FRM financialriskmeter for Cryptos

Michael Althof

Vanessa Guarino

Rui Ren

Anna Shchekina

Humboldt-Universität zu Berlin
lvb.wiwi.hu-berlin.de
Charles University, WISE XMU, NCTU 玉山学者

Tail Events (TE)

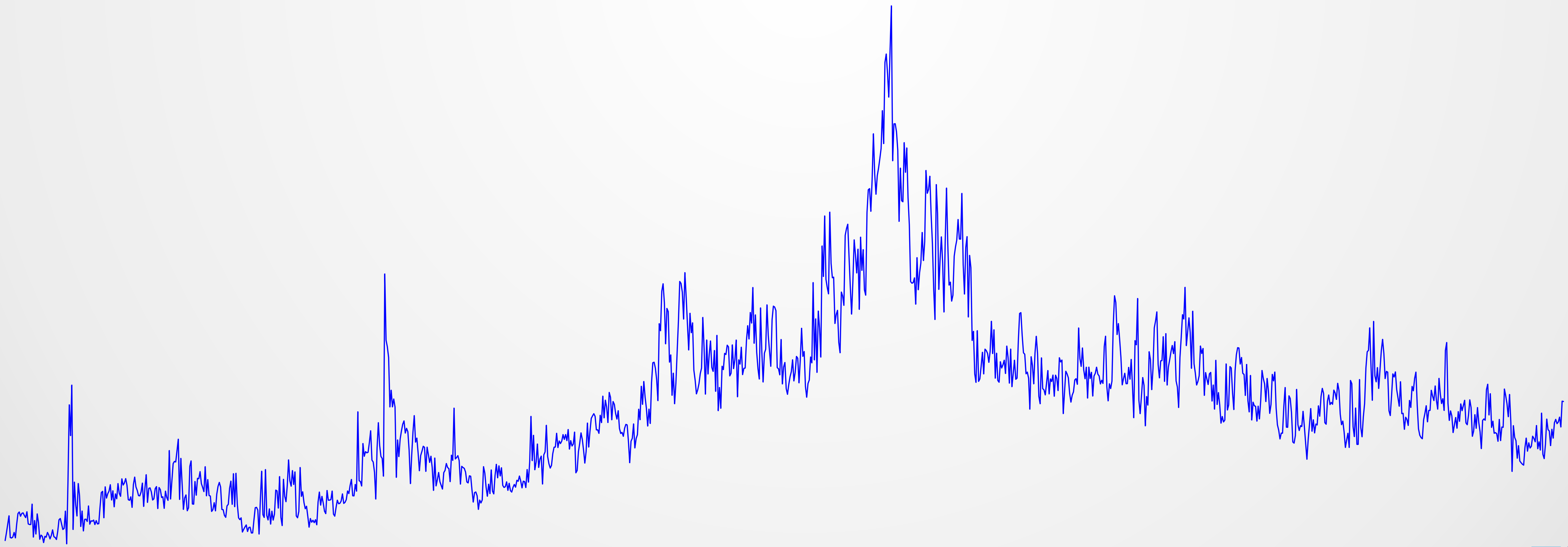
- TEs across Cryptos indicate increased risk
- CoVaR measures joint TEs between 2 risk factors
- CoVaR and other risk factors?
- TENET Tail Event NETwork risk, Härdle Wang Yu (2017) J E’trics
- FRM Financial Risk Meter for joint TEs

Dash

libra

Risk Measures

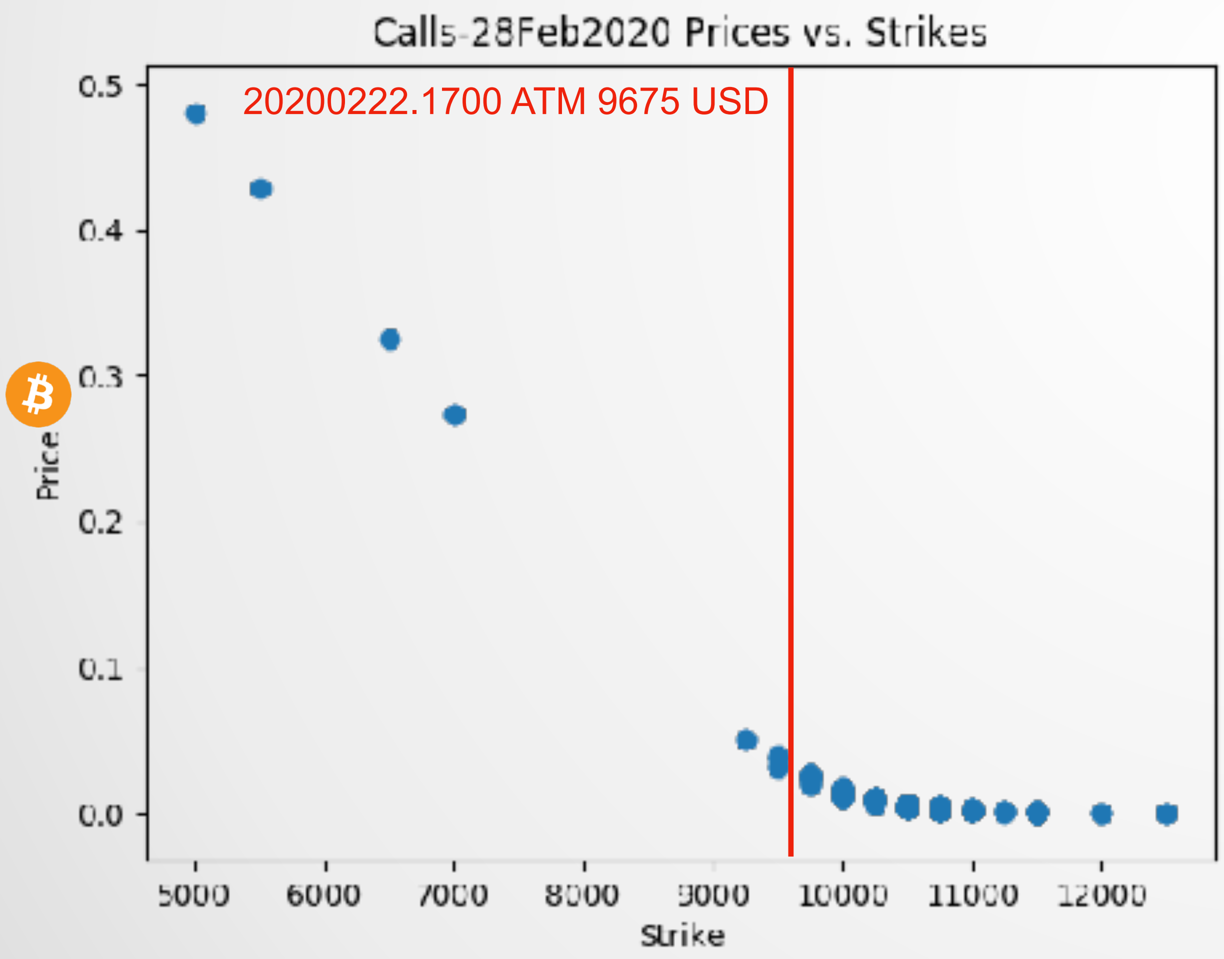
- VIX: IV based, does not reflect joint TEs
- CoVaR concentrates on a pair of risk factors
- CISS, Google trends, SRISK, …
- FRM displays the full picture of TE dependencies
- Firamis.de/FRM financialriskmeter

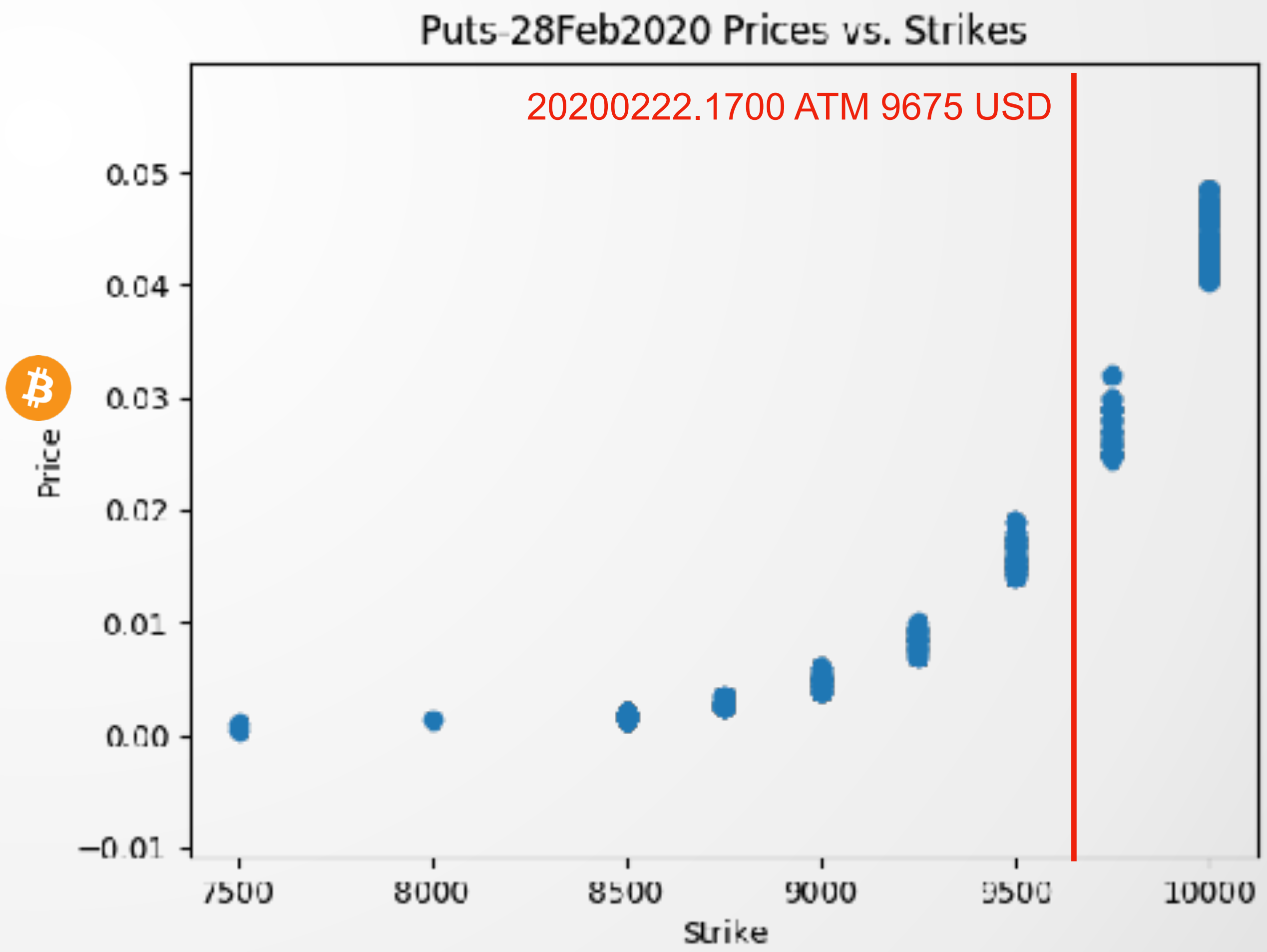


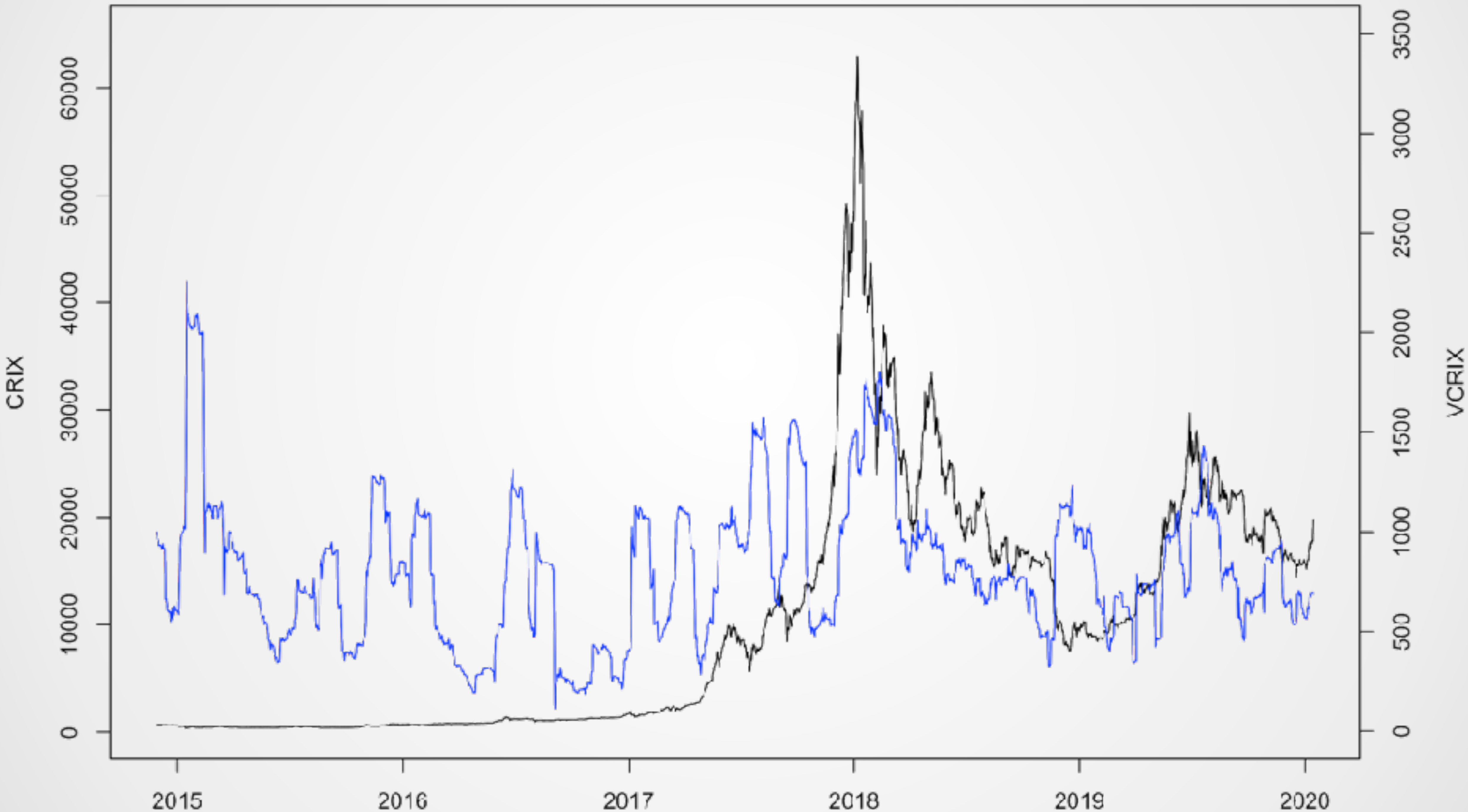
Call and Puts on BTCs

- Listed at Bloomberg since 20200113

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






CRIX
VCRIX
0
10000
20000
30000
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60000
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2000
2500
3000
3500
2015
2016
2017
2018
2019
2020

