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Macroeconomic conditions in models of Loss Given Default for retail credit

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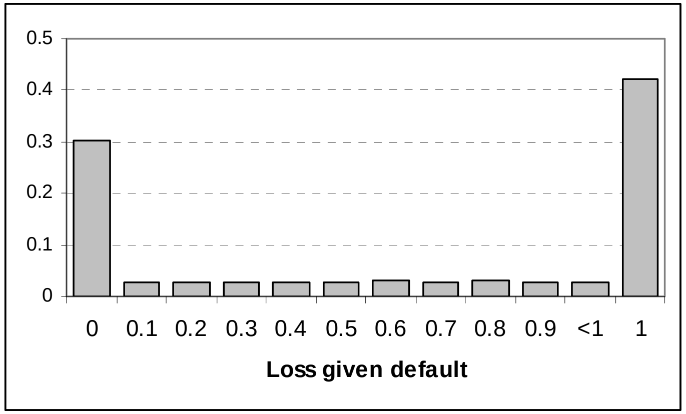
Loss Given Default

- **Loss given default (LGD) is the fraction of debt not recovered some period of time following default.**

- **If RR is recovery rate then LGD = 1 – RR.**

- **LGD depends on:-**
  - Defaulter's personal circumstances and attitude to debt.
  - Lender's collections process:
    - This can include follow-up mailings, phone calls, repayment plans, outsourcing to debt recovery agencies, sale of bad debt.

- **Typically, LGD lies between 0 and 1 and typical distribution is bimodal:-**



Illustrative simulation of an LGD distribution for unsecured loans based on study by Querci (2005).

Querci F (2005). Loss Given Default on a medium-sized Italian bank's loans: an empirical exercise. *European Financial Management Association* conference 2005 (Milan, Italy).

Macroeconomic data and LGD

- **How do macroeconomic conditions affect modelling and prediction of LGD?**
- **For example, we may expect that increases in bank interest rates may increase LGD.**
- **We include values of macroeconomic variables (MV) at date of default into models of recovery rates.**
  - Alternatively, MVs can be included with some lag.
  - MVs supplement a ***basic AV model*** which includes application variables (AVs) such as income, housing and employment status, age and demographics along with credit score.
- **We measure explanatory and predictive power of MV models against models without MVs.**

Macroeconomic variables

- **The following macroeconomic variables (MVs) are considered for modelling LGD. They are expected to have a direct affect on consumer LGD.**

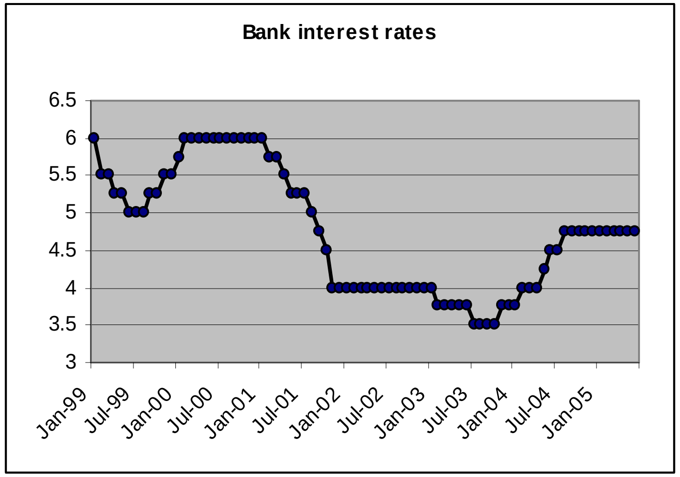
  - Bank interest rates (IR): selected UK retail banks base rates
  - Unemployment index
  - Earnings *: real earnings (ratio of UK earnings and RPI)

* to reduce the effect of the time trend the log of Earnings is taken and the difference over 12 months is used.

