FRM financialriskmeter AI for Blockchain Cryptos

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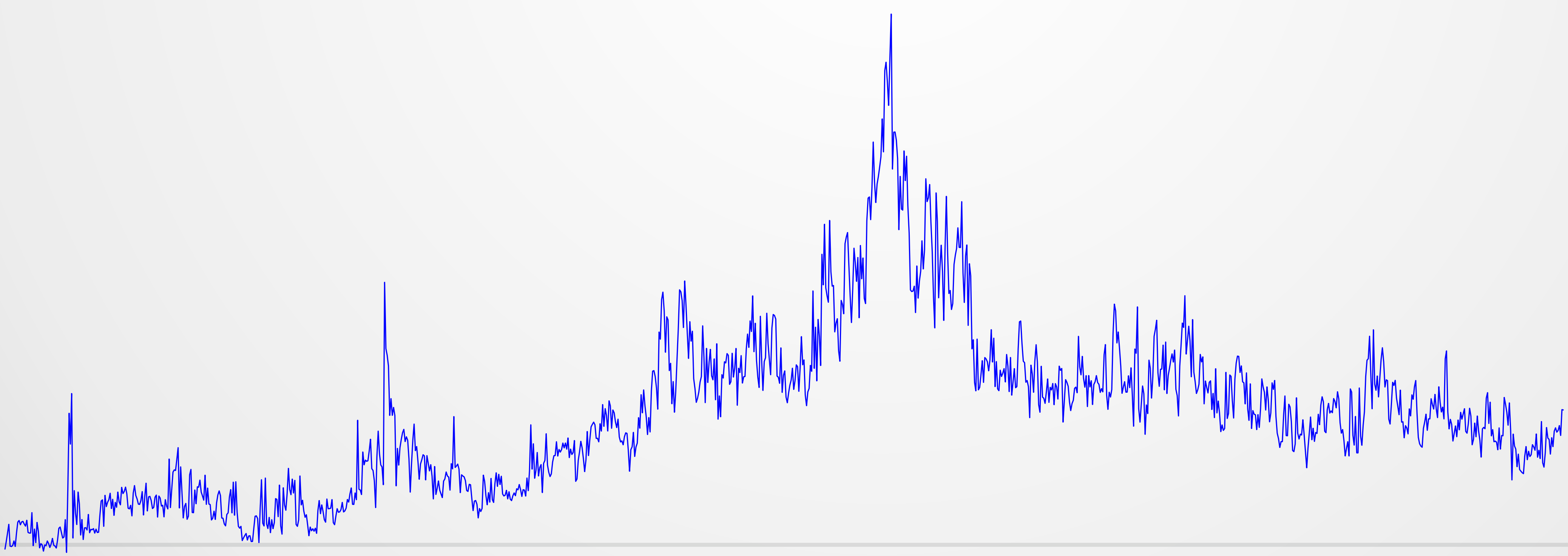
Tail Events (TE)

- 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 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
- Quantlet in WU Vienna



FRM

Outline

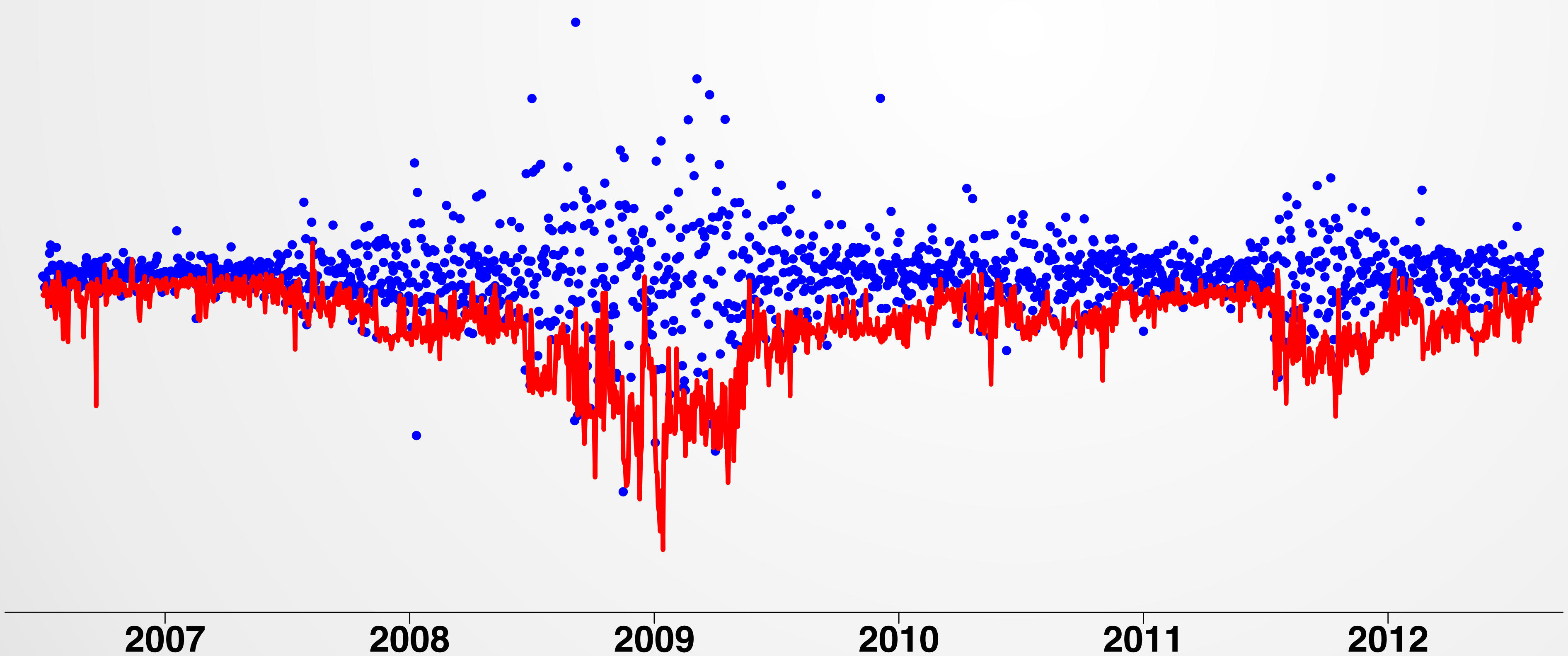
1. Motivation ✔
2. Genesis
3. Framework
4. Applications
5. Node influence metrics
6. Sensitivity analysis
7. Network centrality
8. Conclusions

VaR Value at Risk

- Probability measure based

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

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



Linear Quantile Lasso Regression

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

$$A_{j,t}^{s\top} \stackrel{def}{=} \left[M_{t-1}^{s}, X_{-j,t}^{s}\right]$$

where:

- $X_{-j,t}^{s}$ log returns of all other cryptos except $j = \{1,\ldots,J\}$ at time $t = \{2,\ldots,T\}$
- s length of moving window
- M_{t-1}^{s} log return of macro prudential variable at time $t-1$
- Application, $J = 15,\ s = 63$

▶ Crypto List ▶ Macroprudential

Lasso Quantile Regression

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

- Check function $\rho_\tau(u) = |u|^c \, |\tau - \mathrm{I}_{\{u<0\}}|$ with $c = 1, 2$ corresponding 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 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)

$$(\alpha - \gamma)^{\top} = \tau \, \mathrm{I}_{\{Y - X\beta(\lambda) > 0\}} + (\tau - 1) \, \mathrm{I}_{\{Y - X\beta(\lambda) < 0\}}$$

- Average penalty: indicator for tail risk,

$$FRM^t \stackrel{def}{=} J^{-1} \sum_{j=1}^{J} \lambda_j^t$$

- The FRM time series is **one** index for joint TEs!

λ Selection

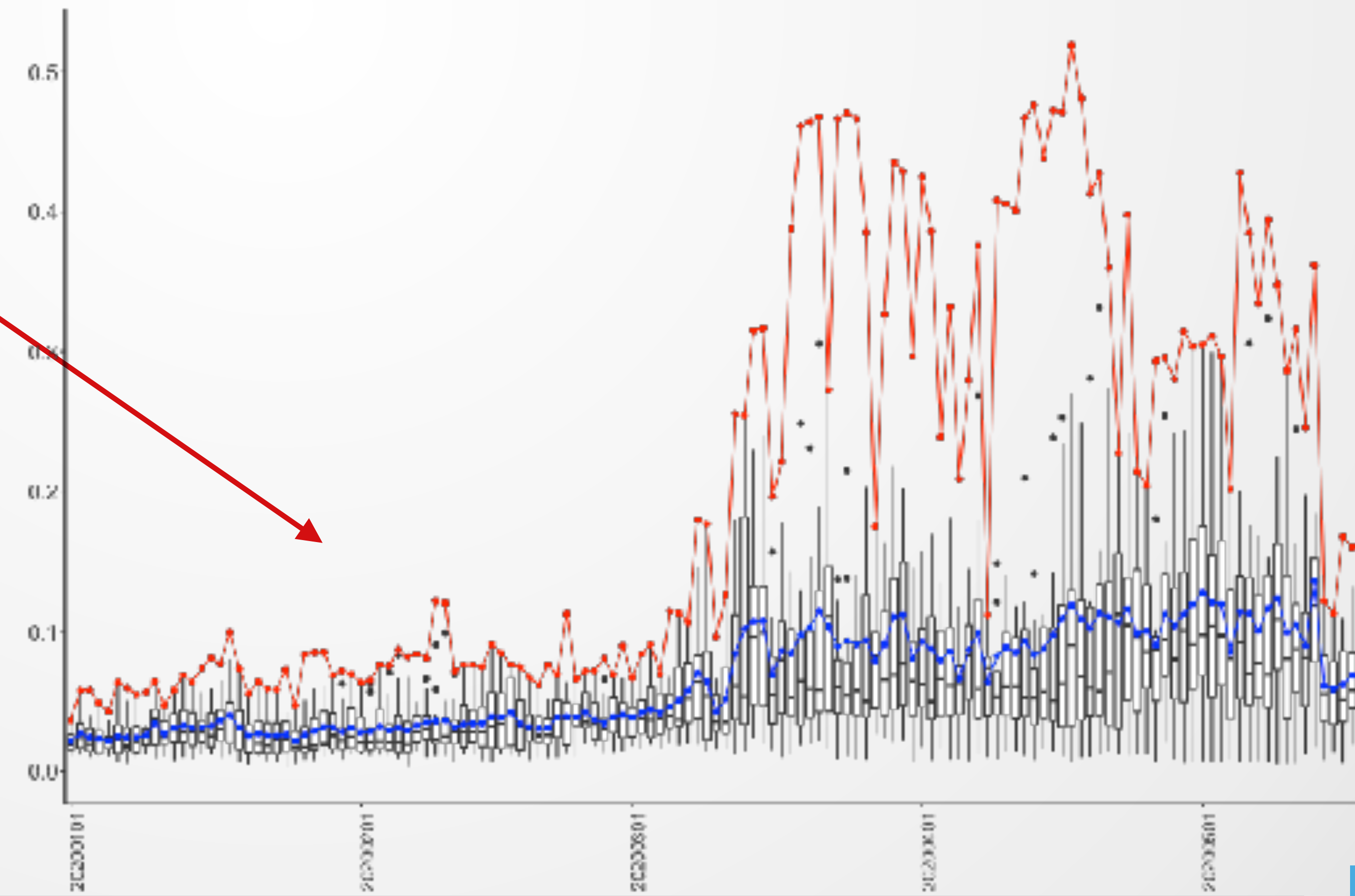
- Generalized approximate cross-validation (GACV)

$$\min GACV(\lambda_j^s) = \min \frac{\sum_{t=s}^{s+(n-1)} \rho_\tau(X_{j,t}^s - \alpha_j^s - A_{j,t}^{s,\top}\beta_j^s)}{n - df} \qquad (3)$$