Outline

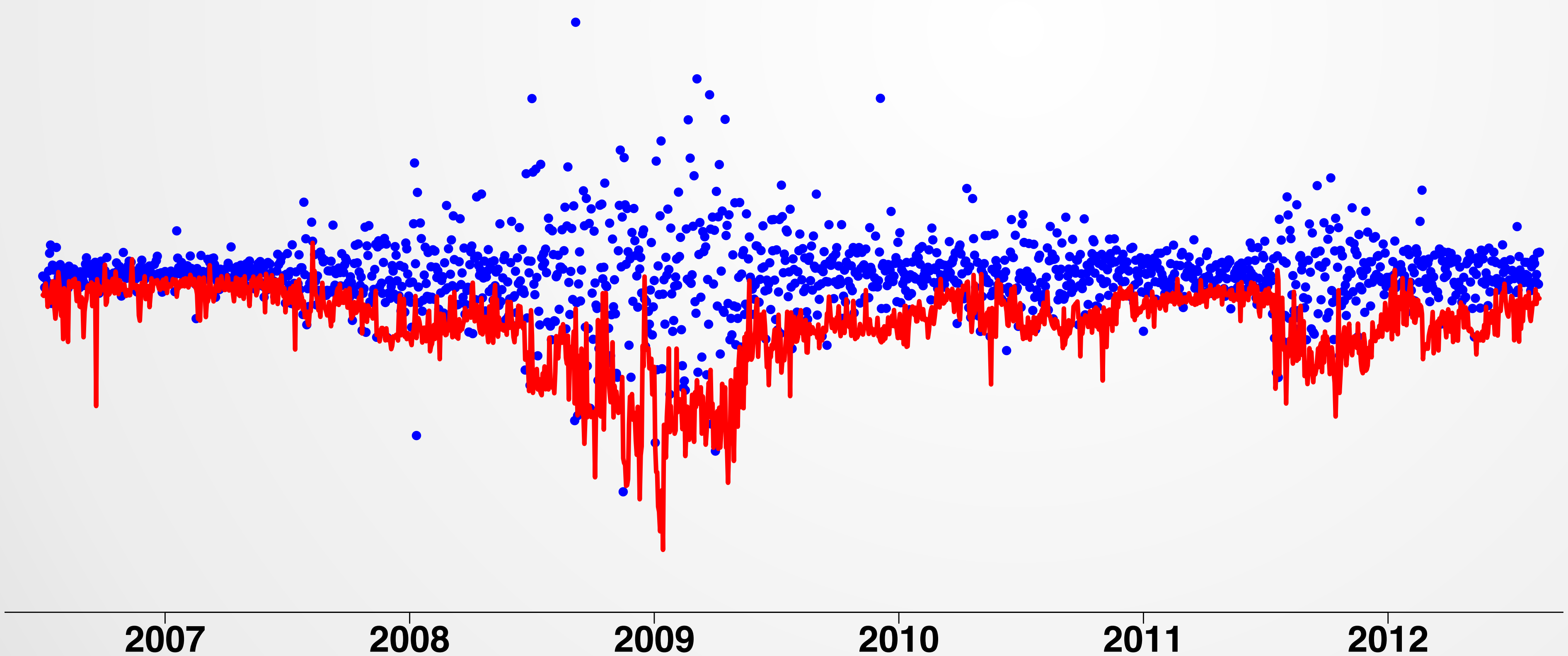
1. Motivation ✔
2. Genesis
3. Framework
4. Applications
5. Node influence metrics
6. Sensitivity analysis
7. Network centrality
8. Portfolio Construction
9. Conclusions

VaR Value at Risk

- Probability measure based

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

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



Quantiles and Expectiles

For r.v. Y obtain tail event measure:

log returns

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

asymmetric loss function

$$\rho_\tau(u) = |u|^c\,|\tau - \mathrm{I}_{\{u<0\}}|$$

$c = 1 \succ$ quantiles

$c = 2 \succ$ expectiles

▶ Expectile as Quantile

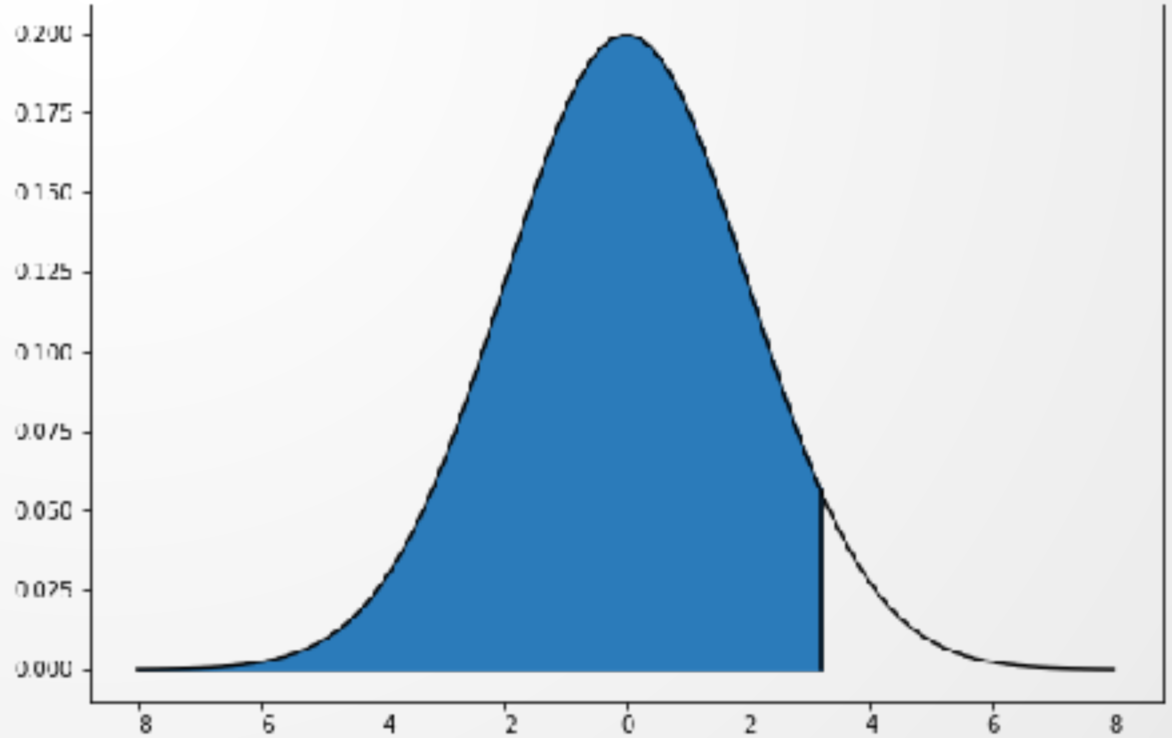


Figure: Quantile of $N(0,2)$, $\tau = 0.7$, $q^\tau = 3.2$

Conditional Value at Risk

- Adrian and Brunnermeier (2016) introduced CoVaR

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

- M_{t-1} vector of macro-related variables
- Nonlinear features, $\tau = 0.05$

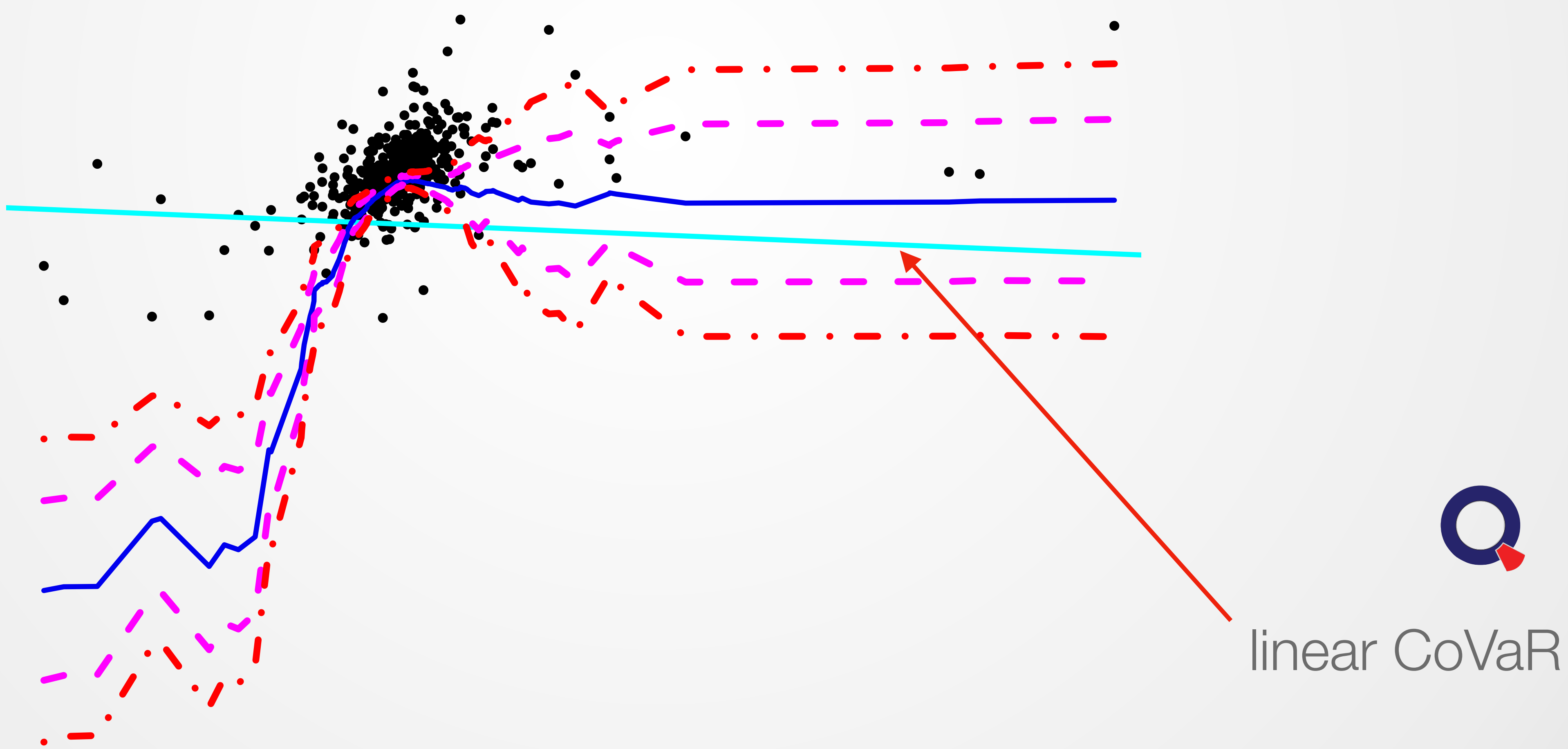


Figure: Goldman Sachs (Y), Citigroup (X), Confidence Bands, see Chao et al (2015)

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

$$r^s_{j,t} = \alpha^s_{j,t} + A^{s\top}_{j,t}\beta^s_j + \varepsilon^s_{j,t} \tag{1}$$

$$A^{s\top}_{j,t} \stackrel{\text{def}}{=} \left[M^s_{t-1}, r^s_{-j,t}\right]$$

where:

- $r^s_{-j,t}$ log returns of all cryptos except $j \in 1:J$ at $t \in 2:T$
- s length of moving window
- M^s_{t-1} log return of macro prudential variable at time $t-1$
- For application, consider $J = 15$, $s = 63$

