Modelling Profitability using Survival Combination Scores

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Abstract

The paper presents the first empirical investigation of the relationship between present value of net revenue from a revolving credit account and times to default and to second purchase. The analysis is based on the data for a store card which is used to buy 'white' durable goods in Germany. It is demonstrated that there exists a relationship between the above given measures. It appears that there is a scope for improving profit if an application for a store card is assessed by using a model which estimates the revenue and includes the survival probability of default and the survival probability of second purchase (a survival combination model) rather than merely a static probability of default predicted by a logistic regression.

Keywords: Decision support systems, risk analysis, survival analysis, profitability

1. Introduction

Since the early 1990s the literature on consumer credit risk assessment has progressed from predictions of the probability of default on a particular loan towards the theoretical and empirical prediction of the profits which may be earned from that loan (Keeney and Oliver, 2005; Oliver and Wells, 2001; Stepanova and Thomas, 2001). Several authors have noted that the profitability of extending a credit facility is related to the length of time the client retains the credit, whether it be a fixed term loan or a revolving type of credit (Hopper and Lewis, 1992; Leonard, 1997). Previous research has demonstrated the use of survival analysis to estimate the time to default or to the surrender of a credit facility (Andreeva, 2006; Banasik et al., 1999; Hand and Kelly, 2001; Narain, 1992; Stepanova and Thomas, 2001; Stepanova and Thomas, 2002), and for *fixed term loans* this information has been used to determine the expected profit from the facility by combining the estimated probability of default in each month with the monthly repayment amount (Stepanova and Thomas, 2001;

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Stepanova and Thomas, 2002). But for a *revolving credit* facility the estimation of expected profit is more complicated than for a fixed term loan. In the latter case the lender knows the scheduled repayment amount in every month at the time the loan is made. In the former case this is unknown since the card holder can choose to increase the credit outstanding, and he can also choose how much, if any amount at all, to repay in any month. If a card holder increases his amount outstanding at the end of any month, the interest received by the lender is increased and the profits gained from issuing the revolving facility are increased. This is true of any revolving credit product including a store card which is the subject of this paper. Profitability, in such a context, should therefore be related not only to the time to default and time to the account closure, but also to the usage of the card. The aim of this paper is to explore this relationship. Although several papers have modelled the probability of default of a credit card account (Banasik et al., 1996; Crook et al., 1992) or of a store card account (Andreeva et al., 2005) no papers have been published which empirically model the expected profitability, at the time of application, of a revolving credit product. This is surprising since in the UK credit card debt extended has rapidly increased its share of total non-mortgage consumer debt over the last decade. For example in the UK in 1995 net lending on credit cards was 25.54% of total non-mortgage net consumer credit extended whereas by 2004 this proportion had risen to 43.58%.[2] Furthermore the entry into the UK credit card market by several American issuers over the last decade and the much greater penetration of the market over this period made the UK credit market highly competitive, and so the accurate assessment not merely of risk but of expected profitability as well has become critically important to issuers. There is also evidence that in the US the credit card market has also become highly competitive in the same period (Crook, 2002).

Initially we examine the observed descriptive relationship between revenue (our proxy for profit) and purchase rate. We then build a survival model for time to the second purchase using the credit facility, then a survival model of the time to default and finally we estimate a model of revenue given predictions from these survival models and other information available at the time of application. Our results suggest that this can be a productive avenue to explore for risk modellers, but that future research is needed to increase the accuracy likely to be achieved.

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[2] Data from National Statistics online: http://www.statistics.gov.uk/statbase/TSDdownload2.asp

The paper starts by describing the context of the research and the data used. We define the variables and explain the empirical model between them. The predictions from two survival analyses are described: one for time to default and the other for time to second purchase. The relationship between profit and these predictions is explored and the final section concludes.

2. The Data

The data consists of all applications for a store card issued in Germany which were accepted during a 14 month period, from 11/1998 till 12/1999. The repayment performance of each account was followed between the date of issue of the card and 11/2000. Whilst many different definitions of default have been explored in the literature (Kelly, 1998), the requirement to have an adequate number of defaults in each month to be able to estimate monthly survival probabilities meant that the most suitable definition of default in this study was two consecutive missed payments. Details are given in Table 1.

Table 1. Details of the Sample.

