

Consumer Credit Modelling: Context and Current Issues

L.C.Thomas

School of Management, University of Southampton, Southampton, UK

1. History of consumer credit

As Lewis (Lewis 1992) records consumer credit has been around for 3000 years since the time of the Babylonians. For the last 750 years of that time there has been an industry in lending to consumers, beginning with the pawn brokers and the usurers of the Middle Ages, but the lending to the mass market of consumers in the non-Islamic world is a phenomenon of the last fifty years. In the 1920s, Henry Ford and A.P.Sloan had recognised that it was not enough to produce products, like cars, for the mass market but one also had to develop ways of financing their purchase. This led to the development of finance houses, e.g. GE Capital, GM Finance. The advent of credit cards in the 1960s meant that consumers could finance all their purchases from hair clips to computer chips to holiday trips by credit.

Subsequently the growth in credit card purchases was matched by the growth in credit extended by other products such as personal loans, car loans, bank overdrafts, store cards, payment of utilities in arrears, and dwarfed by the growth in consumer credit via mortgage lending. Each of these products has its own unique features, so that financial markets include a mix of credit and interest rate risk in a complex economic and financial environment. Consumer credit is large not only in monetary terms but also in the huge numbers of consumers involved and also the impact on those who are denied consumer credit. Because credit and debit cards are often used in lieu of checks and cash payments there has been an enormous influence on money payment mechanisms. Most of the adult population have some financial product from a bank or other financial institution, and most have more than one. Major banks typically have millions of customers and carry out billions of transactions per year. The enormity of the role of consumer retail debt is suggested by the fact that the average debt of an individual over all sectors is about one dollar per dollar of disposable income.

The growth in consumer credit outstanding over the last fifty years is truly spectacular see figure 1. The marketplace in the U. S. and Canada for total retail banking and consumer lending is enormous; it exceeds corporate debt by about 75% with household debt in the United States exceeding \$8.4 trillion in the year 2002, more than double the amount owed in 1992. This number compares with corporate bond debt in the same period of about \$2.5 trillion. Home mortgages and equity loans in the United States account for about 70% of this total (by contrast with 80% in the U.K.) with the next largest categories being credit card and then nonrevolving credit, (see figure 2). In 2002 there were over 500 million

credit cards in Europe and the number of transaction was approaching 2,000,000,000.

Not all of this growth is because of the borrowing on credit lines. Credit cards (and debit cards) have become increasingly important as a method of money transmission,. In 1993 in the UK there were 1316 million transactions by plastic card of which 724 million were by credit card compared with 3728 million transactions by cheques. By 2002 plastic card had overtaken cheque usage with 4814 million transactions on plastic cards of which 1687 million were by credit card while there were only 2393 million cheque transactions. Moreover the newer forms of commercial channels like the internet are dominated by credit card usage. Between 1999 and 2002 the number of UK adults using the internet has increased from below 10 million to 26 million, while the number using cards to pay for internet purchase increased from 1.3 million to 11.8 million with a total transaction value of £9 billion. More than 70% of internet payments are by credit card and this percentage is increasing all the time.

