

FRM financialriskmeter for Cryptos

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Money

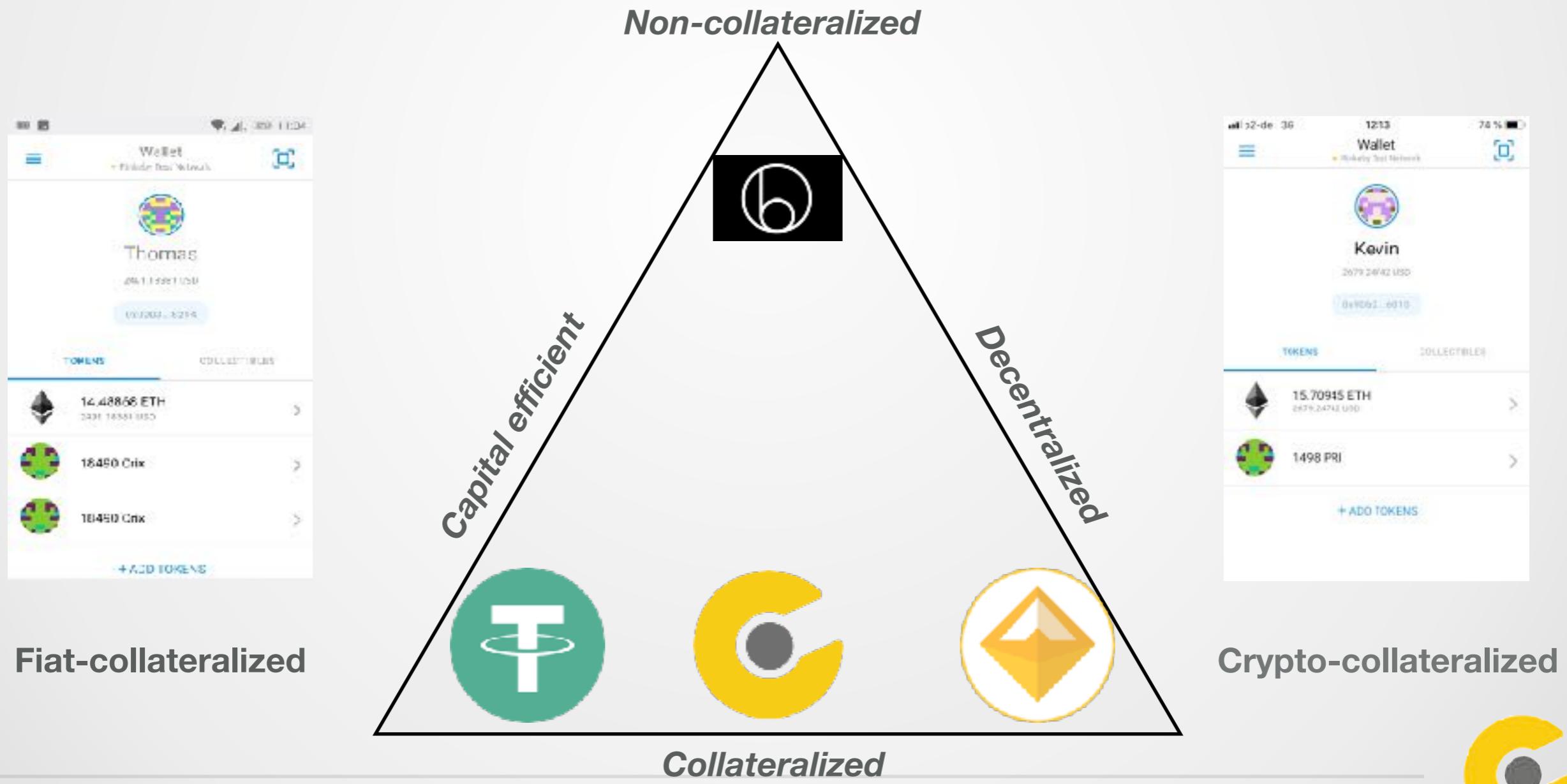
- Groucho Marx: „Money frees you from doing things you dislike. Since I dislike doing nearly everything, money is handy.”
- David Hume: „Money is () the instrument () to facilitate the exchange of one commodity for another. It is () the oil which renders the motion of the wheels more smooth and easy.
- Friedrich Hayek: „Instead of a national government issuing a specific currency () private businesses should be allowed to issue their own forms of money, deciding how to do so on their own.“



CRIX - the Coin

- Smart Contract: Solidity
- EVM Ethereum Virtual Machine (gas)
- Safemath library

Create your own wallet!

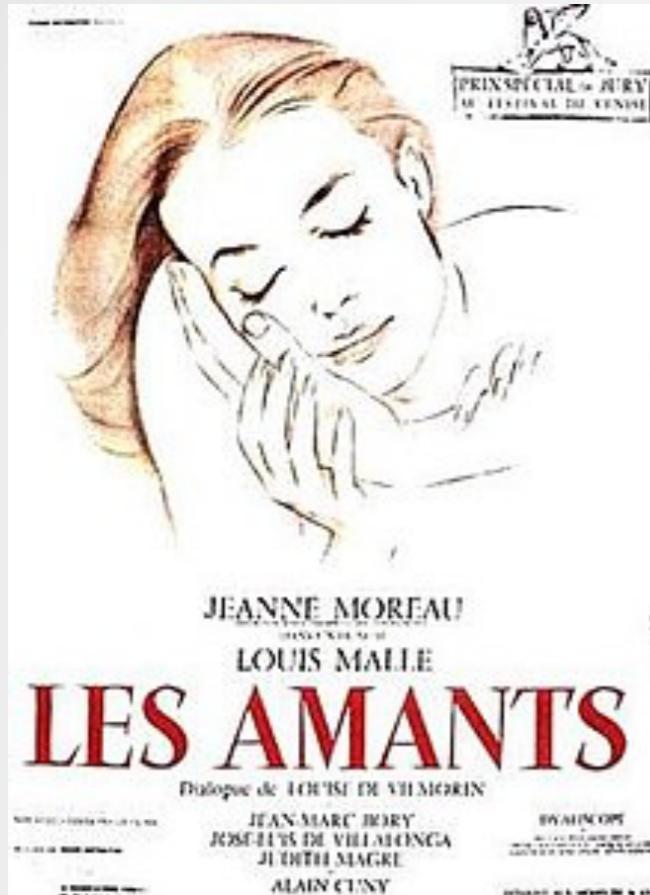


Tail Events (TE)

- TEs across Cryptos 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.”, Vitor 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)

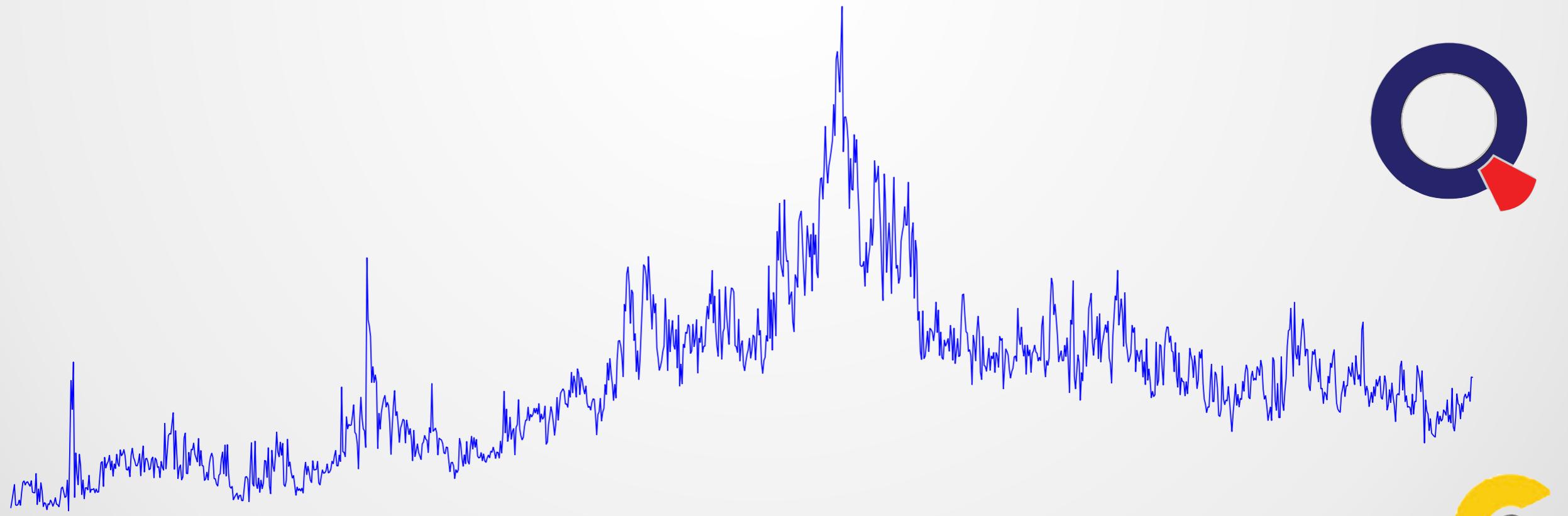
„I know it when I see it”, Justice Potter Stewart (1964)

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



Risk Measures

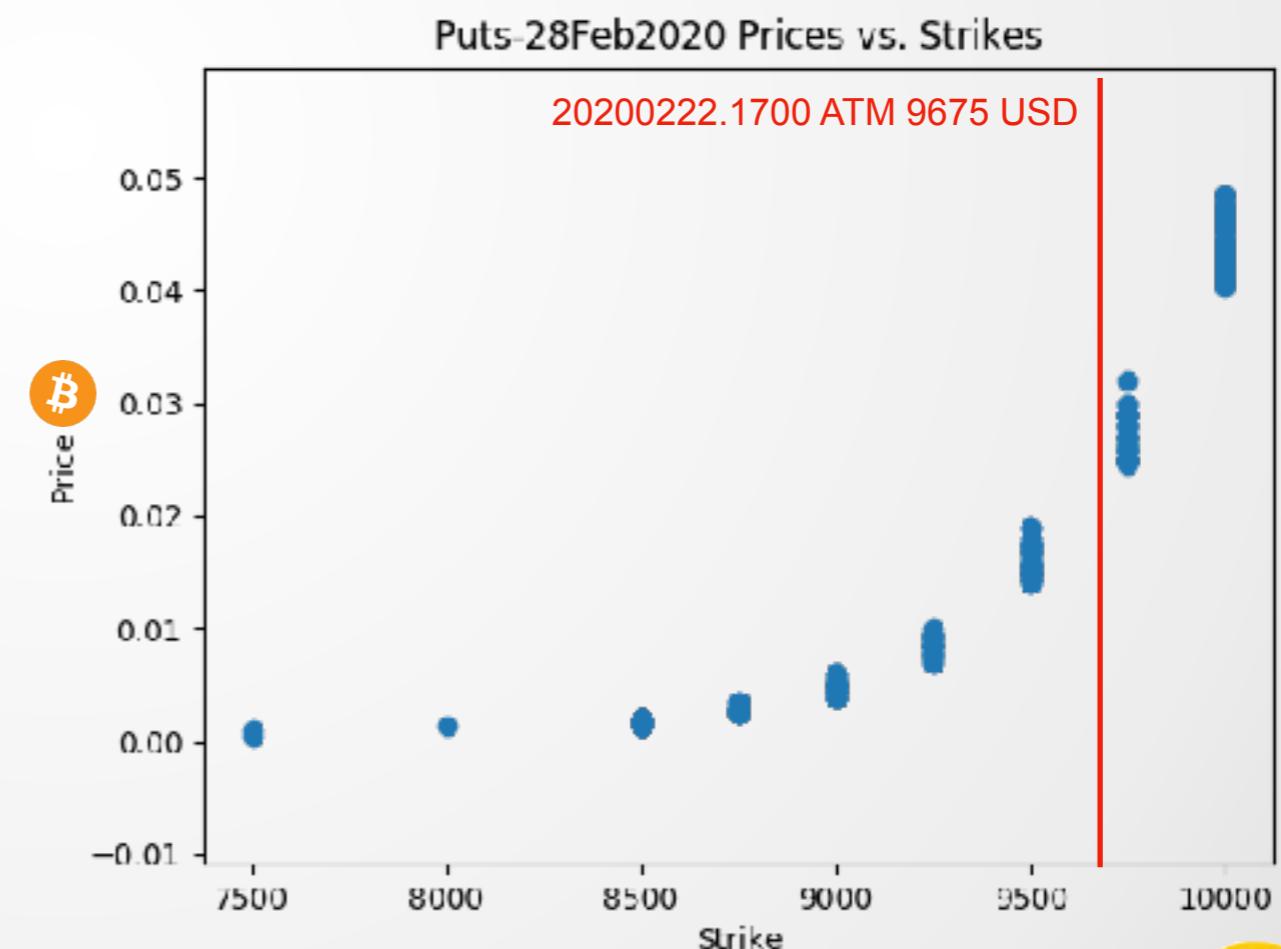
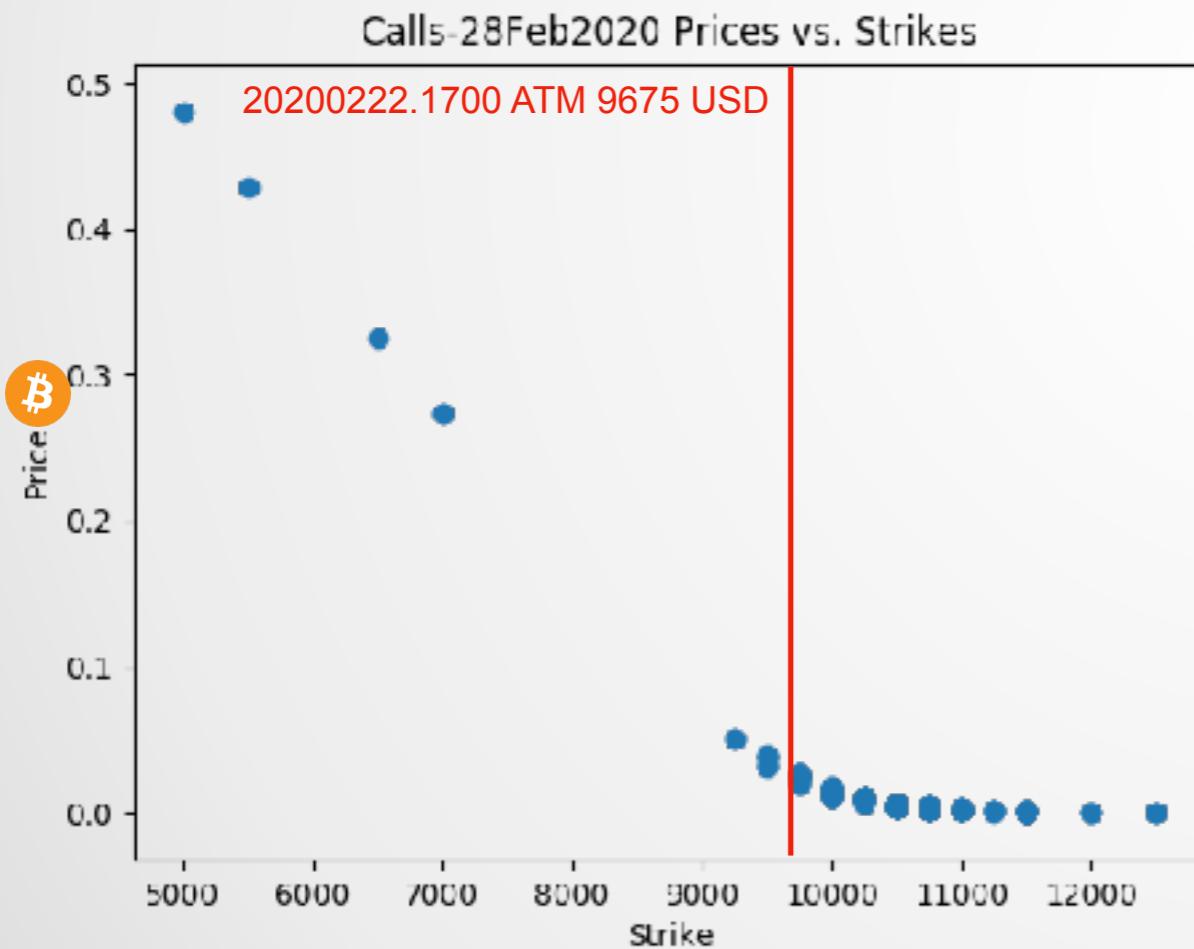
- VIX: IV based, does not reflect joint TEs
- CoVaR concentrates on a pair of risk factors
- CISS, Google trends, SRISK, ...
- FRM displays the full picture of TE dependencies
- Firamis.de/FRM **financialriskmeter**

