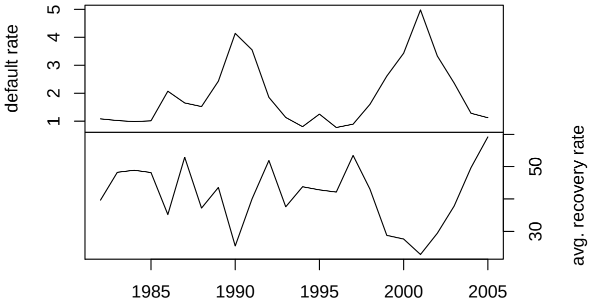
Recovery Rates, Default Probabilities, and the Credit Cycle

Max Bruche and Carlos González-Aguado

CEMFI

Motivation


default rate
1
2
3
4
5
avg. recovery rate
30
50
1985
1990
1995
2000
2005

The research questions & method

- Can you exploit the joint time-series behaviour of these variables to look at credit risk?

$\Longrightarrow$ Let both default probabilities and recovery rate distributions be driven by an unobserved factor (Markov chain).

- How bad is it to treat recovery rates as constant?

Related literature

- Default probabilities vary with the cycle.
  (Bangia et al. (2002), Nickell et al. (2000))
- Recovery rates $\uparrow \implies$ default probabilities $\downarrow$
  (Altman et al. 2006, Acharya et al. 2007)
  Is the amplification effect of recovery rates large?
- Recovery rates and default probabilities can be modelled as functions of observed covariates.
  (Chava et al. 2008)
- Theory:
  - Recovery rates should be related to the state of the industry: Shleifer and Vishny (1992).
  - RBC and credit: Bernanke and Gertler (1989), Williamson (1987)

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- slightly higher estimates of tail risk,
  (the 99% VaR e.g. 3.3% $\rightarrow$ 3.4%, or 3.4% $\rightarrow$ 3.7%.)
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Caveats?

The basic idea

The DGP works as follows:

- The state of the credit cycle is determined by a two-state Markov chain.
- The number of defaulting firms is drawn using the state-dependent default probability.
- For each defaulting firm, we draw a recovery rate from the state-dependent recovery rate distribution.

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Dependence:

- Conditional on the state, defaults are independent, recoveries between firms are independent, and the number of defaulting firms and recoveries are independent.
- As a consequence, (unconditional) dependence is driven entirely by the (unobserved) state of the credit cycle.

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- Conditional on the state of the cycle, default arrival is described by discrete hazards of the form

$$\lambda_t = \left(1 + \exp\left\{\gamma_0 + \gamma_1 c_t + \gamma_2 X_t\right\}\right)^{-1}.$$

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- Recoveries for each default event are drawn from a beta distribution.
- The parameters of this beta distribution are given by:

$$\alpha_{ti} = \exp\left\{\delta_0 + \delta_1 c_t + \cdots + \delta_6 X_t\right\} \quad (1)$$

$$\beta_{ti} = \exp\left\{\zeta_0 + \zeta_1 c_t + \cdots + \zeta_6 X_t\right\} \quad (2)$$

(t: time, i: firm)

Estimation

- The model can be easily be estimated using a version of the Hamilton filter (MLE).
- For this we need the number of defaulting firms, and non-defaulting firms in each period, and a recovery rate for each default event.

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- We augment this with GDP growth, investment growth, unemployment, the S&P 500 index, the VIX, the slope of the term structure, and an NBER recession indicator.

Macro variables versus the business cycle

	Model 1	Model 2	Model 3	Model 4
Explanatory variables for λ (default probability)				
	constant	constant	constant	constant
		cycle	log GDP growth	cycle
				log GDP growth
Explanatory variables for α,β (recovery rates)				
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		cycle	log GDP growth	cycle
				log GDP growth
	seniority	seniority	seniority	seniority
AIC	-20.43	-309.18	-86.45	-314.26
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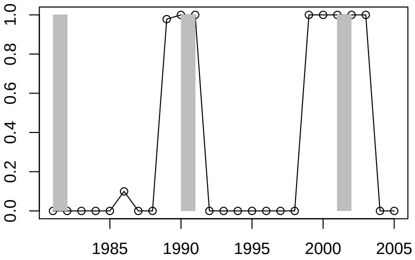
$\Longrightarrow$ Macro variables are significant, but do not contribute much to the fit.

