"ENHANCING PROFIT MEASURES OF CUSTOMER'S PROFITABILITY IN REVOLVING RETAIL CREDIT"

Luis Javier Sánchez Barrios[1]

Galina Andreeva [2]

Jonathan Ansell [3]

ABSTRACT

Previous studies of profit scoring have used monetary measures of profit. Profitability analysis of customers offers further opportunities to improve portfolio profits and returns; this is a priority especially after the global credit crunch. This is the first study that explores return measures that can be useful for scoring purposes. It presents measures based on cumulative and average profits and returns. In addition it presents an opportunity cost analysis of using default scoring from the perspective of various profit measures. The paper compares several measures of profit/return using a sample of revolving credit accounts from Colombia. Results show that in the long term, return measures have a potential for maximising both marginal coverage against default and marginal profits. Finally, the financial trade-off of enhancing the social scope of the credit programme is analysed. This is a relevant theme for social inclusive businesses as the one under analysis.

1. INTRODUCTION

Credit scoring tools assist lending institutions in the decision of granting credit to those individuals that are most likely to repay their loans (Crook et al. 2007). Increasingly it is acknowledged that decisions about whether to grant customers credit should migrate from scorecards solely based on default to those that incorporate profit measures per customer (Andreeva et al. 2007 ; Oliver and Wells 2001; Keeney and Oliver 2005; Finlay 2008; Ma et al. 2009; Thomas 2009).

Previous studies of profit scoring have used various absolute/ monetary measures of profit (Stepanova and Thomas 2001; Verstraeten and Van den Poel 2004; Seow and Thomas 2006; Andreeva et al. 2007; Banasik and Crook 2009; Ma et al. 2009; Finlay 2010; Lieli and White 2010). This is the first study that contemplates using relative measures that might be used for scoring purposes. It presents four measures based

[1] Luis Javier Sánchez Barrios, Lecturer in Finance, Universidad del Norte, Colombia and PhD student, University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh, EH8 9JS, Scotland, s0915007@sms.ed.ac.uk, Phone: +44 7411155522.

[2] Galina Andreeva, Lecturer in Management Science, University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh, EH8 9JS, Scotland, Galina.Andreeva@ed.ac.uk, Phone: +44 131 651 3293.

[3] Jake Ansell, Professor of Risk Management, University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh, EH8 9JS, Scotland, Jake.Ansell@ed.ac.uk, Phone: +44 131 650 3806.

on cumulative and average profits and returns: EBITcum, ROAcum, AVEBIT and AVROA. Another contribution of the study is that it explores an objective framework to choose between the measures listed above. Given the nature of the credit product analysed which has aspects of social inclusion in the credit programme, a third contribution can be identified. This is analysing the financial trade-off arising from enhancing the social scope of the credit programme

Overall results show that granting credit to customers from the non-privileged background, the so-called 'base of the pyramid', is a profitable business. At a customer level findings show that using either profits or returns yield different relative scores. At a portfolio level, in the long term, the marginal coverage against default is maximised if returns are used instead of profits. This is relevant for the lending industry, especially after the credit crunch. Resources are limited and need to be allocated among those customers that provide more coverage against default. This will place the company in a safer position in adverse economic conditions.

This document is organised as follows: Section 2 presents the data set used for the study. Section 3 explains profit and return measures that can be estimated in order to decide which customers are more attractive to lenders. Section 4 explores possible time differences between cohorts of customers applying for credit at different time periods, and validates the use of a single aggregated cohort in the long term. Section 5 presents the results of correlation and association tests between the measures considered in this study, at a customer level. In section 6 portfolio profits and returns are characterised for the complete sample, defaulters and non-defaulters. Section 7 includes an opportunity cost analysis to decide between profits and return measures to maximise portfolio results. In Section 8, the trade-off between coverage against default and profits in social inclusive businesses is analysed. Section 9 presents a logistic regression model for default prediction and observations are made on the opportunity cost of using default scoring. Finally, a set of conclusions is presented in section 10.

2. THE DATA SET

The data set consists of 35,565 customers (15 cohorts from April 2007 to June 2008) of a lending institution in Colombia that grants revolving credit accounts with some credit limit to those customers that have not defaulted in the payment of utility bills during the preceding two years. The programme is directed mainly to customers from low income segments or so-called, the base of the pyramid (Prahalad 2010).

Instead of dispensing cash amounts to customers, they purchase products from partner retailers. The objective is to improve the quality of life of customers that are considered high risks by traditional banking services. The social scope of the programme is hence evident, as usually these customers cannot access bank loans as they lack previous credit records.

The data set reflects the behaviour of customer during, before and after the global credit crunch. It should be noted that overall, the impact of the global credit crunch in Latin America was not as severe as in other emerging countries (Kamil and Rai 2010).

Each customer was observed for 30 months. This choice agrees with the marketing literature which considers that a long term perspective should be adopted to assess a customers' lifetime value to the company (Andon et al. 2001; Gupta and Lehmann

2003; Collings and Baxter 2005; Pfeifer et al. 2005; Ryals and Knox 2005). Three points in time were chosen to analyse results in the short and long term: t=12, 24 and 30 months. T is the time from the start of the first loan taken by each customer.

3. SUGGESTED MEASURES

This section presents the basic profit and return measures calculated per customer. These measures were further used to form cumulative and average measures per customer that can then be estimated for scoring purposes. Values were calculated using monthly actual payments instead of expected payments or accrued profits. This is the usual practice to design behavioural scorecards (Andreeva et al. 2007; Finlay 2008; Finlay 2010).

3.1 Basic measures

Given that variable costs and fixed overheads of the credit unit were readily identifiable, a variable contribution (*VC*) was initially obtained per customer, for t=1 to 30:

$$VC_t = NETCOMMISSION_t + INTERESTS_t \quad (1)$$

The net commission results from adding commissions from sales and insurance payments to backup the loans. Interests may be ordinary and at arrears (if applicable).

The allocation basis of overheads was the total number of active customers. Therefore, it was assumed that all customers demanded the same effort to be served. This was supported by various interviews with the management team. Additionally, the company representatives stated that customers were served during the sales and collection processes. This justified the allocation of overheads from the first purchase onwards.

The *EBIT* (Earnings before interests and taxes) is the operational profit per customer, before financial expenses. It captures the ability of customers to generate profits regardless of financing decisions and country tax regimes:

$$EBIT_t = VC_t - Overheads_t \quad (2)$$

The *EBIT* per customer can be expressed in relative terms as the *ROA* (return on assets). It takes into account the capital invested per customer via the outstanding balance (i.e. receivables) at month t:

$$ROA_t = EBIT_t \Big/ finalbalance_t \quad (3)$$

Even though the assets invested in the credit programme include fixed assets, these are irrelevant for scoring purposes. All customers are served with the same fixed assets. Furthermore, the information systems of the company do not distinguish the proportion of the overall premises that are being deployed by the credit unit.

