Cyclicality in Losses on Bank Loans

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Bank loans

- Banks face credit risk:
  - Risk that borrower of bank loan defaults

- Default:
  - Inability of borrower to meet payments
  - For example: (i) being overdue on payment or (ii) bankruptcy

- Portfolio loss depends on three components:
  - Default rate (DR)
  - Loss given default (LGD) (0 is no loss, 1 is full loss)
  - Exposure at default (EAD) (taken as given)
Research question

- Does LGD of bank loans show cyclical variation?
  - Related to default rate variation?
  - Related to the business cycle?

- Relevance:
  - Practitioners: Basel II says that LGD should “reflect economic downturn conditions where necessary to capture the relevant risks.”
  - Academics: A lot of research on cyclicality in bonds, but hardly any on loans
  - Complement literature that finds cyclicality for bonds (Altmann et al, 2005 etc.)
  - Note that bank loans are very different from bonds
    - Banks monitor more closely
    - Loans are more senior
    - Recovery is more flexible
What do we do?

- We study a unique data set from the PECDC database.
  - Previous research on bank loan LGD: Calabrese & Zenga (2010, JBF), 150,000 Italian loan recoveries 1999.
    Hartmann-Wendels et al. (2014, JBF), 14,000 German leasing defaults in 00s.

- We develop a new model that links LGD and DR to a common latent factor.
  - Mixed measurement model
  - Mixture of normals for LGD; usually beta distribution for bond LGD (Creal et al., 2014; REStat etc).

- Link latent factor to macro variables.
Default data

- Pan European Credit Data Consortium (PECDC) database
  - Consortium of 44 banks (not all of them European)
  - Pooled data-set with LGD and DR
  - Includes loan-specific information (industry, asset class etc.)

- NIBC subset
  - Restrict to 2003–2010 (median workout period of 1 year).
  - Small loans (EAD < € 100,000) and outlier LGDs (LGD < −0.5 and LGD > 1.5) excluded.
  - 22,080 defaults remain.
LGD: Empirical distribution

- Bimodal
- Not restricted to [0, 1]-interval.
  > 1 principal advances, costs of default.
  < 0 sale of collateral, principal advances, penalty fees.
LGD: Time-variation of the mean

Average LGD per quarter

- Average LGD varies
- Either caused by (i) variation in means of components or (ii) variation in probability of components?
LGD: Time-variation of empirical distribution

Empirical distribution per quarter

- Modes stay at 0 and 1.
- Probability of components (relative size of peak) varies.
Mixed measurement model (1)

- $y_{it}^l$: LGD on loan $i = 1, \ldots, N_t$ that goes into default at time $t$ and is part of group $j$ (i.e. particular industry etc.)

\[
y_{it}^l \sim \begin{cases} 
    N(\mu_j, \sigma^2_j) & \text{if } s_{it} = 0 \text{ (good loss)} \\
    N(\mu_j, \sigma^2_j) & \text{if } s_{it} = 1 \text{ (bad loss)} 
\end{cases} \tag{1}
\]

where $\mu_j < \mu_j^1$.

- Probability of loss type linked to latent factor.

\[
P(s_{it} = 1) = p_{jt} = \Lambda \left( \beta_{j0}^l + \beta_{j1}^l \alpha_t \right) \tag{2}
\]

where $\Lambda(x) = 1/(1 + e^{-x})$, logistic function.
Mixed measurement model (2)

- $y_{jt}^d$: number of defaults at time $t$ for group $j$,
  - $L_{jt}$: number of loans and $q_{jt}$: default rate.
  - $y_{jt}^d \sim \text{Binom}(L_{jt}, q_{jt})$ (3)

- Link default rate to latent factor.
  - $q_{jt} = \Lambda (\beta_{j0}^d + \beta_{j1}^d \alpha_t)$ (4)

- $y_t^m$ vector of macro variables at time $t$
  - $y_t^m = \beta_0^m + \beta_1^m \alpha_t + \nu_t$ (5)
  - where $\nu_t \sim \text{N}(0, \Sigma)$.
  - Latent factor $\alpha$ follows AR(1) process.
Results of basic model

No macro variables, no difference between industry, asset class, etc.

