEL	H	AUC
M	0.06	0.96
LN	0.05	0.96
QUADRATIC	0.06	0.96
CUBIC	0.06	0.96
MONTHLY DUMMIES	0.05	0.96
QUARTERLY	0.05	0.96

Table 5.5.4: ROC comparison

APPROACH 1: LAST OBSERVATION MONTH PER CUSTOMER

$TRAINING_3$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	-0.0046	0.0001	<.0001
TIME DIRECT VS CUBIC	-0.006	0.0002	<.0001

$HOLDOUT_4$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	-0.0042	0.0002	<.0001
TIME DIRECT VS CUBIC	-0.0055	0.0003	<.0001

APPROACH 2a: ASSUMING SURVIVAL AT T=12 MONTHS

$TRAINING_3$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	-0.0002	0.0001	0.0326
TIME DIRECT VS CUBIC	-0.0002	0.0001	0.1995

$HOLDOUT_4$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	-0.0002	0.0001	0.1641
TIME DIRECT VS CUBIC	-0.0002	0.0001	0.1641

APPROACH 2b: ASSUMING SURVIVAL AT T=24 MONTHS

$TRAINING_3$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	0	0	0.0002
TIME DIRECT VS CUBIC	-0.0001	0	<.0001

$HOLDOUT_4$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	-0.0001	0	0.0024
TIME DIRECT VS CUBIC	-0.0001	0	0.0002

APPROACH 2c: ASSUMING SURVIVAL AT T=30 MONTHS

$TRAINING_3$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	0	0	0.0157
TIME DIRECT VS CUBIC	0	0	0.9601

$HOLDOUT_4$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	0	0	0.2026
TIME DIRECT VS CUBIC	0	0	0.2365

APPROACH 3: CUSTOMER-MONTHS

$TRAINING_3$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	-0.0001	0	0.0171
TIME DIRECT VS CUBIC	0	0	0.3962

$HOLDOUT_4$ SAMPLE

MODELS	Estimate	Std Error	Pr > ChiSq
TIME DIRECT VS QUADRATIC	-0.0001	0.0001	0.2393
TIME DIRECT VS CUBIC	0.0001	0.0001	0.1864

Finally, the accuracy of the model that uses time directly was calculated per rank and decile. Table 5.5.5 shows the ranks, customers that were covered against default identified per rank (n), n as a percentage of the total customers covered against default (%) and the cumulative percentage of customers identified per rank (cum%) for $holdout_4$ sample. Similarly, Table 5.5.6 shows results per decile. Results were very similar in both cases. The model identifies better customers in top bands than in the lower categories, which is a positive feature for scoring purposes.

Up to t=12 months, results were poor for both ranks and deciles; the model only placed 36% of customers that were covered against default in the top 4 ranks and deciles. This is consistent with results obtained when using overall accuracy measures.

Accuracy results improve up to t=24 and t=30; cum%= 87% and 85%, respectively. This proportion of customers was included in the top three ranks (deciles). The difference in results for the top two deciles in t=24 and 30 months is a consequence of the lower number of customers that actually were covered against default up to t=24 months (410) versus t=30 months (1591), which magnifies the accuracy effect in the top two deciles (ranks). Given the inclusiveness nature of the credit programme, such difference in results is not critical, as in practical terms the Company would use at least the third decile to select customers.

Overall, the scores obtained from the model place 94% of the customers that were covered against default in the top 4 deciles up to t=24 and 30 months. Therefore, the accuracy of prediction of the model that uses time directly improves in the long term. This model will be referred as time-to-profit scorecard S1.

Table 5.5.5: Accuracy ranks, direct model, holdout$_4$ sample

TIME DIRECT

UP TO T=12

RANK	n	%	cum%
1	**0**	**0%**	**0%**
2	**4**	**36%**	**36%**
3	**0**	**0%**	**36%**
4	**0**	**0%**	**36%**
5	4	36%	73%
6	0	0%	73%
7	0	0%	73%
8	1	9%	82%
9	1	9%	91%
10	1	9%	100%

UP TO T=24

RANK	n	%	cum%
1	**264**	**64%**	**64%**
2	**77**	**19%**	**83%**
3	**17**	**4%**	**87%**
4	**29**	**7%**	**94%**
5	17	4%	99%
6	0	0%	99%
7	2	0%	99%
8	1	0%	99%
9	2	0%	100%
10	1	0%	100%

UP TO T=30

RANK	n	%	cum%
1	**575**	**36%**	**36%**
2	**453**	**28%**	**65%**
3	**319**	**20%**	**85%**
4	**155**	**10%**	**94%**
5	60	4%	98%
6	4	0%	98%
7	10	1%	99%
8	6	0%	99%
9	4	0%	100%
10	5	0%	100%

Table 5.5.6: Accuracy deciles, direct model, holdout$_4$ sample

TIME DIRECT

UP TO T=12

DECILE	n	%	cum%
1	0	**0%**	**0%**
2	4	**36%**	**36%**
3	0	**0%**	**36%**
4	0	**0%**	**36%**
5	4	36%	73%
6	0	0%	73%
7	1	9%	82%
8	0	0%	82%
9	1	9%	91%
10	1	9%	100%

UP TO T=24

DECILE	n	%	cum%
1	264	**64%**	**64%**
2	77	**19%**	**83%**
3	17	**4%**	**87%**
4	29	**7%**	**94%**
5	17	4%	99%
6	0	0%	99%
7	3	1%	99%
8	0	0%	99%
9	2	0%	100%
10	1	0%	100%

UP TO T=30

DECILE	n	%	cum%
1	577	**36%**	**36%**
2	496	**31%**	**67%**
3	284	**18%**	**85%**
4	145	**9%**	**94%**
5	60	4%	98%
6	4	0%	98%
7	14	1%	99%
8	2	0%	99%
9	5	0%	100%
10	4	0%	100%

5.5.2.3 Comparison of profit, return and time-to-profit application scorecards

This section compares the overall impact on portfolio profits and returns if either OLS or survival models are used to score customers. As explained in Section 4.3.3.3.5, Model S1 was produced using $training_3$ and was tested on $holdout_4$ sample. Therefore, in order to compare the impact of a time-to-profit scorecard on portfolio profits (returns) with that of models P1 and R1, model S2 was produced using $training_2$ and tested on $holdout_3$ sample. Table 5.5.7 shows the estimates and odds ratios per significant variable in model S2. Results are similar to those of model S1.

The predicted probability of being completely covered against default by t=30 according to model S2 was taken as the survival score.

Table 5.5.7: Parameter estimates and Odds ratios, model S2

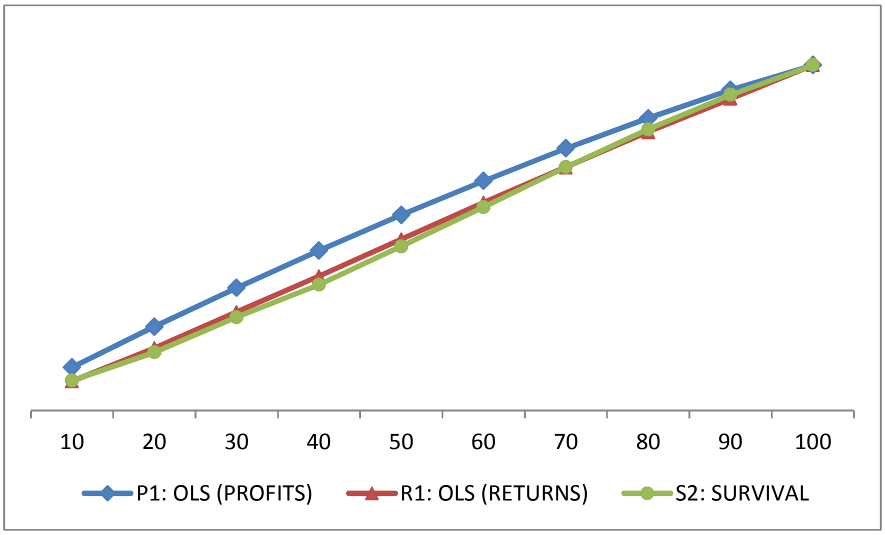
PARAMETER	ESTIMATE	Odds ratio
Intercept	-15.77	
dumcitur	0.14	1.15
dumcontcon	0.14	1.15
dumstra35	0.27	1.31
dumloan4243	-1.18	0.31
dumloan4855	-3.70	0.02
dumloan6061	-5.88	0.00
dumloanmis	-2.21	0.11
dumloanpr2	1.09	2.97
dumloanpr310	1.31	3.71
dumprod3	-0.37	0.69
m	0.46	1.58

Figures 5.5.4 and 5.5.5 depict portfolio profits per acceptance rate for $training_2$ and $holdout_3$ samples, respectively. Profit scorecard P1 outperforms both R1 and S2 as of the obtained portfolio profits. This was expected, as profit scorecards by definition maximise portfolio profits.

Figures 5.5.6 and 5.5.7 show portfolio returns per acceptance rate for $training_2$ and $holdout_3$ samples, respectively. P1 is always dominated by R1 and S2 in terms of portfolio returns.