The *variable contribution*, *EBIT*, and *ROA* per customer vary from month to month and do not take into account previous profit or return values. Therefore, additional measures based on cumulative and average values were obtained to provide further

insight in understanding the profit behaviour of customers throughout time, as explained below. Each perspective provides two measures for scoring based on profit (*EBIT*) and return *(ROA*).

3.2 Cumulative perspective

First, the *EBIT* and *VC* excluding those of April 2007 (base period when the credit programme was launched) were deflated using the monthly inflation *i* for each year of the observation period, for t=1 to 30:

$$VCdef_t = VC_t / (1+i)^{t-1} \quad (4)$$

$$EBITdef_t = EBIT_t / (1+i)^{t-1} \quad (5)$$

Second, deflated figures for cohorts 2 to 15 were discounted during (*t-1)* periods at the real average WACC (weighed average cost of capital) of the company. At this stage, figures for all cohorts had a common starting point: April 2007:

$$VCdisc_t = VCdef_t / (1+WACC_t)^{t-1} \quad (6)$$

$$EBITdisc_t = EBITdef_t / (1+WACC_t)^{t-1} \quad (7)$$

Discounted values include the time value of money through the rates of return expected by capital suppliers. Specifically, receivables are funded via bank loans (90%) and shareholders' funds (10%). Given that profit calculations were made before taxes, the tax shield effect on discount rates was ignored.

Third, discounted values were compounded and added to produce cumulative figures per month. The cumulative *variable contribution* is the total variable profit (loss) generated per customer, regardless of the fixed overheads in which the company had to incur to serve customers. It measures solely the cumulative profit resulting from the purchase and payment behaviour of customers:

$$VCcomp_t = VCdisc_t * (1+WACC_t)^{t-1} \quad (8)$$

$$VCcum_t = \sum_{n=1}^{t} VCcomp_n \quad (9)$$

Fourth, a cumulative *EBIT per* customer was obtained. It measures the total operational profit (loss) generated per customer until month t, after accounting for variable costs and fixed overheads:

$$EBITcomp_t = EBITdisc_t / (1+WACC_t)^{t-1} \quad (10)$$

$$EBITcum_t = \sum_{n=1}^{t} EBITcomp_n \quad (11)$$

Under the usual profit-oriented scoring practices, customers with higher profits are better ranked; a natural minimum is $EBITcum_t >= 0$. Such profits ignore the investment on receivables at time t; they do not provide a fair basis to compare the

actual relative performance of customers. Hence a cumulative return that includes the scaling effect of the outstanding balance was calculated per customer:

$$ROAcum_t = EBITcum_t \Big/ finalbalancedef_t \qquad (12)$$

This ratio is based on past behaviour on its own. However, it can be understood as a predictive measure. It is the coverage against default at time t (i.e.: it measures how covered is the company against a complete default if the credit unit discontinues operations at time t). Ideally one would expect ROAcum $_t$ >=1 to avoid full debt provisioning in future periods of time. When this occurs, customers are considered to break even regardless of future payments.

A novel feature shared by EBITcum$_t$ and ROAcum$_t$ is that both embrace the concept of value creation. This follows from the use of a discount rate (WACC) that considers the expectations of shareholders and third parties. Therefore these measures can be understood as well as the total value generated by customers throughout time. Particularly, EBITcum$_t$ can be reinterpreted as the accumulated value generated by each customer to cover her against default from t+1 onwards. This is an alternative perspective to traditional profit scoring which only considered returns ignoring costs.

3.3 Average perspective

A different approach to profit and return scoring is using averages instead of cumulative values. Average measures are benchmarks that are easy to interpret. Additionally, they stabilise monthly fluctuations arising from the changing purchase and payment behaviour of customers. A disadvantage of averages is that they smooth extreme profits or losses as time goes on. This could provide a better overview of customers that cumulatively have not performed well. Besides, averages overcome the fact that longer periods produce higher cumulative measures. If one wants to mix periods of different lengths, averages can handle it.

Average measures were calculated at t=1 to 30 for the variable contribution, EBIT, and ROA per customer:

$$AVVC_t = \frac{\sum_{n=1}^{t} VCdef_n}{t} \qquad (13)$$

$$AVEBIT_t = \frac{\sum_{n=1}^{t} EBITdef_n}{t} \qquad (14)$$

$$AVROA_t = \frac{\sum_{n=1}^{t} ROA_n}{t} \qquad (15)$$

Ideally, minimum for these measures should be:

Min (AVVC$_t$) =0, Min (AVEBIT$_t$) = 0, Min (AVROC$_t$) = WACC$_t$

That is, the return per customer should be at least equal to the cost of capital related with funding receivables. As figures were not discounted to obtain averages, values need to be compared against the opportunity cost to guarantee that actually value is being generated.

4. DATA SET VALIDATION

Since customers enter the data set at different points of time, this section aims to validate if customers from the 15 cohorts could be gathered in a single cohort for profit analysis purposes. The two most distant cohorts (1 and 15) were chosen to test the hypotheses of means' equality for both cumulative and average measures. It was assumed that if any, major differences between mean results for the 15 intakes would occur between these cohorts as they are 14 months apart from each other. The significance level used was 1%.

In general terms it can be consistently inferred from month 14 onwards that the means of *ROAcum* and *AVROA* of both cohorts are the same. Where applicable, the p-values for returns are higher than those for profits. It is evident that the scaling effect provides a more reliable basis to compare individuals in a relative basis.

It takes a longer time (t=23) to infer that the means of *EBITcum* and *AVEBIT* are equal. Significant variations in the means of profits in the short term (t=12) can be investigated in later phases of this research project through an analysis of the covariates that characterise customers at different points of time. Variations in the short term are offset at t=30 (i.e.: the means of both cohorts converge in the long term).

The above results validate the chosen observation period and confirm that time plays an important role for customer profitability analysis. Nevertheless, given that the standpoint adopted in this study is to analyse customers' profits and returns in the long term, customers from the 15 cohorts were gathered in a single cohort, since in longer term significant differences disappear.

5. PROFIT MEASURES VERSUS RETURN MEASURES (CUSTOMER LEVEL)

The measures of profit and return described above can be used as a dependant variable in estimation that would subsequently result in profit or return scoring. Yet before do this, it would be beneficial to explore where there are differences in observed values of these measures from the point of view of credit-granting decision. It is possible to rank-order customers according to these measures and check whether a rank of a customer changes depending on the measure used. A rank here shows a relative attractiveness of a customer to the lender. Two tests were conducted on ranks based on ROA and EBIT from t=1 to 30: The Spearman correlation test and the Chi Square test. The Chi Square test was applied to bands of ranks (each band comprising 10% of the sample) to clearly validate any differences (if any) in ranking when using profit scoring or return scoring. From this section onwards comparisons will be made between *ROA* and *EBIT*, as both are operational measures but offer different angles.

5.1 Spearman correlations: EBITcum vs. ROAcum and AVEBIT vs. AVROA

During the first 6 months profits and returns have similar correlation values in cumulative and average terms. Therefore, if one had to choose between the set of measures to assess customers, any of them could be used.