Performance	Total	Second Purchase	Censored	% Censored
Good	66939	45217	21722	32.45%
Bad	8909	4529	4380	49.16%
Total	75848	49746	26102	34.41%

Before describing the model it is necessary to define the measures used in this analysis. Profit is often difficult to ascertain for a single individual account and usually an institution will take an overview of the profit of their portfolio of accounts. This is because there is a need to take account of fixed costs across the set of accounts. These are notoriously difficult to apportion meaningfully (Hopper and Lewis, 1992; Shank and Govindarajan, 1992). However if we restrict our objective to be that of obtaining a ranking of accounts which is monotonically related to the profit of each account and if we assume the fixed costs are equal for every account we do not need to ascribe fixed cost to each account. Higher variable costs for defaulting accounts than for non-defaulting accounts consist of higher administrative costs and write-off costs. We included write-offs in our calculation of net revenue but we did not have access to administrative costs. However the value of these costs for a defaulting account are considerably less than any write-off costs and so we have included the largest proportion of variable costs. The last portion of costs, the cost of funds, can be assumed to be constant across all borrowers since borrowed funds are costlessly transferable between all accounts. We therefore decided to use revenue from the accounts net of write-offs as a proxy for profit from an individual account, but mindful that we are gaining a ranking of accounts only on the basis of profit contribution gross of certain administrative costs.

Net revenue is defined as the sum of monthly payments from an account to the bank over the period of observation minus the amount written-off for defaulting accounts. Monthly payments were inferred by taking the difference between the outstanding balance at period t and the balance at period $t+1$. A positive difference meant this amount was paid back to the bank. These positive differences were discounted using the Bundesbank base rate for the corresponding period and summed up. A negative difference would mean either a missed payment or a further purchase. The delinquency indicator for the corresponding period was used to discriminate between the two. Negative differences were set to zero. For accounts marked as written off the last recorded outstanding balance was taken off from the sum of receipts received from this account. Thus

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

$r_{it} = b_{it} - b_{it+1}$ if $r_{it} > 0$

$r_{it} = 0$ if $r_{tj} \leq 0$

where b_{it} = outstanding balance at the end of month t case i;

vr_i = present value of net revenue at the end of month 0, case i;

l_i = value of amount written off during period T, case i,

θ_t = value of Bundesbank monthly base rate, month t,

T = month of account closure or end of the observation period.

Other measures used relate to default and usage of the credit facility or propensity to purchase. Given our definition of default the measure of interest is time to 2 missed consecutive payments, referred to as time to default.

It is possible to define a rate for the propensity to purchase but some accounts are over a limited period and a good number do not make a second purchase, hence it was decided that the most appropriate measure of propensity to purchase was time to second purchase. Those who intend to use the card frequently will make their second purchase early, those who are likely to use it rarely will be expected to either not make a second purchase within the period of observation or to make one later in the period of observation.

Figures 1 and 2 show the plot of the present value of net revenue against time to default and time to second purchase. For the purpose of graphical presentation the times for censored accounts were set to 26. So the last pair of data points in Figure 1 corresponds to good accounts. In Figure 2 time period 26 corresponds to accounts that do not make the second purchase. As expected, the longer an individual holds the card without defaulting the more net revenue accrues. For bad accounts there seems to be no difference whether the second purchase is made. But at period 26 second purchase shows higher mean net revenue, indicating that the latter is increased when a good account makes second purchase.

Figure 1. Mean net revenue per account for 25 months against time to default.