Coeff's depend on λ

where: df dimensionality of fitted model

- λ as function of j, t
- Distribution of λ^s
- ID the TE drivers



FRM codes

FIRAMIS app HU Berlin app

FRM@Americas

FRM@Asia

FRM@Crypto

FRM@Europe

FRM@iTraxx

FRM@Crypto Data

- 15 largest cryptocurrencies
- 6 macro related variables
- Quantile level $\tau = 0.05, 0.10, 0.25, 0.50$
- Time window $s = 63, 21$
- Time frame: 2014–2020
- 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

LQ Lasso Regression

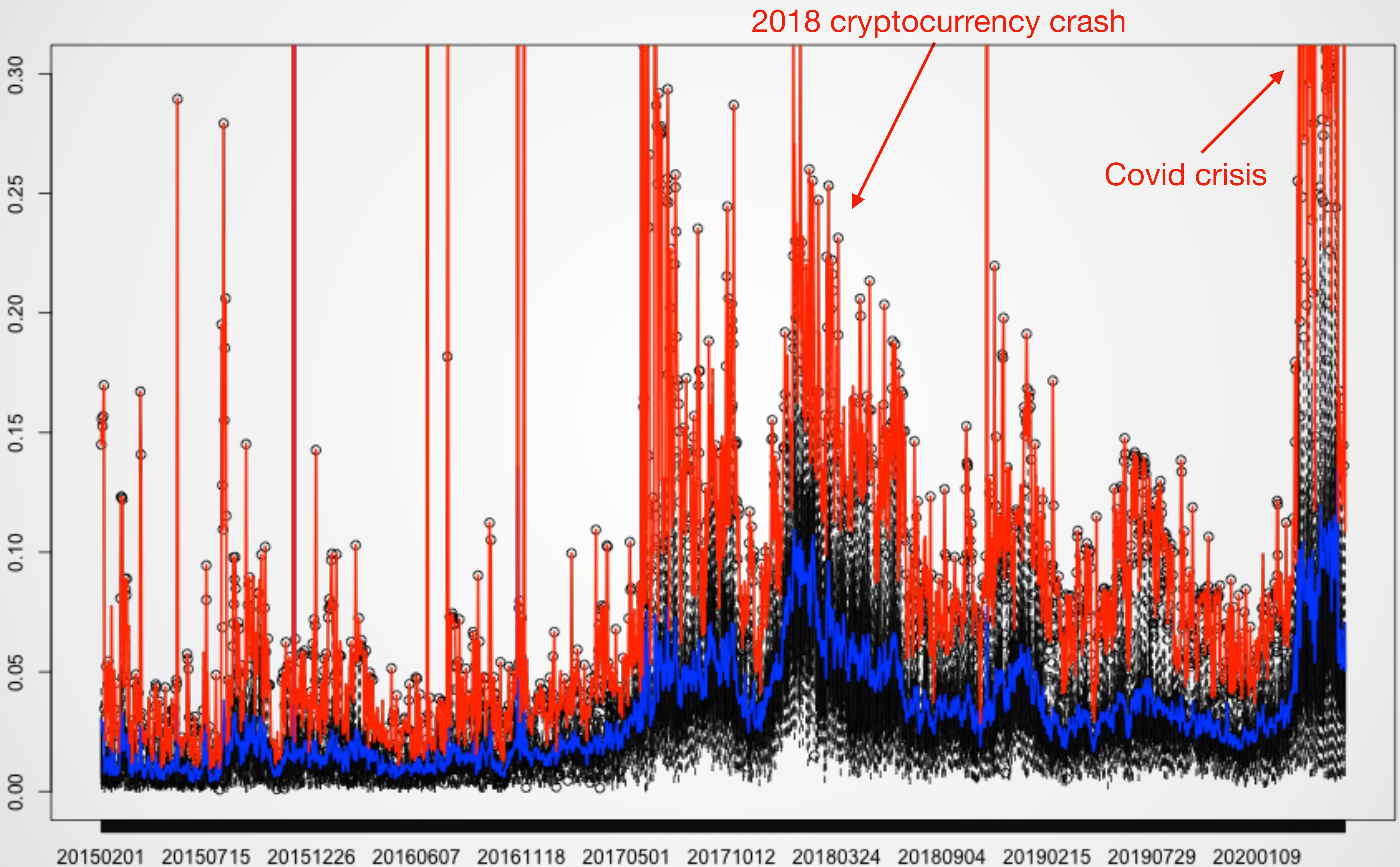
Methodology

- Create risk drivers list of active index members
- Download daily rates in same currency (USD)
- Sort by market cap
- 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

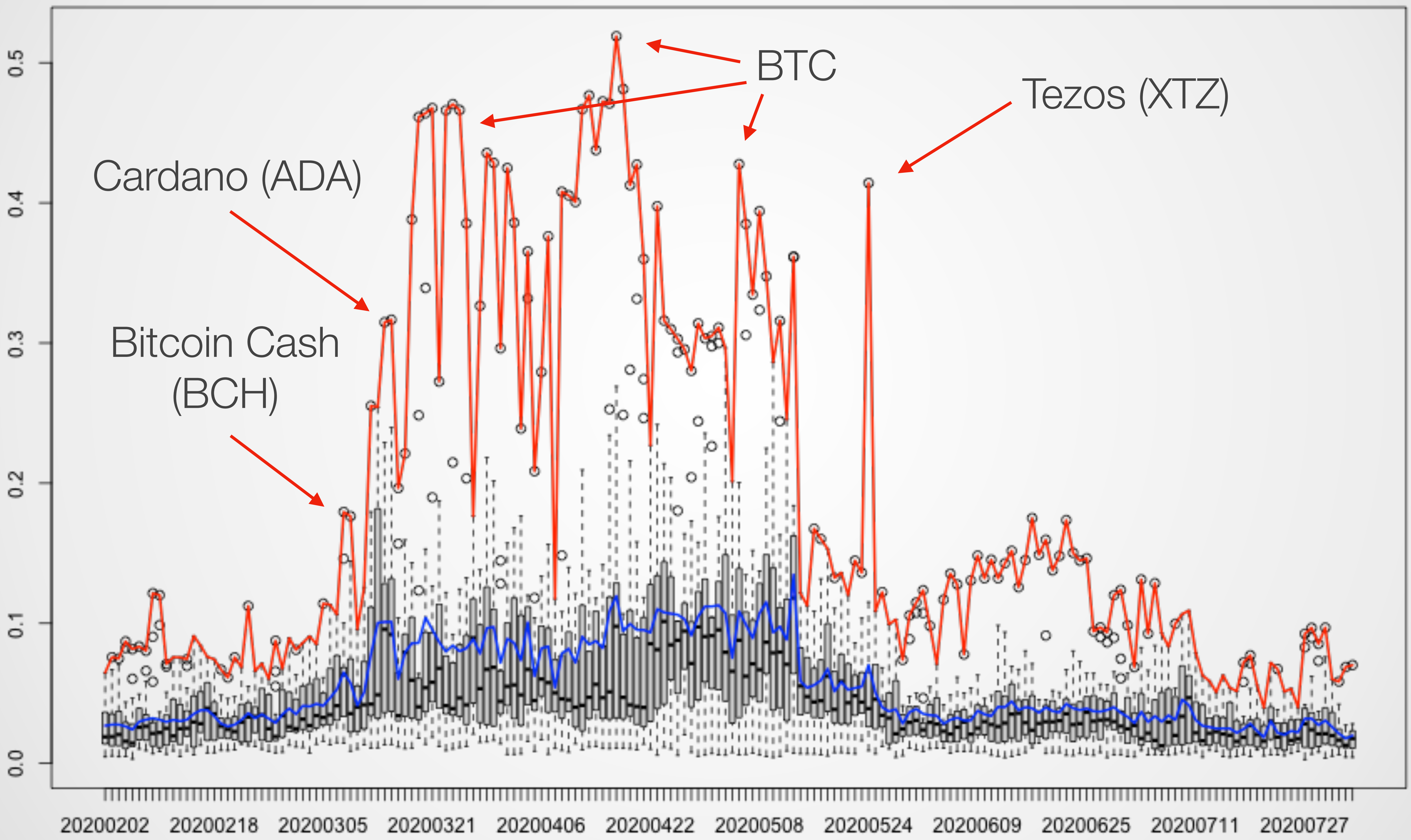
LQ Lasso Regression

FRM@Crypto Index

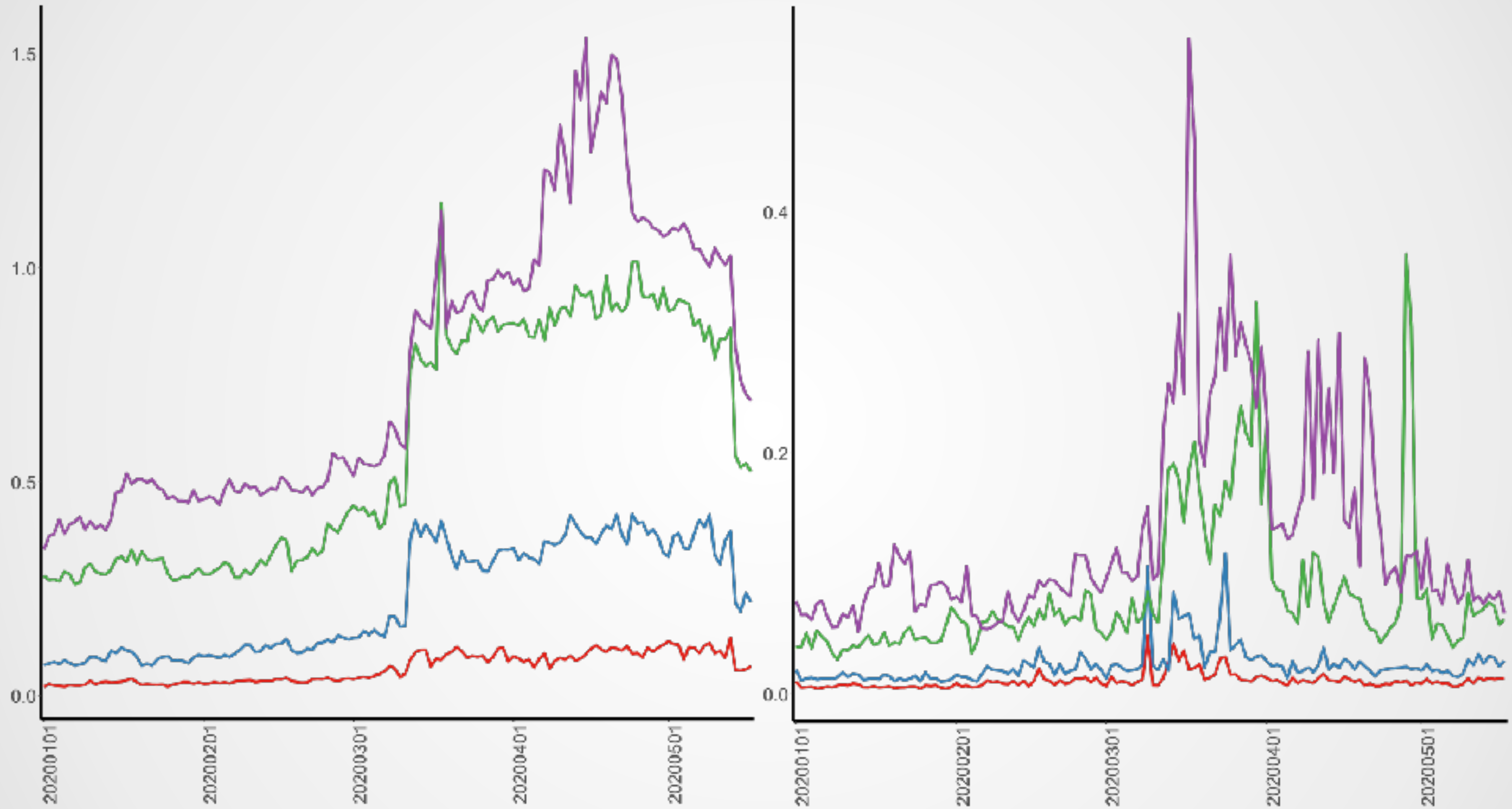
http://frm.wiwi.hu-berlin.de



FRM Distribution under Covid Crisis



Tail risk and window size sensitivity: FRM@Cryptos



FRM@Crypto index for tail risk $\tau = 5\%, 10\%, 25\%, 50\%$ for $s = 63$ (left) and $s = 21$ (right).
Data from 01 January 2020 to 17 May 2020.