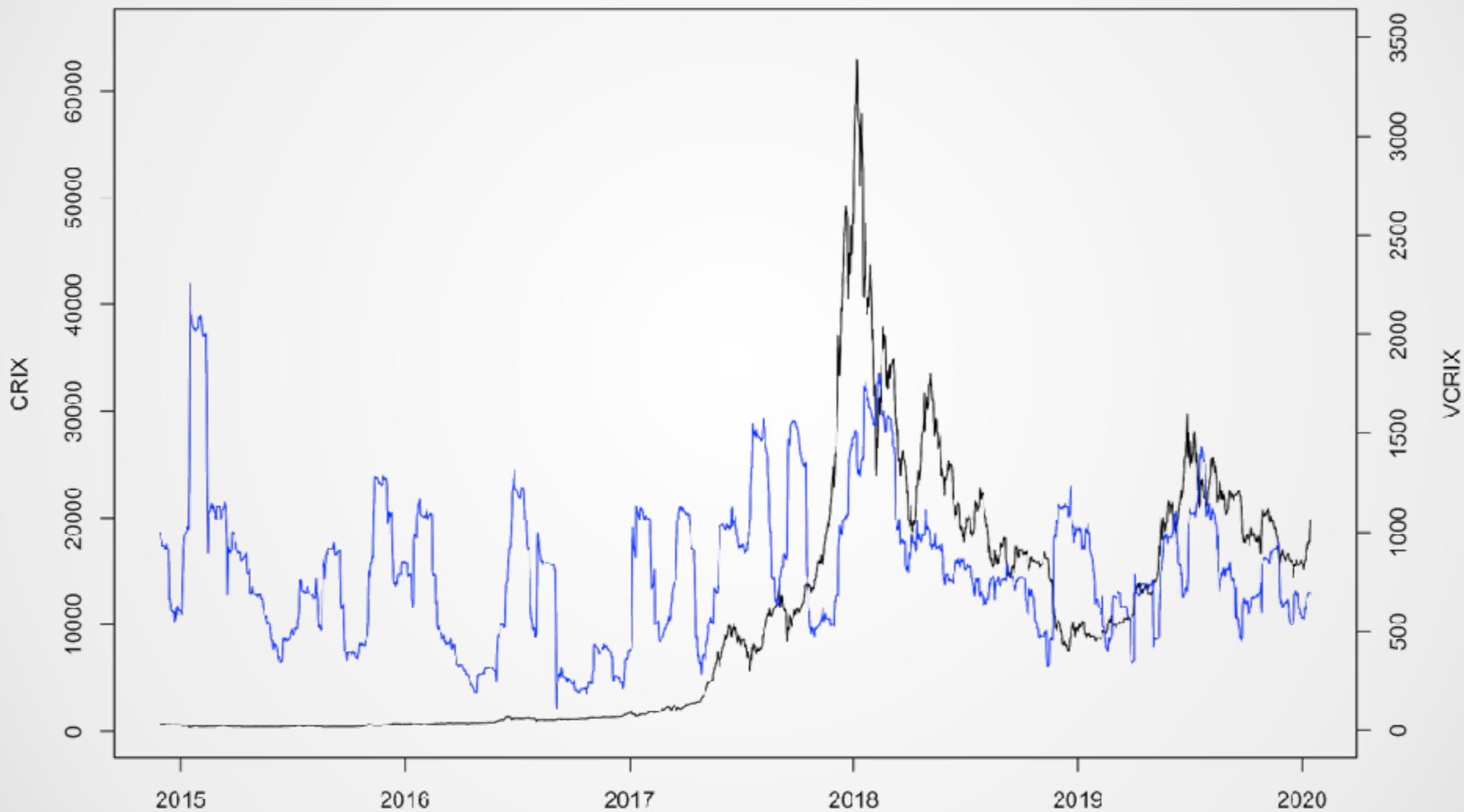


Call and Puts on BTCs

- >Listed at Bloomberg since 20200113

Prices from 20200221.1600 - 20200222.1100
Timestamps precise in the range 1E-3 sec.
Calls, Puts with maturity 20200228





Outline

1. Motivation ✓
2. Genesis
3. FRM Framework
4. CoStress ID, Active Set
5. Extension to other asset classes
6. FRM a predictor for recession
7. Conclusions

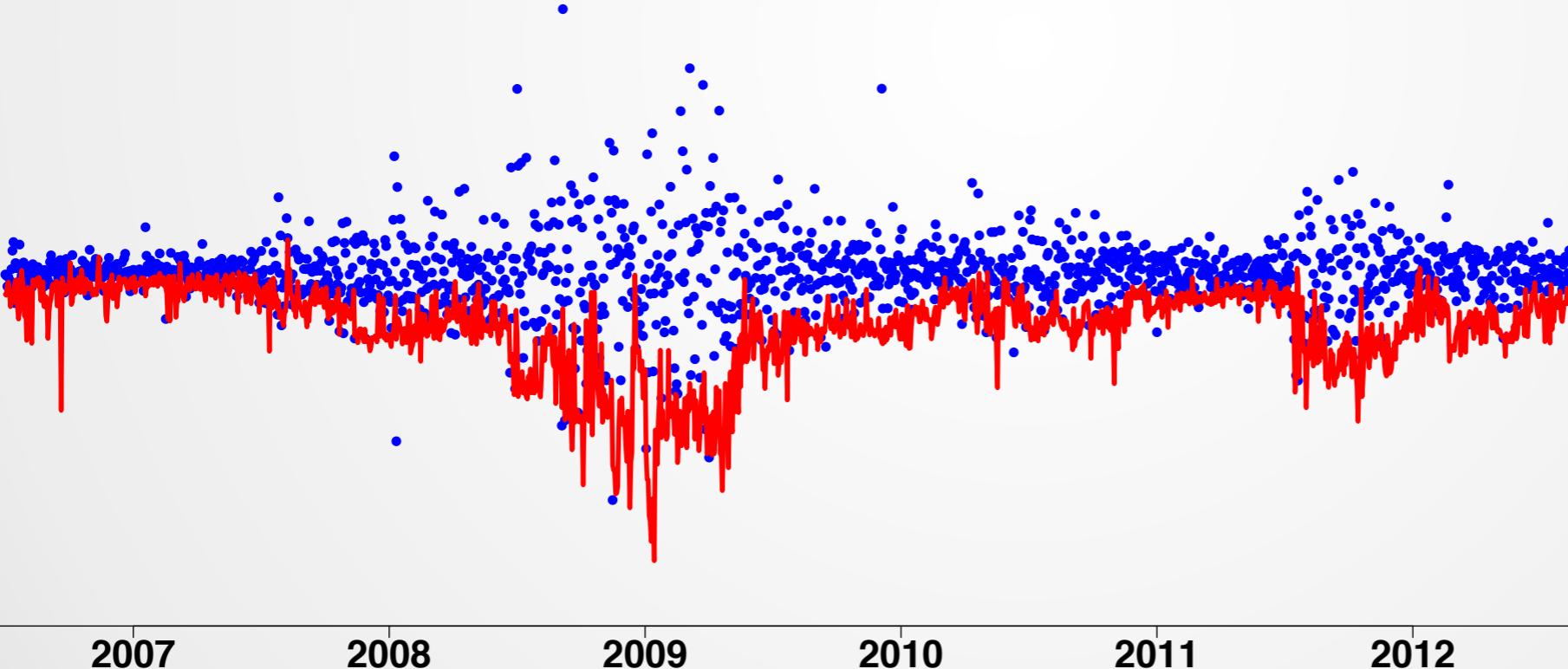


VaR Value at Risk

- Probability measure based

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

- $X_{i,t}$ 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:

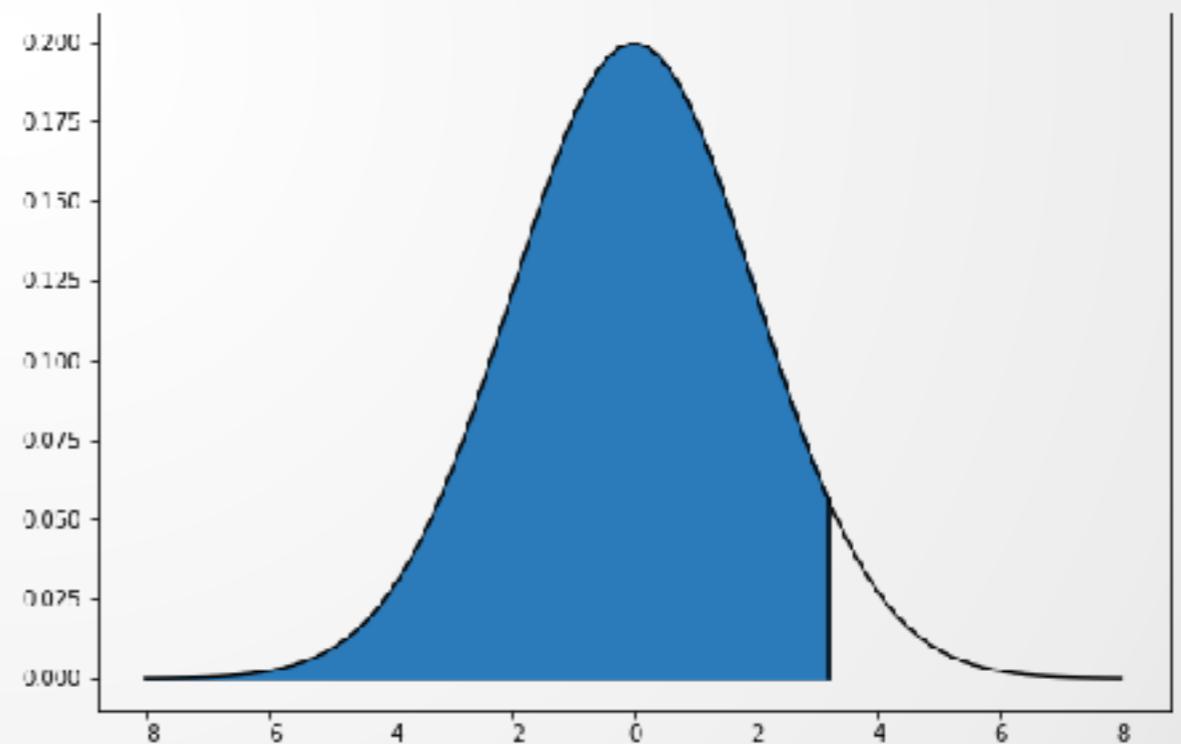
$$q^\tau = \arg \min_{\theta} E \{ \rho_\tau (Y - \theta) \}$$

log returns

asymmetric loss function

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

$\alpha = 1$ for quantiles,
 $\alpha = 2$ for expectiles

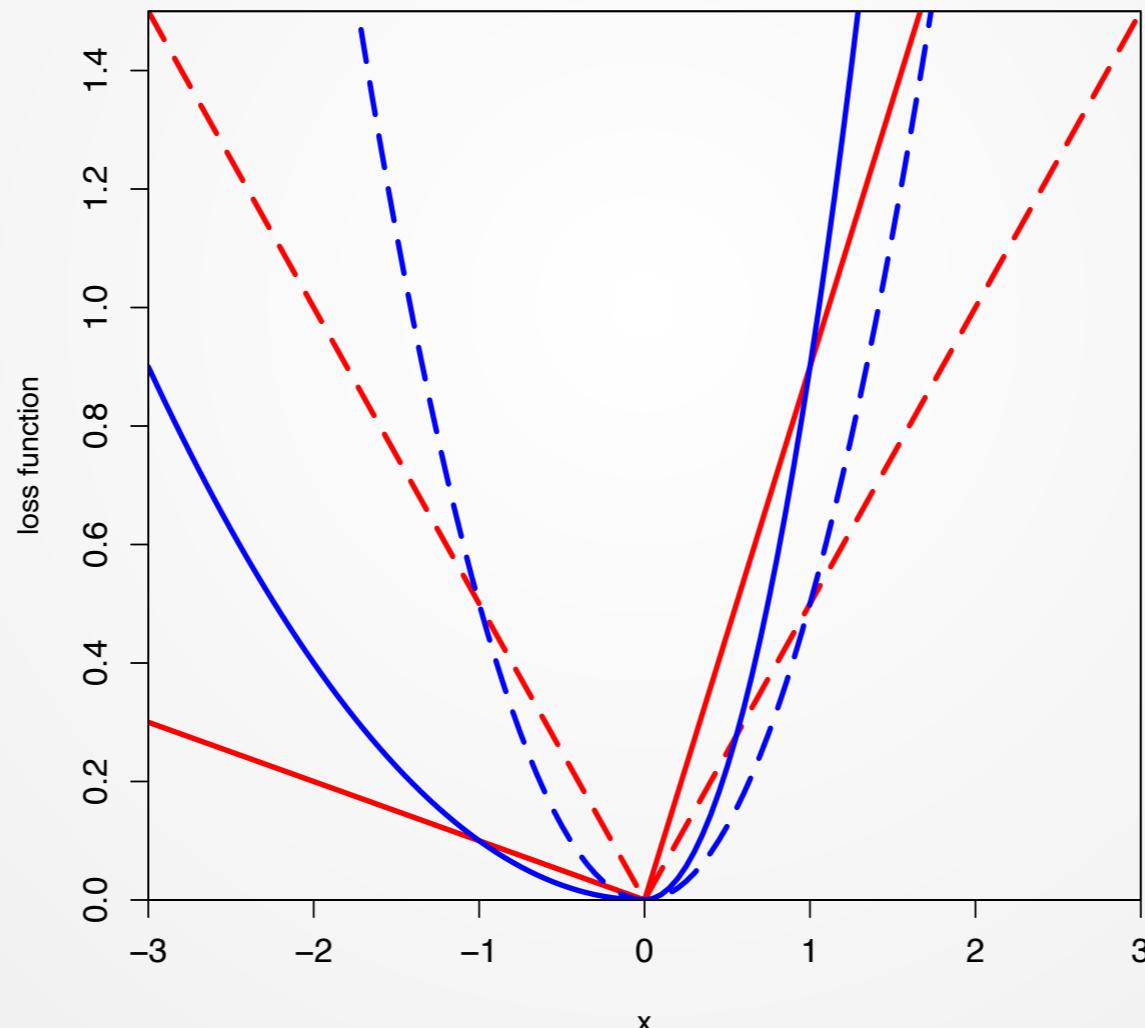


$$\tau = 0.7, \quad N(0, 2) \quad \text{Quantile} = 3.2$$

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)



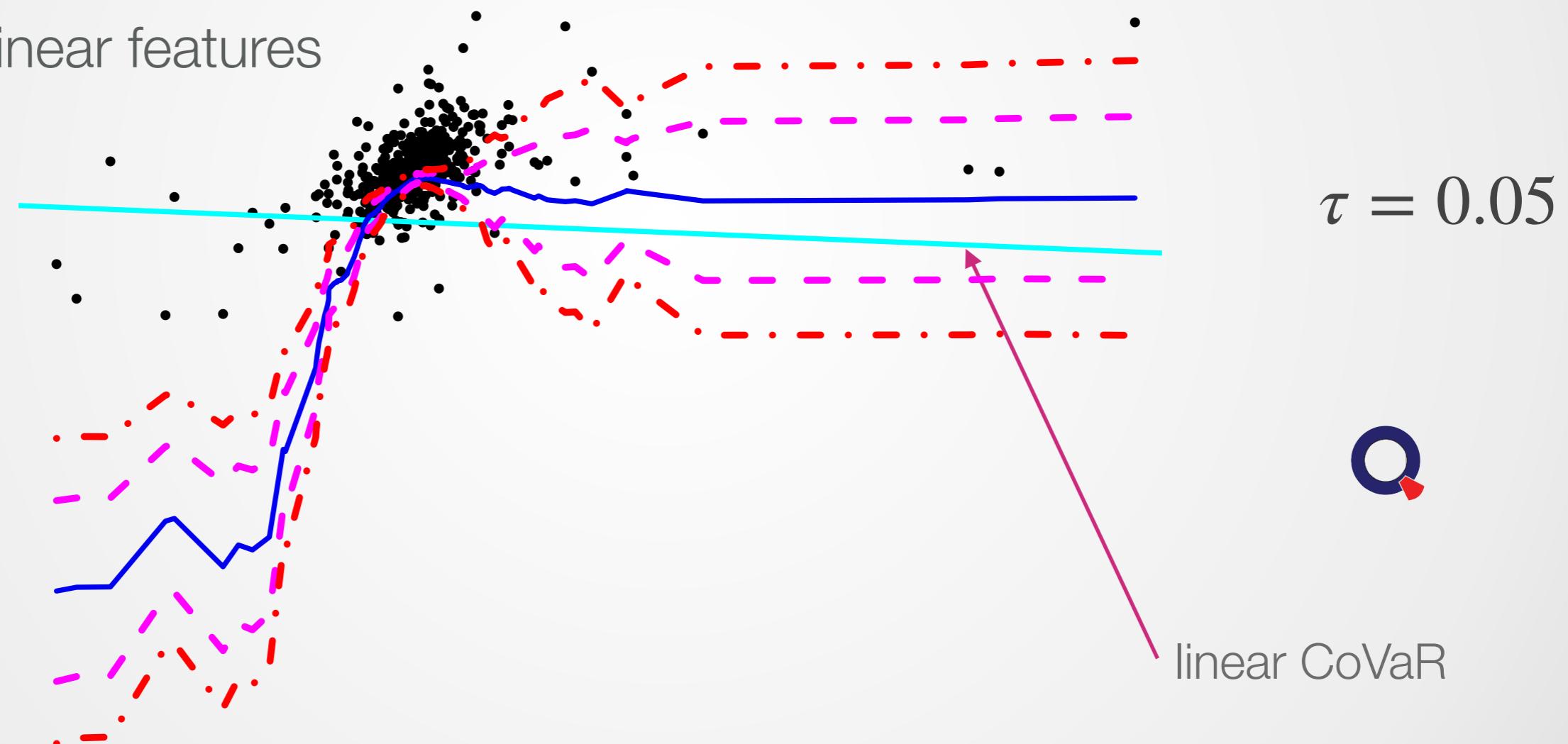
Conditional Value at Risk

- Adrian and Brunnermeier (2016) introduced CoVaR

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

- 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

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

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

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

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

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

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



Linear Quantile Lasso Regression

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

- ◻ Where $A_{j,t}^{s\top} \stackrel{def}{=} [M_{t-1}^s, X_{-j,t}^s]$
- ◻ $X_{-j,t}^s$ 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 $j = 1, \dots, J, t = 2, \dots, T$

$$J = 100, T = 2700, s = 63$$

3M



Lasso Quantile Regression

$$\min_{\alpha_j^s, \beta_j^s} \left\{ n^{-1} \sum_{t=s}^{s+(n-1)} \rho_\tau(X_{j,t}^s - \alpha_j^s - A_{j,t}^{s\top} \beta_j^s) + \lambda_j^s \|\beta_j^s\|_1 \right\}, \quad (2)$$

- Check function $\rho_\tau(u) = |u|^c |1(u \leq 0) - \tau|$,
- 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

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

←
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 Li Y, Zhu JL (2008)

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

↗ 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!



