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Competing risks survival model for mortgage loans with simulated loss distributions

Mindy Leow[1], Christophe Mues[2] & Lyn Thomas[2]
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[1] Credit Research Centre, University of Edinburgh; [2] School of Management, University of Southampton

Agenda

Introduction

Research aims

Methodology

- Competing risks survival model
- Monte Carlo simulation
- Stress testing

Results

Conclusions

Discussion

Introduction

Mortgage loans

- Already in default
- Application variables, default time variables, final loss
- Different to other retail loan default: repossession or otherwise (assume no loss)

Repossession & recovery

- Sell the security
- How much?
- When?
- Loss?

Survival Models

- Previous work to estimate LGD combination of logistic and linear regression
- Time-dependent macroeconomic variables
- Probabilities not just for whether event will happen, but when

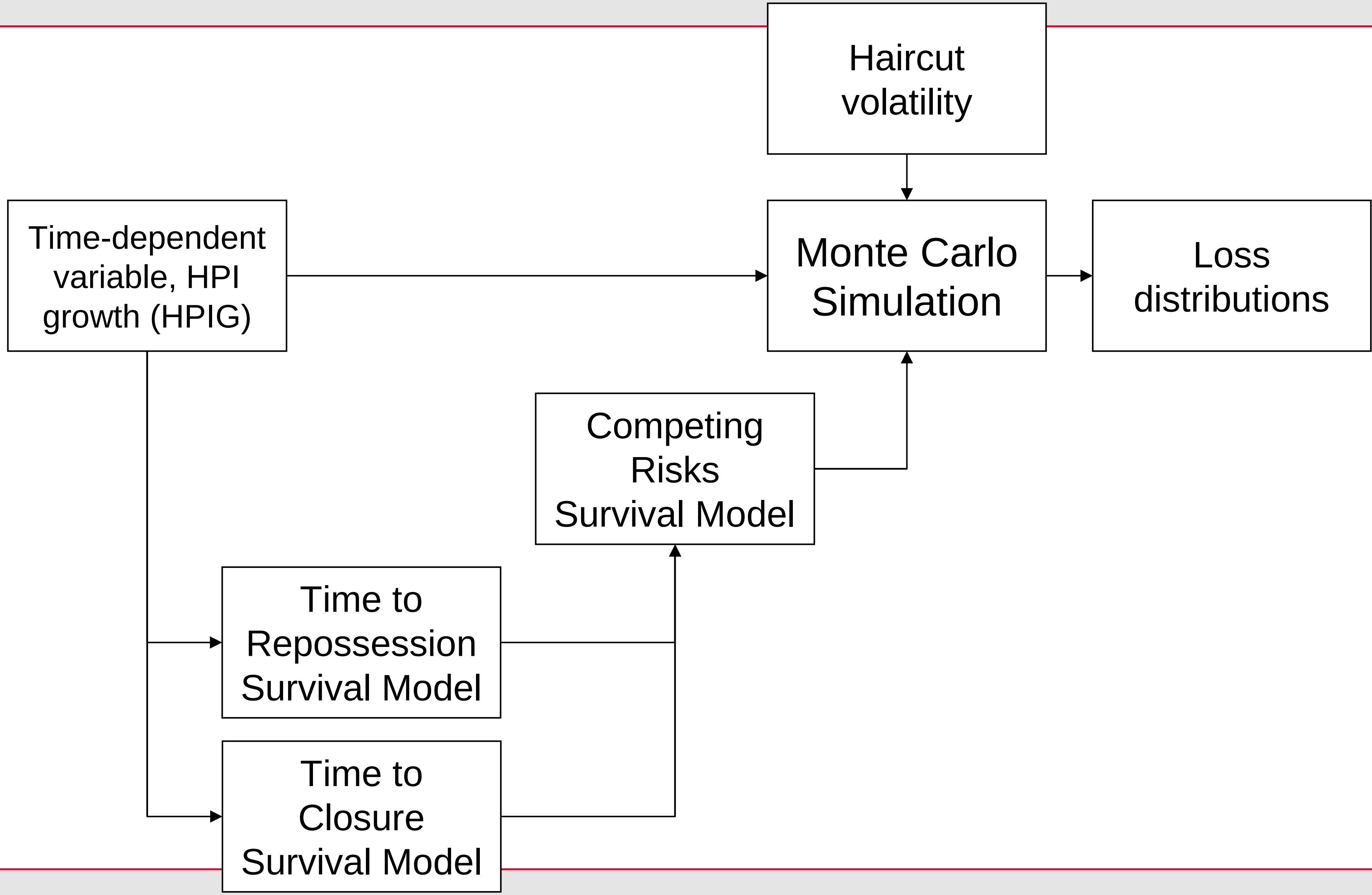
Research Aims

By modelling the period from default to some event (repossession or otherwise), a more accurate prediction of mortgage LGD (discounting, delays, etc) can be made

Investigating the impact of time-dependent macroeconomic variables on repossession risk

Illustrating how the model can be used for stress test purposes by applying Monte Carlo Simulation and varying economic forecasts to get different predicted loss distributions

Methodology



Component Survival Models

Use Cox Regression Survival Model

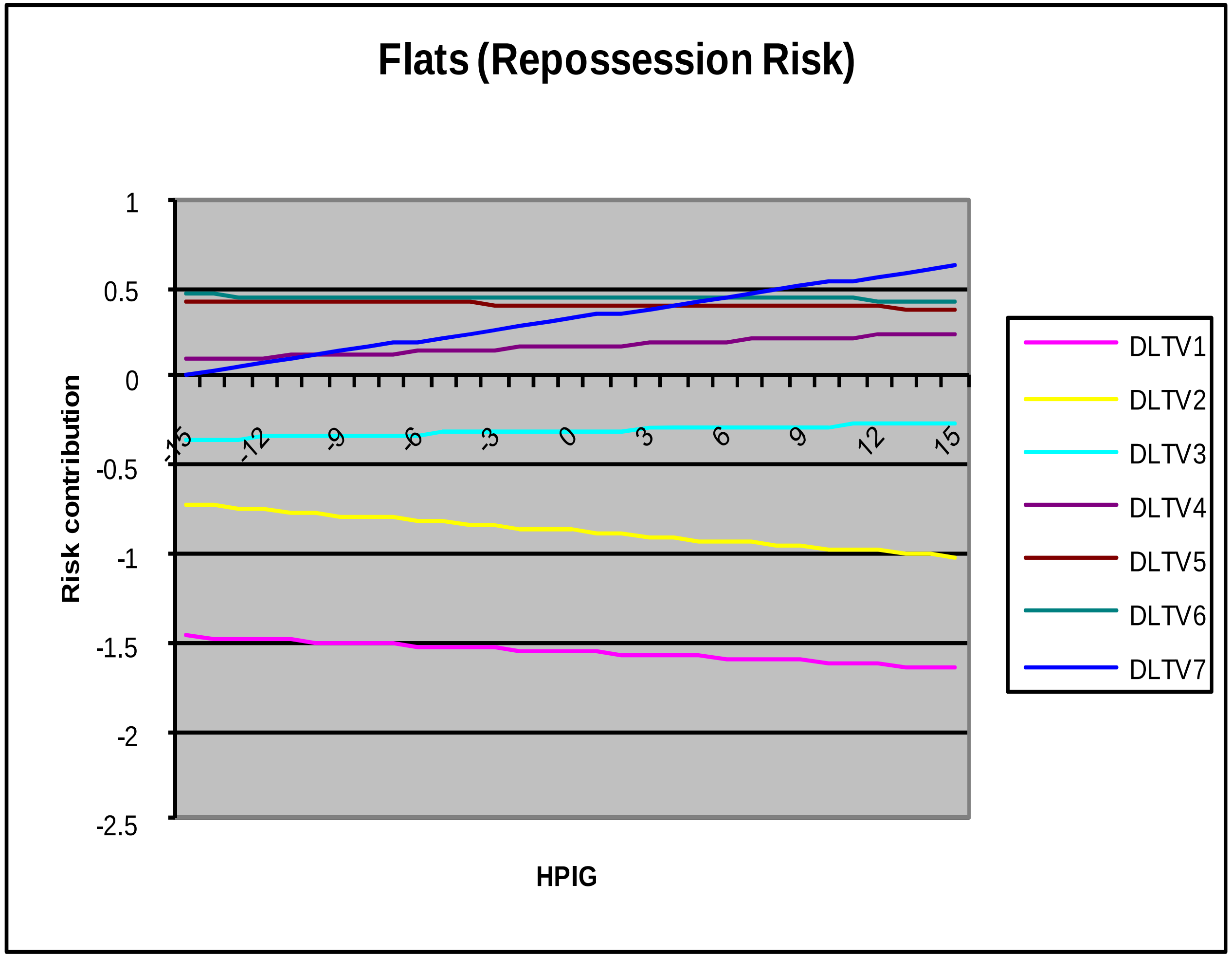
When modelling each time to event, assume all other events were censored