Tail risk and window size sensitivity: CoStress

$\tau = 0.05$		$\tau = 0.10$		$\tau = 0.25$		$\tau = 0.50$	
Crypto	Frequency	Crypto	Frequency	Crypto	Frequency	Crypto	Frequency
BTC	112	BTC	95	XRP	93	BTC	116
ETH	76	LTC	83	INNBCL	90	XRP	97
LTC	61	ETH	63	TAGZ5	80	INNBCL	87
BSV	57	INNBCL	57	ETH	73	BSV	65
INNBCL	57	BCH	44	BTC	70	TAGZ5	65

$\tau = 0.05$		$\tau = 0.10$		$\tau = 0.25$		$\tau = 0.50$	
Crypto	Frequency	Crypto	Frequency	Crypto	Frequency	Crypto	Frequency
BCH	74	BCH	79	BCH	81	EOS	85
LINK	74	EOS	63	ADA	79	XMR	84
XMR	70	XMR	63	BNB	73	XLM	81
BNB	64	XTZ	62	XMR	69	BCH	78
EOS	59	ADA	60	XTZ	65	ADA	72

Crypto currencies with high (top table) and low (bottom table) CoStress with the number of days they appeared in top/bottom 5 for tail risk $\tau = 5\%, 10\%, 25\%, 50\%$.
Data from 01 January 2020 to 17 May 2020.

Flight into money

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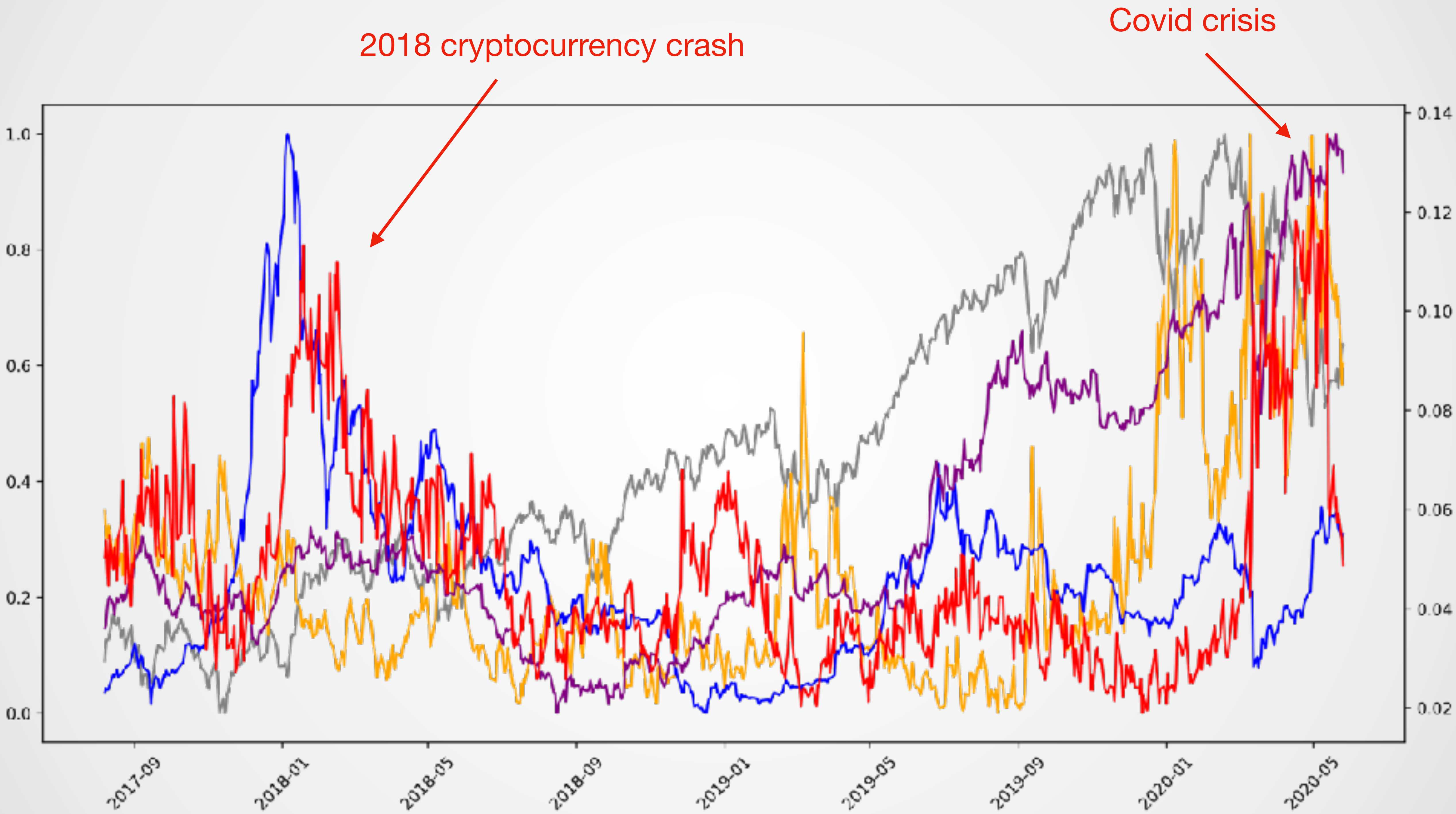


Normalised SP500 Index, VIX Index, CRIX Index, Gold Price and FRM@Crypto

Crypto’s CoStress

- 12 February 2018:

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

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

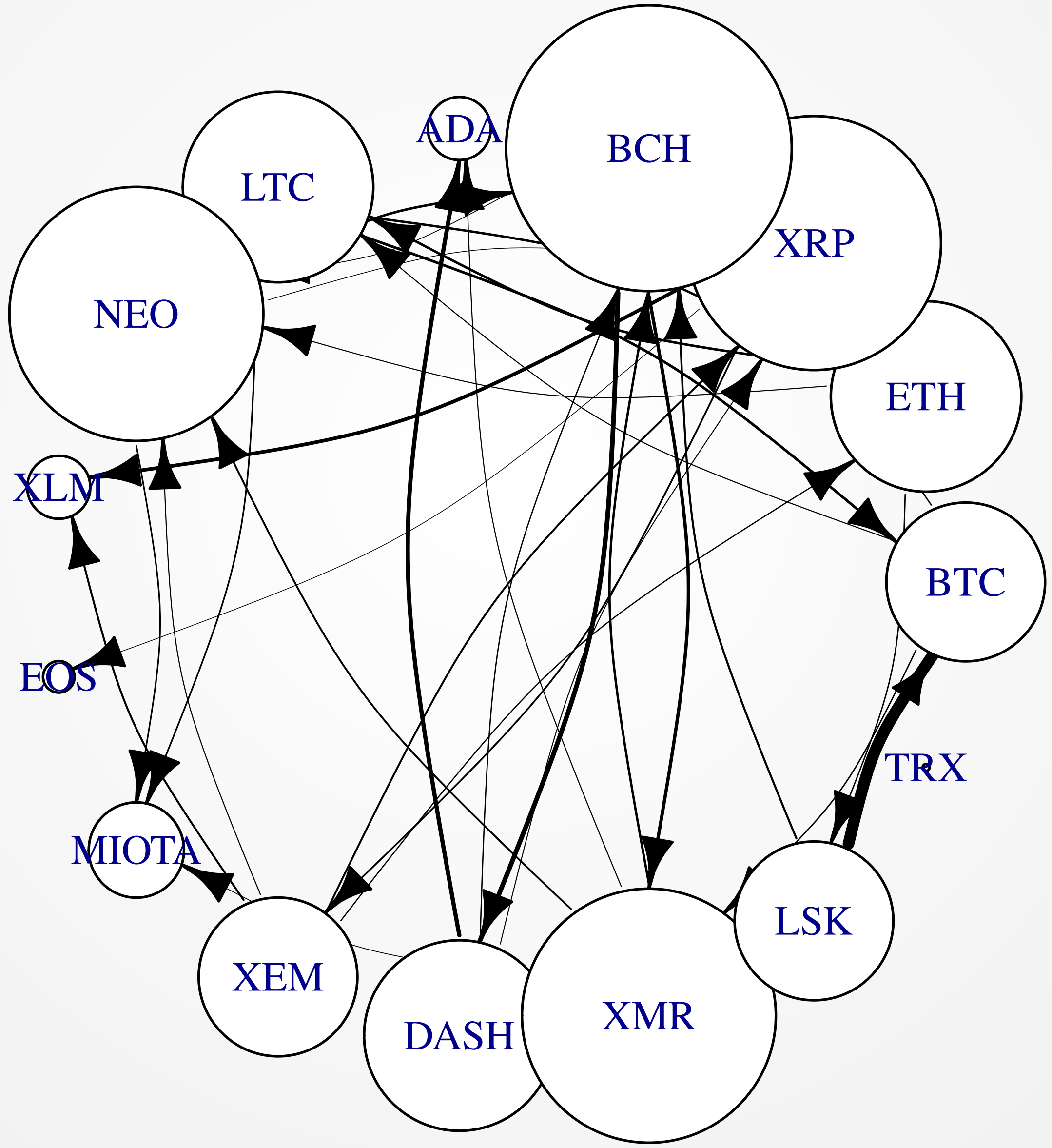
- 19 March 2020:

  High CoStress: **BTC**, ETH, INNBCL, BNB, BSV

  Low CoStress: TAGZ5, XTZ, BCH, EOS, XLM

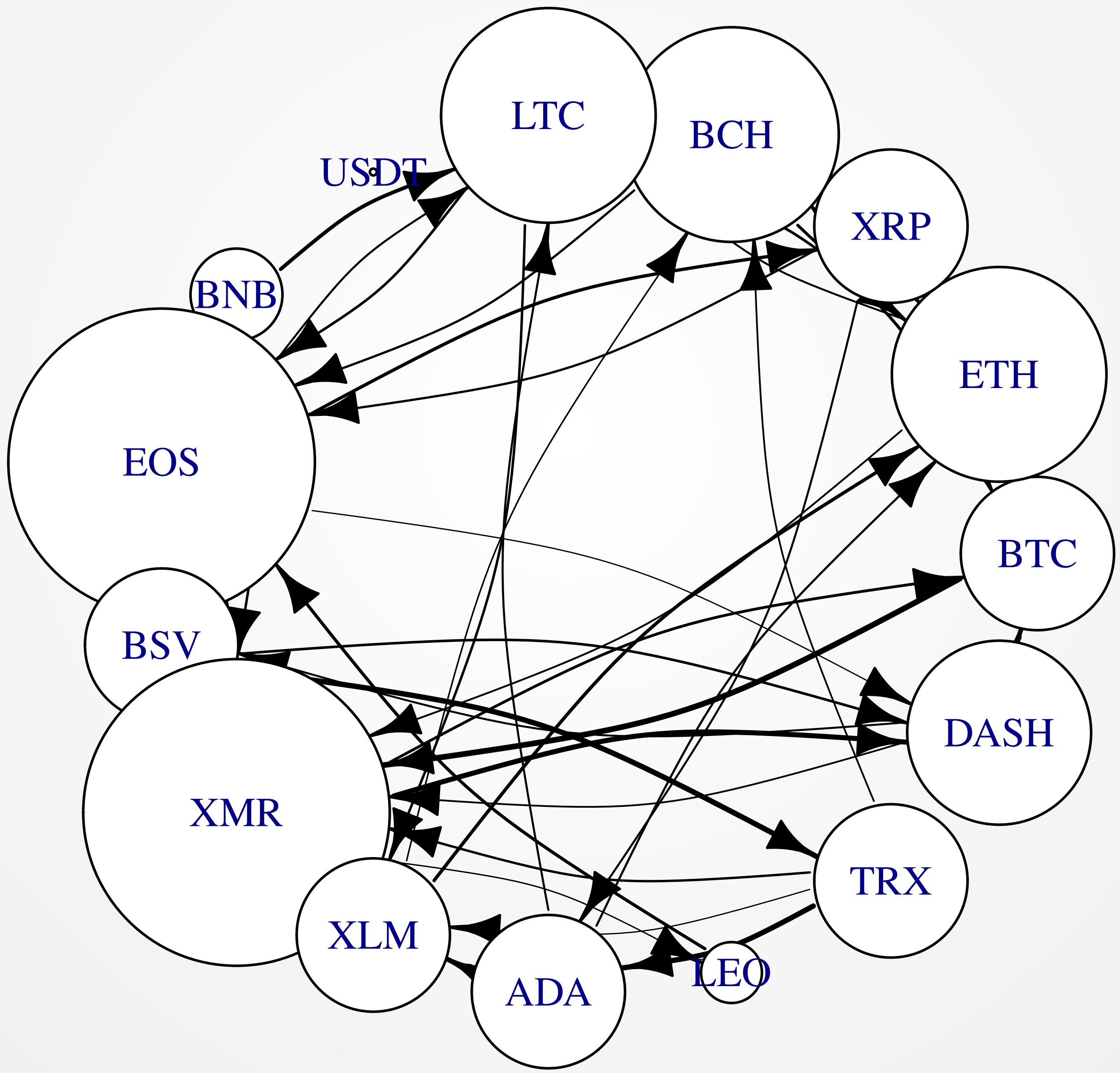
Visualising the Active Set: Total Degree Centrality

- $\tau = 0.05$, 12 February 2018, FRM@Crypto



Visualising the Active Set: Total Degree Centrality

- $\tau = 0.05$, 27 August 2019, FRM@Crypto



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		0.00	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																0
	2	3	8	7	5	4	8	4	3	7	7	3	5	3	7	