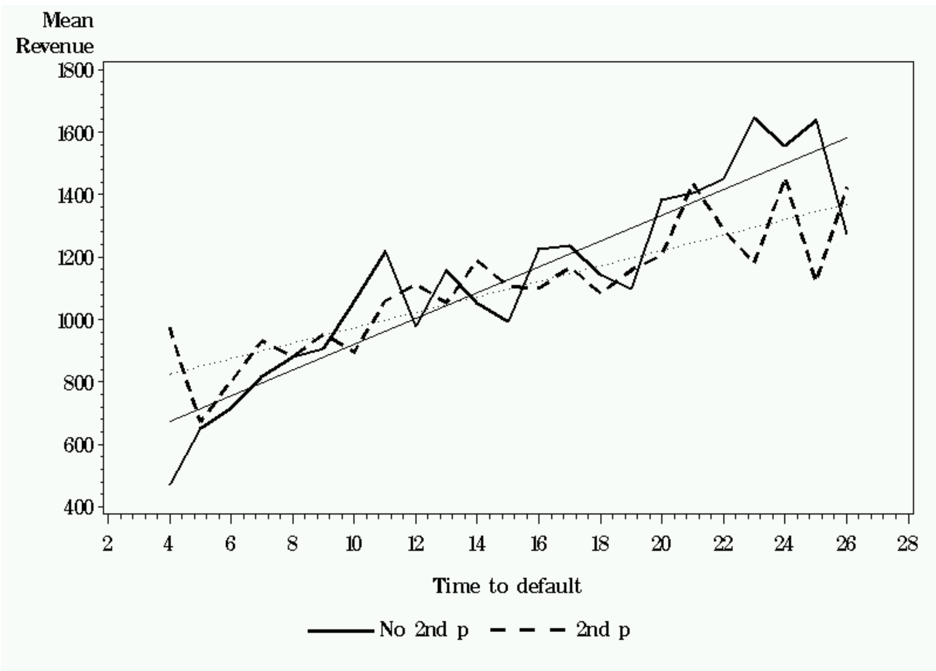
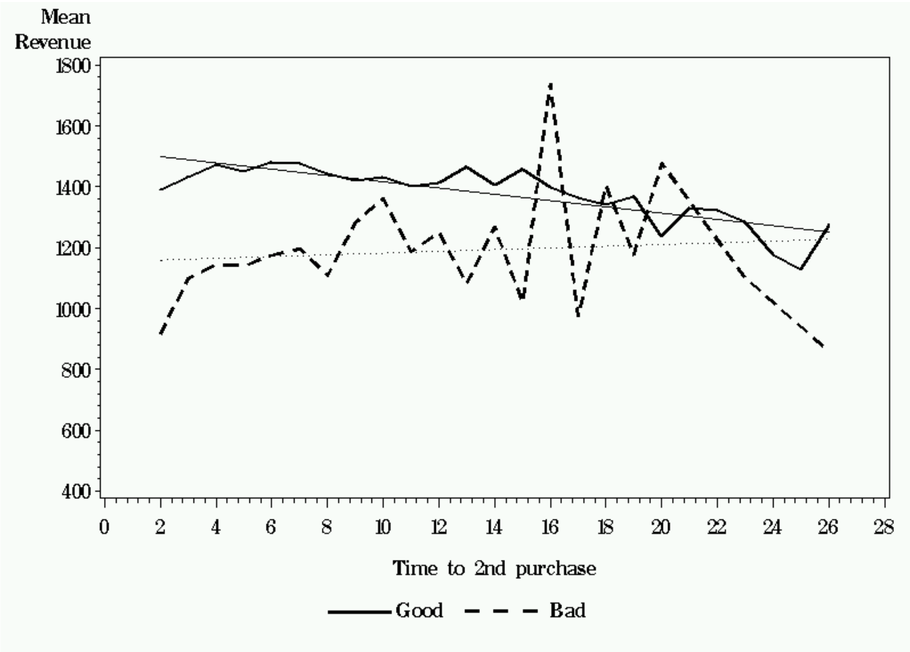


Figure 2. Mean net revenue per account for 25 months against time to second purchase.



For time to second purchase the picture is not so obvious, since there is an interaction between good and bad accounts. For good accounts earlier time of the second purchase increases the net revenue, whilst there is an opposite relationship for bad accounts.

It would seem that generally knowledge about time to default and time to second purchase may provide guidance to the profit of the individual customer. Clearly these two measures are unknown before acceptance and will have to be predicted based on available information. In the next section prediction of these two quantities will be pursued.

3. Prediction of Time to Second Purchase

As time progresses from the date a client makes a first purchase (approximately the time when the card was issued) he/she may choose to purchase a second product or not. Time was measured from the period of the first purchase (t=1) to the period of the second purchase or account closure/end of observation. The latter case of no further purchase was considered censored. If the account experienced default before making second purchase time to purchase was measured from the period the account recovered, since while in default the client is prevented from using the card.

Survival analysis allows us to model the probability that a case will survive up until a particular time period, *T*, before an event, such as default or a second purchase occurs, *S*(*t*):

$$S(t) = 1 - F(t)$$

Equivalently one can form the hazard function *h(t)* which is the instantaneous probability that the event will occur in the next instant of time, given that it has not occurred before:

$$h(t) = \frac{P(t \le T < t + \Delta t \mid T \ge t)}{\Delta t}$$

Various distributions for the hazard function have been considered in the literature. The proportional hazards (PH) model assumes:

$$h(t, \mathbf{x}) = h_0(t) e^{\beta' \mathbf{x}}$$

Where h_0 is a baseline hazard and β is a vector of parameters to be estimated. This implies that the relative ranking of hazard rates does not vary with time because the covariates act multiplicatively on the baseline hazard. Alternative assumptions for the baseline hazard function include the exponential, Weibull, lognormal, log-logistic, and Gamma distributions of time until default (or second purchase) occurs. As an alternative to the PH model one can assume that the covariates act multiplicatively on time as well as on the baseline hazard (accelerated life time models). The hazard function then becomes:

$$h(t, \mathbf{x}) = h_0(t e^{\beta' \mathbf{x}}) e^{\beta' \mathbf{x}}$$

In this case the covariates speed up or slow down the time until the event occurs, T (Kalbfleisch and Prentice, 1980).

