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Editorial

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Editorial

This Feature Cluster on Credit Risk Modelling consists of papers that were submitted from the Credit Scoring and Credit Control XIII conference that was organised by the Credit Research Centre at the University of Edinburgh in August 2013 and some papers that were submitted under an open Call. Forty six papers were submitted of which thirteen made it through the screening and reviewing processes. We would like to thank the many referees who generously gave their time to read and re-read many of the manuscripts. Each paper was accepted on its own merits, but it turned out that some themes were common. Here we summarise each paper. For the reader interested in an introduction to the area we would suggest Crook et al (2007) and Thomas (2010).

Survival analysis has gained increasing popularity as a way to estimate not just *whether* loan customers will default but also *when* they are more likely to default. Barrios et al propose another novel application of survival analysis – to model time to profitability. For a high-risk portfolio of revolving consumer credit issued by a Colombian lender, a discrete-time survival model is parametrised and tested that predicts time to profitability, defined in terms of monthly cumulative return. The reported results indicate that this approach compares well against the use of OLS models to estimate direct profit or return, in terms of their impact on portfolio results; also, it is shown how the proposed method can be a useful tool for investment planning.

The next two papers consider the optimisation of return and risk for a loan portfolio, but in different contexts. Quite often lending decisions are subject to limits on available capital for certain types of loans. These limits are typically imposed by financial regulators. In their interesting paper, So, et al explore this lending constraint and show it is a type of polygamous marriage problem, which has been discussed extensively in the statistical and operational research literature. The authors propose Markov Decision Processes to solve the lending problem to derive an optimal lending policy and demonstrate some of its properties.

Guo et al look at peer to peer lending where the lender has very few historical observations to each borrower to assess their likelihood of default. Instead they propose comparing an application with those of borrowers with similar profiles. The expected return for a loan is a weighted average of returns on similar loans and the expected variance is the weighted average of variances on similar loans. Two key questions are which loans are similar and how to gain the weights? The authors' solutions are to determine closeness by the absolute value of the difference in default probabilities and to estimate the weights using the relative value of a kernel function evaluated at the differences between default probabilities. Adopting a Markowitz type model the application of the methodology to find the optimal portfolio with a capital constraint is illustrated for two portfolios of Peer to peer loans.

Sparseness of default observations is a theme in the paper by Fitzpatrick and Mues too. They consider mortgage default modelling. Modelling mortgage default is important for decision-making on new mortgage applications and also for accurately computing regulatory capital buffers. There remain serious challenges, not least because of the relatively low number of defaults in mortgage portfolios. In their paper, Fitzpatrick and Mues conduct a comparison of several alternative modelling techniques including boosted regression trees, random forests, penalised linear and semi-parametric logistic regression models on several mortgage data sets. They find that the alternative methods, in particular, boosted regression trees, perform well in comparison with the traditional logistic regression approach.
Three papers investigate some of the challenges to model building and performance raised by the recent financial crisis and subsequent downturn. First, Lee et al address the following question: are factor-based credit portfolio risk models capable of producing sufficiently conservative estimates in

such severe economic downturns. Using a US subprime mortgage dataset, their paper analyses the accuracy of default rate forecasts and whether actual loss realisations are covered by Value-at-Risk (VaR) estimates. Importantly, the findings indicate that, whereas quarterly VaR estimates did suffice, for an annual forecast horizon the actual losses exceeded VaR estimates. Uninformative maximum likelihood and informative Bayesian techniques were compared and the analysis considers both the impact of model risk and the inclusion of an autoregressive adjustment.

A second paper by Leow and Crook examined to what extent parameter estimates in survival models for time to default have remained stable over this period. The dataset used in this study was provided by a UK bank and contains observations of credit card accounts over a period stretching from the early 2000s to the recent downturn. Two discrete-time survival models were fitted – one to accounts accepted prior to the crisis and one to those accepted during it. One finding is that their sets of parameter coefficients are indeed significantly different. When applied to a common test set, both models also produced different estimates of default rates; e.g. the pre-crisis model underestimated default risk in the first twelve months on book. Further analysis suggests that changes in cohort quality, varying macroeconomic conditions and the estimated model parameters all contributed to this change in distribution.