influences only two other crypto currencies

FRM

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

FRM@Crypto

- Adjacency Matrix for 12 February 2018

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

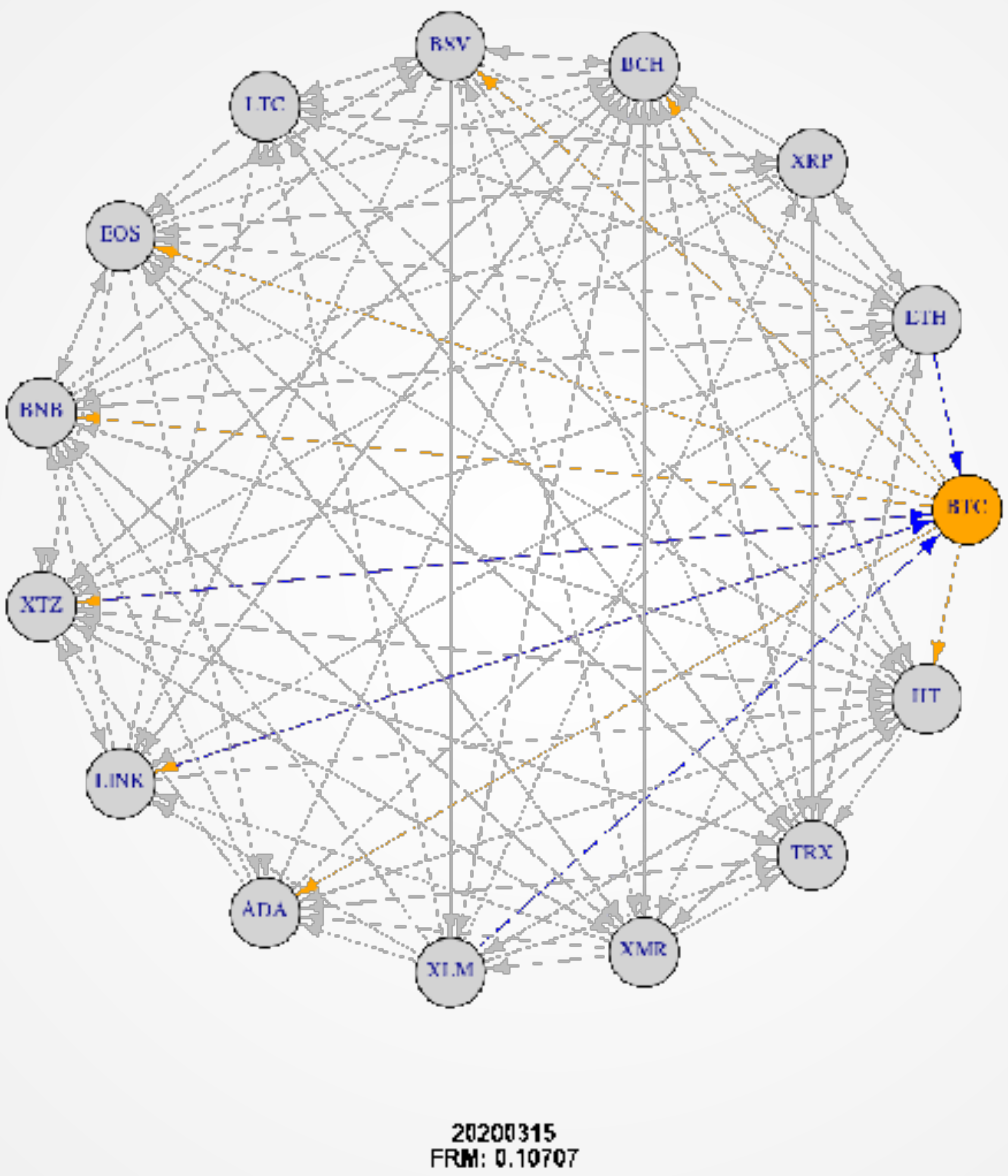
XMR

BCH	0.32
DASH	0.25
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

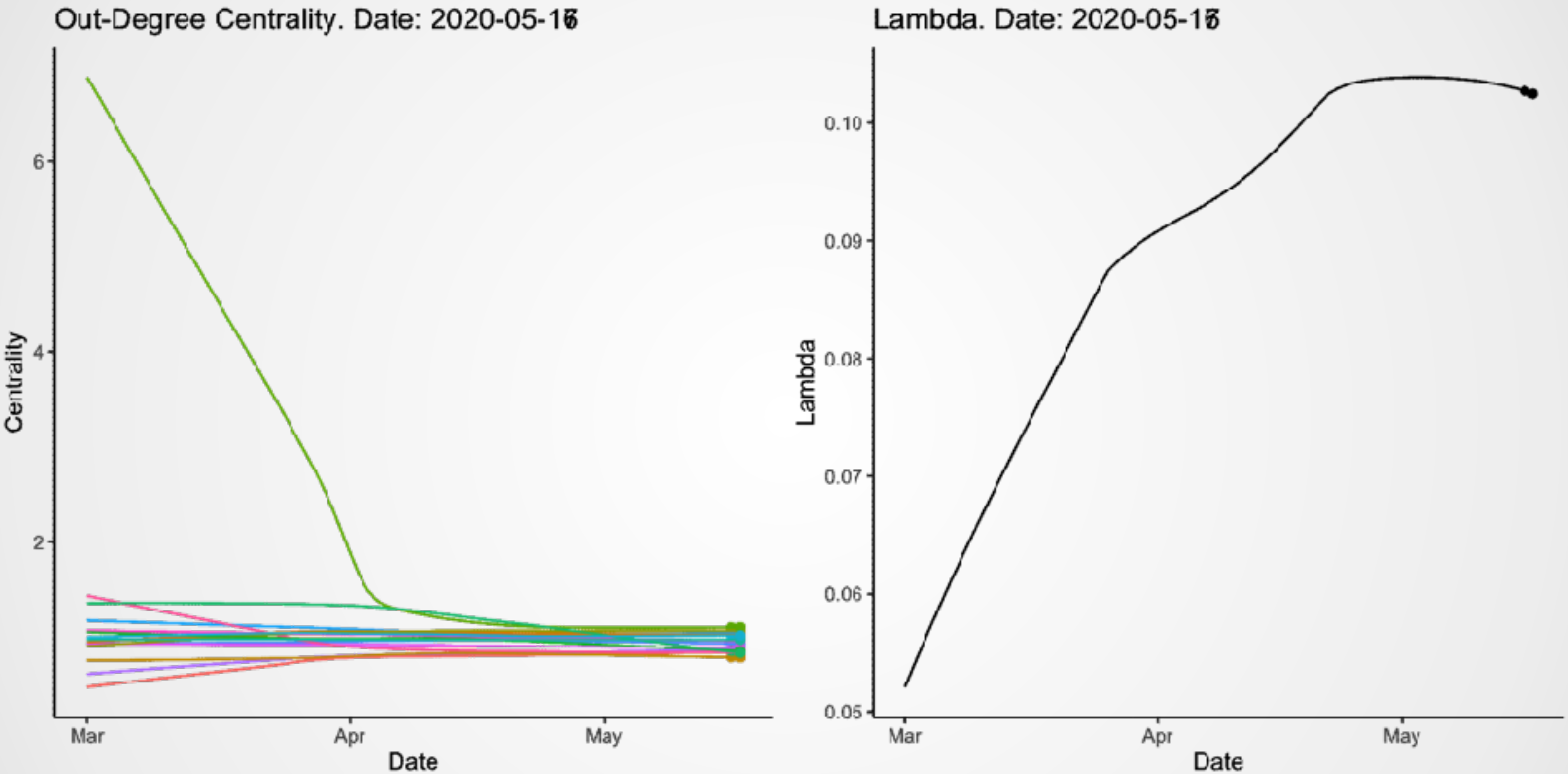
XMR in high Co-Stress

Visualising the Active Set: FRM@Crypto the Movie



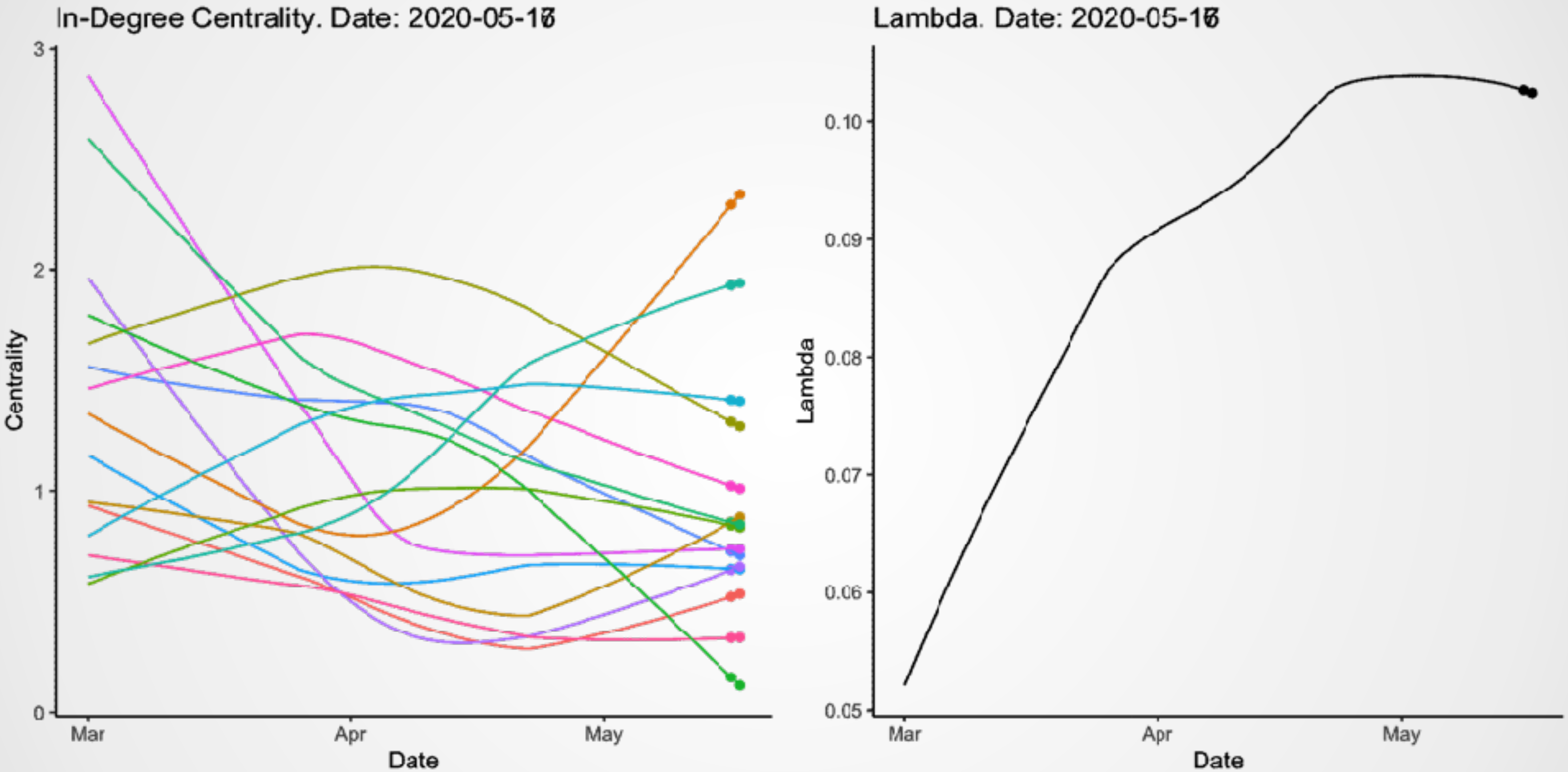
Network analysis for FRM@Crypto from 3 March 2020 to 17 May 2020

FRM@Crypto Out-Degree Centrality



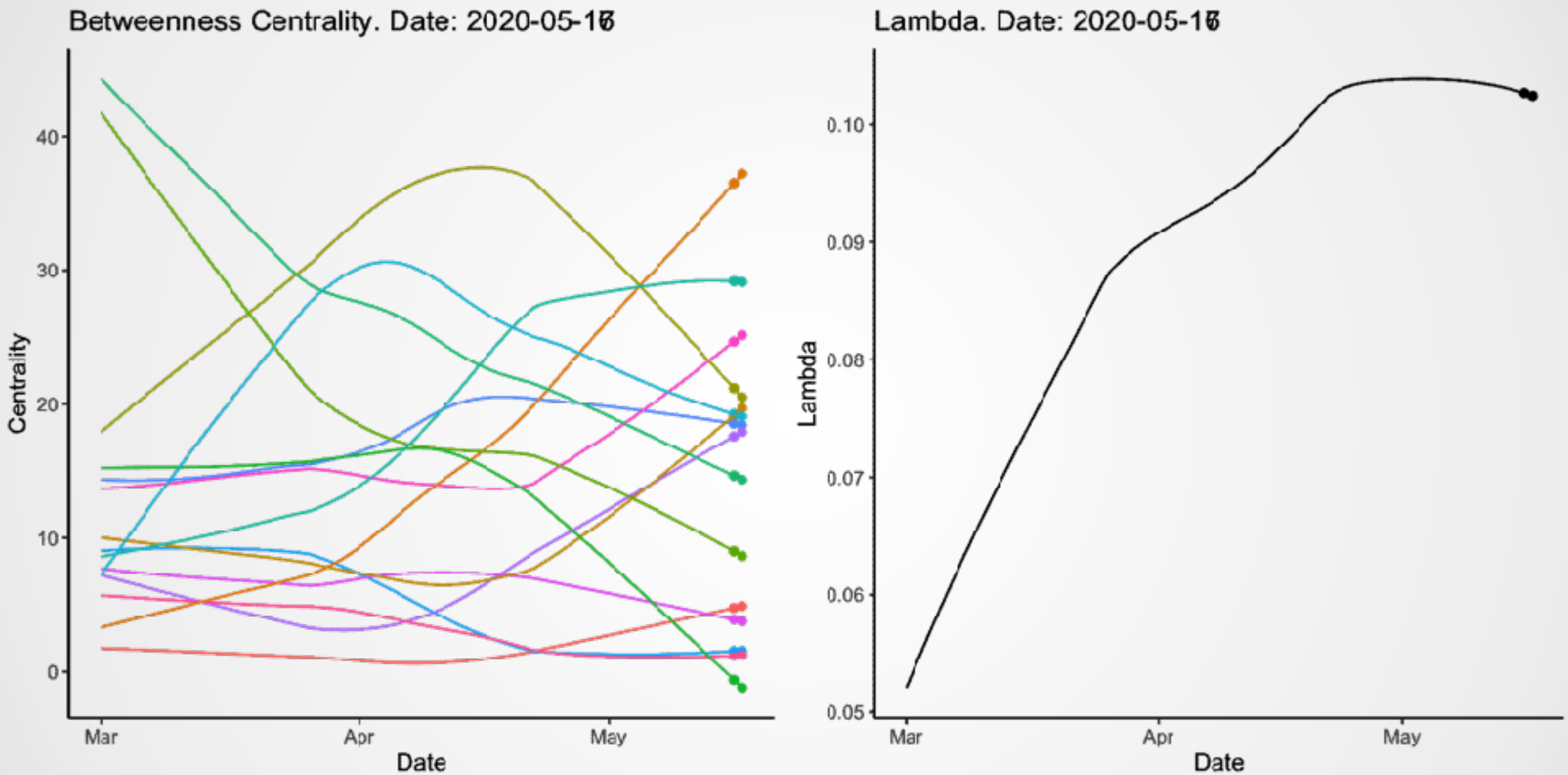
Left-hand side panel: # of outbounds links of BTC, ETH, XRP, BCH, BSV, LTC, EOS, BNB, XTZ, LIN, ADA, XLM, XMR, TRX, HT. Right-hand side panel: FRM index over time.
Data from 01 March 2020 to 17 May 2020

FRM@Crypto In-Degree Centrality



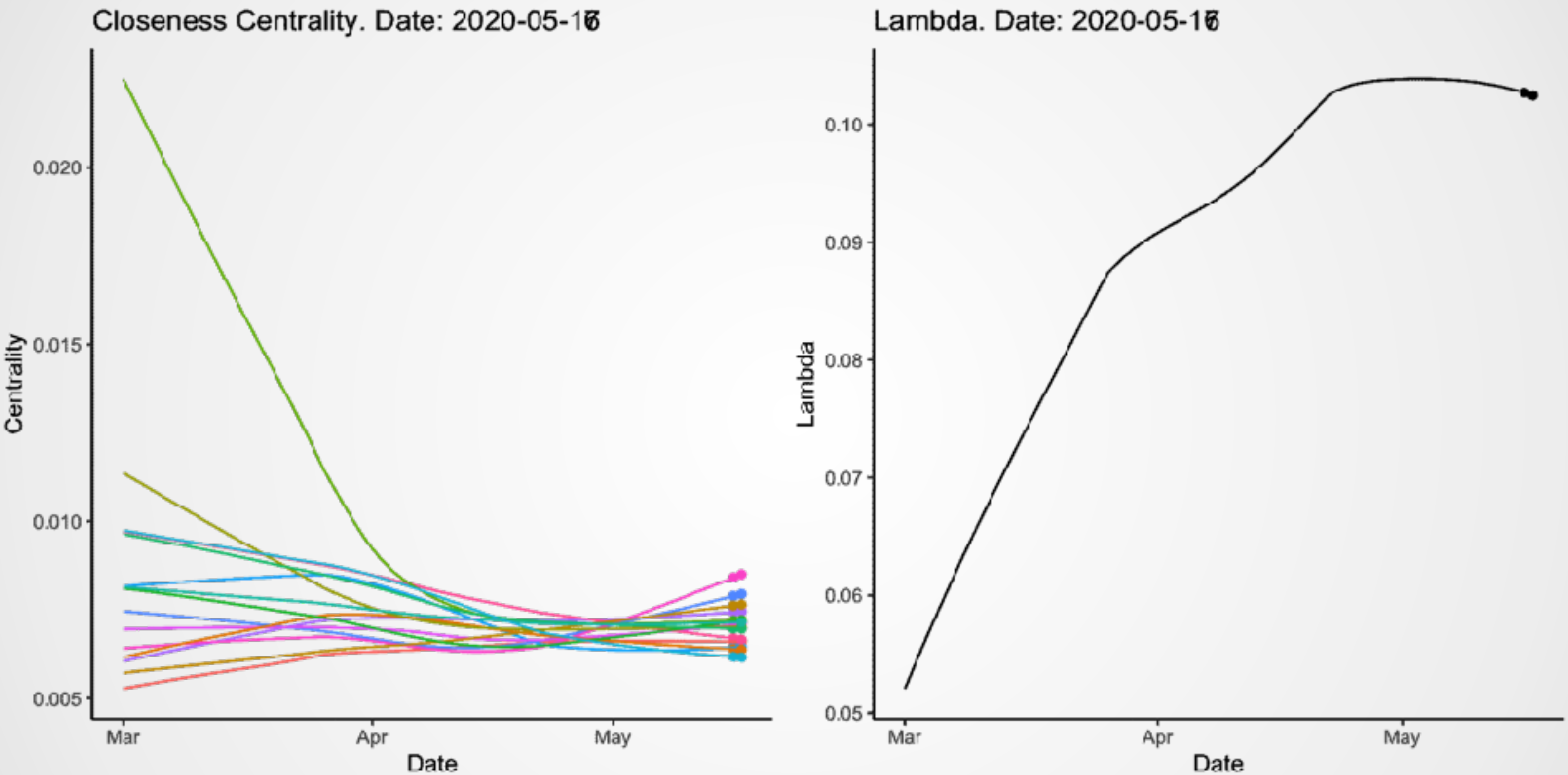
Left-hand side panel: # of inbound links of BTC, ETH, XRP, BCH, BSV, LTC, EOS, BNB, XTZ, LIN, ADA, XLM, XMR, TRX, HT. Right-hand side panel: FRM index over time.
Data from 01 March 2020 to 17 May 2020

