Systemic Risk: What Defaults Are Telling Us

Baeho Kim
Assistant Professor
Korea University Business School
baehokim@korea.ac.kr

Joint work with **Kay Giesecke**

Systemic risk

- Systemic risk is difficult to measure, making it hard for regulators and policy makers to address it effectively
- A major challenge is to capture the risk spillovers that can occur in an increasingly complex financial network
  - Information based spillovers related to imperfectly observed risk factors influencing several firms
  - Contagion through derivatives exposures, interbank loans, etc.
  - The Lehman Brothers and AIG events highlight the importance of these network effects

Contributions

- We propose a measure of systemic risk that focuses on the risk of failure clusters in the financial industry
  - Maximum likelihood estimators of the term structure of dynamic systemic risk
  - Complements existing measures that focus on significant changes in market prices or rates
- We estimate the measure from data on US default timing
  - Capture the statistical implications of risk spillovers
- We show that the fitted measure accurately predicts systemic risk in the US financial system

Applications

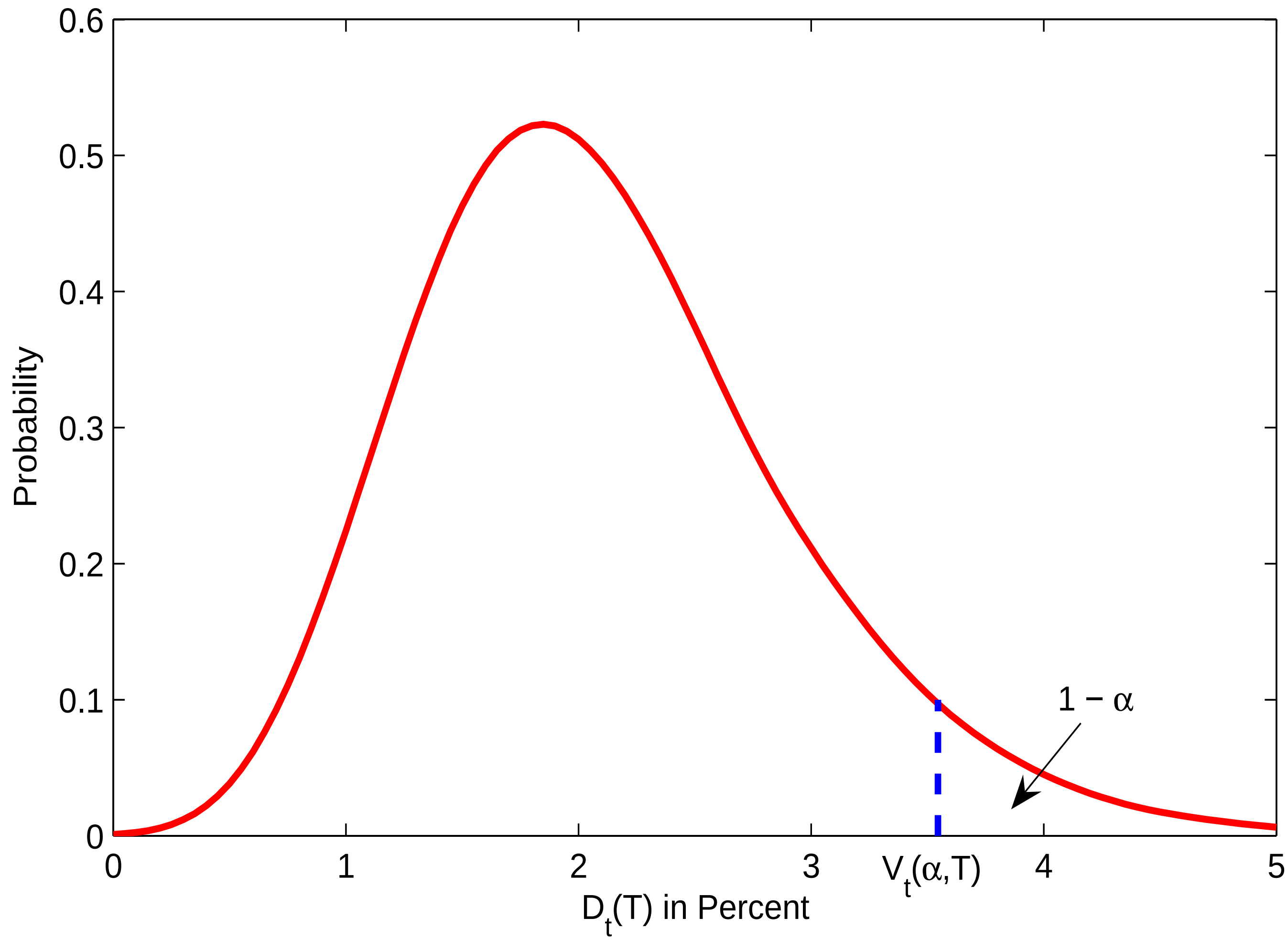
- Monitoring systemic risk
  - Time series perspective
  - Term structure perspective
- Applicable as early warning tools for regulators and policy makers to monitor the financial system
- Macro-prudential supervision of financial institutions
- Further steps are required to allocate risk to individual institutions

Measures of systemic risk

- Systemic risk is the probability of failure of a sufficiently large fraction of the total population of firms in the financial system
  - Cluster of failures, potentially part of larger economy-wide default cluster
- It is represented by the tail of the conditional distribution at t of the default rate $D_t(T)$ in the financial system during $(t, T]$
  - Extension: value-weighted default rate
- The value at risk $V_t(\alpha, T)$ at level $\alpha \in (0, 1)$ measures the tail
  - Depends on conditioning time t: time series
  - Depends on risk horizon T: term structure
- Alternatives: expected shortfall (average value at risk)

Measures of systemic risk

Value at risk $V_t(\alpha, T)$ of the default rate $D_t(T)$ in the financial system



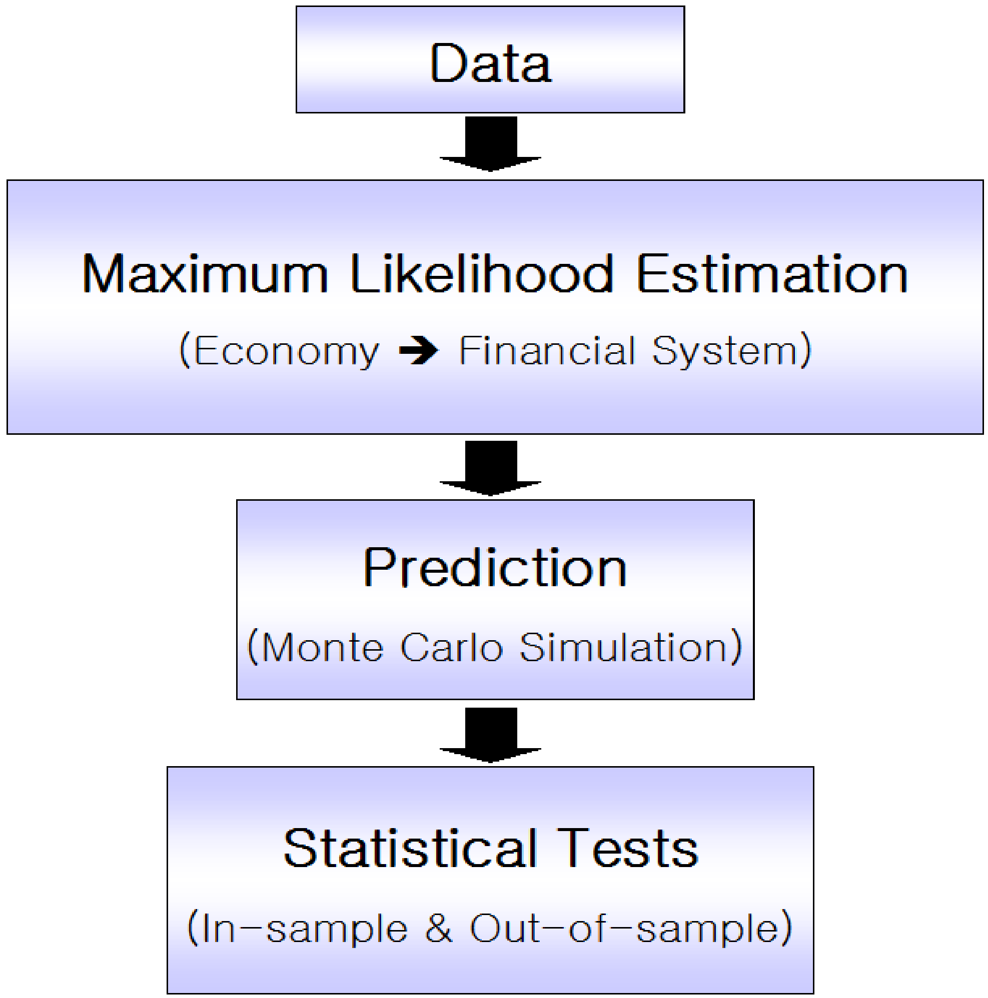
Measures of systemic risk

- The VaR is tied to the failure rate in the financial system
  - Adrian & Brunnermeier (2009) and Acharya, Pedersen, Philippon & Richardson (2009) relate systemic risk to the distribution of the change in market value
- The VaR is calculated under the statistical measure
  - Avesani, Pascual & Li (2006), Chan-Lau & Gravelle (2005), Huang, Zhou & Zhu (2009) and others define systemic risk in terms of a risk-neutral probability
- The VaR is estimated from actual default experience
  - Economy-wide default timing and default volumes
  - Time-varying explanatory covariates, including market values