As time goes on *AVEBIT* and *AVROA* are clearly more correlated than *ROAcum* and *EBITcum*. This follows from the smoothing effect of averages, which offsets differences that may occur between monetary measures and ratios.

Since cumulative measures are not smoothed, the scaling effect introduced in *ROAcum* explains the weaker correlation between cumulative measures. As cumulative profits do not increase monotonically with cumulative returns, a customer with high profits is not necessarily covered in the same proportion from default. Likewise, a high coverage from default does not increase in the same proportion with high cumulative profits. These results confirm the belief that profits and returns offer different perspectives in a scoring context.

5.2 Spearman correlations: EBITcum vs. AVEBIT and ROACUM vs. AVROA

Regardless of the time scope, it would not make a difference to use either *EBITCUM* or *AVEBIT* as they are almost perfectly correlated. These results make sense, as average profits increase (decrease) when profits increase (decrease), which is reflected in higher (lower) cumulative profits. It is acceptable to use either of them, as each has a different interpretation by definition.

In contrast, *ROAcum* and *AVROA* are less correlated as time goes on. These results derive from the definitions of each measure, as the former depends directly on the cumulative profit and the final balance, whereas the latter is a simple average of returns. A customer may have a high coverage against default but a lower average *ROA* because of a deficient behaviour in terms of return in a specific month. Similarly, higher average returns do not guarantee a higher coverage against default in the same proportion**.** See **figures 1** and **2.**

Figure 1

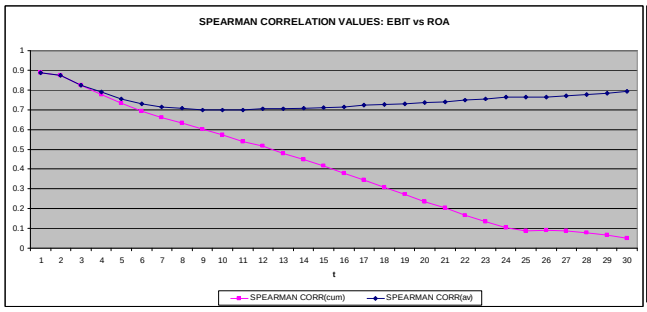
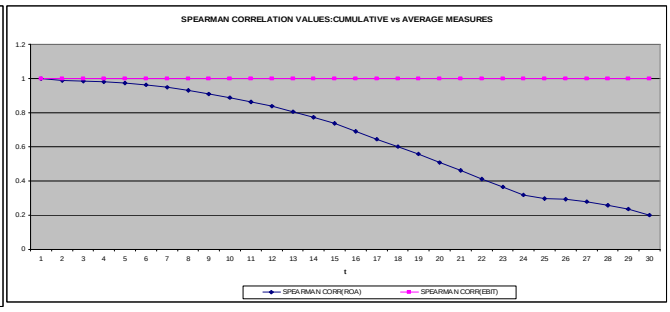


Figure 2



5.3 Chi square tests

It is useful to rank customers based on profits and returns to validate if each criterion may potentially lead to different decision on credit granting. A set of hypotheses were tested at a 1% S.L. for each month:

Ho: Distribution of RANKEBITcum= Distribution of RankROAcum
Ha: Distributions are different

Ho: Distribution of RANKROAcum= Distribution of RankAVROA
Ha: Distributions are different

Ho: Distribution of RANKEBITcum= Distribution of RankAVEBIT
Ha: Distributions are different

Ho: Distribution of RANKROAcum= Distribution of RankAVEBIT
Ha: Distributions are different

In all cases, it can be inferred at 1 % significance level that profit scoring and return scoring yield different distributions both in cumulative and average terms. Similarly, cumulative and average profit and return scoring produce different results. Any of the measures score customers in different deciles within the overall distribution. Therefore a customer would be not unequivocally accepted under profit or return scorecards.

Results from the Spearman correlation test and Chi square test show that any of the four measures could be equally used to score customers. Each measure offers a different criterion to score customers; the user's preferences and specific aims will favour one or another.

A consequence of having various alternatives to score customers is that two decisions need to be made: Is profit or return the priority? Should cumulative or average measures be used? These questions are addressed in the following sections.

6. ASSESSING PORTFOLIO RESULTS

Deciding between profit and return measures at a customer level depends on their impact at the portfolio level. The objective is to provide monetary reasons rather than solely basing the decision on practitioners' preferences for profit or return.

Prior to presenting a decision rule, it is useful to characterise portfolio profits and returns. Opportunities of profit maximisation can be identified at this stage.

6.1 Dependence and subsidisation

Portfolio profits and returns were explored following the sequential behaviour of cumulative profits. Customers join the cumulative graphs following their profit ranks, starting with the top performers (Storbacka 1997).

Two coefficients can be used to measure the dependence of profits on a small group of customers and the losses subsidised by profit makers: STC (Stobachoff coefficient) and VF (vulnerability factor) (Storbacka 1995 in Helgesen 2007). A joint analysis of these measures and cumulative curves is useful to identify high risk situations and to define marketing strategies for different segments (Van Raaij 2005; Helgesen 2007). In a scoring context, these tools may be helpful to identify hidden opportunities of profit maximisation in specific segments (i.e.: defaulters and non-defaulters).

Portfolio measures were calculated as follows:

$$CorporateEBITcum_t = \sum_{i=1}^{n} EBITcum_{i,t} \qquad (16)$$

$$CorporateROAcum_t = \sum_{i=1}^{n} ROAcum_{i,t} \times w_{i,t} \qquad (17)$$

$$CorporateAVEBIT_t = \sum_{i=1}^{n} AVEBIT_{i,t} \qquad (18)$$

$$CorporateAVROA_t = \sum_{i=1}^{n} AVROA_{i,t} \times w_{i,t} \qquad (19)$$

w_i is the weight of the final balance at time t per customer *i*, compared with the total outstanding receivables of the company.

Almost all of the portfolio profits and results come from non-defaulters. Overall, the current acceptance policy based on previous payment behaviour of utility bills has been effective to generate profits. Between 1% and 2% of the profits and returns were generated by defaulters. This suggests that a minority of customers default in their payments but eventually clear their outstanding balance at arrears and hence are profitable for the company.

In general, there is no high risk in terms of dependence and subsidisation of profits and returns (See **Table 1).** The STC values for the complete sample are low (between 1.9% and 17.1%), excluding those for *AVROA.* These results originate from the sharp decrease in returns when loss-makers are included in the analysis. The overall shapes of these curves do not display major concentrations, though. Unprofitable customers are a minority (VF varies between 0.3% and 0.6%). This confirms that the credit programme is a good business in profit and return terms.

Since non-defaulters are the majority of the sample, results are almost identical to those explained above. However, the figures and coefficients for defaulters show that profits and returns of defaulters are less evenly distributed than those of the total sample; STC varies between 17% and 24% and VF varies between 3.3% and 4.7%. **See figures 3 to 6.**
Given that the contribution of figures for defaulters is considerably lower than that of non-defaulters, the impact of profitable and unprofitable customers is higher in this segment.