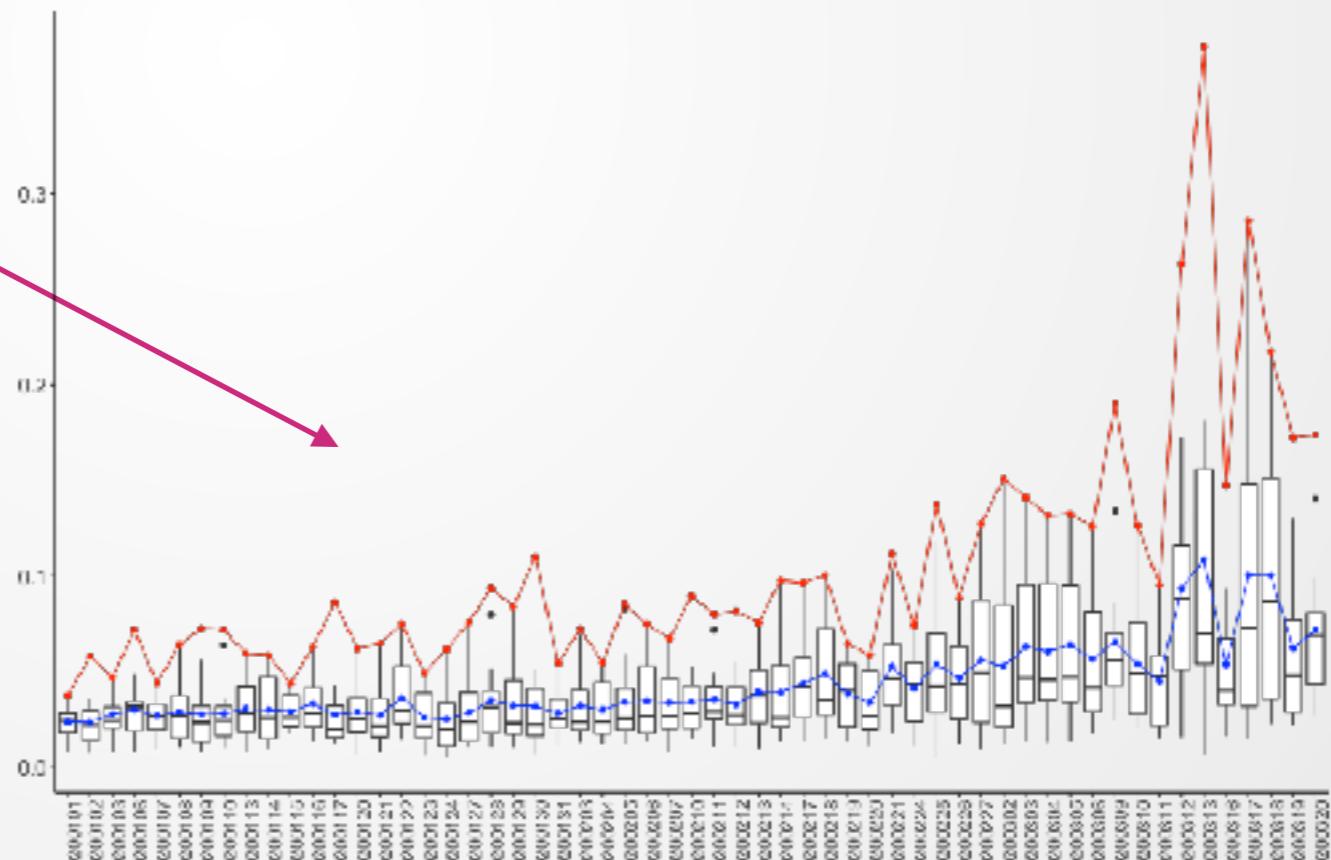
λ Selection

- Generalized approximate cross-validation (GACV)

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



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



FRM codes



FIRAMIS app

HU Berlin app



FRM@Americas



FRM@Asia



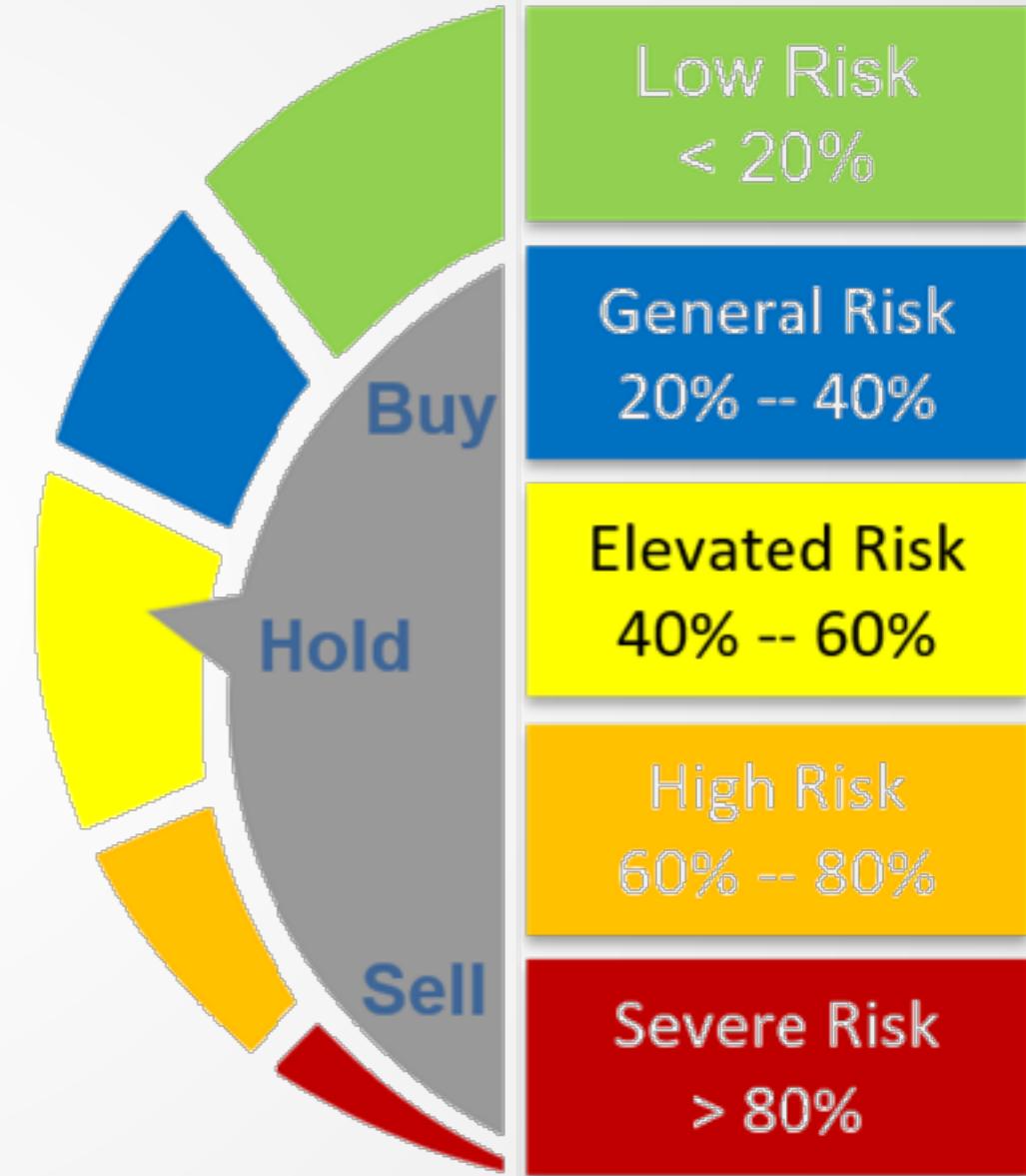
FRM@Crypto



FRM@Europe



FRM@iTtraxx



Methodology

- Obtain risk driver list of all historically active index members
- Download daily rates in same currency (USD)
- Sort market cap decreasingly (to select J biggest risk drivers)
- Calculate returns
- On every trading day,
 - ▶ Select J biggest risk driver's returns over s trading days
 - ▶ Attach returns of macroeconomic risk factors
 - ▶ Calculate λ for all companies
 - ▶ Calculate average λ , etc.
 - ▶ Store active set

LQ Lasso Regression



Data

- 100 largest U.S. and Canadian publicly traded financial institutions
- 6 macro related variables
- Quantile level $\tau = 0.05, \tau = 0.01, \dots$
- Time frame: 2000-2019
- Macroeconomic risk factors:
 - CBOE Volatility Index
 - S&P 500
 - REIT Index
 - 3M Treasury Constant Maturity Rate
 - 10Y Treasury Constant Maturity Rate
 - Moody's Seasoned Baa Corp Bond Yield Spread