Statistical methodology

- 2-step maximum likelihood
  - Dynamic hazard model of economy-wide default timing
  - Dynamic hazard model of system-wide default timing: thinning the economy-wide event sequence
- Advantages over 1-step alternative
  - Capture the statistical implications of industrial defaults for financial failures
  - Higher predictive power of system-wide estimators

Major Steps


Data
Maximum Likelihood Estimation
(Economy ➔ Financial System)
Prediction
(Monte Carlo Simulation)
Statistical Tests
(In-sample & Out-of-sample)

Economy-wide default timing

- Consider the hazard rate or **intensity** λ^*, the conditional mean default rate in the economy, measured in events per year

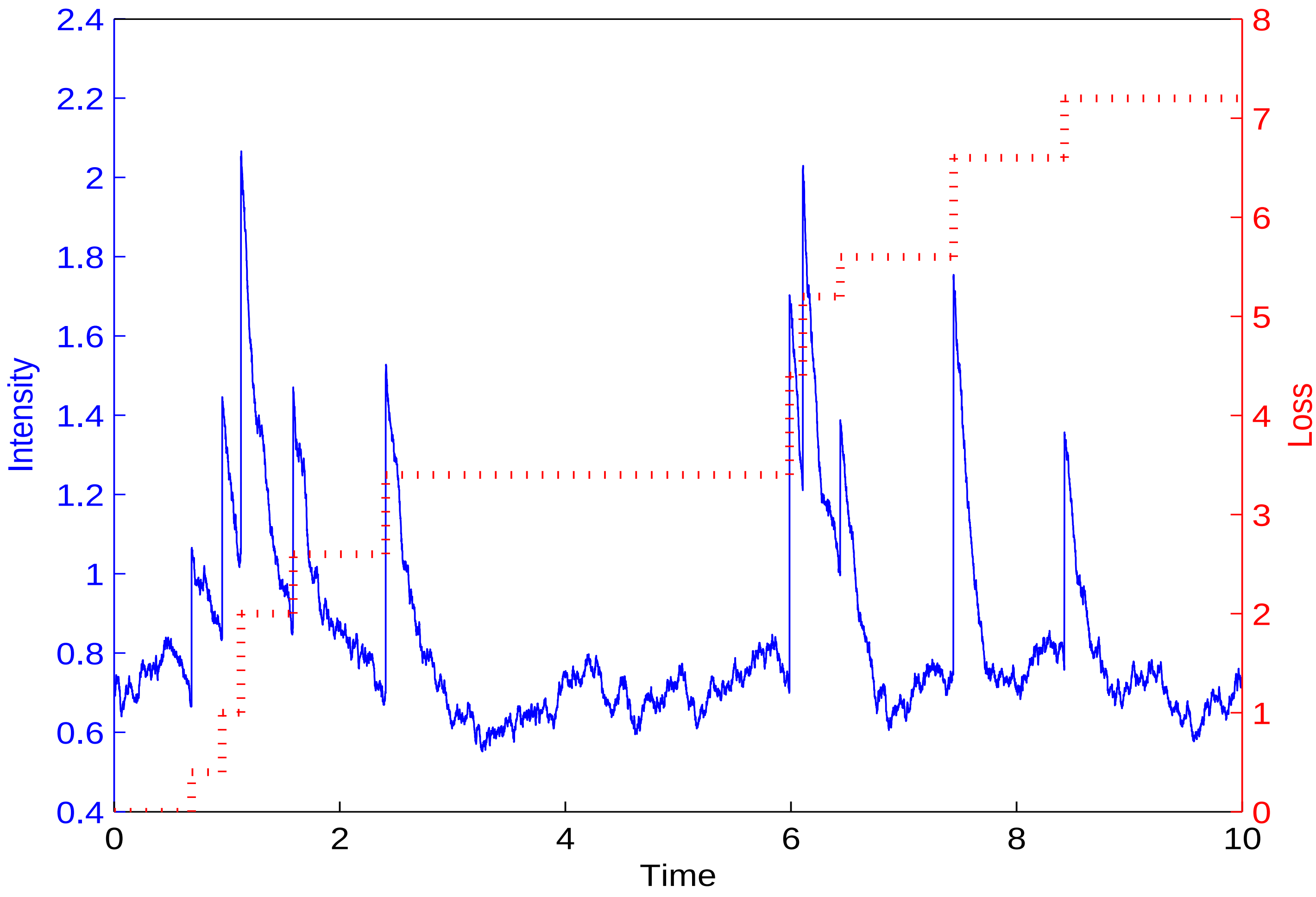
- We assume that λ^* evolves through time according to the model

$$\lambda_t^* = \exp(\beta^* X_t^*) + \int_0^t e^{-\kappa(t-s)} dJ_s$$

  - X^* is a vector of explanatory covariates
  - β^* is a vector of parameters
  - $J_t = \nu_1 + \cdots + \nu_{N_t^*}$ where $\nu_n = \gamma + \delta \max(0, \log D_n^*)$
  - D_n^* is the default volume (million dollars)
  - $\theta = (\beta^*, \kappa, \gamma, \delta)$ is a parameter vector to be estimated

Economy-wide default timing

Sample path of (λ^*, J)



Economy-wide default timing

- **Baseline hazard** $\exp(\beta^* X_t^*)$ takes proportional hazard form
  - Models influence on default timing of explanatory covariates
  - Used by Duffie, Saita & Wang (2006) and many others to predict industrial defaults, and by Wheelock & Wilson (2000) and others to predict bank failures
- **Spillover hazard** $\int_0^t e^{-\kappa(t-s)} dJ_s$
  - Not present in traditional proportional hazards formulation
  - Capture the statistical implications of risk spillovers without needing to be precise a priori about the economic mechanisms behind them

Economy-wide default timing

Maximum likelihood estimators

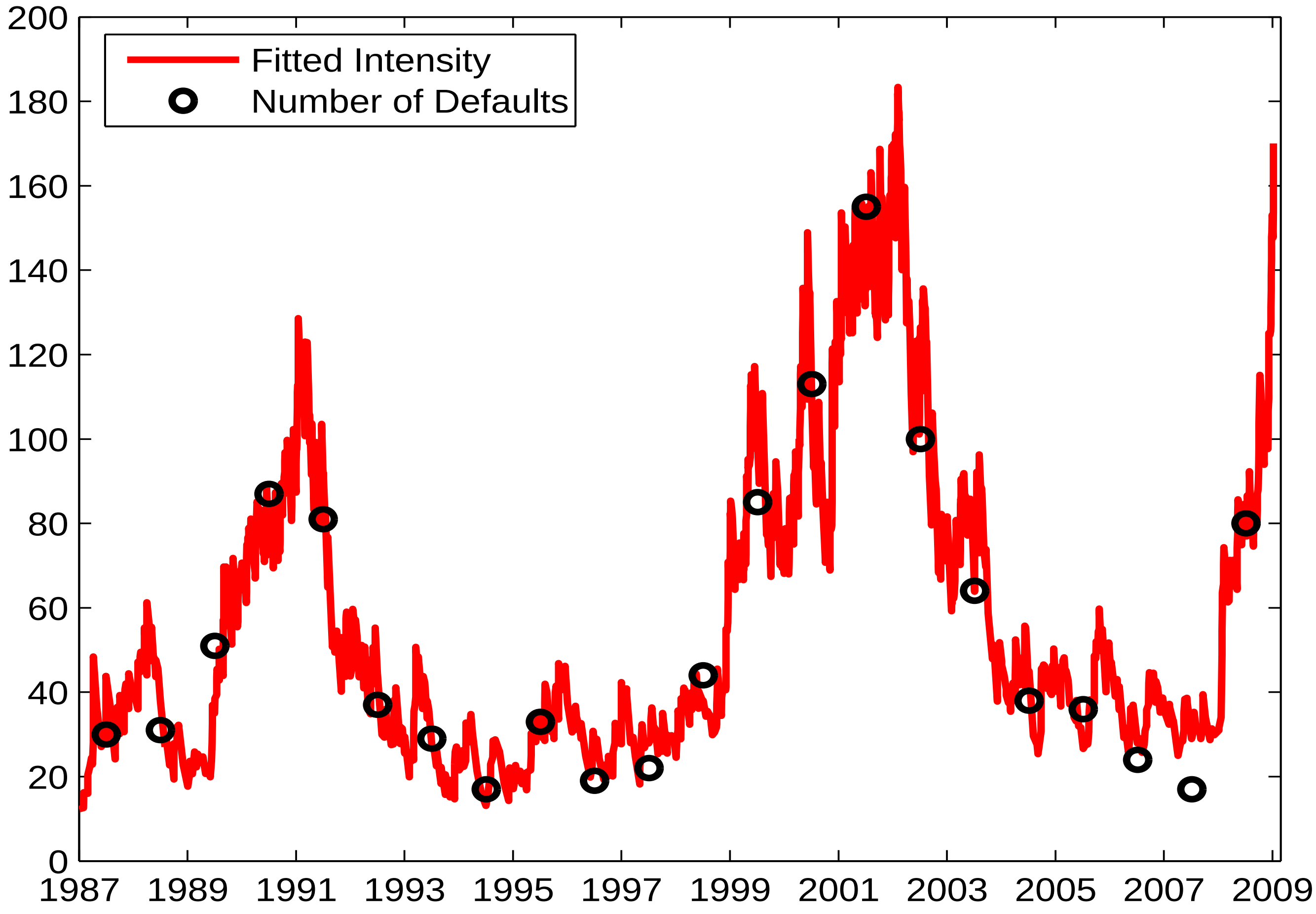
<table>
<tr><th rowspan="2"></th><th colspan="4">Baseline Hazard</th><th colspan="3">Spillover Hazard</th></tr>
<tr><th>Constant</th><th>S&P500</th><th>Yield Slope</th><th>Baa-Aaa</th><th>κ</th><th>γ</th><th>δ</th></tr>
<tr><td>MLE</td><td>2.3026</td><td>-0.4410</td><td>-0.2140</td><td>0.5092</td><td>6.0592</td><td>2.3205</td><td>0.4781</td></tr>
<tr><td>SE</td><td>0.0605</td><td>0.0524</td><td>0.0336</td><td>0.0534</td><td>0.1108</td><td>0.0811</td><td>0.0233</td></tr>
<tr><td>t-stat</td><td>38.04</td><td>-8.42</td><td>-6.37</td><td>9.53</td><td>54.71</td><td>28.60</td><td>20.56</td></tr>
<tr><td rowspan="2">Bayes</td><td></td><td>0.1298</td><td>3.0987</td><td>1.8310</td><td colspan="3" rowspan="2">213.4039</td></tr>
<tr><td colspan="4">26.5308</td></tr>
</table>

