FRM financialriskmeter

Andrija Mihoci

Cathy Yi-Hsuan Chen

Wolfgang Karl Härdle

Michael Althof

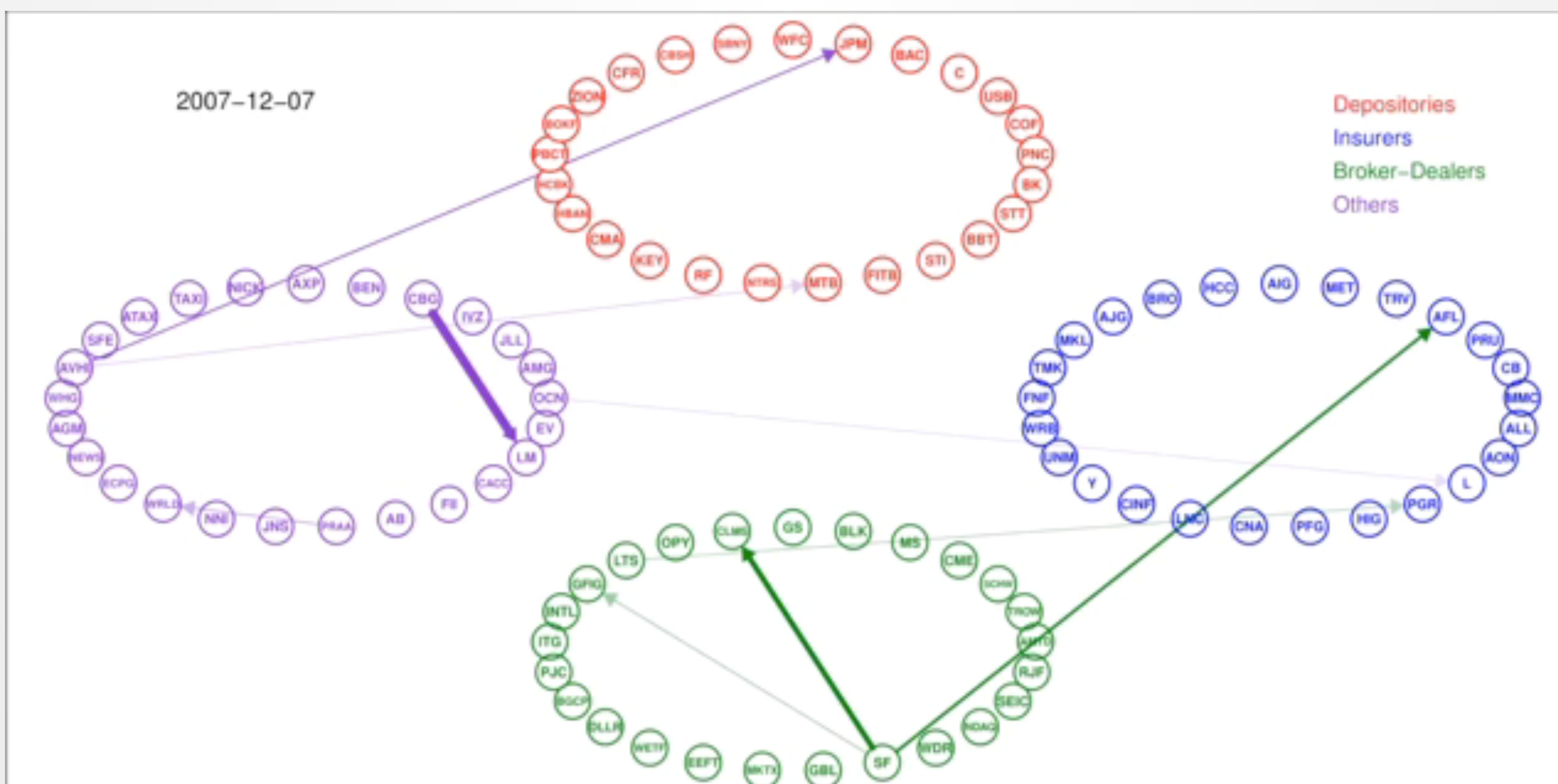
Ladislaus von Bortkiewicz Chair of Statistics
Humboldt-Universität zu Berlin
lvb.wiwi.hu-berlin.de

Brandenburg University of Technology

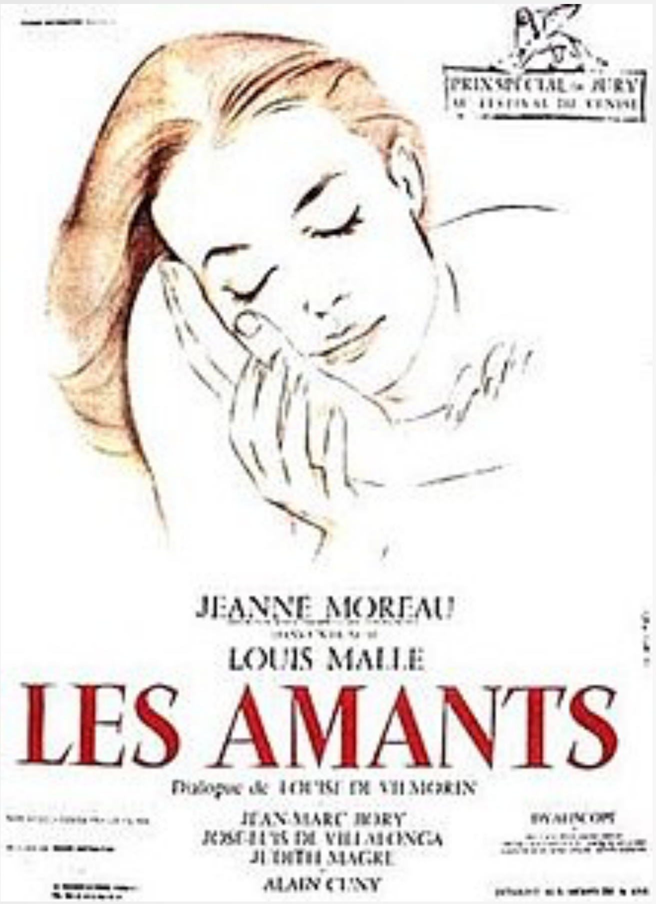
University of Glasgow

Tail Events (TE)

- TEs across companies indicate increased risk
- CoVaR measures joint TEs between 2 risk factors
- CoVaR and other risk factors?
- TENET Tail Event NETwork risk, Härdle Wang Yu (2017) J E'trics
- FRM Financial Risk Meter for joint TEs



Risk, Model Risk, Systemic Risk



The financial cycle and the business cycle are not synchronised, implying that risks can emerge especially in the periods of „disconnect" between the two cycles.", Vítor Constâncio, VP ECB, 2015

"Broadly speaking, model risk can be attributed to either an incorrect model or to an incorrect implementation of a model" , Buraschi and Corielle (2005)

„I know it when I see it", Justice Potter Stewart (1964)

- Tail Behaviour
- Ultra High Dimensions
- Nonlinear in Time and Space (=Network)

Risk Measures

- VIX: IV based, does not reflect joint TEs
- CoVaR concentrates on a pair of risk factors
- NBER recession indicator, Google trends, SRISK, …
- FRM employs the full picture of TE dependencies
- HU.berlin/FRM financialriskmeter

Outline

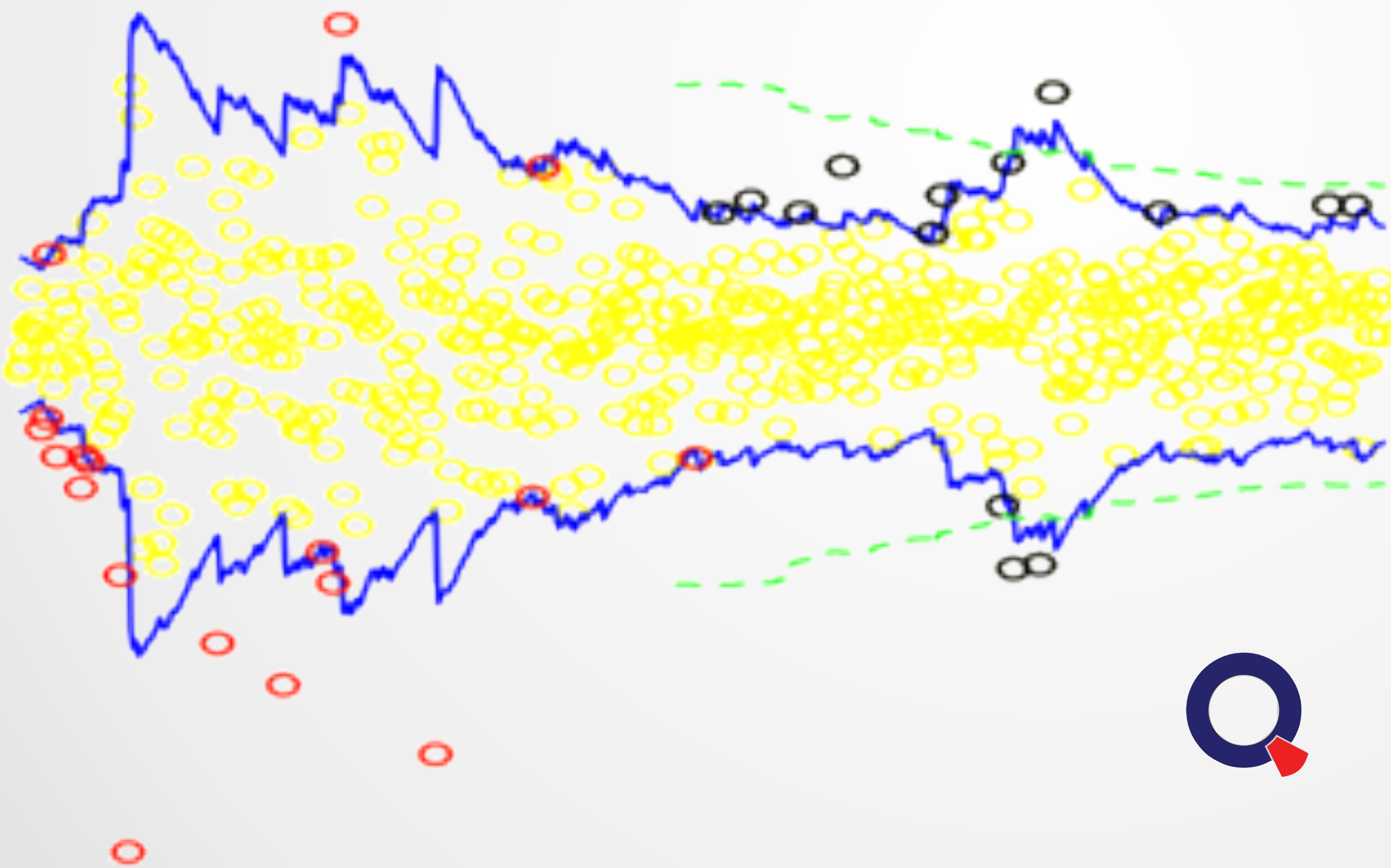
1. Motivation ✔
2. Genesis
3. FRM Framework
4. CoStress ID
5. FRM a predictor for recession
6. Conclusions

VaR Value at Risk

- Probability measure based

$$\mathrm{P}(X_{i,t} \leq VaR_{i,t}^{\tau}) \overset{def}{=} \tau, \quad \tau \in (0,1)$$

- $X_{i,t}$ log return of risk factor (company) *i* at *t*
- VaRs (0.99, 0.01) based on RMA, Delta Normal Method