Final set of variables include

- Loan-related variables (DLTV bands and type of security)
- Year-on-year HPI growth
- Interaction terms between loan-related variables and HPI growth (HPIG*DLTV bands; HPIG*type of security)

Find that type of security and DLTV bands affect event risk differently

Component Survival Models



For flats:

Accounts in higher DLTV bands have higher risk of repossession

Accounts with very high DLTV are more affected by changes in HPI (see slope)

Monte Carlo Simulation

Generate random numbers to compare against (conditional) survival probabilities at each time point

Repeat until an event happens, for all observations

Each observation to have (a) a predicted event, and (b) a predicted event time

From predicted event and predicted event time, to calculate (a) expected sale price including applied haircut (if applicable), (b) expected shortfall including relevant discounts, (c) expected LGD

Monte Carlo Simulation

VALIDATION

Two cohorts of loans selected

- 1991 (downturn)
- 1995 (non-downturn)

Actual observed HPI as given by Halifax HPI (regional, quarterly)

Simulation of 1,000 runs

STRESSED

Two cohorts of loans selected

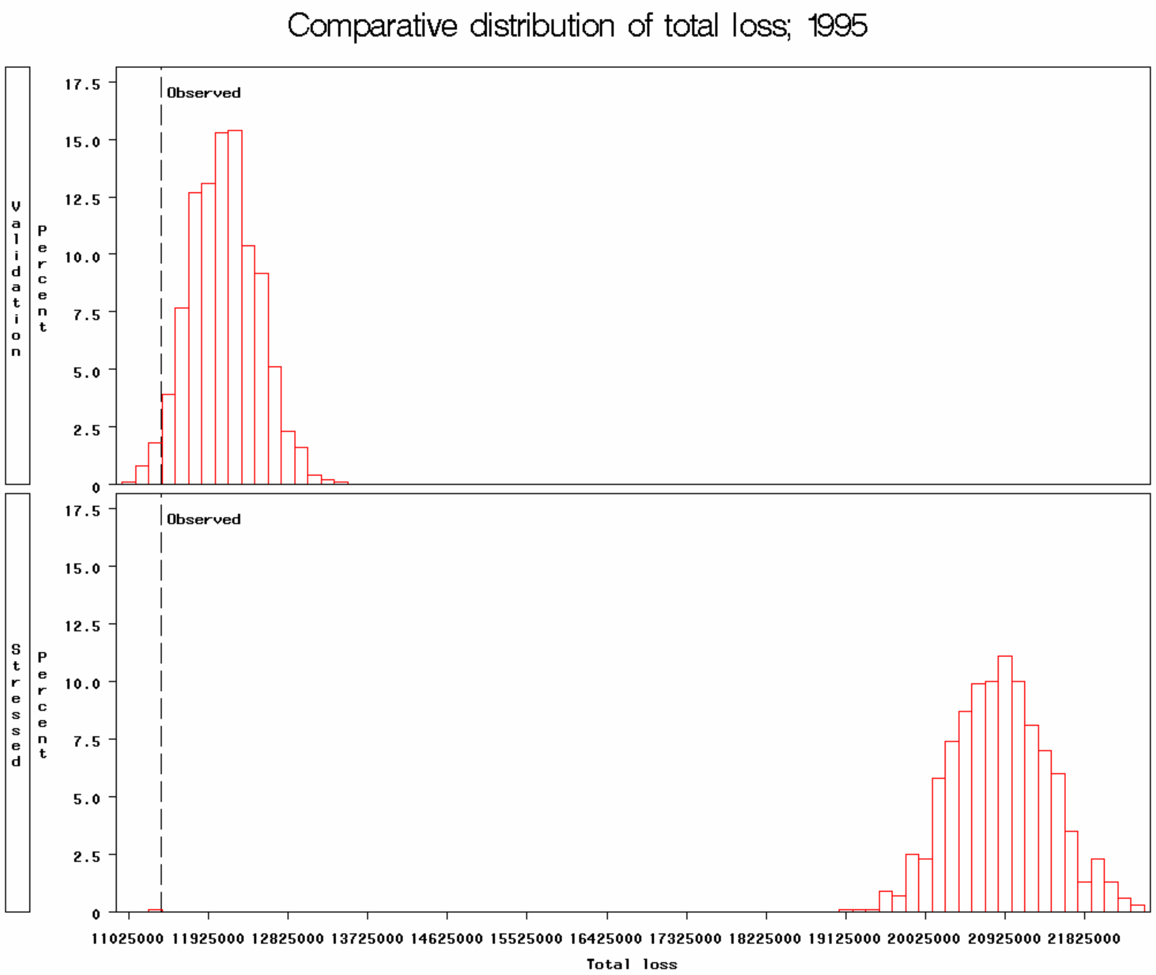
- 1991 (downturn)
- 1995 (non-downturn)

Stressed HPI, a combination of doubling any negative HPI growth and HPI values observed in recent crisis of 2008 (regional, quarterly)