In previous work (Andreeva et al., 2005) we explored a series of hazard rate models to predict time to second purchase using data for (the same) storecard in Belgium. We use that modelling approach here. The information about the customer comes in the form of data obtained from the application form and also the details of the customer's purchase behaviour such as type of product and product price. Other information is recorded such as payment date and contract type. The list of characteristics used is presented in Table 2. All of the variables were coarse classified by similarity of p_k where p_k denotes the probability that those cases within a raw data group k made a second purchase. m-1 dummy variables were created to indicate membership of coarse classification group m for variable n. It is these dummy variables that were used as covariates in the estimation of the model. Cox's PH model was used. The sample, consisting of all of the applicants that applied during the period November 1998 to December 1999, was split randomly so that 70% of the cases made up the training sample and 30% made up the holdout sample. The purchase behaviour of accounts was observed between 12 and 25 months depending on when the card was issued, whether the card was withdrawn and whether the customer closed the account. The distribution of survival probabilities at the end of the 25 months observation window across the holdout sample were taken as the predictions of the model to assess its predictive performance.

Table 2. List of characteristics used.

Application Variables	
Home Telephone	Time in Employment
Residential Status	Type of business
Marital Status	Employer's phone
Occupation	Number of Dependants
Applicant's Age	Spouse's Age
Time at Address	Card Insurance
First Tansaction Variables	
Credit Insurance	Product Price
Product Type	Payment Date
	Contract type

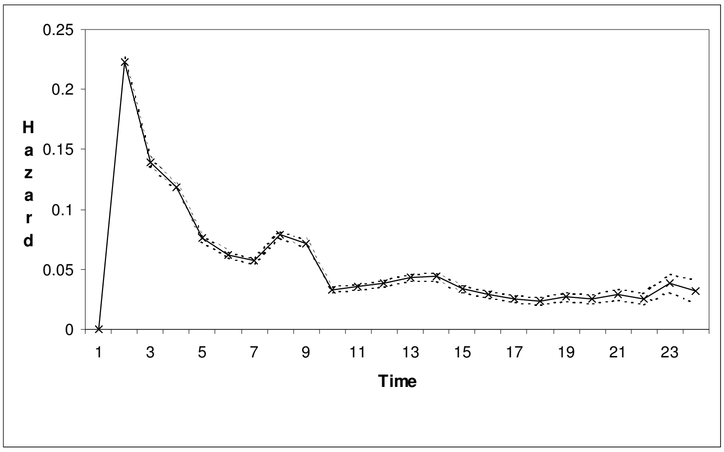
The predictive performance of the second purchase survival model is shown in Table 3. It is noticeable that there is a substantial gain in predictive power when the purchase variables were added to those from the application form[3].

Table 3. Predicting time to Second Purchase for Germany.

Model	*AUROC*
Personal Data	0.553
Personal + Purchase	0.774

The hazard rate for the time to second purchase model is shown in Figure 3. The contingent probability of making a second purchase declines relatively sharply up to month 5, then declines more slowly until month 10 where it remains for the remainder of the 25 months.

Figure 3. Hazard Rates with 95% Confidence Interval for Time to Second Purchase.



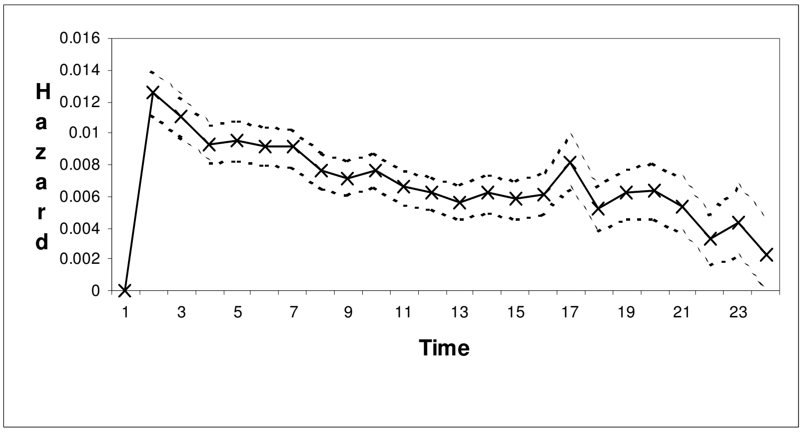
[3] The predictive accuracy of the models over the outcome window was assessed by the area under the ROC curve (AUROC). The ROC curve plots the proportion of bads predicted to be bad against the proportion of bads predicted to be good, at each score. An AUROC varies between 0.5 (meaning the model predicts no better than randomly) to 1.0 (which implies perfect prediction).