▶ Crypto List ▶ Macroprudential

Lasso Quantile Regression

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

- 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 Lasso Regression

- Osborne et al. (2000)
- Dependence, time-varying, institution-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

- 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)

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

- 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

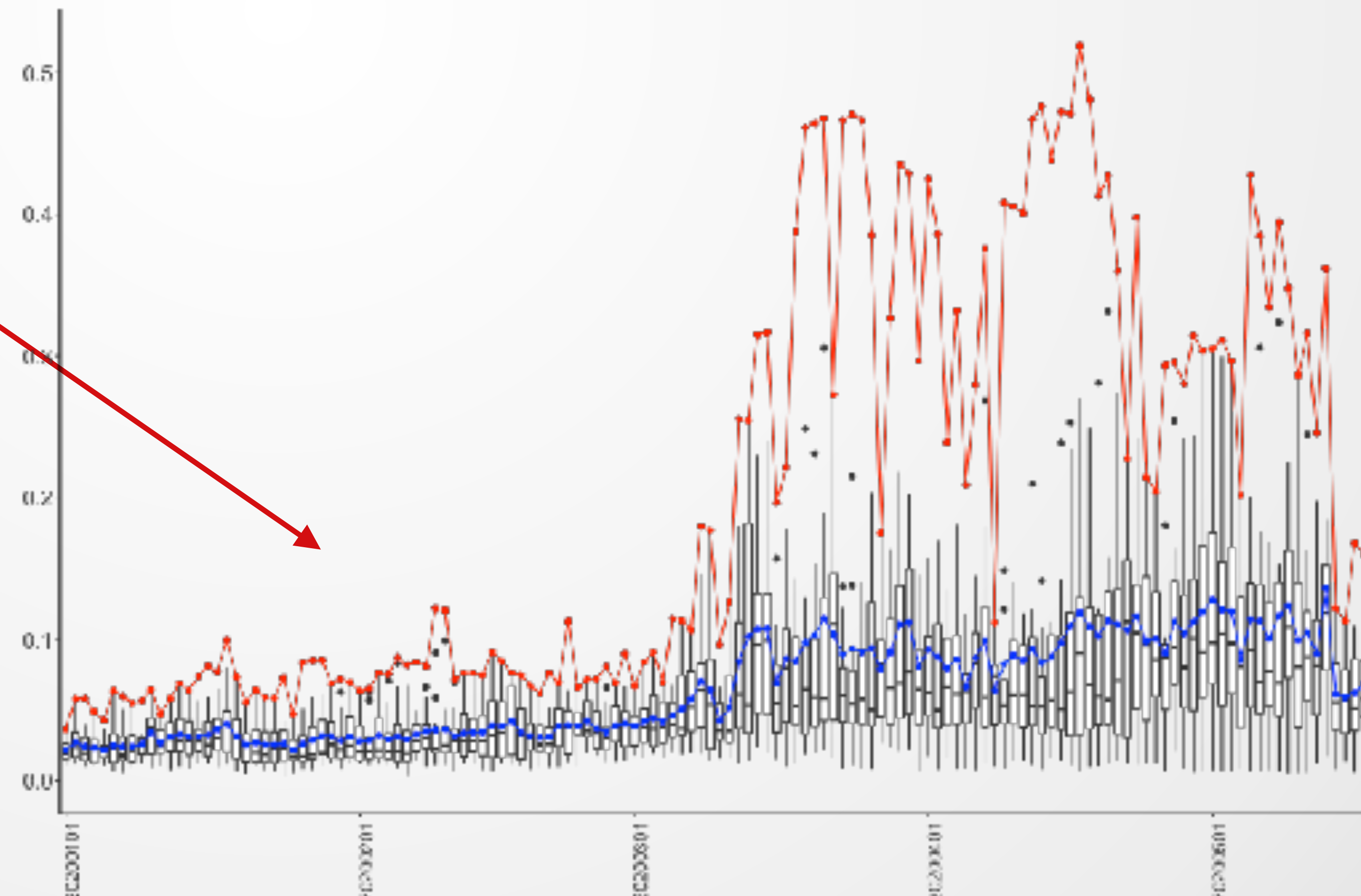
- Generalized approximate cross-validation (GACV) (Yuan, 2006)