- $\theta = (\beta^*, \kappa, \gamma, \delta) \Rightarrow$ parameters of $\lambda^* = \lambda^*(\theta)$
- Given observations of default times and volumes and covariates X^* during $[0, t]$, we solve the log-likelihood problem

$$\sup_{\theta \in \Theta} \left(\int_0^t \log \lambda^*_{s-}(\theta) dN^*_s - \int_0^t \lambda^*_s(\theta) ds \right)$$

Economy-wide default timing

Fitted economy-wide default intensity λ^*



System-wide default timing

- **Proposition.** There is a (predictable) thinning process $Z \in [0,1]$ such that the intensity of system-wide failures $\lambda = Z\lambda^*$
  - Extract λ from economy-wide intensity λ^*
  - The value Z_t is the conditional probability at t that a firm in the financial system defaults next, given a default in the economy in the next instant
- Use probit regression to estimate Z from system-wide failures

$$Z_t = Z_t(\beta) = \Phi(\beta X_{t-})$$

  - Φ is the CDF of a standard normal variable
  - X_t is a vector of explanatory covariates
  - β is a vector of parameters

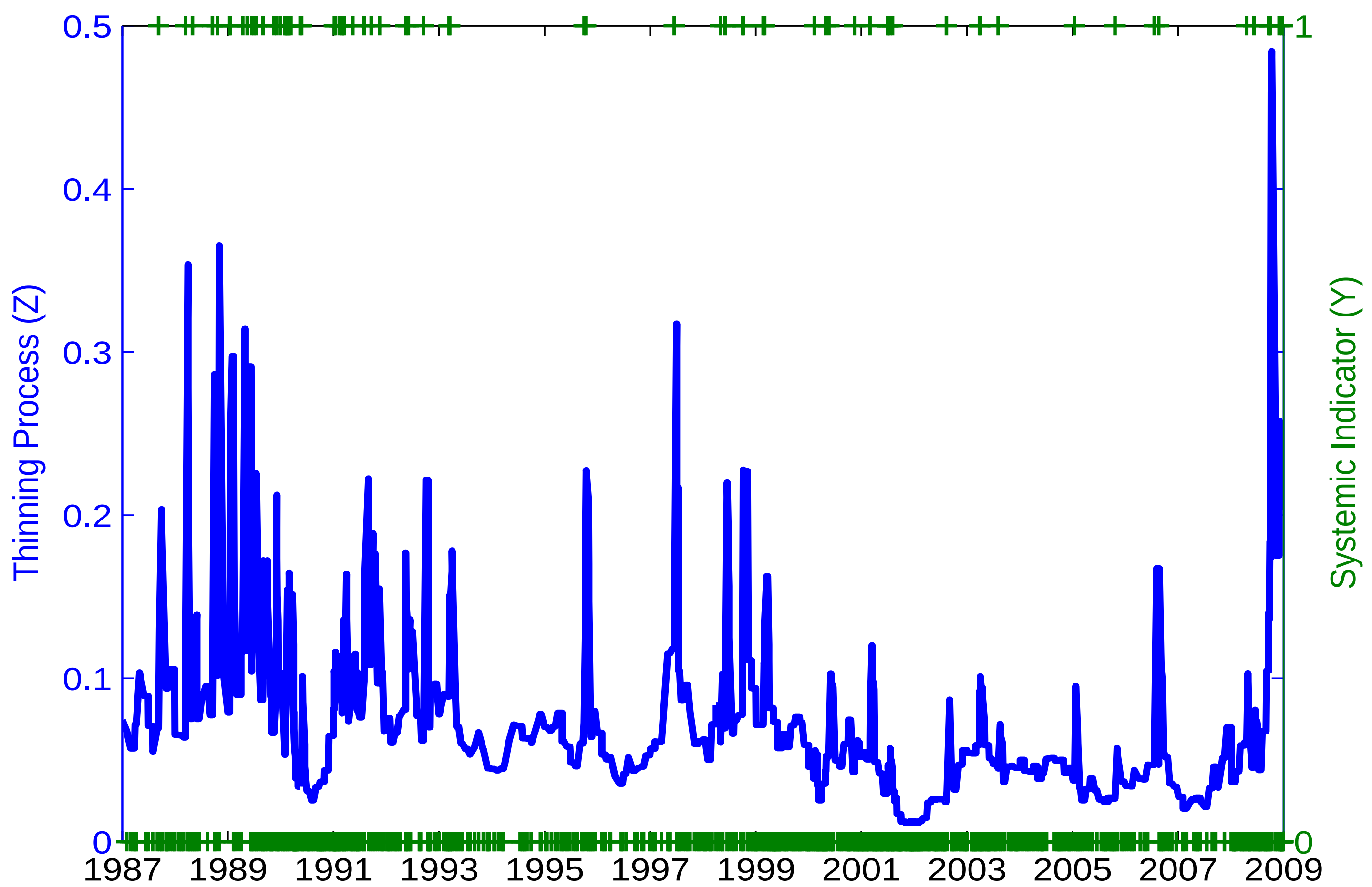
System-wide default timing

Maximum likelihood estimators

Covariate	Coefficient	SE	t-statistic	p-value	Bayes
Constant	-2.0873	0.1484	-14.0659	0.0000	-
Yield Slope	0.1256	0.0585	2.1469	0.0318	4.6502
TED Spread	0.3710	0.1506	2.4632	0.0138	5.8223
Banking	0.8952	0.3462	2.5856	0.0097	6.6832
Real Estate	-0.8073	0.2973	-2.7218	0.0065	7.4439
Default Ratio	1.4171	0.4351	3.2572	0.0011	10.1015
Model Fit	LR-ratio $(\chi^2) = 36.8117$			p-value < 0.0001	

