Transition matrix models of consumer credit ratings

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ABSTRACT

Although the corporate credit risk literature includes many studies modelling the change in the credit risk of corporate bonds over time, there has been far less analysis of the credit risk for portfolios of consumer loans. However, behavioural scores, which are calculated on a monthly basis by most consumer lenders, are the analogues of ratings in corporate credit risk. Motivated by studies of corporate credit risk, we develop a Markov chain model based on behavioural scores for establishing the credit risk of portfolios of consumer loans. Although such models have been used by lenders to develop models for the Basel Accord, nothing has been published in the literature on them. The model which we suggest differs in many respects from the corporate credit ones based on Markov chains — such as the need for a second order Markov chain, the inclusion of economic variables and the age of the loan. The model is applied using data on a credit card portfolio from a major UK bank.

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1. Introduction

Since the mid 1980s, banks' lending to consumers has exceeded that to companies (Crouhy, Galai, & Mark, 2001). However, not until the subprime mortgage crisis of 2007 and the subsequent credit crunch was it realised what an impact such lending had on the banking sector, and also how under-researched it is compared to corporate lending models. In particular, the need for robust models of the credit risk of portfolios of consumer loans has been brought into sharp focus by the failure of the ratings agencies to accurately assess the credit risks of the Mortgage Backed Securities (MBS) and collateralized debt obligations (CDO) which are based on such portfolios. Many reasons for the subprime mortgage crisis and the subsequent credit crunch have been put forward (Demyanyk & van Hemert, 2008; Hull, 2009), but, clearly, one reason why the former led to the latter was the lack of an easily updatable model of the credit risk of portfolios of consumer loans. This lack of a suitable model of portfolio level consumer risk

was first highlighted during the development of the Basel Accord, when a corporate credit risk model was used to calculate the regulatory capital for all types of loans (Basel Committee on Banking Supervision, 2005), even though the basic idea of such a model — that default occurs when debts exceed assets — is not the reason why consumers default.

This paper develops a model for the credit risk of portfolios of consumer loans based on the behavioural scores of the individual consumers whose loans make up that portfolio. Such a model is attractive to lenders, since almost all lenders calculate behavioural scores for all of their borrowers on a monthly basis. The behavioural score is usually translated into the default probability over a fixed time horizon (usually one year) in the future for that borrower, but one can also consider it as a surrogate for the unobservable creditworthiness of the borrower. We build a Markov chain credit risk model based on behavioural scores for consumers which has similarities with the reduced form mark to market corporate credit risk models based on the rating agencies' grades (Jarrow, Lando, & Turnbull, 1997). Such behavioural score based Markov chain models have been developed by lenders for their Basel modelling, but no analysis has appeared in the literature; in this paper, we discuss the features which

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should be included in such models and compare a standard and a more sophisticated version of the model. The methodology constructs an empirical forecasting model for deriving a multi-period distribution of the default rate for long time horizons based on migration matrices built from a historical database of behavioural scores. Although it is possible to calibrate the scores to the long run probability of default if one has data for a sufficiently long outcome period, such data are not available in practice. The transition matrix approach allows one to undertake such a calibration using much shorter data series. In our case study we use the lenders' behavioural scores, but we can also use the same methodology on generic bureau scores.

The approach also helps lenders to make long term lending decisions by estimating the risk associated with the change in the quality of portfolio of loans over time. Since the model includes economic conditions, the approach allows banks to stress test their retail portfolios, as required by the Basel Accord and other banking regulations. In addition, the model provides insights on portfolio profitability, the determination of appropriate capital reserves, and the creation of estimates of portfolio value by generating portfolio-level credit loss distributions.