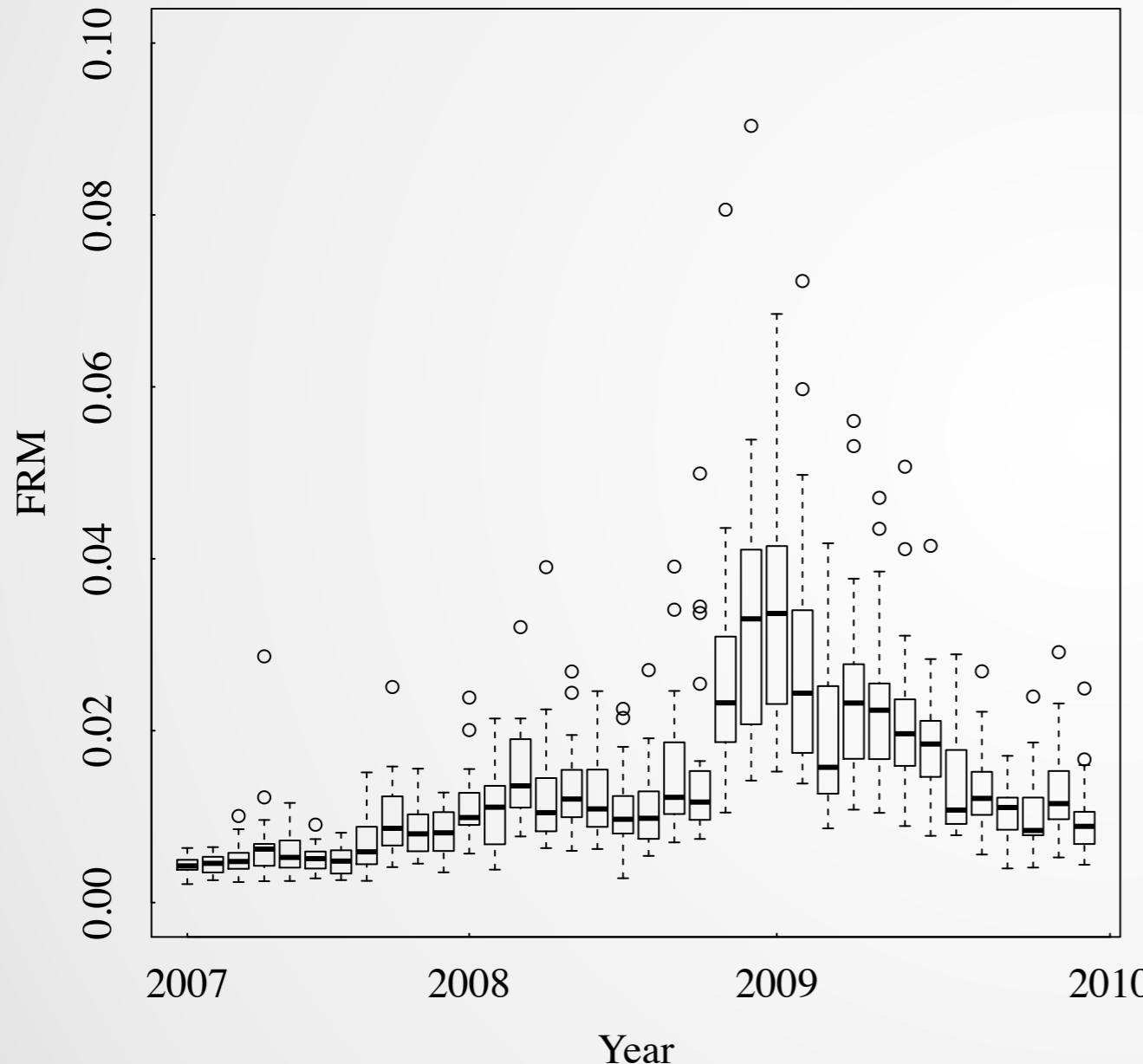
LQ Lasso Regression



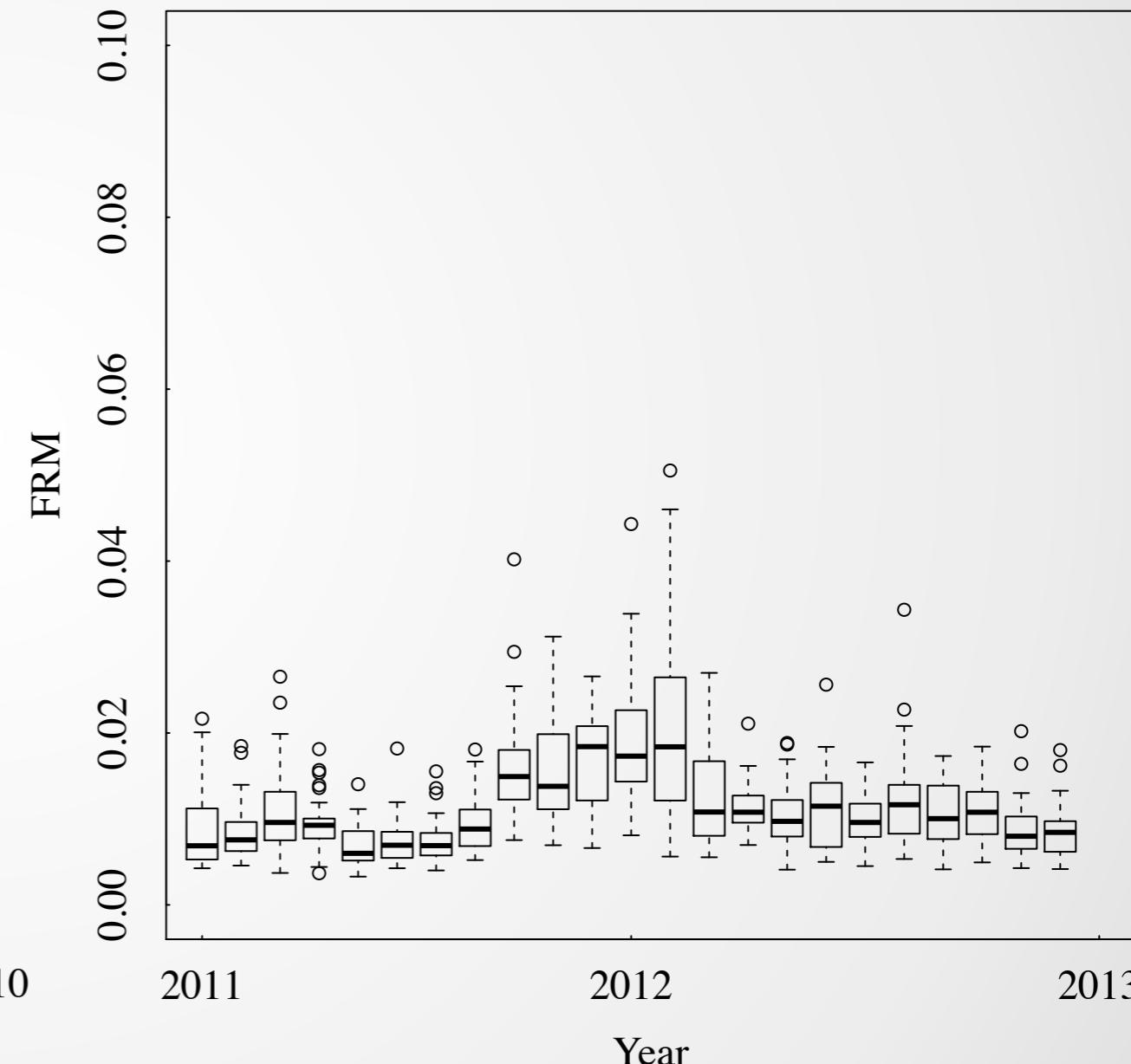
Distributional characteristics

- Identifying companies CoStress $\tau = 0.05 \ J = 25$

Americas Lambda Boxplot



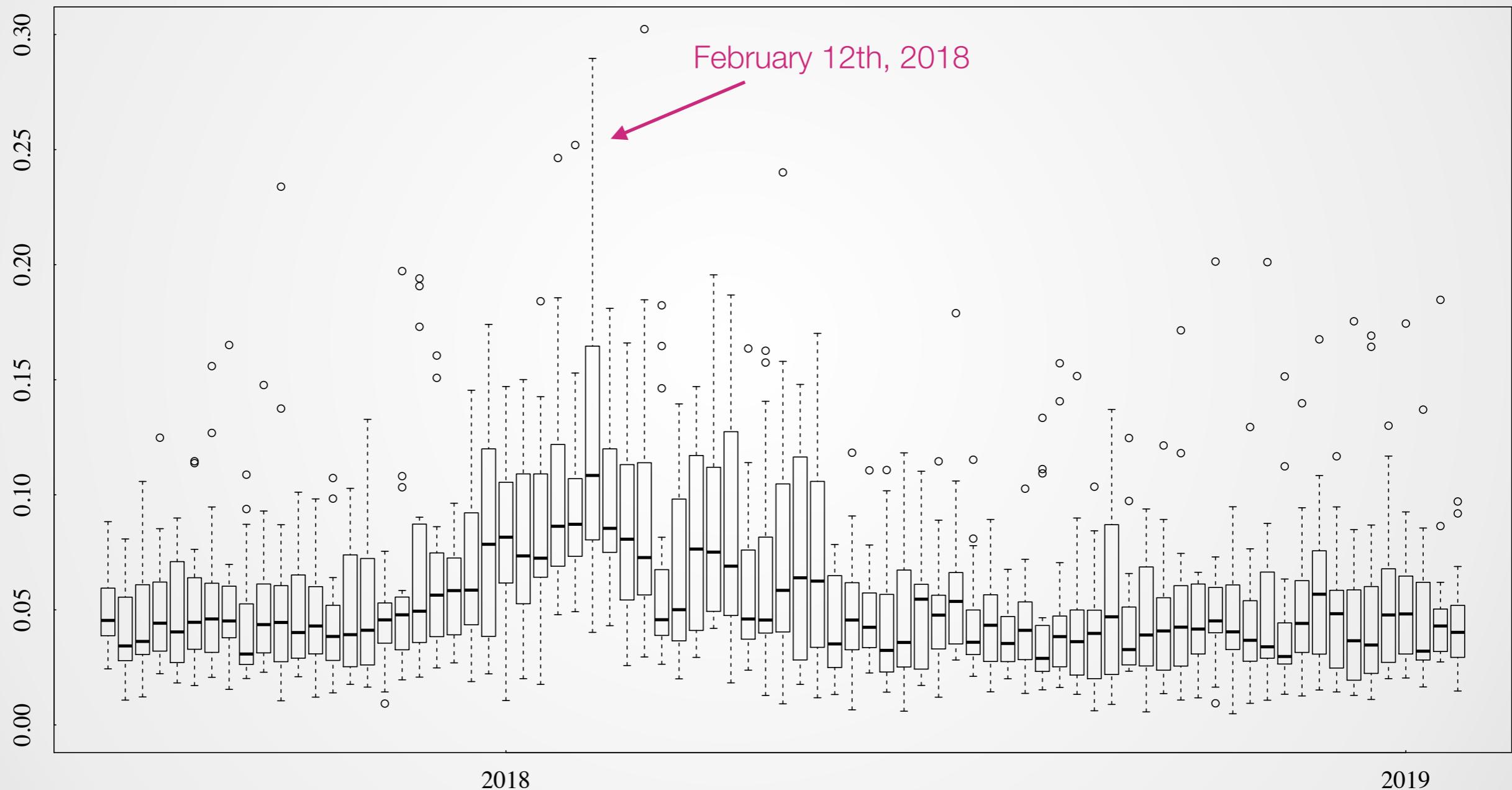
Europe Lambda Boxplot



Distributional characteristics of $\lambda_j, j = 1, \dots, J$

Distributional characteristics

- Identifying Crypto Currency CoStress $\tau = 0.05 \ J = 15$



Distributional characteristics of $\lambda_j, j = 1, \dots, J$

Crypto's CoStress

□ February 12th, 2018:

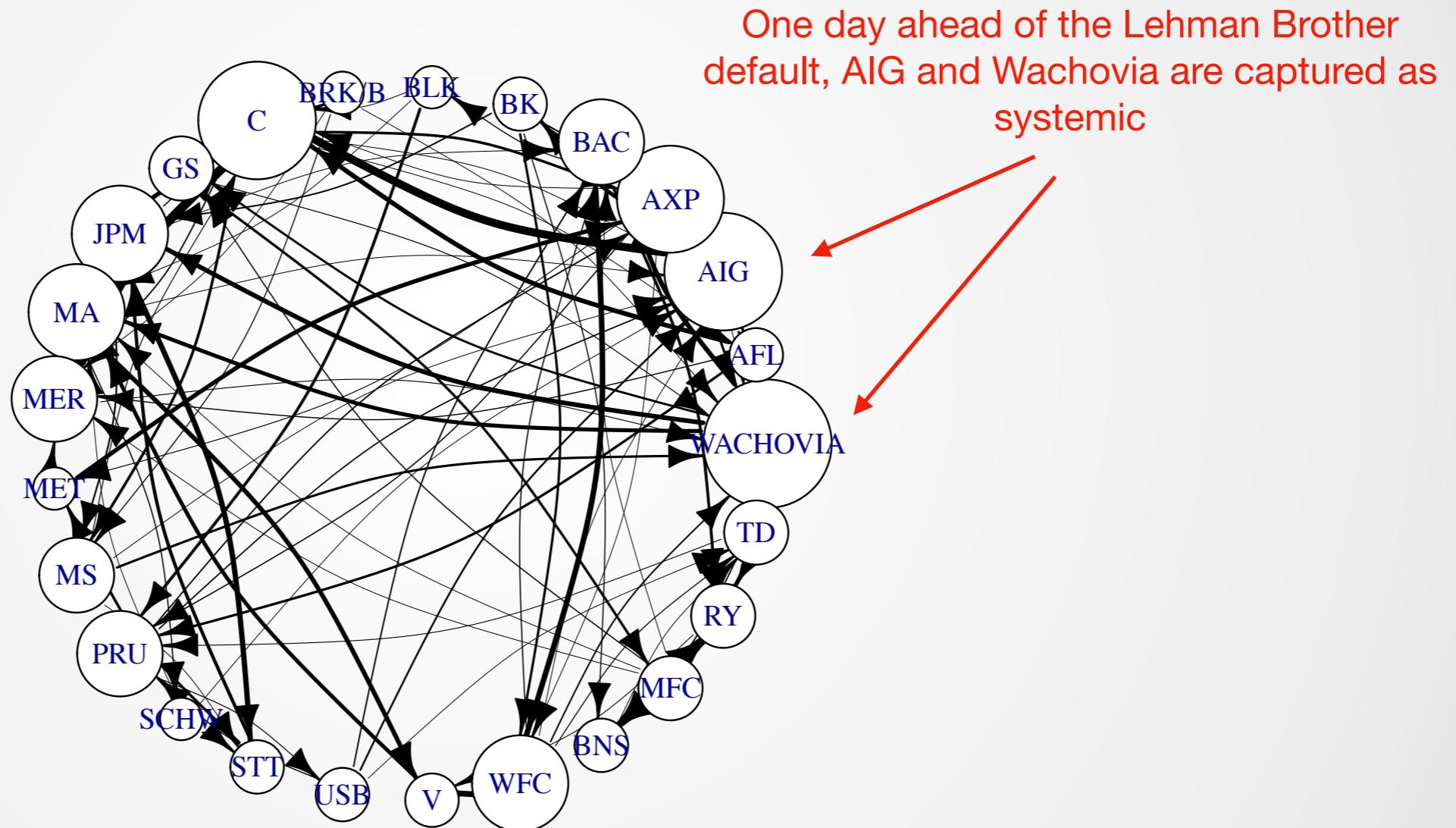
High CoStress: XMR, XML, DASH, EOS, ETH, LTC

Low CoStress: XEM, NEO, LSK, BTC, BCH



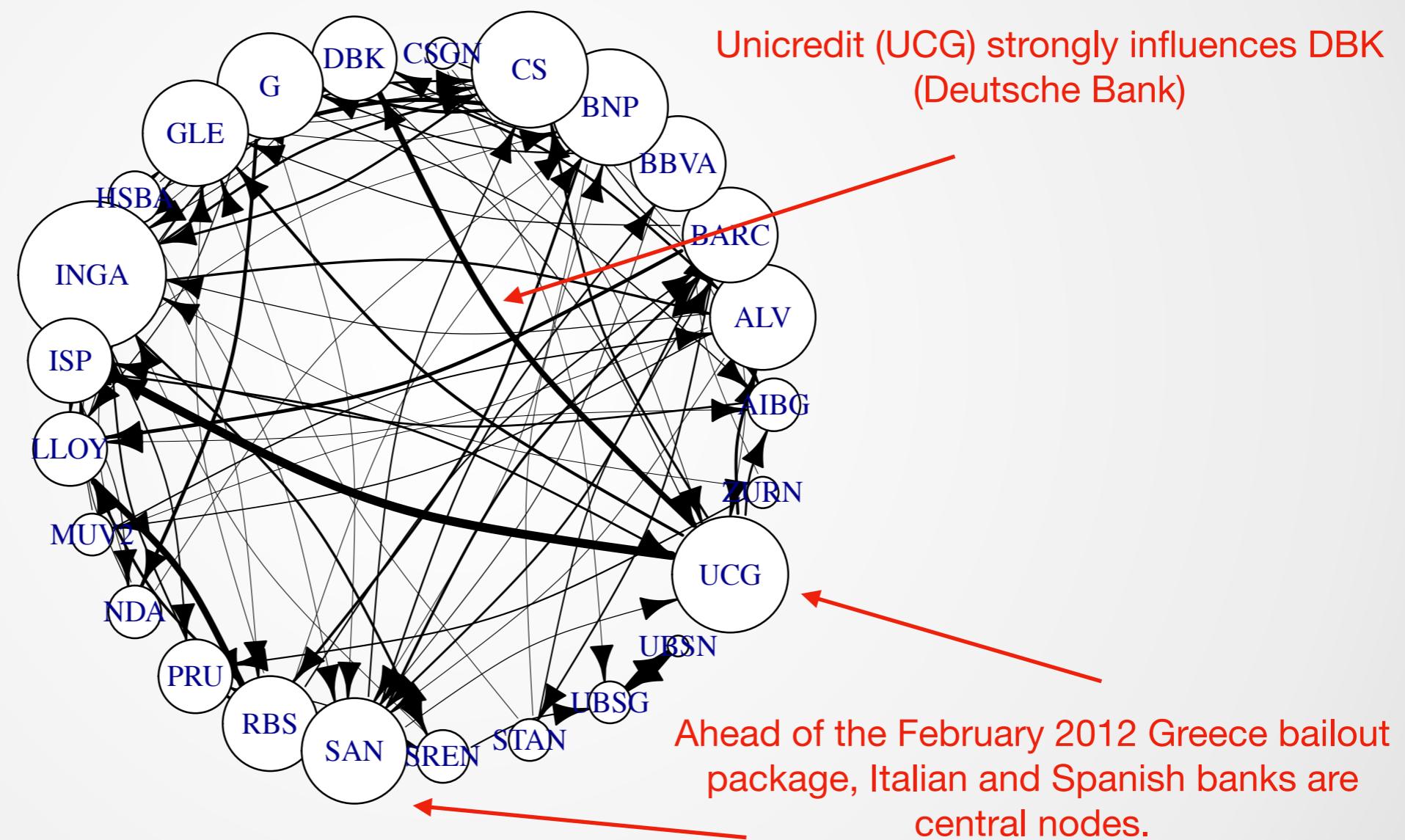
Visualising the Active Set: Total Degree Centrality

□ September 5th, 2008, FRM@Americas, $J=25$



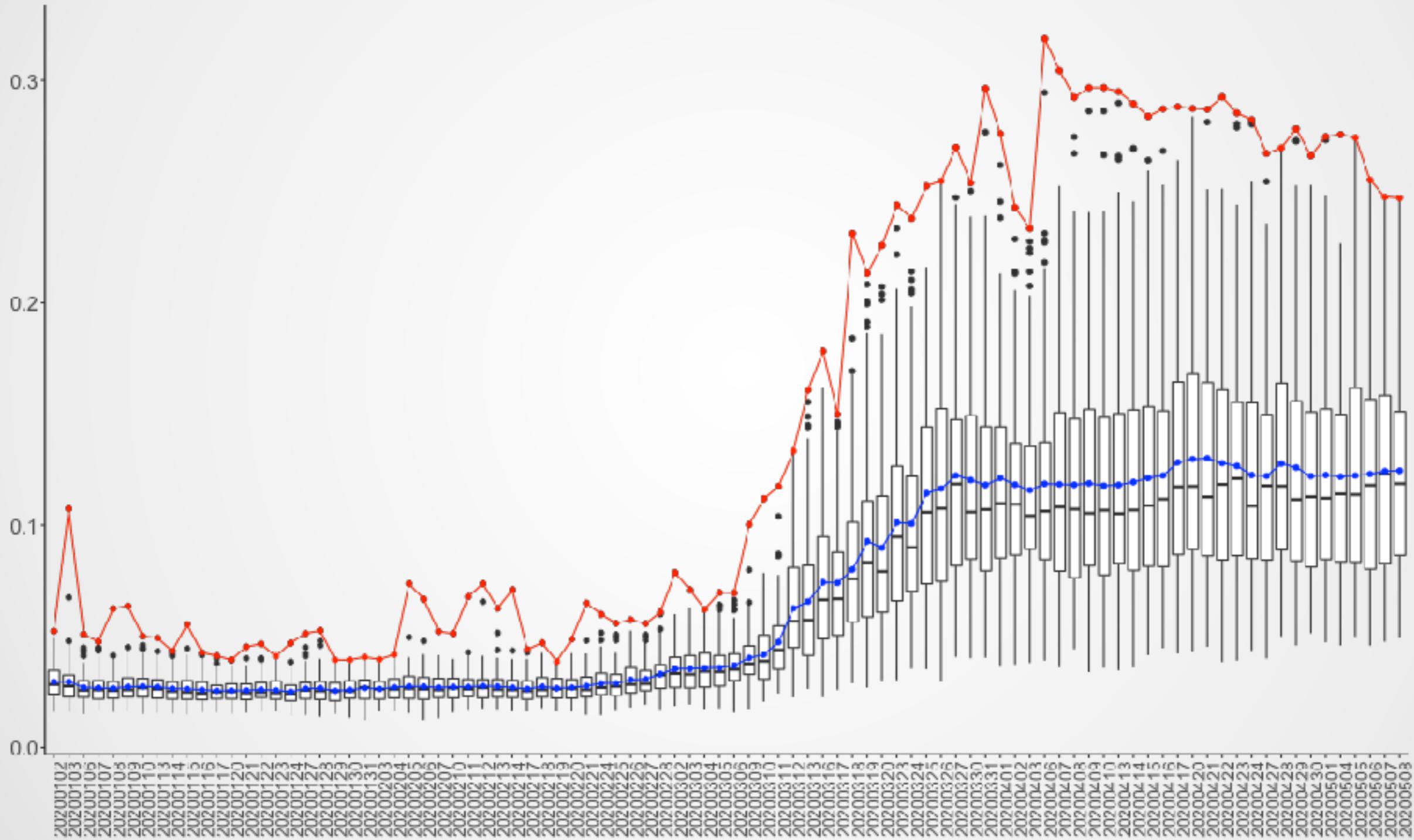
Visualising the Active Set: Total Degree Centrality