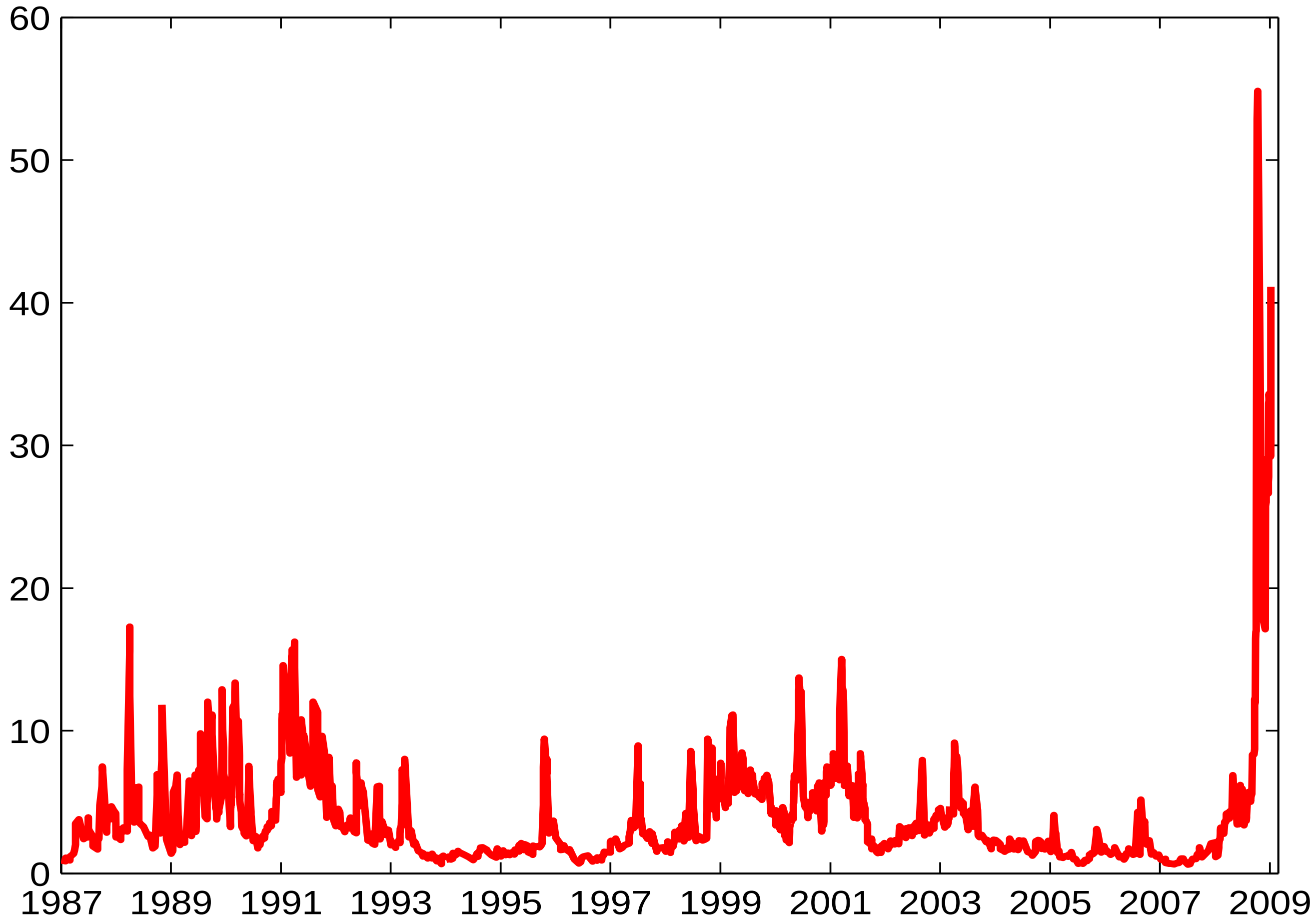
System-wide default timing

Observed binary response variables and fitted process Z



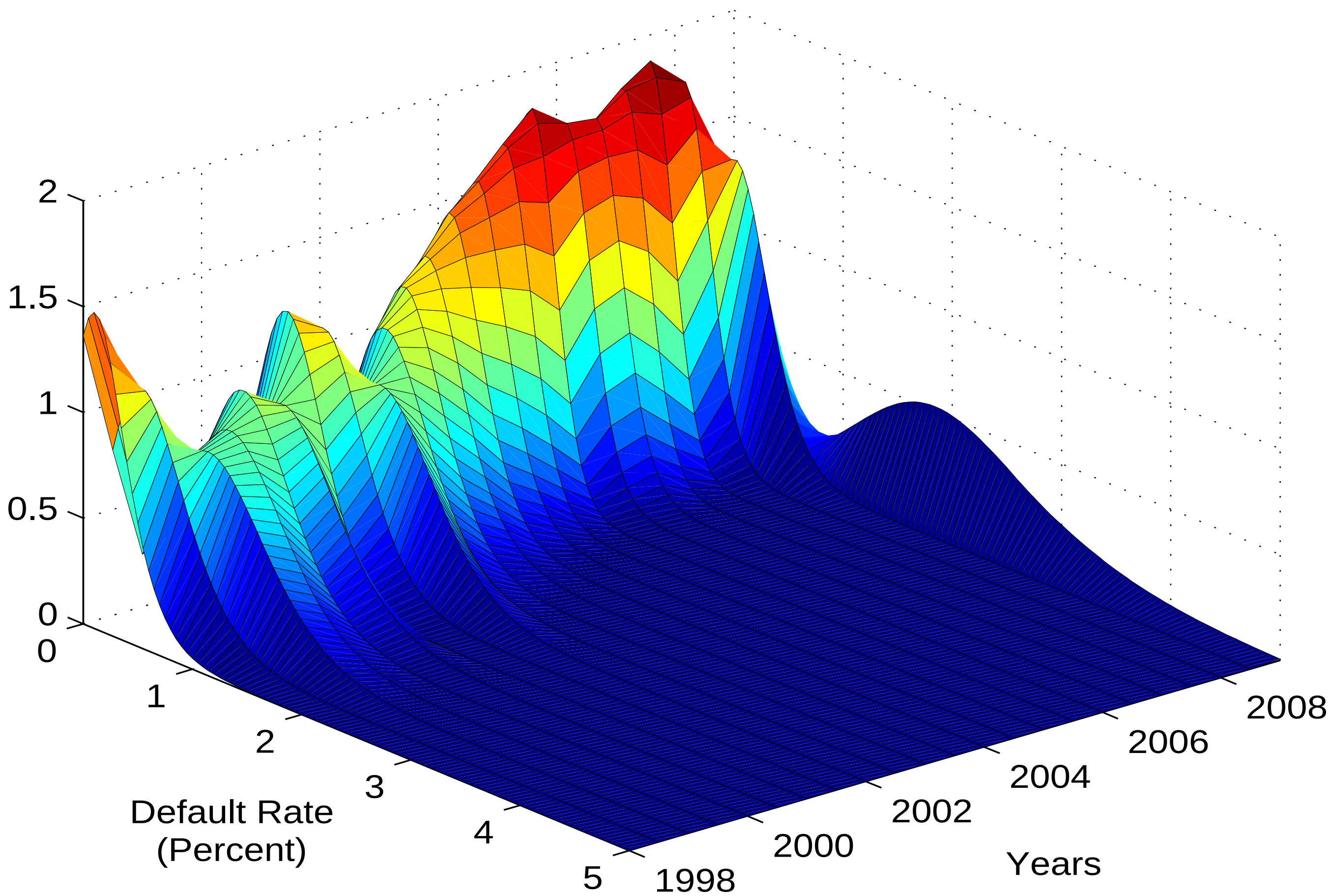
Systemic risk

Fitted system-wide failure intensity $\lambda = Z\lambda^*$



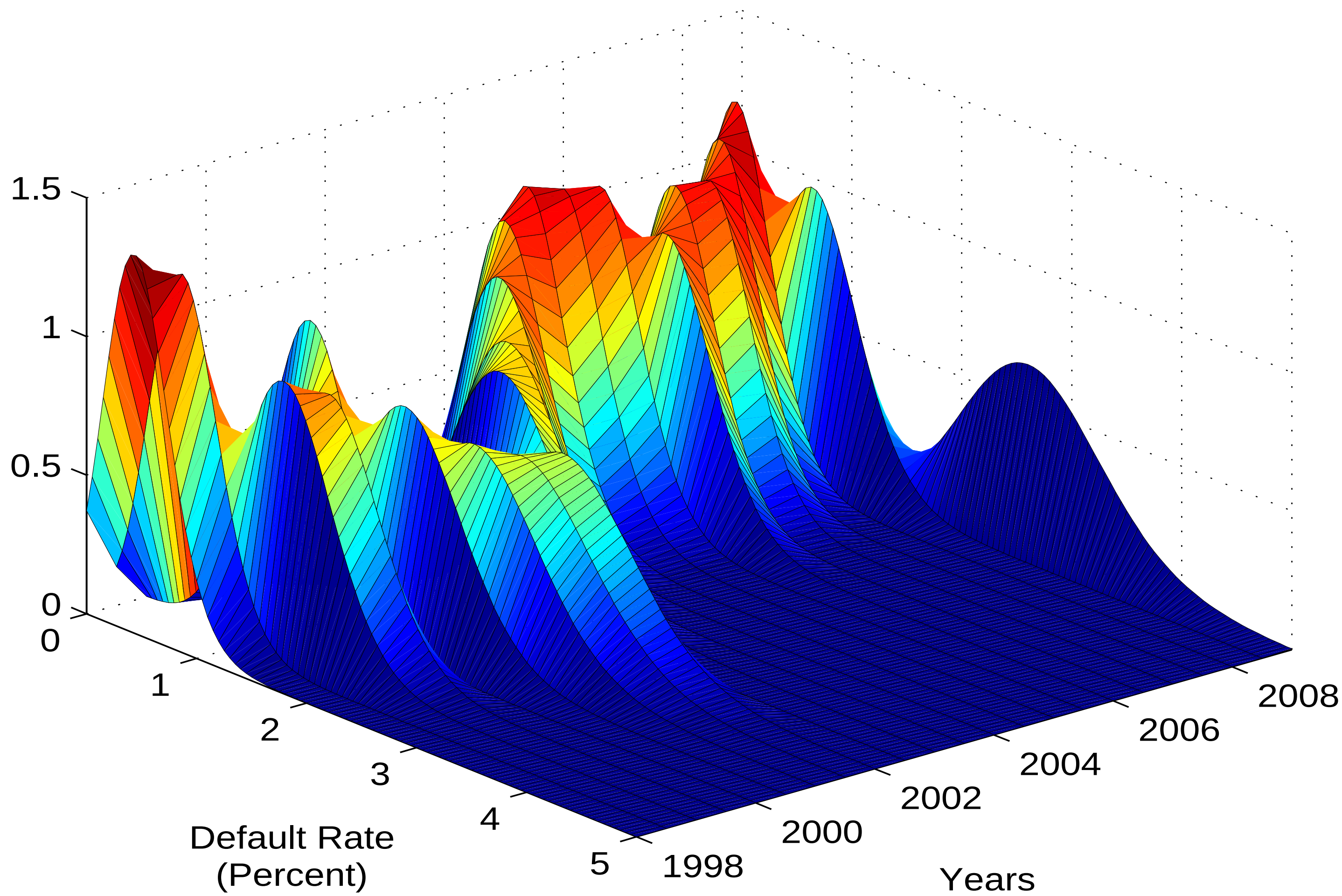
Systemic risk

Fitted conditional distribution of system-wide default rate $D_t(t+0.5)$



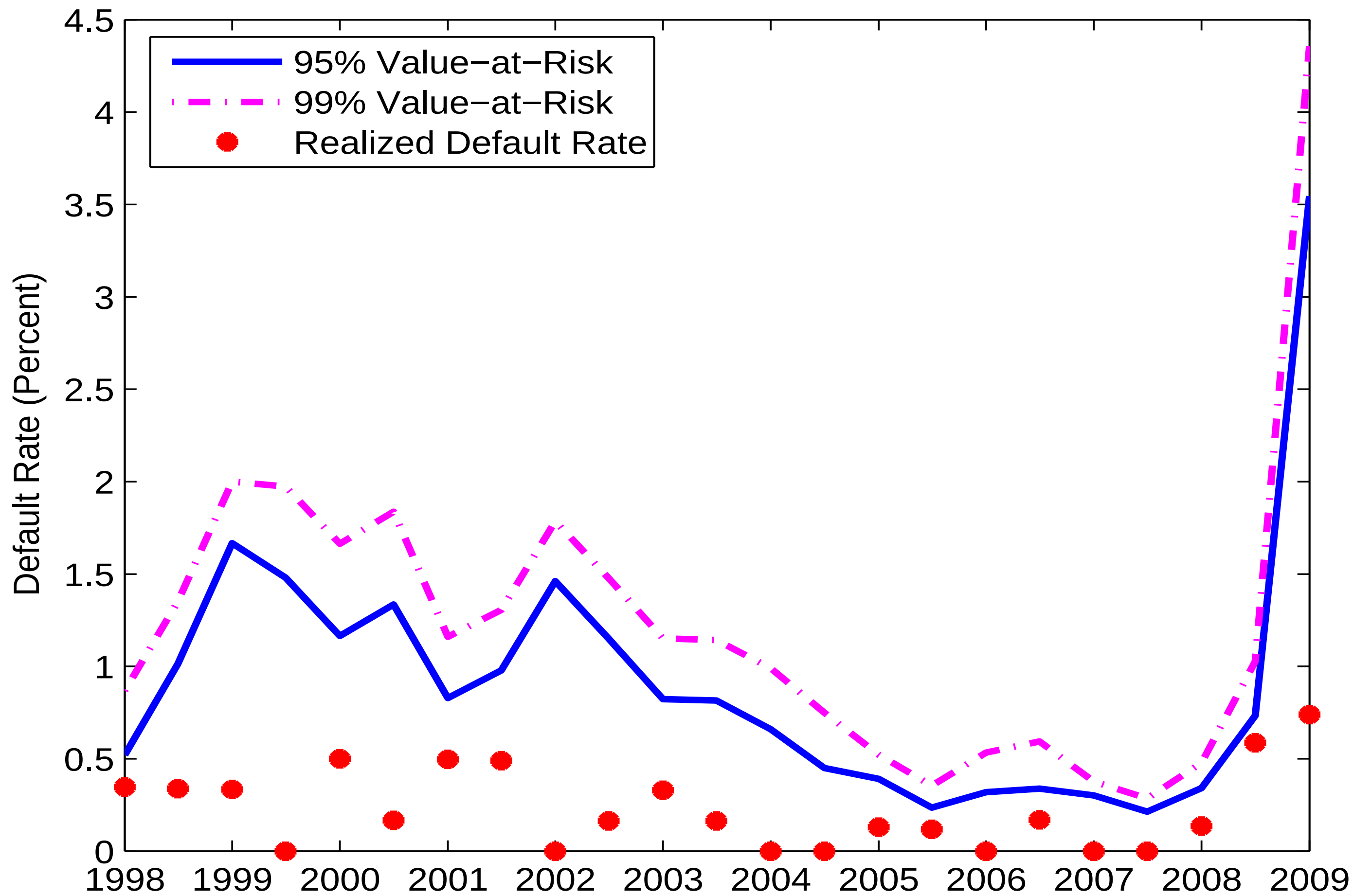
Systemic risk

Fitted conditional distribution of economy-wide default rate



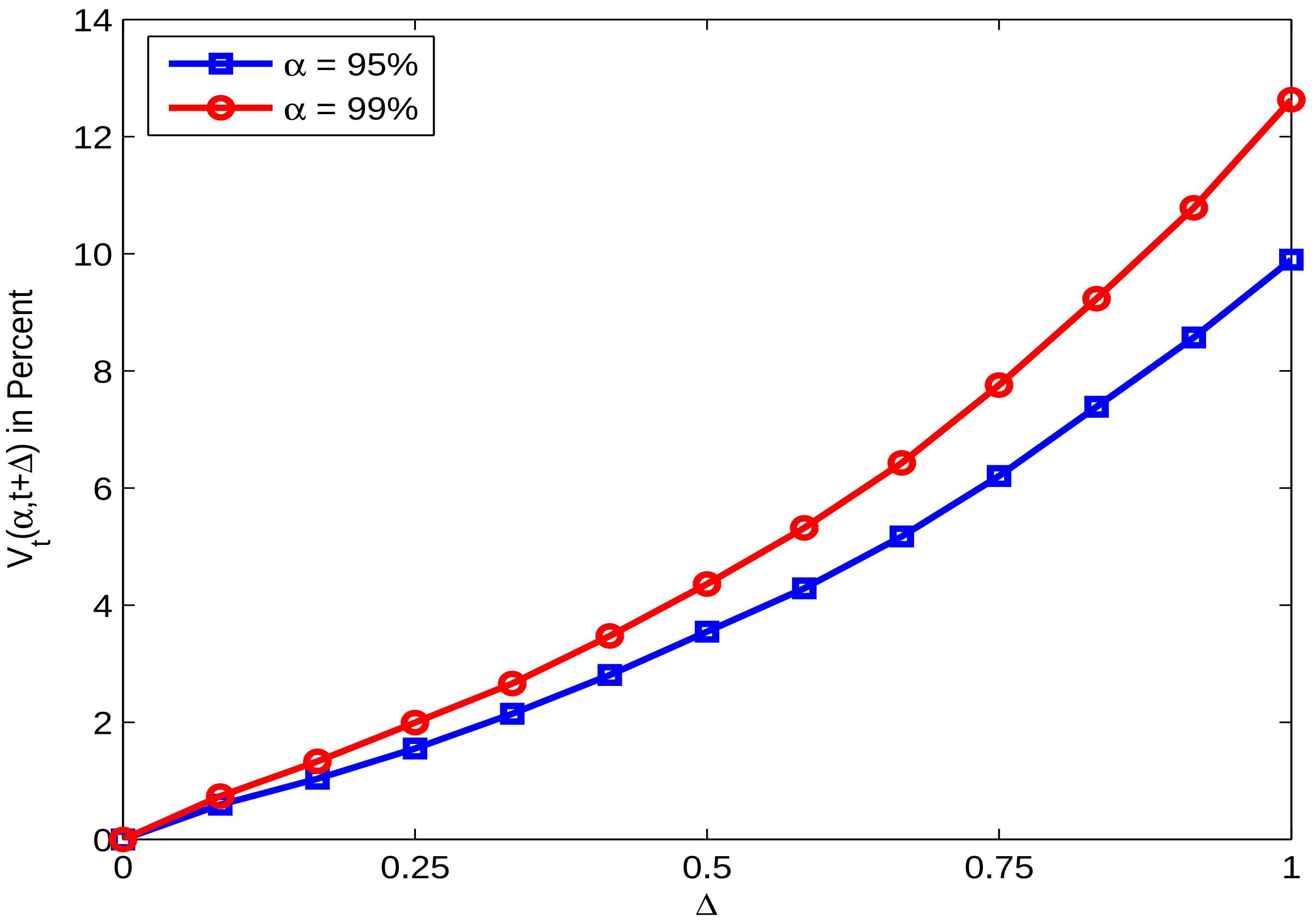
Systemic risk

Fitted value at risk $V_t(\alpha, t + 0.5)$ of system-wide default rate



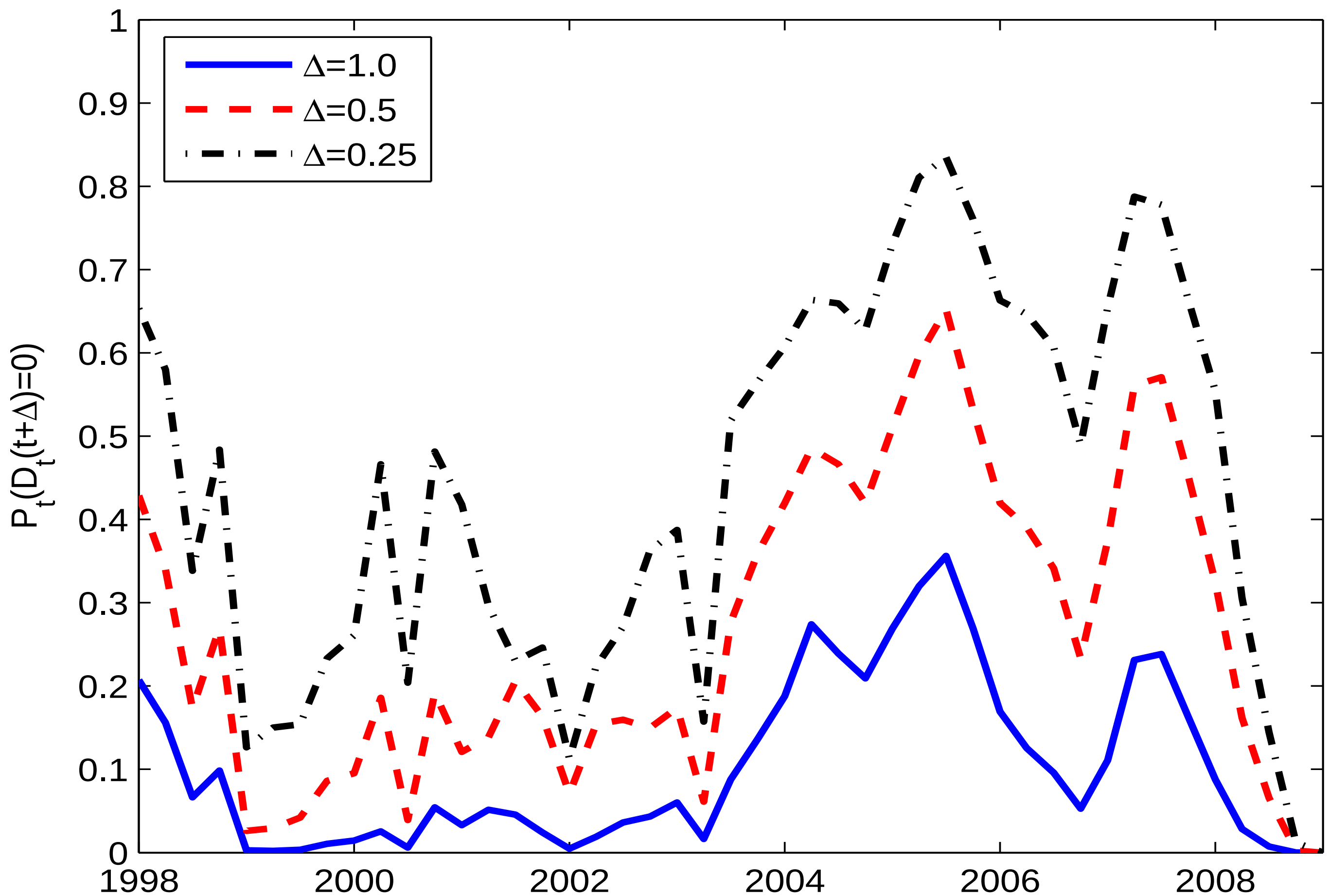
Systemic risk

Fitted term structure of $V_t(\alpha, t+\Delta)$ on 12/31/2008



Systemic risk

Fitted conditional probability $P_t(D_t(t+\Delta)=0)$