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

Coeff's depend on λ

where: df dimensionality of fitted model

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



FRM codes

FIRAMIS app HU Berlin app

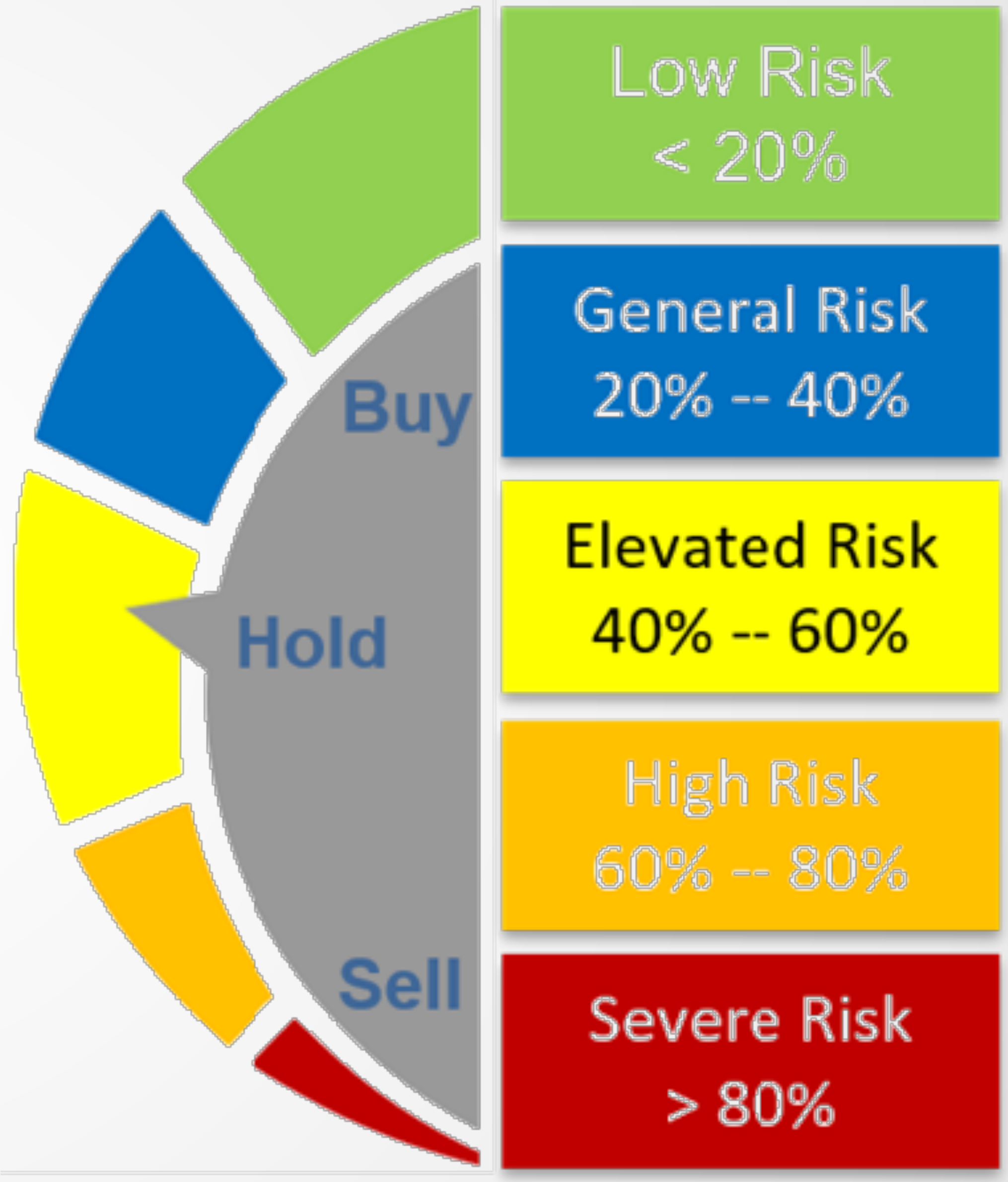
FRM@Americas

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)
  - S&P500

LQ Lasso Regression

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

FRM@Crypto Distribution

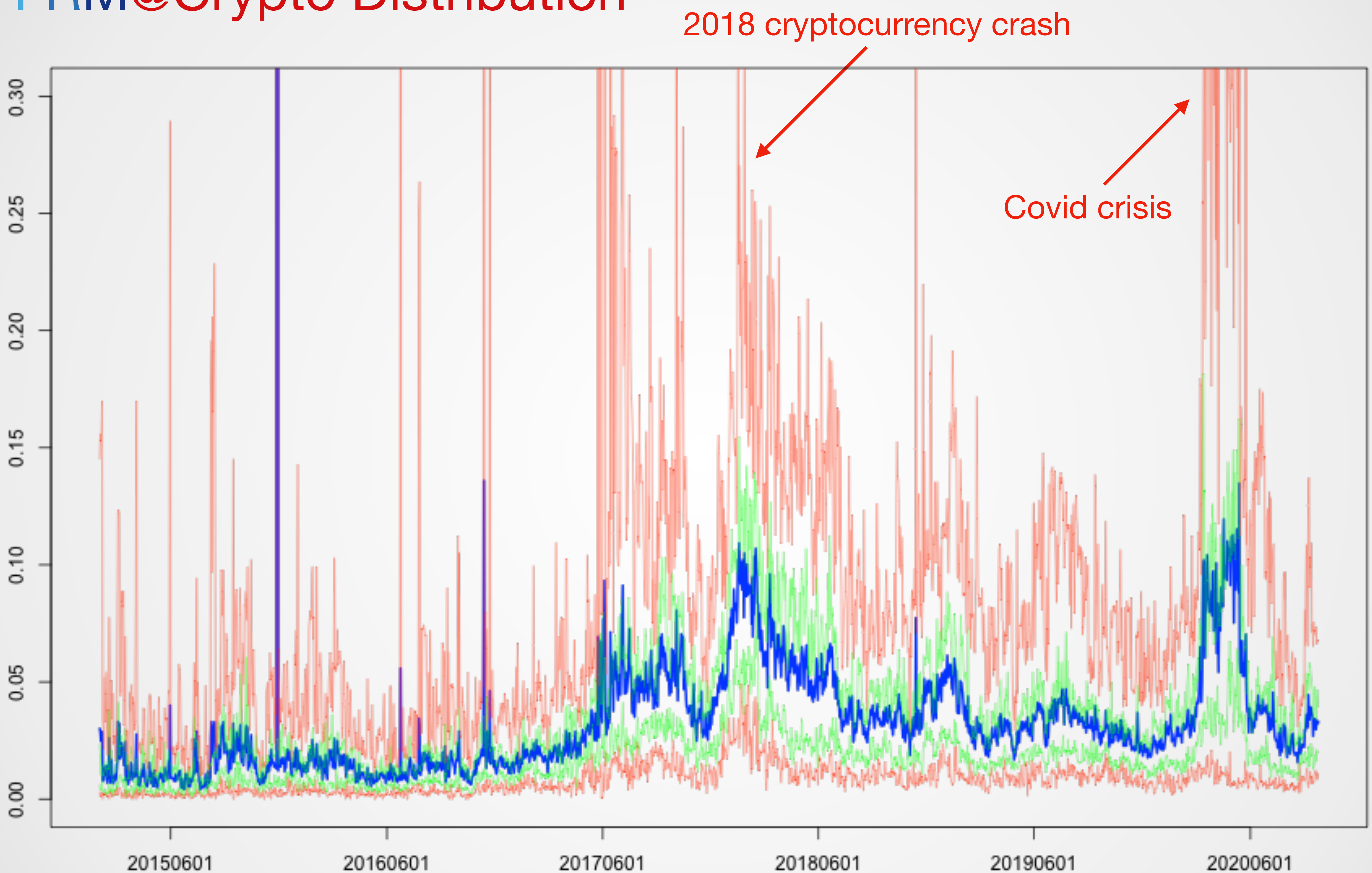


Figure: FRM@Crypto, Max and Min and 75 % and 25 % Quantiles for $\tau = 5\,\%$

FRM@Crypto Distribution

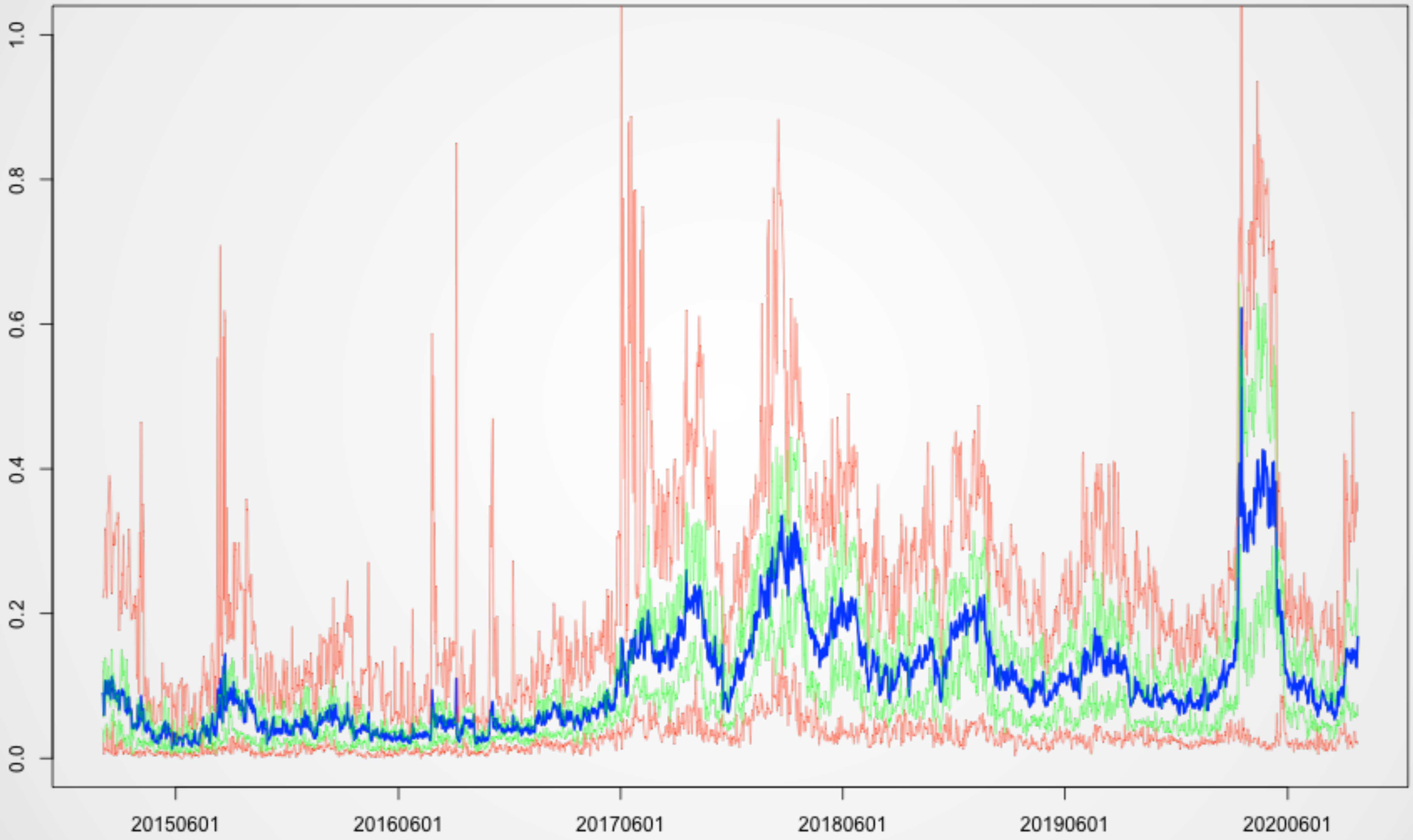


Figure: FRM@Crypto, Max and Min and $75\,\%$ and $25\,\%$ quantiles for $\tau = 10\,\%$

FRM@Crypto Distribution

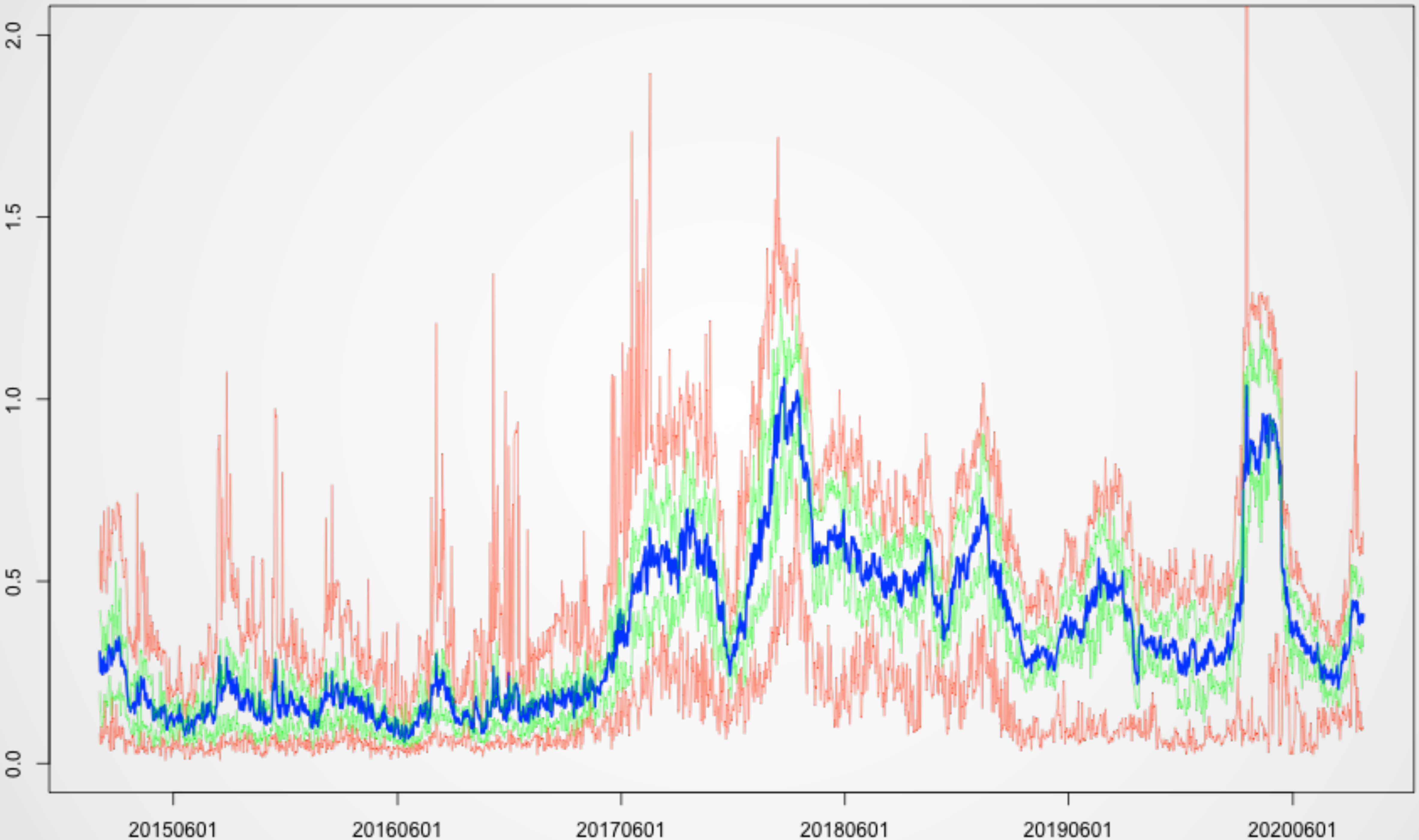


Figure: FRM@Crypto, Max and Min and 75 % and 25 % quantiles for $\tau = 25\ \%$

FRM@Crypto Distribution

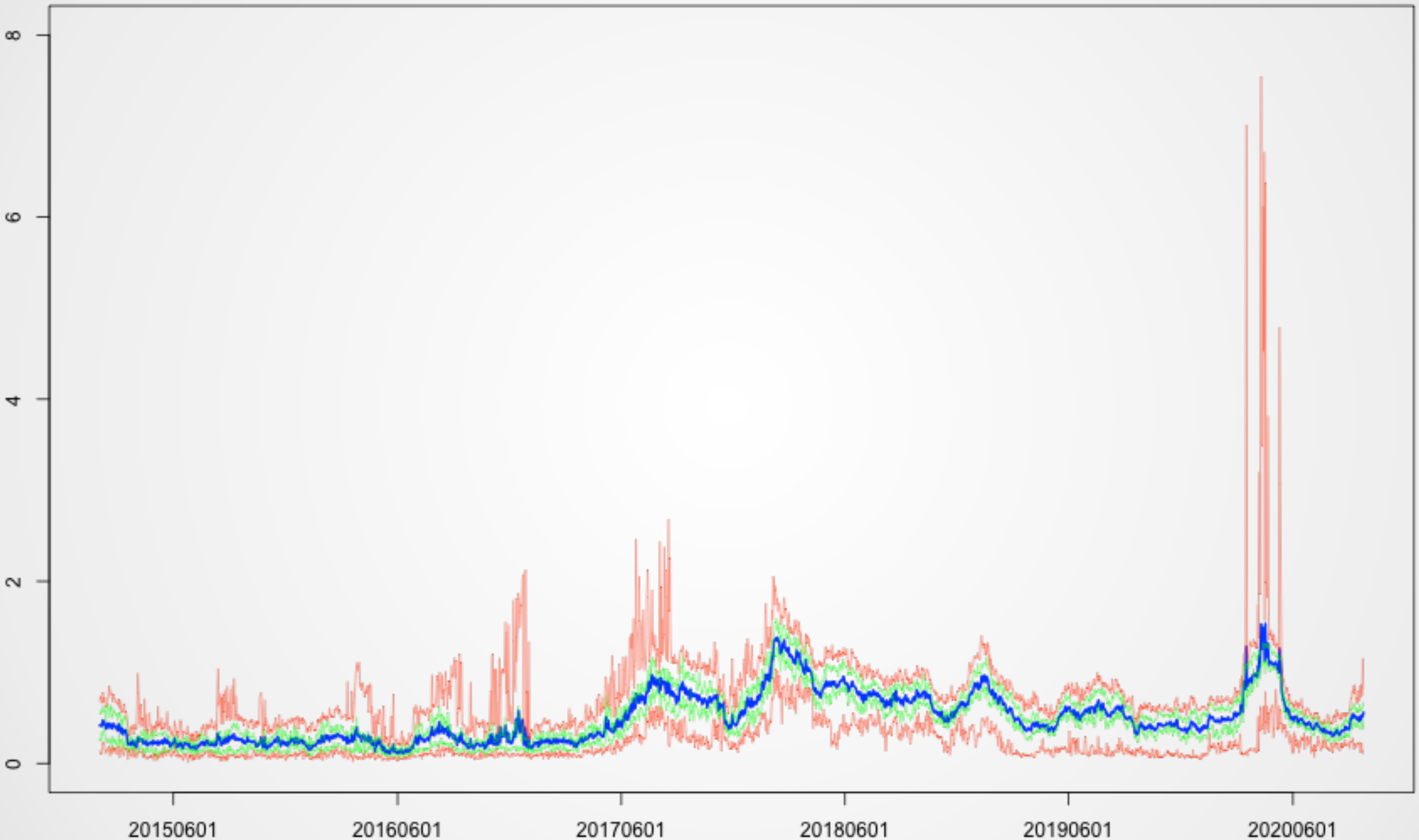
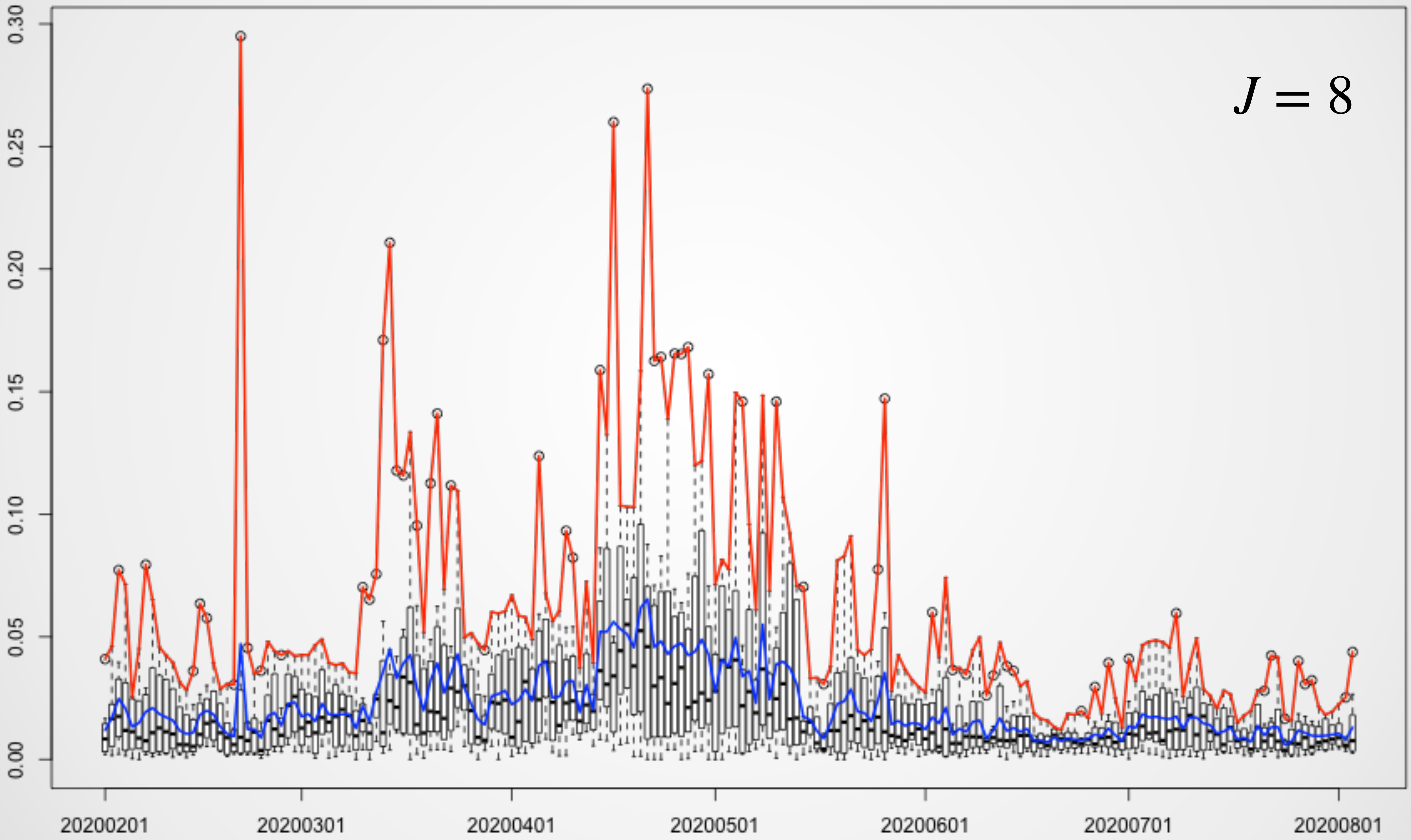
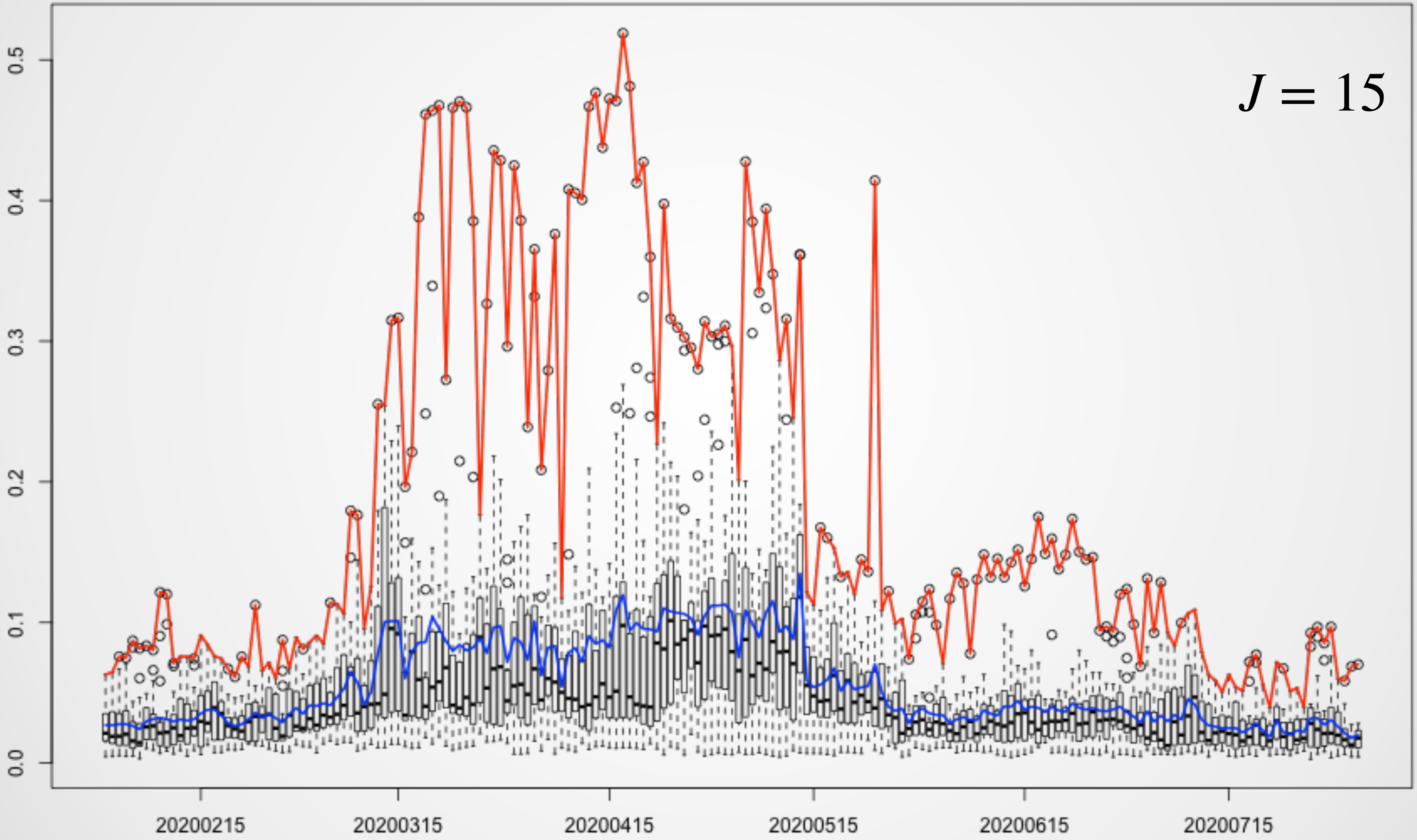