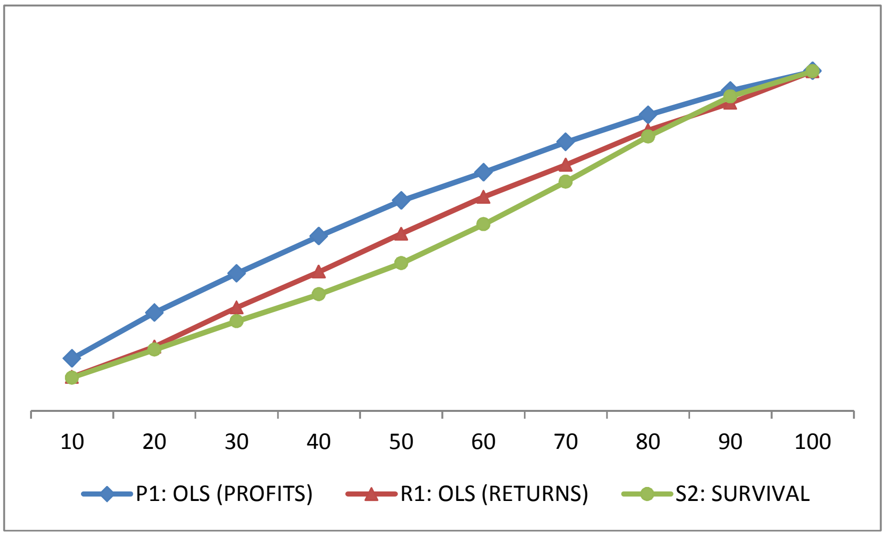
It is clear that S2 yields better results than R1 in $holdout_3$ sample. This follows from the fact that survival scorecards perform better at higher bands as the model focuses on the occurrence of being completely covered against default (i.e.: $CASHROACUM_t \geq 1$); emphasis is given to customers that clearly outperform the rest. This was not the case for the training sample. These results are understandable, since $training_2$ sample does not include outliers, whereas under more extreme conditions survival models outperform the OLS model. This is an advantage of using survival scorecards, since it is unrealistic to assume that return measures will be free of outliers under real circumstances.

Figure 5.5.4: Impact of models P1, R1 and S2 on portfolio *OPCASHcum30*, $training_2$ sample



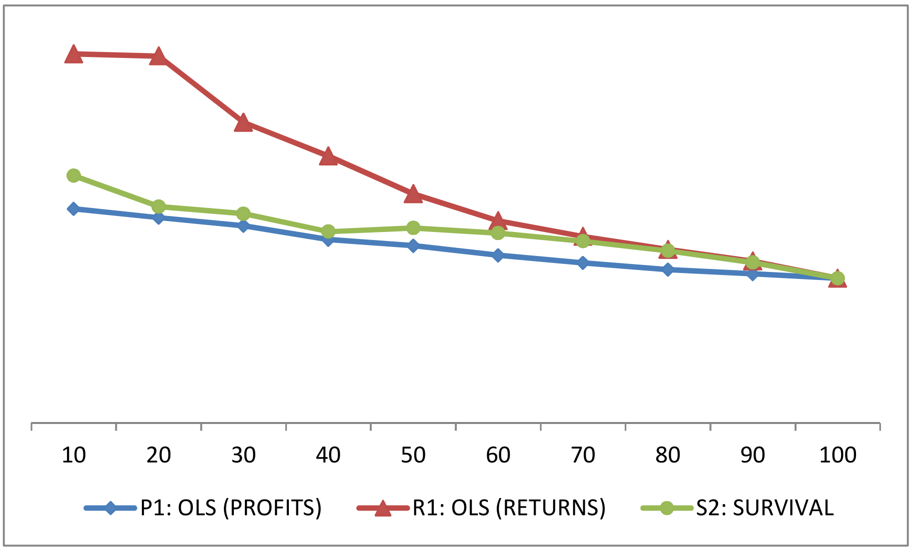
Values are not displayed for confidentiality reasons

Figure 5.5.5: Impact of models P1, R1 and S2 on portfolio *OPCASHcum30*, holdout$_3$ sample



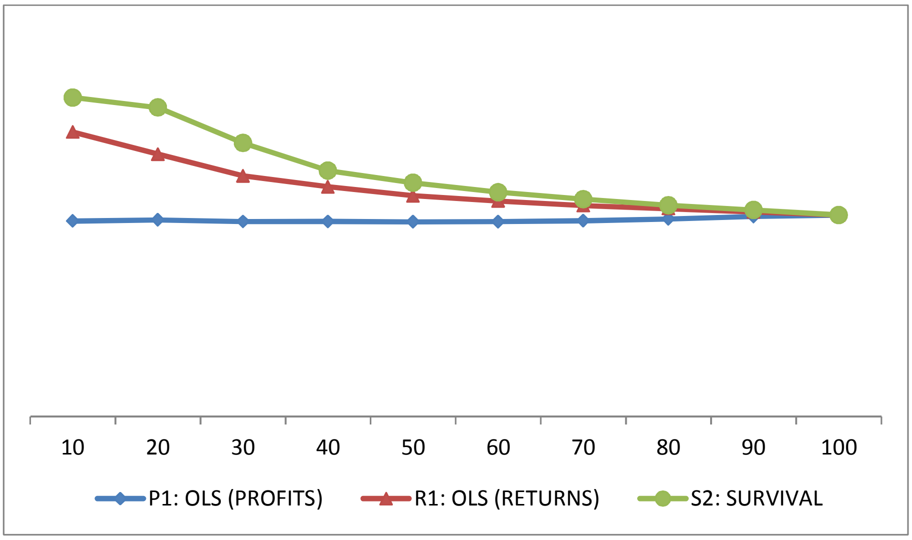
Values are not displayed for confidentiality reasons

Figure 5.5.6: Impact of models P1, R1 and S2 on portfolio *CASHROAcum30*, training$_2$ sample



Values are not displayed for confidentiality reasons

Figure 5.5.7: Impact of models P1, R1 and S2 on portfolio *CASHROAcum30*, holdout$_3$ sample



Values are not displayed for confidentiality reasons

5.5.2.4 Results per loan duration

Table 5.5.8 shows the number of customers in holdout$_4$ sample per loan duration and decile according to time-to-profit scorecard S1. This was done because of the significance that loan duration has on time-to-profit. An analysis of scores based on the probability of being covered against default assuming customers survived until t=30 months shows that shorter term loans (i.e..: up to 43 months) are scored in the top 4 deciles. This makes sense, since these loans are by their own nature expected to be covered against default for the first time before longer term loans. These results confirm the importance of loan duration on time-to-profit for the credit programme under analysis and justify the use of segmented models according to that variable, as explained in Section 4.3.3.3.6.1. This was the approach taken in the next section.

Table 5.5.8: Holdout$_4$ sample, based on Pr (Event for t ≤30 months)

LOANDUR	DECILES (PR UNTIL T=30 MONTHS)										
	0	1	2	3	4	5	6	7	8	9	Total
-1	0	0	97	664	215	0	0	0	0	0	976
12	2	21	6	0	0	0	0	0	0	0	29
18	28	22	3	0	0	0	0	0	0	0	53
24	234	116	41	0	0	0	0	0	0	0	391
25	6	3	1	0	0	0	0	0	0	0	10
30	183	6	4	0	0	0	0	0	0	0	193
31	10	0	0	0	0	0	0	0	0	0	10
36	200	505	204	28	0	0	0	0	0	0	937
37	47	38	4	0	0	0	0	0	0	0	89
42	0	0	309	19	9	0	0	0	0	0	337
43	0	0	41	0	1	0	0	0	0	0	42
48	0	0	0	0	359	10	1	1	0	0	371
49	0	0	0	0	34	0	0	0	0	0	34
54	0	0	0	0	36	0	0	0	0	0	36
55	0	0	0	0	7	0	0	0	0	0	7
60	0	0	0	0	45	557	641	677	697	697	3314
61	0	0	0	0	5	143	69	32	14	14	277

-1=missing loan duration

5.5.3 Time-to-profit prediction

This section presents time-to-profit predictions for investment planning purposes, as explained in Section 4.3.3.3.6. Apart from loan duration, the same coarse classified covariates were used to predict time-to-profit. The objective was to compare results of specific models for segments [12, 25], [30, 31] and [36, 37] with those of a generic model in training$_3$ and holdout$_4$ samples. In the generic model, results for dummy variables related to loan duration are relative to category [12, 13].

The linear hazard alternative that includes the variable time directly was used to develop these models. From (4.3.30) and (4.3.32) it follows that:

$$m_i = \frac{[\text{Log}\,(\text{P} \,/\, (1 - \text{P}))] - \alpha_{\text{k}} - \beta^{'}\text{x}_{\text{i}})}{\beta_{\text{m}\,i}} \qquad (6.5.1),$$

where x_i's are significant covariates at application time and m is the month in which customer i can be covered against default at various probability levels.

5.5.3.1 Segmented models

Table 5.5.9 shows parameters, estimates and odds ratios for each segmented model: Models S3, S4 and S5 correspond to segments [12, 25], [30, 31] and [36, 37], respectively. Results show common and distinctive features per segment.

As customers use more their credit limit, it is more likely they will be covered against default for the first time regardless of their segment (see results for dumloanpr2 and dumloanpr310). This makes sense, since these customers are less likely to default in the short term. As loan duration increases from [12, 25] to [36,37], the impact of credit limit usage increases.

Regarding the effect of time (e.g.: variable *m*), as it increases there is a greater probability of being covered against default, regardless of loan duration. This is a result of the linear increasing hazard throughout time. It is evident that as loan duration increases, the impact of time is more pronounced as more interests are paid for longer periods of time (i.e.: the odds ratio of variable *m* increases).

In particular, socioeconomic stratum is a significant covariate in segments [12, 25] and [36, 37]. Customers with any type of contract in segment [30, 31] are more likely to be covered against default than those that lack it; this results from more financial stability in the former group. Finally, customers in segment [36, 37] that do not work in traditional industries are more likely to be covered against default, whereas the contrary occurs to those that bought product type 3.