A common feature of defaulters and non-defaulters is that returns are less concentrated than profits. This is depicted in figures that are closer to straight lines. Hence using ratios reduces even more the risk of dependence and subsidisation as a result of the scaling effect explained before.

A time-oriented analysis of the Figures shows that as time goes on (from t=12 to 30), long term cumulative curves dominate those calculated for the short term. See **Figures 3 to 6**. By definition, these measures increase as time goes on. Therefore, these results were expected. Average measures present a different angle: In the short term, average profits reach the highest values; average returns increase as time goes on. That is, higher profits in the short term do not guarantee higher returns. Likewise, higher returns in the long term do not guarantee higher profits.

Table 1

	COMPLETE SAMPLE			NON-DEFAULTERS			DEFAULTERS		
MEASURE	VALUE*	STC	VF	VALUE*	STC	VF	VALUE*	STC	VF
EBITCUM12	1.00	17.1%	0.3%	1.00	16.9%	0.2%	1.00	22.4%	3.7%
EBITCUM24	1.74	17.1%	0.6%	1.75	17.0%	0.6%	1.33	26.6%	4.3%
EBITCUM30	1.97	16.5%	0.3%	1.98	16.4%	0.2%	1.64	24.6%	3.8%
AVEBIT12	1.00	17.1%	0.3%	1.00	16.8%	0.2%	1.00	22.4%	3.7%
AVEBIT24	0.87	17.1%	0.6%	0.87	16.9%	0.6%	0.67	26.6%	4.3%
AVEBIT30	0.79	16.5%	0.3%	0.79	16.3%	0.2%	0.66	24.6%	3.8%
ROACUM12	1.00	9.8%	0.3%	1.00	9.4%	0.2%	1.00	19.3%	3.7%
ROACUM24	2.13	2.7%	0.6%	2.13	2.3%	0.6%	1.63	20.4%	4.3%
ROACUM30	2.67	1.9%	0.3%	2.68	1.7%	0.2%	2.22	17.1%	3.8%
AVROA12	1.00	89.6%	0.4%	1.00	90.7%	0.4%	1.00	19.3%	3.3%
AVROA24	3.95	58.5%	1.6%	4.38	59.0%	1.5%	0.81	24.4%	4.7%
AVROA30	4.12	69.1%	1.3%	4.57	69.6%	1.2%	0.85	21.1%	4.0%

* Relative to those at t=12 because of confidentiality reasons

Figure 3: EBITcum, non-defaulters

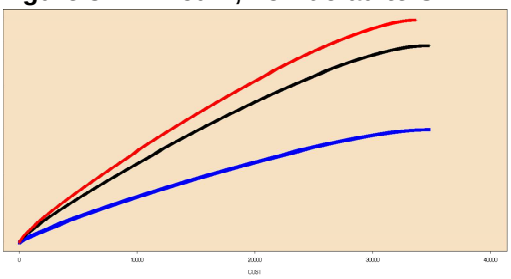


Figure 4: EBITcum, defaulters

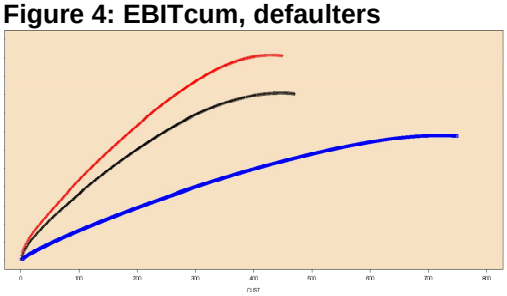


Figure 5: ROAcum, non-defaulters

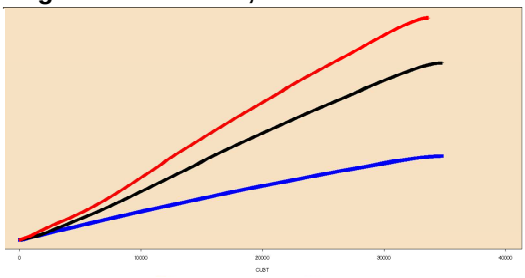
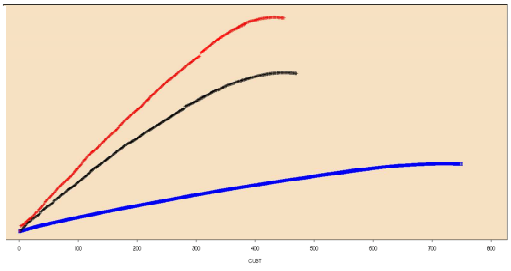
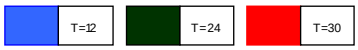


Figure 6: ROAcum, defaulters





Values are not displayed for confidentiality reasons.

7. PROFITS VERSUS RETURN MEASURES (PORTFOLIO LEVEL)

In order to get a better understanding of differences between profit/return measures at the portfolio level, the customers were ranked according to a particular profit/return measure, e.g. from lowest observed EBITcum to the highest one. Then certain percentage (50 to 95) of customers with the highest/ best values were selected as if accepted for credit and profit/return measures were calculated for 'accepted' customers to see how these measures behave across a range of potential acceptance rates. For all the acceptance rates from 50 to 95, profit (return) measures yielded higher values for each group than those obtained with return (profit) measures (either cumulative or average). See **Figures 7 and 8.** Results are available for average measures.

As the acceptance rate increases, marginal profits and returns obtained through either alternative decrease. At acceptance rate=95, both measures almost converge. It is indifferent to use one or another, as almost everyone would be accepted. An exception to this behaviour is *AVROA.* At t=12, 24 and 30, the marginal average return forgone increases at acceptance rate=95. Performers at the bottom end in terms of return experience a sharper decrease in returns when a profit measure is used instead of a return measure.

It is evident that if acceptance is based on profit (return), this does not necessarily lead to higher portfolio returns (profits). In order to choose between profit and return, a marginal approach was used, as explained below.

Figure 7

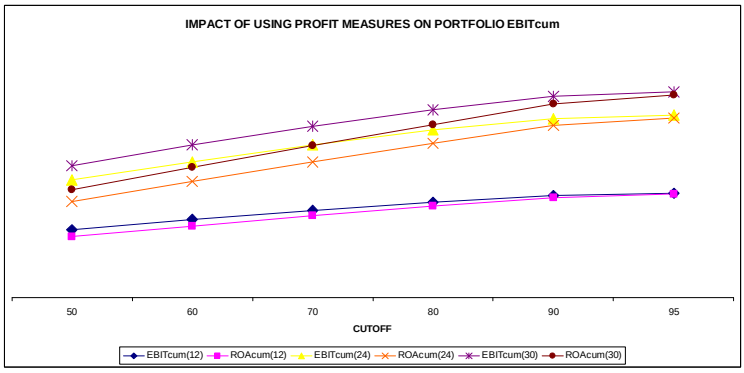
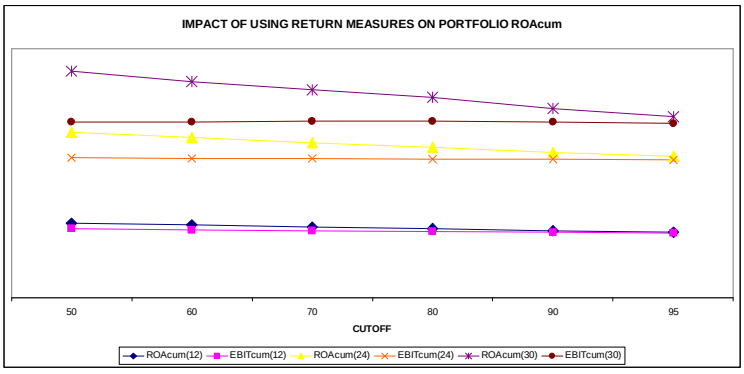