Figure: FRM@Crypto, Max and Min and 75 % and 25 % quantiles for $\tau = 50\,\%$

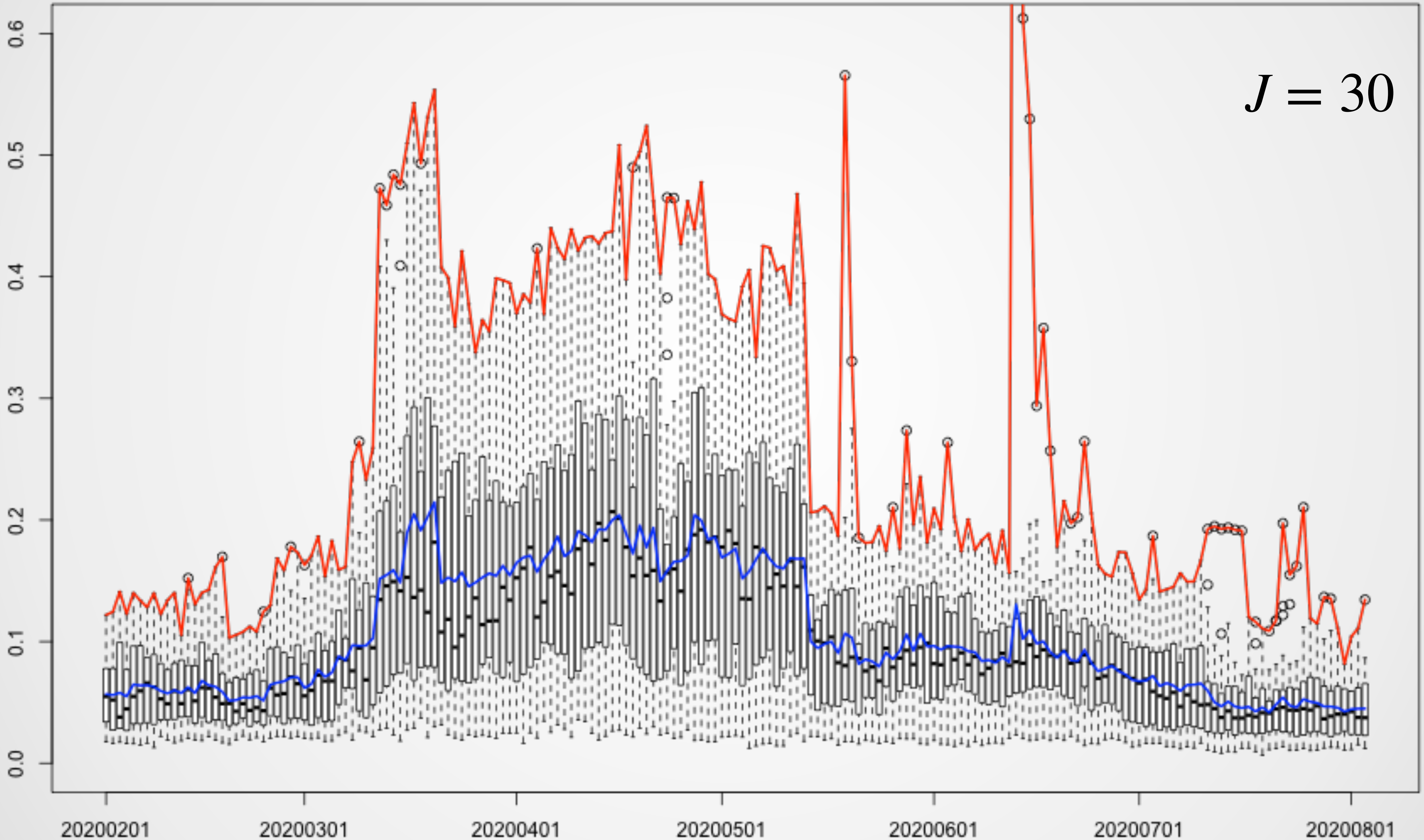
BTC and ETH dominate the market - FRM reflects?



BTC and ETH dominate the market - FRM reflects?



BTC and ETH dominate the market - FRM reflects?



Tail risk and window size sensitivity: FRM@Crypto Index

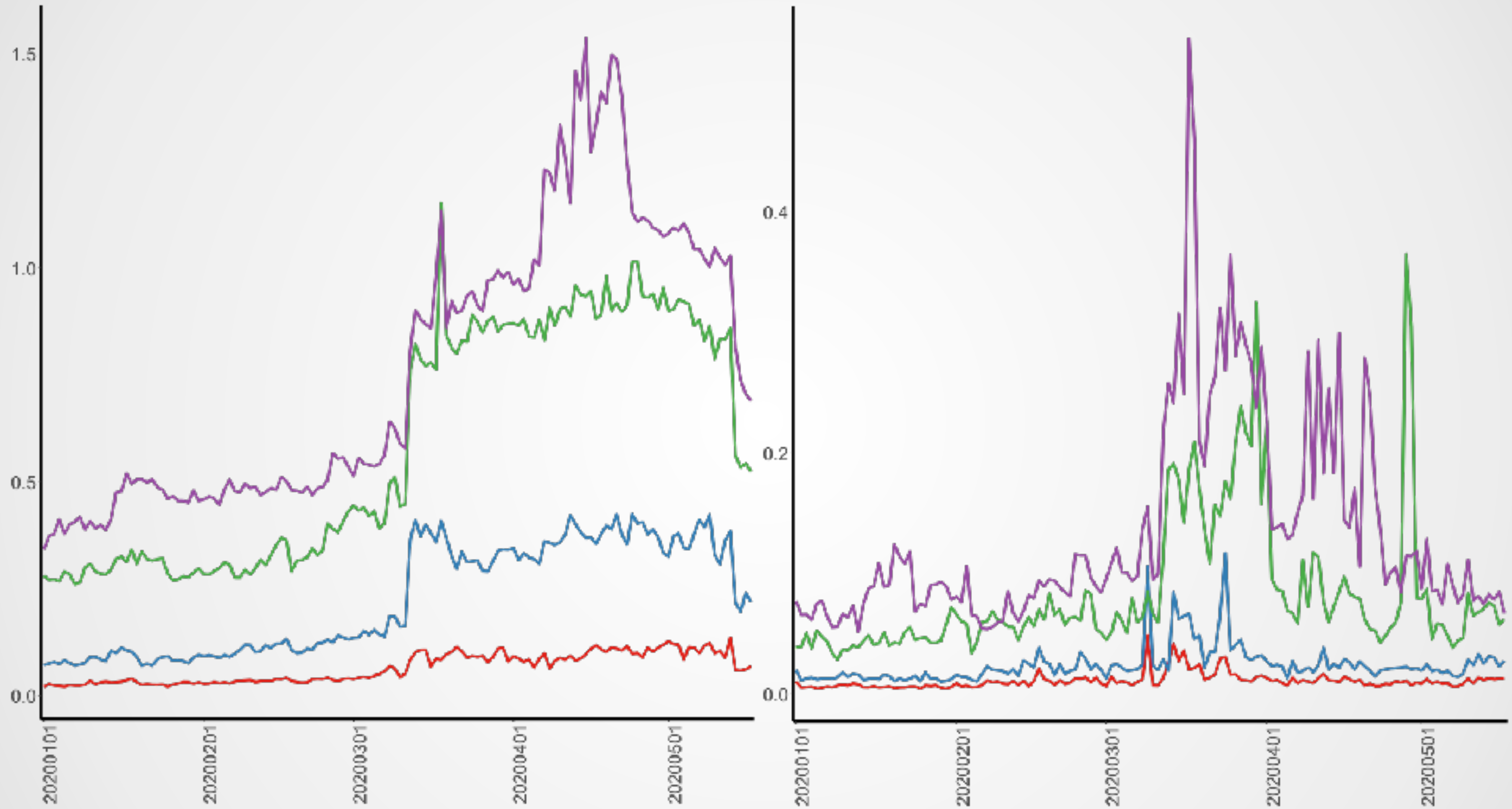


Figure: FRM@Crypto index for tail risk $\tau = 5\%, 10\%, 25\%, 50\%$ for $s = 63$ (left) and $s = 21$ (right).
Data from 01 January 2020 to 17 May 2020.

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

Table: 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 1 January 2020 to 17 May 2020.