Table 5.5.9: Results, segmented models S3, S4 and S5

MODEL S3 SEGMENT [12,25]

PARAMETER	ESTIMATE	ODDS RATIO
Intercept	-7.38	
dumstra35	0.22	1.24
dum2425	-0.43	0.65
dumloanpr2	1.07	2.93
dumloanpr310	1.67	5.29
m	0.19	1.21

MODEL S4 SEGMENT [30,31]

PARAMETER	ESTIMATE	Odds ratio
Intercept	-11.80	
dumcontcon	0.31	1.36
dumloanpr2	1.45	4.24
dumloanpr310	1.45	4.27
m	0.34	1.40

MODEL S5 SEGMENT [36,37]

PARAMETER	ESTIMATE	Odds ratio
Intercept	-21.13	
dumstra35	0.33	1.38
dumloanpr2	2.12	8.34
dumloanpr310	2.74	15.46
dumactna	0.23	1.26
dumprod3	-0.49	0.62
m	0.62	1.87

Optimal percentiles for segments [12, 25], [30, 31] and [36, 37] were 9, 13 and 32, respectively. The increasing trend in the percentiles as loan duration increases is related to the fact that shorter term loans experience the event earlier and hence lower percentiles reflect this feature. These percentiles were used to obtain a predicted value for time-to-profit (rounded to zero decimal places) per customer.

5.5.3.2 Generic model

Table 5.5.10 shows parameters, estimates and odds ratios for generic model S6. Significant covariates are similar to those obtained in model S1. This was expected; S1 was also generic and was also based on the probability of occurrence of coverage against default throughout time. Even though training[3] sample in model S1 included all segments, the majority of customers that were excluded to produce the models in this section did not experience the event; this explains the similarity between results.

Table 5.5.10: Results for generic model S6

MODEL S6		
PARAMETER	**ESTIMATE**	**Odds ratio**
Intercept	-11.28	
dumage7	0.14	1.15
dumcontcon	0.17	1.19
dumstra35	0.23	1.26
dumloan2425	-0.49	0.61
dumloan3031	-1.11	0.33
dumloan3637	-2.01	0.13
dumloanpr2	1.49	4.43
dumloanpr310	1.86	6.43
dumprod1	0.27	1.30
dumprod2	0.12	1.13
m	0.35	1.41

This survival model yielded a probability distribution of occurrence of the event and accordingly a probability distribution of time-to-profit (m). The optimal percentiles that minimized the prediction error for segments [12, 25], [30, 31] and [36, 37] were 93, 93 and 97, respectively. These percentiles are almost identical and show that the minimum MAE_p is obtained when it is very likely that a customer is covered against default at later stages. This is a direct consequence of the generic nature of the model, which only acknowledges the differences in loan duration across segments through the use of dummy variables instead of accounting for the specificity of each segment via separate models. These percentiles were then used to obtain a predicted value for time-to-profit per customer. Values were rounded to zero decimal places to ensure discrete time values.

5.5.3.3 Model classification accuracy

As explained in Section 4.3.3.3.6.3, confusion matrices were used to assess the classification accuracy of models. Tables 5.5.11, 5.5.12 and 5.5.13 show results of confusion matrices for segments [12, 25], [30, 31] and [36, 37], respectively.

Total classification accuracy results in each segment show that segmented models outperform the generic model: 63% vs. 6%, 49% vs. 20% and 73% vs. 32% for segments [12, 25], [30, 31] and [36, 37], respectively. These models by definition capture the particularities of loan duration, which has been an important predictor in the various scorecards developed in previous sections. An important feature of the generic model is that regardless of its poor accuracy results across segments, its sensitivity always exceeds that of segmented models; it is 100% in the three segments. Conversely, specificity of generic model is 0% in the three segments. The generic model is more efficient in identifying customers type 6 which are not covered against default during the observation period. However, it fails to identify those that actually generate organic funds (i.e.: customers type 1).

Even though the classification accuracy of segmented models for segments [12, 25] and [36, 37] was good, that of segmented model for [30, 31] was marginally lower than 50%. These results follow from the fact that t_{median}=25 months for this segment, which is 5 months earlier to $t_{investment}$=30 months. In the other two cases, the median time is just a month earlier than the control point: (t_{median}=23 and 29 for segments {12, 25] and [36, 37], respectively). This suggests that application covariates become less relevant to predict time to event as the investment period is further apart from the median time to event. Behavioural features may be more relevant to predict time to event.

The above results suggest that the generic model is very conservative compared with the segmented models; according to it no customer will be covered against default in the observation period. This does not reflect the reality of the inclusive lending programme under analysis. Therefore, it was confirmed that loan duration is an important variable to predict time-to-profit and hence that segmented models are more adequate than a single generic model.

Table 5.5.11: Confusion matrices: Generic vs. segmented models, Segment [12, 25] in $Holdout_4$ sample

Generic model S6 up to t=24

	Actual goods	**Actual bads**	**Total predicted**
Predicted goods	0	0	**0**
Predicted bads	281	17	**298**
Total actual	**281**	**17**	**298**

Specificity	0%
Type I error	100%
Sensitivity	100%
Type II error	0%
Total error	94%
Total classification accuracy	**6%**

Segmented model S3 up to t=24

	Actual goods	**Actual bads**	**Total predicted**
Predicted goods	189	17	**206**
Predicted bads	92	0	**92**
Total actual	**281**	**17**	**298**

Specificity	67%
Type I error	33%
Sensitivity	0%
Type II error	100%
Total error	37%
Total classification accuracy	**63%**

Table 5.5.12: Confusion matrices: Generic vs. segmented models, Segment [30, 31] in Holdout$_4$ sample

Generic model S6 up to t=30

	Actual goods	**Actual bads**	**Total predicted**
Predicted goods	0	0	**0**
Predicted bads	162	41	**203**
Total actual	**162**	**41**	**203**

Specificity	0%
Type I error	100%
Sensitivity	100%
Type II error	0%
Total error	80%
Total classification accuracy	**20%**

Segmented model S4 up to t=30

	Actual goods	**Actual bads**	**Total predicted**
Predicted goods	100	56	**156**
Predicted bads	47	0	**47**
Total actual	**147**	**56**	**203**

Specificity	68%
Type I error	32%
Sensitivity	0%
Type II error	100%
Total error	51%
Total classification accuracy	**49%**

Table 5.5.13: Confusion matrices: Generic vs. segmented models, Segment [36, 37] in Holdout$_4$ sample

Generic model S6 up to t=30

	Actual goods	**Actual bads**	**Total predicted**
Predicted goods	0	0	**0**
Predicted bads	701	325	**1026**
Total actual	**701**	**325**	**1026**

Specificity	0%
Type I error	100%
Sensitivity	100%
Type II error	0%
Total error	68%
Total classification accuracy	**32%**

Segmented model S5 up to t=30

	Actual goods	**Actual bads**	**Total predicted**
Predicted goods	682	253	**935**
Predicted bads	19	72	**91**
Total actual	**701**	**325**	**1026**

Specificity	97%
Type I error	3%
Sensitivity	22%
Type II error	78%
Total error	27%
Total classification accuracy	**73%**

5.5.3.4 Impact on investment scheme

As presented in Table 4.3.17, six categories of customers were identified: category 1 includes customers that were covered against default and were correctly predicted within an investment period, category 2 refers to customers incorrectly predicted later, category 3 includes customers that were not predicted at all even though they were covered against default, category 4 refers to customers incorrectly predicted earlier, customers in category 5 were incorrectly predicted even though they were not covered against default and customers in category 6 were not covered against default and were predicted as so.

Tables 5.5.14, 5.5.15 and 5.5.16 show results of the impact on investment scheme of generic and segmented models for segments [12, 25], [30, 31] and [36, 37], respectively in $holdout_4$ sample. Each cell represents the cumulative profits (losses) generated per customer category, per investment period (i.e.: t=12, 24 and 30), expressed as a percentage of portfolio outstanding balance resulting from the first purchase. The last column includes the cumulative net organic funding per investment period. This was explained in Section 4.3.3.3.6.4.

Poor classification accuracy of the generic model across segments is reflected in poor monetary results in the investment scheme, accordingly. It fails to capture organic funding opportunities and hence the growth potential of the credit programme. Tables 5.5.14, 5.5.15 and 5.5.16 show that net organic funding detected by the generic model was -68%, -83% and -73% in the last investment period of segments [12, 25], [30, 31] and [36, 37], respectively. If the Company relies on organic funding, using the generic model would hinder its growth by the rates mentioned above. Furthermore, the risk perception of shareholders and third parties that fund it might be affected, increasing as well their opportunity cost. Additionally, implementing the generic model would imply a social cost.

Foregone profits from customers in category 3 which were actually covered against default but were not predicted as so by the generic model represent between 68% and 83% of the total funds invested in the portfolio. These customers have to bear additional costs as they would have to obtain loans from more costly and informal lending sources.

On the other hand, the generic model identifies customers in category 6 that account for 2% to 27% of the initial investment. These funds would therefore not be allocated in new loans if the Company adopts the conservative perspective implicit by the generic model. Overall, results for the generic model in Tables 5.5.14 to 5.5.16 show that "lost" funds implicit by profits from customers in category 3 significantly exceed the "benefits" obtained from identifying customers in category 6 across segments (see categories 3 and 6).

Results for segmented models in Tables 5.5.14 to 5.5.16 show that the misclassification of customers at lagged periods (category 2) is a distinctive feature of segmented models, compared with the generic model. Only segmented model S4 for [30, 31] produced predictions at earlier periods of time (8% of initial portfolio of loans in category 4). In contrast with the generic model, all segmented models predict customers in category 5. These results occurred because the generic model does not predict at all the occurrence of the event.

None of the segmented models entails a social opportunity cost (see category 3 in results for segmented models). This implies as well that segmented models do not impose growth constraints to the credit programme. All segmented models outperformed the generic model as they identify organic funding opportunities (34%, 1% and 47% of the initial investment for segments [12, 25], [30, 31] and [36, 37], respectively).

Consistent with poor classification accuracy results, segmented model for [30, 31] in Table 5.5.15 is barely useful to identify organic funding opportunities.

Finally, a longitudinal analysis sheds light on the growth strategy per segment and the related funding scheme resulting from the implementation of segmented scorecards. Segmented models in Tables 5.5.14 and 5.5.16 show that the earliest points of time in which segments [12, 25] and [36, 37] can grow organically are t=24 and 30, respectively; before those investment periods net organic funding is zero and/or negative. An improved model for segment [30, 31] is required to identify its growth opportunities.