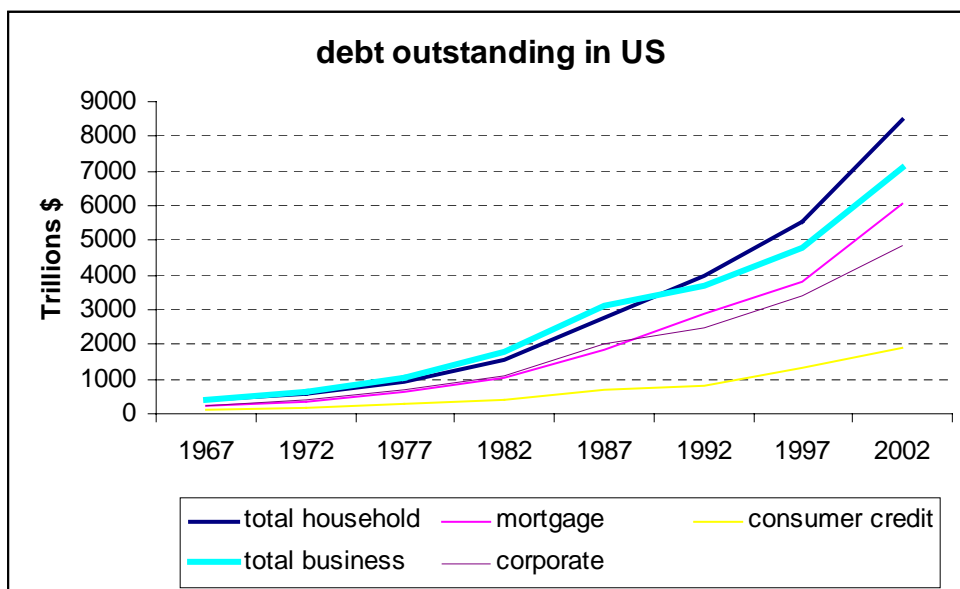


Figure 1: Comparison of household debt with business debt in US 1967-2002

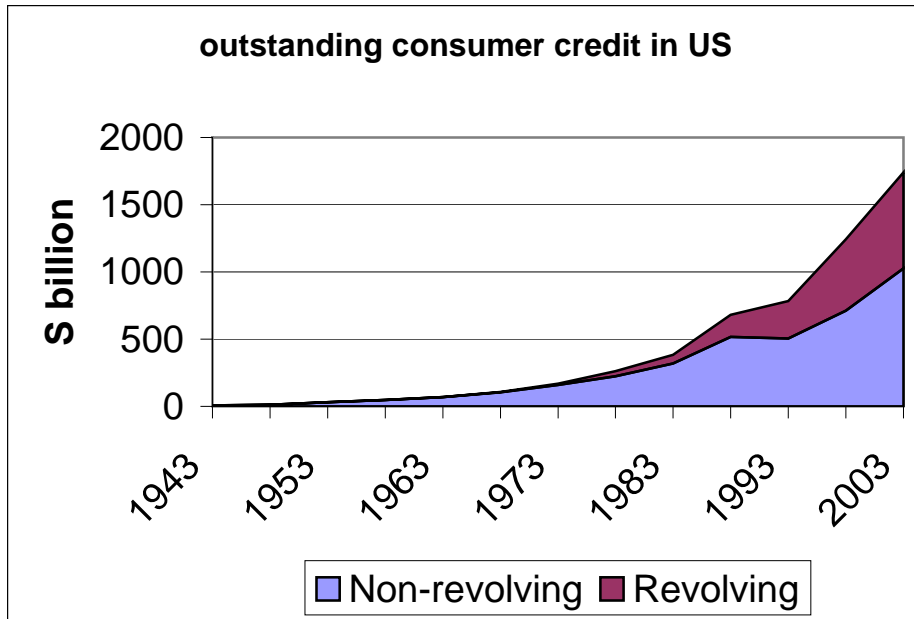


Figure 2: Outstanding consumer credit in US 1943-2003

2. History of consumer credit modelling

Consumer credit modelling has been shaped by the decisions it sought to support, particularly the initial decision of whether to accept a new applicant for credit. Application scoring or credit scoring initially sought to improve these decisions and to make them more consistent and then subsequently to automate them so that organisations could deal with the high number of applications for loans. The underlying philosophy was pragmatic and the underlying assumption was that credit worthiness was time independent. The idea was to use the lender's data on past applicants to order current applicants in order of default risk. Any information on the applicant which improved the prediction of default should be considered (see the interesting exchanges in the Congressional hearing leading to the US Equal Credit Opportunity Acts (Johnston 1992)) and there was no attempt to build a causal or explanatory model. Moreover an application scoring model was usually built using data on those who applied more than two years ago and looked at their credit performance of at least a year ago. The idea was that this should be still valid for current applicants and their future performance.

Moreover although the objective was to assess a very specific risk –the chance that an applicant will miss three consecutive payments in the next 12 months for example – the actual values did not matter provided the relative ordering of the applicants was correct. This is because the lender chooses the cut-off score , i.e. the point at which applicants are accepted, subjectively or at least using empirical evidence like accept rate or marginal good:bad rates. So the actual estimated default risk probability does not come into the final decision.

The data that is available for application scores was greatly enhanced with the development of credit bureaus. These were able to pool data on the performance of a consumer with different lenders and to check official documents like the electoral roll and court rulings to obtain further information on the consumer and those around him. The data held by credit bureaus varies substantially between countries because of the countries' culture concerning data protection. So on the one extreme one has the US where information is available on all the credit lines held by an individual whereas in some European countries the data is limited to the official publicly available documents. There are also legal constraints on what information can be used and what must be used and again there are considerable international variations. The US Equal Opportunity Acts mentioned earlier prohibited the use of gender, race, religion and even put restrictions on age and other countries have similar but not identical lists of legally prohibited variables. Australia on the other hand requires that all lenders do an affordability calculation as part of their credit modelling process by looking at the income and current outgoings of a potential creditor to ensure that they can "afford" the loan. The differences in the laws governing consumer credit models will lead increasingly to problems of jurisdiction. Whose laws should apply to someone living in the UK who has a euro based credit card with a US credit card organisation and uses it for his travels in Australasia?

There was an obvious extension from application (credit) scoring to behaviour scoring where one uses the information on the payment and purchase behaviour of a current customer as well as their social demographic information to determine their risk of default over a fixed future time horizon. The approach was exactly the same as credit scoring but using many more variables which described the customers performance during some previous observation period. Sometimes as many as a 1000 variables were used initially to try and describe the nuances of a customers performance in this observation period. Two aspects tended to be ignored in the move from application to behavioural scoring. Firstly what decisions were these behavioural scores to be used for? It was not simply whether to advance the customer further credit which they had applied for but also for other decisions such as whether to send them a new mail order catalogue (one of the earliest applications), whether to direct market other products to them, whether to give them unsolicited increases in their credit limit (or at least in their shadow credit limit) or even whether to offer them better features on their credit product so as to keep them as customers and prevent attrition to other lenders. Secondly that instead of building a statistical classification model one could use the dynamics of their past behaviour to build a dynamical probabilistic model of their future behaviour. Such models based on Markov chain ideas were suggested as early as 1962 by some authors (Cyert et al, 1962) but the industry concentrated on behavioural scoring models which used classification techniques to identify potential defaulters.