FRM@Crypto Model Selection Methods

	$\tau = 0.05$			$\tau = 0.10$			$\tau = 0.50$		
	λ_j	SIC_j	$GACV_j$	λ_j	SIC_j	$GACV_j$	λ_j	SIC_j	$GACV_j$
BTC	0.039	-6.633	0.001	0.266	-5.928	0.002	0.837	-4.387	0.011
ETH	0.018	-2.495	0.074	0.030	-1.974	0.130	0.702	-1.644	0.193
XRP	0.034	-6.871	0.001	0.368	-5.683	0.003	0.828	-4.702	0.008
BCH	0.071	-6.742	0.001	0.307	-5.947	0.002	0.763	-4.794	0.007
BSV	0.058	-6.686	0.001	0.292	-5.773	0.003	0.504	-5.011	0.006
LTC	0.052	-6.396	0.001	0.097	-5.747	0.003	0.729	-4.516	0.010
EOS	0.030	-4.516	0.009	0.064	-4.128	0.015	0.402	-3.609	0.025
BNB	0.088	-7.206	0.001	0.039	-6.633	0.001	0.929	-4.459	0.011
XTZ	0.091	-6.505	0.001	0.206	-5.885	0.002	0.742	-4.577	0.009
LINK	0.132	-6.824	0.001	0.236	-5.980	0.002	0.698	-4.750	0.008
ADA	0.051	-6.314	0.002	0.229	-5.667	0.003	0.802	-4.509	0.010
XLM	0.058	-6.534	0.001	0.194	-5.680	0.003	0.579	-4.523	0.010
XMR	0.160	-6.584	0.001	0.277	-5.835	0.003	0.770	-4.778	0.008
TRX	0.080	-6.236	0.002	0.220	-5.250	0.005	0.541	-4.684	0.009
HT	0.059	-6.513	0.001	0.226	-5.716	0.003	0.526	-4.679	0.008

Table: λ_j and effective dimension of the j-fitted models, via solution path of the $L1$-norm QR algorithm and formula for $\tau = 5\%, 10\%, 50\%$. In all the settings $s = 63$, $J = 15$.

Data from 1 January 2020 to 17 May 2020.

Flight into Cash: 2018 vs 2020 Crises

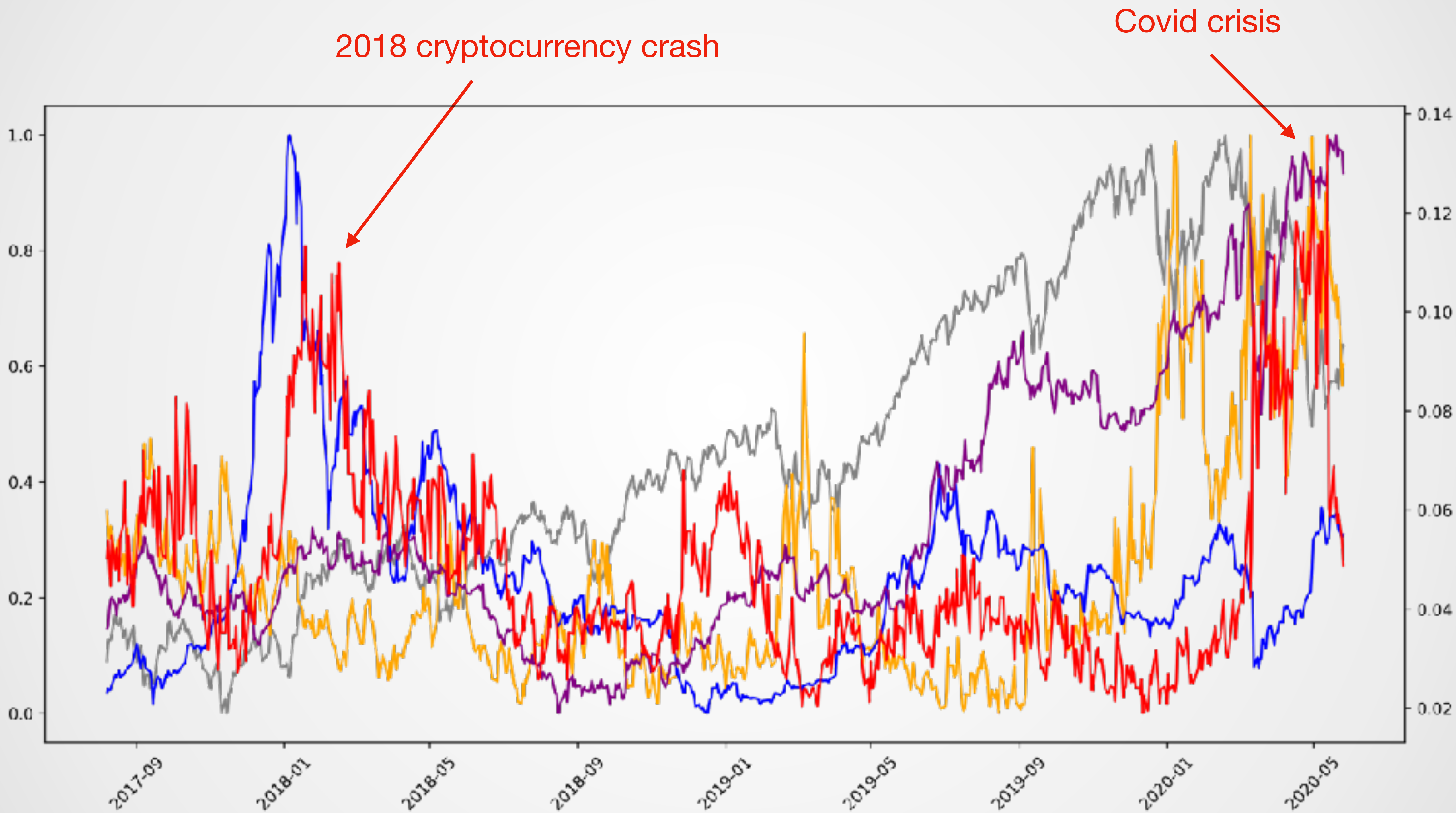


Figure: Normalised S&P500 Index, VIX Index, CRIX Index, Gold Price and FRM@Crypto

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

Visualising the Active Set: FRM@Crypto the Movie

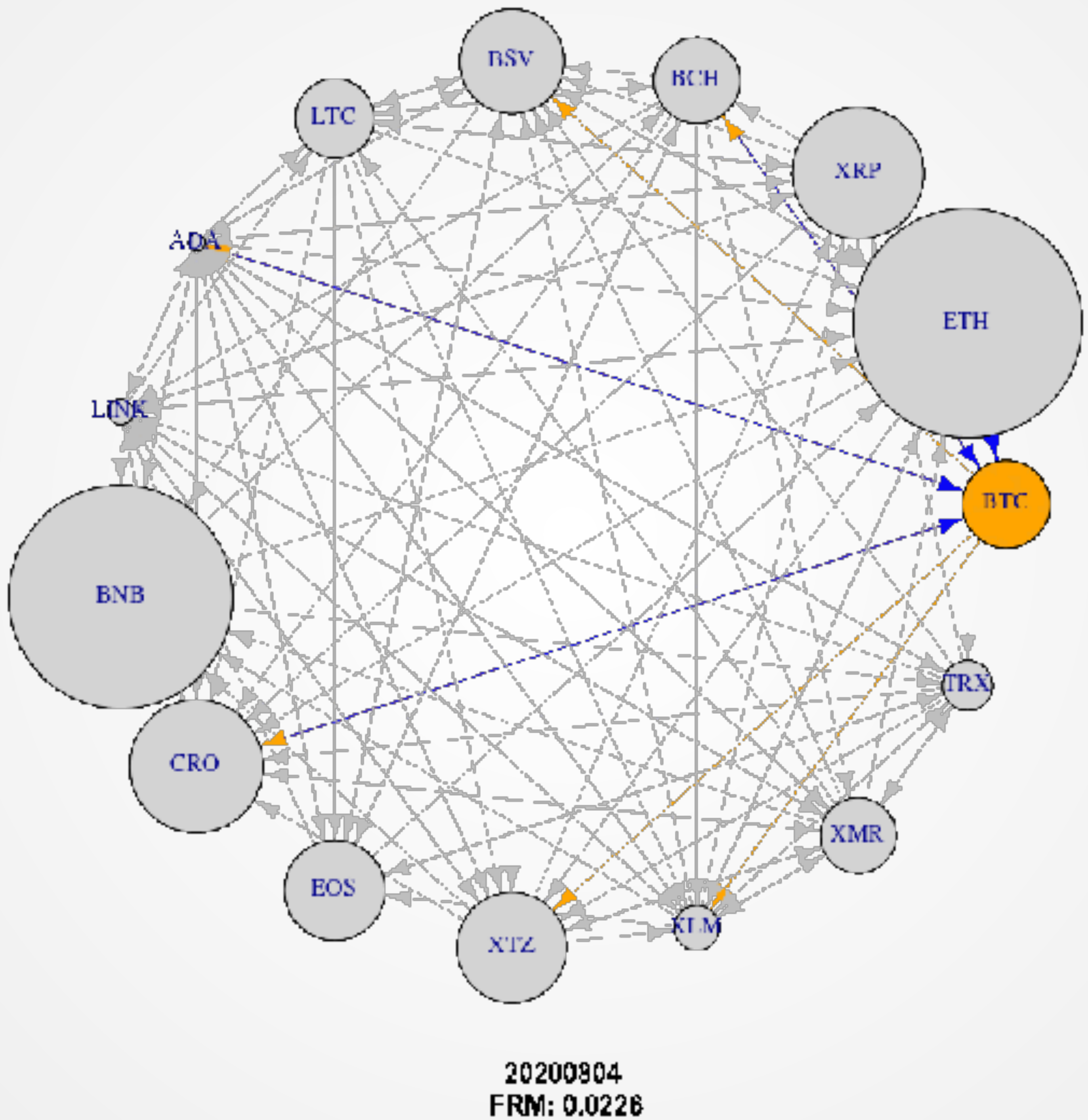
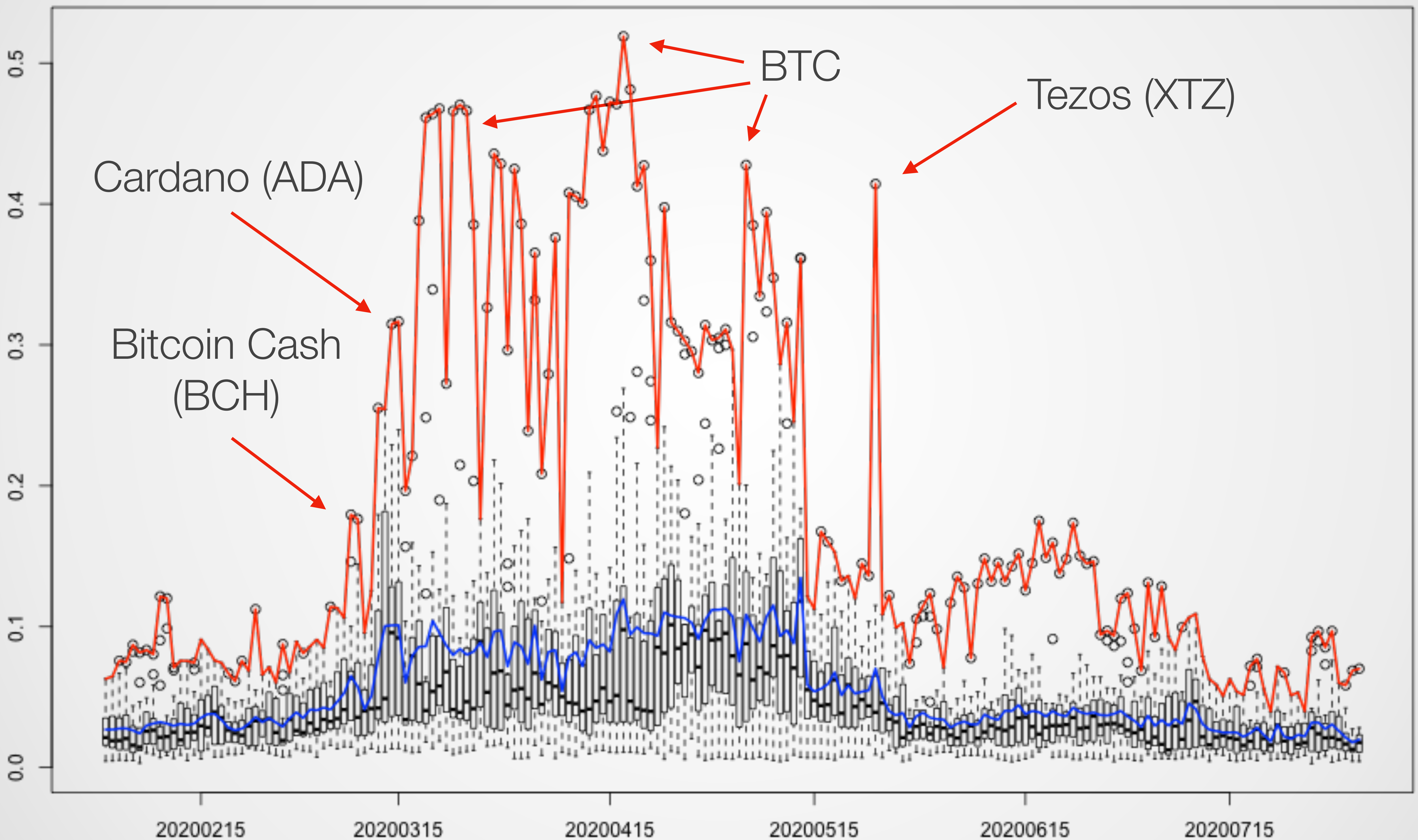
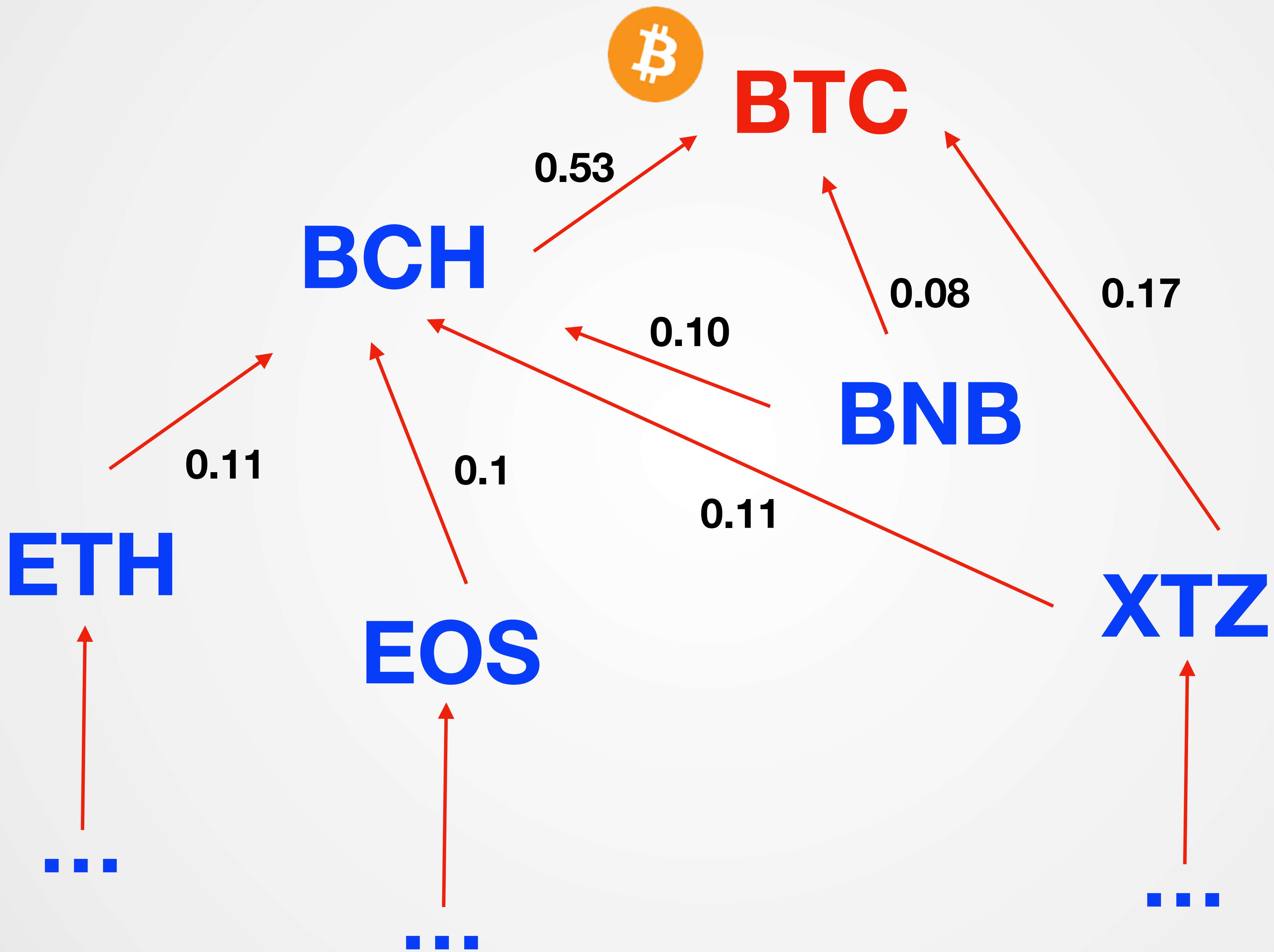


