Decision Support Systems 59 (2014) 143–151

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Using a transactor/revolver scorecard to make credit and pricing decisions

Mee Chi So [a,*], Lyn C. Thomas [a], Hsin-Vonn Seow [b], Christophe Mues [a]

[a] *Southampton Management School, University of Southampton, Southampton SO17 1BJ, United Kingdom*
[b] *Nottingham University Business School Malaysia, University of Nottingham Malaysia Campus, Jalan Broga, 43500 Semenyih, Selangor Darul Ehsan, Malaysia*

ARTICLE INFO

Article history:
Received 14 March 2013
Received in revised form 8 October 2013
Accepted 8 November 2013
Available online 16 November 2013

Keywords:
Pricing
Risk decision analysis
Credit scoring

ABSTRACT

In consumer lending the traditional approach is to develop a credit scorecard which ranks borrowers according to their risk of defaulting. Bads have a high risk of default and Goods have a low risk. To maximise the profitability of credit card customers, a second classification between revolvers and transactors becomes important. Building a transactor/revolver scorecard together with a Good/Bad scorecard over the revolvers, gives rise to a risk decision system whose ranking of risk is comparable with the standard approach. The paper develops a profitability model of card users including the transactor/revolver score leads. This gives more accurate profitability estimates than models which ignore the transactor/revolver split.

1. Introduction

For many years credit card organisations have split users into transactors and revolvers [8]. Transactors are credit card users who pay off their balance every month and so incur no interest charges. Revolvers are credit card users who do, occasionally or regularly, pay off only part of their monthly balance and so do incur interest charges. Credit card companies currently do not attempt to make this distinction when initially deciding whether to give an applicant a credit card. Instead they estimate the probability the applicant will be Bad — i.e. default or be written off within a given period, usually 12 months. Applicants who are not Bad are considered Good. Lenders develop application scorecards which estimate the probability of the applicant being Good.

The transactor/revolver split affects these Good/Bad estimates because if a transactor pays the balance off every month for a period which is longer than the performance period in the Good/Bad definition then all transactors must be Goods. Thus transactor/revolver is a useful segmentation of the population in terms of default risk. In terms of profitability the transactor/revolver split is even more important. Transactors do not produce any income to the lender from the interest charged on the card. On the other hand, transactors tend to use their card to fund more expensive purchases than revolvers. Thus for pricing decisions a transactor/revolver scorecard will improve the underlying profitability model.

This paper proposes that lenders develop a transactor/revolver score as well as a Good/Bad score to aid their decision on what "price" or interest rate to charge and which applicants to accept for a card. We show how such a transactor/revolver score can be built using logistic regression by applying it to a real credit card data set. Using such a score together with a Good/Bad score based on the revolver segment of the population produces a risk assessment system that compares well with the standard approach of building a Good/Bad scorecard on the whole population.

We also build a profitability model for the portfolio of potential credit card applicants. This model includes the chance that the applicants will take the credit card offered and this take probability depends on the interest rate charged on the card and on the riskiness of the applicants. The profitability model is applied both with and without a transactor/revolver score available. We compare the outcomes of these two models on the same numerical example. The results show how much more sophisticated the accept/reject policy is when the transactor/revolver score is available compared with when it is not available. Moreover the resultant model is more representative of the real situation because the model without a transactor/revolver score overestimates the profits by assuming that all transactors take a long time to pay off their balances. Thus the pricing decision of what interest rate to charge is more robust if the underlying model has a transactor/revolver score.

The standard approach to building scorecards [1] involves univariate analysis and stepwise regression to identify the borrower characteristics that most impact on the borrower's subsequent Good/Bad status. The important characteristics are then modified using coarse classification. Over the last twenty years, numerous regression, mathematical programming or machine learning techniques have been used by researchers in the final step of combining the characteristics into a scorecard that estimate default risk [12,14,17]. In practice, logistic regression is still the most popular techniques [23]. Since the focus of this paper is to propose a new mechanism for making credit and pricing decision but not to benchmark the performance of various techniques, we build all the scorecards using logistic regression.

* Corresponding author. Tel.: +44 23 8059 8964.
E-mail addresses: m.so@soton.ac.uk (M.C. So), l.thomas@soton.ac.uk (L.C. Thomas), hsin-vonn.seow@nottingham.edu.my (H.-V. Seow), c.mues@soton.ac.uk (C. Mues).

0167-9236/$ – see front matter
http://dx.doi.org/10.1016/j.dss.2013.11.002

References to transactors and revolvers are common in the financial press but less so in the academic literature. Field and Walker [8] outlined the difference between revolver and transactor. They and other writers commented on the lack of precision in the definition of transactor. Over what period should a borrower repay fully every month the balance on his credit card to be deemed a transactor? More recently the financial press has looked at whether lenders are favouring transactors [6] or revolvers [4]. The Federal Reserve Bank of Philadelphia [11] studied the characteristics of revolvers and transactors and not surprisingly found transactors to be older and richer than revolvers.

Kim and DeVaney [15] looked at who had credit cards and then among credit card holders what were the characteristics of revolvers and transactors. They applied a Heckman two stage model to identify the important characteristics. The data were taken from the 1998 Survey of Consumer Finances and so many of the important variables were ones that are not available to credit card lenders. These included the amount of liquid and investment assets, the attitudes of the borrowers to using credit for different expenses, and their income expectations. Our transactor/revolver scorecard uses the information normally supplied on a credit card application form or held by a credit bureau. So and Thomas [20] examined the different ways changes in economic conditions affected the default risk of revolvers and transactors. For example the default risk of revolvers reacts much more to changes in the unemployment rate than that of transactors.