3. Current issues in consumer credit modelling

There are several issues that are impinging on consumer credit modelling at the start of its second fifty years of its history. These are the changes in lender objectives from assessing default risk to other business objectives directly linked to shareholder value of the firm. Secondly the realisation that lenders have a number of decisions that they want to optimise not just whether or not to accept a customer for a “vanilla” loan or credit card product. Thirdly the market for consumer credit in Western countries is becoming more mature and so this means there is more emphasis on customer retention and customer acquisition with the realisation that one cannot choose a portfolio of loans and keep the portfolio constant. Finally, the advent of Basle II has put the spotlight on the need to be able to model the credit risk of portfolios of consumer loans rather than just deal with each loan independently the proposed new regulations require the lenders to provide equity capital as a function of the risk of the loans being funded.

In the last decade there have been moves both to expand and to unify the objectives of consumer credit models. In some ways credit scoring was the grandfather of data mining techniques and especially in developing propensity functions and so it was an obvious extension for lenders to build scorecards to estimate the propensity of a consumer to do other things apart from default. Thus there are now response scorecards (will the consumer respond to a direct marketing offer), usage scorecards (will the consumer use the credit product if given it), and attrition scorecards (will the consumer continue with the lender especially if there is some special offer available for an introductory period only). So there are increasing numbers of scores attached to a consumer. On the other hand there has been a desire among lenders to concentrate more on the profitability of the consumer rather than their default probability. Thus there has been a limited movement from product default scoring (which tried to estimate the chance of the probability the customer will default on a particular credit product in a fixed future time period) to customer default scoring (which tries to estimate the customer defaulting on some credit relationship with the lender) to product profit scoring (which seek to estimate the profit the lender makes on this product from the customer) to customer profit scoring (which try to estimate the total profitability of the customer to the lender). Most of these approaches are still at pilot scheme levels. Some have involved using turnover or other financial measures as surrogates for the reward to the lender with a standard default score as a measure of risk. These are then combined in some way. Others have sought to use regression to estimate directly the relationship between profit and the customers application and behavioural characteristics or to use Bayesian learning networks or survival analysis to indirectly connect profit and the customer's characteristics. A fourth approach has been to return to the probability models based around Markov chains so as to use dynamic programming to identify profit maximising policies (Trench et al 2002).

One of the reasons for these changes in objective is that lenders want to optimise the decisions related to a customer rather than just forecast the customer's default risk. Lenders realise they can initially choose the credit

limit, the interest rate, and the other product features to offer so as to maximise the profitability of the customer to them and they can adjust these as well as making other operating and marketing decisions during their relationship with the customer. It may be necessary to build different models with different objectives to help decide these different decisions.

In particular the market is beginning to become accustomed to risk based pricing for credit products. The idea that customers with different risk profiles should pay different amounts for the same product has long been accepted by consumers in the insurance industry but it has taken some time to be accepted in the credit industry or even for the industry to seek to introduce risk-based pricing policies. The problem of deciding which price to charge a customer for a product needs more sophisticated modelling than whether one should accept or reject a customer at a given "price" or interest rate. However there are movements towards this type of product and hence a need to model the situation to choose the optimal "price" for a given risk. These models need to use both risk ideas and marketing assumptions on coping with attrition and churn of customers. Few such models have been attempted.

Traditionally consumer credit modelling has modelled each loan/customer in isolation, but the lenders are really interested in the characteristics of their portfolios of retail loans. This interest has been reinforced by the emphasis on internal ratings based modelling in the new Basle Capital Accord, which will regulate banks' lending from 2007. This allows banks to insert their own parameter estimated for the probability of default and loss given default into a corporate credit risk type model to estimate the distribution of default loss for segments of their consumer loan portfolio. This has highlighted the need to develop accurate estimates of default probability and to be able to segment a loan portfolio in an "optimal way" so as to have estimates which are accurate overall and can minimise the capital required to cover those expected and unexpected default losses. Even more crucially it has pointed out that consumer credit has not developed its own models of the default risk of portfolios of loans and so the regulators have imposed a corporate credit risk model with arbitrarily chosen correlation parameters. Consumer credit modellers need to decide whether such models are appropriate for portfolios of consumer loans and if not to develop appropriate models.

Another pressure to improve the models for understanding credit risk of portfolios of consumer loans comes from the increase in volume of securitization of such loans. This occurs when combinations of loans or different loan portfolios of similar products are bundled together by the lender and sold to a third party or issued as tranching bonds in the public marketplace. The third party assumes the profit and risk of default from the new portfolio of bundled borrowers ; because of the presence of third-party processors this may be possible without detailed management of the portfolios. The price that one should pay for a bundled portfolio clearly depends on the credit risk involved. Although the credit score distribution of the loans is considered when the portfolio is securitized there do not seem to

be any consistent objective models of how to price this bundled portfolio. There is also the problem of which are the desired return and risk tranches to bundle together in a securitized package. Currently this seems to be done using subjective judgement and ease of implementation (for example all car loans for cars of a given make) rather than any modelling approach.