4. Prediction of Time to Default

As time progresses, from the time of acceptance, a client will either (1) default or (2) close the account before 11/2000 or (3) remain up to date with payments, that is survive past the end of the observation period. For the purpose of modelling time to default, the latter two cases were considered censored. Thus time to default was measured in months from the point of the first purchase (that is when the card is normally taken) until the first instance of two missed monthly payments or until closure/end of observation.

The survival model of the time to default is the model relating to Germany that was presented in (Andreeva, 2006). In that paper coarse classification was used where membership of a coarse classification group was based on probability of default. Dummy variables were then used as covariates in the survival modelling. The hazard rates of time to default are given in Figure 4.

Figure 4. Hazard Rates with 95% Confidence Interval for Time to Default.



The same data was used with the same training sample and holdout sample as was used for the estimation of time to second purchase models in the previous section. However in this model we experimented with alternative hazard rate distributions that were fitted as accelerated lifetime models and compared to non-parametric Cox PH model and logistic regression, a current industry standard. As can be seen from Table 4 there is little to choose between the models. With the usual assumption that a more *parsimonious* model is preferable in such circumstances we accepted the exponential distribution.

Table 4. Predicting Time To Default.

Model	AUROC
Exponential	0.7408
Weibull	0.7405
Loglogistic	0.7406
Lognormal	0.7406
Gamma	0.7404
PH	0.7412
Logistic	0.7417

Source: Andreeva (2006).

The accuracy of predictions, based on AUROC, appears to be reasonably sound, though as explained in Andreeva et al. (2005) the prediction of default is less volatile than that of the second purchase.

5. Prediction of Profit via Default and Purchase Propensity

Whilst it would be possible to predict profit directly from the characteristics for each individual there are good management reasons for considering them separately. Firstly, time to default is becoming a common measure within credit scoring and so will allow monitoring of performance of the specific behaviour of this type of credit against others. Secondly, time to default may be used within the Basel II Accord calculations to ensure compliance. For the purchase propensity measures there are issues surrounding the level of processing required by the lender to service the card and also it may be a useful feature of behaviour in the detection of fraud. Separating purchase propensity in the model .allows the analyst to examine changes in purchase propensity scores if the profits from a portfolio of loans decline. Besides, the majority of banks have already both default scoring systems and propensity scoring systems in place, so it would be logical to investigate how the output from these systems can be used in relation to profit.

The quality of profit prediction was tested on the out-of-time sample, in contrast to results reported in previous sections which relate to hold-out samples for the same time period as training ones. In business environment the model would be tested on the most recent out-of-time sample. However, we could not go beyond the end of observation period (Dec 2000), therefore a cohort of earlier 22,262 accounts opened in 11/1997 and 12/1997 were taken as a holdout out-of-time sample. That extended the total observation period to 36 months, which enables us to assess model performance over a longer time period.

First we explored the implications for net revenue of using merely survival probabilities of default as the criterion to accept applicants. The predicted probabilities of surviving default in 36 months were used to rank-order the accounts, as opposed to a more traditional probability of 'being good' obtained from logistic regression. The cut-off was selected to retain the observed acceptance rate (70%), so 70% of accounts with the highest predicted probability of surviving default or with the highest probability of being 'good', were marked as accepted. For these accepted accounts the traditional measures of model quality were calculated: the number of 'bads', the percentage of 'bads' (bad rate among the accepts), and two alternative profit-related measures: average net revenue per accepted account and total net revenue for accepts. The results are summarised in Table 5.

Table 5. Traditional and profit-related measures of model performance for different models predicting default, German Marks.

	Logistic	Exponential	Weibull	Log-logistic	Log-normal	Gamma	Cox PH
Accepted bad	939	937	937	940	941	936	935
Bad rate among accepts	6.09	6.08	6.08	6.1	6.1	6.07	6.06
Average revenue	1,905	1,915	1,917	1,917	1,917	1,918	1,914
Total revenue	29,369,297	29,523,069	29,554,132	29,565,780	29,561,254	29,579,525	29,510,491

The results suggest that if the survival probabilities of default were used alone to accept applicants more net revenue would be earned than if the traditional logistic regression model was used, but the difference is small: a mere 0.67% of the value under logistic regression.