FRM@Crypto Betweenness Centrality



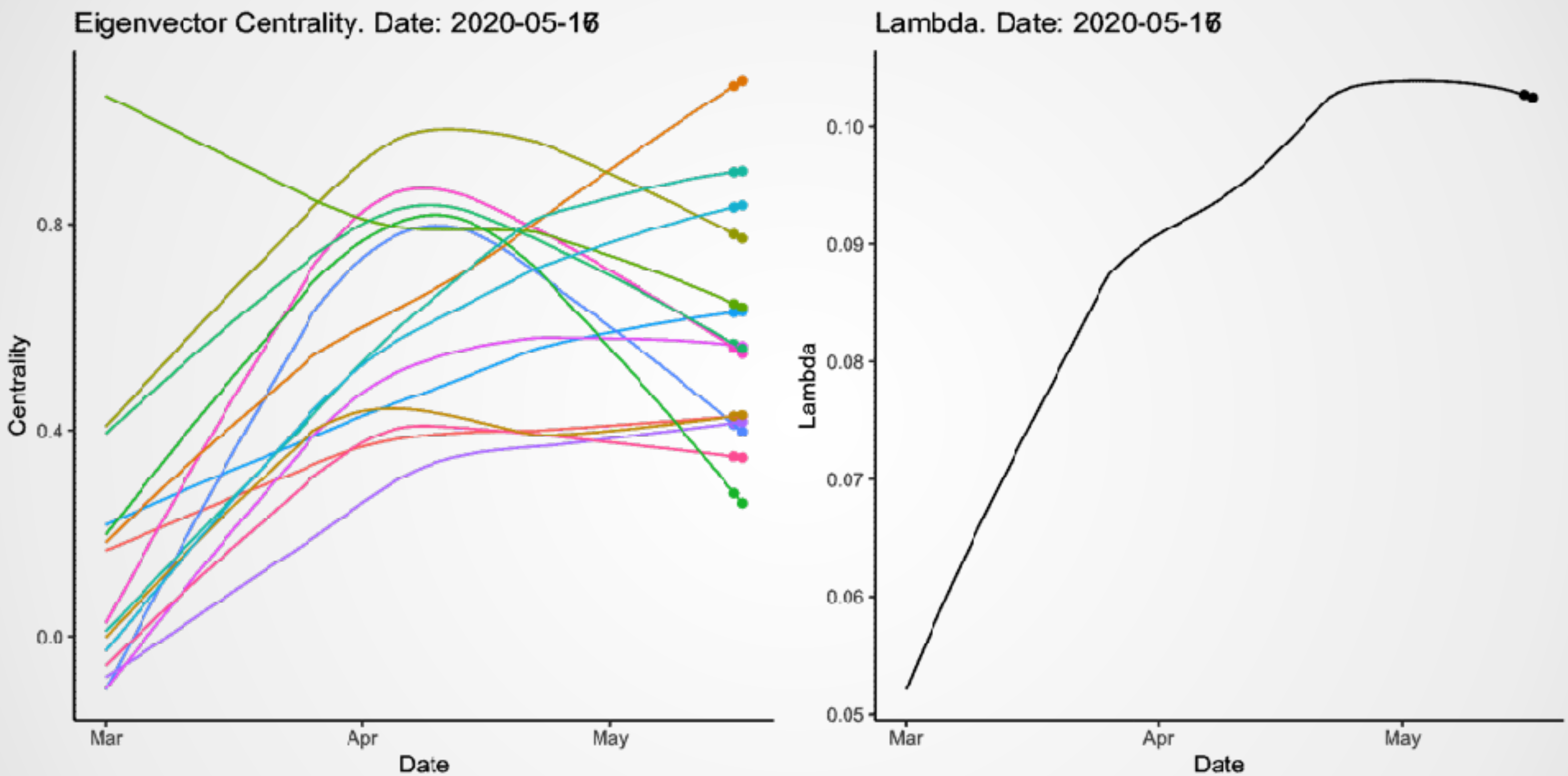
Left-hand side panel: „bridge“ behaviour measure for BTC, ETH, XRP, BCH, BSV, LTC, EOS, BNB, XTZ, LIN, ADA, XLM, XMR, TRX, HT. Right-hand side panel: FRM index over time. Data from 01 March 2020 to 17 May 2020

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

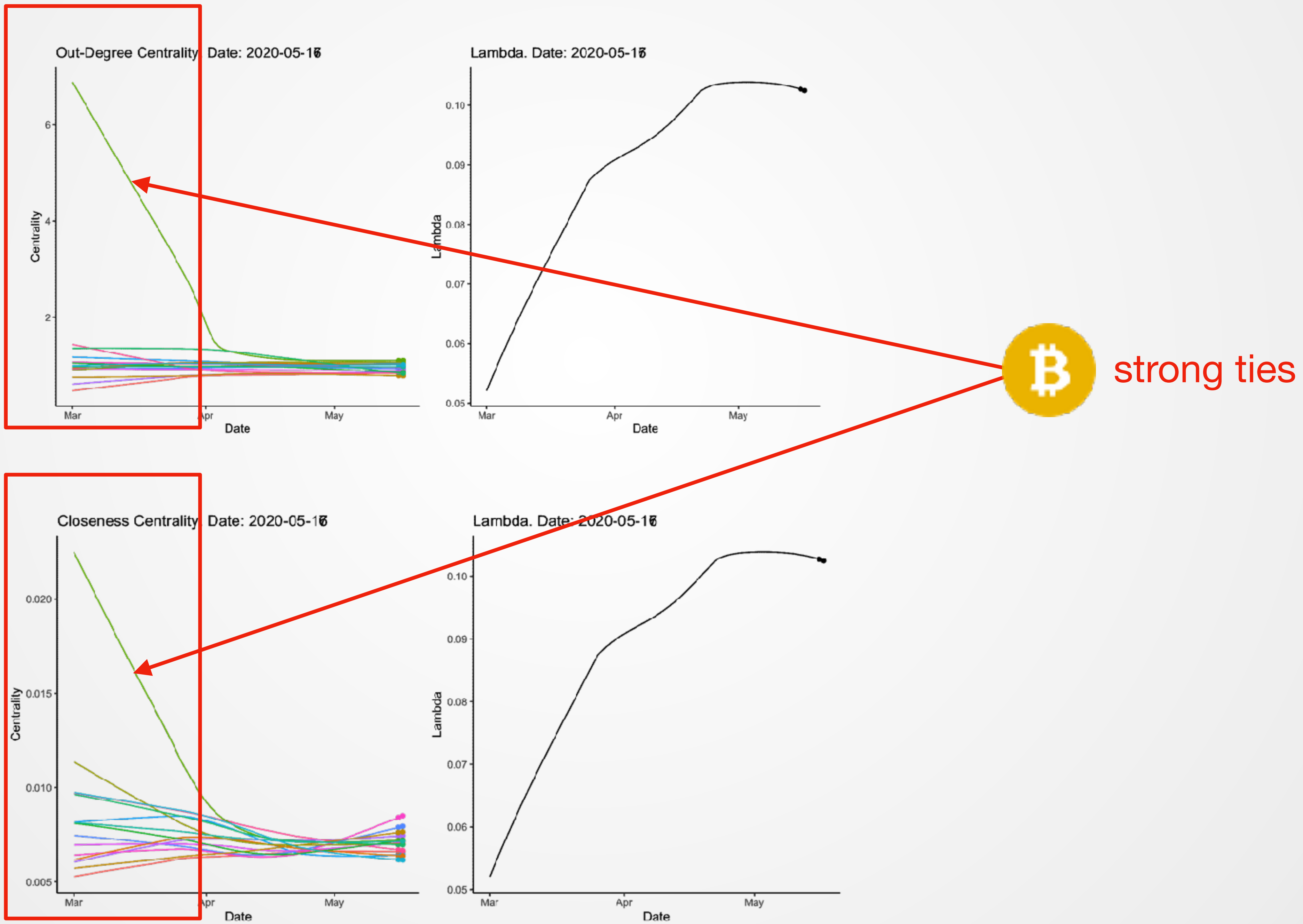
FRM@Crypto Eigenvector Centrality



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

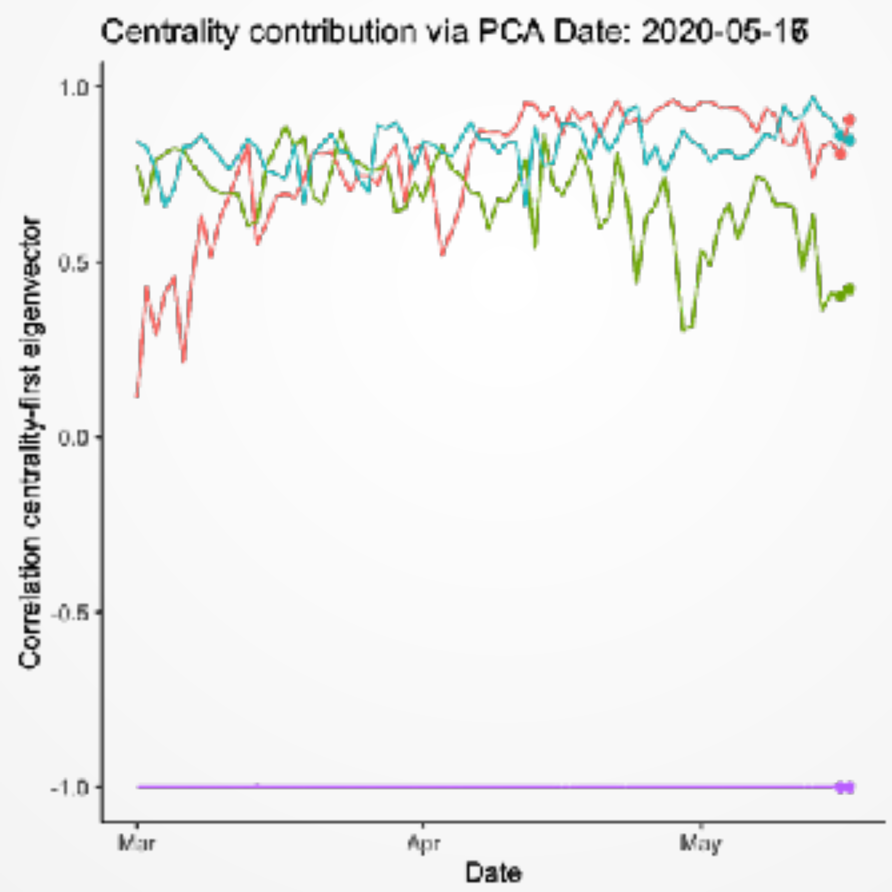
FRM@Crypto nodes influence

- Does cointegration hold for periods of financial distress?