4. Improvements in existing areas of consumer credit modelling

There are two areas where consumers are constantly seeking to improve existing consumer credit models. The first is to look at new approaches to the classification problem and the second is to deal with practical business problems that keep arising.

Traditionally estimating the default risk of an applicant or current borrower has used linear or logistic regression, mathematical programming or classification trees, with logistic regression now being the most common approach. The regression approach to linear discrimination says that p , the probability of default, is related to the application characteristics $X_1, X_2 \dots X_m$ by

$$p = w_0 + w_1 X_1 + w_2 X_2 + \dots + w_m X_m$$

This has one obvious flaw. The right hand side of the above equation could take any value from $-\infty$ to $+\infty$ but the left hand side is a probability and so should only take values between 0 and 1. It would be better if the left hand side was a function of p which could take a wider range of values. One such function is the log of the probability odds. This leads to the logistic regression approach where one matches the log of the probability odds by a linear combination of the characteristic variables, i.e.

$$\log (p/(1-p)) = w_0 + w_1 X_1 + w_2 X_2 + \dots + w_m X_m$$

In both these cases the right hand side of the equation gives a linear score and the lender decides what the cut off c will be so that those with score c or above are accepted and those with score below c are rejected (high score is equivalent to low probability of default). Linear programming also leads to a score for each person and a cut-off c by trying to minimise the errors e where for the goods their score should satisfy

$$w_1 X_1 + w_2 X_2 + \dots + w_m X_m \geq c - e$$

while for the bads their score should satisfy

$$w_1 X_1 + w_2 X_2 + \dots + w_m X_m \leq c + e$$

This is like trying to minimise the l_1 error while regression is like minimising the l_2 error. Classification trees on the other hand split the population into two groups which are more homogeneous in the bad rate and keep repeating this procedure until one has a number of groups which are identified either as good or bad and cover the whole set of a possible characteristics. Sometimes the methods are combined with a classification tree used to identify subpopulation and then regression is used to build a scorecard for each

population. In other cases the variables in a regression scorecard may be the outcomes of a small classification tree. The received wisdom is that the difference in classification accuracy of the different methods is less important than errors that may arise because one does not have a timely, relevant, error free sample.

Authors	Linear reg	logistic reg	Class trees	LP	neural nets	GA
Henley(1995)	43.4	43.3	43.8	-	-	-
Boyle (1992)	77.5	-	75	74.7	-	-
Srinivisan(1987)	87.5	89.3	93.2	86.1	-	-
Yobas (1997)	68.4	-	62.3	-	62.0	64.5
Desai(1997)	66.5	67.3	67.3	-	6.4	-

Table 1 :Classification accuracy of different approaches

Several authors have looked at the differences and academics have published some comparison results which are summarized in Table 1. As well as the established methods several others have been suggested in the last decade. These include nearest neighbour methods, where a metric is developed on customers' attributes to measure how close customers are to one another. When a new customer arrives he is classified good or bad (and hence accepted or rejected) depending on the numbers of good and bads among his nearest neighbours. Determining a suitable metric for this approach is very similar though to developing a linear scorecard. Neural nets are a well established method of classifying and have been piloted in various ways on consumer credit data and with more success on business failure data. Genetic algorithms have been used to find the "fittest" scorecards among populations of scorecards where fitness corresponds to correct classification. More recently vector support machines have been used in classification problems. Superficially these look like the linear programming approach but where not linear functions of the variable are allowed.

Baesens (Baesens 2003) made a careful study of 1 different methods using 8 different consumer and small business data sets. The methods were linear regression (and its quadratic variant), logistic regression, linear programming, 4 variants of vector support machines, 4 variants of classification trees, 2 variants of nearest neighbours, neural net, naïve Bayes and tree augmented naïve Bayes. In the last two the probability of being good is firstly the independent product of the conditional probabilities of being good dependent on each characteristic value in turn and second allowing some dependence between the characteristics through a tree structure. What is startling (but confirms the closeness of the methods) is that six different methods are best

in terms of classification accuracy (PCC – percentage correctly classified) among the eight data sets – linear regression, logistic regression, linear programming, classification tree, neural nets (twice) and Support vector machines (twice). The average relative ranking among the 17 methods on the 8 data sets is given in Table 2 for the significant approaches. Only Naïve Bayes is significantly worse than the others in the statistical sense.