□ January 20th, 2012, FRM@Europe, $J=25$



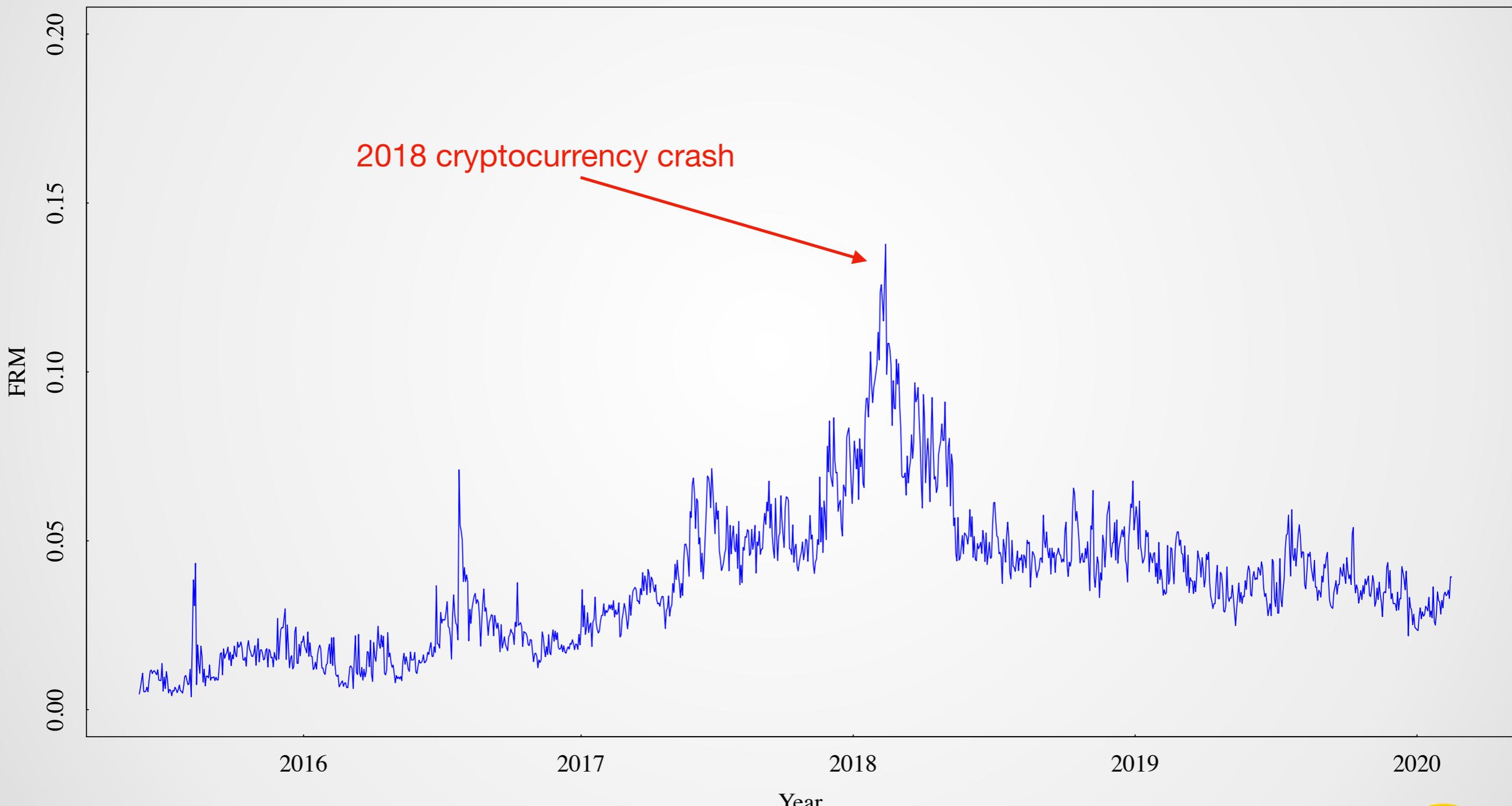
Visualising the Trend: FRM the Boxplot

□ January 2020 to May 2020, FRM@Europe



FRM@Crypto

FRM@Crypto, $\tau = 0.05$, $J=8-15$

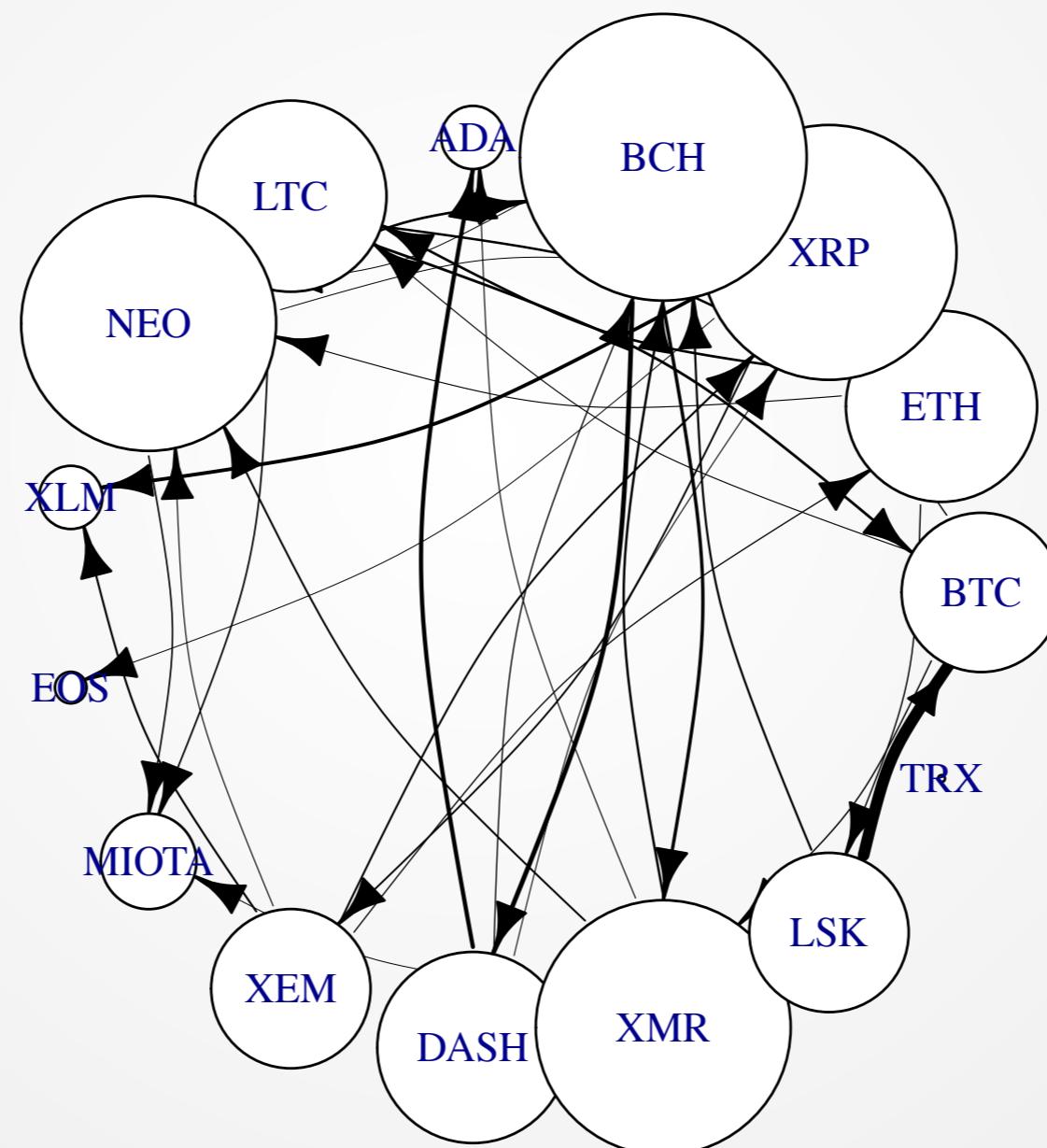


<http://frm.wiwi.hu-berlin.de>



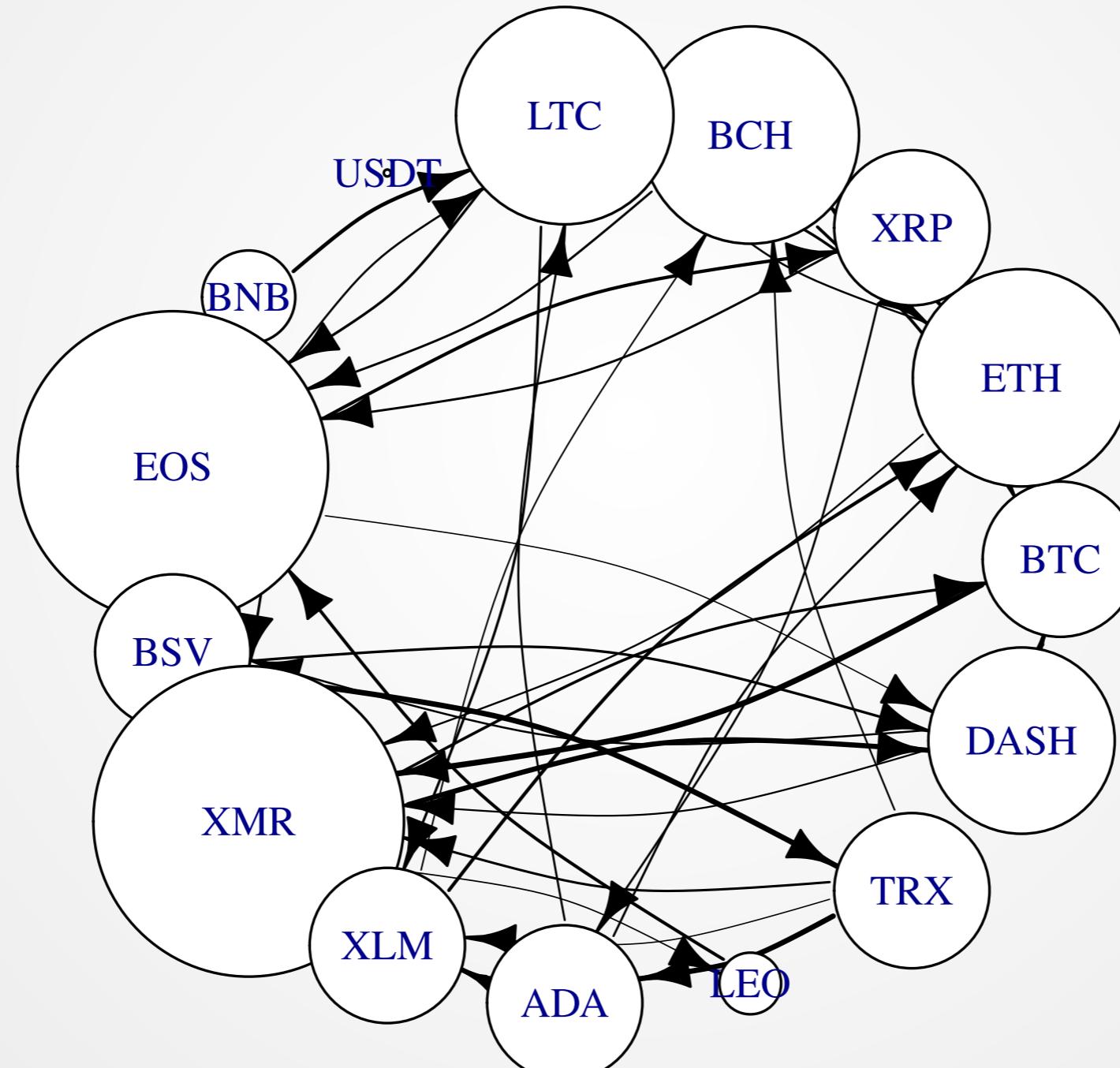
FRM@Crypto - Network Total Degree Centrality