There have recently been several papers which have looked at modelling the credit risk in consumer loan portfolios. Rosch and Scheule (2004) take a variant of the one factor Credit Metrics model, which is the basis of the Basel Accord. They use empirical correlations between different consumer loan types and try to build in economic variables to explain the differences during different parts of the business cycle. Perli and Nayda (2004) also take the corporate credit risk structural model and seek to apply it to consumer lending, assuming that a consumer defaults if his assets are below a specified threshold. However, consumer defaults are usually more about cash flow problems, financial naiveté or fraud, and thus such a model misses some aspects of consumer defaults.

Musto and Souleles (2005) use equity pricing as an analogy for changes in the value of consumer loan portfolios. They use behavioural scores, but take the monthly differences in behavioural scores as the return on assets when applying their equity model.

Andrade and Thomas (2007) describe a structural model for the credit risk of consumer loans, where the behavioural score is a surrogate for the creditworthiness of the borrower. A default occurs if the value of this reputation for creditworthiness, in terms of access to further credit, drops below the cost of servicing the debt. Using a case study based on the Brazilian credit bureau, they found that a random walk was the best model for the idiosyncratic part of creditworthiness. Malik and Thomas (2010) developed a hazard model of the time to default for consumer loans, where the risk factors were the behavioural score, the age of the loan, and economic variables, and used it to develop a credit risk model for portfolios of consumer loans. Bellotti and Crook (2009) also used proportional hazards to develop a default risk model for consumer loans. They investigated which economic variables might be the most appropriate, though they did not use behavioural scores in their model. Thomas (2009b)

reviewed the existing consumer credit risk models and pointed out the analogies with some of the established corporate credit risk models.

Since the seminal paper by Jarrow et al. (1997), the Markov chain approach has proved popular in modelling the dynamics of the credit risk in corporate portfolios. The idea is to describe the dynamics of the risk in terms of the transition probabilities between the different grades the rating agencies award to the firm's bonds. There are papers which look at how both economic conditions and the industry sector of the firm affects the transition matrices (Nickell, Perraudin, & Varoli, 2001), while others generalise the original idea of Jarrow et al. by using Affine Markov chains (Hurd & Kuznetsov, 2006) or continuous time processes (Lando & Skodeberg, 2002). However, none of these suggest increasing the order of the Markov chain or considering the age of the loan, which are two of the features which we introduce here, in order to model the consumer credit risk using Markov chains. This is surprising, because there has been work on downgrading by rating agencies which suggests that there is a momentum effect where, once a company has been downgraded, it is more likely to be further downgraded than to be subsequently upgraded (Bangia, Diebold, & Schuermann, 2002).

Markov chain models have been used in the consumer lending context before, but none of the published papers have used the behavioural score as the state space, nor has the objective of the models been to estimate the credit risk at the portfolio level. The first such application was by Cyert, Davidson, and Thompson (1962), who developed a Markov chain model of customers' repayment behaviours. Subsequently, more complex models have been developed by Ho (2001), Thomas, Ho, and Scherer (2001) and Trench et al. (2003). Schniederjans and Loch (1994) used Markov chain models to model the marketing aspects of customer relationship management in the banking environment.

Behavioural score based Markov chain models are sometimes used in the industry (see Scallan, 1998), but mainly as ways of assessing provisioning estimates, and they do not include the economic drivers and months on the books effects presented in this paper. Moreover, the introduction of economic factors into the model allows one to deal with the correlations between defaults on individual loans in a portfolio, since they are affected by common economics. One can obtain the mean default rate in a portfolio from the long run distributions, while a Monte Carlo simulation using the transitions of individual loans would give the distribution of the default rate.

In Section 2, we review the properties of behavioural scores and Markov chains, while in Section 3 we describe the Markov chain behavioural score based consumer credit risk model developed. This is parameterised by using cumulative logistic regression to estimate the transition probabilities of the Markov chain. The motivation behind the model and the accuracy of the model's forecasts are shown by means of a case study, and Section 4 describes the data used in the case study. Sections 5–7 give the reasons why the model includes higher order transition matrices (Section 5); economic variables for explaining the non-stationarity of the chain (Section 6); and the age of