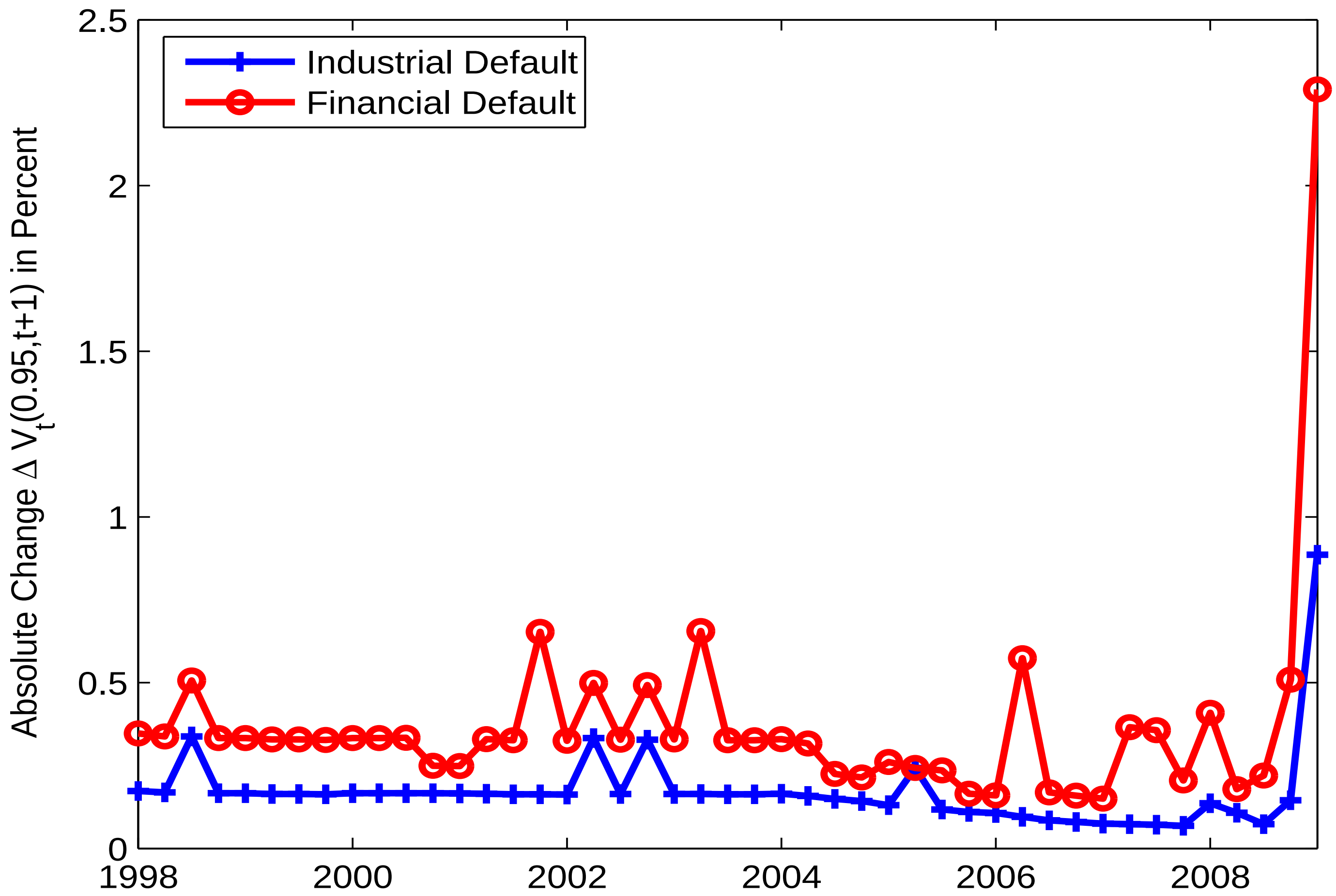
Predictive performance

			Uncond. Coverage		Markov		CAViaR	
	Δ	Obs.	LR	p-value	LR	p-value	LR	p-value
95% VaR	1Y	11	0.3153	0.5744	0.5157	0.7727	2.3203	0.5086
	6M	23	2.3595	0.1245	2.3595	0.3074	2.2569	0.5208
	3M	45	0.9143	0.3390	0.9609	0.6185	5.5926	0.1332
	1M	133	2.6284	0.1050	2.6900	0.2605	4.5851	0.2048
99% VaR	1Y	11	0.2211	0.6382	0.2211	0.8953	0.2211	0.9741
	6M	23	0.4623	0.4965	0.4623	0.7936	0.4422	0.9314
	3M	45	0.9045	0.3416	0.9045	0.6362	0.8844	0.8292
	1M	133	0.0905	0.7636	0.1057	0.9485	0.6689	0.8805

- Compare fitted value at risk to realized default rate
  - Hit indicators I_t should follow sequence of iid Bernoulli variables with success probability $(1 - \alpha)$
- The result suggests our fitted measures accurately quantify systemic risk