- $\tau = 0.05$, 12 February 2018

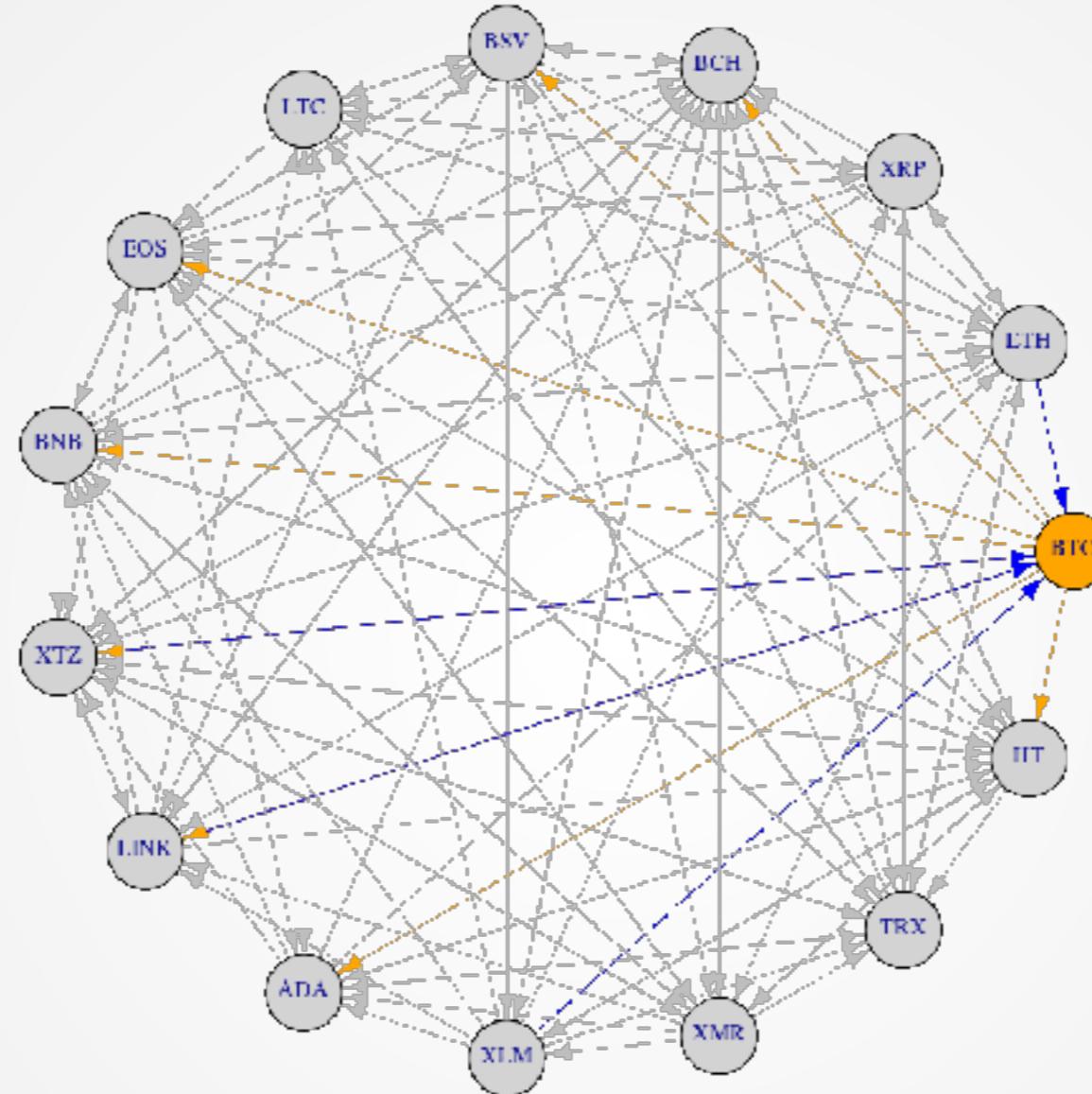


FRM@Crypto - Network Total Degree Centrality

- $\tau = 0.05$, 27 August 2019



Visualising the Active Set: FRM@Crypto the Movie

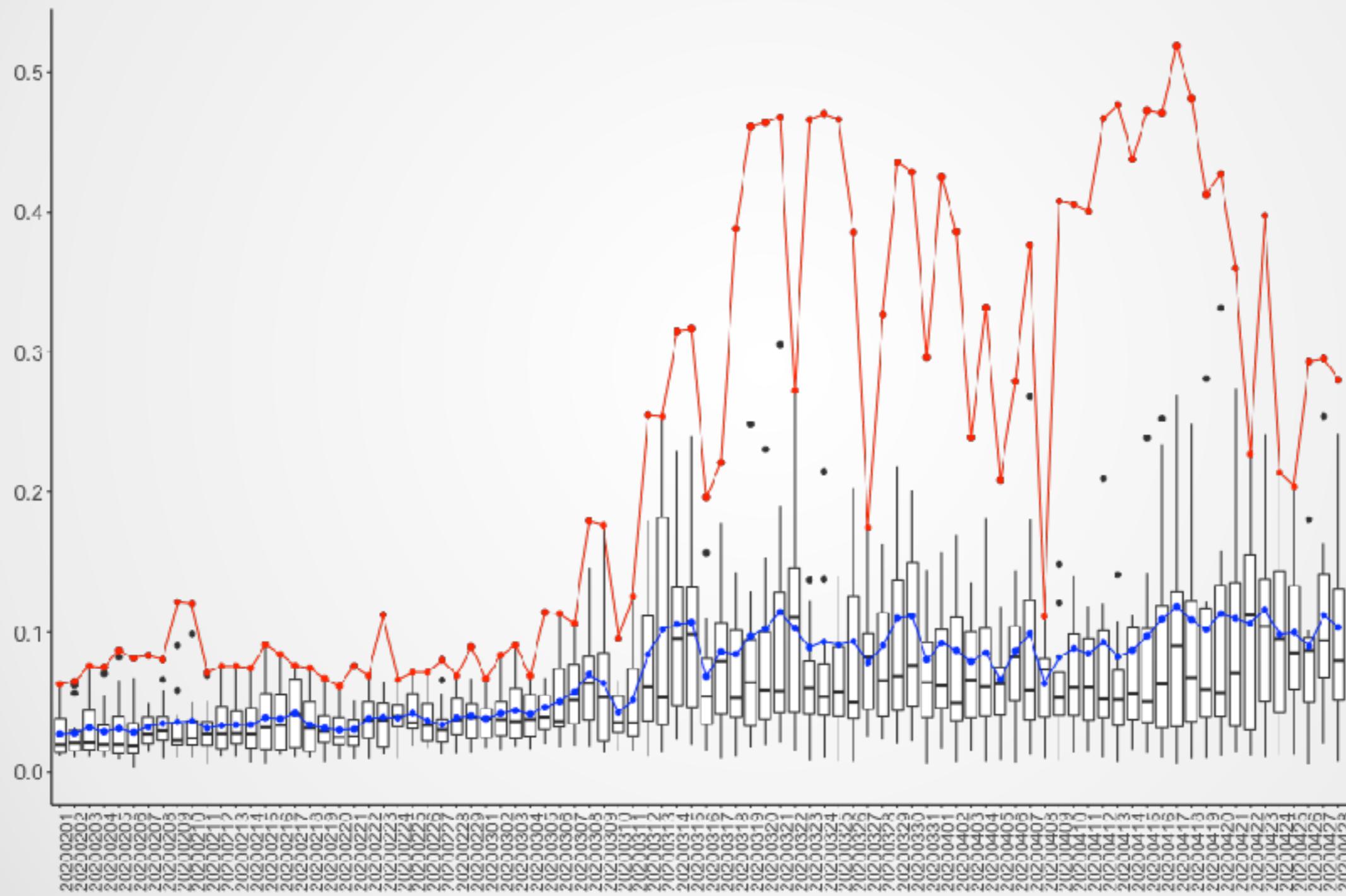


20200315
FRM: 0.10707

Network analysis of FRM from 03 March 2020 to 17 May 2020

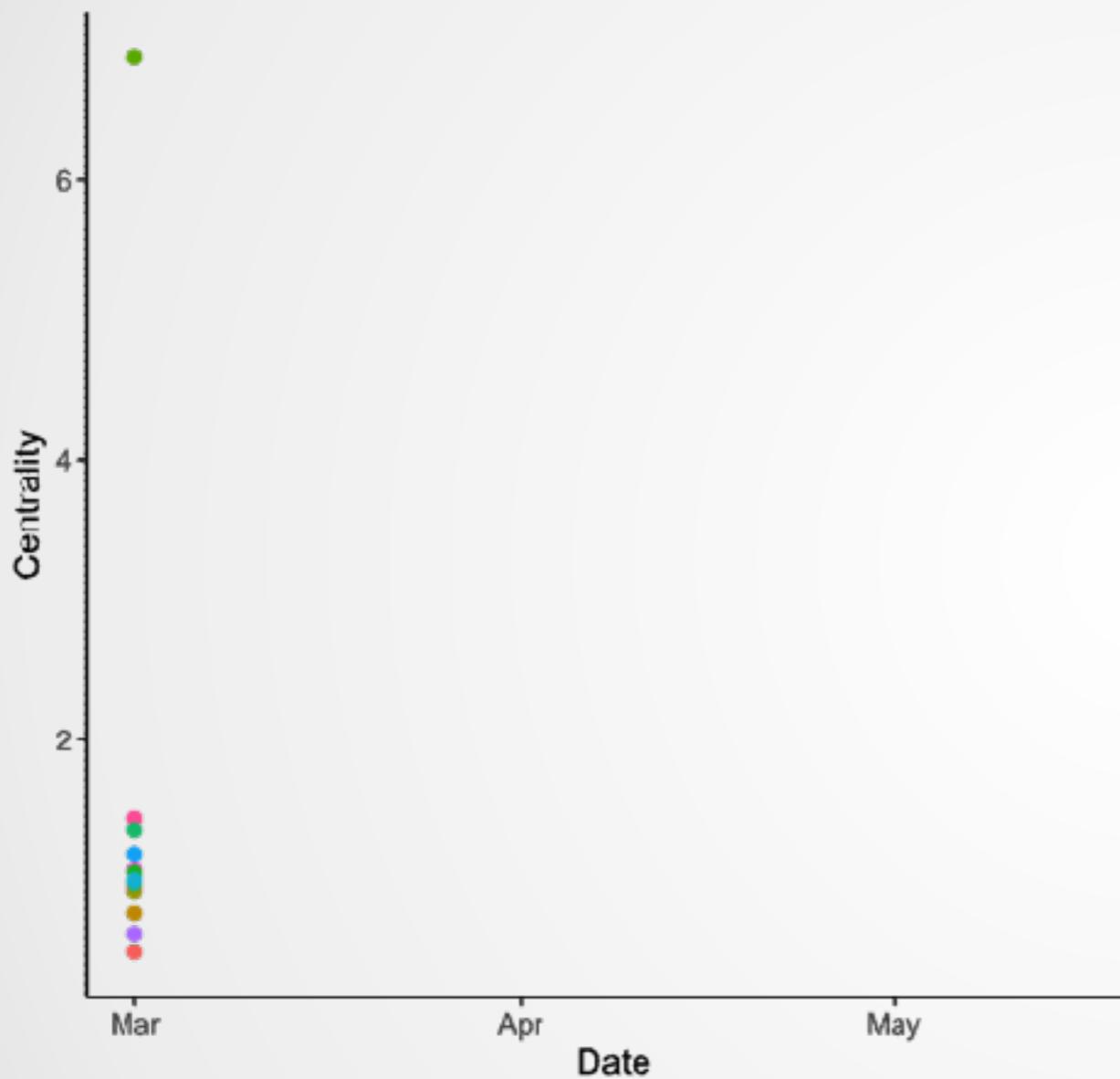
FRM scaled to risk

□ February 2020 to May 2020, FRM@Crypto

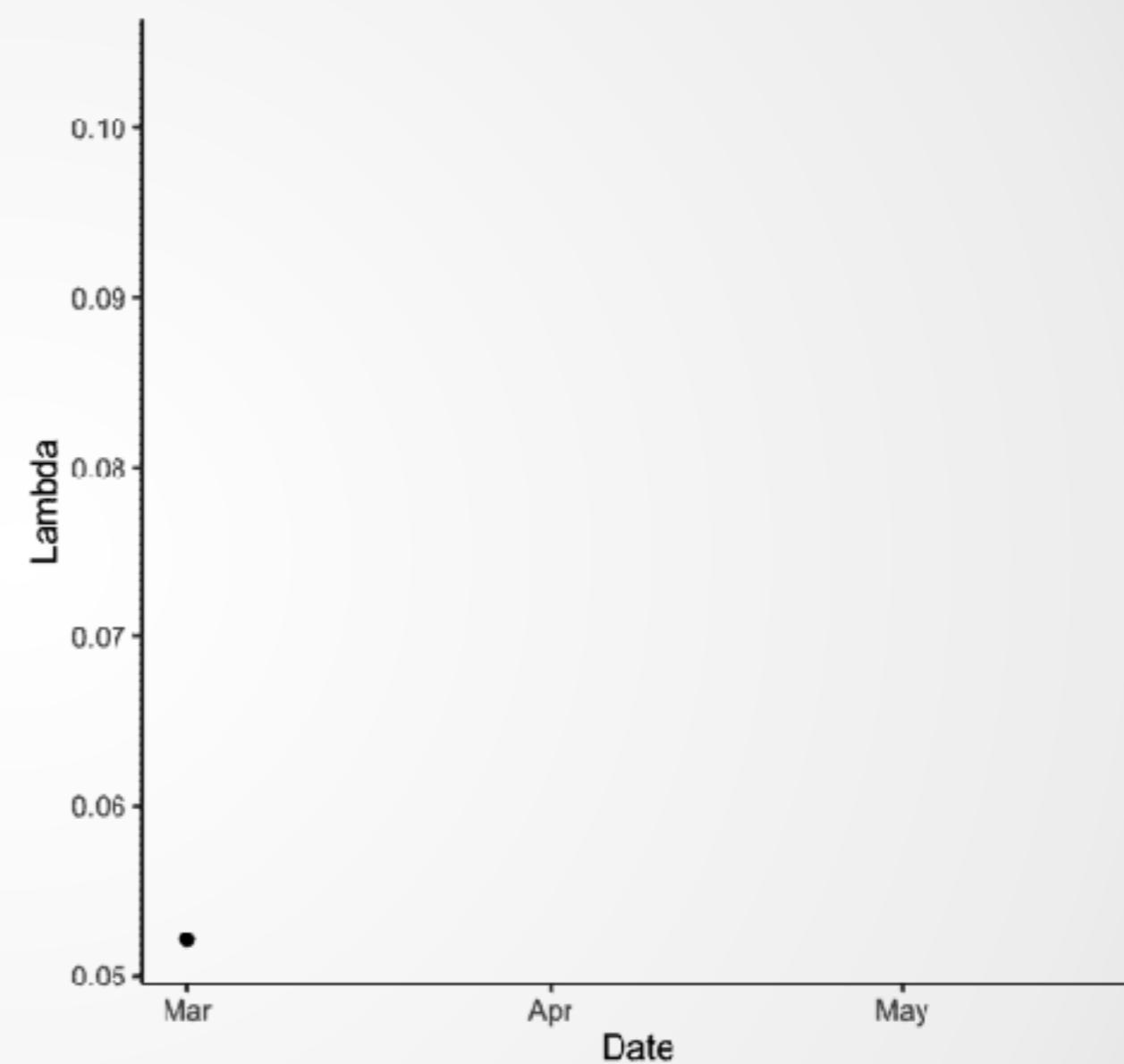


FRM@Crypto Out-Degree Centrality

Out-Degree Centrality. Date: 2020-03-01



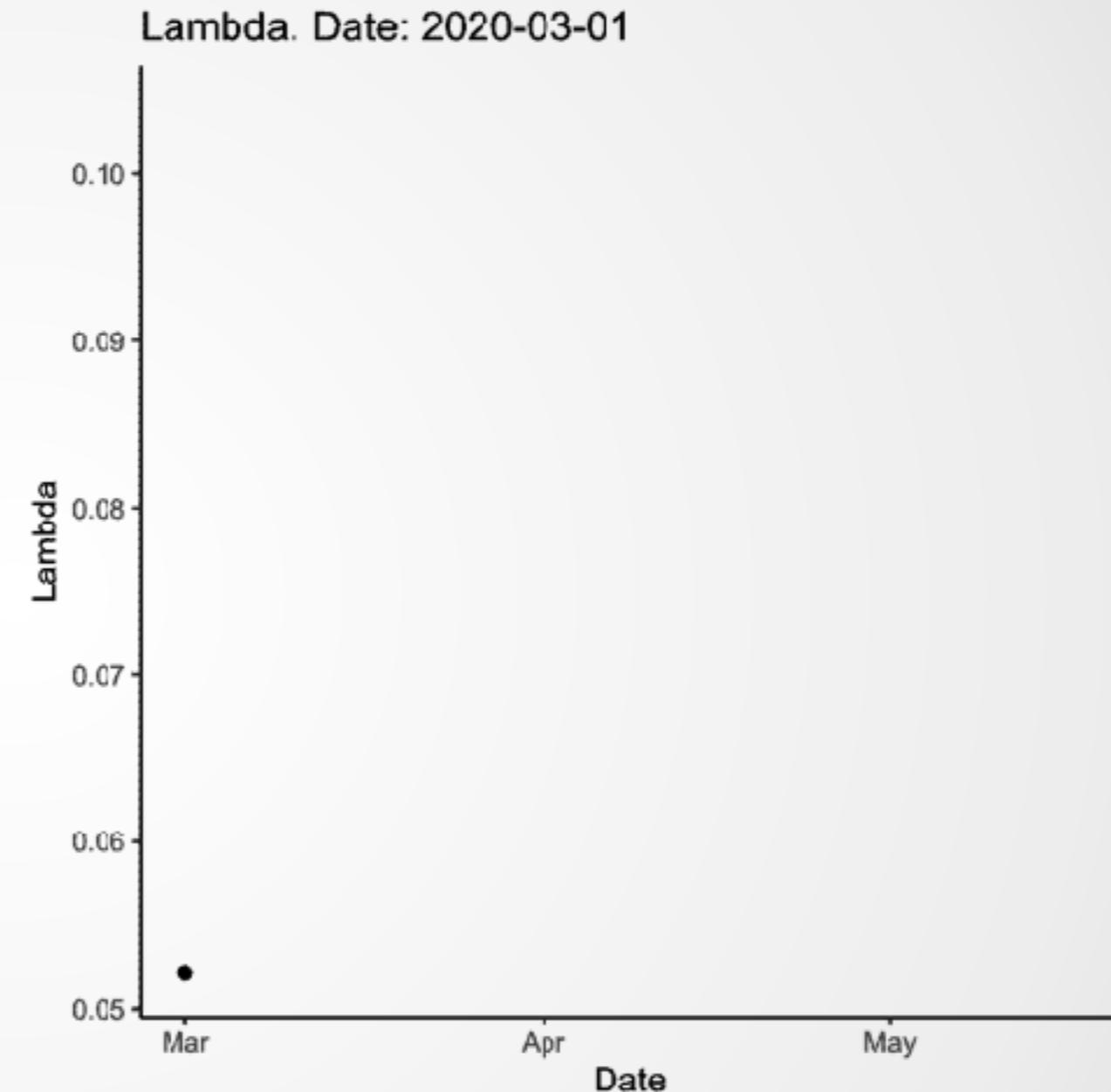
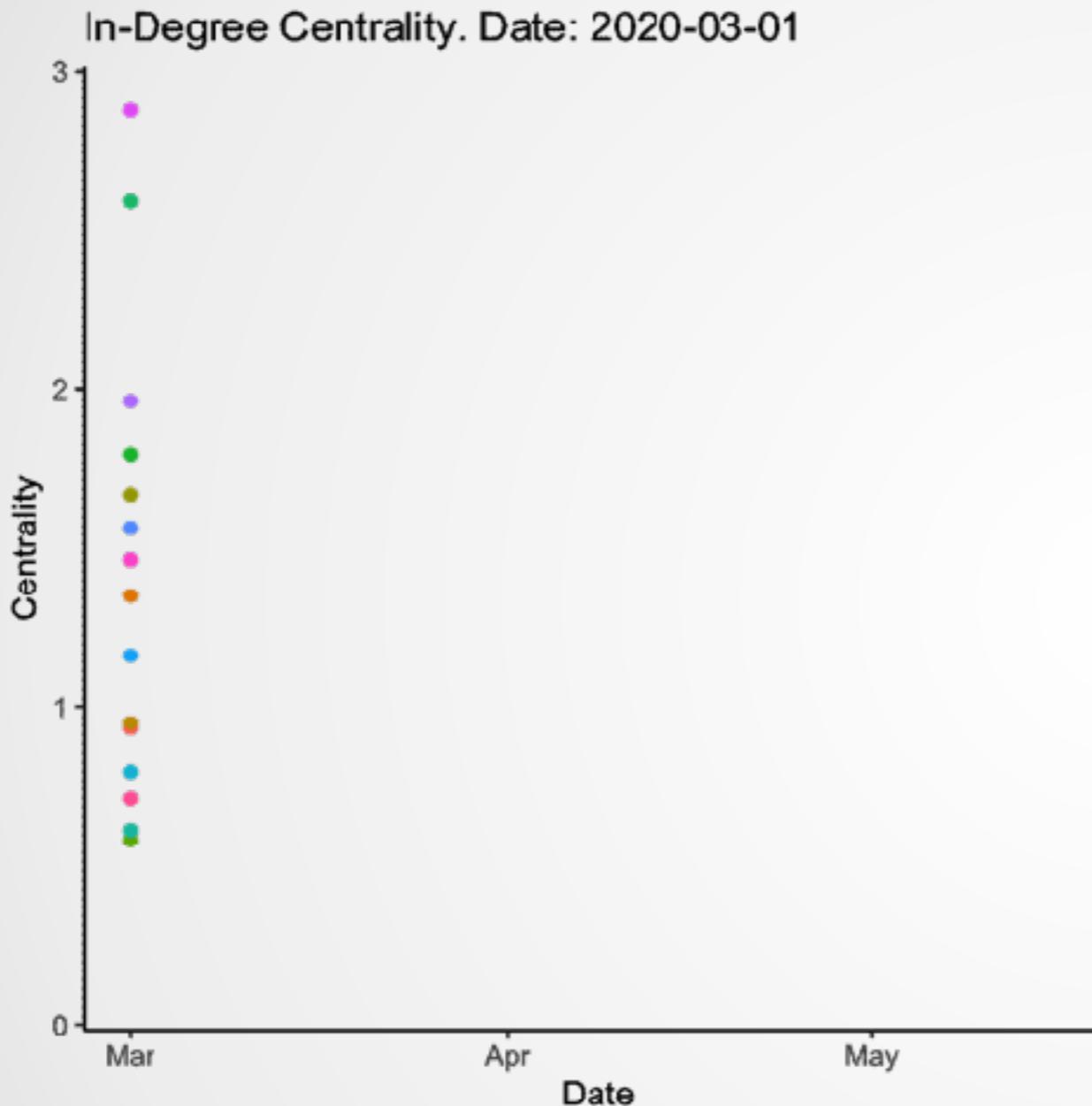
Lambda. Date: 2020-03-01



Left-hand side panel: # of outbounds links of **BTC**, **ETH**, **XRP**, **BCH**, **BSV**, **LTC**, **EOS**, **BNB**, **XTZ**, **LIN**, **ADA**, **XLM**, **XMR**, **TRX**, **HT**. Right-hand side panel: FRM index over time.

Data from 01 March 2020 to 17 May 2020

FRM@Crypto In-Degree Centrality

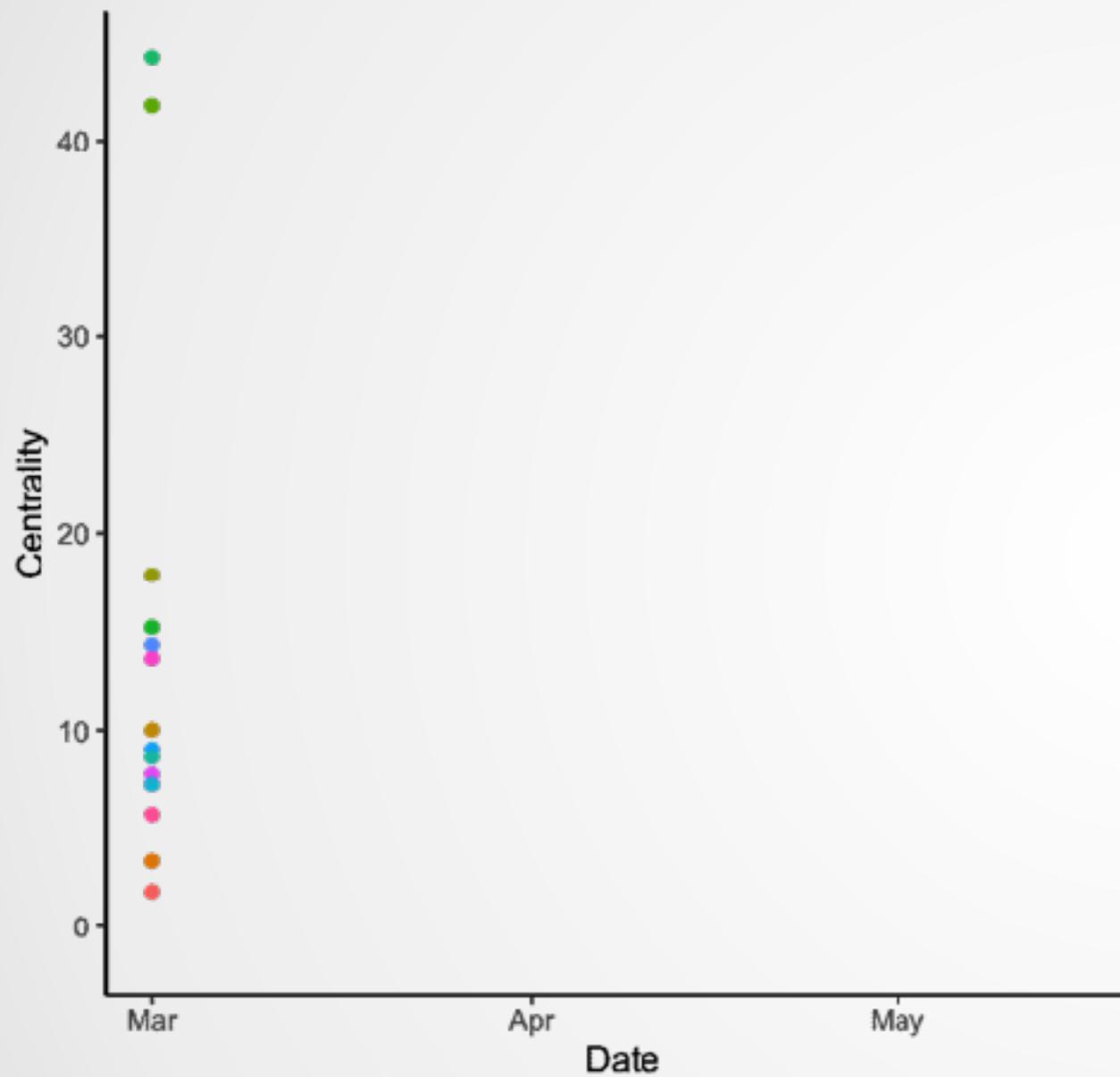


Left-hand side panel: # of inbound links of **BTC**, **ETH**, **XRP**, **BCH**, **BSV**, **LTC**, **EOS**, **BNB**, **XTZ**, **LIN**, **ADA**, **XLM**, **XMR**, **TRX**, **HT**. Right-hand side panel: FRM index over time.