The results presented above show that inclusive lending programmes are profitable and generate organic funds to foster their growth. It was further confirmed that loan duration has a major effect on time-to-profit. In general, loans reach the event earlier than the anticipated time as a result of profit accumulation throughout time. The investment plan presented in this section per loan duration allows for the efficient allocation of cash surpluses among new customers instead of holding them for longer periods of time.

Table 5.5.14: Impact on investment scheme: Generic vs. segmented models, Segment [12, 25] in $Holdout_4$ sample

Generic model S6

RECOVERED FUNDS/TOTAL INITIAL INVESTMENT	CATEGORY						NET ORGANIC FUNDING PER PERIOD: (1)-(2)-(3)-(4)-(5)
	1	2	3	4	5	6	
UP TO T=12	0%	0%	1%	0%	0%	1%	-1%
UP TO T=24	0%	0%	68%	0%	0%	2%	-68%

Segmented model S3

RECOVERED FUNDS/TOTAL INITIAL INVESTMENT	CATEGORY						NET ORGANIC FUNDING PER PERIOD: (1)-(2)-(3)-(4)-(5)
	1	2	3	4	5	6	
UP TO T=12	0%	1%	0%	0%	1%	0%	-1%
UP TO T=24	52%	16%	0%	0%	2%	0%	34%

Table 5.5.15: Impact on investment scheme: Generic vs. segmented models, Segment [30, 31] in $Holdout_4$ sample

Generic model S6

RECOVERED FUNDS/TOTAL INITIAL INVESTMENT	CATEGORY						NET ORGANIC FUNDING PER PERIOD: (1)-(2)-(3)-(4)-(5)
	1	2	3	4	5	6	
UP TO T=12	0%	0%	0%	0%	0%	0%	0%
UP TO T=24	0%	0%	32%	0%	0%	1%	-32%
UP TO T=30	0%	0%	83%	0%	0%	17%	-83%

Segmented model S4

RECOVERED FUNDS/TOTAL INITIAL INVESTMENT	CATEGORY						NET ORGANIC FUNDING PER PERIOD: (1)-(2)-(3)-(4)-(5)
	1	2	3	4	5	6	
UP TO T=12	0%	0%	0%	0%	0%	0%	0%
UP TO T=24	7%	25%	0%	0%	1%	0%	-19%
UP TO T=30	50%	25%	0%	8%	17%	0%	1%

Table 5.5.16: Impact on investment scheme: Generic vs. segmented models, Segment [36, 37] in Holdout$_4$ sample

Generic model S6

RECOVERED FUNDS/TOTAL INITIAL INVESTMENT	CATEGORY						NET ORGANIC FUNDING PER PERIOD: (1)-(2)-(3)-(4)-(5)
	1	2	3	4	5	6	
UP TO T=12	0%	0%	0%	0%	0%	0%	0%
UP TO T=24	0%	0%	1%	0%	0%	0%	-1%
UP TO T=30	0%	0%	73%	0%	0%	27%	-73%

Segmented model S5

RECOVERED FUNDS/TOTAL INITIAL INVESTMENT	CATEGORY						NET ORGANIC FUNDING PER PERIOD: (1)-(2)-(3)-(4)-(5)
	1	2	3	4	5	6	
UP TO T=12	0%	0%	0%	0%	0%	0%	0%
UP TO T=24	0%	1%	0%	0%	0%	0%	-1%
UP TO T=30	72%	1%	0%	0%	24%	3%	47%

5.5.4 Overall implications of time-to-profit

An immediate result of using return measures is that it facilitated the implementation of a concept as time-to-profit has been not defined before in a scoring context. The natural threshold of zero considered in previous studies for cumulative profits has been redefined in order to provide a scaled and more relative profit scorecard.

In terms of model performance, results for time-to-profit scorecard showed that it is possible to obtain good results both in terms of classification accuracy and according to their impact on portfolio results for a survival model based on the prediction of a binary measure.

Time-to-profit goes beyond recovering the initial investment made by a lender when a customer makes her first purchase. Revolving credit by definition is an open-ended product in which profits and returns change as a result of default and/or repurchase. It is a conservative measure that acknowledges when the cumulative profits generated by a customer is enough to cover the outstanding balance. This does not mean that a particular lender may not consider a threshold different to 1 when defining the event. Choice will depend on risk considerations and even on regulatory frameworks.

It is clear that segmented models outperform a generic model in terms of identifying and scheduling organic growth opportunities. This is related to the role that loan duration has on the calculation of instalments and eventually of payment behaviour.

6. CONCLUSIONS

This chapter presents the conclusions resulting from this research project. Each subsection corresponds to a research question stated in Chapter 2.

6.1 Return scorecards

The first contribution of this study is that it presents for the first time return scores for revolving credit. It was shown that it is possible to define and implement a relative profit measure for scoring purposes as an alternative to traditional profit scores used in previous studies.

The implementation of return scorecards entails tackling similar challenges to those faced when defining profit measures: identifying income and expenses per customer and allocating fixed overheads through an agreed costing system. The outstanding balance per customer is also required; this figure should be readily available for receivables collection purposes. Therefore the implementation of return scorecards does not pose major data requirements compared with traditional profit scorecards.

The opportunity cost analysis conducted to compare average versus cumulative measures showed that the latter offered additional insight to the credit granting policy in place at the moment for the credit programme under analysis. Cumulative measures are adequate to calculate monetary profits and returns as both embrace the concept of value creation per customer through the use of compounded cash flows. Therefore, profit and return scorecards are useful to select customers that can contribute to increase a lending institution's value in either monetary or relative terms.

On the other hand, return measures are by definition more susceptible to outliers than monetary profits. Minimum profits (losses) can be magnified in terms of returns if the outstanding balance is very low. This is an additional feature of using continuous cumulative return measures compared to traditional default scoring. Such outliers should not be excluded for model testing purposes.

Conceptually, the suggested cumulative return measure offers additional insight to traditional cumulative profit measures. It scales monetary profits and hence facilitates the fair comparison of customers for scoring purposes. This transcends the traditional criterion of monetary profits which ignores the invested amount per customer; it focuses on profitability rather than on profits. It takes into account both monetary profits and the outstanding balance which can be potentially at default. This measure provides an additional perspective to monetary profits; it entails a more conservative standpoint compared with monetary profits.

It is evident that customers are scored differently if either cumulative returns or profits are used. This follows from Spearman rank correlations and Chi-square significance tests. Time has an essential role when scoring customers according to profits or returns; differences are more evident as time goes on. This confirms that a long term perspective should be taken in the design of profit and return scorecards for revolving credit, a product that is dynamic by definition.

At a portfolio level, profits and returns can not be simultaneously improved through either profit or return scorecards. This dilemma between profits and returns holds as well at a customer level. Therefore, return scorecards should be considered an alternative to rather than a substitute for monetary profit scorecards. Choosing between return and profit scorecards will depend on corporate objectives in terms of risk perception, scope and liquidity needs.

In the case of the credit programme under analysis, a profit scorecard would be preferred to a return scorecard if the lender considers as low a bad rate of at most 3.15% during the observation period. In that case, portfolio returns (i.e.: coverage against default) would not be a priority to the lender; monetary profits would be priorised instead. Such bad rate is a result of strict credit granting decisions based on utility payment during the previous two years. Furthermore, in general these customers have continued to pay loan instalments regardless of adverse weather conditions that mainly affect low income segments. Consequently, these customers might not be considered high risks as would be the case of inclusive lending programmes.

Increasing the scope of the credit programme would also justify adopting profit scorecards, as these would favour accepting more customers to maximise marginal portfolio profits. This would further support the inclusive lending nature of the credit programme, which aims to serve more people that are not being served by traditional lending institutions. Additional liquidity needs further justify using profit scorecards, as these rank in top deciles customers with the highest profits regardless of the funds invested per customer via the outstanding balance.

Conversely, return scorecards would be preferred if portfolio coverage against default was prioritised. This could be the result of financial authorities' regulations that may perceive inclusive lending a high risk business and hence would require a "healthy" portfolio of receivables. This would prevent an increase in the cost of capital of the lending institution and potentially a decrease in its corporate value.

Potential socioeconomic and/or political instability might also justify implementing return scorecards, particularly in this case as loans are unsecured and the risk of losses is high.

Under liquidity constraints, credit granting policies would be stricter and hence fewer customers would be granted credit in order to maximise portfolio marginal returns. This strategy would reduce the scope of the credit programme and hence, its inclusiveness. It makes sense to adopt return scorecards when credit units/banks are assessed as investment centres that are accountable for maximising profits relative to the amount invested per customer.

Finally, it was confirmed in the case under analysis that not all defaulters are loss-makers; similarly not all non-defaulters are profitable. These results justify the use of both profit and return scorecards instead of default scorecards if the aim is to improve portfolio profits and returns, respectively. An advantage of using return scorecards is that portfolio returns are less concentrated in specific customers, which reduces the dependency of overall results and hence diversifies the risk more compared with monetary profit scorecards.

6.2 Direct and indirect profit and return scorecards

The second contribution of this study is to show how direct and indirect models can be used to model profit and return scores for revolving credit. This has not been done before for monetary and relative profit scorecards for revolving credit.

The dilemma of improving either profits or returns through the use of profit and return scorecards still holds. This makes sense, given that each scorecard was designed to rank and hence select customers according to either measure. Direct models were useful, however, to shed light on specific individual attributes that simultaneously improve profits and returns. This justifies lending to segments that would usually be excluded by traditional commercial banks. If the Company targets customers that are not single, live in urban areas, buy non-traditional products, have secondary education and belong to wealthier stratums, the trade-off between portfolio profits and returns could be decreased. The dilemma will continue to exist, however, as monetary and relative profits entail two related but distinctive concepts on their own.