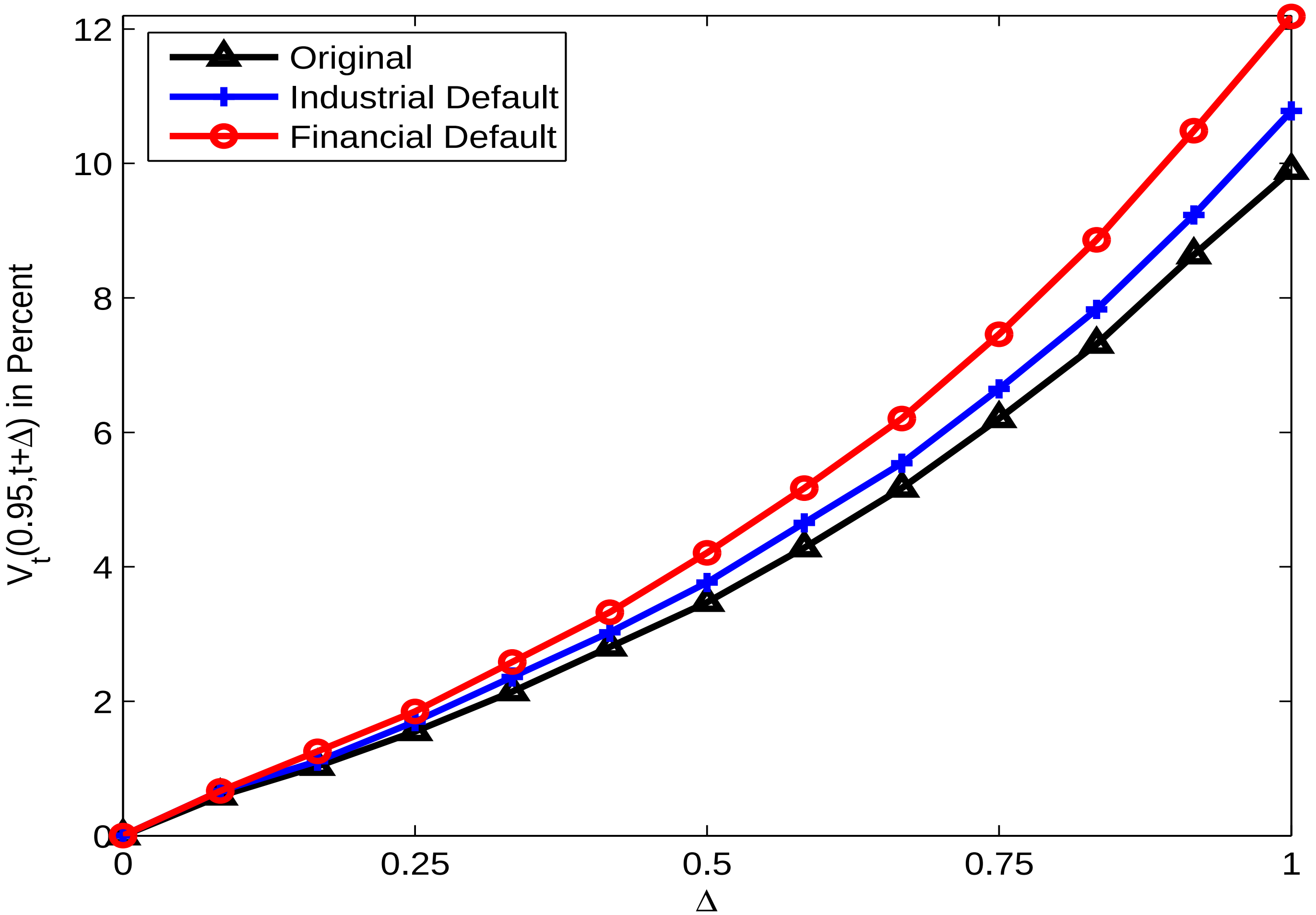
Sensitivity of systemic risk

Fitted absolute impact of default on value at risk $V_t(0.95, t+1)$



Sensitivity of systemic risk

Fitted impact of default on term structure of $V_t(0.95, t+\Delta)$, 12/31/08



Conclusion

- We propose a measure of systemic risk that quantifies the risk of failure clusters in the financial industry
  - Complements existing measures focusing on market values
  - Time-series and term structure perspectives
- We develop maximum likelihood estimators of this measure
  - Based on actual default experience and time-varying explanatory covariates
  - Account for the statistical implications of risk spillovers
  - Capture interaction between real and financial sectors
- We show that the measure accurately predicts systemic risk in the US financial system