Method	Linear Regression	Logistic regression	Linear Prog	Support Vector machines	Neural Nets	Naïve Bayes	Classification Trees	Nearest Neighbour
Average ranking in PCC	6.9	6.1	6.5	3.6	5.2	15.1	6.7	7.9

Table 2: Relative ranking of methods

As well as trying new methodologies to improve the default risk classification, there are also pilot studies on changing the objective of the classification. Instead of asking if a customer will default or stop using a credit card in a given time period one can ask when will these events happen. This question is then very similar to the survival analysis ideas in mortality and equipment reliability and several authors (for example Stepanova and Thomas 2002) have shown how the techniques from survival analysis can be used in this context. Other authors have suggested an indirect approach to estimating default or profitability by estimating first the variables like future balances and payment levels that relate to these objectives. Bayesian learning networks have been tried to build models connecting the consumer’s characteristics and these intermediate and final objective variables (Whittaker 1990)

The practical problems of consumer credit modelling relate to how to measure a scorecard’s performance, how to build a scorecard for a new product when there is little data, how to improve the monitoring of scorecards and how and when to adjust and rebuild scorecards or change the operating policy they underpin. These have been issues since scorecards were developed but are still of considerable importance. The amount of data available means scorecards can be measured on holdout samples rather than the training samples they were built on (which would give optimistically biased estimates). The efficacy of the scorecard in general is normally measured using Gini Coefficient (related to Concordance statistic), Kolmogorov Smirnov statistics and can be displayed in terms of a ROC curve. Note that these measures assume some ordering of the customers, i.e. a score and so techniques like classification trees have to have scores (good:bad rate in the various final nodes) imposed on them. In operating a scorecard though one has to choose a specific cut-off value and then one has to compare pairs of statistics such as acceptance rate, bad rate among the accepts, marginal bad rate etc, to measure the effect of the system . When comparing two scorecards or two cut-offs, it is useful to compare the effects of swap sets which have different effects under the two systems. . Recently some of the work (Oliver and Wells 2002) of comparing expected losses with expected profits at a portfolio level could lead to new ways of comparing scoring systems.

If the organisation has little data on how consumers have performed on a product (because it is new or little used) standard scoring approaches do not work and there is a need to use generic bureau scores in these cases. Monitoring scorecards has two purposes – to check if the power of the connections between the characteristic used and the incidence of default is as strong as in the training sample and to check whether there are changes occurring in the “through the door” population compared with that in the training sample. The letter can be done from the start by looking at statistics of the distribution of the score and the attributes of the characteristics. The former needs time to see the relationship unfold though dynamic delinquency reports segmented by cohort allow one to identify early changes and project them forward. This is an area where survival analysis models may make early detection of changes easier.

Deciding when and how to adjust scorecards or their operating systems has been greatly influenced by the champion v challenger approach that current operating software allows. In this one need not use just one operating policy or even just one suite of scorecards but one can be testing out alternate policies and/or scorecards on randomly chosen minorities of the population. Thus there is an ethos of constant improvement at least in terms of operating policy. As to adjusting and rebuilding scorecards there tends to be regular checks for alignment of the actual good:bad odds with the scores and if these are not too far out of line fixes like F-delta adjustments can be used to make minor modifications. Once the alignment of the scorecard or the underlying population has changed substantially though one tends to build a new scorecard. Thus even though the time between rebuilds of a scorecard is probably increasing somewhat in the industry one is still expecting scorecards to last no more than 3-5 years. This begs the question why cannot one build more robust models and if the models do deteriorate so quickly are there important factors which are not being considered in the modelling.

5. Data cleaning and parameter estimation problems

There has always been considerable emphasis in consumer credit modelling on ensuring the data is timely, valid and free from error. Thus the industry takes great care to ensure that all standard data checking and data cleaning techniques are used, though unlike other areas it would recognise missing data as an attribute to a characteristic if the relevant information is not supplied. It has always recognised that the data set of past customers used in building the models is biased because there is no payment and ordering information on those it rejected. Ways of dealing with this bias – reject inference – have been and continue to be the subject of considerable debate and research (Hand and Henley 1993). It is the case though that one can overcome this bias by randomly accepting 1 in n of those which the system said to reject, where n could be a function of the risk score. Surely one can choose n so this is an acceptable cost for any organisation.

What is less prominently considered are the more recent biases in the data which are also more difficult to remove. Firstly in the current saturated credit market an increasing number of consumers do not take up the offer of the loan they had applied for or if given a credit card do not ever use it. Thus one cannot tell whether such consumers would default if they used the loan or what their purchase performance would be like. Should such consumers be part of the sample because we may have changed the product features so such consumers would now use the lending facility? Moreover how do we decide what features of the lending facility make the consumers decide whether to accept it or not and how should they be changed, if they can be so as to make the customer most profitable to the lender. This issue will be discussed more in the next section.

In order to increase the profit from an individual consumer, the lender can change the credit limit available, the interest rate charged, the way the product or related products are marketed to that individual. Thus the performance of the consumer depends on the operations and marketing strategy the lender uses on him. How does one deal with these biases – policy inference- when one wants to develop models of consumer behaviour in order to apply different policies in future. Can one construct what would be the consumer's performance under a "vanilla" operating policy and then recognise what impact the different operating and marketing decisions will have. In some ways this is a more intractable and yet more important question than reject inference that has yet to be addressed by anyone.

