Institution: The University of Edinburgh

Unit of Assessment: 19 Business and Management Studies

Title of case study: Designing the Next Generation of Retail Credit Risk Models

1. Summary of the impact

Research carried out by members of the Credit Research Centre (CRC) at the University of Edinburgh has changed the way that credit risk modelling teams in major multinational retail banks think about and model the probability that an applicant will default on a loan. Such models are used monthly to assess the risk associated with most of the 58 million credit cards in the UK and hundreds of millions of credit cards elsewhere in the world. The research has also changed the way banks model a crucial parameter in the amount of capital they have to hold to comply with international regulations, and has allayed their concerns about estimating models based on only samples of previously accepted applicants.

2. Underpinning research

The CRC has hosted a programme of research carried out by Crook (1993-), Bellotti (2006-), Banasik (1993-2010), Ansell (1997-), Andreeva (2005-), Leow (2010-) and several PhD students (Andreeva, Ma, Kay, Moreira, Hanley, Li, Osipenko). The specific projects highlighted here concern the way banks assess the riskiness of making a loan. All of the research described was carried out in Edinburgh. It covers three main areas.

1. **The design of survival models of consumer credit default**. Banks have to assess the creditworthiness of (a) each applicant for credit, to decide whether to grant credit, and of (b) those account holders who already have revolving credit facilities. Typically, banks use a parameterised cross sectional logistic regression model to make a prediction of the probability of default within a defined time period (e.g. 18 months) for each applicant. This is compared with a critical value to decide if credit will be granted or limit increased. The research [3.1] carried out since 1997 showed that a bank could predict the probability of default not just over a *predefined* time period but in *any* future period, so long as the parameters of the model continued to represent behaviour. Research since 2006 [3.2] also showed that one should include predicted values of macroeconomic indicators in such a model to make the predicted probabilities of default in each month depend on the expected future states of the macro-economy. This allows a bank to predict the chances of a borrower defaulting in a month the bank chooses given the bank's forecast about the macro-economy. It also allows the bank to predict the default rate for an entire portfolio of loans for a predicted state of the economy.

2. **Reject inference**. Banks develop credit scoring models using samples of people they have lent to in the past. They wish to estimate a model that represents the behaviour of any potential borrower. There are statistical reasons why the former may not represent the latter. If the difference is major, banks will be accepting the wrong applicants for loans. Reject inference is a procedure whereby bank statisticians try to "correct" models that have been parameterised on a sample of *accepted* applicants to make the model "representative" of *all* applicants. In a series of papers ([3.3], [3.4] also *Journal of the Operational Research Society* (2010), *European Journal of Operational Research* (2007)), Crook and Banasik showed that (a) the "bias" resulting from estimating a model based on only accepted applicants was minimal and that known estimators made only a modest improvement to predictive accuracy; (b) that techniques that were conventionally used by statisticians in the industry had little effect unless a very large proportion of loan applications were rejected; and (c) that when the conventional industry method is applied to a survival model, again there is little improvement.

3. **Loss Given Default (LGD)**. The Basel II and III Accords require that banks hold an amount of capital, mainly equity, equal to at least a given percentage of risk weighted assets. The latter depend partly on the proportion of a loan that is lost in the event of default (LGD). The research [3.5] examined the predictive accuracy of a range of algorithms and data transformations and,

crucially, the empirical role for states of the macro-economy to find which algorithm and which transformation led to the most accurate predictions. The inclusion of macroeconomic variables was crucial because it offered a new way of computing "stressed" levels of LGD, which are what is required in the Accords.

3. References to the research

Research Grant:
March 2006 – February 2009 EPSRC: EP/D505380/1 (PI: D Hand, Imperial College, Co-I: J Crook (Edinburgh) and L Thomas (University of Southampton) £504,000 to fund research into risk management in the personal financial services sector.

Research Publications:

3.1 Banasik, J., Crook, J. & Thomas, L. (1999) 'Not if but when will borrowers default?' *Journal of the Operational Research Society*, 1185-90. Awarded 1999 Goodeve Medal by UK OR Society (DOI: 10.1057/palgrave.jors.2600851).

3.2 Bellotti, T. & Crook, J. (2009) 'Credit scoring with macroeconomic variables using survival analysis'. *Journal of the Operational Research Society*, 60(12), 1699-1707 (DOI: 10.1057/jors.2008.130).

3.3 Crook, J., Banasik, J. & Thomas, L. (2004) 'Does reject inference really improve the performance of application scoring models?' *Journal of Banking and Finance*, 28, 857-874 (DOI: 10.1016/j.jbankfin.2003.10.010).

3.4 Crook, J. Banasik, J. & Thomas, L. (2003) 'Sample selection bias in credit scoring models' *Journal of the Operational Research Society*, 54, 822-832 (DOI: 10.1057/palgrave.jors.2601578).

3.5 Bellotti, T. & Crook, J. (2010) 'Loss given default models incorporating macroeconomic variables for credit cards'. *International Journal of Forecasting* (DOI: 10.1016/j.ijforecast.2010.08.005)

4. Details of the impact

Since the early 2000s, and especially since the crisis, when they were found to be short of capital, banks across the world have been keen to predict the impact of changes in the macro-economy on the future riskiness of individual loans. Unfortunately their current models did not allow them to do this. Our work showed how banks could incorporate macro-economic factors into credit risk models.