DLTV changes with HPI changes

Simulation of 1,000 runs

Results: Total Loss – 1995

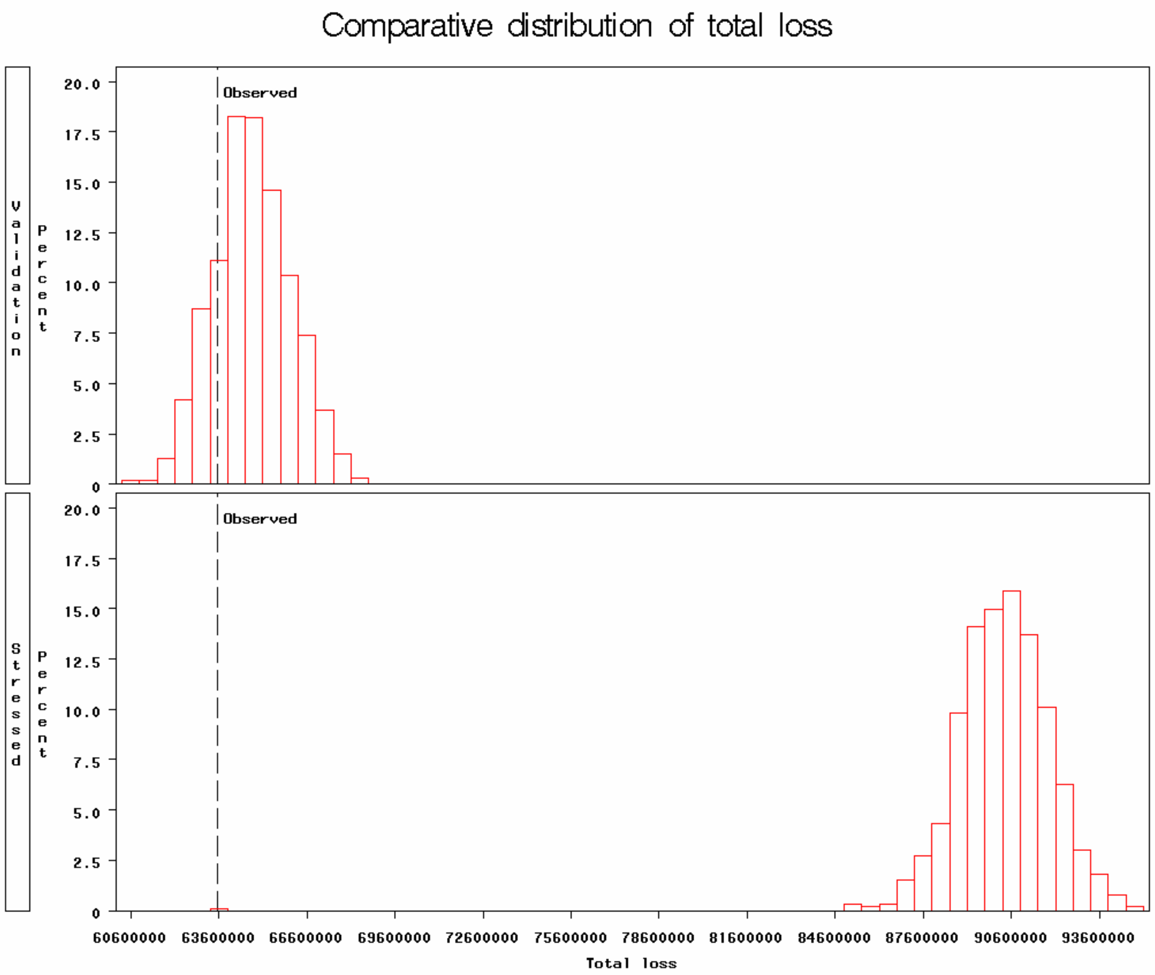


Dotted line represents actual total loss observed (predicted loss is over-estimated)

Stressed simulation has higher loss (about 75% more)

1995 is a non-downturn year, results from stressed scenario is more obvious

Results: Total Loss – 1991



Dotted line represents actual total loss observed (slightly over-estimated)

Stressed simulation has higher loss (about 50% more)

Since 1991 is a downturn year, stress scenario used affected losses to a lesser extent