Quantiles and Expectiles

For r.v. Y obtain tail event measure:

log returns

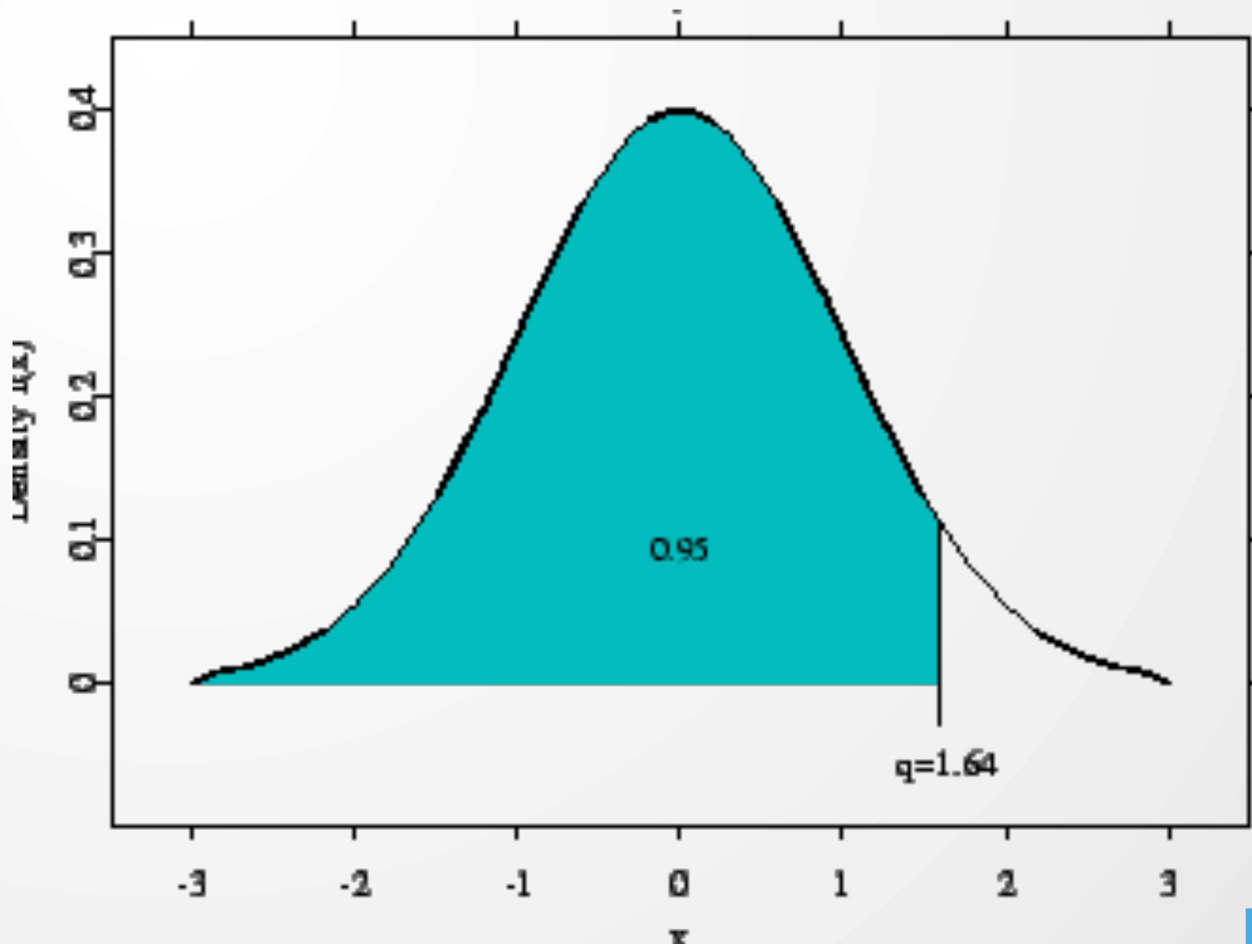
$$q^{\tau} = \arg\min_{\theta} \mathrm{E}\left\{\rho_{\tau}\left(Y - \theta\right)\right\}$$

asymmetric loss function

$$\rho_{\tau}(u) = |u|^{\alpha} \left|\tau - \mathbf{I}_{\{u<0\}}\right|$$

α = 1 for quantiles,
α = 2 for expectiles

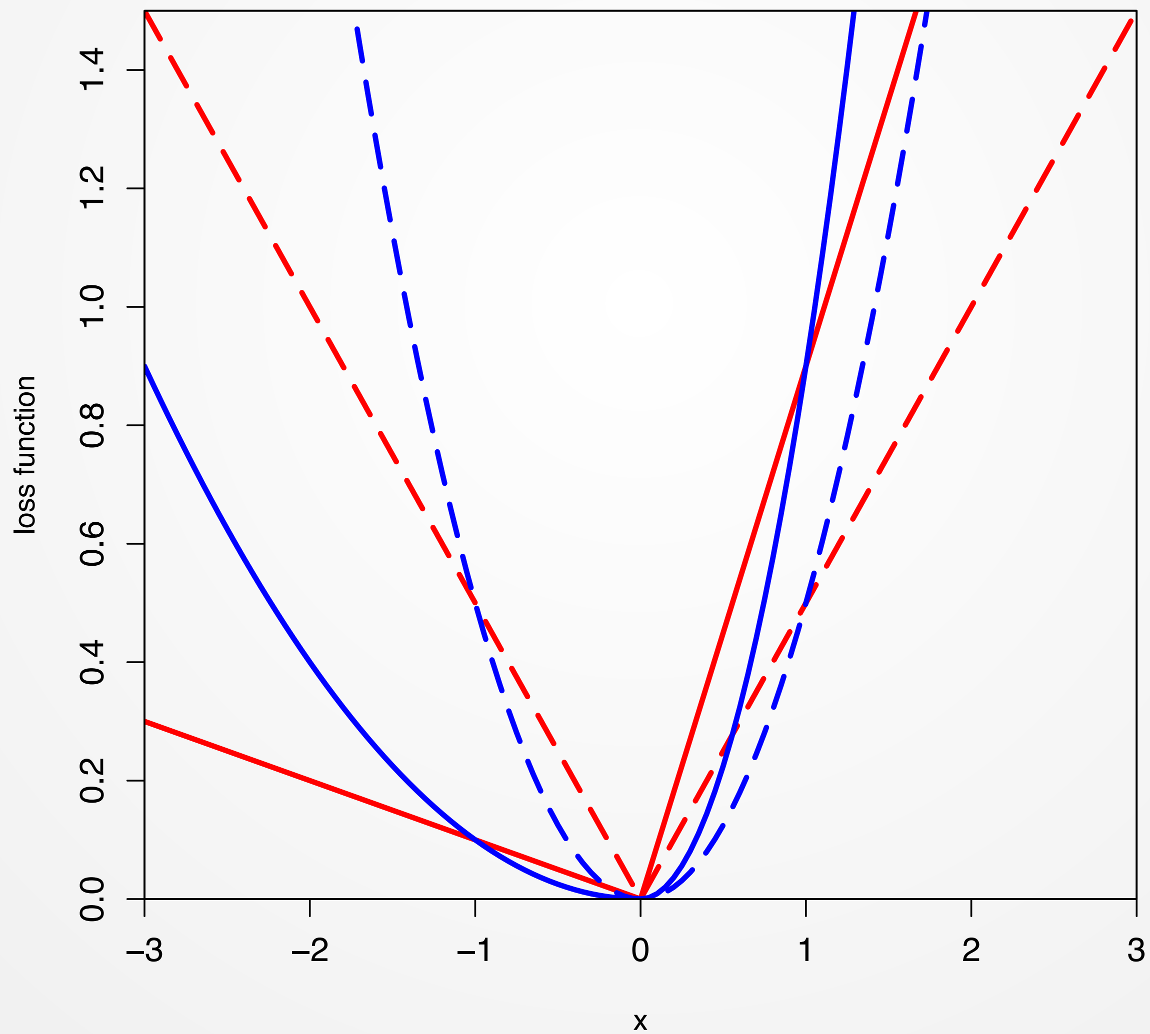
τ = 0.05



Expectile as Quantile

Quantiles and Expectiles

- Quantiles/Expectiles focus on TEs
- SRM Spectral Risk Measures
- LAWS algorithm fast and efficient



LQRcheck

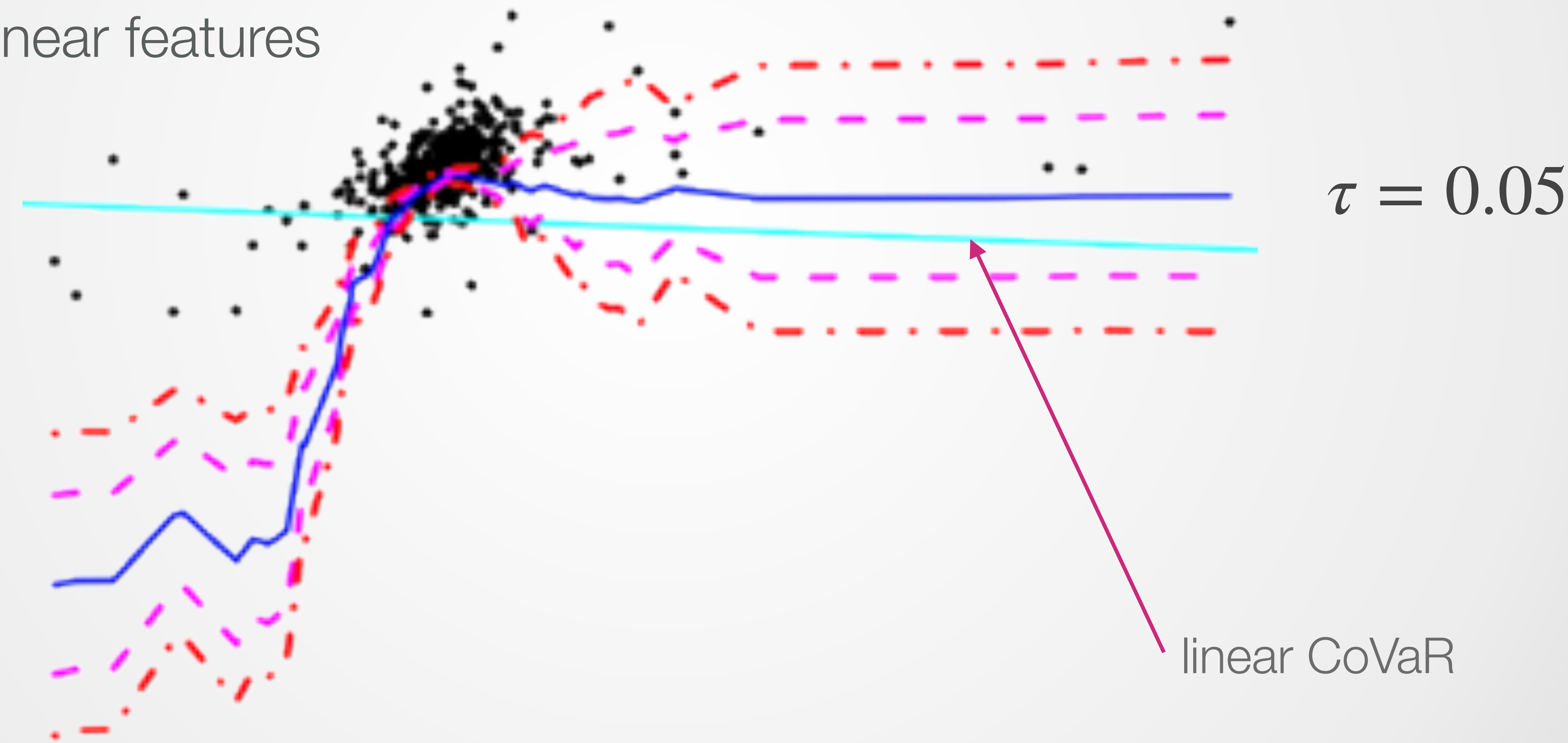
Figure: Loss function of expectiles and quantiles for $\tau = 0.5$ (dashed) and $\tau = 0.9$ (solid)

Conditional Value at Risk

- Adrian and Brunnermeier (2016) introduced CoVaR

$$\mathrm{P}\{X_{i,t} \leq CoVaR^{\tau}_{j|i,t} \mid X_{i,t} = VaR^{\tau}(X_{i,t}), M_{t-1}\} \stackrel{def}{=} \tau,$$

- M_{t-1} vector of macro-related variables
- Nonlinear features



Goldman Sachs (Y), Citigroup (X), Conf Bands, Chao et al (2015)

CoVaR and the magic of joint TEs

- CoVaR technique

$$X_{i,t} = \alpha_i + \gamma_i^\top M_{t-1} + \varepsilon_{i,t},$$

$$X_{j,t} = \alpha_{j|i} + \beta_{j|i} X_{i,t} + \gamma_{j|i}^\top M_{t-1} + \varepsilon_{j,t}\,.$$

- $F^{-1}_{\varepsilon_{i,t}}(\tau \mid M_{t-1}) = 0$ and $F^{-1}_{\varepsilon_{j,t}}(\tau \mid M_{t-1}, X_{i,t}) = 0$

$$\widehat{VaR}^{\tau}_{i,t} = \widehat{\alpha}_i + \widehat{\gamma}_i^\top M_{t-1},$$
$$\widehat{CoVaR}^{\tau}_{j|i,t} = \widehat{\alpha}_{j|i} + \widehat{\beta}_{j|i} \widehat{VaR}^{\tau}_{i,t} + \widehat{\gamma}_{j|i}^\top M_{t-1},$$

CoVaR: First calculate VaRs, then compute the TE given a stressed risk factor.