6. Customization of loan product and risk based pricing

Perhaps the greatest surprise in the consumer lending industry has been how long it has managed to keep to one uniform product at one uniform price, particularly in the credit card market. The differences in the APR on interest rates has been traditionally very small and credit cards moved into and out of the annual fees, changes in interest free periods, and initial interest free periods on balance transfers almost en block. However it is clear that there is more diversity appearing in the industry as some lenders chase niche markets and go into high quality relationship banking or sub prime lending. This leads to the need to customize the product to an individual so as to maximise the profit from that individual and in particular to price the product according to the risk. For most lending products the price is the interest rate charged though in some cases there are up-front fees involved.

It is only very recently (Oliver 2001 , Keeney and Oliver 2003) that the first models for risk based pricing are appearing. These models seek to identify price-setting policies as a function of default probability that maximise the overall profit. This function can be changed by changing interest rates but the profit functions will also depends on the attractiveness of the offer to the consumer. So one needs to look at both the lender's and the consumer's utility preference among the features of a lending product. Again little has been done here but Keeney and Oliver (2003) have developed a theoretical example based on two features interest rate and credit limit. This is clearly an

area where one needs a multi-disciplinary approach involving experts in marketing models and utility theory as well as consumer credit.

One of the difficulties is that because customisation of a product is so new there is little data available to investigate different models. There are very small data sets available using application characteristics and subsequent take not take decisions for fantasy loan products using students or in-house employees. One of these has been used to build models of the probability that an individual will take a product with specific features using three different approaches. The first extends the usual logistic regression scoring approach while the other two use the idea of a dominant offer feature to build models based on linear programming and accelerated life approaches (Jung 2003). This idea of identifying what features affect a consumer's probability of accepting a loan product and how the offer features and the consumer's characteristics interact might also be amenable to Bayesian learning network modelling.

7. Impact of New Basel Capital Accord

The Bank of International Settlement (BIS) – the banking regulators of the major economies – has been seeking to reform the regulatory capital requirement of the 1988 settlement for five years and a final version of the New Accord is expected by the end of 2003 for implementation at the start of 2007. Its emphasis is on separating out the risks facing banking institutions – market risk, credit risk and operational risk – and on letting banks use their own internal ratings models to assess the credit quality of their loans. Lending is divided into five sectors – corporate, retail, sovereign, bank and equity – and the retail sector covers what we consider to be consumer lending- residential mortgages, revolving credit and unsecured consumer loans. In this sector banks can either take the standardised approach which means setting aside a fixed percentage of the loan to cover the risk of default as at present or use the advanced Internal ratings based (IRB) approach which involves segmenting their loan portfolio and for each segment estimating the probability of default in the next 12 months and the percentage loss given default. These parameters are then used in a one factor corporate credit model to identify the capital to be set aside to cover losses due to borrowers defaulting. In early version of the draft Accord there was the view that once a bank uses the IRB approach for one part of loan book, it must implement it across all areas, which would mean that to take advantage of their corporate credit risk models banks must use IRB on the retail side. The latest version of the accord is less prescriptive in that it will “ allow a phased rollout of IRB across banking group, but banks must produce an implementation plan”. It is clear though that major international banks will seek to implement IRB in the retail area for two reasons – pride and the economic advantage. Pride because a “ proper” bank will have IRB in all areas, and the carrot is that the real savings in using IRB come in the retail area as Table 3 implies.

Portfolio	% of current capital requirement	% increase caused by Advanced IRB	% increase in total requirement
Corporate	30%	-14%	-4%
Sovereign	1%	28%	1%
Bank	5%	16%	0%
Retail: Total	21%	-50%	-10%
Mortgage component of retail	11%	-60%	-6%
Non-revolving component of retail	8%	-41%	-3%
Revolving component of retail	2%	14%	0%
SME total	18%	-13%	-3%
Equity	2%	114%	2%
Total credit		-14%	-14%
Operational risk			12%

Table 3: Changes in capital requirement between current position and using Advanced IRB using data from QIS3.

The New Accord impacts on consumer credit modelling in three ways – two concerning its implementation and one in the lacunae in the modelling that it highlights. Firstly there are minimum requirements that a bank must reach in order to use IRB and in the consumer lending area these concentrate on the data available and the way segmentation is performed. When the Accord is fully functional the estimates of default probability and loss given default must be based on five years of data (three at the start of the transition period). The system must consider both borrower and transaction risk – so there is a question about using customer scores. Segmentation must involve product type and default characteristics so must separate delinquent from non-delinquent loans and over-rides must be separated out. Thus there will be a need for banks to collect and analyse large data sets involving five years of data and be able to calculate the essential parameters for whatever segments they want to create. There will also be a need to model which way of segmenting is most appropriate for the bank within the rules laid down.

The second implementation issue raised by the Accord is the validation and verification of the estimates of probability of default (PD) and loss given default (LGD) These estimates should be the long run average of the PD and LGD for the next 12 month period. This seems to imply that one needs to include adjustments for changes in the economy and market conditions. So suddenly a credit score is not just an ordering of the risk of individual consumers but has to be an accurate forecast of the probability of default on or before the end of the next 12 months; preferably one that is unbiased over the economic cycle.. Ensuring scoring systems have such properties is a real challenge for modellers and suggests a much closer tie with economic forecasting literature than has been the case up to now.