Figure 8



Values are not displayed for confidentiality reasons

7.1 EBITcum vs. ROAcum

The objective is to maximise portfolio coverage against default at t=12, 24 and 30. If customers were accepted according to EBITcum, the portfolio profit would be:

$$\boldsymbol{PORTFOLIOCOVERAGE}_{\boldsymbol{EBITCUM}_t} = \sum_{i=1}^{n_1} \boldsymbol{EBITCUM}_{i,t} \quad (20)$$

Where: n_1= acceptance rate according to $EBITcum_t$

If ROAcum was used instead, the portfolio coverage would be:

$$\boldsymbol{PORTFOLIOCOVERAGE}_{\boldsymbol{ROACUM}_t} = \sum_{i=1}^{n_2} \boldsymbol{EBITCUM}_{i,t} \quad (21)$$

Where: n_2= acceptance rate according to $ROAcum_t$ $(n_1=n_2)$

The opportunity cost of choosing (20) instead of (21) would be:

$$\boldsymbol{OC}_{\boldsymbol{1COVERAGE}_t} = \boldsymbol{PORTFCOVERAGE}_{\boldsymbol{EBITCUM}_t} - \boldsymbol{PORTFCOVERAGE}_{\boldsymbol{ROACUM}_t} \quad (22)$$

Since: $\boldsymbol{PORTFCOVERAGE}_{\boldsymbol{EBITCUM}_t} > \boldsymbol{PORTFCOVERAGE}_{\boldsymbol{ROACUM}_t}$

Then (22) is the marginal portfolio coverage that would be obtained if profits are used instead of returns.

On the other hand, if customers were accepted according to their ROAcum, the portfolio percentage coverage would be:

$$\boldsymbol{PORTFOLIO\%COVER}_{\boldsymbol{ROACUM}_t} = \sum_{i=1}^{n_2} \boldsymbol{ROACUM}_{i,t} \times \boldsymbol{w}_{i,t} \quad (23)$$

Where: $$w_{i,t} = \frac{finalbalance_{i,t}}{\sum_{i=1}^{m} finalbalance_{i,t}}$$

m= customers accepted according to the acceptance rate, based on *ROAcum.*

If *EBITcum* was used instead:

$$\boldsymbol{PORTFOLIO\%COVER}_{\boldsymbol{EBITCUM}_t} = \sum_{i=1}^{n_2} \boldsymbol{ROACUM}_{i,t} \times \boldsymbol{w}_{i,t} \quad (24)$$

Where: Where: $w_{i,t} = \frac{finalbalance_{i,t}}{\sum_{i=1}^{m} finalbalance_{i,t}}$

m= customers accepted according to the acceptance rate, based on *EBITcum.*

Since the starting point was to accept customers according to *EBITcum*, the opportunity cost of choosing (24) instead of (23) would be:

$$\boldsymbol{OC_{\%COVERAGE_t} = PORTFOLIO\%COVER_{EBITCUM_t} - PORTFOLIO\%COVER_{ROACUM_t}} \quad (25)$$

Since: $\boldsymbol{PORTFOLIO\%COVER_{EBITCUM_t} < PORTFOLIO\%COVER_{ROACUM_t}}$

Then (25) is the marginal percentage coverage return that would be lost as a result of using profits instead of returns.

Since (22) and (25) are expressed in monetary units and percentages respectively, to obtain the marginal coverage in monetary units, $OC_{\%COVERAGE_t}$ was converted to $OC_{2COVERAGE_t}$:

$$OC_{2COVERAGE_t} = OC_{\%COVERAGE_t} \times finalbalance_{cutoff_t} \quad (26)$$

Where:

$$finalbalance_{cutoff_t} = \sum_{i=1}^{n_1} finalbalance_i \quad (27)$$

The marginal coverage gained or lost when using profits instead of returns is:

$$MARGINALCOVERAGE_t = OC_{1COVERAGE_t} + OC_{2COVERAGE_t} \quad (28)$$

7.2 AVEBIT vs. AVROA

An equivalent analysis was conducted for *AVEBIT* and *AVROA*. In this case, the objective is to maximise portfolio profits based on average profits and returns per customer.

The marginal profit gained or lost if profits are used instead of returns is:

$$MARGINALPROFIT_t = OC_{1PROFIT_t} + OC_{2PROFIT_t} \quad (29)$$

Where:

$$\boldsymbol{OC_{1\,PROFIT_t} = PORTFPROFIT_{AVEBIT_t} - PORTFPROFIT_{AVROA_t}} \quad (30)$$

$$OC_{2PROFIT_t} = OC_{2ROA_t} \times finalbalance_{cutoff_t} \quad (31)$$

$$\boldsymbol{OC_{2\,ROA_t} = PORTFOLIOROA_{AVEBIT_t} - PORTFOLIOROA_{AVROA_t}} \quad (32)$$

$$finalbalance_{cutoff_t} = \sum_{i=1}^{n_3} finalbalance_i \quad (33)$$

n_3= acceptance rate according to $AVEBIT_t$

Tables 2 and **3** show the values obtained for the marginal coverage and marginal profit, respectively. The shaded cells are those acceptance rates for which using profit measures is more beneficial at a portfolio level.

7.3 Portfolio coverage results: EBITcum vs. ROAcum

Table 2 shows the marginal coverage resulting from using profit measures to accept customers. In the short term (t=12), using profit measures maximises the marginal coverage; cash is more important than returns. In the mid and long term (t=24 and t=30, respectively), it is improved if returns are used instead. After the first year, the relative performance of customers gains importance against the cumulative profits generated throughout time. As time goes on, cumulative profits should be scaled according to the outstanding balance to maximise the marginal coverage against default.

The suggested acceptance rates at t=12, 24 and 30 are 50, 90 and 50, respectively. Therefore, in the long term the criterion for accepting customers is as strict as in the short term. Once again, the objective is to maximise coverage against default. This justifies adopting the strictest acceptance rate.