Results: Average Number of Repossessions – 1995

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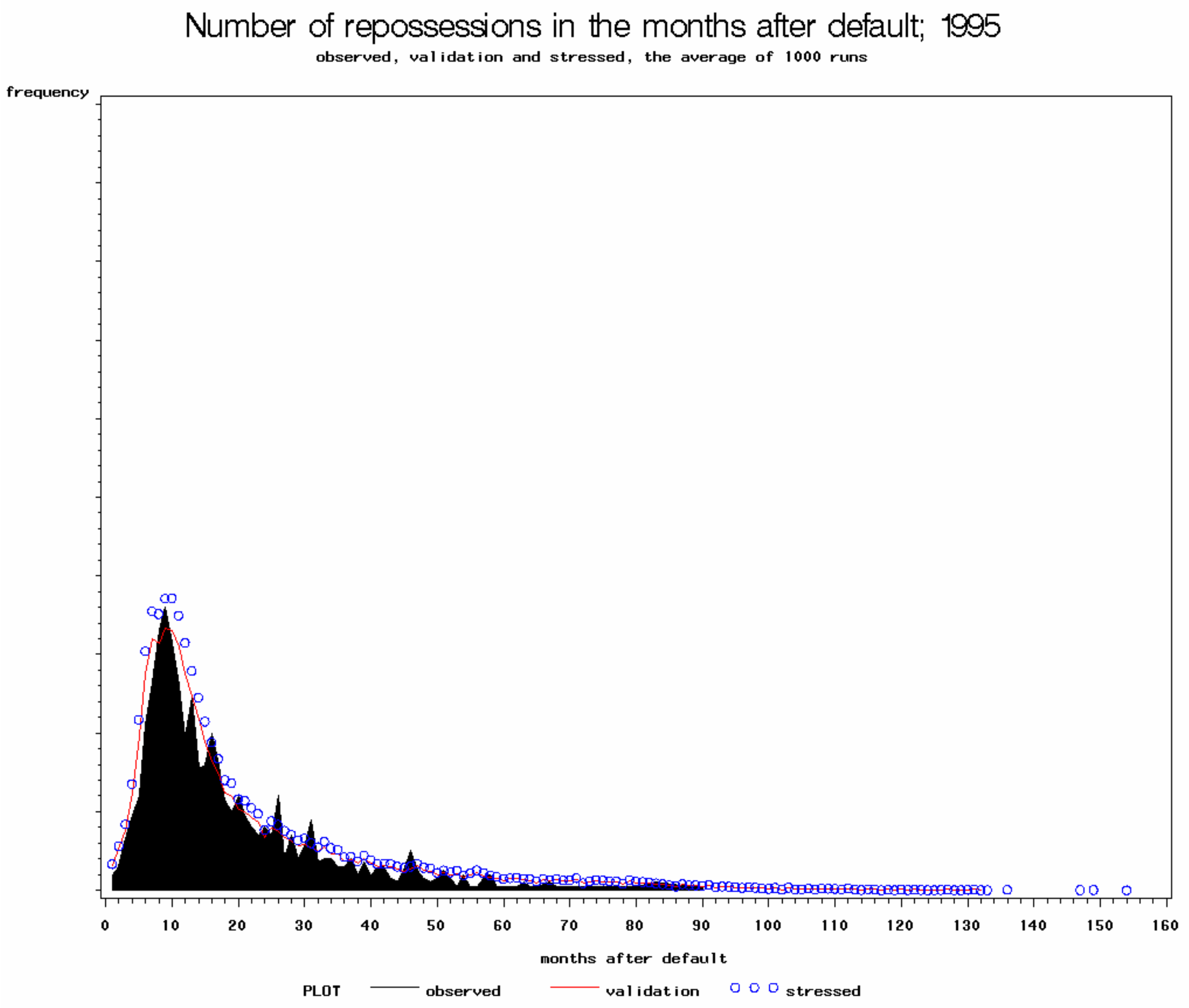
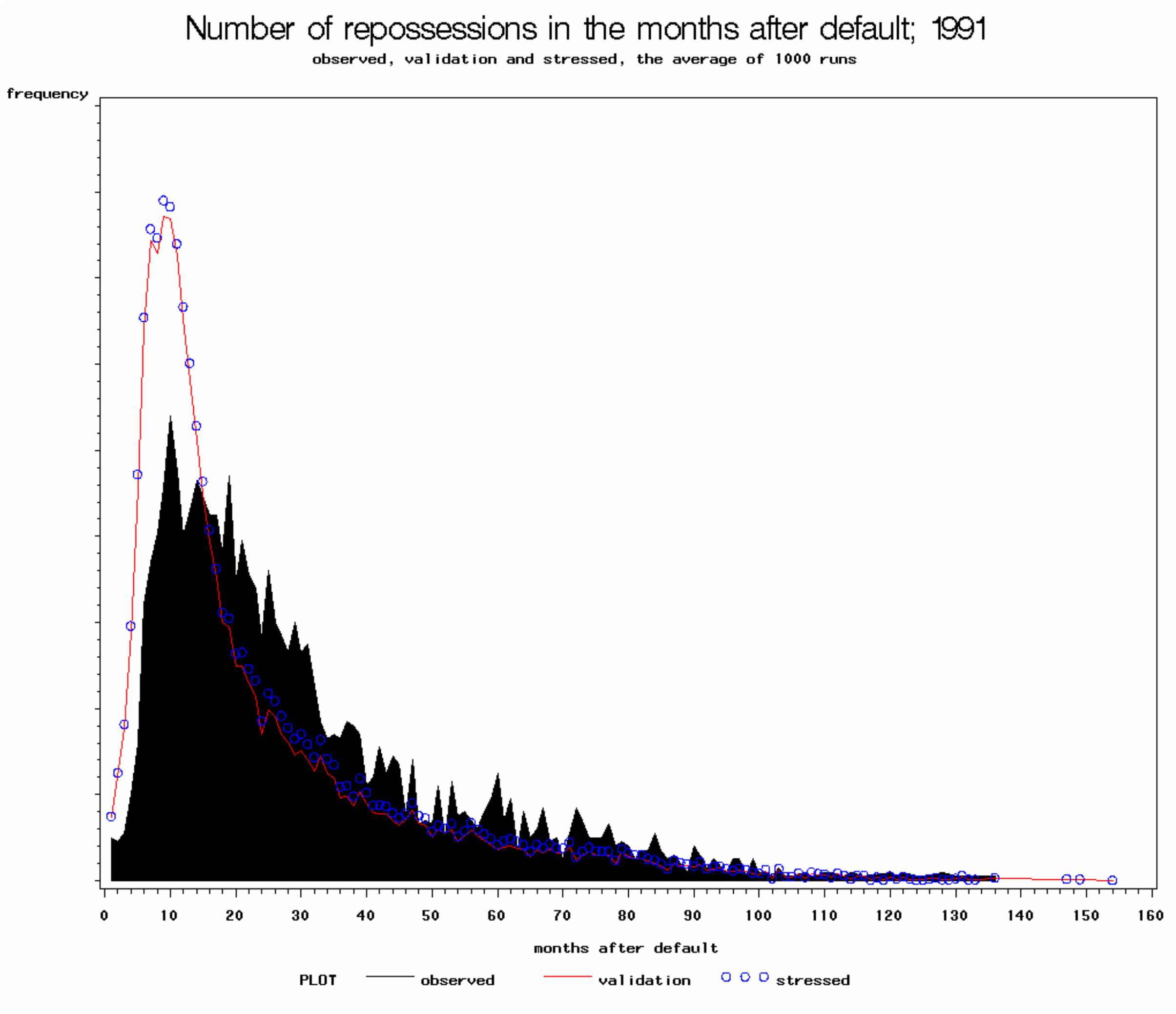