The final issue is that the new Accord has shown the lack of models of portfolios of consumer loans up to the present. What the regulators have done is to stipulate that such portfolios can be modelled satisfactorily by using a simple one factor Merton type corporate model akin to the Credit Metrics

(Finger 2002) with correlation values chosen using some empirical but not published procedure (BIS 2003).

Thus for residential mortgages the correlation is set at $R=0.15$ and the capital to be set aside as a function of PD and LGD is given by

$$\text{Capital } K = \text{LGD} * N \left(\left(\frac{1}{1-R} \right)^{1/2} N^{-1}(PD) + \left(\frac{R}{1-R} \right)^{1/2} N^{-1}(0.999) \right)$$

where N is the value of the cumulative normal distribution function and N^{-1} its inverse function. This says that the amount set aside is that required by a value at risk calculation where the cut-off is some where between the estimate of the probability of default and the 99.9% level. If the correlations between defaults of loans is very high ($R=1$) it becomes the 99.9% level while if it very low ($R=0$) it is the PD estimate. The model itself which gives rise to the normal distributions is based on Merton's model for the pricing of corporate debt (Merton 1974).

For revolving exposures the correlation varies according to the PD and in this case the capital set aside assumes that 75% of expected credit losses can be covered by the marginal income gained from these loans. This leads to the formulae

$$\text{Correlation } R = 0.02 \left(\frac{1 - e^{-50 PD}}{1 - e^{-50}} \right) + 0.11 \left(1 - \frac{1 - e^{-50 PD}}{1 - e^{-50}} \right)$$

$$\text{Capital } K = \text{LGD} * N \left(\left(\frac{1}{1-R} \right)^{-1/2} N^{-1}(PD) + \left(\frac{R}{1-R} \right)^{1/2} N^{-1}(0.999) \right) - 0.75 \text{LGD} . PD$$

For other retail loans, which can include those to small businesses up to one million euro (with a transitional formulae for loans between 1 and 50 million euros until it becomes the corporate model) the capital equations are

$$\text{Correlation } R = 0.02 \left(\frac{1 - e^{-35 PD}}{1 - e^{-35}} \right) + 0.17 \left(1 - \frac{1 - e^{-35 PD}}{1 - e^{-35}} \right)$$

$$\text{Capital } K = \text{LGD} . N \left(\left(\frac{1}{1-R} \right)^{-1/2} N^{-1}(PD) + \left(\frac{R}{1-R} \right)^{1/2} N^{-1}(0.999) \right)$$

The fact that these are corporate credit risk models applied to a different set of loans with correlations chosen to make them empirically acceptable does lead to some strange outcomes. There are three fairly obvious properties one would expect of the capital set aside to cover a portfolio of consumer loans.

- 1- the capital set aside should not exceed the value of the loans
- 2- as the probability of default increases the amount set aside should increase
- 3- if one is able to segment the portfolio into a larger and more precise set of segments according to probability of default then this extra information should mean the capital set side should decrease

None of these properties is true as Figure 3 indicates. The maturity term put into the transitional formulae connecting loans to Small businesses between 5 and 50 million euros means the capital needed can exceed 100%. The deduction of 75% of the expected losses from the capital set aside on the revolving credit capital formulae means this turns down as the PD values increases for large PD. The “other credit” formula is not concave in the 0.05 to 0.1 PD region and hence fails property 3. This failures need not mean that the formula are inappropriate and there is work to be done to check empirically if they give satisfactory answers. However the failure of such basic properties should make us look more closely at what are appropriate models for the credit risk involved in portfolios of consumer loans and how these models should depend on the default based credit scores already developed for individual consumers. One could argue that the mean of these score give us the mean of the portfolio default probability distribution and what is needed is to model the correlations and hence the higher moments of the default probability