Is the business cycle = credit cycle?



- The estimated credit downturns start earlier than NBER recessions, and end later.
- We investigate lead-lag relationships between macro variables and credit variables and find that recovery rates Granger cause log GDP growth (very significant!).

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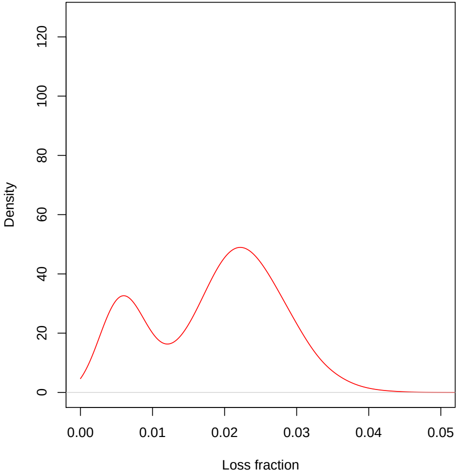

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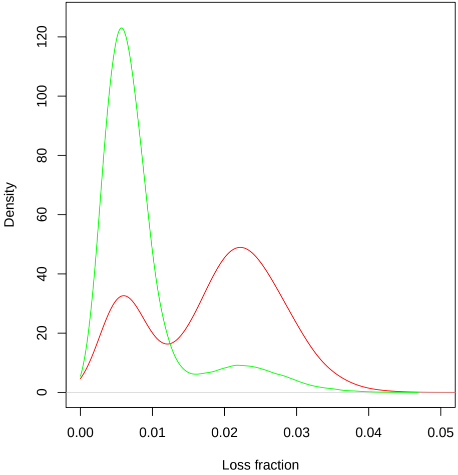

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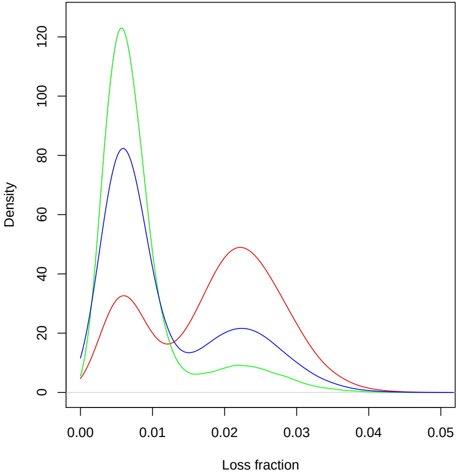

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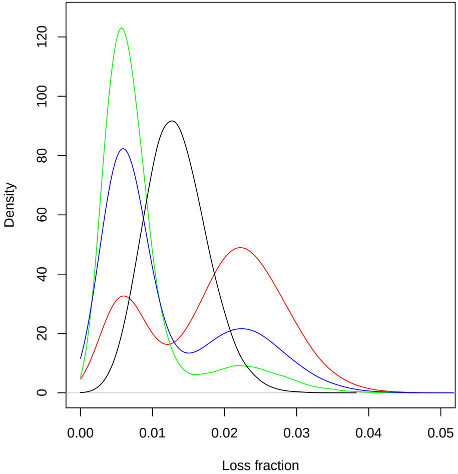

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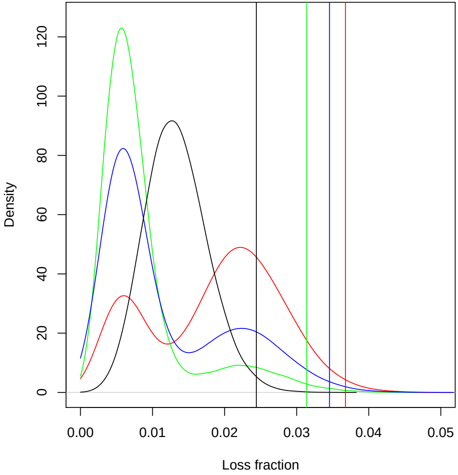