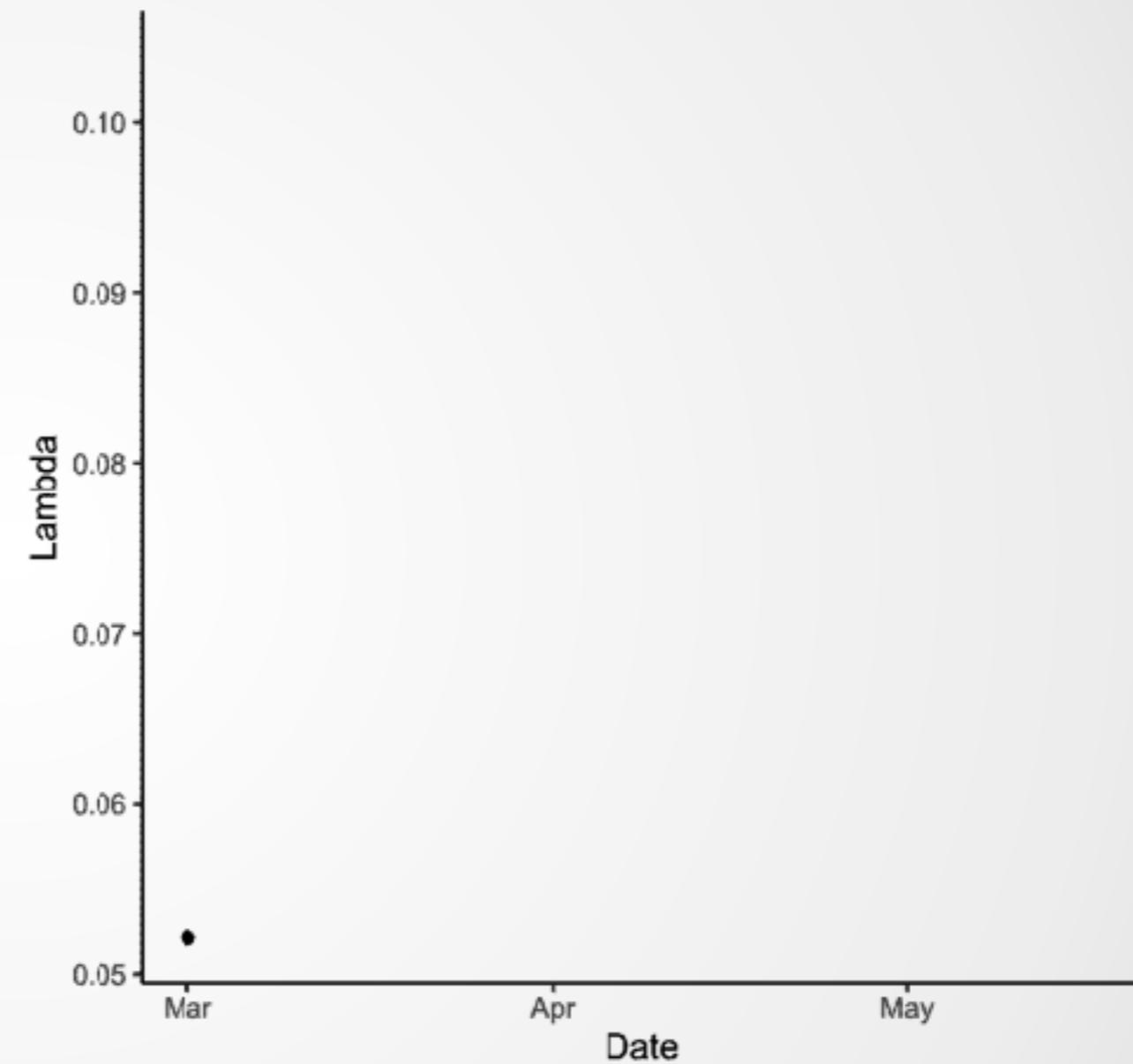
Data from 01 March 2020 to 17 May 2020

FRM@Crypto Betweenness Centrality

Betweenness Centrality. Date: 2020-03-01



Lambda. Date: 2020-03-01

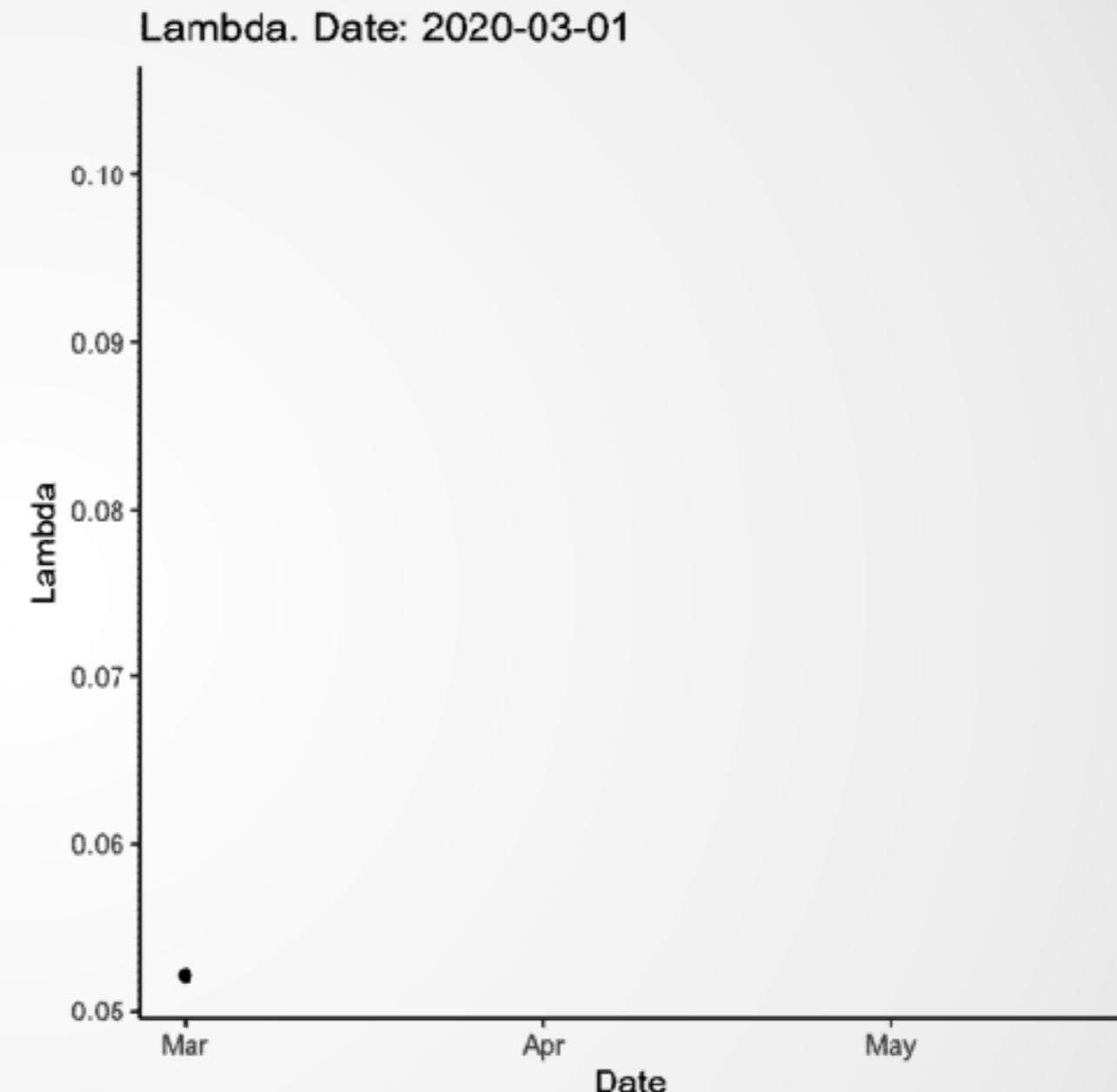
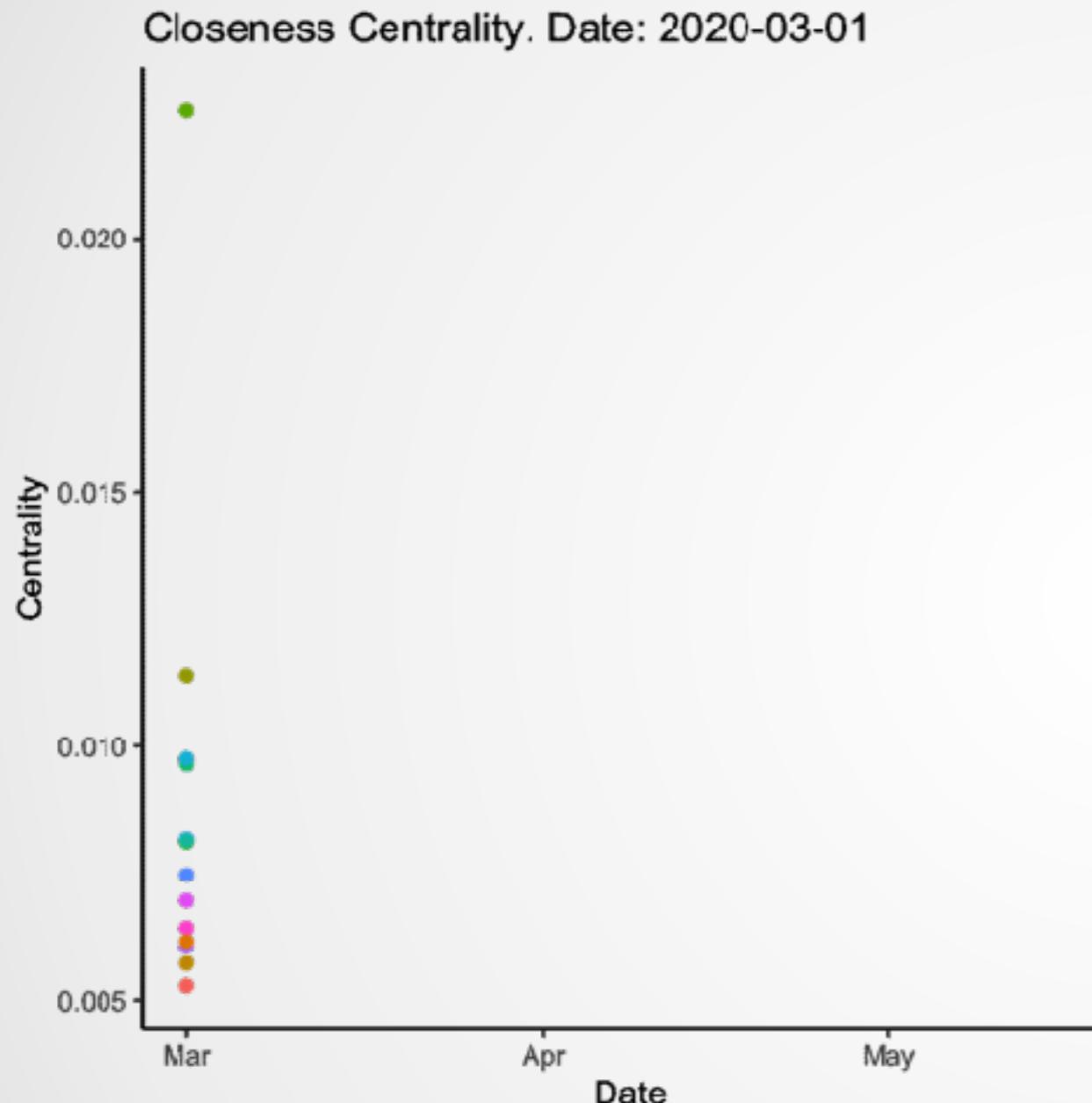


Left-hand side panel: „bridge“ behaviour measure for **BTC, ETH, XRP, BCH, BSV, LTC, EOS, BNB, XTZ, LIN, ADA, XLM, XMR, TRX, HT**. Right-hand side panel: FRM index over time.

Data from 01 March 2020 to 17 May 2020



FRM@Crypto Closeness Centrality



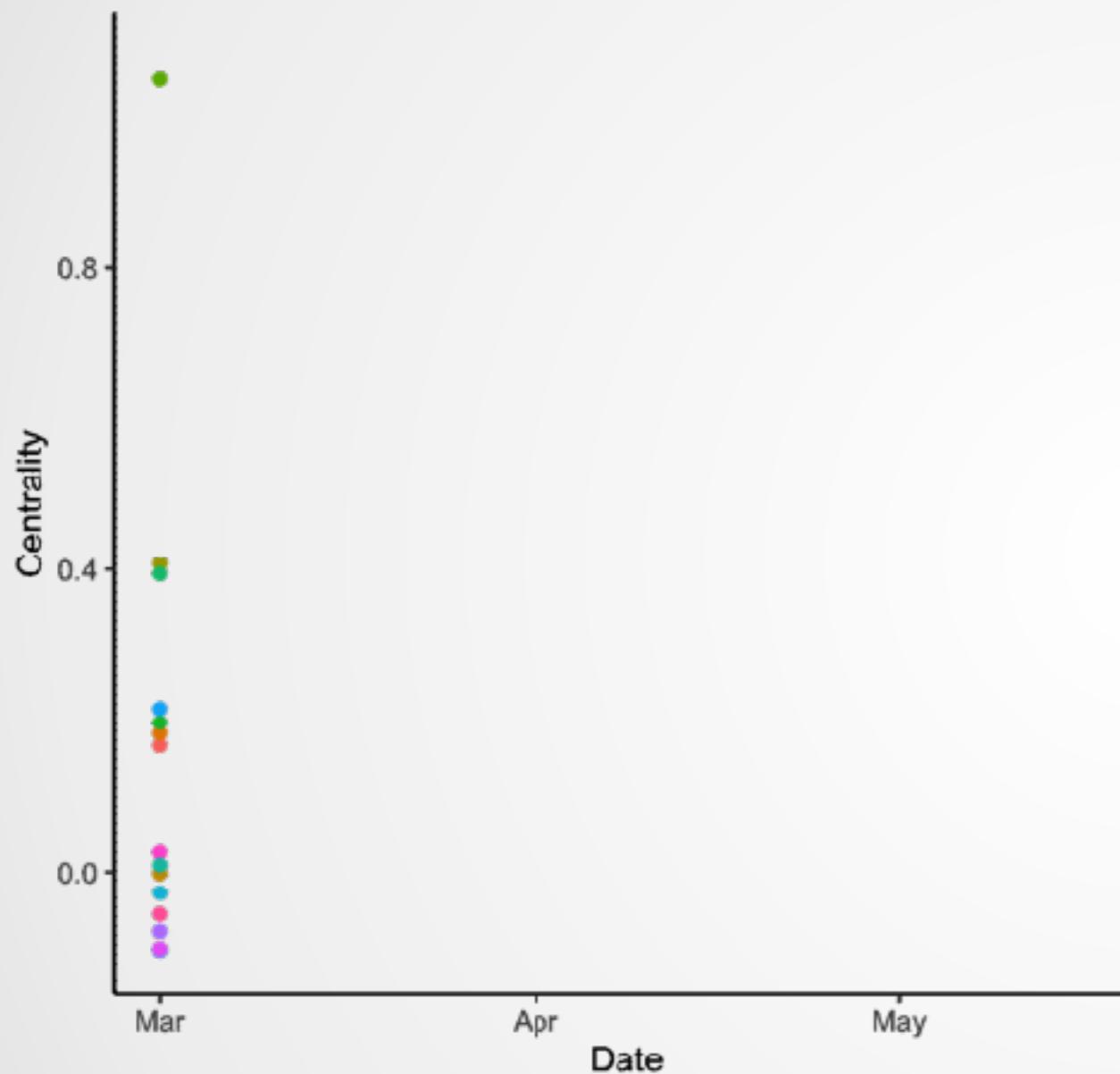
Left-hand side panel: fastness in influencing of **BTC, ETH, XRP, BCH, BSV, LTC, EOS, BNB, XTZ, LIN, ADA, XLM, XMR, TRX, HT**. Right-hand side panel: FRM index over time.