Linear Quantile Lasso Regression

$$X_{j,t}^{s} = \alpha_{j,t}^{s} + A_{j,t}^{s\top}\beta_{j}^{s} + \varepsilon_{j,t}^{s}, \qquad (1)$$

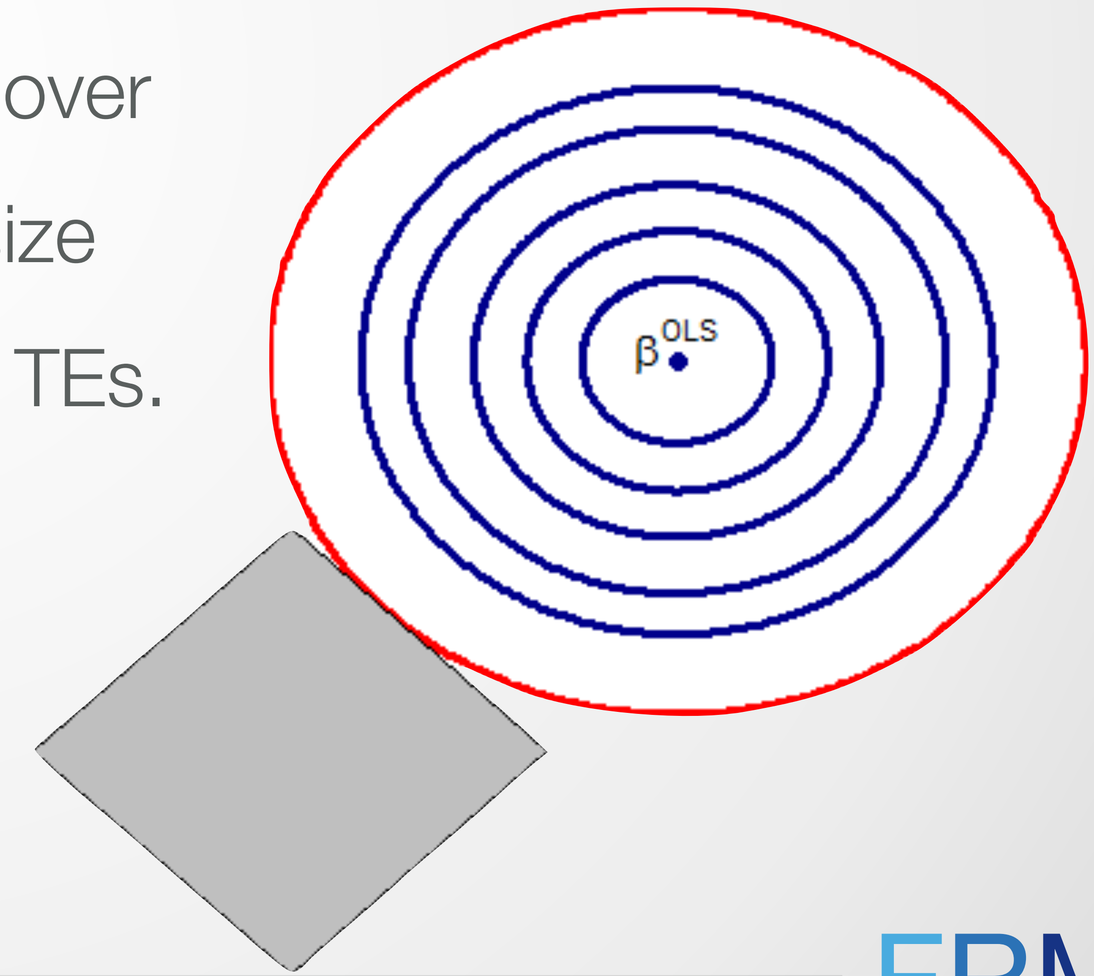
- Where $A_{j,t}^{s\top} \overset{def}{=} \left[M_{t-1}^{s}, X_{-j,t}^{s}\right]$
- $X_{-j,t}^{s}$ log returns of all other firms except j at time t
- s length of moving window
- M_{t-1}^{s} log return of macro prudential variable at time $t-1$
- Application $j = 1,\ldots,J,\ t = 2,\ldots,T$
  $J = 100,\ T = 2700,\ s = 63$

Company List Macroprudentials

Lasso Quantile Regression

$$\min_{\alpha_j^s, \beta_j^s} \left\{ n^{-1} \sum_{t=s}^{s+(n-1)} \rho_\tau (X_{j,t}^s - \alpha_j^s - A_{j,t}^{s\top} \beta_j^s) + \lambda_j^s \parallel \beta_j^s \parallel_1 \right\}, \qquad (2)$$

- Check function $\rho_\tau(u) = | u |^c \mid 1(u \leq 0) - \tau \mid$,
- here $c = 1{,}2$ correspond to quantile, expectile regression
- λ creates size of „active set“, i.e. spillover
- λ is sensitive to residual size, i.e. TE size
- λ reacts to singularity issues, i.e. joint TEs.



λ Role in Linear Lasso Regression

- Penalisation (Lagrange) parameter λ , Osborne et al. (2000)
- Dependence, time-varying, company-specific
- Size of model coefficients depends on

$$\lambda = \frac{\left(Y - X\beta(\lambda)\right)^{\top} X\beta(\lambda)}{\|\beta\|_1}$$

Coeff's depend on λ

- Penalty λ depends on:
- **residual size, condition of design matrix, active set**

λ Role in Linear Quantile Regression

- λ size of estimated LQR coefficients

$$\lambda = \frac{(\alpha-\gamma)^{\top} X\beta(\lambda)}{\|\beta\|_1}$$

Coeff's (λ)

$$(\alpha-\gamma) = \tau\, I(Y - X\beta(\lambda) > 0) + (\tau - 1)\, I(Y - X\beta(\lambda) < 0)$$

- Penalty λ depends on:
- **residual size, condition of design matrix, active set**
- Average penalty: an indicator for tail risk

$$FRM_t \stackrel{def}{=} J^{-1} \sum_{j=1}^{J} \lambda_{jt}$$

- The FRM time series is ONE index for joint TEs!

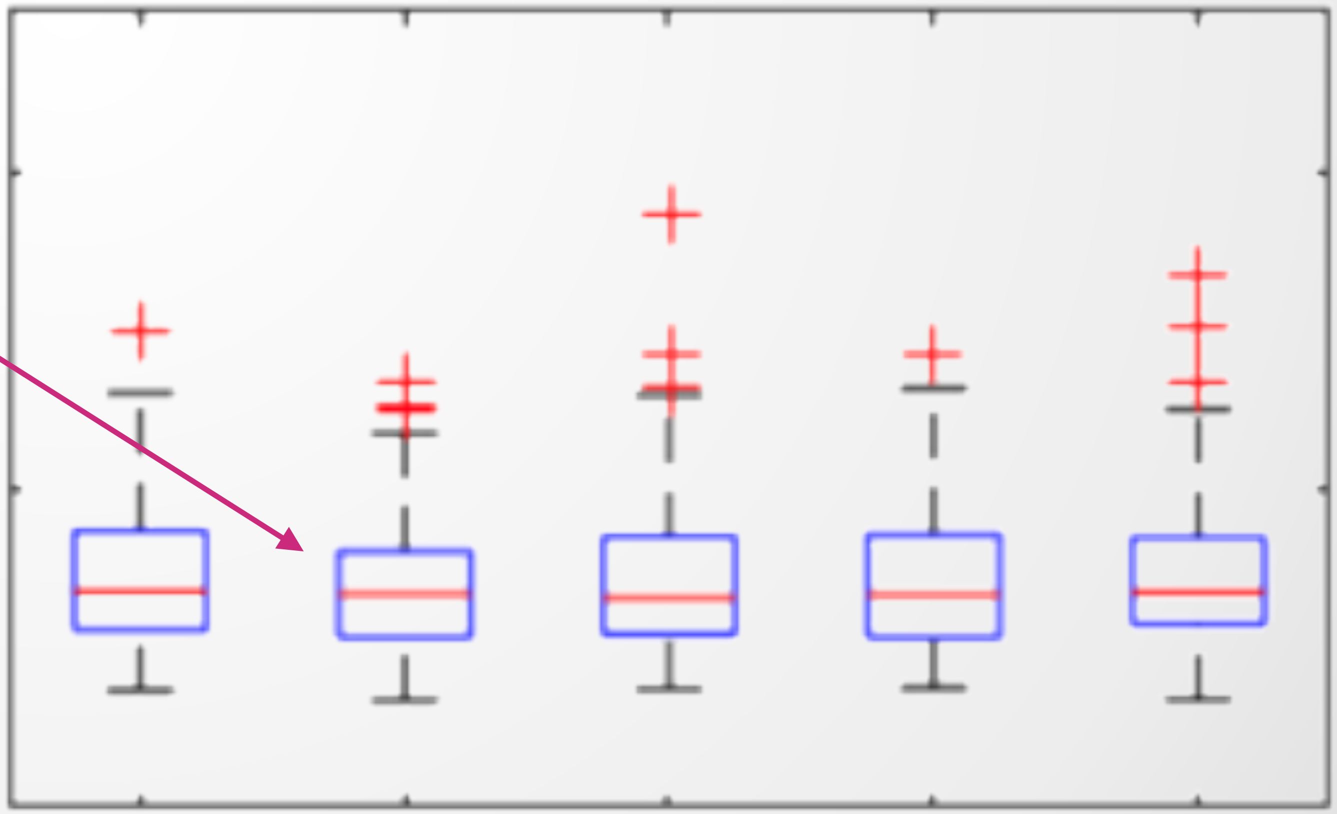
λ Selection

- Generalized approximate cross-validation (GACV)

$$\min GACV(\lambda_j^s) = \min \frac{\sum_{t=s}^{s+(n-1)} \rho_\tau(X_{j,t}^s - \alpha_j^s - A_{j,t}^{s,\top}\beta_j^s)}{n - df}$$

Coeff's depend on λ

- df degrees of freedom
- λ is a function of j, t
- Distribution of $\lambda_{j,t}$
- ID the TE drivers