A feature that was distinctively different in direct profit and return models was loan duration. Longer term loan durations increase monetary profits but decrease returns instead. These modelling results confirm descriptive findings from the previous section. This highlights the usefulness of using return scorecards, as profits received during longer periods of time come at the expense of holding receivables from customers. Therefore, return scorecards provide additional insight regarding the role that loan duration has on profits and returns. This variable is directly related to time, which is an essential feature in the revolving credit under analysis.

Direct models should be preferred in terms of model predictive accuracy and impact on portfolio results. These models consistently outperformed indirect models both for profit and return scorecards.

A reason behind the better performance of direct models versus indirect models might be that predicted probabilities of default and repurchase were used as predictors of profits and returns in the latter. These predicted probabilities include errors that ultimately affect prediction errors of profits and returns. On the other hand, attributes used to predict directly profits and returns might be capturing additional customer features that are not completely reflected in simpler indirect models based on default and repurchase. Moreover, there might be issues of double counting resulting from some correlation between default and repurchase.

Other practical reasons such as unstable collection policies and hence varying default especially during the first year of the observation period might justify the inferior performance of indirect models. In particular, AUC of default models was lower than that of repurchase models. Unless major changes occur to individuals, basic attributes such as those used in direct models remain in the long term and hence should result in more stable models.

The reasons stated above do not justify, however, overlooking the economic significance of default and repurchase on profit and return scorecards throughout time.

First, it is clear that the probability of default in the short term has an important economic significance for both profits and returns. This reflects specific features of the credit programme under analysis, in which delaying payments and taking advantage of a mixed utility-loan instalment results in arrears status before the utility is suspended. Predictions in the short and long term of the probability of repurchase are required, in contrast, given the revolving and hence dynamic nature of revolving credit. This will depend on credit limit availability and loan duration, among other variables. Therefore, indirect models were useful to shed light on profit and return drivers such as default and repurchase in the short and long terms; this has not been done before for revolving credit.

Second, regardless of the inferior results obtained from indirect models, they are useful to identify individual attributes behind probabilities of default and repurchase. This allows implementing joint strategies that consider default, repurchase and profit (return) scorecards to maximise portfolio profits or returns. As shown on Figure 3.3.3, where possible, attributes can be related to default and repurchase. This analysis scheme was particularly useful, for instance, to understand the relationship between socioeconomic stratum and profits (returns). Customers from less favoured segments are usually referred as high risks in terms of default. Direct models showed that these customers are less profitable than those in wealthier stratums because of their lower purchase capacity and hence lower probability of repurchase. Default is not an issue to be tackled, as these customers were granted credit limits based on their positive utility payment similarly to customers in wealthier stratums.

Consequently, direct models should be used in conjunction with indirect models, but for different purposes. Direct scorecards should be used to score credit applicants. Indirect scorecards per se are useful for information purposes as to understand the role that default and repurchase have on profits and returns. Predicted probabilities of default and repurchase used in indirect scorecards are useful to make informed decisions regarding the joint use of default and repurchase scorecards together with profit (return) scorecards.

Finally, it was shown that qualitative data provide useful insight for direct and indirect scorecards. In particular, data related to payment habits, collection strategies, penalties, motivations for taking formal credit for the first time and default risk factors were useful to interpret significant variables in the models. This shows that mixed methods are useful for profit scoring. It also provides further evidence of the relevance that qualitative data such as analyst's criterion has on credit granting of microcredit programmes.

6.3 Time-to-profit

The third contribution of this study is that it defines time-to-profit for the first time and presents two alternative applications: one to grant revolving credit and another to plan investment schemes of lending institutions.

Time-to-profit can be defined as the time it takes a customer to be profitable. This can be understood as the time it takes a customer to break even (i.e.: being fully covered against default). This occurs when actual returns exceed a predefined threshold. This definition can be easily implemented once periodic data has been gathered.

The use of a cumulative measure such as $CASHROAcum_t$ is more appropriate than return on investment as it accounts for the dynamic nature of revolving credit. The outstanding balance may increase as a result of repurchase. This is not the case for fixed term loans. The event definition used in this study further expands the application of return scorecards introduced previously to use a clearly defined status that makes practical sense in the lending industry. Such definition goes beyond the definition of goods and bads based on the minimum threshold of zero, used in previous studies to compare scorecards based on binary and continuous profit measures.

In terms of significant variables in predictive time-to-profit scorecards, results were similar to those obtained for return scorecards. This was expected, given that both scorecards are based on the same measure. Two variables were particularly significant for customers to breakeven: loan duration and credit limit usage. Once again, the relevance that time has on the returns of revolving credit was confirmed. Customers with longer loan durations require more time to be completely covered against default. This makes sense, given that instalments are lower compared with those of shorter term loans and hence the outstanding balance is at risk of default for longer periods of time. Customers that use more of their credit limit in the first purchase are more likely to be covered against default for the first time; these customers are less likely to repurchase in the short and long terms and to default in the short term.

Portfolio results in terms of profits and returns obtained when using time-to-profit scorecards contribute to the debate regarding the use of either continuous modelling or binary classification for profit scoring purposes. Profit scorecards outperformed both return and time-to-profit scorecards in terms of their impact on portfolio profits. This agrees with the rationale explained before regarding the use of scorecards to assess “same-to-same” objectives per customer and at a portfolio level. Portfolio returns were improved when time-to-profit scorecards were used instead of returns and profit scorecards in the holdout sample. These results show that scorecards based on binary classification measures can outperform those that use continuous measures instead. Furthermore, it does make a difference in portfolio returns to develop models that account for the effect of time. This is consistent with the relevance that loan duration has on profits and returns throughout this study.

Time-to-profit scorecards are stricter and hence more conservative than return and profit scorecards. This is a consequence of using a criterion that identifies customers that outperform sooner than the rest in relative terms. This explains why customers that took shorter term loan durations (i.e. less than 60 months) were ranked in the top 4 deciles; these segments are covered against default sooner than those that took longer term loans as they exceed the threshold for the first time earlier. It would make sense to adopt time-to-profit scorecards instead of return scorecards under more stringent socioeconomic conditions or when the perceived risk of targeted customers increases.

The relevance of loan duration on time-to-profit was further explored through the comparison of generic and segmented models. It was confirmed for segments [12, 25], [30, 31] and [36, 37] that specific models outperformed a single generic model as of models' classification accuracy. Loan duration is a key feature for time-to-profit and hence segmented models are more accurate than a single model based on a "mixed" revolving credit portfolio. An attribute that gained more significance in segmented models was credit limit usage as loan duration increases.

Another contribution of this study is that it presents for the first time a framework to translate model classification accuracy of time-to-profit scorecards to monetary terms. This was based on the time-to-event nature of these scorecards, compared with return scorecards. They are useful to identify organic growth opportunities through funds liberated from existing customers to be allocated among new customers and/or to further grant credit among existing customers. Funding schemes based on internal and/or external funding can be defined accordingly.

Consistent with classification accuracy results, the generic model failed to identify customers that are covered against default. Apart from the limitations that such model would impose to the credit programme under analysis, this has implicit social costs. Customers that could be covered against default but that are not identified by a generic scorecard would take loans at higher rates. This has negative social and economic implications. Therefore, from a customer perspective segmented models are more beneficial as well.

Results for the case under analysis shed light on the sustainability potential of this inclusive lending programme. This is a positive feature for similar programmes that might bear a higher risk but that might generate cash flows to contribute towards their continuity. In general customers were covered against default in the case under analysis, before the initial loan duration was due.

Finally, time-to-profit scorecards further justify using measures based on liquidity rather than on accrued profits such as the worth per customer. Profits might only exist in accounting books, whereas cash flows adequately reflect the liquidity generated per customer.

7. LIMITATIONS AND EXTENSIONS

This chapter presents the limitations and extensions of this research project.

7.1 Limitations

This section presents various limitations of this study regarding the calculation of profit (return) measures, the observation period, model design and validation samples.

First, the definition of default is standardised to some extent in banking (i.e.: three or more missed consecutive payments). In contrast, the design of profit (return) scorecards implies agreeing on the treatment of variable income and expenses. In the case of profit (return) calculations to design scorecards, variable income and expenses vary across lending institutions and are not necessarily constant in the long term. In the credit programme under analysis, commercial agreements between the lending institution and partner retailers should be fairly stable in the coming periods for the designed scorecards to hold; net sales commissions vary with products and in some cases with sales channels. Even though profit (return) measures are scores rather than actually predicted values for budgeting purposes, the scorecards produced in this study should be reviewed and recalibrated periodically, if necessary.

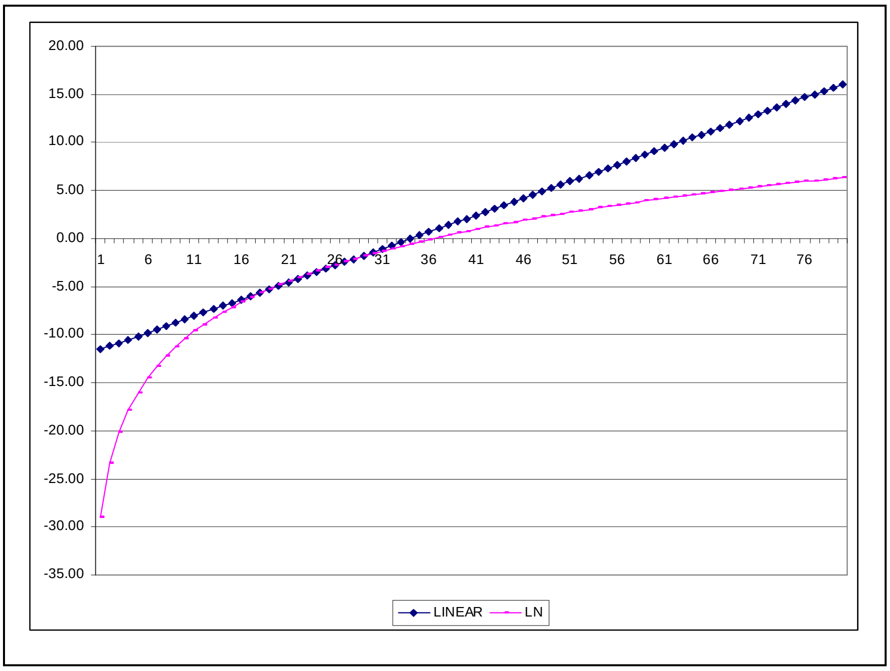
Second, fixed overheads were allocated using the total active customers of the lending institution. This is not constant throughout different observation periods. This does not have implications in terms of scoring customers as all customers were equally allocated fixed overheads; consistency across individuals is what matters. A limitation is, however, that results are based on the use of a fixed overheads allocation system instead of another fully customer-focused (e.g.: activity based costing). Some customers might be unprofitable as a result of fixed cost allocation rather than as a consequence of their own costs/expenses. Obtaining more detailed customer data is a usual issue in profit scorecards; this is also the case for return scorecards.