As a second step, we combine survival probabilities of default with survival probabilities of a second purchase. An OLS regression was fitted to model the net revenue, using the price of the first purchase and transformations of survival probabilities as predictors. We will refer to this as the "survival combination model".

Survival probabilities were calculated using only the exponential survival distribution model. The results are shown in Table 6.

Table 6. Results of Regression Model To Predict Net Revenue: the Survival Combination Model.

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	215.25	35.18	6.12	<.0001
Borrowed value at 1st purchase	1	0.24	0.04	6.79	<.0001
Default survival probability	1	-179.31	29.86	-6	<.0001
'Second purchase' survival probability	1	402.70	39.52	10.19	<.0001
Borrowed value * Default survival probability	1	0.19	0.04	4.69	<.0001
Borrowed value * 'Second purchase' survival probability	1	0.23	0.08	2.93	0.0033
Borrowed value * Default survival probability * 'Second purchase' survival probability	1	-0.30	0.09	-3.55	0.0004
R^2 = 0.2449					

Table 7 compares the performance of this survival combination score approach with that of a traditional approach of using logistic regression to predict default. In both cases the acceptance rate is kept at the current rate of 70%.

Table 7. Survival combination scores compared to default scores.

	Logistic default score	Survival combination score
Accepted bad	939	1397
Bad rate among accepts	6.09%	9.06%
Mean net revenue	1,905	2,085
Total net revenue	29,369,297	32,142,998
Total written off amount	630424	1,179,135

Table 7 shows some interesting results. In comparison with the traditional use of a default model alone to decide whether to accept or reject an applicant, more bads are accepted and the bad rate amongst the accepts is higher using the survival combination model, and so is the amount written off. But despite this the average net revenue per account (and so total net revenue for the portfolio) is 9.44% *higher*.

Obviously, the choice between two decision rules depends on the risk appetite of a particular lender, but given the increasing competition, the subprime market is becoming increasingly attractive and therefore it is becoming even more important to discriminate between profitable and unprofitable high risk applicants. Table 8 and

Figure 5 present the mean net revenue for a holdout cohort using traditional default risk score and combination score. The risk score is a probability of 'being good' derived from logistic regression and banded into groups, each containing 10% of observations. Lower bands correspond to high risk applicants. The combination scores are derived from the model presented in Table 5 and are also banded into 10% groups with lower bands containing less profitable customers. The shaded rows in Table 8 indicate cases that would be rejected according to the existing acceptance policy.

Table 8. Mean net revenue for each 10% band of combination score and each 10% band of default score, German Marks.

	Combination Score									
Default Score	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
10	1,141	1,271	1,377	1,659	1,757	1,868	1,988	2,272	2,375	3,485
20	1,365	1,131	1,417	1,512	1,762	1,909	2,114	2,458	2,650	3,263
30	1,795	1,039	1,327	1,343	1,691	1,792	2,095	2,229	2,527	3,532
40	1,889	1,045	1,248	1,308	1,511	1,723	2,057	2,194	2,456	3,423
50	1,977	1,052	1,205	1,328	1,585	1,805	2,074	2,248	2,463	3,420
60	1,878	905	1,173	1,379	1,369	1,646	1,934	2,158	2,498	3,482
70	1,857	917	1,053	1,277	1,369	1,584	1,879	2,194	2,476	3,350
80	1,697	956	1,061	1,226	1,346	1,534	1,838	2,063	2,516	3,289
90	1,742	844	1,066	1,178	1,481	1,590	1,828	2,125	2,516	3,366
100	2,053	619	869	1,154	1,400	1,642	1,888	2,115	2,366	3,362

Figure 5. Mean net revenue for each 10% band of combination score and each 10% of default score.