FRM codes

- hu.berlin/frm

Low Risk	**<20%**
General Risk	**20% - 40%**
Elevated Risk	**40% - 60%**
High Risk	**60% - 80%**
Severe Risk	**>80%**

severe risk of crisis

high risk of crisis

elevated risk of crisis

general risk of crisis

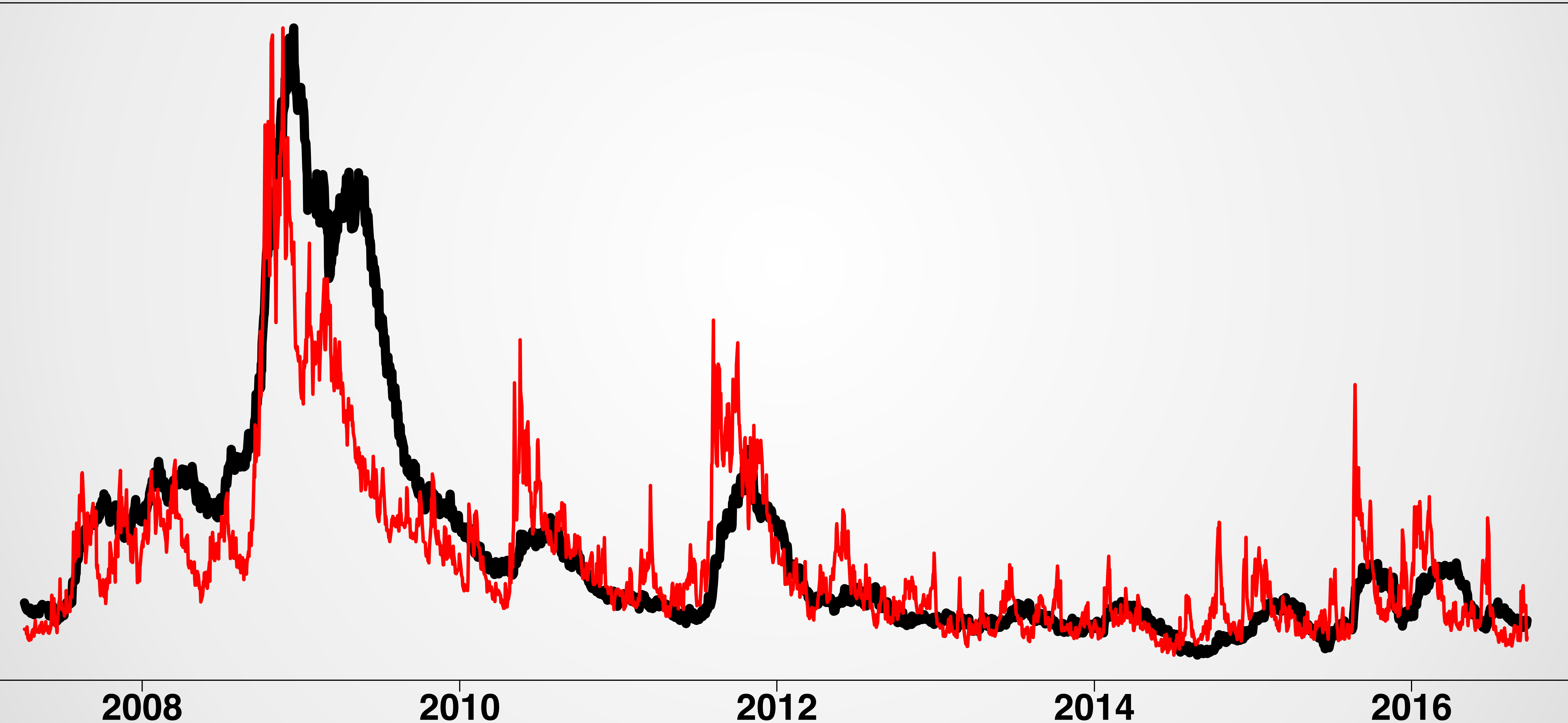
X low risk of crisis

Data

- 100 largest U.S. publicly traded financial institutions
- 6 macro related variables
- Quantile level $\tau = 0.05, \tau = 0.01, \ldots$
- Time frame: 01.04.2007 - 15.03.2019
- Macroeconomics CBOE Volatility Index, ^VIX
  S&P 500, ^GSPC
  iShares US Real Estate ETF, IYR
  3M Treasury Constant Maturity Rate, DGS3MO
  10Y Treasury Constant Maturity Rate, DGS10
  Moody's Seasoned Baa Corp Bond Yield, DBAA