- **This is monthly data provided by the Office of National Statistics (UK).**

- **Default date is also included in the model to ensure model is not simply picking up a time trend in MVs.**

Macroeconomic data



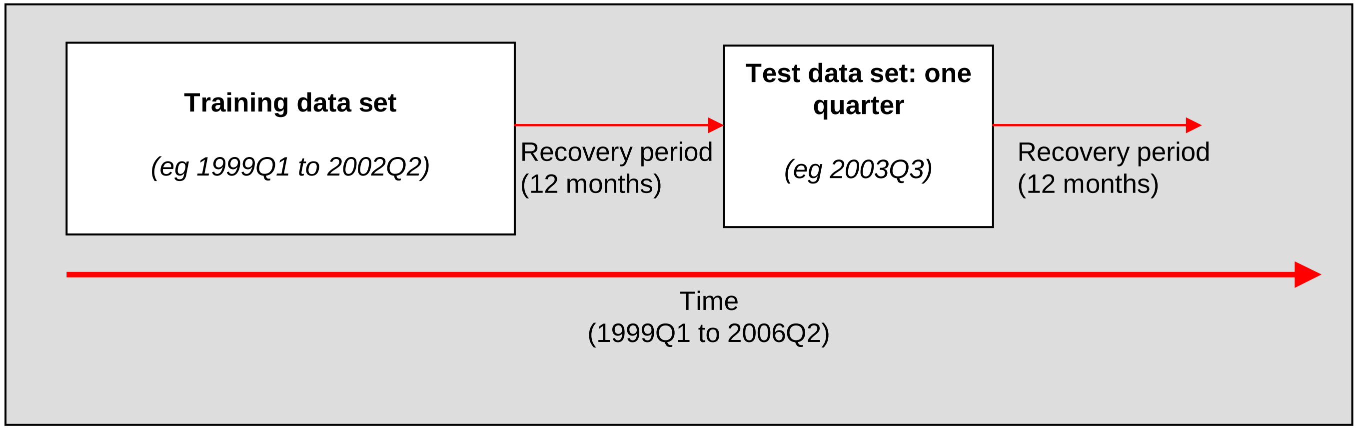
Macroeconomic variable	***Correlation coefficient with mean monthly RR***
Bank interest rate	-0.80
Unemployment index	-0.35
Earnings (log) difference	-0.37
Calendar time	0.76

Modelling and assessment

- **Several different credit card products combined: over 55,000 accounts in default from 1999 to mid-2006.**
- **Performance of the OLS model with MVs is compared with the basic OLS model without MVs.**
  - Previous studies showed that simple OLS performs well for prediction of LGD.
- **MV model with interaction terms between MVs and application variables is also considered.**
  - Interaction terms are added to the model using forward selection.
- **Performance measures used to compare predicted against observed values in test set:-**
  - Mean square error (MSE);
  - Mean recovery rate (RR) across a cohort of test data.

Test procedure

- The impact of MVs is time-dependent, so we use post, out-of-sample tests.
- This also gives a test close to expected operational use of LGD models for *forecasts*.
- Each test set cohort is constructed from all cases that default together in a given quarter.
- Training data is taken from all cases that defaulted previously with sufficient time to measure RR before test set.
- The MV and basic models are trained and tested on the same data sets, so results are comparative.



Results:
Model fit

Model fit statistics based on training on all available data.

Model	***Adj-R^2***
Basic (no MVs)	0.105
MV model	0.110
MV model with interaction terms	0.111

- The R^2 are quite low, even in comparison with other LGD studies. However, this is because our data set is so large. If we reduce sample size to 500 random cases, comparable to other studies, we achieve R^2 of 0.20. This is why we recommend reporting Adj-R^2 since this takes sample size into account.
- Even with low R^2, the models are still statistically significant.

Results:
Parameter estimates for MVs

Results for recovery rates (RR) model:

Variable	*Parameter estimate*	*t value*	*P-value*
Bank interest rate	negative	-17.3	<.0001
Unemployment index	negative	-2.96	0.003
Earnings (log difference)	positive	1.48	0.139
Calendar time (years)	positive	-1.62	0.105

- **In particular, a rise in interest rates lowers expected RR (increases LGD).**
- **MV and calendar time variables are shown for MV model without interaction terms. Parameter estimates for application variables are not shown.**