Third, regarding OLS models for $OPCASHCUM_{30}$ and $CASHROAcum_{30}$, it was not possible to clearly differentiate outliers from the rest of observations in terms of customer, product or credit attributes. Even though these customers were included in the holdout sample, additional insight could have been gained from a segment where most of them are extremely positive. This would be useful to further improve portfolio profits (returns), compared with the designed scorecards.

Fourth, data was available for 30 months since the credit programme was launched. This is appropriate given the long term perspective associated with profit scoring, compared with default scoring. Yet the majority of first loan durations in the sample were of at least 55 months, it would have been more convenient to use a longer observation period. This would have given shorter term accounts more time to revolve. Longer term accounts would exhibit full profit (return) behaviour; hence value created per customer in the long term would have been better captured. Therefore, the profit (return) scorecards developed in this study are not definitive in the longer term (periods greater than 30 months); they are useful to score customers according to their contribution towards customer lifetime value in monetary (relative) terms during the observation period. Provided that additional data is available, they might need to be validated and if required, recalibrated.

Finally, in line with the length of the observation period, time-to-profit scorecards could not account for repeated events resulting from a large sample of customers with repurchases. Furthermore, the various models used showed that the hazard of being covered against default increases with time rather than being constant. This might be the case at the initial stages (before first time to profit); in the longer term one would expect such hazard to be constant when customers have accumulated enough interests as to outweigh any outstanding balance. For illustration purposes, consider Figure 7.1.1. A linear model might not necessarily hold in the longer term, compared with a more conservative logarithmic model. Consequently, these scorecards are useful to design investment schedules of at most 30 months. Longer term planning activities require further data.

Figure 7.1.1.: Linear versus logarithmic hazard of being covered against default



7.2 Extensions

This section presents further research opportunities resulting from this research project.

Cumulative return is by no means the only measure that can be used to design return and time-to-profit scorecards. Some customers might be more profitable as a result of margin and/or turnover. Therefore, margin and/or turnover return scorecards could be designed to improve portfolio returns, following a rationale similar to decomposing profitability (Palepu et al. 2010):

$$CASHROAcum_t = \underbrace{\frac{OPCASHcum_t}{CASH\ \ income_t}}_{\text{Margin}} \times \underbrace{\frac{CASH\ \ income_t}{Outstanding\ \ balance_t}}_{\text{Turnover}} \qquad (7.1).$$

This would build on the findings of this and previous studies, where the probability of repurchase is a profit (return) driver. This approach could also further enhance the joint use of return and repurchase scorecards, as higher turnover results from repurchase.

Other performance measures such as cash return on equity could also be used to design return scorecards. These scorecards account for the effect that external funding has on the return available to shareholders. Therefore, not every customer that is profitable in operational cash terms (i.e.: based on $CASHROAcum_t$ scores) is necessarily profitable from a shareholder's perspective. Alternative scorecards based on customer profitability at both levels could be designed using multinomial regression techniques.

Depending on data availability, creditworthiness scorecards (Quirini and Vannucci 2009) based on $CASHROAcum_t$ could be designed. These scorecards would assess actual versus anticipated coverage against default per customer.

It was shown that $CASHROAcum_t$ is more susceptible to outliers than $OPCASHcum_t$ given its relative nature by definition. An alternative to testing predictive models in holdout samples under more extreme conditions (i.e.: through the inclusion of all outliers in such sample) would be to explore the sensitivity of scorecards to winsorized outliers by using different decimal significant digits.

Regarding return predictors, additional variables could improve the predictive accuracy and the effect on portfolio results. Provided such data is available, other predictors in indirect models could include arrears/default/refinancing status in the payment of utility, service cross-selling and the length of the previous relationship with the lender as a utility provider.

Given the relevance of qualitative data in scorecard design, qualitative variables could be included to produce in-context scorecards. This could enrich quantitative scorecards to take into account individual features such as customers' values, preferences and financial illiteracy, which ultimately affect customer behaviour and hence their returns. This will require the use of scales and other tools that have been validated in a consumer behaviour context.

The predictors mentioned above can be gathered once the first purchase occurs and as time goes on. This will facilitate the design of behavioural scorecards that include time dependant attributes and hence agree with the long term dynamic nature of revolving credit. Once again, this could contribute towards improving the predictive accuracy of return scorecards.

Finally, the time-to-profit scorecards presented in this study were based on the event that customers were profitable, that is, when $CASHROAcum_t$ exceeds 1 for the first time. This is not the only alternative, as views regarding coverage against default can be stricter or more relaxed depending on industry regulations and corporate strategies. Further research could explore the impact of redefining the threshold on scorecards and ultimately on portfolio coverage against default. Similarly, events could be defined for each ratio in (7.1) according to industry standards regarding profit margins and turnover. That is, time-to-margin and time-to-turnover scorecards could be defined with the aim of improving portfolio results.

Strictly speaking, customer life time value is based on the discounted values of future cash flows expected per customer in the long term. Therefore, it is reasonable to develop time-to-profit scorecards that account for repeated events, provided the length of observation period allows doing so. This is different to high returns during consecutive months resulting from marginal outstanding balances due to collection/payment behaviour.

Further avenues of research regarding time-to-profit scorecards could include the design of behavioural scorecards to enhance the usefulness of survival techniques. From a practitioners view, this facilitates the proactive management of individual accounts based on profit (return) profiles.

Alternative time-to-profit scorecards could be produced by taking into account the effect of frailty on being covered against default. This would expand the initial models presented in this study and would reflect better the particularity of individuals.

The results, conclusions, limitations and extensions presented in Chapters 5, 6 and 7 show that return scoring is an emerging research theme despite the use of both monetary and relative measures to assess the performance of lending institutions at a portfolio level. A challenging and fascinating research agenda will continue to progress in the coming years.

APPENDIX 1

This chapter presents the detailed results obtained from qualitative data analysis (Sections A1.1 to A1.5). Bold fonts highlight findings from qualitative data analysis. Categories, themes and subthemes obtained from the interviews (Table A1.1), the definitions of dimensions per category (Table A1.2) and the cross-company comparison of categories and themes (Table A1.3) are presented at the end of this chapter. Each Company was identified as follows: CP=Credit programme under analysis, CO=Competitor, ED=Education, U(1,2,3) =Utility Company(1,2,3) and L(1,2,3,4)= Lending institution(1,2,3,4).

A1.1 Offer

This category includes various features of each financing service (i.e.: access to service, product portfolio and channels).

A1.1.1 Access to service

It reflects the scope of the financing service in terms of the individuals that can **actually access it**. The manager of CP stated that it is equally accessible by anyone, provided specific conditions are met:

"Given that one is a customer of the utility company, ***there are no geographical restrictions****. Basic connection services need to be already paid and two years of good payment behaviour.* ***Neither the stratum nor the neighbourhood are relevant*** *if those requisites are met. Credit limit is defined per stratum".*

Even though CP serves customers excluded by traditional banking services, it is neither as accessible to everyone (e.g.: Companies such as U2 and U3 must provide as utilities by law) nor limited to individuals with certain income and a clean credit history as occurs in lending institutions. L1 does not require credit records for a specific segment of customers; it requires instead a minimum job permanency. U1 reviews credit records of individuals for credit granting purposes; the service it provides is not public and hence it can be more selective than other utility companies. Even though ED grants credits to those that would usually be financially excluded because of the lack of credit records, it requires a guarantor for the credit.

CO is mainly owned by a financial conglomerate; hence access to credit is more restrictive than CP as credit bureau records are a requirement for credit granting purposes. This has not been embraced by traditional financial institutions, which consider CP a **high risk** business, as inferred from a statement of the manager of CP:

*"When I talk with people of the financial industry about the credit programme, they consider it **madness**".*

A1.1.2 Product portfolio

The credit limit granted by CP can only be used to purchase products that improve customer' quality of life. CO finances similar products, but the product portfolio is **wider** than that of CP:

*"We finance everything that is a need such as: construction materials, property renovations, electrical hardware, technology, furniture, **plastic surgeries** and **dental treatments**, among others".*

U2 offers financing to hire maintenance services and to purchase insurance; U3 offers a credit limit and insurance in partnership with CP. At the other end of the spectrum are the lending institutions, which have defined specific financing services for different purposes. This is possible through a customised **offer** for different customers, as stated by the manager of L3:

*"The Bank analyses **each segment under a different perspective**".*

EDU and U1 have the least diversified portfolios; customers can only finance the service traditionally offered by them. More inclusive credit programmes offer less variety of uses of the credit. The common aim is to cover a perceived basic need (i.e.: either a utility or a product). As the credit granting decision is more informed in terms of using credit bureau records and supporting application documents, customers can access a wider variety of services, usually customised to their own needs. This is mainly based on a segmented approach towards serving customers, rather than on offering commoditised services.