FRM vs VIX

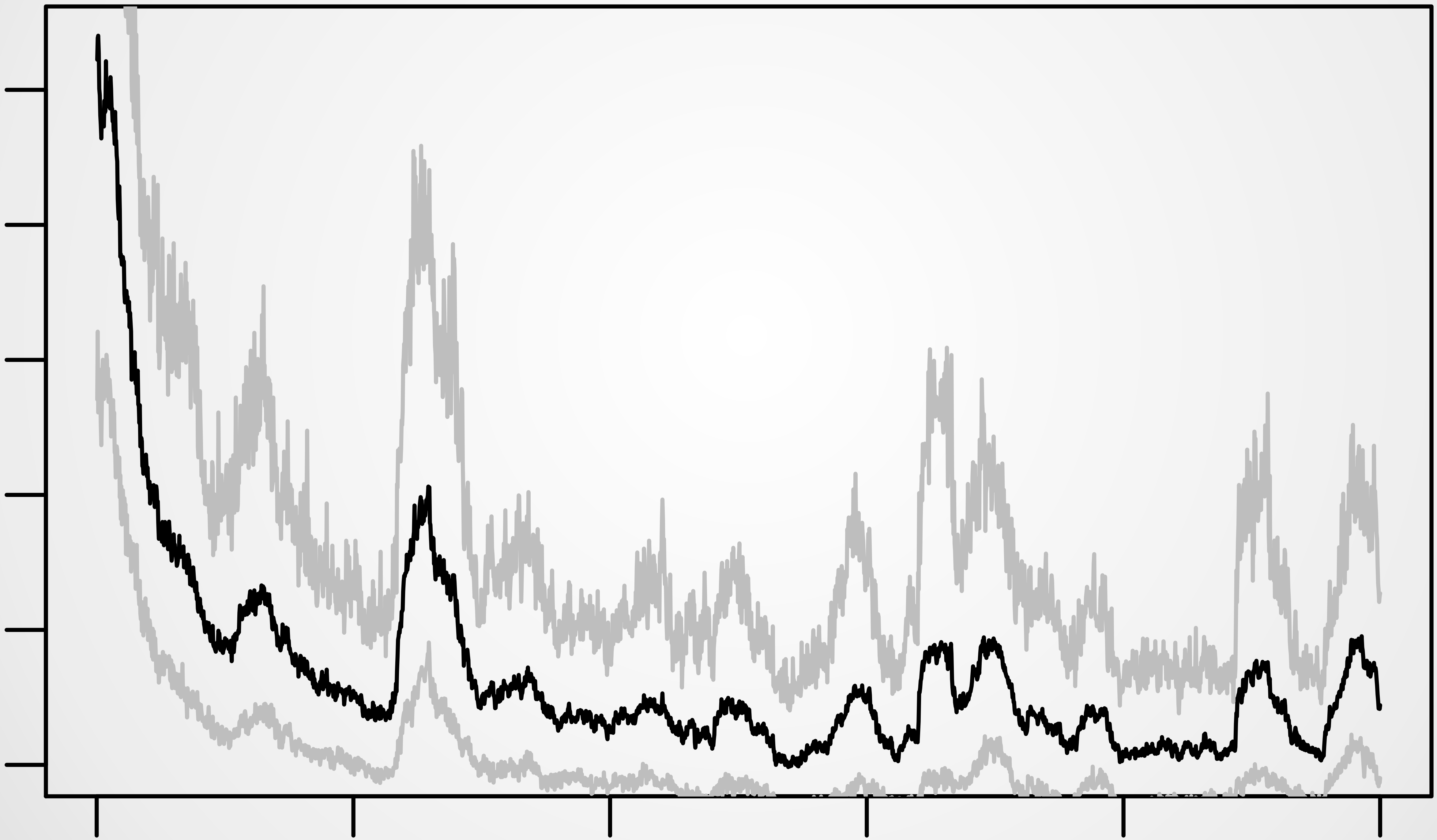
- The evolution of FRM relative to VIX



FRM

Confidence band

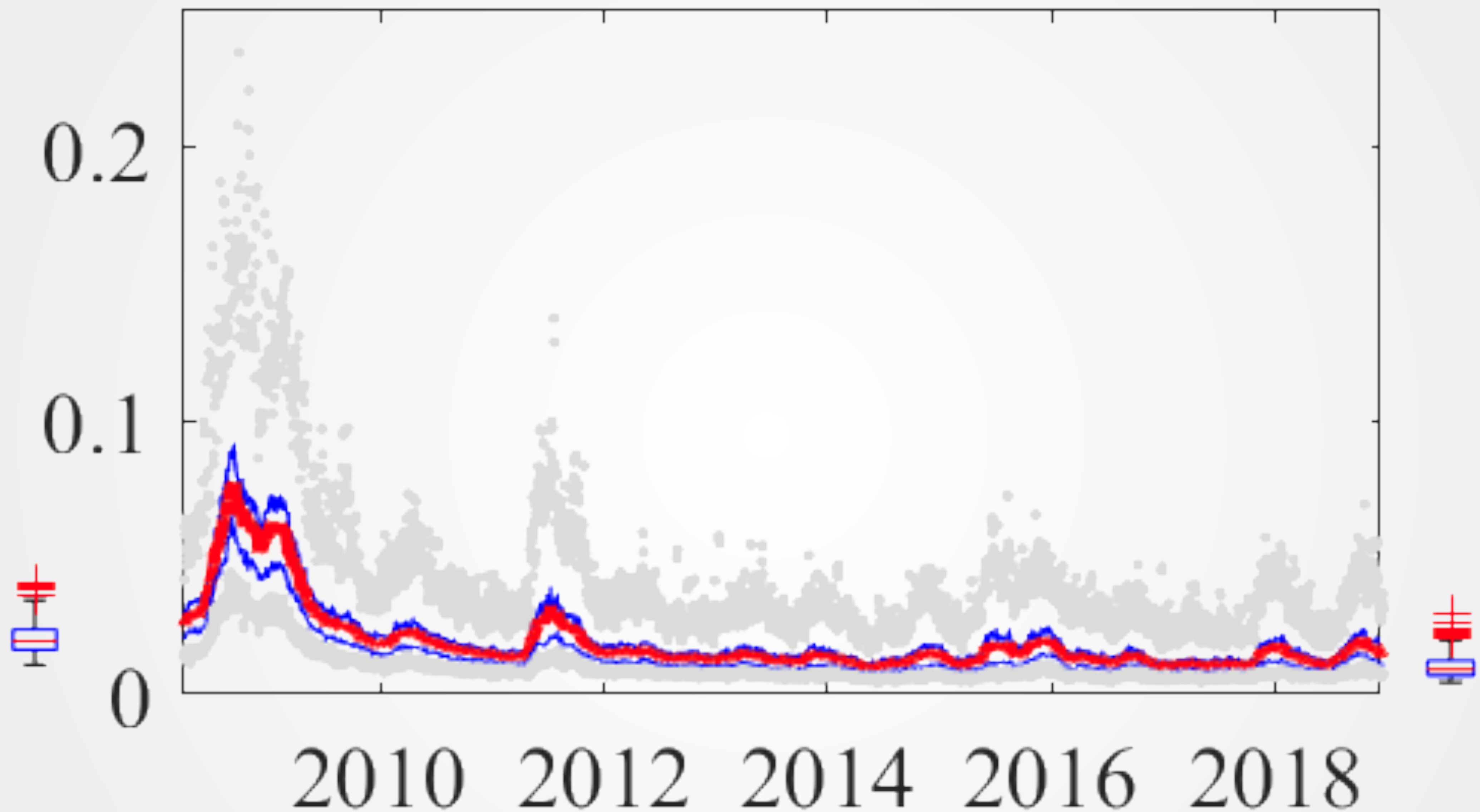
- 95% and 5%



FRM

Distributional characteristics

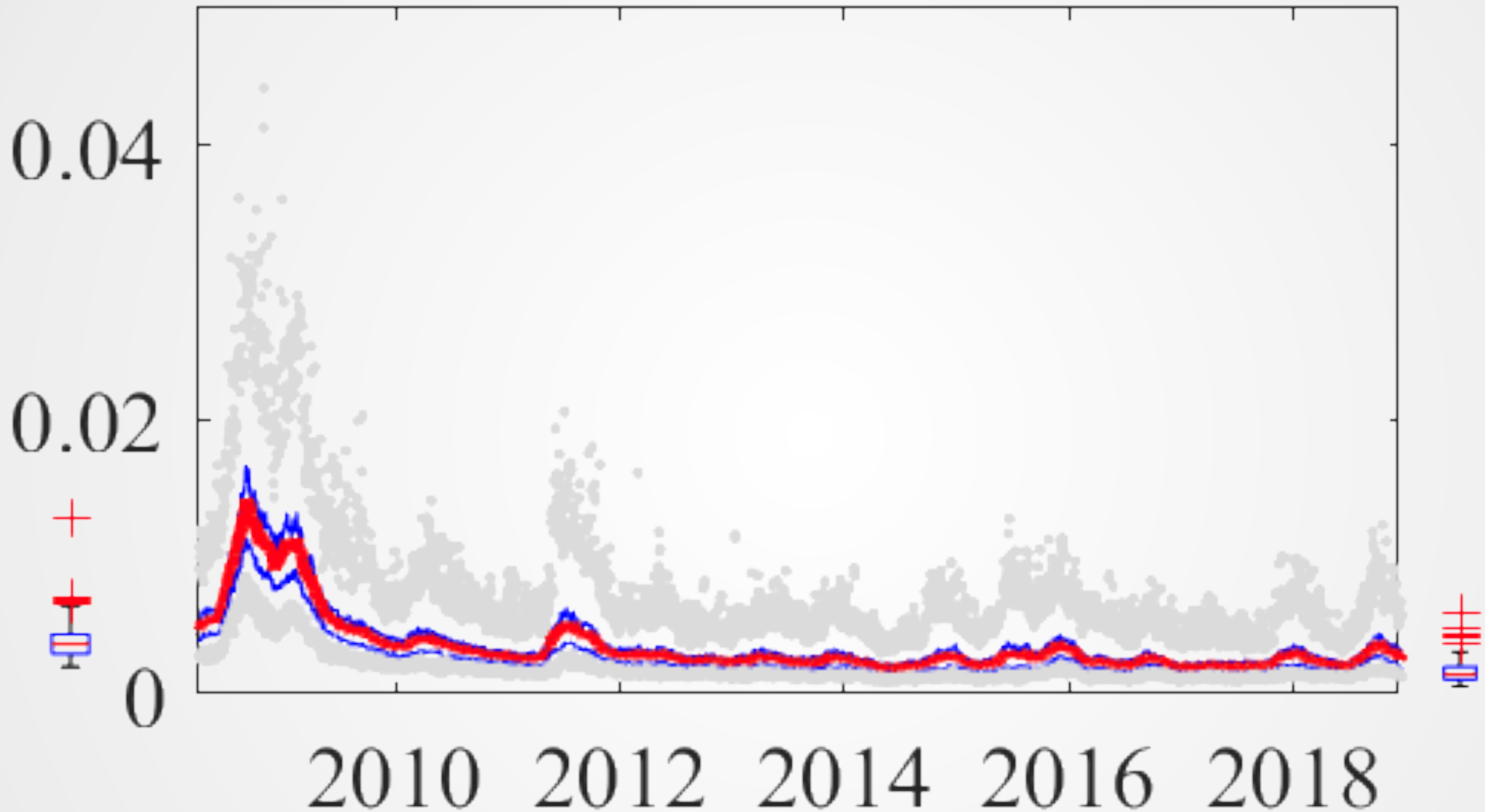
- Identifying companies CoStress $\tau = 0.05$



Distributional characteristics of $\lambda_j, j = 1,...J$
20080402 (left boxplot), 20190327 (right boxplot);
FRM, quartiles and extremes.

Distributional characteristics

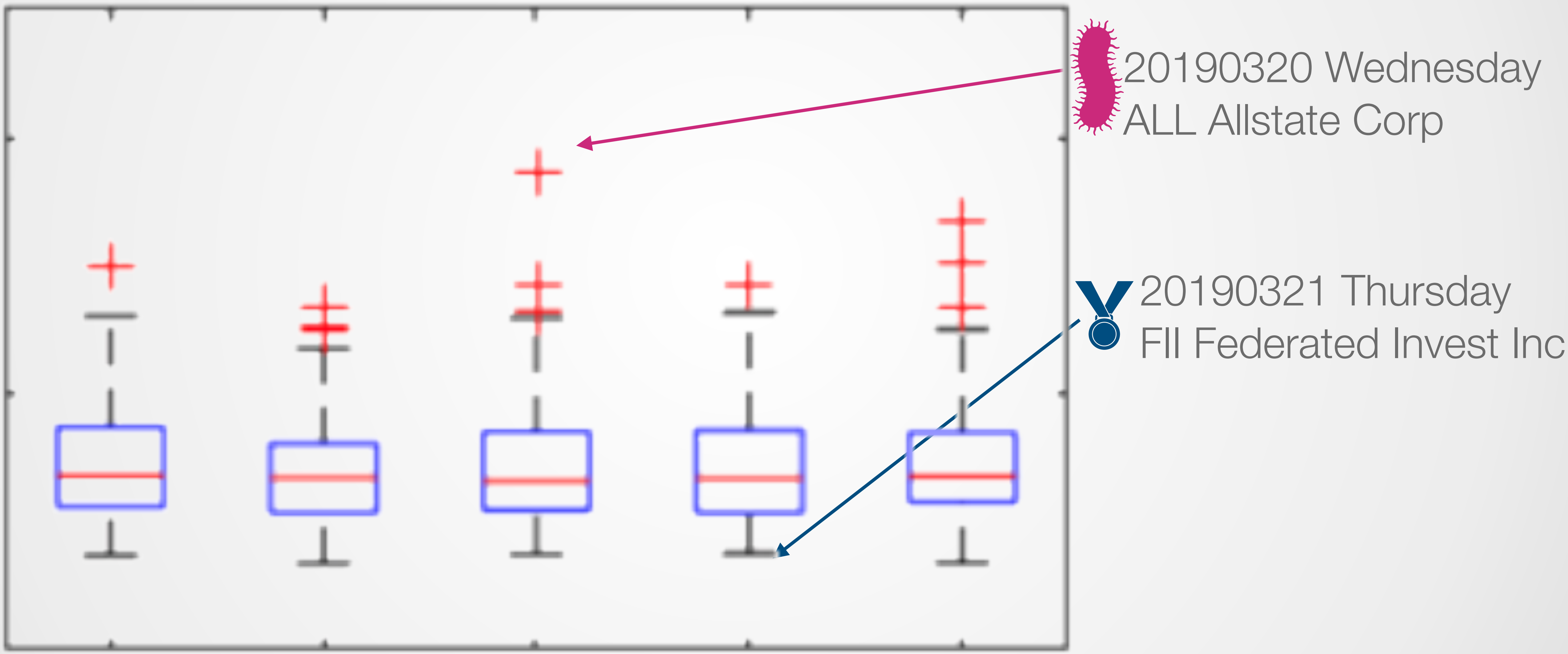
- Identifying companies CoStress $\tau = 0.01$



Distributional characteristics of $\lambda_j, j = 1,\ldots J$
20080402 (left boxplot), 20190327 (right boxplot);
FRM, quartiles and extremes.

CoStress IDs

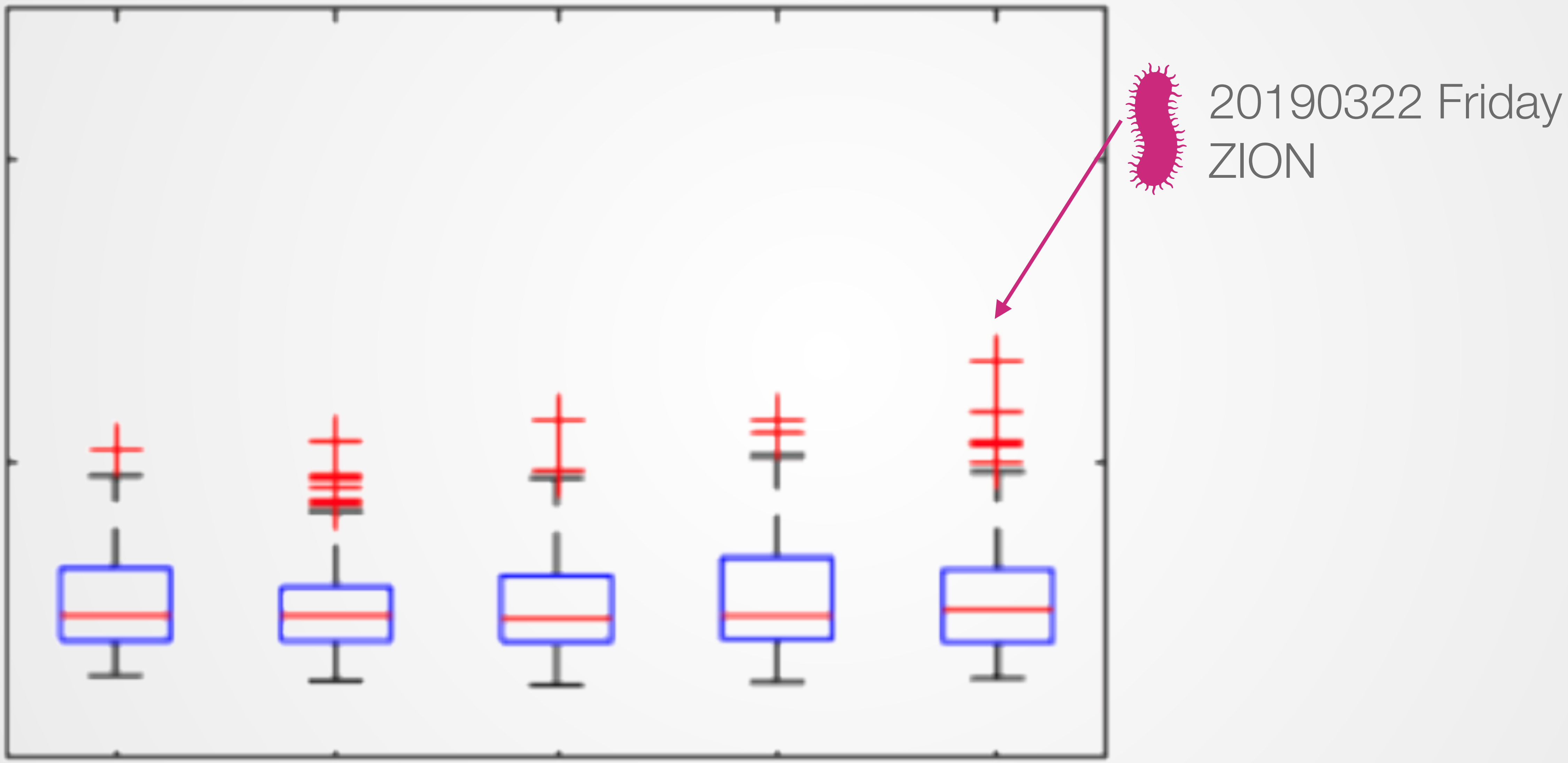
- ID CoStress via size of $\lambda_j, j = 1, \ldots J \quad \tau = 0.05$



Boxplots from 20190318 to 20190322. Max CoStress: FITB, ZION, ALL, AFG, ZION. Min CoStress: LM, AMG, AMG, FII, FII

CoStress IDs

- ID CoStress via size of $\lambda_j, j = 1,\ldots J \quad \tau = 0.01$



Boxplots from 20190318 to 20190322. Max CoStress: ZION, ZION, UNM, AFG, ZION. Min CoStress: EFX, AMG, LM, MORN, LM.