7.4 Portfolio profit results: AVEBIT vs. AV ROA

Table 3 shows that at any point of time, returns should be used instead of profits to accept customers. Even though at t=24 customers within deciles 50 to 70 should be scored according to *AVEBIT*, marginal profits are maximised when using *AVROA.*

At any point of time the suggested acceptance rate is 95. These results follow from the situation explained in the previous section, regarding *AVROA*. In average, customers in the lower percentiles experience a sharper drop in their returns when profits are used instead of returns. Therefore, when such marginal return is magnified

in monetary terms when the forgone profit is calculated. In practical terms, this suggests that almost everyone should be accepted, as in average overall results are positive. This should be seen with caution, as it has been shown that still a minority yields losses.

In the long term, using return measures to accept customers increases both marginal coverage and profits. That is, assessing customers on a same-to-same basis guarantees that overall results are improved. Using profit measures is still useful if the objective is coverage in the short term. It provides as well a sound basis to benchmark results obtained from using return measures. Using return measures not only maximises portfolio returns, but also portfolio coverage in the long term.

Table 2: Marginal coverage*

EBITCUM vs ROACUM	12	24	30
50	**1.00**	1.00	**1.00**
60	**0.81**	1.04	0.91
70	**0.35**	1.96	0.80
80	0.01	3.89	0.72
90	0.22	**7.56**	0.55
95	0.35	6.80	0.35

Table 3: Marginal profit*

AVEBIT vs AVROA	12	24	30
50	1.00	**1.00**	1.00
60	0.84	**2.07**	0.96
70	2.76	**0.10**	0.94
80	3.53	89.90	4.42
90	0.24	92.41	4.80
95	**236.69**	**97.21**	**5.63**

***Values are relative to those for acceptance rate=50 because of confidentiality reasons.

8. MAXIMISING COVERAGE AGAINST DEFAULT OR PROFITS

As seen in the previous section, maximising cumulative results involves maximising the portfolio coverage against default. On the other hand, maximising average results implies maximising portfolio profits. Each objective leads to different acceptance rates. In general, coverage requires stricter acceptance rates, as the standpoint should be more conservative than solely generating profits. As both objectives not necessarily agree at every point of time, there is a trade-off depending on a company's priorities.

The long term implies higher levels of uncertainty arising from macroeconomic conditions that might affect the payment behaviour of customers. Another source of risk is the changing weather conditions in Latin America, which affect substantially the economic stability and living conditions of low income segments, and hence, their payment behaviour. The dashed arrows in **Figure 9** show the overall marginal coverage traded-off when the acceptance rate is increased to percentile 95, following a marginal profit maximisation criterion. In the long term (t=30), the trade-off is greater as coverage gains more relevance.

In the short term, more profits are forgone if the objective is maximising coverage. The overall marginal profit traded-off when the acceptance rate is decreased to percentiles 50, 90 and 50 at t=12, 24 and 30, respectively is represented by the dashed arrows in **Figure 10.** During the first year of the observation period portfolio profits are more relevant than coverage, as the time period of bearing risk is the lowest. Another implication of adopting stricter acceptance rates is that the social scope of the programme is reduced.

In both cases, t=24 is roughly the broken even point, where almost no coverage (profit) is traded-off for profit (coverage), as the acceptance rates are similar (90 and 95).

Two courses of action may be taken depending on the standpoint of the management team, as explained below. In the long term more risk is taken as a result of the changing behaviour of customers. Consequently one would be inclined to take a more conservative standpoint and therefore define the acceptance rate based on coverage rather than on profits at t=30. An alternative course of action taking into consideration the social inclusion feature of the programme is to adopt a range of acceptance rates.

At t=30:

Acceptance rate range = [min $_{\text{social scope}}$, max $_{\text{coverage}}$] (34)

In this particular case:

Acceptance rate range = [95,50]

One should be aware of the coverage traded off as the acceptance rate is relaxed. There is a cost of enhancing the social scope of the programme and therefore an additional risk attached to such decision.

Figure 9

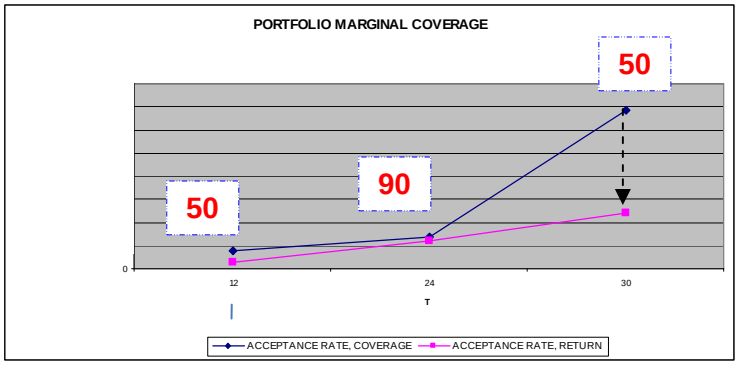
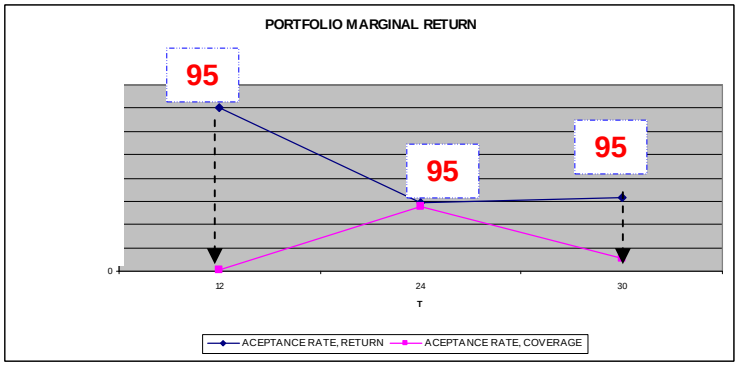


Figure 10



Values are not displayed for confidentiality reasons

9. PREDICTING PROBABILITY OF DEFAULT

Given the significance of defaulters in portfolio profits, it is useful to conduct an opportunity cost analysis to assess the impact of using solely default scoring regardless of their profitability. For that purpose, a model to predict the probability of default at t=12 months was developed using variables available when the first purchase took place. The complete sample was split randomly (80-20) to generate training and holdout samples.

Sociodemographic and purchase-related variables were collected when the first purchase occurred. This corresponds to the starting point of the observation period. **Table 4** shows the variables that were collected per customer. These variables were chosen as they are directly related with the credit usage and purchase behaviour of customers, as well as individual characteristics that may differentiate defaulters from non-defaulters.