A1.1.3 Channels

CP and the other companies use both inbound and outbound channels to serve their customers. Lending institutions mostly rely on their network of branches; this is not the case of lenders such as CP and CO, which rely on outbound strategies such as door-to-door visits to offer financing services. According to the manager of CO this strategy is **useful** to reach low income segments:

*"**Banks do not have the infrastructure** to visit these customers and tell them about the service and they are very rigid as well; it is very expensive for them to allocate these resources. Banks do not set a sales force for a customer that takes low credits".*

This is an advantage of credit programmes such as those offered by CP and CO. The utility companies they work in partnership with already manage large data sets of customers and reach them regardless of their location. Lending institutions would need to explore and penetrate those markets that might be unknown to them. This might explain as well the financial exclusion of those segments.

A1.2 Customer preferences

This category includes various reasons behind customers' choice of a particular financing alternative.

In particular, the manager of CP highlighted the **easy access** to the credit programme and **favourable payment conditions** as the main reasons for choosing this alternative:

"The most important reason is that the credit limit is preapproved. Customers ***are scared to submit the documents*** *for a credit analysis and find out that they are rejected. 85% of our customers do not have a formal employment; they are informally employed therefore* ***it is difficult for them to justify their income****".*

"Customers ***do not ask for the interest rate****; they want to know the instalment value. When you can defer payments to 60 months,* ***the instalment is low; this is a great aid for them".***

The lack of inquiry regarding interest rates suggests some level of financial illiteracy regarding lending services. This is a major concern for the Colombian Government (Colombian Treasury et al., 2010). Customers seem to prioritise the impact that a loan's repayment has on monthly cash flows rather than on its long term effect (i.e.: the number of times they end up paying the initial loan).

Another reason mentioned by the manager of CO is the **convenience of paying** in a single bill both the loan and the utility:

"They consider our payment scheme convenient, given they pay through the utility bill and ***it is easier, since they do not have to go to a bank branch to pay the instalment****; they use a single utility bill".*

Excluding L4 and U2, prices, payment conditions and interest rates (where applicable) are common drivers for customers to choose among alternatives. This is understandable, as L4 offers a very specific, differentiated product and it focuses more on service quality. The industry to which U2 belongs is heavily regulated; therefore there are no major price differences among the service providers. Service quality, promptness and access are distinctive features to choose utility companies and lending services. Other reasons mentioned to choose utility companies are the local relatedness and the Company's credibility.

Consequently, customers seem to prefer credit programmes such as CP because of its unique access and payment conditions.

A1.3 Competition

This category refers to the acknowledgment of the overall competitive arena in which Companies operate (i.e.: formal and informal competitors and overall competitive strategies).

A1.3.1 Alternative formal sources

CP and CO face competition from **stores** that offer direct financing through their own credit cards. According to the manager of CO:

"There are stores in the city centre that sell electrical hardware and furniture; I am not going to mention them, ***because it is all of them****".*

In the financial industry arena, there are **plenty of alternatives** to choose from, provided that customers fulfil the minimum requirements. The manager of L3 stated:

"I think that ***all financial institutions offer the same products*** *but under different names; but the product base is the same".*

Given the inclusive characteristics of CP, traditional lending institutions cannot be considered direct competitors. CP would be only competing with CO and other retailers that review credit records for part of the remaining 15% of customers that actually have credit bureau records (i.e.: not all customers with negative credit records are accepted by the competitor).

A1.3.2 Alternative informal sources

This was the first source mentioned by the manager of CP:

"Research has shown us that they use informal credit. They talk in terms of relatives and ***friends, but we know they are loan sharks****".*

Managers from CP, CO, ED and lending institutions acknowledged that customers use of alternative informal sources. Such sources include relatives, friends and according to CP, loan sharks, **which are not always acknowledged by people.**

Almost all lending institutions acknowledged the use of such informal sources. Utility companies did not mention them. This makes sense, as they finance a utility that can not be financed by such sources.

Pay day informal lenders are relatively easy to access in Colombia, where still the majority of the population remains unbanked. This alternative is embedded in the national culture and even though they are subject to legal prosecution, they still operate especially in low income segments.

A1.3.3 Strategies

In general, companies design various strategies to increase their scope of operations. Smaller scale lenders such as CP and CO are embedded in utility companies and establish strategic alliances with retailers to increase the access of customers. ED works together with lending institutions to offer joint solutions to credit applicants. Lending institutions take advantage of the network of branches of the **financial conglomerates** to which they belong. According to the manager of L2:

"One of our strengths is that different services from various lending institutions of our group are offered through the joint network of branches. ***As a customer I don't consider them separate companies; they are rather a portfolio of alternatives****".*

A1.4 Default

This category includes various aspects related to default such as: its definition, customer assessment, customised treatment, collaterals and reasons behind default.

A1.4.1 Definition

CP defines default as three missed consecutive payments onwards. So did CO, ED, U3 and the lending institutions. This definition agrees with the standards usually adopted in the banking industry. The match between the definitions of default implemented by CP and CO and those of the utility companies they work in partnership with is aligned with the easiness of payment of the credit through the utility bill, as explained before.

U1 and U2 define default as 120 and 30 days, respectively. This is understandable, since customers of CP have a clean payment history prior to being offered a credit limit, whereas anyone that by law is entitled to access the service can be a customer of U2. This justifies **adopting a stricter criterion for default definition.** According to its credit manager:

"In this type of companies, credit risk is not contemplated by regulating authorities. We have to collect 100% of the receivables; ***what is not collected is lost****".*

On the other hand, **commercial reasons** guide U1 in the decision of adopting a more lax definition of default, as inferred from its credit manager's statement:

"The limit to reach a stage where the service is cancelled is 120 days. ***The objective is that billing does not stop".***

Therefore, even though the definition of default varies across service industries, some of them follow the usual definition adopted by the banking industry. This sends a common message in terms of guidelines to those customers that have taken credit through programmes such as CP.

A1.4.2 Assessment

All companies assess their credit programmes based on payment punctuality. Lending institutions are required to do so by the Financial Superintendence. For utility companies that provide a public service, it is logical to use arrears as a key assessment criterion given the variety of customers that they serve. Even though financing services offered by ED, CP and CO are not regulated by the Financial Superintendence, they assess customers **solely** based on their arrear status. In the case of CP:

"We assess arrears and default at a customer level. Total profits of the credit programme are assessed as well".

U1 and the lending companies also assess customers based on product usage and profit profiles. This is understandable, as the competitive arena in those industries is strong and profitability supports their continuity in the long term.

A1.4.3 Customised treatment

A common feature among all companies is the importance they give to customised treatment throughout their relationship with customers. Personal lending requires that banks know their customers and offer them products to fulfil their needs. The manager of L2 stated:

"We offer advice and are very close to our customers' needs and expectations. We inquire a lot of information very often not only to sell a product ***but also to truly identify their needs****".*

This was not a major feature for U2 and U3, as they provide public services that are commodities by nature. It is evident that the collection process requires a continuous interaction with customers. This includes contacting them and reviewing payment conditions on a personal basis. Customers are contacted through various means from their first day at arrears onwards. Companies **treat each case individually** and try to reach an agreement once customers are at arrears. The manager of CP simulated a conversation with a customer at arrears as follows:

"Ok, pay something, ***how much do you have? Why aren't you paying?*** *Because I don't have the full amount. Well, then* ***how much do you have?*** *We aim for the user at least to* ***pay something*** *and then the debt can be restructured".*

This suggests that even though the objective is to collect the full instalment, partial payments are allowed, which highlights the importance given by the Company to generate a commitment from the customer in terms of payment behaviour. This is an important feature for customers that are new to inclusive lending programmes such as CP.

A1.4.4 Collaterals

Lending institutions require evidence of income and equity (if applicable) to grant credit. Personal loans usually are backed up with personal guarantees. Customers are fully responsible of loan repayment. In the case of ED, a co-guarantor is required to **support** the credit application:

"The only condition is a co-guarantor different to the student's parents. She must provide evidence of income, either as employees or self-employed. Parents do not care if they are reported to credit bureaus, ***but if a third party is involved, it is better****".*

This is not the case of U2 and U3, which provide public utilities and any outstanding balance not only affects a customer's record but also the property. Legal action is required to demonstrate that the owner and hence, the property is not liable for debts taken by previous tenants or property owners. **Therefore, fraud can occur because of this, compared with traditional lending services.**

Credit programmes such as CP and CO that are jointly offered with utility companies have to cope with this situation too. The manager of CP cited an answer from a customer that was asked about an outstanding debt of the property she occupied at the moment:

*"**That loan is not mine**. The loan was taken by someone else that used to live here and left".*

These findings offer further insight to the high risk nature of CP, given that it does not have any personal guarantee attached to it; only a good reputation in the payment of utility bills supports the loans. Unless proven, there is no guarantee that the property's owner will repay the loan in the event of fraud.

A1.4.5 Reasons

The most relevant features mentioned by companies that lead customers to default are liquidity problems and culture.

A1.4.5.1 Liquidity problems

Liquidity problems may derive from unfavourable economic conditions, weather conditions and/or overindebtness. In particular, floods affect rural communities and hence their payment behaviour. At the time when the interview was conducted, CP implemented a temporary measure **to prevent a rise in those at arrears** that live in the affected areas:

*"For those whose payment behaviour could be affected because of the floods, we are only collecting interests and no payment to principal **to help them during difficult times".***

Excluding L3, lending institutions identified **overindebtness** as a reason given by customers for being at arrears:

"We have customers that are employees ***with income of £5000 and financial expenses of £6000.*** *How do they live? It is like a snow ball, with continuous use of cash advance until they lose their jobs and they go bankrupt".*

Lending institutions can track the credit record of customers by accessing credit bureau data bases. However, those records do not include informal lending and hence the situation is not completely clear. Customers of more inclusive programmes are exposed to those informal sources, which potentially leads to overindebtness and ultimately, to arrears and default.