TOP Extreme CoStress

- TOP 5 companies exhibiting extreme CoStress $\tau = 0.05$

Maximal		Minimal	
BBT	94	CACC	172
MS	86	SEB	159
RJF	83	MKTX	103
STI	75	WTM	99
AMP	68	OZM	97

TOP 5 companies: # days of CoStress all companies from 20080402 to 20190327 (2700 trading days)

TOP Extreme CoStress

- TOP 5 companies exhibiting extreme CoStress $\tau = 0.01$

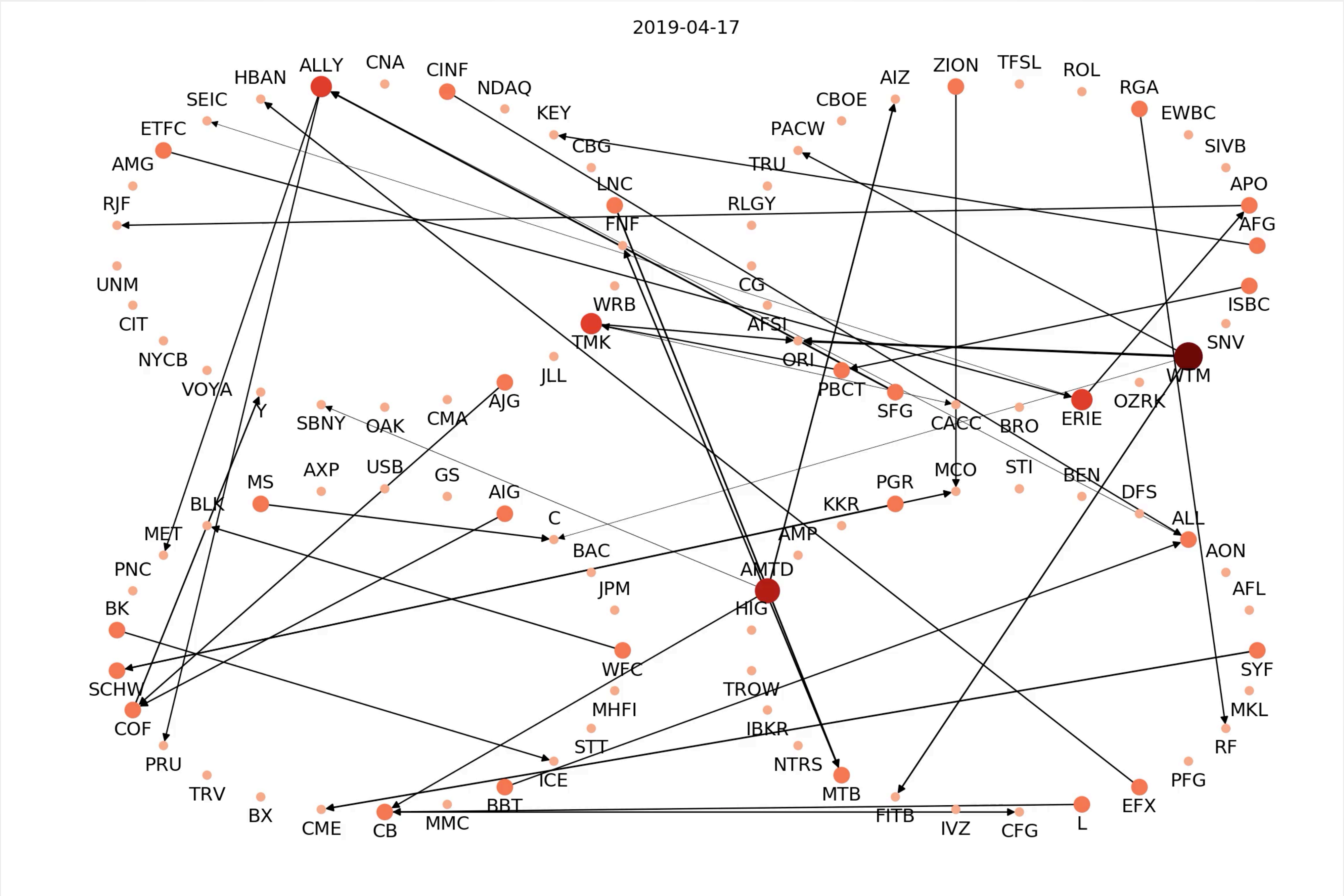
Maximal		Minimal	
STI	92	CACC	113
SNV	71	SEB	114
IVZ	69	OZM	111
BBT	67	MKTX	100
RJF	64	MORN	73

TOP 5 companies: # days of CoStress all companies from 20080402 to 20190327 (2700 trading days)

