Recovery Rates, Default Probabilities and the Credit Cycle

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CEMFI

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Motivation


default rate
0.5
2.0
3.5
avg. recovery rate
30
50
1985
1990
1995
2000
2005

The research questions & method

The questions:

- Can you exploit the joint time-series behaviour of default rates and recovery rates to characterize and forecast credit risk?
- How bad is it to treat recovery rates as constant (or independent of default probabilities)?

The method:

- We propose an econometric model in which both the time variation in default probabilities and recovery rate distributions is driven by an unobserved Markov chain, the "credit cycle".

Related literature

- Default probabilities or rating transitions vary over time, and are related to macro variables.
  (Bangia et al. (2002), Nickell et al. (2000))
- Recovery rates and default probabilities are contemporaneously negatively related.
  (Altman et al. 2006, Acharya et al. 2007)
- Recovery rates and default probabilities can be modelled as functions of observed covariates.
  (Chava et al. 2006)
- 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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- higher estimates of tail risk,
  (for a sample portfolio, the 99% VaR goes from 2.6% to 2.9%.)
- the same expected losses,
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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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- The parameters of this beta distribution are given by:

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

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

(i: firm, s: seniority)

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)				
	constant	constant	constant	constant
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	seniority[a]	seniority[a]	seniority[a]	seniority[a]
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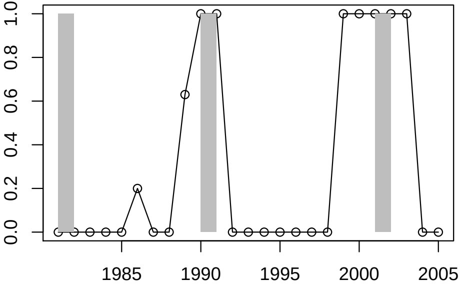
$\Longrightarrow$ Macro variables are significant, but do not contribute much to the fit.

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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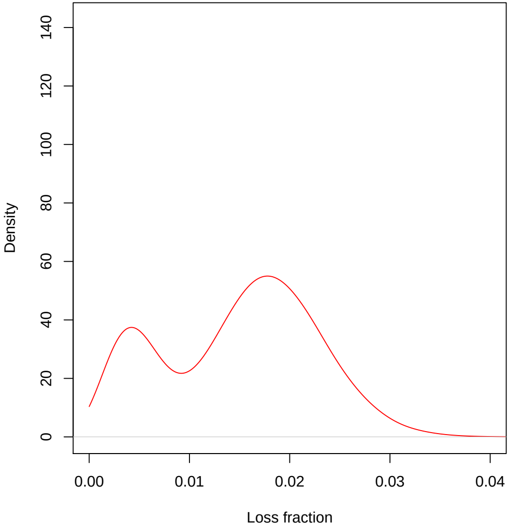

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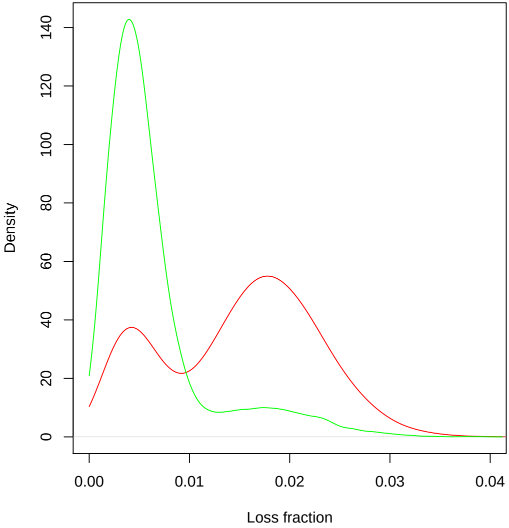

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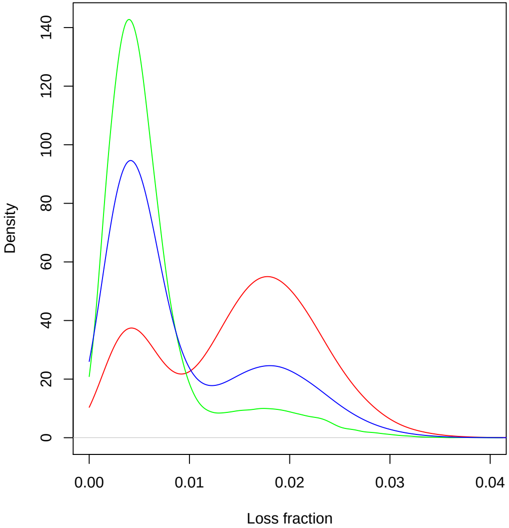

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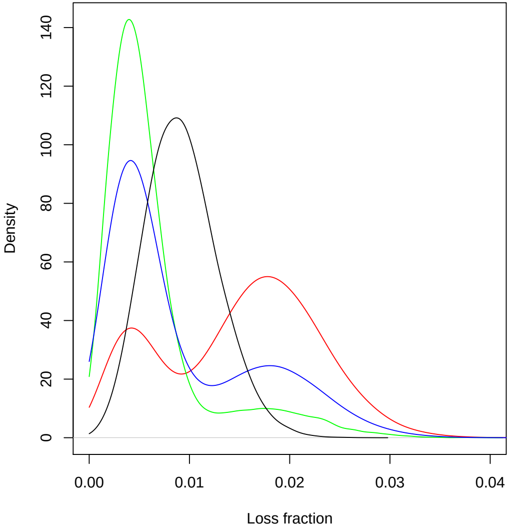