Zinman [24] built a neoclassical choice model to explain why some consumers use debit cards while others act as credit card transactors. Initially it would appear the latter is a much more rational choice than the former because of the interest free period that it allows. The paper looks at reasons why it might be rational for a consumer to prefer the former to the latter. Further work on this problem was undertaken by Sprenger and Stavins [21]. Using data from the 2004 Survey of Consumer Finance, they showed that credit card revolvers are more likely to using debit cards if they can.

There is a literature on modelling credit card profitability, but with one exception, the models do not involve the transactor/revolver split. The papers split into ones which model the cash flow between a credit card user and the lender and those which use a sample of credit card users to estimate the relationship between spend or profit over a given period and the characteristics of the users and their behaviour.

In the first camp, Hussain [13] is the only paper which includes the transactor/revolver split in its model. It includes profit from interest payments, merchant service charges, and a fixed fee. However, it assumes that revolvers repay the cost of a purchase over an infinite number of periods and sets the cost of default as a fixed amount for each user. Moreover the model is applied only at the portfolio level. Our model starts at the individual user level and so allows analysis of the optimal accept/reject initial decision on each potential applicant. Oliver and Oliver [16] introduced the take probability of whether a potential used will accept the credit card given the rate of interest offered. This is also a feature of our cmodel, but the cost structure of the Oliver model is of a one-off loan rather than a credit card.

The second stream of papers models the profit and the spending using data from a card portfolio. Stewart [22] assumes spend is a function of risk grade and that the profit depends on spend and default risk. A spend model is built for each default risk band. Singh et al. [19] use a DEA (Dynamic Envelopment Analysis) approach where the outputs are the revenues from the interest rate charged, the merchant service charge and the fixed fees. The mean and variance of the fixed fees is considerably smaller than the other two sources of income.

Finlay [9] and Andreeva et al. [2] estimate credit card profitability by first estimating two other quantities and then combining them in a profit formula. Finlay [9] builds a regression model where the dependent variable is a combination of the average payments made in a period and the balance of the account when in arrears. This is compared with a standard default risk based scorecard based. The former gives more accurate rankings in terms of the actual profits than the latter. This approach of estimating the individual aspects of profitability before combining them in a profit formula was expanded further in Finlay [10]. In that paper the default probability, the bad debt levels and the revenue are estimated using genetic algorithms and neural nets as well as logistic regression. These are combined in a profitability formula and the results compared with those from using the standard default risk scorecards. Andreeva et al. [2] looked at a sample of a retailer's credit card accounts. They used the proportional hazards models to estimate the time to default and the time to the next purchase in terms of the user characteristics. The net present value of revenue was then estimated using regression based on the estimates of these two times. Not surprisingly this proved to give a more accurate ranking than that based on a default risk scorecard.

The book by Phillips [18] and the book chapter by Caufield [5] describe the current position of credit cards pricing both theoretically and at a practical level. The "price" of credit cards is essentially the interest rate charged, though it could involve the fixed fees if they are charged. Neither Phillips [18] nor Caufield [5] refers to credit card models which involve a transactor/revolver split.

The profitability model we propose assumes the lender thinks of a revolver as paying off debts in the order they are incurred. The lender first sets any payment to repay the oldest debt, and then the second oldest debt and so on until the payment is used up. This is exactly the ordering that credit card companies use when dealing with balance transfer to a new credit card. They set the payments against the balance transferred before using them to pay off the new purchases on the credit card. This approach implies revolvers pay off the interest caused by a specific purchase after a few periods provided they have not defaulted in the meantime. Any other assumption would be equivalent to a borrower paying off the interest on a purchase which they have already paid for. Other models in the literature either assume the interest is paid indefinitely or ignore the interest. Both approaches are unrealistic. Our model also includes the take probability which is how likely applicants will accept the credit card offer made. This is important when considering what optimal interest rate to charge. We will show the profitability for a few interest rates and we concentrate on finding the most profitable cut-off score on the Good/Bad scorecard under these different interest rates. This allows us to find the optimal interest rate to charge.

In the next section, we build a Good/Bad scorecard on a credit card data set from Hong Kong. This will be used as a comparator for the approach to default risk using the transactor/revolver scorecard. In Section 3, we build a transactor/revolver scorecard on the same data set. In Section 4 we develop a Good/Bad scorecard built only on revolvers. This together with the transactor/revolver scorecard produces a risk assessment system. We compare this risk assessment system with the standard approach of Section 2. In Section 5, we describe the credit card profitability model when we do not distinguish between transactors and revolvers. We derive the cut-off score that maximises profitability and apply the model to a numerical example. Although there is no analytic expression for the optimal interest rate to charge we can find this by calculating the profitability for different interest rates. In Section 6 we extend the profitability model to the case where a transactor/revolver score is available. We again find the Good/Bad cut-off strategy which maximises the profitability of the portfolio. This is more complicated since the cut-off score is a function of the transactor score. We apply this model to a numerical example which reduces to the numerical example in Section 5 if the transactor/revolver split is ignored. Finally in Section 7 we draw some conclusions from our analysis and some areas for future research concerning the use of transactor/revolver scorecards.

2. Building Good/Bad scorecards

The traditional approach in credit scoring is to build an application scorecard which estimates the probability of an applicant not defaulting