Network Dynamics

- 100 risk factors

$$\tau = 0.05$$



Coeffs of all companies from 20190417 to 20190426

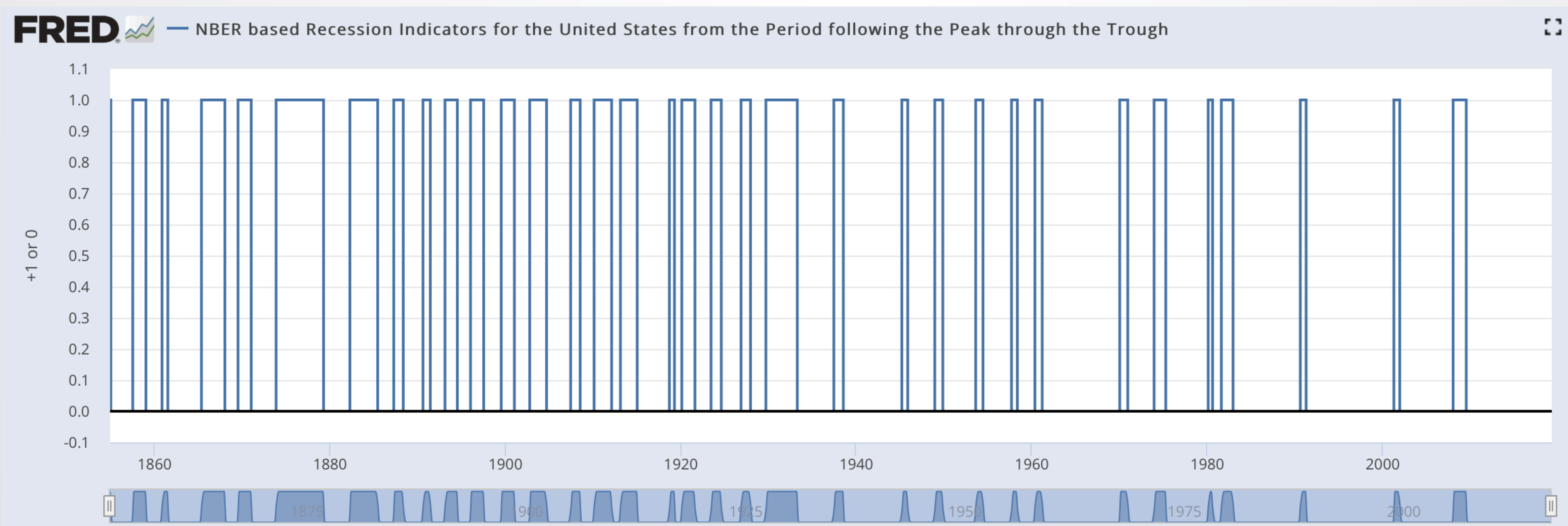
FRED meets FRM

- Logistic linear regression

$$\log \frac{P(y=1\,|\,x;\beta)}{P(y=0\,|\,x;\beta)} = \beta_0 + \beta_1 x$$

y National Bureau of Economic Research (NBER) recession indicator

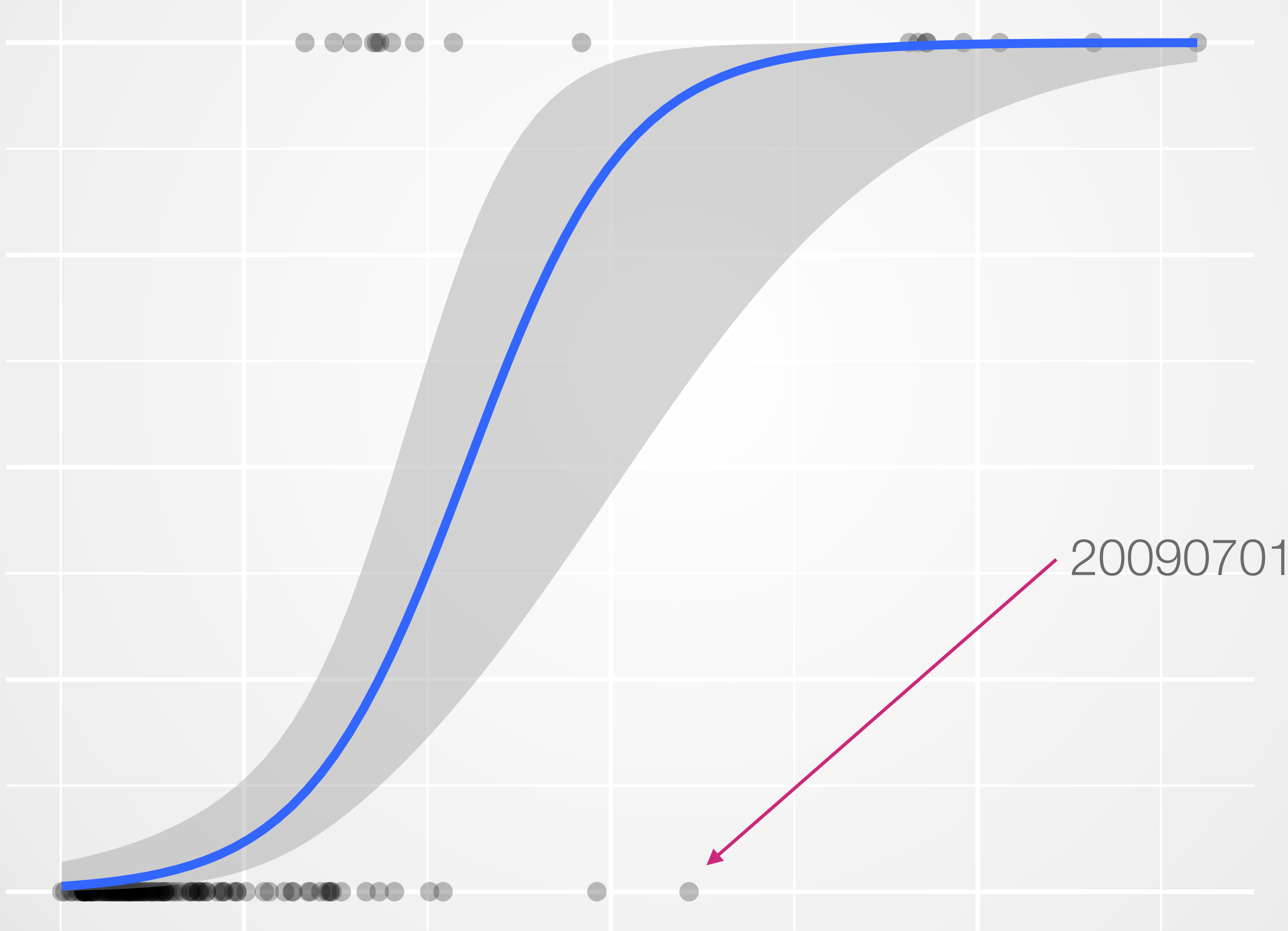
x FRM



FRM

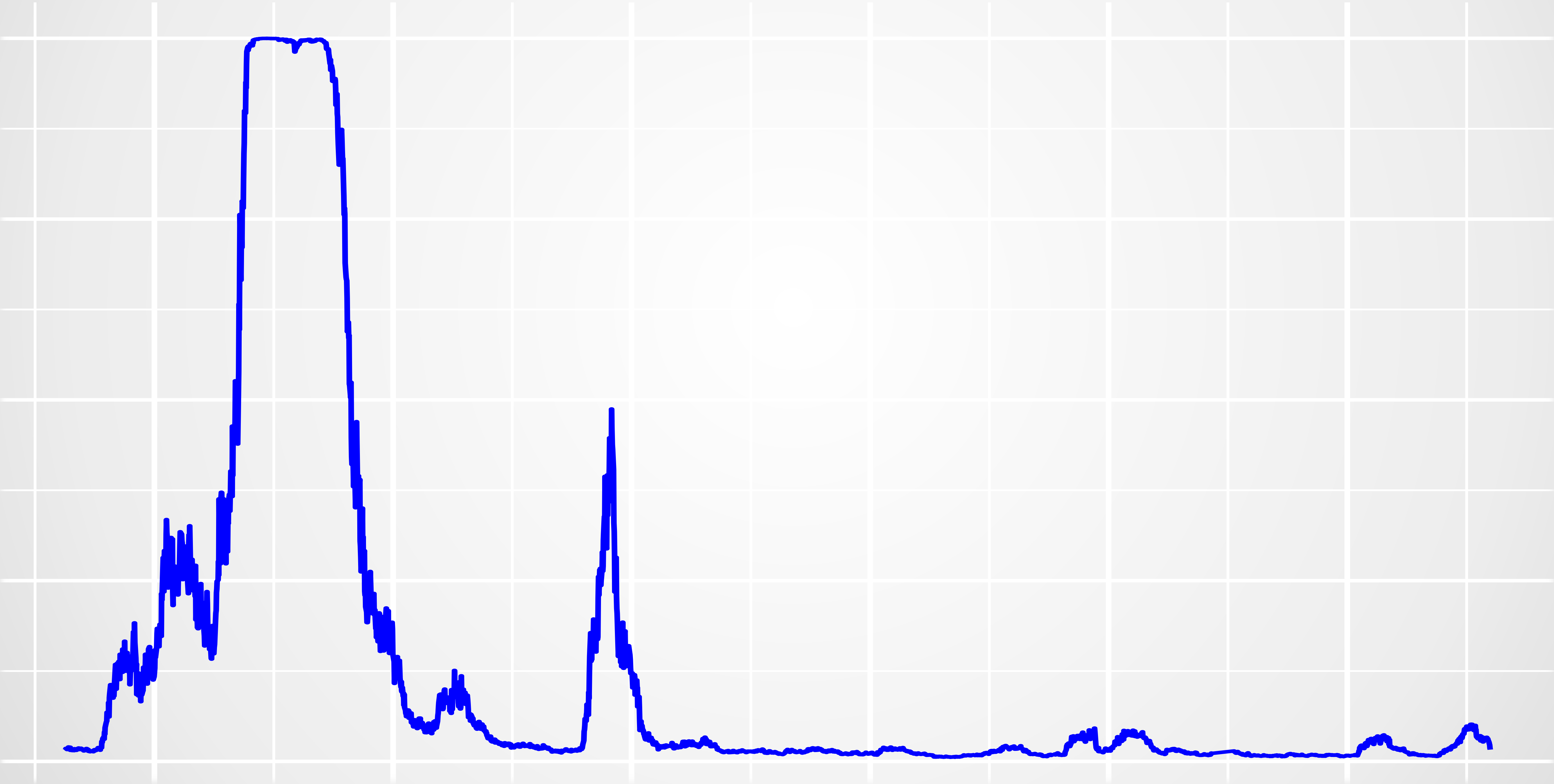
Result

- Coeffs $\beta_1 = 215.5 \ \ \beta_0 = -5.8 \ \ \tau = 0.05$



Implied recession probability

- FRM scales



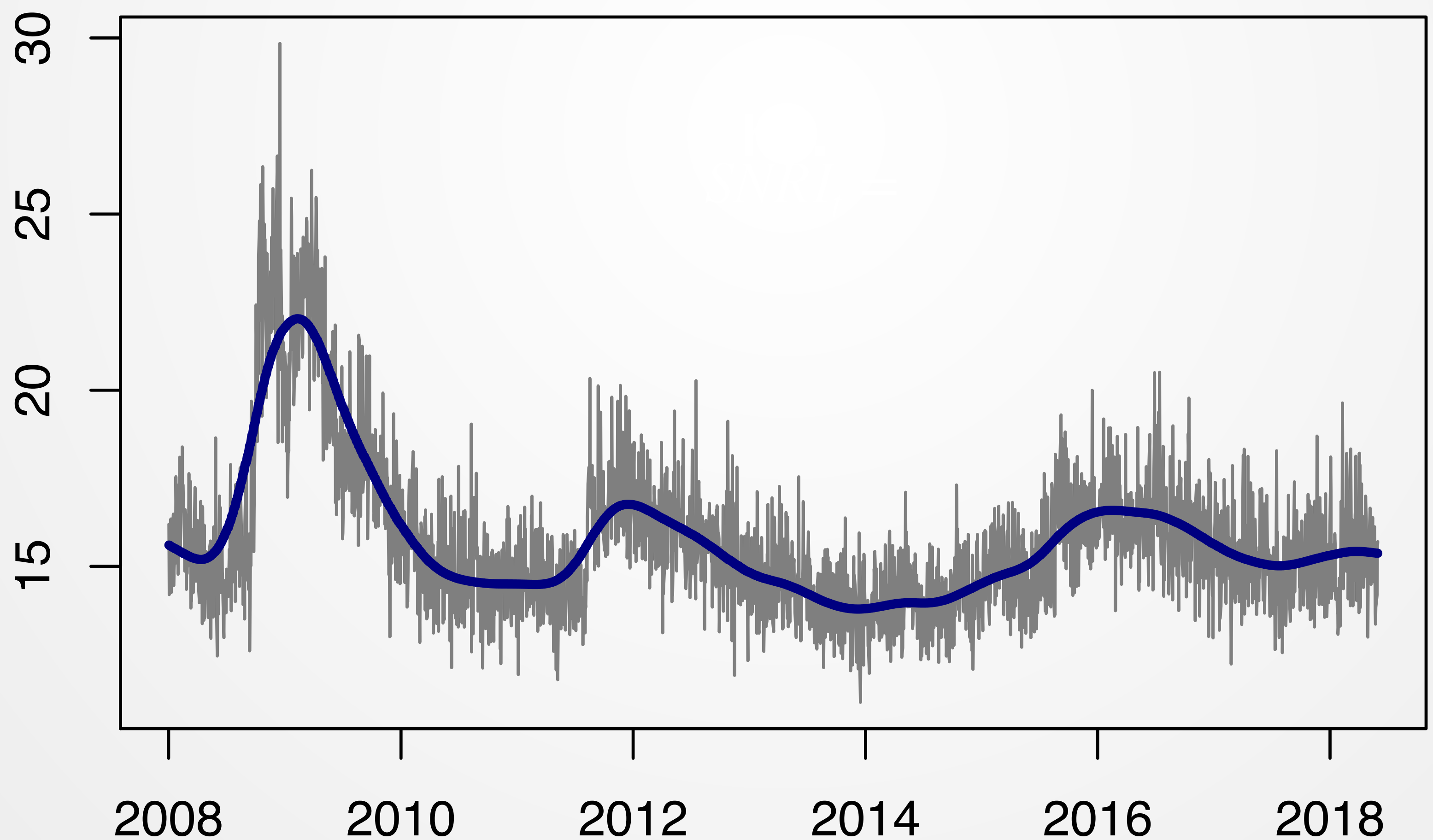
Extensions

- Use national or EU data to construct localised FRM
- Adaptive LASSO
- Global contagion effect of FRMs
- Relate Network Centrality to Max/Min CoStress nodes
- Besides equal weights, weights by degree of centrality
- LASSO in Time and Space
- Aggregate global FRMs

Extensions: Neural Network CoVaR (Keilbar, 2018)

- *Systemic Network Risk Index (SNRI)* measures total systemic risk
- Incorporates bivariate risk spillover effects $a_{ji,t}$

$$SNRI_t = \sum_{j=1}^{k} \sum_{i=1}^{k} (1 + |\mathrm{VaR}^{\tau}_{i,t}|)(1 + |\mathrm{CoVaR}^{\tau}_{j,t}|) \cdot a_{ji,t}$$



Extensions: Neural Network CoVaR (Keilbar, 2018)

- *Systemic Hazard Index (SHI)* measures the risk of bank *i* imposes to the financial system

$$SHI_{i,t} = \sum_{j=1}^{k} (1 + |\mathrm{CoVaR}_{j,t}^{\tau}|) \cdot a_{ji,t}$$

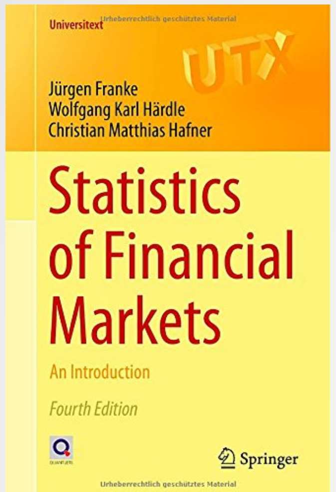
- *Systemic Fragility Index (SFI)* measures the exposure of bank *j* to the financial system

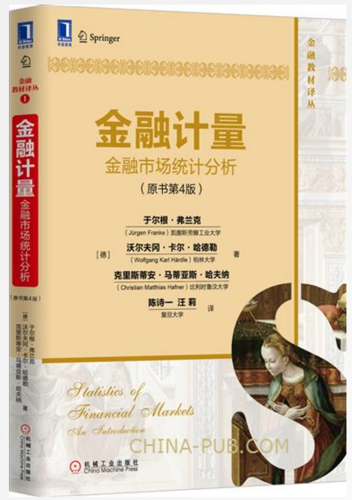
$$SFI_{i,t} = \sum_{i=1}^{k} (1 + |\mathrm{VaR}_{i,t}^{\tau}|) \cdot a_{ji,t}$$

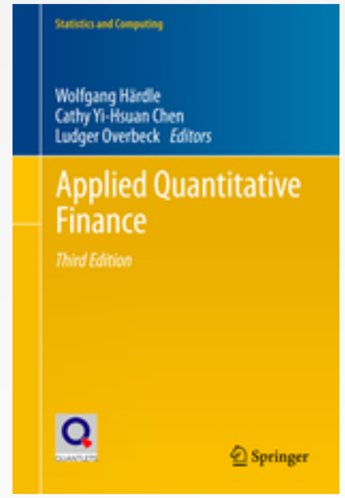
Conclusions

- FRM financialriskmeter = Flexible Risk Meter
- FRM has systemic risk components
- FRM predicts recession periods
- FRM can be tuned to any TE risk
- FRM reacts to coagulation of risk emitters via active set