Information flow variability

- Most informative measures distinguished via Principal Component Analysis (PCA)
  - Degree centralities highly correlated with four largest PCs



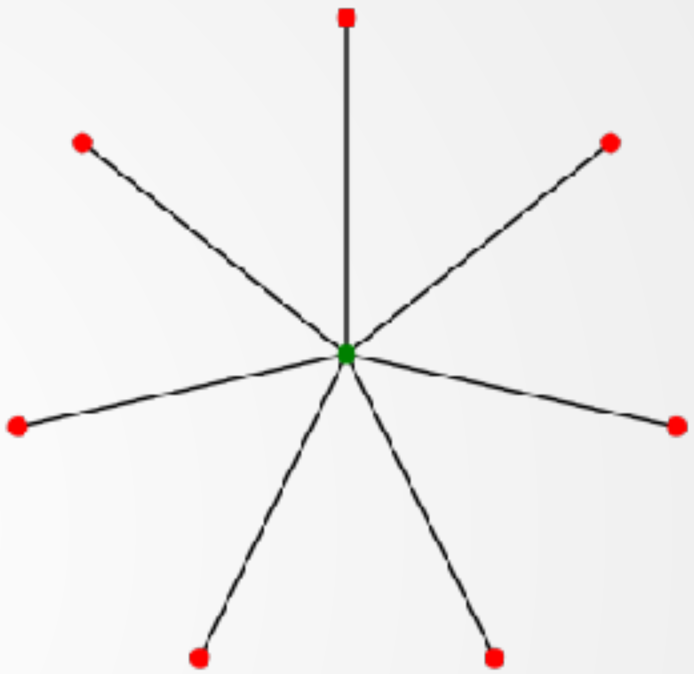
Contribution of out-Degree, in-Degree, closeness and betweenness measures to the variability of the FRM central nodes from 1 March 2020 to 17 May 2020

From Nodes to Network Centralisation

Extend the notion of *point centrality* on the entire network.

1. Average of all nodes $\succ$ spirit of FRM

$$C = \sum_{i=1}^{M} C(p_i)$$

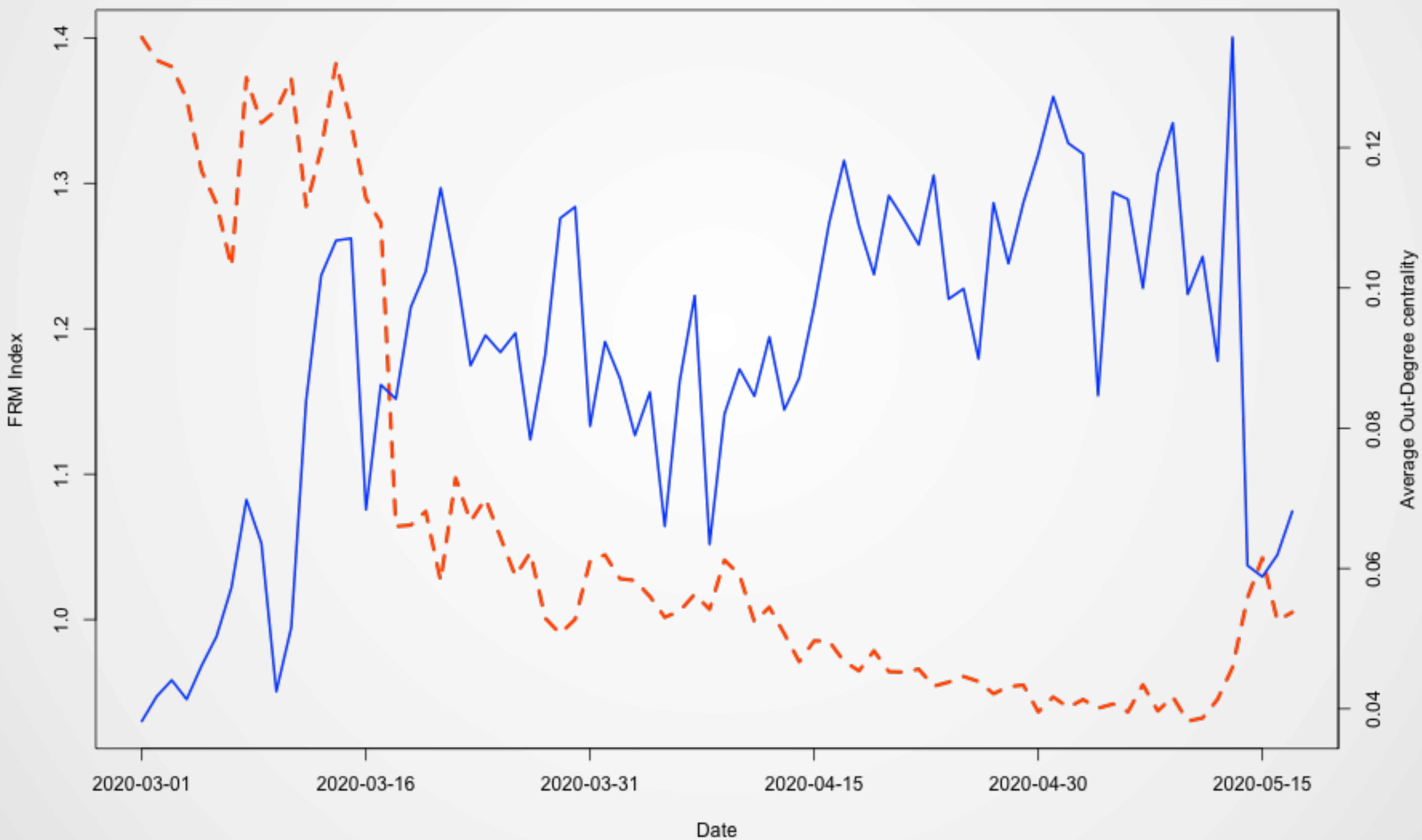


2. Freeman centralisation

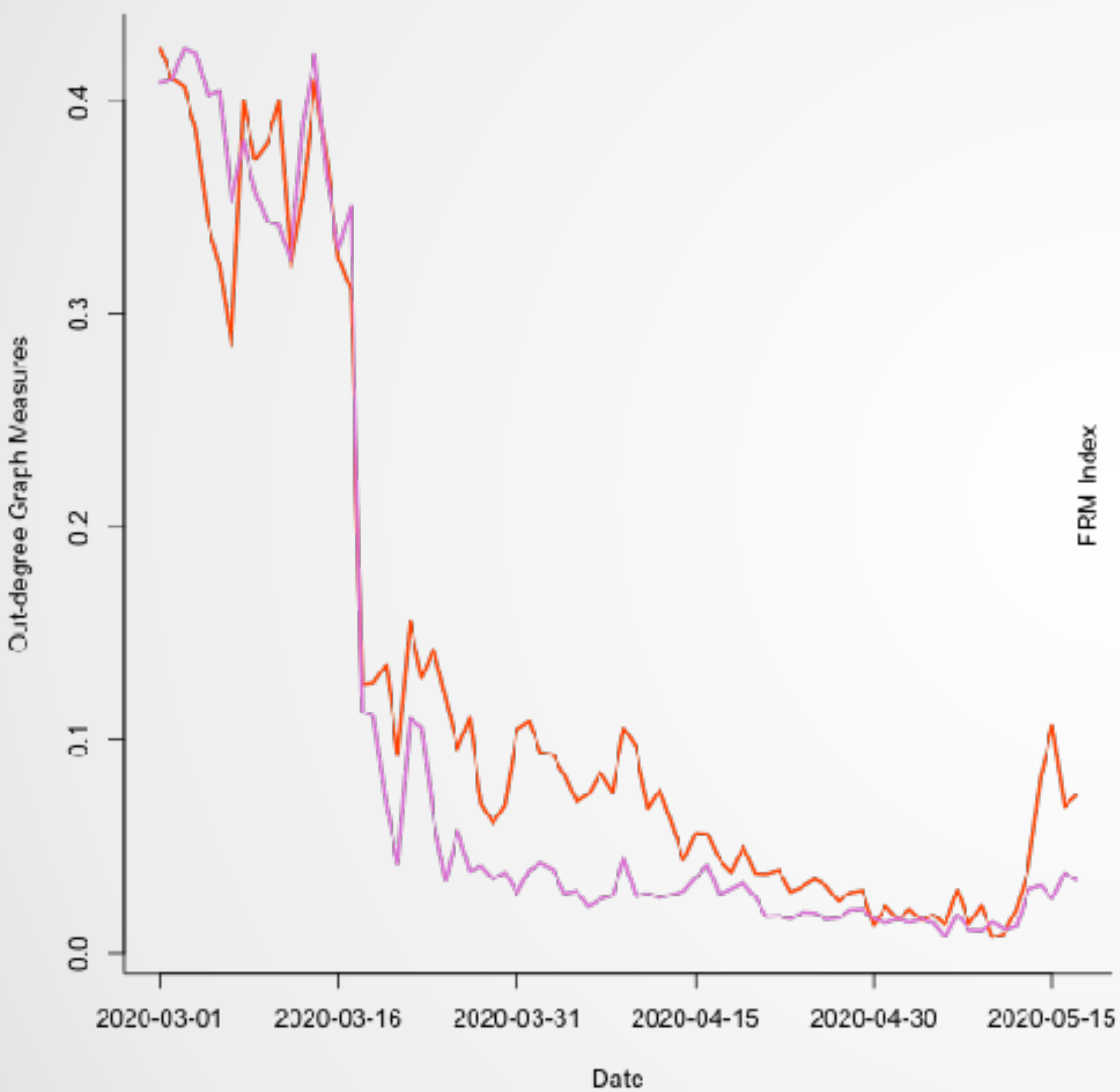
$$C = \frac{\sum_{i=1}^{M} [C(p_*) - C(p_i)]}{\max \sum_{i=1}^{M} [C(p_*) - C(p_i)]} \underset{\text{star}}{=} \frac{\sum_{i=1}^{M} [C(p_*) - C(p_i)]}{M^2 - 3M + 2}$$

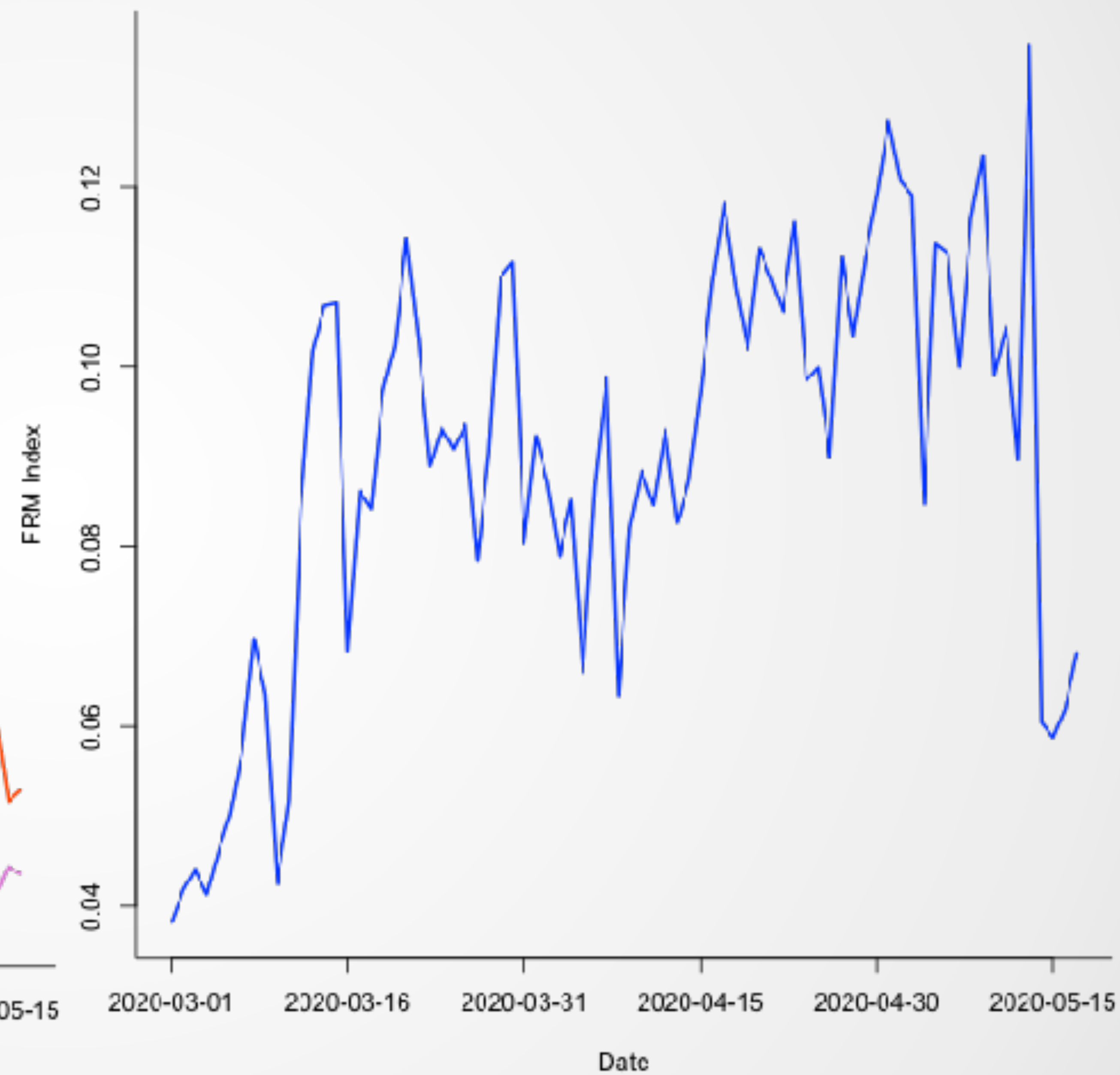
p_* is most central node, max is over all graphs with M nodes.