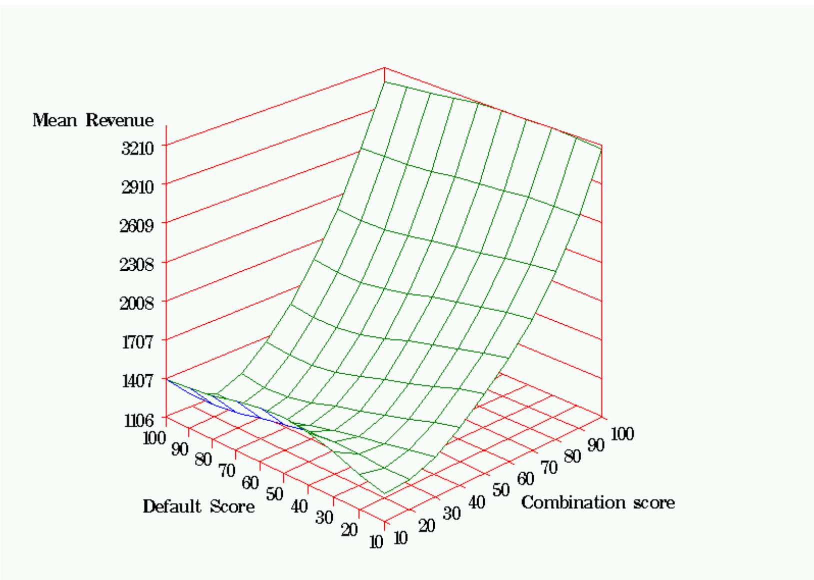


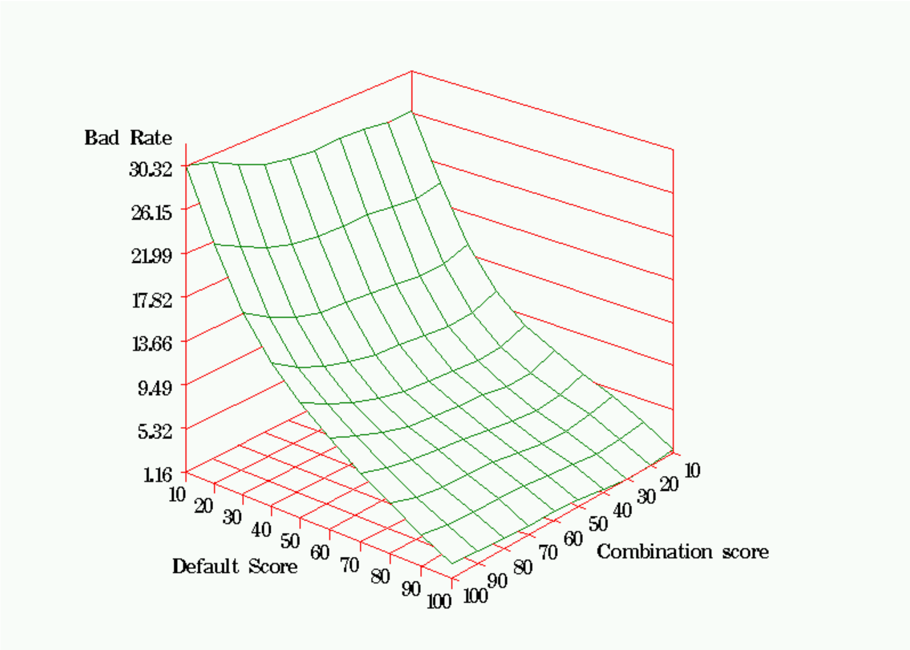
Figure 5 shows there is some non-linearity between observed mean net revenue and combination score in the lower bands of the combination score, but generally there is a positive relationship between observed net revenue and combination scores. Therefore it is possible to select profitable customers with each risk band including the lower risk bands: applicants that would normally be rejected on default probability alone. Alternatively, one may want to trade off low risk accounts with low net revenue for high risk customers with high combination scores id one wishes to accept only a given proportion of applicants with high combination scores.

Table 9 and Figure 6 give the bad rate for each combination of default and combination score bands. There is an increase in bad rate as the combination score increases, and this increase is most pronounced for high risk applicants. This indicates once again that increased profitability is associated with higher risk, and it is to a certain extent a policy decision what level of risk the bank is prepared to accept in order to increase its profit.

Table 9. Bad rate for each 10% band of combination score and each 10% band of default score, %.

	Combination Score									
Default Score	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
10	30.70	25.92	33.15	31.65	22.12	29.82	27.73	30.91	39.56	32.00
20	18.18	13.70	20.63	18.35	21.83	19.01	17.86	17.42	19.76	20.34
30	14.21	11.17	11.24	14.34	12.08	16.10	12.26	13.55	13.41	16.76
40	10.30	7.88	9.59	9.23	11.62	8.41	13.14	11.54	12.11	14.56
50	9.93	6.04	7.61	8.12	6.64	6.25	9.63	7.69	12.00	12.57
60	8.07	5.30	5.36	11.41	8.17	5.37	7.32	8.26	10.71	11.02
70	8.00	2.06	1.38	6.08	4.14	8.15	5.56	6.40	5.48	5.68
80	5.19	8.43	3.06	2.40	2.33	5.09	5.43	3.45	3.52	7.92
90	2.89	0.00	2.87	2.81	4.17	2.95	4.62	2.75	3.30	2.97
100	2.65	0.00	0.87	2.45	2.48	2.48	1.97	2.04	3.66	2.88

Figure 6. Bad rate for each 10% band of combination score and each 10% band of default score.