Thirdly, Allen et al explore the use of Conditional VaR (CVaR) as a coherent risk measure for credit, as an alternative to VaR which was criticized after the recent financial crisis. The authors apply CVaR in the context of four alternative models: structural models, transition models, quantile regression models, and the authors' unique iTransition model. They show that VaR and CVaR can give highly different estimates of extreme credit risk. Additionally, they demonstrate how the models respond to market conditions and show how CVaR can be used to compute capital buffers to deal with extreme credit risk.

Whereas in the past the credit scoring literature tended to focus on building models to estimate Probability of Default (PD), since the arrival of the Basel II and III accords, a growing body of literature investigates two other risk parameters: Loss Given Default (LGD), i.e. the proportion of the outstanding balance that will be lost in the event of a default, and Exposure At Default (EAD). There have been several interesting developments in LGD modelling over the past few years. In many approaches, a regression model is used to forecast LGD sometime ahead, based on data collected prior to or at the time of default. However, arguably, there may be much useful data within the collections process itself that could better inform LGD estimation. Taking this approach, Thomas et al explore making use of the collections process to improve the accuracy of LGD estimates at portfolio level. In particular, the authors explore the use of Markov chains and survival analysis to model repayment patterns. Leow and Crook propose a new model to estimate EAD that exploits the general occurrence that a credit card account's limit is easier to predict than its balance, yet is closely related to the balance. The model involves weighting a predicted balance and predicted limit by the probability that the balance is below the limit and vice versa. The accuracy of the model is compared with those of established methods.

Hon and Bellotti focus on forecasting credit card balance, not at default but unconditional on default. Doing so, they argue, has useful applications apart from risk management, e.g. for revenue prediction. Using a large dataset of UK credit cards, several alternative approaches are compared: three models fitted to a cross-sectional sample (a linear OLS model, a two-stage model, and a mixture model), as well as a random effects panel model that takes into account the time-series structure of the data. This analysis identifies several drivers, the strongest being previous (lagged) balance. The panel model is found to be the most accurate model when performance is quantified using Mean Absolute Error (MAE), whereas in terms of Root Mean Squared Error (RMSE) the two-stage regression comes out on top.

A further group of papers focuses not on consumer lending but lending to small and medium-sized enterprises (SMEs). First, Andreeva et al investigate the drivers for SME failure in two different European countries – Italy and the UK. Their cross-country comparison includes both financial and non-financial variables and includes the sovereign debt crisis of 2011. Three types of models were fitted: logistic regression, Generalised Extreme Value (GEV) regression (which unlike logistic regression has an asymmetric link function), and a non-parametric additive variant of the latter which ended up giving the best predictive performance. Two ways to deal with missing values were considered – a multiple imputation procedure and an approach based on Weights of Evidence (WoE) transformation. The latter tended to show better prediction, thereby suggesting that values may not be missing at random. Similarities are found between the different sets of drivers, but there are also some notable differences; e.g. whereas gearing is a significant driver in all UK models, it is not significant in any of the models for Italy.

Second, Fernandes and Artesa suggest that SMEs may be impacted by local factors and the performance of nearby businesses. Hence, they hypothesise it could be beneficial to include a spatial factor in SME credit scoring models, particularly in settings where local economic variables are unavailable or traditional coarse classification of (a potentially large number of) postcodes presents major challenges. Specifically, the approach proposed in the paper is to apply a spatial interpolation method, viz. ordinary kriging, and include the resulting measure of local risk of default as an extra explanatory variable in a logistic regression model. By doing so on a large Brazilian dataset, Fernandes and Artesa are able to report a substantial uplift in discrimination performance.

In the final paper Leung and Kim outline a framework for the valuation of financial contracts subject to reference and counterparty default risks with collateralisation requirements. For these complex financial contracts, a fixed point approach and corresponding iterative numerical algorithm are proposed. The authors apply their method to a number of relevant over-the-counter (OTC) market instruments. Their model produces valuable insights into how counterparty risk and collateralization affect the formation of bid-ask spreads.

We hope you enjoy this feature cluster.

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