Conclusion

- The part of systemic risk *not* explained by the observable covariates can be substantial, and tends to be higher during periods of adverse economic conditions
- Systemic risk in the U.S. financial sector can be much greater than would be estimated under the common assumption that bank failure clusters arise only from exogenous shocks affecting financial institutions across the board
- Potential applications
  - Early warning tools for regulators and policy makers
  - Macro-prudential supervision of financial institutions

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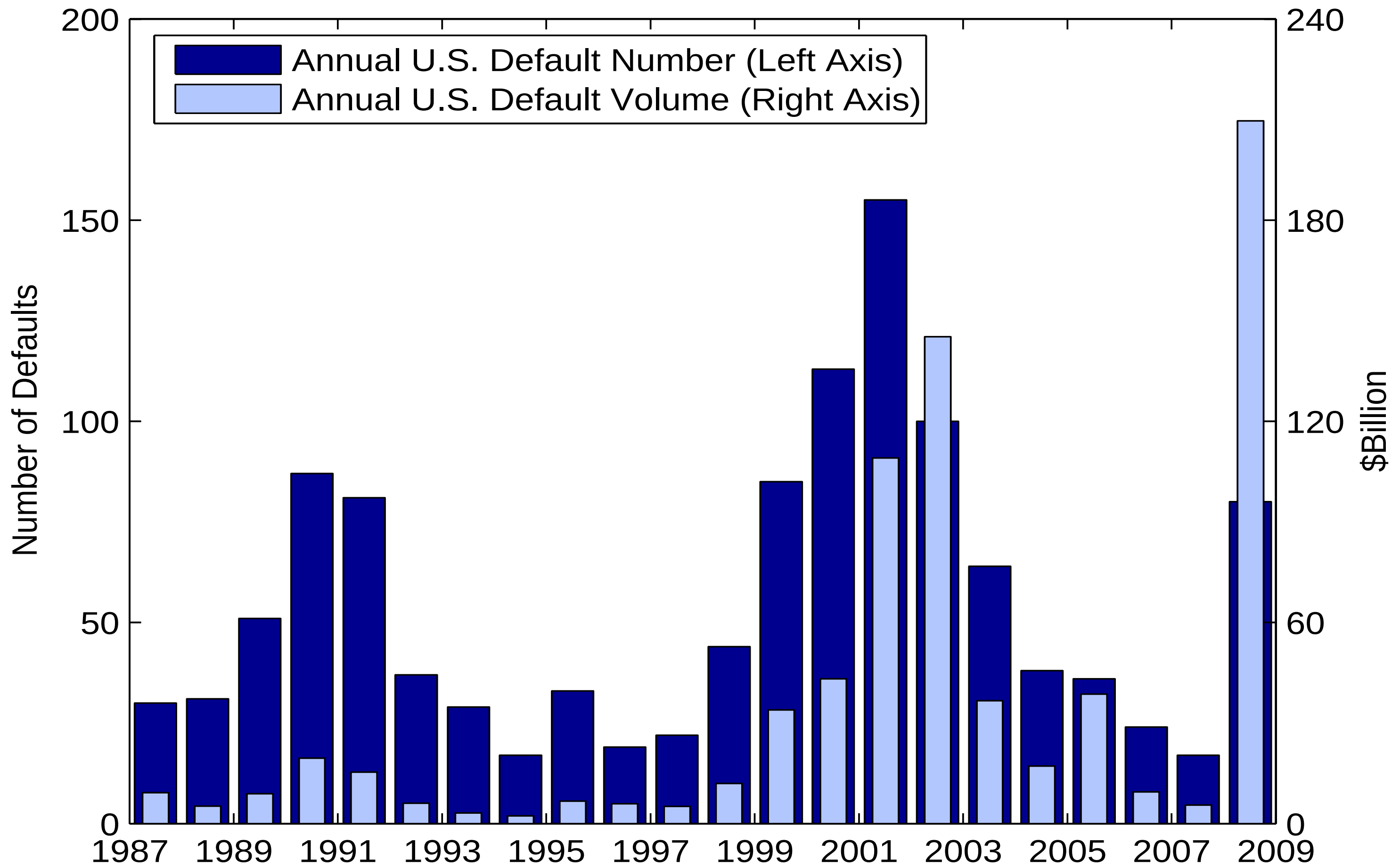
Appendix: Default timing data

Moody's Default Risk Service Corporate, 1/1/1970–12/31/2008



Appendix: Economy-wide default timing

- Sample period: 1/1/1987 to 12/31/2008
- Data on default timing and volumes from Moody's DRS
- Data on explanatory covariates X^*
  - The trailing 1-year return on the S&P500 index
  - The 1-year lagged slope of the yield curve, computed as the spread between 10-year and 3-month Treasury CM rates
  - The default spread, defined as the yield differential between Moody's seasoned Aaa-rated and Baa-rated corporate bonds
  - The TED spread (3m LIBOR minus 3m Treasury rate)
  - The trailing 1-year returns on banking and FIRE portfolios
  - The default ratio, relating the number of failures in the financial system during $(t-h, t]$ to one plus the number of economy-wide defaults during that period

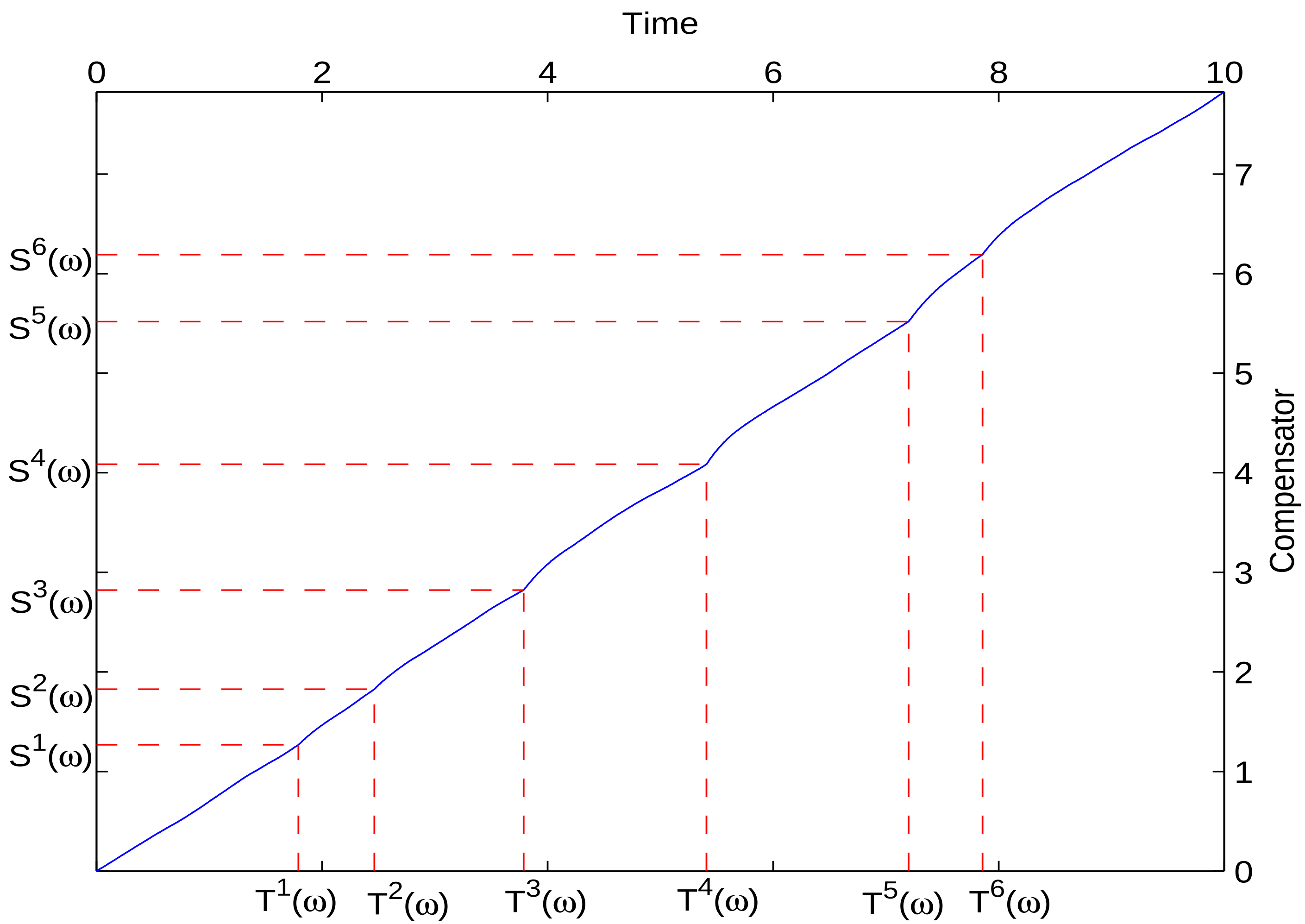
Appendix: Economy-wide default timing

Testing the fit

- Meyer's theorem implies that economy-wide events follow a standard Poisson process under a change of time given by $\int_0^\cdot \lambda_s^* ds$
- If λ^* is correctly specified, then the time-scaled inter-arrival times are independent standard exponential variables
- Tests of the binned arrival time data
  - For bin size c, U_n is the number of observed events in the n-th successive time interval lasting for c units of transformed time
  - With a total of K bins, the null hypothesis is that the $U_1, \ldots, U_K$ are independent Poisson variables with mean c
  - Fisher's dispersion test, upper tail test, serial dependence test cannot be rejected for bin sizes $4, 6, 8, 10$, at standard confidence levels