FRM@Crypto vs Average Out-degree Centrality



Out-degree Graph Centrality

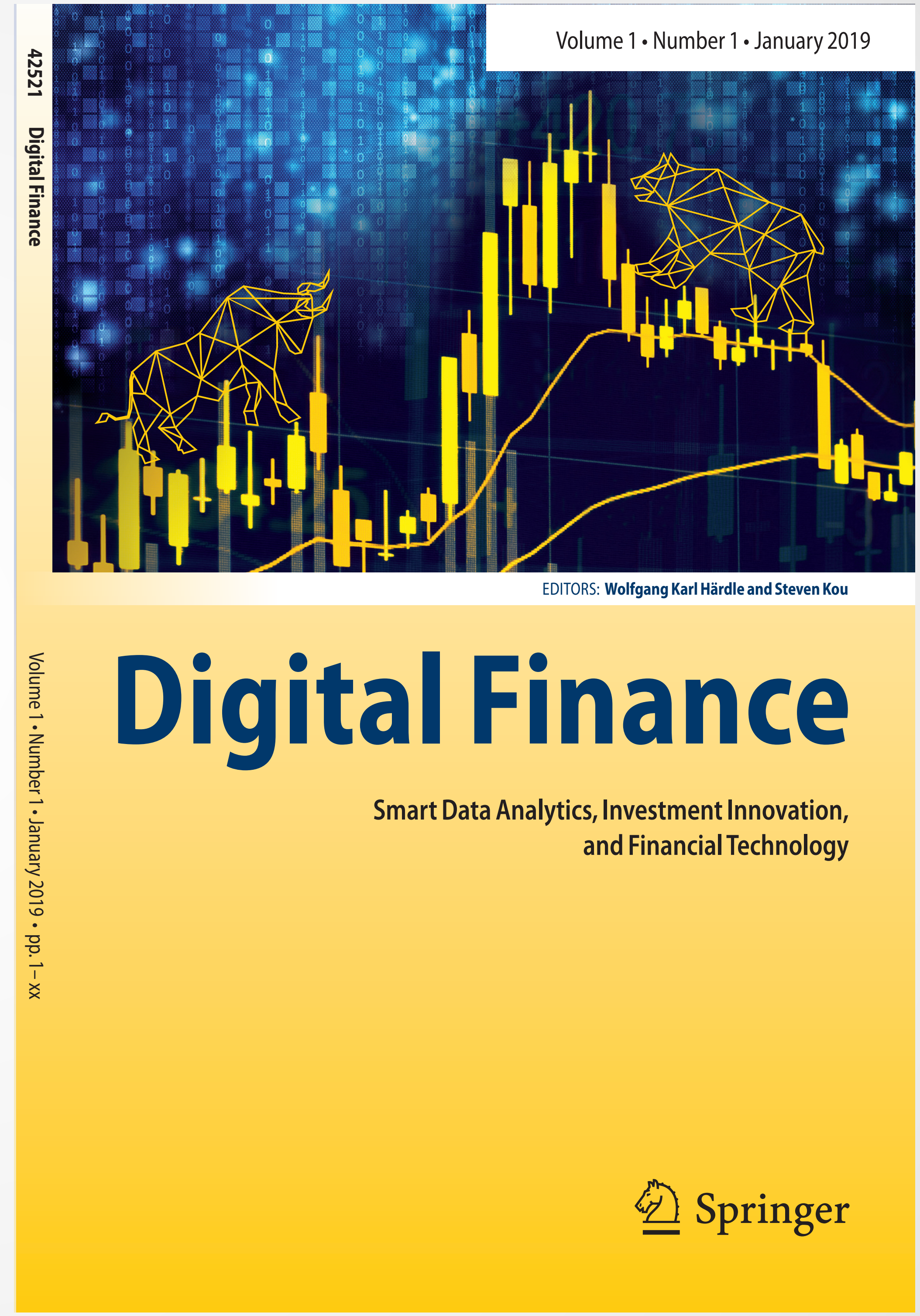




Trend comparison: Average out-degree centrality and Freeman centralisation vs FRM@Crypto index

FRM in FinTech, Cryptos, …

Vol 1. 2019 on Crypto Currencies



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FRM

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Expectile as Quantile

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

$$T(y) = \frac{G(y) - x\,F(y)}{2\{G(y) - y\,F(y)\} + y - \mu_Y}$$

and

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

▶ Back to Expectiles

Cryptocurrencies List (as per 24 May 2020)

Symbol	Name	Last Price (USD)	Market Cap (USD)	24H Volumes (USD)
BTC	Bitcoin	8946.62	164481372045	27576284769
ETH	Ethereum	203.41	22618375461	9311268064
XRP	XRP	0.19	8625857668	1236573262
BCH	Bitcoin Cash	226.73	4175489941	2639464553
BSV	Bitcoin SV	189.55	3492449683	939543182
LTC	Litecoin	42.79	2777753749	2307602277
EOS	EOS	203.46	22568743176	9923363991
BNB	Binance Coin	16.17	2393754841	258305237
XTZ	Tezos	2.70	1923243499	82421482
LINK	ChainLink	3.87	1469368639	358145283
ADA	Cardano	0.053	1656068633	100244607
XLM	Stellar	0.066	1333292859	323203952
XMR	Monero	62.03	1089971286	91193644
TRX	TRON	0.015	970220373	1372904826
HT	Huobi Token	8947.42	164496303531	27970959275

Source: www.coingecko.com

▶ FRM equations

β_j Selection

- Rewrite (2) as

$$\min_{\alpha_j^s,\beta_j^s} \left\{ n^{-1} \sum_{t=s}^{s+(n-1)} \rho_\tau (X_{j,t}^s - \alpha_j^s - A_{j,t}^{s\top} \beta_j^s) \right\} \qquad (4)$$

$$\text{s.t.} \quad |\beta_1^s| + \ldots + |\beta_J^s| \leq d \qquad (5)$$

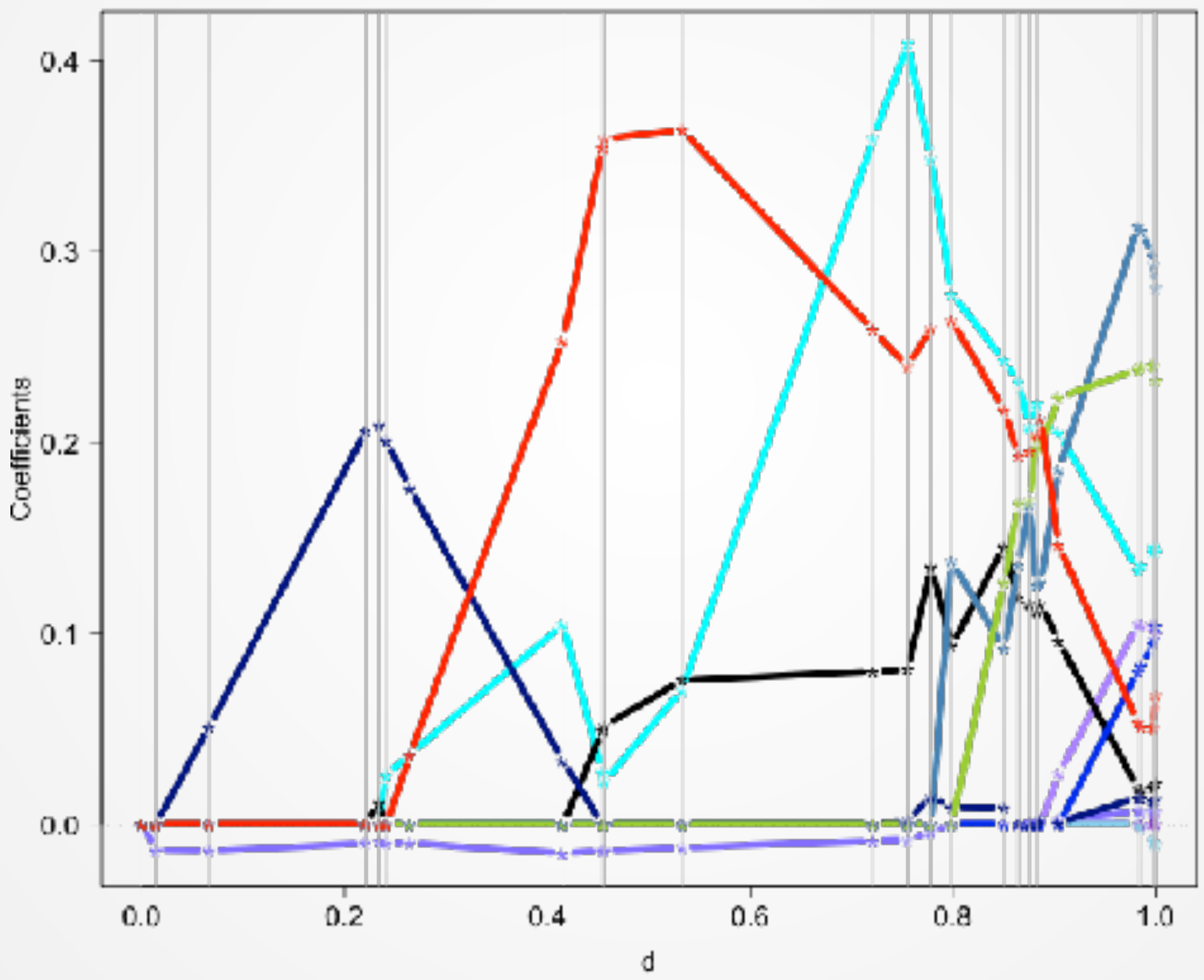
where d, regularisation parameter, plays the same role as λ

- $\beta_j^s(d)$ is piecewise linear $\succ$ # interpolated $y_i \overset{def}{=} df$ in (3)

FRM@Crypto β selection path

17 May 2020 Active Set: subset of 15 crypto currencies predictors

- FRM@Crypto Adjacency Matrix for more details



Entire solution path $\{\beta(d), 0 \leq d \leq \infty\}$ on 17 may 2020 for FRM@Crypto, $\tau = 5\%$, with true coefficients values on the left axis. BTC, ETH, XRP, BCH, LTC, EOS, XTZ, LINK, ADA, XLM, XMR are relevant variables