Data from 01 March 2020 to 17 May 2020

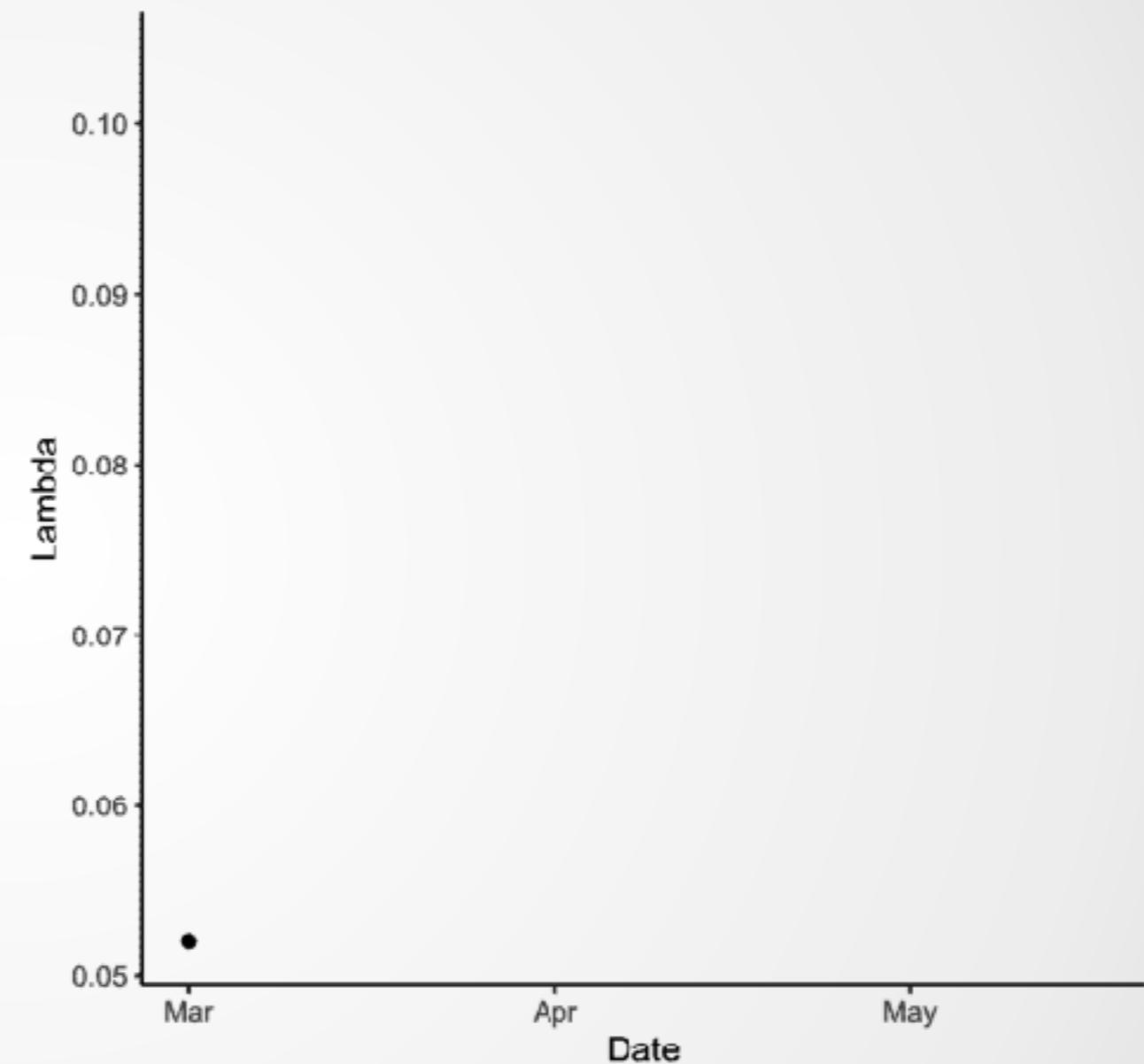


FRM@Crypto Eigenvector Centrality

Eigenvector Centrality. Date: 2020-03-01



Lambda. Date: 2020-03-01



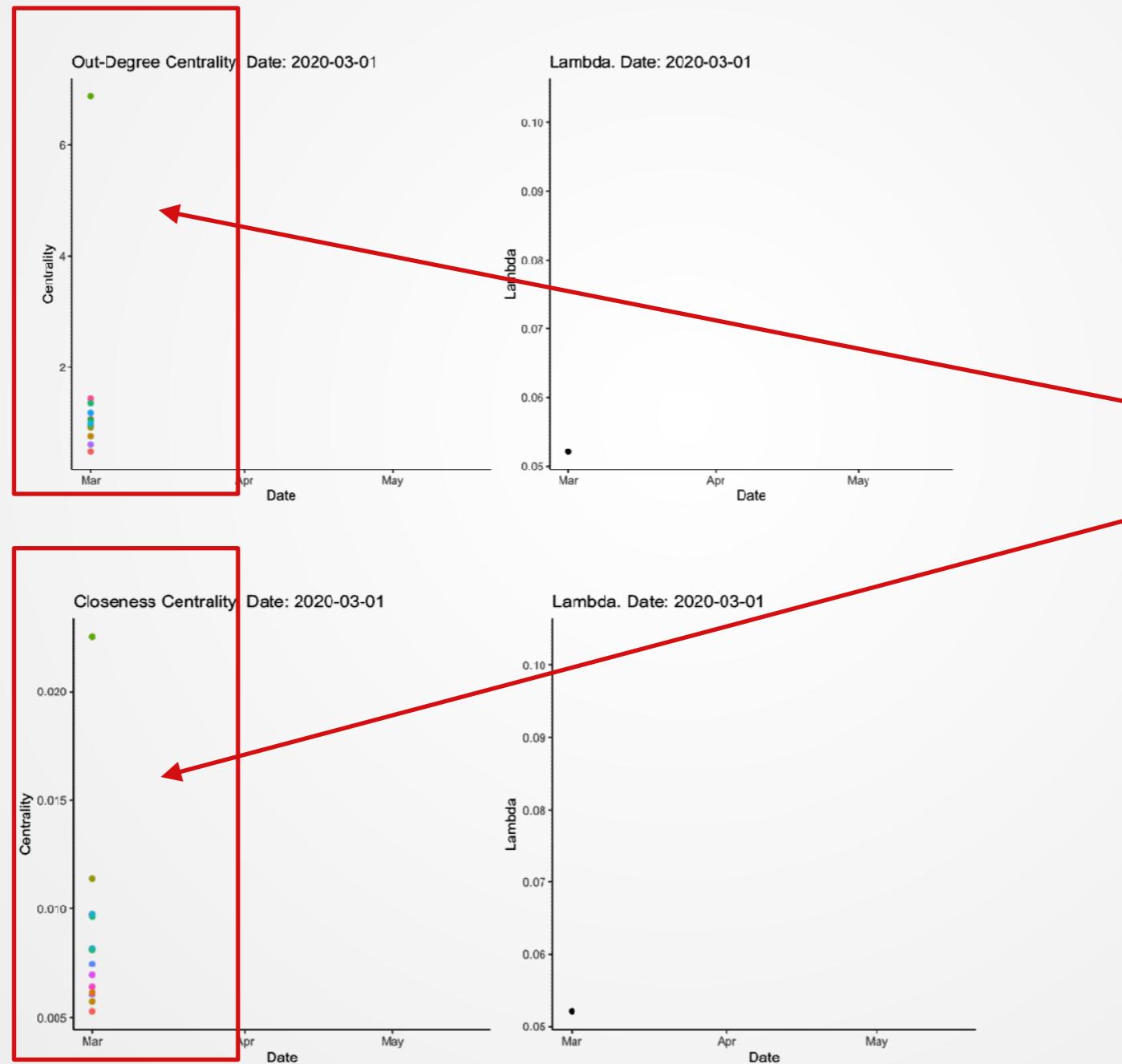
Left-hand side panel: normalised eigenvector centrality of **BTC**, **ETH**, **XRP**, **BCH**, **BSV**, **LTC**, **EOS**, **BNB**, **XTZ**, **LIN**, **ADA**, **XLM**, **XMR**, **TRX**, **HT**. Right-hand side panel: FRM index over time.

Data from 01 March 2020 to 17 May 2020



FRM@Crypto Centrality contribution

- Does cointegration hold for periods of financial distress?

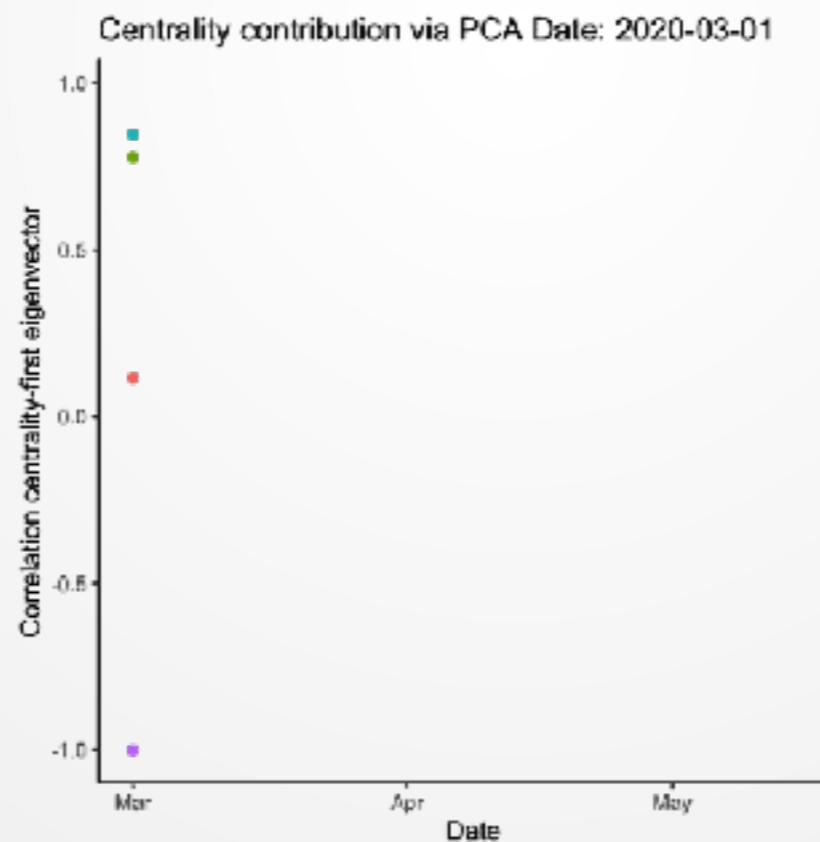


 quickly links
and transmits
information to
many other coins



FRM@Crypto Centrality contribution criterion

- Macroeconomic risk factors:
 - ▶ US dollar index (average of USD vs main non-crypto currencies)
 - ▶ Yield level in USD (carry component for the drift)
 - ▶ VIX
 - ▶ CVIX (same as VIX, but on major fiat currencies)
 - ▶ VCRIX
 - ▶ S&P500



FRM@Crypto

- Macroeconomic risk factors:
 - ▶ US dollar index (average of USD vs main non-crypto currencies)
 - ▶ Yield level in USD (carry component for the drift)
 - ▶ VIX
 - ▶ CVIX (same as VIX, but on major fiat currencies)
 - ▶ VCRIX
 - ▶ S&P500

What are the right macroeconomic risk factors per asset class?



FRM@Crypto Adjacency Matrix

- $\tau = 0.05$, 12 February 2018

	BTC	ETH	XRP	BCH	ADA	LTC	NEO	XLM	EOS	MIOTA	XEM	DASH	XMR	LSK	TRX	
BTC		0.13	0.04	0.10	0.00		0.04	0.07	-0.12	0.13	0.13	0.00	9			
ETH		0.03	0.07		0.24	0.10		0.01		0.04		0.13	0.02	8		
XRP			0.33	-0.03		-0.03	0.35	0.07		0.17			-0.13	7		
BCH		0.18	-0.03			0.08			-0.05	0.00	0.45	0.32		0.01	8	
ADA															0	
LTC	0.26	0.23						0.02	0.16	0.00		-0.01			6	
NEO			0.07	0.24	0.00	0.18	0.23	0.02		0.15	0.01		0.02	9		
XLM															0	
EOS															0	
MIOTA															0	
XEM			0.12	0.19	0.04		0.06	0.10	0.19		0.13		0.06	8		
DASH				0.10	0.12	0.40				0.04	0.07	0.25		-0.14	7	
XMR					0.01	0.23	0.10		0.18		0.08		0.05	0.02	7	
LSK	1.12				0.06	0.20		-0.52	-0.03			0.11	0.16		7	
TRX	2	3	8	7	5	4	8	4	3	7	7	3	5	3	7	0



influences only two
other crypto currencies



FRM@Crypto Adjacency Matrix with Macro Variables

- $\tau = 0.05$, 12 February 2018

	BTC	ETH	XRP	BCH	ADA	LTC	NEO	XLM	EOS	MIOTA	XEM	DASH	XMR	LSK	TRX	1Y	CVIX	DXY	SPX	VIX	VCRIX
BTC		0.13		0.04	0.10	0.00		0.04	0.07	-0.12		0.13	0.00					-0.11	0.17		
ETH			0.03	0.07		0.24	0.10			0.01		0.04		0.13	0.02			-0.14			
XRP				0.33	-0.03		-0.03	0.35	0.07		0.17			-0.13				0.04	0.14		
BCH		0.18	-0.03				0.08			-0.05	0.00	0.45	0.32		0.01				0.08		
ADA																					
LTC	0.26	0.23							0.02	0.16	0.00		-0.01								
NEO			0.07	0.24	0.00	0.18	0.23	0.02		0.15	0.01				0.02						
XLM																					
EOS																					
MIOTA																					
XEM		0.12	0.19	0.04		0.06	0.10	0.19			0.13				0.06						
DASH			0.10	0.12	0.40					0.04	0.07		0.25		-0.14						
XMR				0.01	0.23	0.10		0.18		0.08				0.05	0.02						
LSK	1.12			0.06	0.20			-0.52	-0.03			0.11	0.16					0.26			
TRX																					



Few traditional macro variables
explain crypto currency tail behaviour



FRM@Crypto

- Adjacency Matrix 12 February 2018

BCH	0.23
NEO	0.18
ADA	0.10
MIOTA	0.08
LSK	0.05
TRX	0.02
XRP	0.01

BCH	0.32	
DASH	0.25	
XMR		
LSK	0.16	
BTC	0.13	
LTC	-0.01	

XRP	0.33
NEO	0.24
XMR	0.23
LSK	0.20
DASH	0.12
ETH	0.07
XEM	0.04

XMR in high Co-Stress



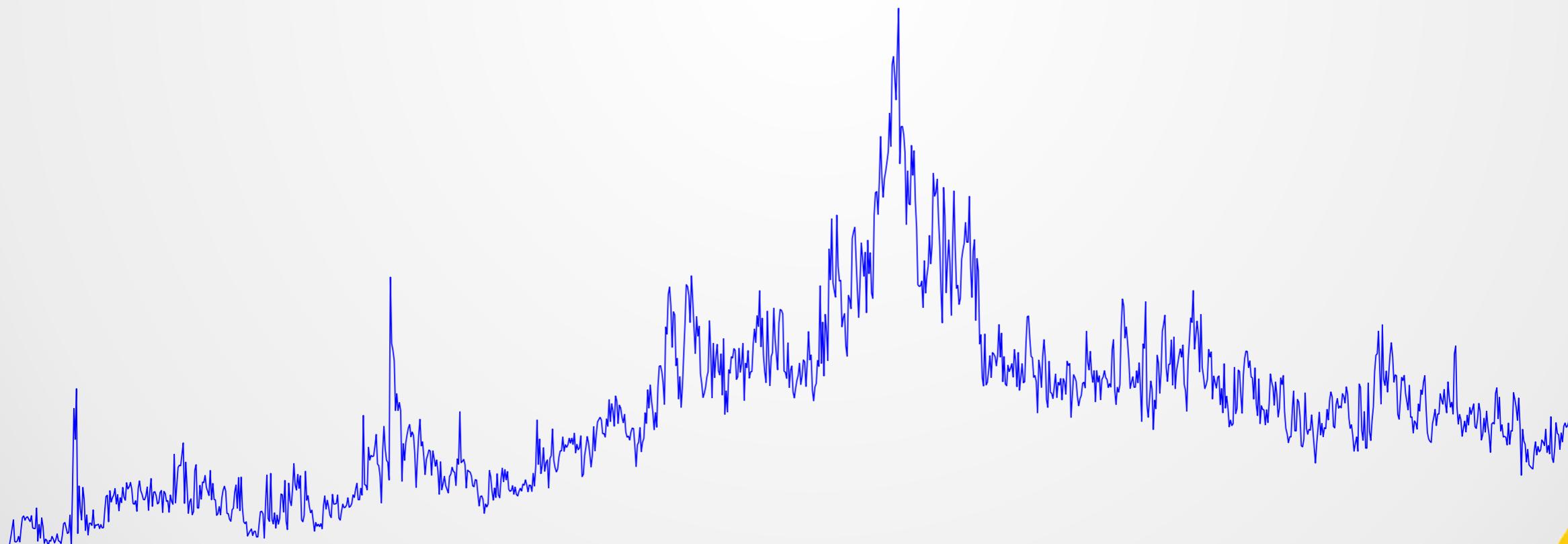
Extensions

- 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, across asset classes
- Price Vectors

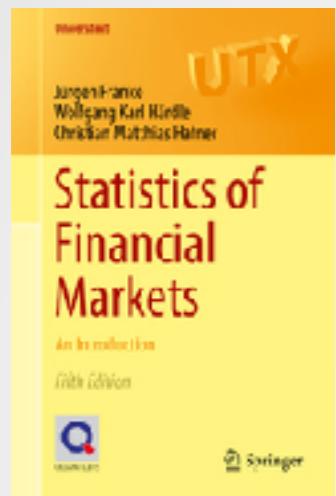


Conclusions

- **FRM financialriskmeter** = Flexible Risk Meter
- can be tuned to any asset class and to any TE risk
- reacts to coagulation of risk emitters via active set



FRM in FinTech, Cryptos, ...



Vol 1. 2019 on Crypto Currencies





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Wolfgang K Härdle



Rui REN



Anna Shchekina



Alla Petukhina



Ang LI



Souhir Ben Amor



AlexTruesdale

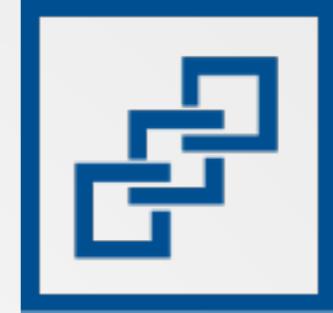


Ilyas Agakishiev

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FRM financialriskmeter for Cryptos



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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 (as of 20180701)



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