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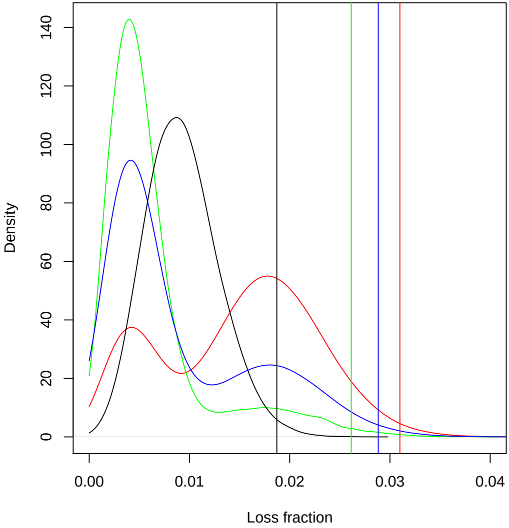
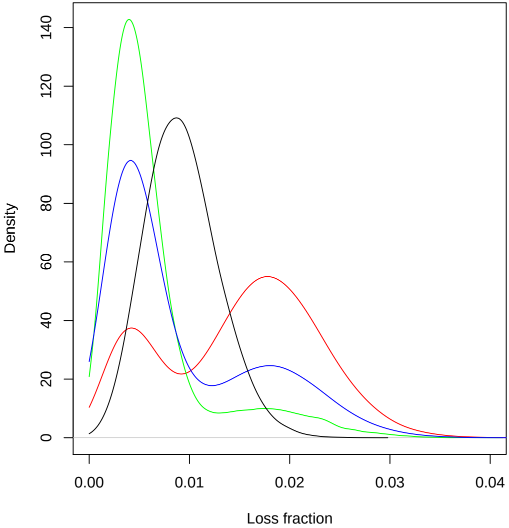


VaR Simulation (2)



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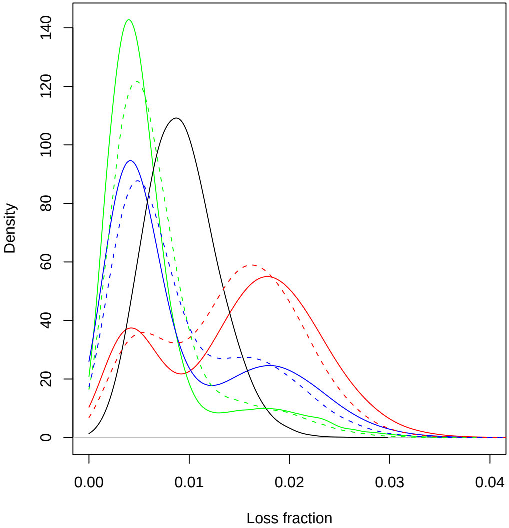
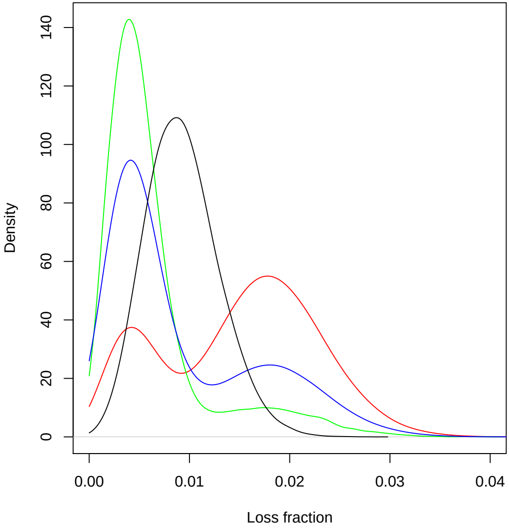


VaR Simulation (3)



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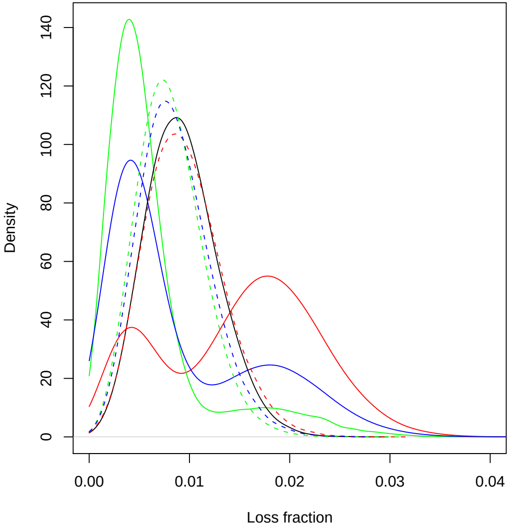

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$$E[L \cdot PD] = .5 \times 30\% \times 0.02 + .5 \times 70\% \times 0.1 = 3.8\%$$
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- But $E[L \cdot PD] - E[L]E[PD] = \mathrm{Cov}(L, PD)$.
- In our data, $\mathrm{Cov}(avg.\, L, dfr) = 5bp$.

Some conclusions

- We propose an econometric model in which default rates and recovery rates are driven by an unobserved Markov chain.
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