1995 being a typical non-downturn year, model is predicting well

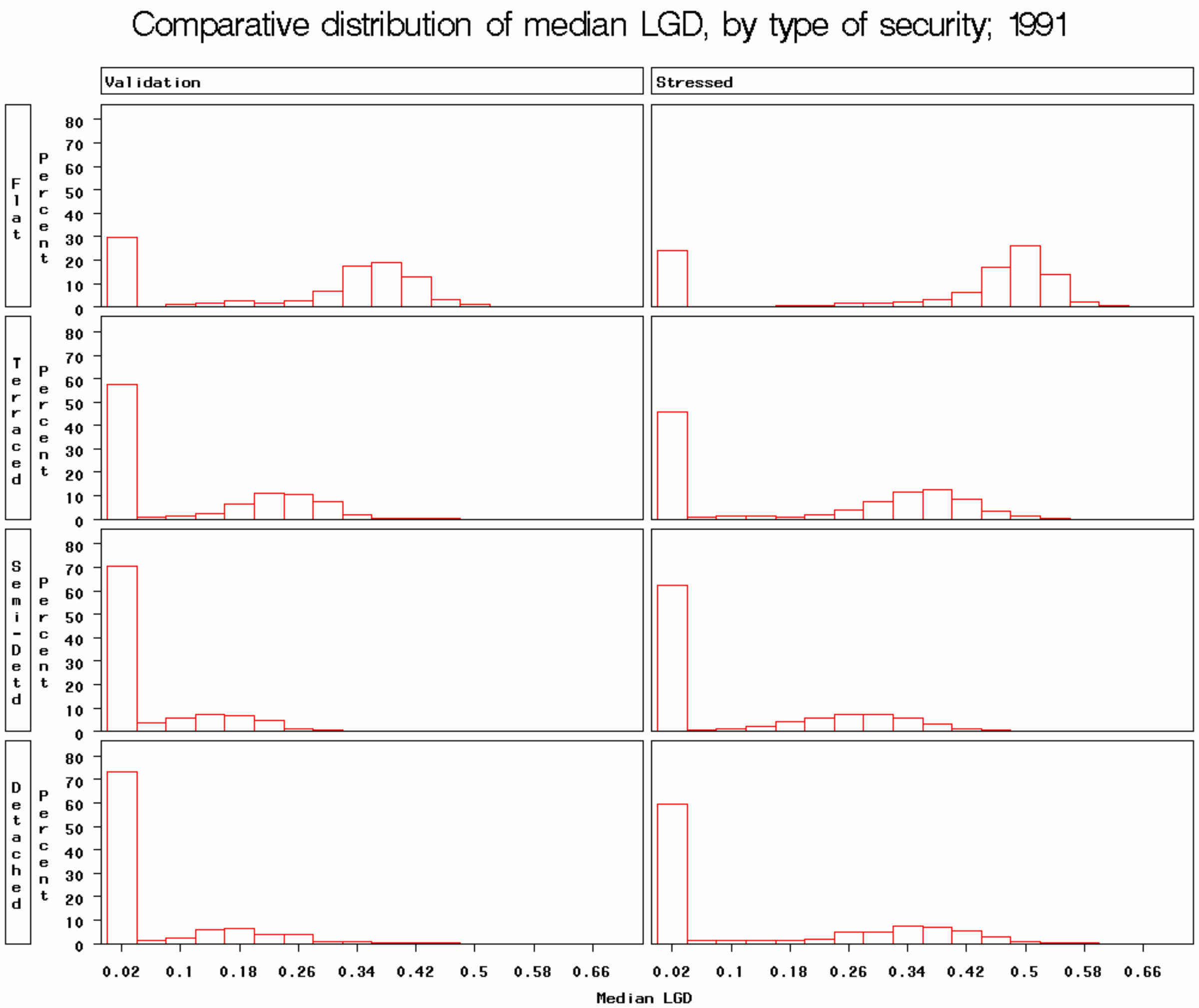
Results: Average Number of Repossessions – 1991



Number of repossessions over-estimated: management issue?

Model identifies that 1991 is a downturn year and predicts more repossession, but not at correct times

Results: Median LGD, by security – 1991



Distribution of median LGD for stressed simulation (right panel) is more severe

Higher loss rates for lower-range properties

LGD of higher-range properties more affected by poor economic conditions

Conclusions

Competing risks survival model for time to repossession or otherwise, which predicts if, and when (if applicable) repossession might happen

Repossession risk based on DLTV, type of security and HPI growth

Time-dependent variable (HPI growth) gives valuable insight on how drivers of risk are different for different types of securities of different DLTV bands in different economic climates

Monte Carlo simulation allowed for translation of (conditional) survival probabilities into predicted events and corresponding predicted event times

Conclusions

Macroeconomic variables do affect survival time and have an impact on potential losses

Model is able to predict higher losses for stressed situations, even before taking into account how macroeconomic variables could affect the number of defaulting accounts as well

Model predicted for plausible distributions of median LGD, in line with expectations for different types of securities

Model is able to predict for higher number of repossessions during downturn year, but not able to accurately predict the time at which repossession would happen – model not sensitive enough to changes in HPI (future work)

Discussion

Thank you

mindy.leow@ed.ac.uk

c.mues@soton.ac.uk

l.thomas@soton.ac.uk

Q&A