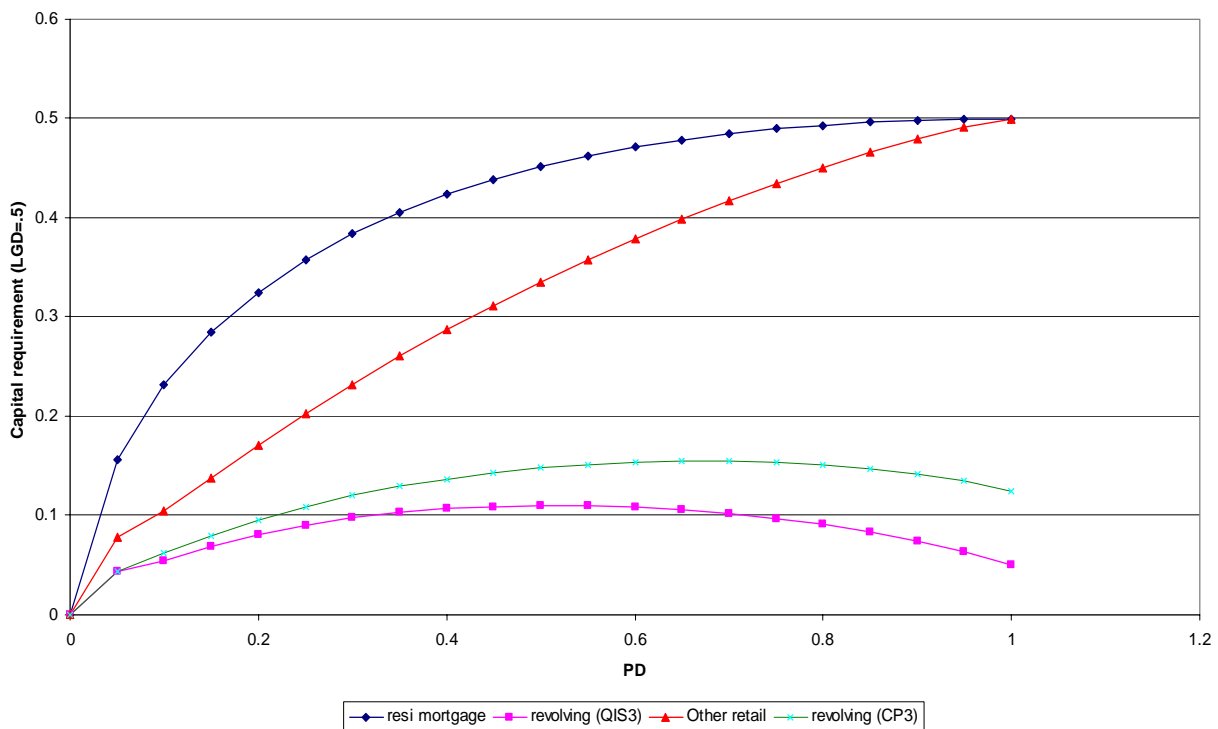


Figure 3: Capital requirements under CP3 New Basle formulae with LGD=0.5

8. Modelling credit risk (and price) of portfolios of consumer loans.

In the last two sections we have argued that the new Basle Accord and the growth of securitization has led to an urgent need to build models of the credit risk of portfolios of corporate loans. The use in the Basle accord of corporate credit risk models for this purpose means that the first requirement in this

research is to understand these corporate models and confirm their appropriateness in consumer lending,.

Initially there seem a number of differences in the two markets which lead one to question the appropriateness of using corporate credit risk models in the consumer context. With consumer loans there is no market mechanism for continuously trading in such loans and hence no continuously available market price. The market in corporate bonds is well established with the bonds in a company being bought and sold several hundred times whereas even if a consumer loan portfolio is securitized its sale is often a one-off event. In the bond market the original company has little control over changes in the debt structure initially issued apart from occasional well defined dates on which some bonds can be called or converted into stock shares.. In the consumer market on the other hand the individual consumers who make up the portfolio can decide at any time to cease using that lending product with consequent changes to the value and composition of the portfolio. Contingent claim based corporate credit risk models assume that default occurs when loans exceed assets or some proportion of the assets, while the reduced form approach suggests that default occurs when the rating of an external agency reaches some level. For consumers, default on a loan is more related to their cash flow and the fact that their income becomes insufficient to service the loan. Few consumers can calculate let alone realise their assets. The ratings approach of the reduced form does have more in common with the behavioural scores of a consumer but such scores are usually only known to the lender and not to the whole market. The correlations between defaults of bonds of different companies is assumed to be related to the correlations in their asset movements and it is assumed the correlations in the share prices of the companies reflect the correlations in the asset movements. There is however no consumer equivalent of a share price. For these reasons it is not clear that existing models of corporate credit risk can be modified to model portfolios of consumer loans.

If this is the case, what models are appropriate for modelling the credit risk in portfolios of consumer loans. It may be that one can still use factor type models but the factors may be related to stability and opportunity of employment, stability of marital or cohabitation status, propensity to illness and loss consequent loss of income, etc. One feature is that some of the reasons for default – financial naivety, fraud, loss of employment may be more prevalent at different periods into the loan facility and hence the survival analysis models may be useful. It may be necessary to look more carefully into the economic and psychological factors that lead to consumers defaulting and to make sure that these are measured and built into new types of models of the dynamics of consumer loans.

9. Conclusions

This paper has sought to describe the environment that consumer credit modelling finds itself in at present and the issues that appear to be high on the research agenda for consumer credit modellers. On a personal note it seems to me that a short list of the critical issues are

- To develop profit based scoring systems to help make decisions on both accepting and rejecting applicants but also the subsequent operating, marketing and portfolio securitization decisions
- To develop models that allow optimal decisions in terms of the product features to offer and the price to charge at an individual customer level
- To devise policy inference techniques that can “clean” the data on past customers of the effect of an historical “operating policy” applied to them
- To evaluate the validity of using corporate credit risk models to model credit risk in portfolios of consumer loans and if necessary develop predictive models. This could mean recommending models for Basle III regulatory capital requirements that achieve sensible tradeoffs between risk and other economic and corporate objectives
- to develop models that better assess and incorporate the tradeoffs between the enormously different utilities of consumers and lenders

That seems a reasonable research agenda for a five day workshop!

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