Senior managers at banks and regulatory agencies across the UK and in over 30 other countries were made aware of the research through four main processes. The first was by giving invited presentations to private banks. For example, the credit analytics team at Itau-Unibanc, Brazil – one of the largest banks in the South American continent – invited Crook to give a presentation on survival analysis methodologies for credit scoring to its team in San Paulo; he was also invited to speak at the jointly created Bank Z-CRC Innovation Forum, and Lloyds Bank invited him to explain the application of survival models to its modelling teams. The second involved presenting the results at public conferences, for example the biennial Credit Scoring and Credit Control X, XI, and XII in Edinburgh 2007, 2009 and 2011 and the International Federation of Operational Research and Management Science conference in Dallas 2010, which were attended by over 1,200 practitioners. Presentations were also made by invitation to a public bank, the Federal Reserve Bank of Philadelphia. Thirdly, awareness was raised by gaining significant BBC coverage which, although occurring in 2007, led to subsequent impact in 2008 [see 5.1]. Fourthly, impact was created through private conversations with influential members of regulatory agencies, for example the Financial Services Authority.

Implementation of the findings of this research has had a direct impact on the improvement in the competitiveness of banks, because the accuracy of a bank's models is a source of competitive advantage. For this reason banks are reluctant to reveal the full impact of our work. Nonetheless, a range of impacts can be demonstrated.

1. Design of Survival Models. Prior to this research, banks were unaware of and so did not use survival models to assess credit risk. The impact of the research was such that it transformed the way credit risk model teams in banks think about both what they are trying to model and the way they do it. This research was vitally significant for several reasons. It meant a bank could change the horizon over which it required a probability of default from 18 months to any period it wished, without re-estimating the model and it could weight scheduled payment amounts in each month by the probability of default to compute *expected* revenue from a loan in each month. Incorporating expected costs would allow a bank to compute the expected profits from making a loan in each month and so did not have to rely on computing just the probability of default over a fixed horizon. The research also meant a bank could compute a probability of default that was insensitive to the macro economy (by fixing the values of the macroeconomic factors and the behavioural factors) as required by the Basel Accords. A bank could also compare the expected profits with the predicted probability of default over a given horizon and so make a loan based on both expected profit and predicted risk. As a result of our research many multinational banks can predict the probability of default in a chosen future time period rather than over a fixed (at the time of modelling) time period, and they can include macroeconomic variables in such models. As the testimonies below demonstrate, the research has had a direct impact on choices made by banks and credit scoring institutions by demonstrating the superiority of using survival (sometimes called "duration") models rather than cross-sectional models.

"*The work you did in 1999 was a useful case study to illustrate its feasibility. Typically the approach is used mainly for credit risk modelling for loans and mortgages where there is a fixed repayment schedule.*" [5.2] (3 June 2013)

"[Quotation removed]". [5.3]

"[Quotation removed]". [5.4], referring to Banasik et al (1999) and Bellotti and Crook (2009)

"…we did use survival analysis (one of my staff constructed the model) along the lines of the paper [3.1 above] (a proportional odds model if I remember correctly). I note that without the preliminary CRC paper we would probably not have had the confidence to do this, as we needed to quote evidence that the model was at least as powerful as a combination of logistic regression and vintage curves" [5.5]

Given the secrecy surrounding the use of techniques by banks these commendations are especially positive.

2. **Reject Inference.** The nature of the impact was to increase the understanding on the part of risk modelling teams of what exactly the statistical problems are when they estimate a model based only on a sample of accepted applicants. This has occurred since the results were first made public in 2001. Thus [5.3] writes:

"[Quotation removed]"

And [5.5] writes:

"In all the scorecard constructions that I have undertaken or supervised for banks and building societies these papers [3.3 and 3.4 above] have changed the way that I approached the 'Rejected Applicant' problem".

3. **Loss Given Default.** The Basel II Accord requires banks to use a level of LGD that would occur

when there is an economic downturn. By providing confirmatory evidence of the robustness of a two step approach, this research has led to a consistent approach across many banks. The research impacts on banks in two ways. First it shows a comparison of the accuracy of methods for predicting LGD in the context of significant secrecy. That is, banks do not reveal their methods publicly and so cannot compare the accuracy of their methods with the accuracy obtained by their competitors. The paper provides a benchmark. Second, by including macroeconomic variables into the model, stressed levels of LGD can be directly computed by choosing hypothetical 'stressed' levels of the macroeconomic variables and substituting them into the model.

"*In agreement with your approach many retail banks apply a two stage LGD model as you described. Confirmation that this was a robust approach was helpful in bringing about [a] reasonably standard approach across many banks".* [5.2]

Because of its awareness of these research projects a multinational bank asked the CRC to undertake consultancy projects that directly altered decisions that the bank made (details confidential and covered by an NDA, but related to portfolios of billions of pounds sterling).

5. Sources to corroborate the impact

5.1. BBC website: http://news.bbc.co.uk/1/hi/scotland/edinburgh_and_east/7087028.stm (or http://tinyurl.com/pj8e2xc) (Corroborates the process described by which impact is created.)

Individual users/beneficiaries who could be contacted by the REF team to corroborate claims:

5.2. [Text removed]) (Corroborates the effects of research on survival analysis that it altered the way banks think about modelling default. Also corroborates effects of research on LGD on bank modelling – [text removed].)
5.3. [Text removed] (Corroborates the effects of research on survival analysis that it altered the way banks think about modelling default. Also corroborates effects of research on reject inference as influencing the way consultancies implement reject inference –[text removed].)
5.4. [Text removed] (Corroborates the effects of research on survival analysis that it altered the way a major consultancy think about modelling default –[text removed].)
5.5. Principal, Avenir Risk (Corroborates the effects of research on survival modelling on bank modelling – [text removed].)