6. Conclusions

This paper has explored the relationship between present value of net revenue from a store card account and times to default and to second purchase. It is the first empirical investigation for a revolving type of credit based on a new profit-related measure for model performance which may be used in parallel to traditional measures of predictive accuracy, such as bad rate.

The estimation of profit from a revolving credit account requires measures for the default risk and the likely usage of the card. The card usage was measured by time to the second purchase. The hazard rates for the second purchase for Germany were investigated, and the contribution of two types of application characteristics (personal and first intended purchase) to predictive accuracy was explored. As we found in previously published results for Belgium (Andreeva et al., 2005), the results for Germany demonstrated a significant contribution of the first purchase information in predicting time to the second purchase.

Default risk was assessed by estimating time taken until two consecutive monthly payments were missed using a number of survival analysis models. Building on a previous study (Andreeva, 2006), the models were benchmarked against the current industry standard – logistic regression - using present value of net revenue. Only marginal differences in predictive accuracy of different hazard functions were found. Given that the predictions from exponential model were selected for further modelling of revenue, being the most parsimonious model.

We demonstrated that there exists a relationship between present value of net revenue and times to default / second purchase and these were incorporated into a survival combination model. The results suggest that there is scope for improving profit if an application for a store card is assessed by using a model which estimates the net revenue and includes the survival probability of default and the survival probability of second purchase (a survival combination model) rather than merely a static probability of default predicted by a logistic regression. However, increased profit comes at a price of an increased risk, and willingness to accept higher risk applicants with higher predicted net revenues depends on the attitude to risk of a particular lender.

Further research will concentrate on improving the accuracy of a survival combination model, and on incorporating time dependency into survival models that would made the approach investigated in this paper applicable not only to application scoring, but also to behavioural scoring.

References

Andreeva, G.,2006. European generic scoring models using survival analysis, Journal of Operational Research Society (accepted for publication).

Andreeva, G., Ansell, J.I., Crook, J.N., 2005. Modelling the purchase propensity: analysis of a revolving store card, Journal of Operational Research Society 56 1041-1050.

Banasik, J., Crook, J.N., Thomas, L.C.,1999. Not if but when will borrowers default, Journal of Operational Research Society 50 1185-1190.

Banasik, J.L., Crook, J.N., Thomas, L.C.,1996. Does scoring a subpopulation make a difference?, The International Review of Retail, Distribution and Consumer Research 6 (2) 181-195.

Crook, J.N., Hamilton, R., Thomas, L.C.,1992. Credit card holders: users and nonusers, Service Industry Journal 12 251-262.

Crook, J.N., 2002. Adverse selection and search in the bank credit card market, Working paper 01/2, Credit Research Centre, University of Edinburgh.

Hand, D.J., Kelly, M.G.,2001. Lookahead scorecards for new fixed term credit, Journal of Operational Research Society 52 989-996.

Hopper, M.A., Lewis, E.M.,1992. Development and use of credit profit measures for account management, IMA Journal of Mathematics Applied in Business and Industry 4 3-17.

Kalbfleisch, J.D., Prentice, R.L.,1980. The Statistical Analysis of Failure Time Data, John Wiley & Sons.

Keeney, R.L., Oliver, R.M.,2005. Designing win-win financial loan products for consumers and businesses, Journal of the Operational Research Society 56 (9) 1030-1040.

Kelly, M., 1998. Tackling change and uncertainty in credit scoring. PhD thesis, Open University.

Leonard, K.J.,1997. Behavior Scores to Predict Profitability, Credit Scoring and Credit Control V Conference Proceedings, Credit Research Centre, The University of Edinburgh.

Narain, B.,1992. Survival analysis and the credit granting decision. In: Thomas, L.C., Crook, J.N., Edelman, D.B (Eds.) , Credit Scoring and Credit Control, Oxford University Press, Oxford, pp. 109-122.

Oliver, R.M., Wells, E.,2001. Efficient frontier cutoff policies in credit portfolios, Journal of the Operational Research Society 52 (9) 1025-1033.

Shank, J.K., Govindarajan, V.,1992. Strategic Cost Analysis of Technological Investments, Sloan Management Review 34 (1) 39-52.

Stepanova, M., Thomas, L.C.,2001. PHAB scores: proportional hazards analysis behavioural scores, Journal of Operational Research Society 52 1007-1016.

Stepanova, M., Thomas, L.C.,2002. Survival analysis methods for personal loan data, Operations Research 50 (2) 277-289.