<table>
<thead>
<tr>
<th></th>
<th>LGD module</th>
<th>Default rate module</th>
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<tbody>
<tr>
<td>$\mu_0$</td>
<td>0.072 (0.001)</td>
<td></td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>0.828 (0.002)</td>
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<tr>
<td>$\sigma$</td>
<td>0.131 (0.001)</td>
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<tr>
<td>$\beta^l_0$</td>
<td>-1.652 (0.100)</td>
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<tr>
<td>$\beta^l_1$</td>
<td>0.311 (0.045)</td>
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<tr>
<td></td>
<td></td>
<td>$\beta^d_0$ -4.545 (0.310)</td>
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<td></td>
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<td>$\beta^d_1$ 0.931 (0.248)</td>
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<th>Latent Factor</th>
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<tr>
<td>$\rho$</td>
<td>0.449 (0.167)</td>
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- Clear distinction between good and bad losses.
- LGD and DR positively correlated because of latent factor.
Goodness of fit

- Clear distinction between good and bad losses.
- Alternative: Student’s $t$ distribution, better fit but problems with interpretation.
Latent factor and implications

*Left:* Smoothed latent factor $\alpha_t$;

*Right:* Implied values for $p_t$, probability of a bad loss and $q_t$, probability of default.

▶ Cyclical pattern, $p_t$: 9–28%, $q_t$: 0.2–7%.

▶ Average marginal effects:

$\alpha_t + 1 \text{ std} \rightarrow p_t + 4.2\%, \ q_t + 1.5\%.$
Relation credit cycle and business cycle (1)

Model with macro variables; no difference between industry etc

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<th>LGD module</th>
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<th>Macro module</th>
<th>Latent Factor</th>
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<tr>
<td>( \sigma )</td>
<td>0.131 (0.001)</td>
<td>( \beta_0^d ) = -4.526 (0.284)</td>
<td>( \beta_1 ) = 0.809 (0.181)</td>
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<td>( \beta_0^l )</td>
<td>-1.656 (0.102)</td>
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<td>( \beta_1^l )</td>
<td>0.299 (0.044)</td>
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<tr>
<td>GDP</td>
<td>-0.499 (0.070)</td>
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<tr>
<td>IP</td>
<td>-0.408 (0.059)</td>
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<tr>
<td>UR</td>
<td>0.415 (0.060)</td>
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<tr>
<td>( \rho )</td>
<td>0.484 (0.162)</td>
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- No changes to model without macro variables for estimates.
- Significant relation of expected sign with macro variables.
Relation credit cycle and business cycle (2)

(a) GDP growth

(b) Unemployment rate

Lag = 5: macro variable at $t + 5$ and factor at $t$

- Lead/lag relation unclear ex ante:
  - Recession $\rightarrow$ losses? Or other way around?
  - Contemporaneous negative relation with GDP
  - Factor leads unemployment rate.
Portfolio losses (1)

▶ Are our findings economically relevant?
   ▶ Do the losses for banks on a given loan portfolios change a lot over time?
   ▶ If yes, banks cannot ignore the cyclicality

▶ What do we do?
   ▶ Consider portfolio of 2,000 loans with EAD of EURO 1
   ▶ Obtain loss distribution by drawing 50,000 scenarios for a particular date (=latent factor)

▶ Economic capital: amount of capital bank should hold to remain solvent
   ▶ Difference between loss at 99.9% and expected loss
   ▶ Hence, accounts for unexpected losses
Portfolio losses (2)

(a) Losses over time

(b) Economic capital over time

- Enormous amount of variation in:
  - Average losses
  - Percentiles in tails
  - Economic capital
Concluding remarks

- Unique dataset leads to unique challenges
  - LGD, DR for bank loans
  - Mixture model for LGD due to observations outside [0,1]

- Results:
  - Mixture model for LGD offers good fit.
  - Latent factor (credit cycle) related to macroeconomic variables.
  - Variation in LGD from variation in probability of bad loss.
  - Credit cycles are not identical for different groups

- Portfolio losses:
  - The distribution of portfolio losses and the economic capital changes substantially over time