Another reason for overindebtness is lifestyle, which is mostly based on **peer pressure**. The manager of U1 stated:

"They did not need the service and they were not using it. They took the service because their son insisted; ***everyone else in the neighbourhood had the service****".*

A1.4.5.2 Culture

Another common feature cited by companies is cultural aspects. In general, customers make their payments close to monthly deadlines. The manager of ED identified **culture** as a cause of being at arrears:

"Culture. They take credits and say they will pay when they get additional employee benefits or ***they are just used to pay at the end of the academic period****".*

Consequently, companies permanently **remind customers** about their payment. According to the manager of L1:

*"****If you don't call them****, it becomes messy".*

A private service such as that provided by U1 may not be considered essential, whereas public services provided by U2 and U3 are perceived as **natural rights** that should not be paid for. The manager of U2 stated:

"In some cases, customers believe or think that they are not obliged to pay the service; they think it is a right they have and ***that the Government is responsible to fulfil such right****".*

A distinctive feature of credit programmes offered by utility companies is that since customers pay their utility and loan instalment in the same bill, previous payment patterns of utility bills can be **extended** to the payment of the loan. According to the manager of CP:

*"****It is a cultural thing that people accumulate two bills before they pay****; it is more expensive for them to pay for public transportation to pay monthly. The utility company does not cancel the service until the second missed payment; they do not do anything during the first month; there is no pressure on paying".*

Furthermore, customers that make partial **payments prioritise the payment of the utility bill** instead of paying their loan instalment. The manager of CP stated that:

"An evident sign of arrears is when the ***customer pays the utility and does not pay the loan instalment.*** *By law, we must receive the utility payment and open the bill".*

These findings are understandable, since utility is more essential than credit payment, especially for customers that are new to using financing services.

A1.5 Collection

This category includes the strategies implemented by the Company to improve the collection process and ultimately to reduce the bad rate.

A1.5.1 Retention strategies

Customers from lending institutions with good previous payment behaviour are offered additional services and in some cases, better. Payment on time is rewarded by U1 and U2 with gifts, points and other incentives. The main reward for customers of U3 that pay on time is access to the credit programme CP. A similar situation occurs with CO through a different utility company. Accessing formal credit and having a clean credit record is **enough for some customers**, as stated by the manager of CO:

"Some customers say that they want to take the ***loan to start a credit history. That is their best cover letter.*** *We do not give out gifts".*

None of the companies grant grace periods for personal loan repayment. Those that offer productive loans (i.e.: CO, L1 and L3) grant grace periods depending on the type of project. Even though such grace periods are not implemented in the credit programme of CP, some customers **may benefit** from the fact that the utility company has various billing cycles, according to the manager:

"The utility company has various billing cycles over the month. When a customer purchases a product, we allow for 20 days to generate the bill and guarantee that they are paying for a full month of financing. Therefore we do not have an explicit grace period but we allow some time so that the ***customer does not receive immediately a bill after the first purchase****".*

A common strategy among all financing services is to offer refinancing options when customers are at arrears. This is understandable, as it is better to refinance than to write off receivables that are unlikely to be repaid. Again, the manager of CP highlights the **cultural features** associated with the payment of the utility bill, which are further extended to the payment of the loan repayment:

"We have particular cases of refinancing; ***we inherited this from the utility payment.*** *Refinancing is a common alternative in the gas service".*

The findings cited above suggest that access to formal lending is a privilege on its own for financially excluded communities. An opportunity cost that CP is taking originates from the various billing cycles, which allows some customers for almost an additional month to start repaying their loans. On the customer side, this is a positive feature as it is free financing for the first month, where applicable.

A1.5.2 Penalties

Lending institutions report customers at arrears to credit bureaus. Utility companies cancel the service even before customers are at default; reconnection payments are applied as well. ED restricts some services such as lending books from the library. In the case of CP, if customers want to make a partial payment of their bill (i.e.: paying only the outstanding utility balance and not the loan), they have to **make an additional effort**; according to the manager of CP:

*"Those customers must go to our headquarter offices; they cannot go to any of our payment facilities to do that. They must do something **additional to the regular practice of each month".***

Inclusive programmes such as CP and ED implement penalties that are more meaningful to customers than reporting them to credit bureaus. The inconvenience and additional expenses for the household because of visiting the central headquarters penalises customers at arrears that are more likely to be in default.

A1.5.3 Bad rate

The bad rate was considered low in all cases excluding U1. It should be noted, however, that the acceptance criteria of CP and CO are strict; this is not always the case.

Table A1.1: Categories, themes and subthemes obtained from the interviews

CATEGORY	THEMES	SUBTHEMES (WHERE APPLICABLE)	NUMBER OF REFERENCES PER INFORMANT									
			CP	CO	ED	U1	U2	U3	L1	L2	L3	L4
OFFER												
	Access to service											
		Financial exclusion										
		Less financial exclusion, less exclusion										
		Least favoured communities										
		Credit bureaus info										
		scoring										
	Channels											
		Inbound										
		Outbound										
	Product portfolio											
		Productive loans										
		Wide offer	12	19	24	13	12	9	19	17	21	8
CUSTOMER PREFERENCES												
	Credibility											
	Promptness, access											
	Favourable service conditions											
	Local relatedness											
	Product differentiation											
	Service quality											
	Health											
	Safety		5	7	8	9	3	3	5	3	3	2
COMPETITION												
	Alternative formal sources											
	Alternative informal sources											
	Competitive arena											
	Strategies											
		Company fusion										
		strategic alliances	4	7	9	7	9	5	8	10	5	3
DEFAULT												
	Default definition											
	Customised treatment											
	Collaterals											
	Assessment											
		Default based assessment										
		Product,profit based assessment										
	Reasons											
		Adverse weather conditions										
		Lifestyle										
		Liquidity problems										
		overindebtness										
		Payment culture										
		Appreciation	28	25	44	25	13	23	19	24	27	14
COLLECTION												
	Retention strategies											
		Privileges										
		Refinancing										
	Penalties											
	Defaulters' proportion											
		High proportion at arrears										
		Low default,arrears,written off	12	6	16	16	8	9	7	7	8	7

Table A1.2: Definitions of dimensions per category

CATEGORY	THEME	DIMENSION 1	DIMENSION 2	DIMENSION 3
OFFER	Access	Complete financial inclusion, credit bureaus only for id validation purposes(if applicable)	Responsible lending	Financial exclusion; segmented banking starting to reach some segments, but still not totally banked;looking at credit bureaus
	Product portfolio	Use of credit for a specific purpose	Use of credit for a wider use, but not completely open	Open use of credit for different purposes
	Channels	Inbound	Outbound	
CUSTOMER PREFERENCES		Company image	Service features	Favourable conditions
COMPETITION	Alternative formal sources	No acknowledgment	Acknowledgment	
	Alternative informal sources	No acknowledgment	Acknowledgment	
	Strategies	Generic (includes mergers)	External (includes strategic alliances)	
DEFAULT	Definition	More lax than Basel II	Same as Basel II (i.e.: from 90 days onwards, assuming monthly billing)	Stricter than Basel II
	Assessment	Default based	Product/profit based	
	Customised treatment	At application time	During collection phase	At application time and during the collections process
	Collaterals	Only individual is affected if at arrears	The property could be affected as well if at arrears	
	Reasons (from the most to the least obvious)	Liquidity problems	Payment culture	
COLLECTION	Retention strategies	Not being at arrears	Grace period	Refinancing options
	Penalties	No penalties	Penalties	
	Bad rate	Low	Medium	High

Table A1.3: Cross-company comparison of categories and themes

CATEGORY/Themes	COMPANY 1	COMPANY 2	COMPANY 3	COMPETITOR 1	COMPETITOR 2	COMPETITOR 3	SERVICE PROVIDERS 1	SERVICE PROVIDERS 2	SERVICE PROVIDERS 3	LENDING INSTITUTIONS 1	LENDING INSTITUTIONS 2	LENDING INSTITUTIONS 3
OFFER												
Access to service							Utility 2 Utility 3	Utility 1 Education				Lending 1 Lending 2 Lending 3 Lending 4
Product portfolio							Education Utility 1	Utility 2 Utility 3				Lending 1 Lending 2 Lending 3 Lending 4
Channels							Education Utility 1 Utility 2 Utility 3	Education Utility 1 Utility 3		Lending 1 Lending 2 Lending 3 Lending 4		
CUSTOMER PREFERENCES							Utility 1 Utility 2 Utility 3	Utility 1 Utility 2 Utility 3	Education Utility 1 Utility 3		Lending 1 Lending 2 Lending 3 Lending 4	Lending 1 Lending 2 Lending 3
COMPETITION												
Alternative formal sources, competitive arena								Education			Lending 1 Lending 2 Lending 3 Lending 4	
Alternative informal sources							Utility 1 Utility 2 Utility 3	Education		Lending 4	Lending 1 Lending 2 Lending 3	
Strategies								Education Utility 1 Utility 2 Utility 3		Lending 1 Lending 2 Lending 3 Lending 4		
DEFAULT												
Definition							Utility 1	Education Utility 3	Utility 2		Lending 1 Lending 2 Lending 3 Lending 4	
Assessment							Education Utility 1 Utility 2 Utility 3	Utility 1		Lending 1 Lending 2 Lending 3 Lending 4		
Customised treatment									Education Utility 1 Utility 2 Utility 3			Lending 1 Lending 2 Lending 3 Lending 4
Collaterals							Education Utility 1	Utility 2 Utility 3		Lending 1 Lending 2 Lending 3 Lending 4		
Reasons							Education Utility 1 Utility 2 Utility 3			Lending 1 Lending 2 Lending 3 Lending 4		
COLLECTION												
Retention strategies							Education Utility 1 Utility 2 Utility 3		Education Utility 1 Utility 2 Utility 3	Lending 1 Lending 2 Lending 3 Lending 4	Lending 1 Lending 3	Lending 1 Lending 2 Lending 3 Lending 4
Penalties								Education Utility 1 Utility 2 Utility 3			Lending 1 Lending 2 Lending 3 Lending 4	
Bad rate							Education Utility 2 Utility 3		Utility 1	Lending 1 Lending 2 Lending 3 Lending 4		

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