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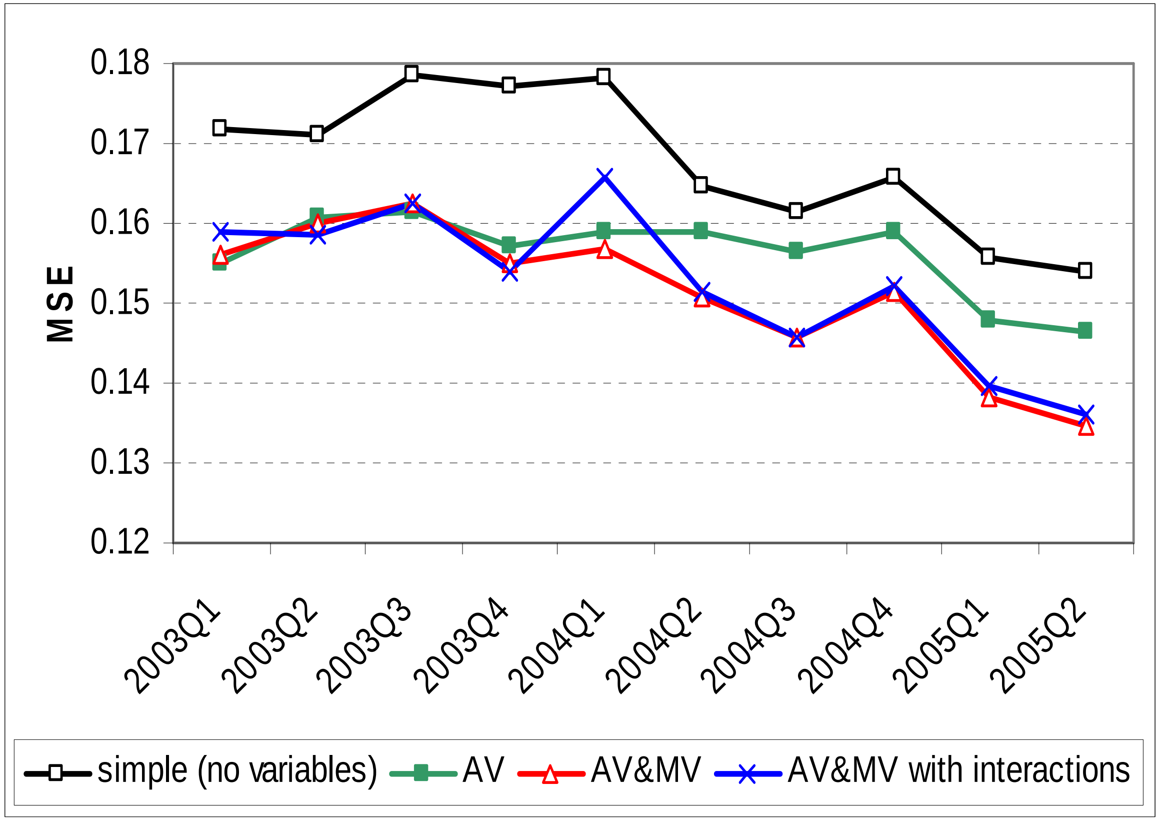
Results: Forecast MSE

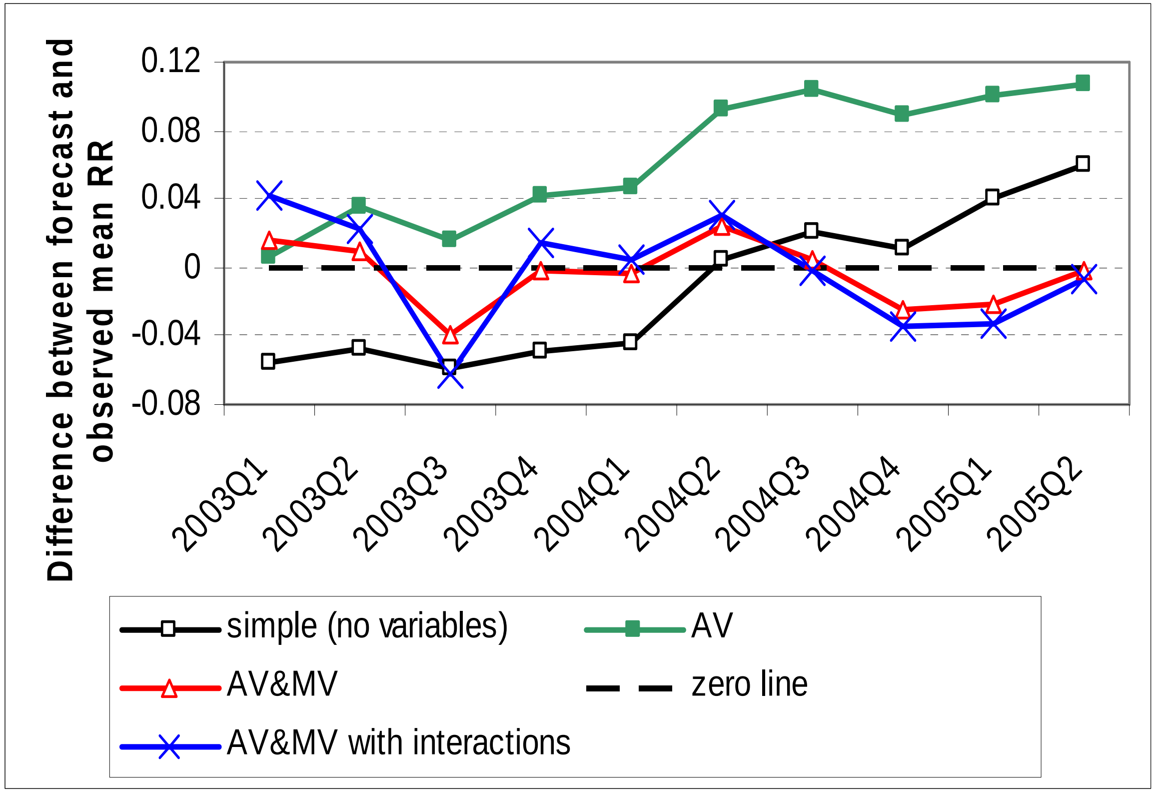
MSE of forecasts at account level, by test cohort and model.