Table 4: Variables used to design the model

VARIABLE	REFERENCE CATEGORY	DUMMIES	Chi square test p-value	IV
Duration of first loan	loandur<=24 months	dumLOAN2 : 24 months <durloan<= 36 months dumLOAN3 : 36 months <durloan<= 48 months dumLOAN4 : 48 months <durloan<= 61 months dumLOAN5 : missing	0.00	44.54
First product purchased	qualifying context-related products and missing values	dumHOM1 : homeappliances dumFURN1 : furniture dumHARDW1 : hardware	0.00	44.04
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	0.00	35.23
Credit limit usage (loan/ACL)	loanpr<=0.404	dumloanpr2 : 0.404<loanpr<= 0.748 dumloanpr3 : 0.748<loanpr<= 3.5	0.00	28.78
Marital status	single	dummar1 : cohabitators, married dummar2 : divorced, widow(er) dummar4 : missing	0.01	26.77
Approved credit limit	ACL=£300	dumACL2 : ACL= £310 dumACL3 : ACL= £350 £400 £500 or £600	0.01	16.33
Dependants	0 dependants	dumDEP1 : 1 dependants dumDEP2 : 2 dependants dumDEP3 : 3 dependants dumDEP4 : 4 dependants dumDEP5 : 5 or more dependants	0.24	11.46
Economic activity	services	dumactNA : Not applicable dumactOTH : Other industries dumactPROD : Manufacturing	0.46	4.25
Years at home	YAH<= 7.9 years	dumYAH2 : 7.9<YAH<= 16.8 years dumYAH3 : 16.8<YAH<= 25.7 years dumYAH4 : 25.7<YAH<= 34.6 years dumYAH5 : 34.6<YAH<= 43.5 years dumYAH6 : 43.5<YAH<= 90 years	0.87	3.15
Proportion of instalment (Instalment/loan)	inspr<=0.0325	dumloanpr2 : 0.0325<loanpr<= 0.0475 dumloanpr3 : 0.0475<loanpr<=0.10	0.52	2.38
Job status	employed	dumJOB2 : retired dumJOB3 : self-employed dumJOB4 : housewife, student, unemployed, missing	0.76	1.95
Type of contract	missing, other, or not applicable	dumcon2 : Any type of contract (permanent, temporary)	0.60	0.45
Socioeconomic stratum	stratum 1 (poor segments)	dumstra35: stratum>1	0.81	0.10
Level of studies	primary or secondary	dumSTU2 : College, higher dumSTU3 : missing	0.99	0.03
Location	rural (different to the capital city)	dumcitURB : urban (capital city)	0.97	0.00

Each variable was then coarse classified. The p-values and information value (IV) resulting from the coarse-classification were calculated per variable to assess the

usefulness of each variable to separate goods (non-defaulters) from bads (defaulters). Once a reference category was defined, dummy variables were created to run the model. See **Table 4**.

Previous to the first iteration of PROC LOGISTIC, variables with high multicollinearity values were excluded. For parsimony reasons, only significant variables were included in the model. The resulting equation to predict probability of default is as follows:

$$P= 1/ (1+\exp (\alpha-\beta_1 duminspr2- \beta_2 dumloanpr3+ \beta_3 dumage6- \beta_4 dumHOM1- \beta_5 dumFURN1- \beta_6 dumHARDW1+ \beta_7 dumACL3)) *$$

* Coefficients are not presented for confidentiality reasons

The obtained AUC was 0.60 and 0.59 for the training and hold out samples, respectively. See **figures 11 and 12.**

Figure 11: ROC Curve, training sample

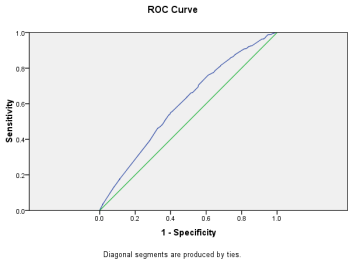
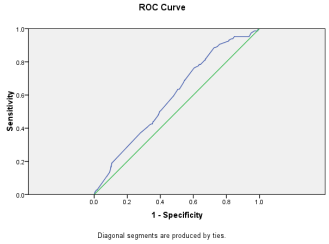


Figure 12: ROC Curve, holdout sample



Results can be interpreted as follows:

Customers that agree to pay higher instalments are more likely to default than those with lower instalments. These results are reasonable, as in monetary terms customers are more likely to default when they commit more of their monthly disposable income to pay their debts.

Customers with higher rates of credit limit usage are more likely to default. This was expected, as the higher the debt taken, the greater the chances of default are.

Older customers are less likely to default when compared against those from the youngest group. This results from a higher responsibility towards debt payment that increases with age. Furthermore, this age group includes customers that are just about to retire or that have recently retired (both men and women). This implies that there are less financial commitments within the household and therefore, a better loan payment capacity.

Productwise, it does make a difference to purchase different types of products. Various reasons may explain this behaviour. Firstly, these products are not directly related to the qualifying context and therefore may lead to default in the payment of new loans. Secondly, some of these products might be considered luxury goods by low income segments. Customers may engage in purchasing products that will give them a higher social status but that under normal circumstances they would not buy.

Finally, the highest odds ratio corresponded to the purchase of hardware products that are added to fixed assets. This may be the consequence of a common belief that compared with other products; these cannot be repossessed by the credit granter in the event of default. This is the usual practice of money sharks that repossess movable goods from customers until the loan is fully repaid. Even though this is not be the case of the Company under analysis, still customers may believe that they are on "safer grounds" if they purchase products that become part of their fixed assets and therefore can be kept regardless of their default status.

Finally, as the approved credit limit increases, the probability of default decreases. Since the approved credit limit increases with the socioeconomic stratum, it can be inferred that still low income segments are more likely to default than wealthier segments. This confirms that still serving the base of the pyramid is a risky business without taking into account profitability considerations.

9.1 Opportunity cost analysis

Once the probability of default at t=12 months was predicted for the training and holdout samples, six acceptance rates were used to assess the impact of implementing the default scorecard presented in the previous section. The opportunity cost for EBITcum and AVEBIT was calculated as follows:

$$OC = \frac{(\sum(netprofit_{rejecteddefaulters}) + (\sum netprofit_{misclassifieddefaulters})}{(\sum loss_{acceptednon-defaulters}) + (\sum netprofit_{missclassifednon-defaulters})} \quad (35)$$

Where: net profit= profits-losses

This ratio measures the overall effect of solely using default scoring. The numerator includes the forgone net profit if defaulters are rejected and the forgone net profit resulting from misclassifying non-defaulters as defaulters. The denominator includes the loss resulting from accepting unprofitable non-defaulters and the net profit (loss) obtained if defaulters are classified as non-defaulters and therefore, are accepted.

This ratio was calculated as well for ROAcum and AVROA, using weighted averages instead of profits or losses.

Table 5 shows the results for the holdout sample. Similar results were obtained for the training sample. As the acceptance rate increases, more non-defaulters are correctly classified at the expense of misclassifying more defaulters. This results in lower values of OC.

Overall, the opportunity cost of using default scoring regardless of the profit profiles of customers is high (at least 11 or 10 times for the training and holdout sample, respectively). A detailed analysis showed that it is more expensive to reject profitable defaulters than it is to accept unprofitable non-defaulters. These results were consistent across the four measures of profits. This confirms that it is profitable for the company to bear the higher risk attached to the recovery of defaulters from their

arrears status. Furthermore, outstanding receivables of defaulters should be seen as a high risk investment in the long term.

On the other hand, the opportunity cost of rejecting non-defaulters as a result of their misclassification as defaulters is high, given the limitations of the predictive model. The impact of misclassification is still lower than that of rejecting defaulters that were actually predicted as defaulters.