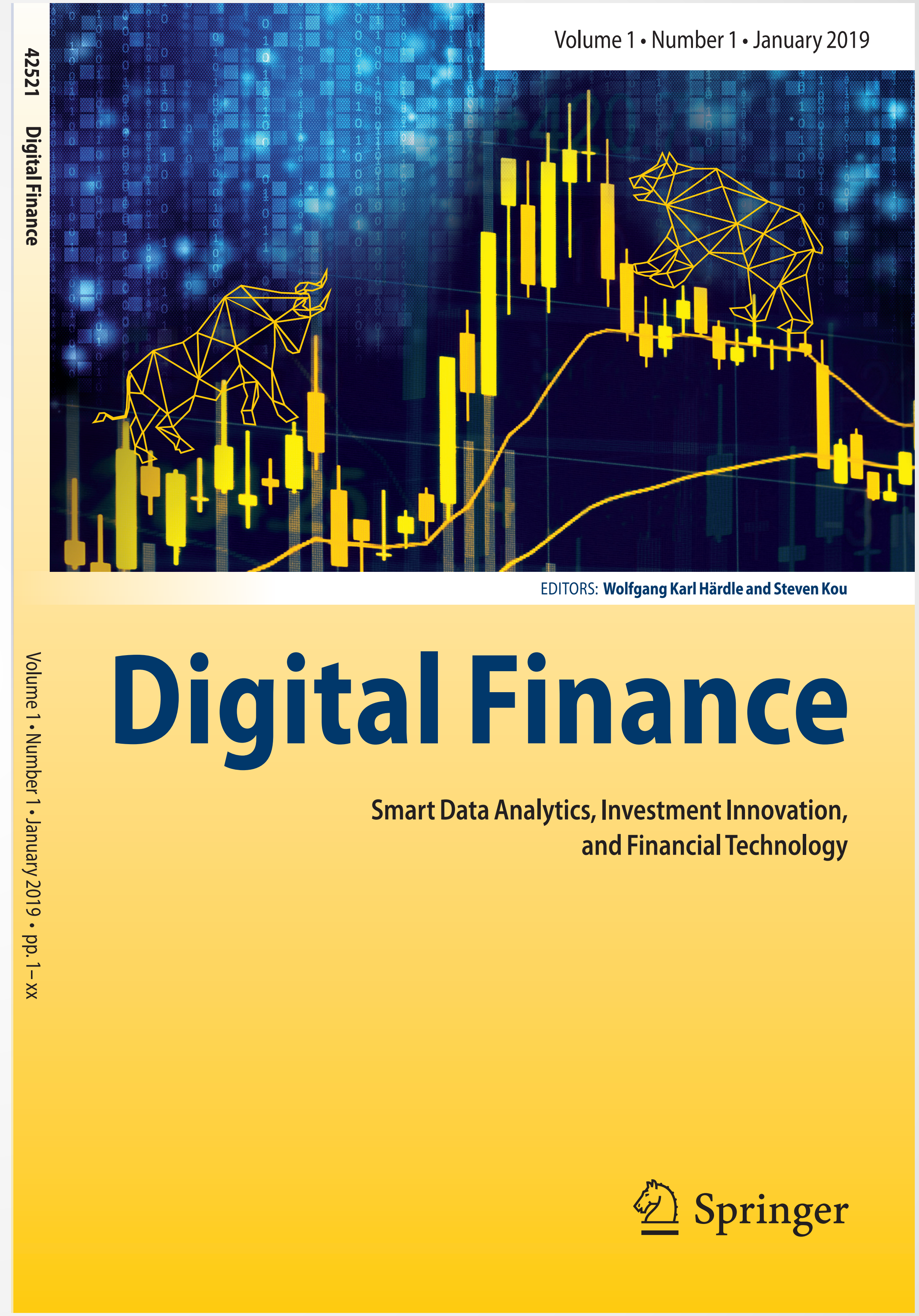
FRMs in FinTech, Cryptos, …





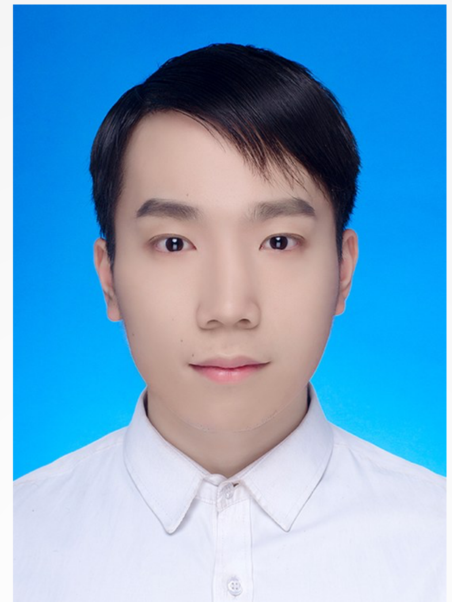
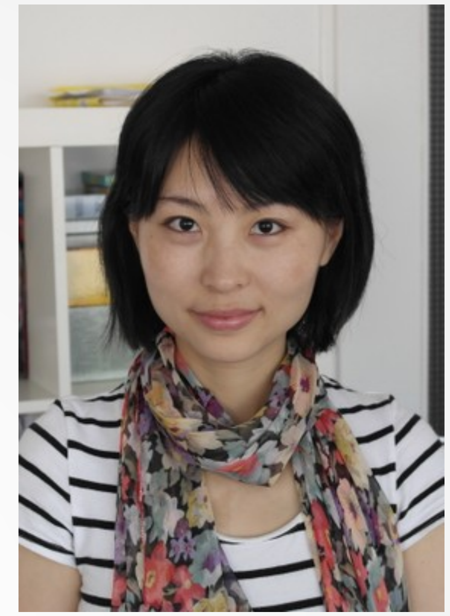


Vol 1. 2019 on Crypto Currencies



Advisors




Georg Keilbar | Alla Petukhina | Keyan LIU | Lining YU | Weining WANG

FIRAMIS

Jochen Papenbrock

FRM Team

Cathy YH CHEN

Wolfgang K Härdle

Andrija Mihoci

Michael Althof

FRM financialriskmeter

Andrija Mihoci
Cathy Yi-Hsuan Chen
Wolfgang Karl Härdle
Michael Althof

FRM

Ladislaus von Bortkiewicz Chair of Statistics
Humboldt-Universität zu Berlin
lvb.wiwi.hu-berlin.de

Brandenburg University of Technology

University of Glasgow

References

- Adrian J, Brunnermeier M (2016) CoVaR, American Economic Review, 106 (7): 1705-41, DOI: 10.1257/aer.20120555
- Buraschi A, Corielle F (2005). Risk management of time-inconsistency: Model updating and recalibration of no-arbitrage models. J Banking and Finance 29: 2883–907
- Chao SK, Härdle WK, Wang W (2015) Quantile Regression in Risk Calibration. in Handbook for Financial Econometrics and Statistics, Cheng-Few Lee, ed., Springer Verlag, DOI: 10.1007/978-1-4614-7750-1_54.
- Härdle WK, Wang W, Zbonakova L (2018) Time Varying Lasso, in Applied Quantitative Finance 3rd ed, (Chen, Härdle, Overbeck eds.) Springer Verlag, ISBN 978-3-662-54486-0
- Keilbar G (2018) Modeling systemic risk using Neural Network Quantile Regression, MSc thesis
- Osborne MR, Presnell B, Turlach BA (200) J Comp Graphical Statistics Vol. 9, 319-337

Expectile as Quantile

$e_\tau(Y)$ is the τ-quantile of the cdf T , where

$$T(y) = \frac{G(y) - xF(y)}{2\{G(y) - yF(y)\} + \{y - \mu_Y\}}$$

and

$$G(y) = \int_{-\infty}^{y} u\, dF(u)$$

Back to Expectiles

Company List

FRM X's

Symbol	Name	LastSale	MarketCap	ADR TSO	IPOyear	Sector	Industry	Summary Quote
WFC	Wells Fargo & Company	51.88	2.65E+11	n/a	n/a	Finance	Major Banks	http://www.nasdaq.com/symbol/wfc
JPM	J P Morgan Chase & Co	62.81	2.31E+11	n/a	n/a	Finance	Major Banks	http://www.nasdaq.com/symbol/jpm
BAC	Bank of America Corporation	16.08	1.67E+11	n/a	n/a	Finance	Major Banks	http://www.nasdaq.com/symbol/bac
C	Citigroup Inc.	50.12	1.49E+11	n/a	n/a	Finance	Major Banks	http://www.nasdaq.com/symbol/c
AIG	American International Group, Inc.	59.75	73911497592	n/a	n/a	Finance	Property-Casualty Insurers	http://www.nasdaq.com/symbol/aig
GS	Goldman Sachs Group, Inc. (The)	169.84	72442901924	n/a	1999	Finance	Investment Bankers/Brokers/Service	http://www.nasdaq.com/symbol/gs
USB	U.S. Bancorp	41.05	71803718395	n/a	n/a	Finance	Major Banks	http://www.nasdaq.com/symbol/usb
AXP	American Express Company	64.42	63405122360	n/a	n/a	Finance	Finance: Consumer Services	http://www.nasdaq.com/symbol/axp
MS	Morgan Stanley	30.5	59054830750	n/a	n/a	Finance	Investment Bankers/Brokers/Service	http://www.nasdaq.com/symbol/ms
BLK	BlackRock, Inc.	330.16	54848693699	n/a	1999	Finance	Investment Bankers/Brokers/Service	http://www.nasdaq.com/symbol/blk
MET	MetLife, Inc.	44.37	49322866962	n/a	2000	Finance	Life Insurance	http://www.nasdaq.com/symbol/met
PNC	PNC Financial Services Group, Inc. (The)	91.6	46515010272	n/a	n/a	Finance	Major Banks	http://www.nasdaq.com/symbol/pnc
BK	Bank Of New York Mellon Corporation (The)	38.82	42428419621	n/a	n/a	Finance	Major Banks	http://www.nasdaq.com/symbol/bk
SCHW	The Charles Schwab Corporation	30.79	40535754347	n/a	n/a	Finance	Investment Bankers/Brokers/Service	http://www.nasdaq.com/symbol/schw
COF	Capital One Financial Corporation	68.55	36471702025	n/a	1994	Finance	Major Banks	http://www.nasdaq.com/symbol/cof
PRU	Prudential Financial, Inc.	76.92	34537080000	n/a	2001	Finance	Life Insurance	http://www.nasdaq.com/symbol/pru
TRV	The Travelers Companies, Inc.	109.04	33172017516	n/a	n/a	Finance	Property-Casualty Insurers	http://www.nasdaq.com/symbol/trv
BX	The Blackstone Group L.P.	27.29	32092061544	n/a	2007	Finance	Investment Managers	http://www.nasdaq.com/symbol/bx
CME	CME Group Inc.	88.93	30079362252	n/a	2002	Finance	Investment Bankers/Brokers/Service	http://www.nasdaq.com/symbol/cme

FRM equations

NBER recession Indicator

- From FRED NBER

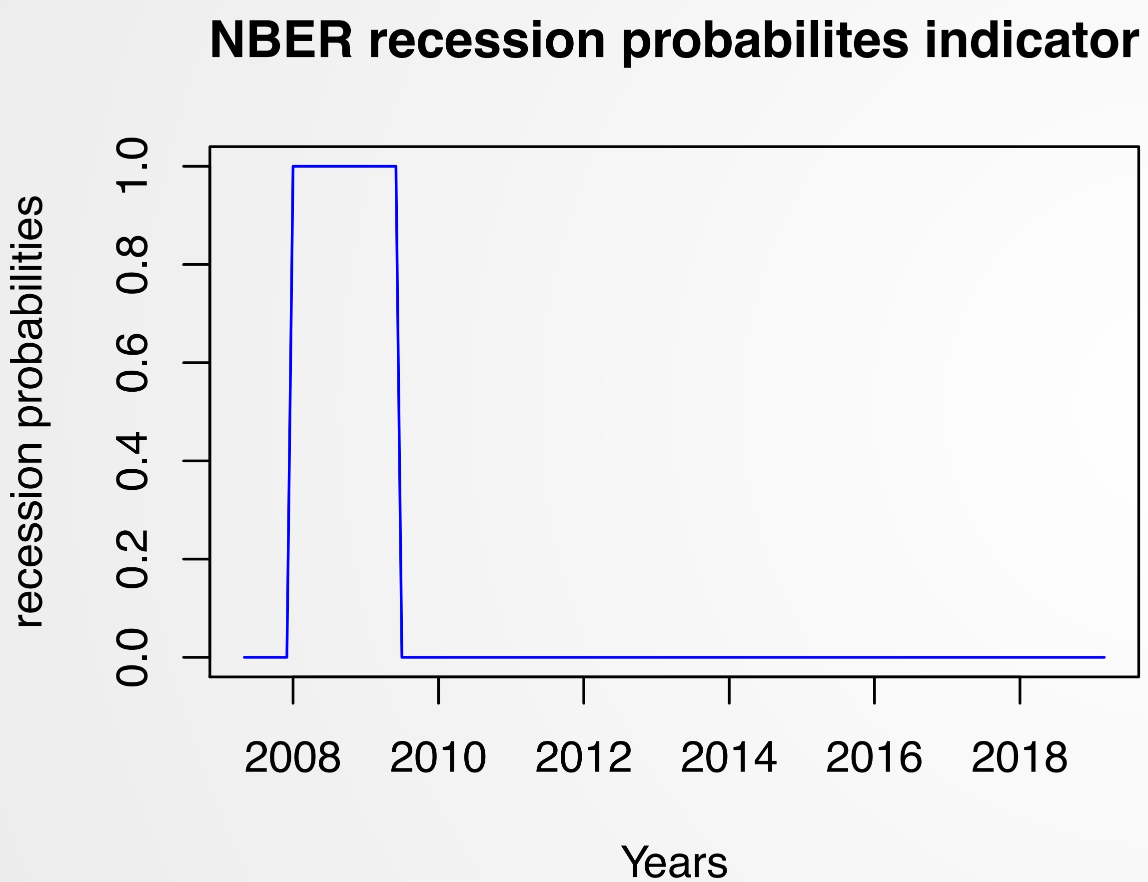


Table 2: Logistic regression results

	Dependent variable:
	recession
frm	215.513***
	(12.978)
Constant	−5.852***
	(0.325)
Observations	1,370
Log Likelihood	-539.147
Akaike Inf. Crit.	1,082.294
Note:	*p<0.1; **p<0.05; ***p<0.01