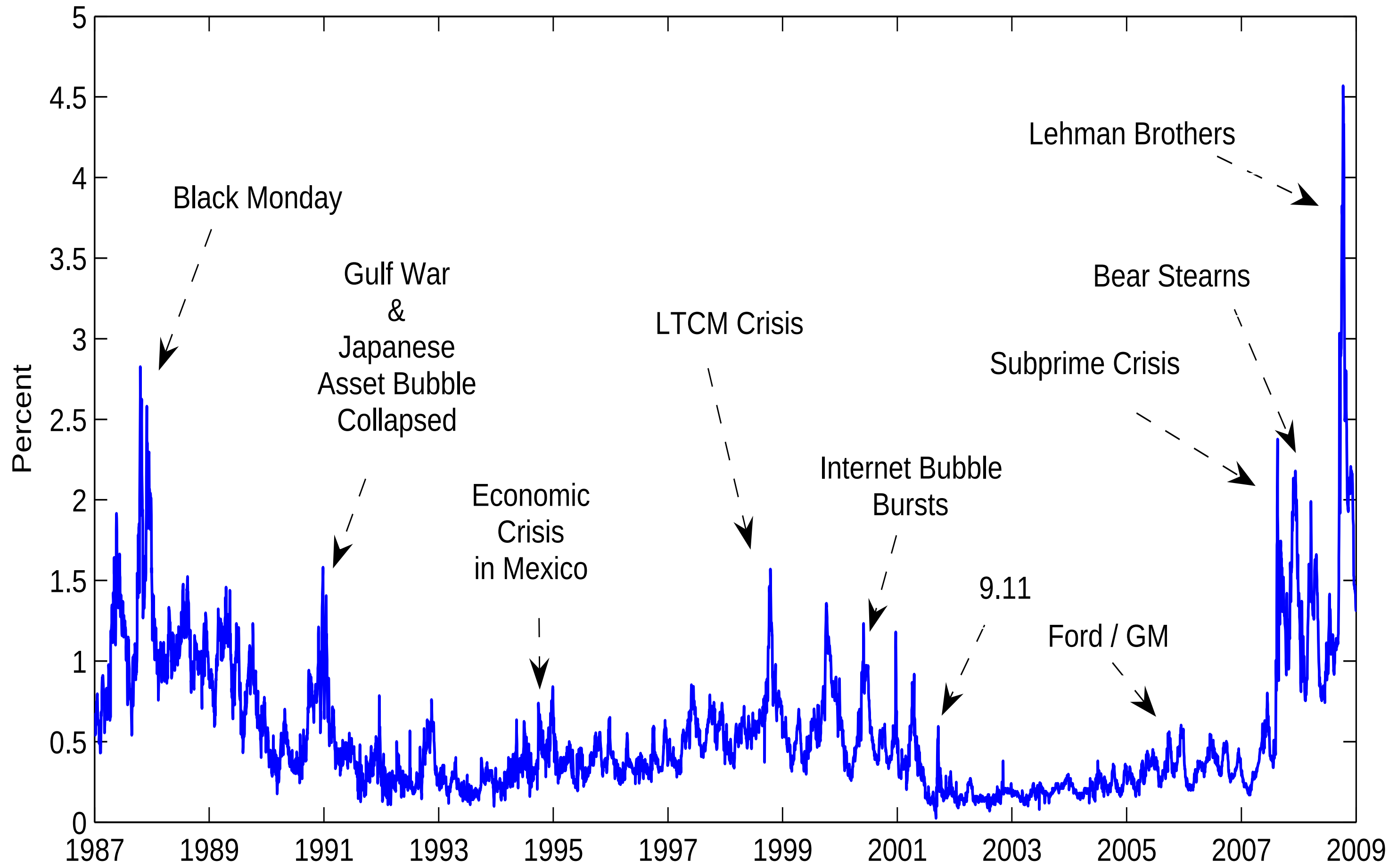
Appendix: Economy-wide default timing

Testing the fit



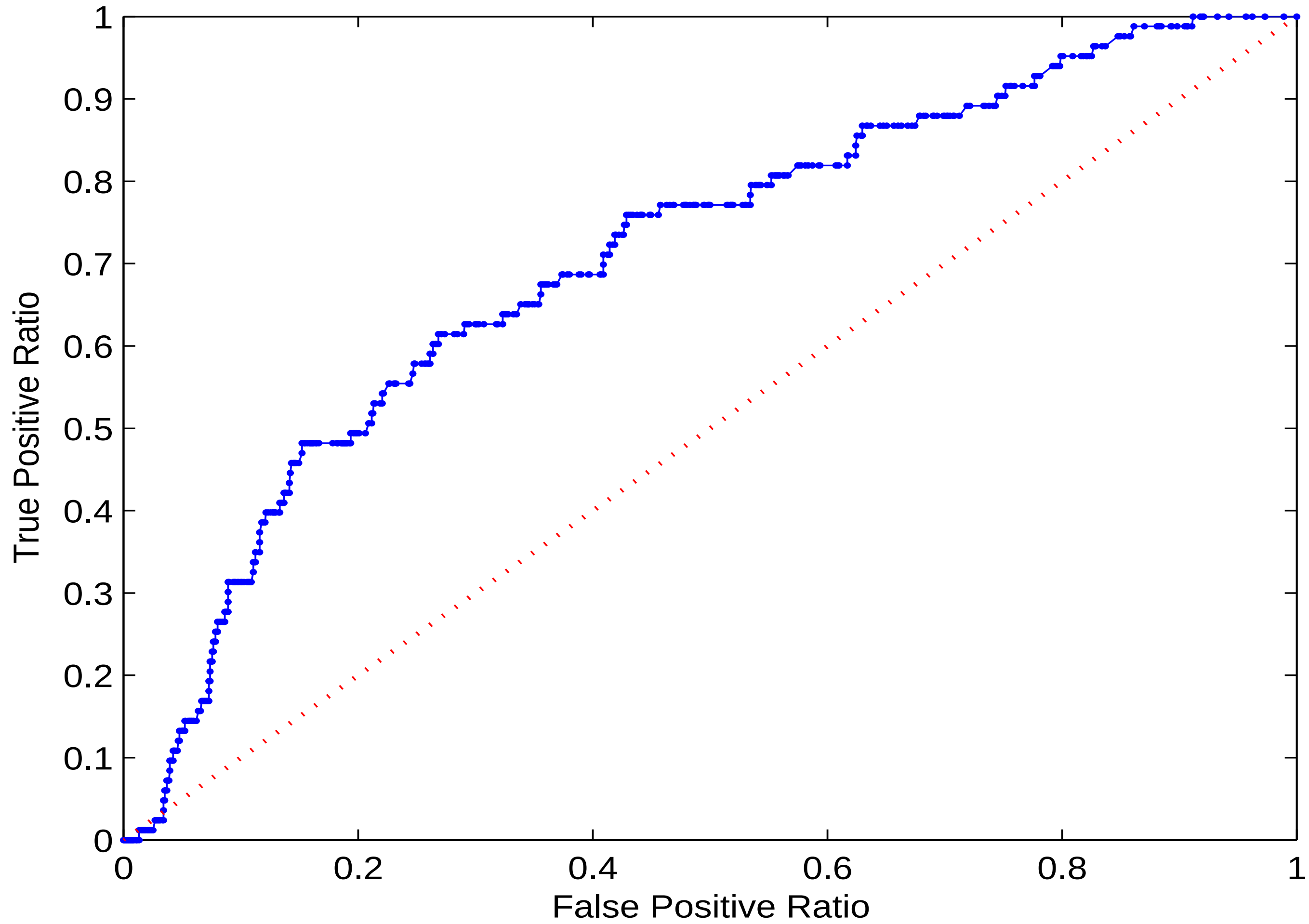
Appendix: Explanatory covariates

TED spread



Appendix: System-wide default timing

Power curve for fitted process Z. AUC $= 0.71$



Appendix: Predictive performance

- Compare fitted value at risk to realized default rate
- Hit indicators I_t should follow sequence of iid Bernoulli variables with success probability $(1 - \alpha)$
- Unconditional coverage: Kupiec (1995)
- Markov test of Christoffersen (1998) jointly tests coverage and independence against a Markov chain alternative
- The CAViaR test of Engle & Manganelli (2004) considers a first-order autoregression for the hit indicator:

$$I_t = \gamma + \beta_1 I_{t-\Delta} + \beta_2 V_t(\alpha, t + \Delta) + \epsilon_t$$

where the error term ϵ_t has a logistic distribution. We test whether the β_i coefficients are statistically significant and whether $P(I_t = 1) = e^{\gamma}/(1 + e^{\gamma}) = 1 - \alpha$.