The above results confirm that default does not necessarily imply losses; similarly non-default does not imply profits. Further opportunities of profit maximisation exist both in defaulters and non-defaulters. This agrees with results from previous studies (Andreeva et al. 2007; Finlay 2008). Results can still be maximised through profit scoring or return scoring.

Table 5: Opportunity cost of using default scoring

HOLDOUT SAMPLE

ACCEPTANCE RATE	52%	60%	61%	65%	66%	89%
PREDICTIVE ACCURACY	0.52	0.60	0.61	0.64	0.66	0.88

	ACCEPTANCE RATE					
OC	52%	60%	61%	65%	66%	89%
EBITCUM12	81	65	60	46	43	11
AVEBIT12	81	65	60	46	43	11
ROACUM12	81	65	60	46	43	11
AVROA12	74	59	54	42	39	10

10. CONCLUSIONS

This study presents for the first time the use of return measures in a scoring context. It shows as well that rejecting profitable defaulters is more expensive than accepting unprofitable non-defaulters, both in monetary and relative terms (ratios). Through the use and comparison of monetary measures and ratios, it introduces a more consistent approach to profit in a scoring context. Additionally, it provides an objective framework to choose between profits and return measures. See **Figure 13.**

At the customer level, maximising customer profits through profit measures did not maximise returns. Similarly, maximising customer returns through return measures did not maximise profits. This leads to the dilemma of choosing between both measures.

Managers guided by the cash criterion will choose profit measures. A disadvantage is that the investment per customer is ignored and therefore, looking at profits can be misleading in relative terms. Profit is just an element of profitability.

On the other hand, those that prefer scaling profits to actually compare customers in relative terms will choose return measures. Strictly speaking, scoring refers to the relative comparison of customers according to their profitability; return measures follow this rationale by definition. An implementation disadvantage is that returns are not always easily embraced because profits are easier to interpret.

The dilemma mentioned above has to be solved at the portfolio level. In this particular case, in the long term using return measures maximises both the marginal

coverage against default and marginal profits. Therefore, using returns offers a “safer ground” both in relative and monetary measures for the company as a whole.

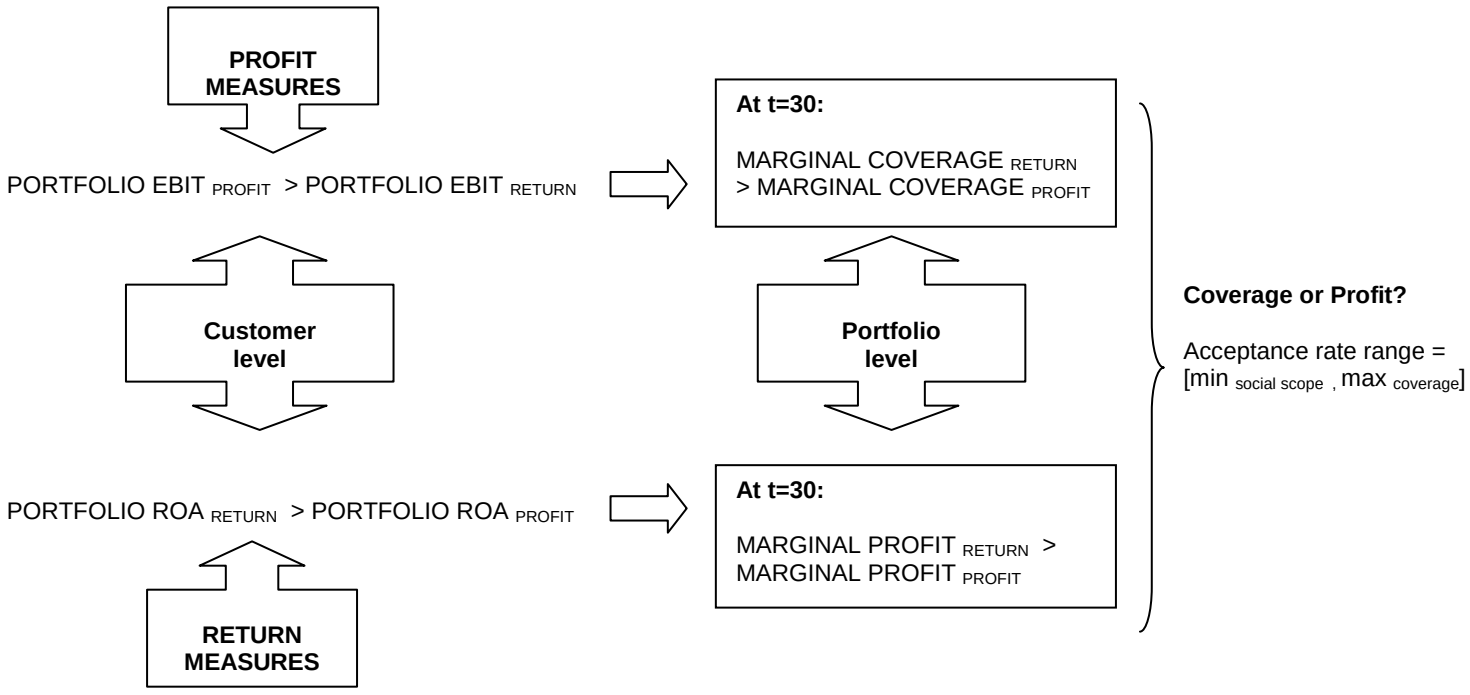
Even though different measures of profits have been used before, this study explores for the first time different measures of profits (absolute and relative) that can be useful for scoring purposes. It explicitly compares results of absolute and relative measures of profits to solve the dilemma mentioned above. Hence it enhances the use of profit measures to determine the attractiveness of customers to lenders. Additionally, it provides the basis to reinterpret profits as the coverage against default. This is relevant especially after the credit crunch.

Having solved the first dilemma, a second one arose: Should marginal coverage or marginal profit be maximised? Rather than deciding between both objectives, a trade-off analysis was conducted. The forgone marginal coverage (profit) was quantified if the priority was maximizing the marginal profit (coverage). In other terms, what is the additional risk taken when the objective is to maximise profits? These concepts are particularly useful for social inclusive businesses, as they should be concerned not only with extending the social dimension of the programme, but also with covering against default.

In the case under analysis, in the long term maximising marginal coverage lead to stricter acceptance rates. Practical implications include adopting a regulatory (conservative) stance and reducing the social scope of the programme. Conceptually, results validate the use of cumulative profit measures used in previous studies. Average profits and returns should be used with caution as they justify being more “generous” from a social perspective (i.e.: relaxing the acceptance rates). Their usefulness relies mostly on the comparative interpretation of results.

Results for this particular case shed light on another topic raised in previous studies but still under development: The relationship between time and profits in a scoring context. In the short term, profit measures are more beneficial than returns. However, revolving credits should be analysed in the long term; this is valid as well from a customer lifetime value perspective. Therefore returns should be preferred to profits. Furthermore, as time goes on the priority should be coverage against default rather than profit maximisation.

Figure 13



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