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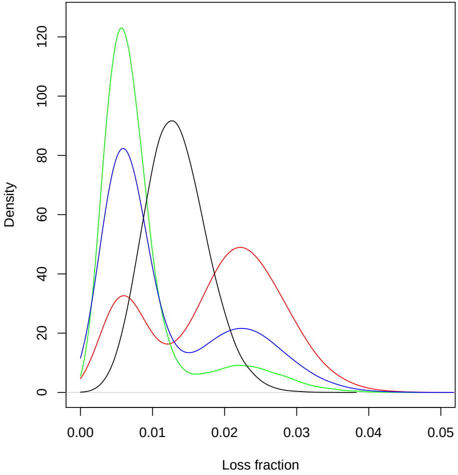

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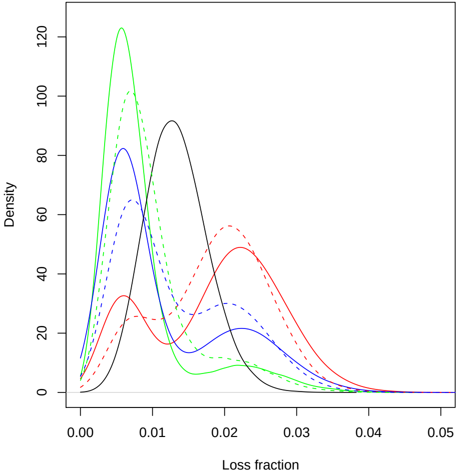

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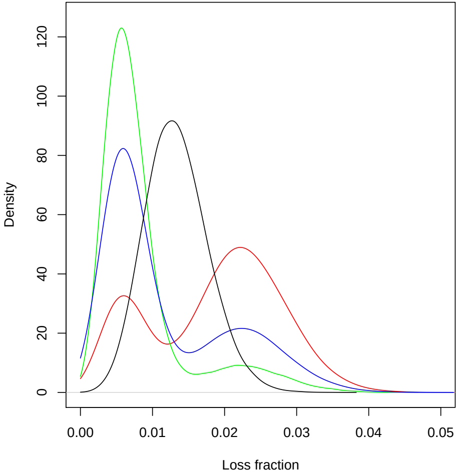

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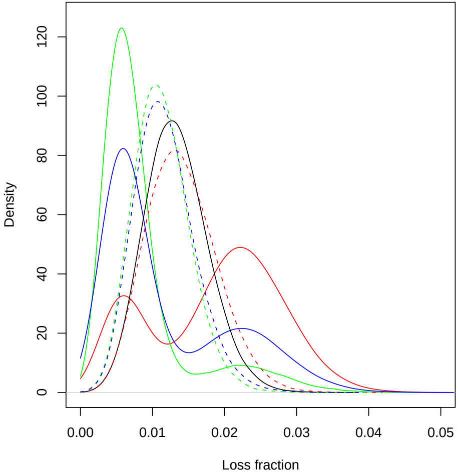

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  Therefore

$$E[L \cdot PD] = .5 \times 30\% \times 0.02 + .5 \times 70\% \times 0.1 = 3.8\%$$
$$E[L] \cdot E[PD] = 3\%$$

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  i.e. expected loss can be bigger if PD and L covary.
- We could calculate the increase in expected loss from our model, but note that
  $E[L \cdot PD] - E[L]E[PD] = \mathrm{Cov}(L, PD)$.
- In our data, $\mathrm{Cov}(\bar{L}, dfr) = 6bp$.

Some conclusions

- We propose an econometric model in which default rates and recovery rates are driven by an unobserved Markov chain.
- This describes the data well, and does better than many models based on observed covariates.
- In particular, macro variables are significant, but don't help much in matching variation in credit risk.

We can use the estimated model to look at what happens when we go from constant to time-varying recovery rate distributions. We get

- slightly higher estimates of tail risk,
- but practically the same expected losses.