- Performance for all models improves over time, which is natural with increasing size of training data.
- However, the MV model improves faster and gives best overall forecasts.

Results:
Forecast mean RR

Forecast mean RR at aggregate (portfolio) level, by test cohort and model.



- The observed (or true) RR shown as a thick line is the target for each model to follow.
- MV model is best estimate of RR.
- Interaction terms do not improve forecasts.

Other observations

- **Using lags and leads on MVs does not improve predictive performance.**
- **Models using MVs still give best predictive performance when built for each credit card product separately.**
- **Models built on 12 month recovery period can be used to predict RR for other recovery periods. For example,**
  - 24 month MV model has MSE of 0.204.
  - 12 month MV model has MSE of 0.182 *for prediction of 24 month* RR.
  - This is because 12 month model has access to more recent training data.

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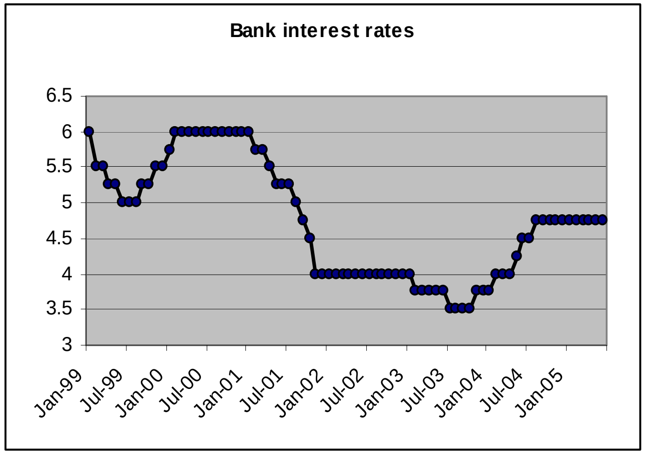
Stress testing

- **Models with MVs can be used for stress testing by substituting values of MVs from economic scenarios.**
  - How does the economic scenario affect LGD estimate?
  - Use Monte Carlo simulation of MVs based on historic data.
- **We perform univariate stress test based on bank interest rate only.**
  - Use MV model reported here.
  - Worst case bank interest rate: 6%:
    - Forecast mean LGD *increases* by 17%.
  - Best case bank interest rate: 3.5%:
    - Forecast mean LGD *decreases* by 28%.



Conclusions

- **Using MVs improves model fit and gives statistically significant parameter estimates.**
- **Using MVs improves forecasts of LGD consistently at both account level (MSE) and aggregate level (mean RR).**
- **Using interaction terms tends to give weaker performance.**
  - We suspect this is due to over-fitting on training data.
  - We suspect that interaction terms are important, but over-fitting needs to be avoided. One way to achieve this is to use expert advise to choose interactions rather than an automated approach.
- **The LGD model with MVs is potentially valuable as a stress testing tool and for estimation of "downturn LGD".**

Contacts

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