Figure: Network analysis for FRM@Crypto from 4 August 2020 to 24 September 2020. Size of the node corresponds to λ

FRM@Crypto Distribution under Covid Crisis



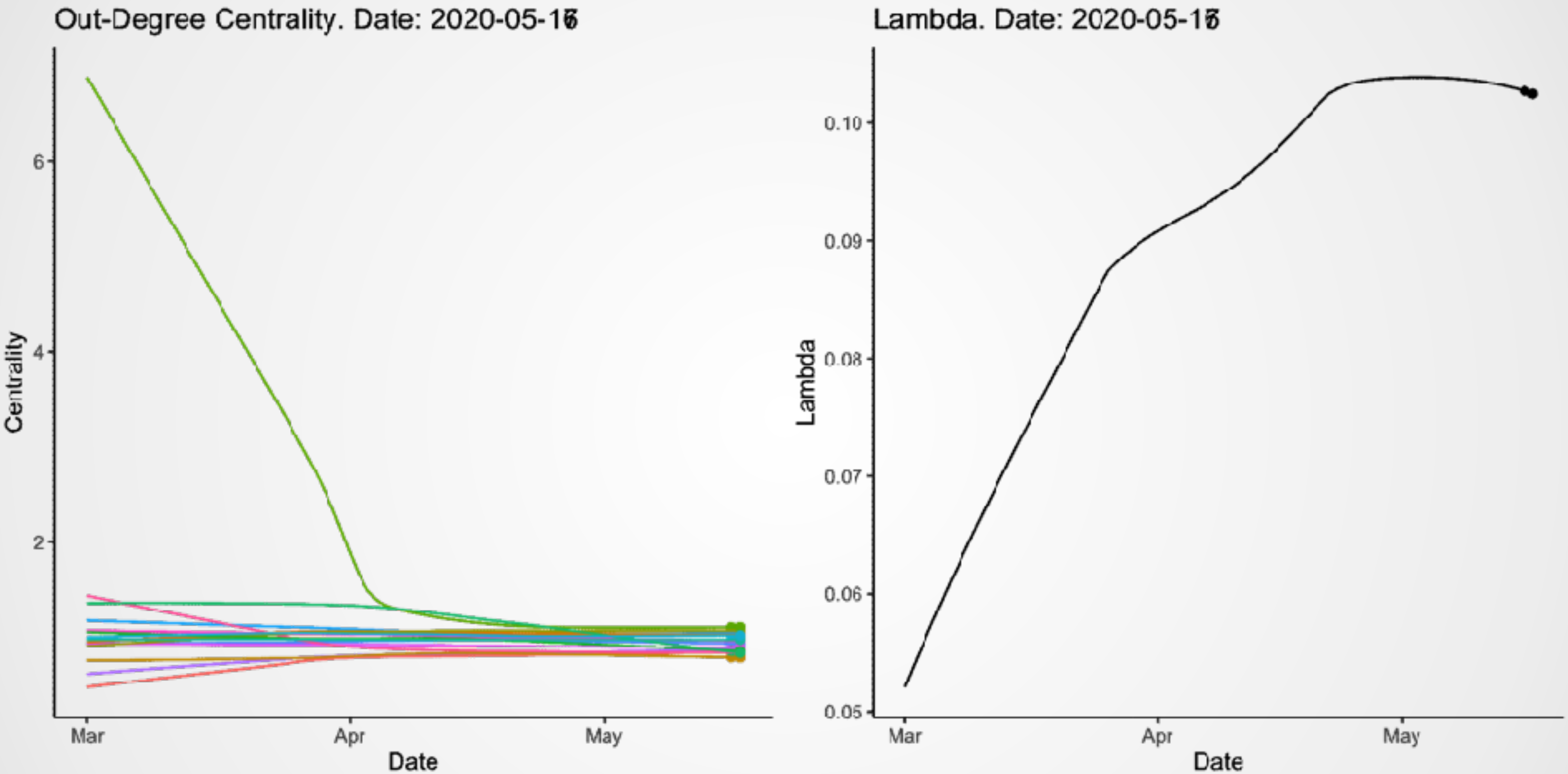
29 April 2020 — Marginal Return Contribution to BTC



Types of Centrality of a Node

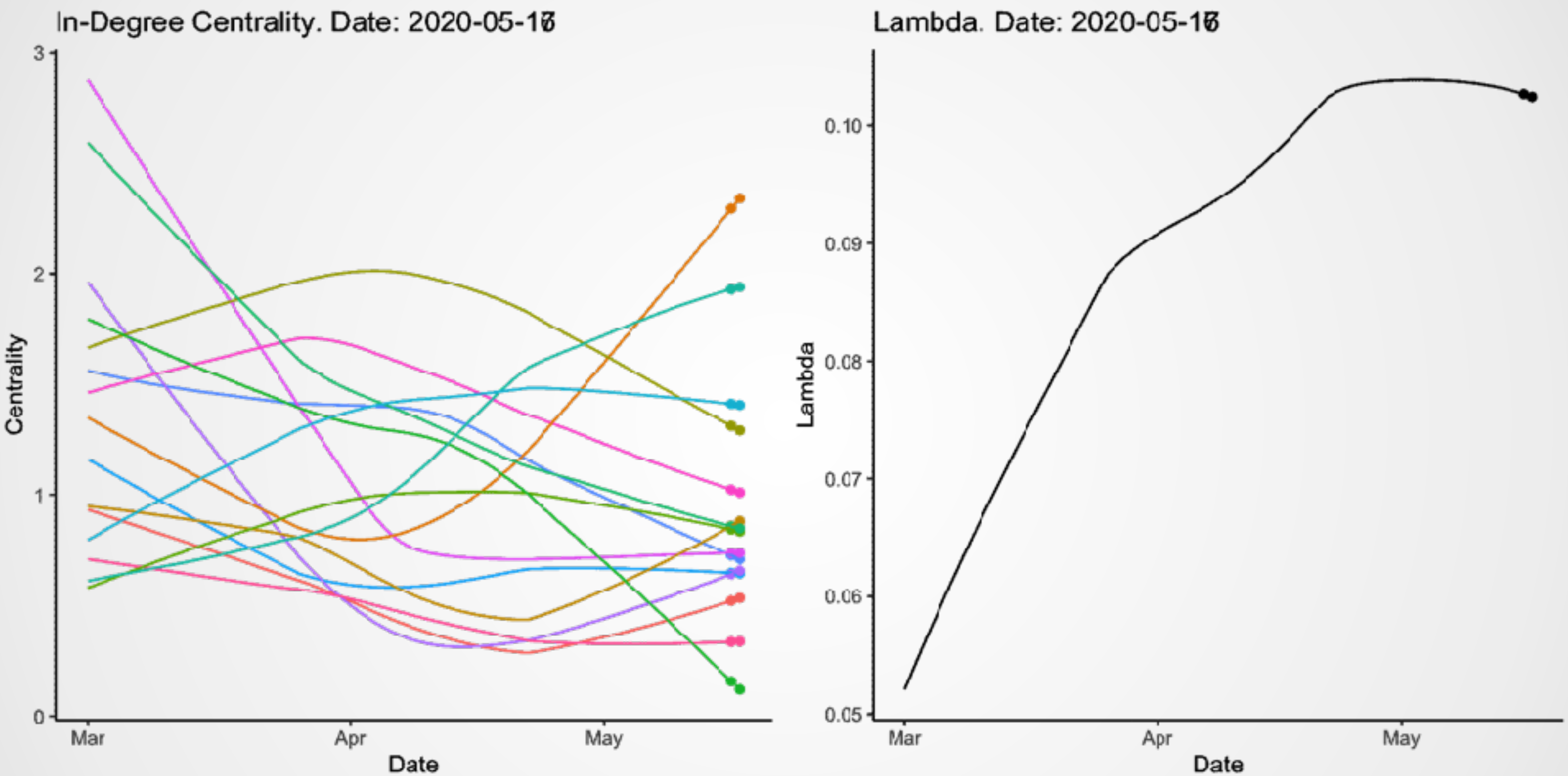
- Degree centrality
  - *In-degree* — how many other coins affect the node
  - *Out-degree* — how many other coins the node affects
- *Closeness* — shortest path between the node and all other nodes
- *Betweenness* — the number of times a node acts as a bridge along the shortest path between two other nodes
- *Eigenvector* — takes into account that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes

FRM@Crypto Out-Degree Centrality



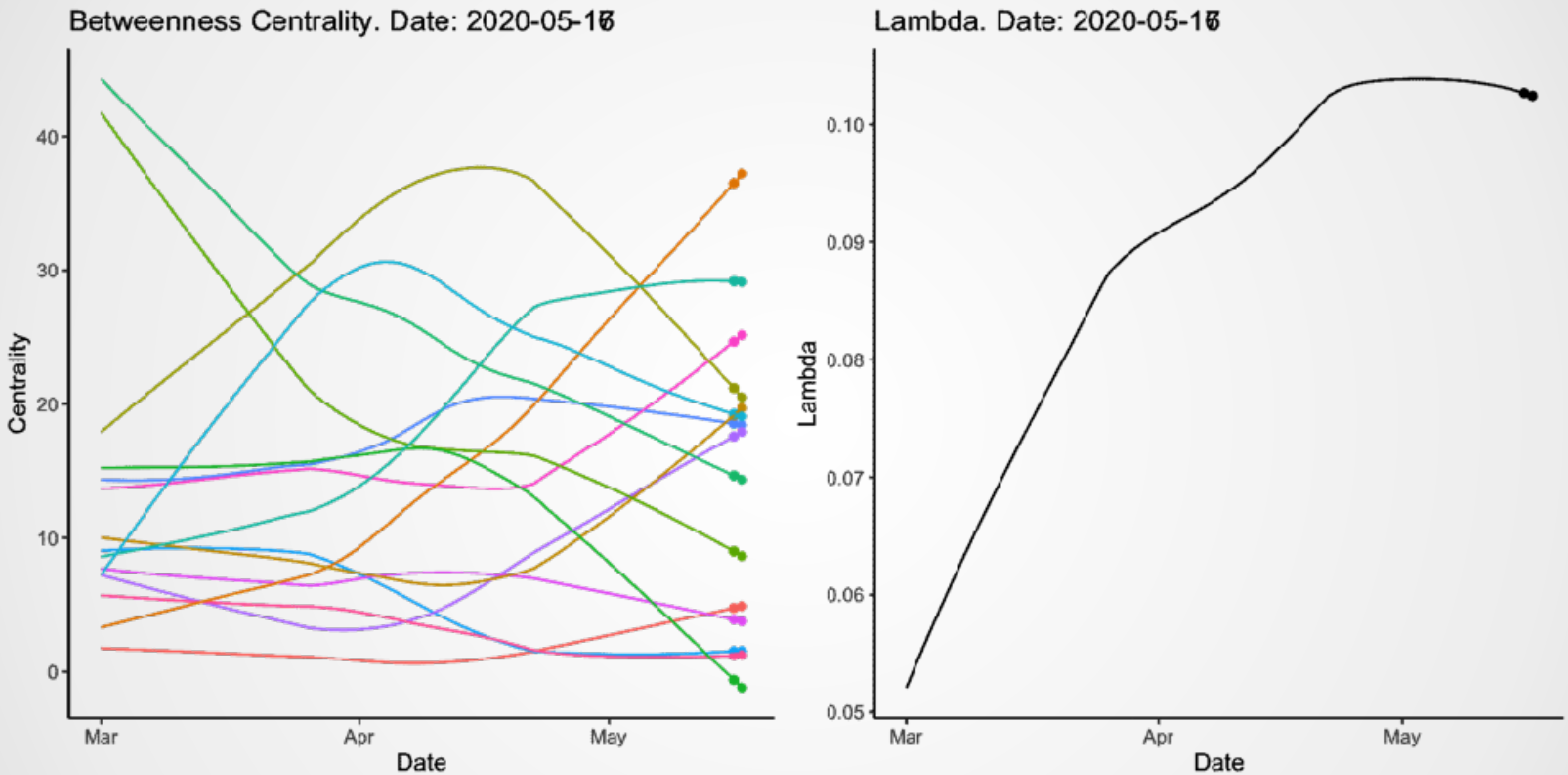
Left-hand side panel: # of outbounds links of BTC, ETH, XRP, BCH, BSV, LTC, EOS, BNB, XTZ, LIN, ADA, XLM, XMR, TRX, HT. Right-hand side panel: FRM index over time.
Data from 01 March 2020 to 17 May 2020

FRM@Crypto In-Degree Centrality



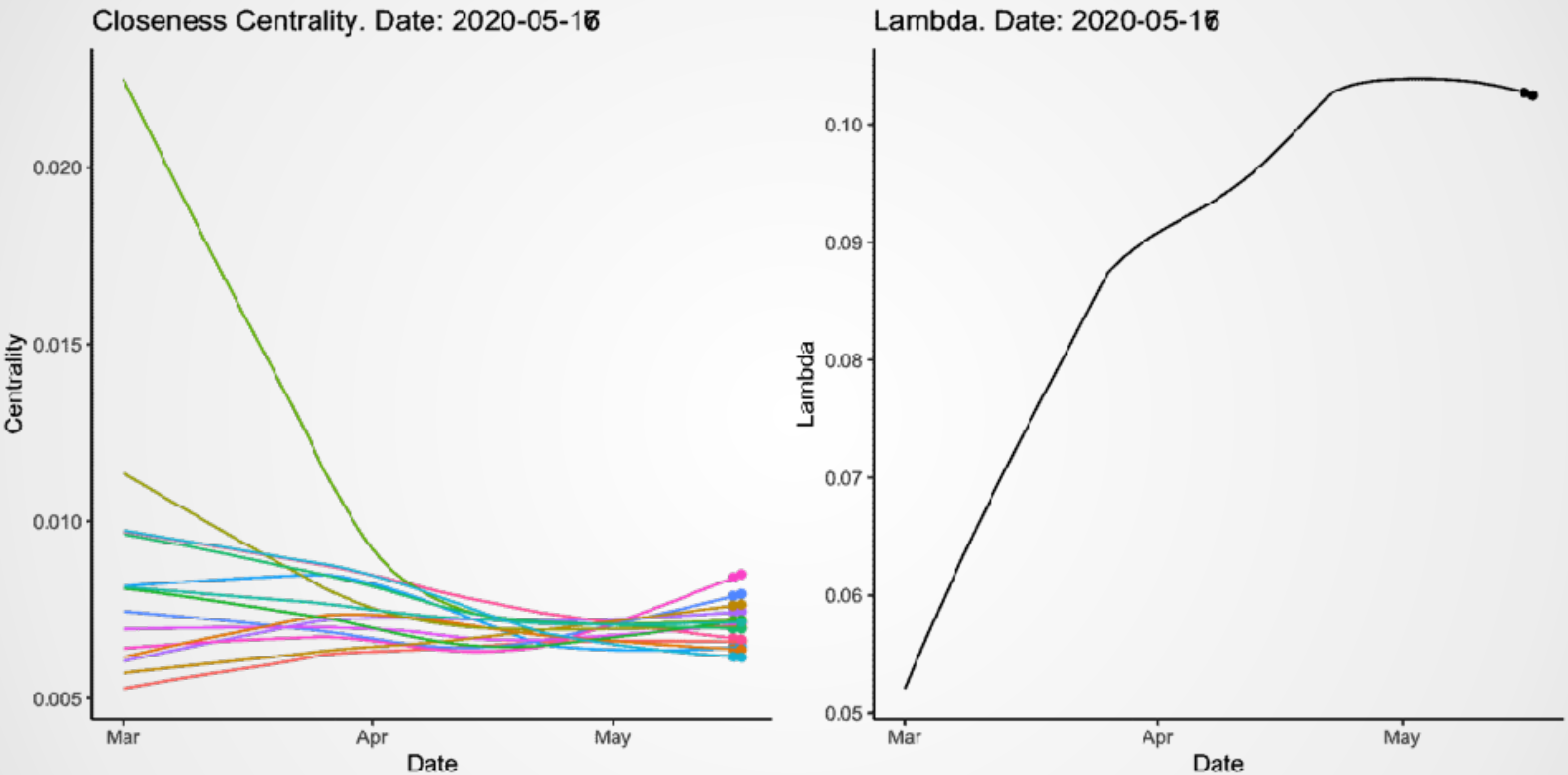
Left-hand side panel: # of inbound links of BTC, ETH, XRP, BCH, BSV, LTC, EOS, BNB, XTZ, LIN, ADA, XLM, XMR, TRX, HT. Right-hand side panel: FRM index over time.
Data from 01 March 2020 to 17 May 2020

FRM@Crypto Betweenness Centrality



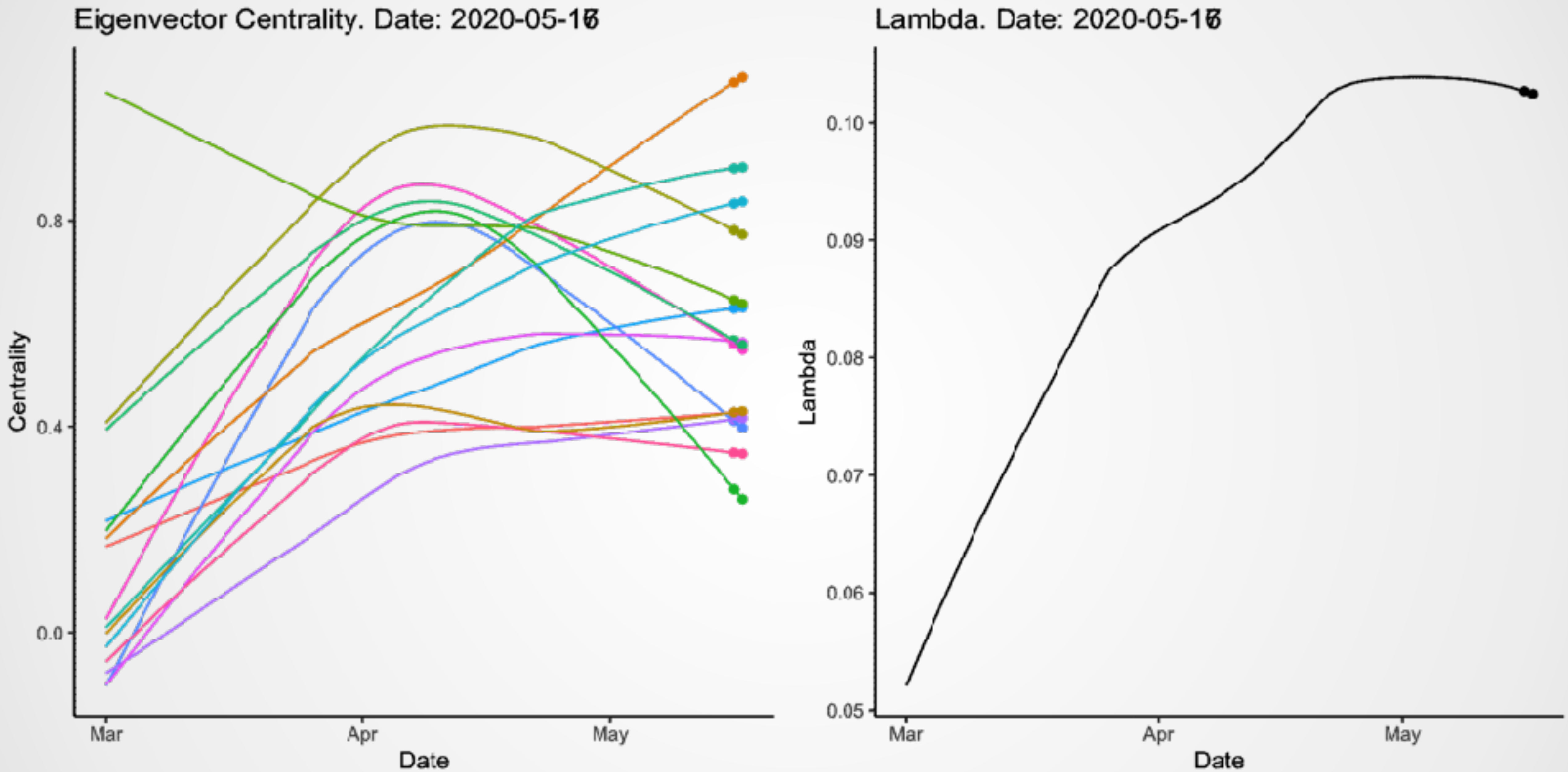
Left-hand side panel: „bridge" behaviour measure for BTC, ETH, XRP, BCH, BSV, LTC, EOS, BNB, XTZ, LIN, ADA, XLM, XMR, TRX, HT. Right-hand side panel: FRM index over time. Data from 01 March 2020 to 17 May 2020

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



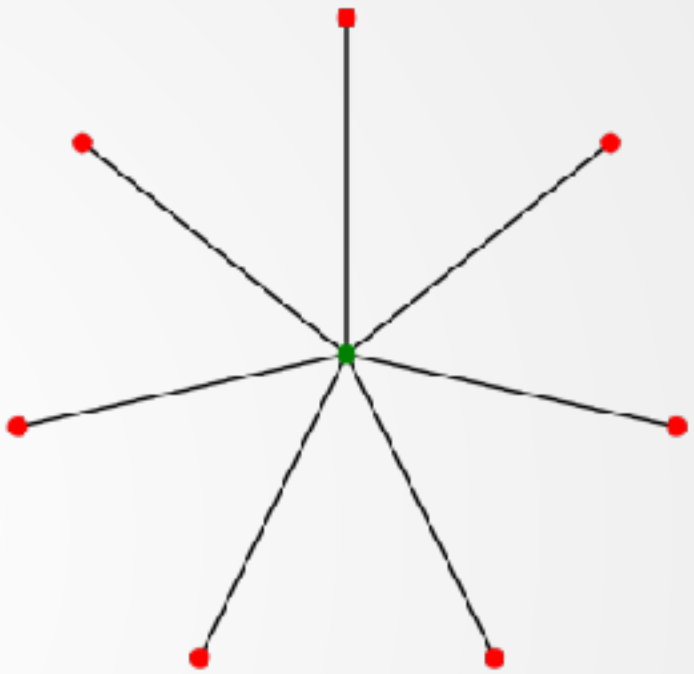
Left-hand side panel: normalised eigenvector centrality of BTC, ETH, XRP, BCH, BSV, LTC, EOS, BNB, XTZ, LIN, ADA, XLM, XMR, TRX, HT. Right-hand side panel: FRM index over time. Data from 01 March 2020 to 17 May 2020

From Nodes to Network Centralisation

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

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

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

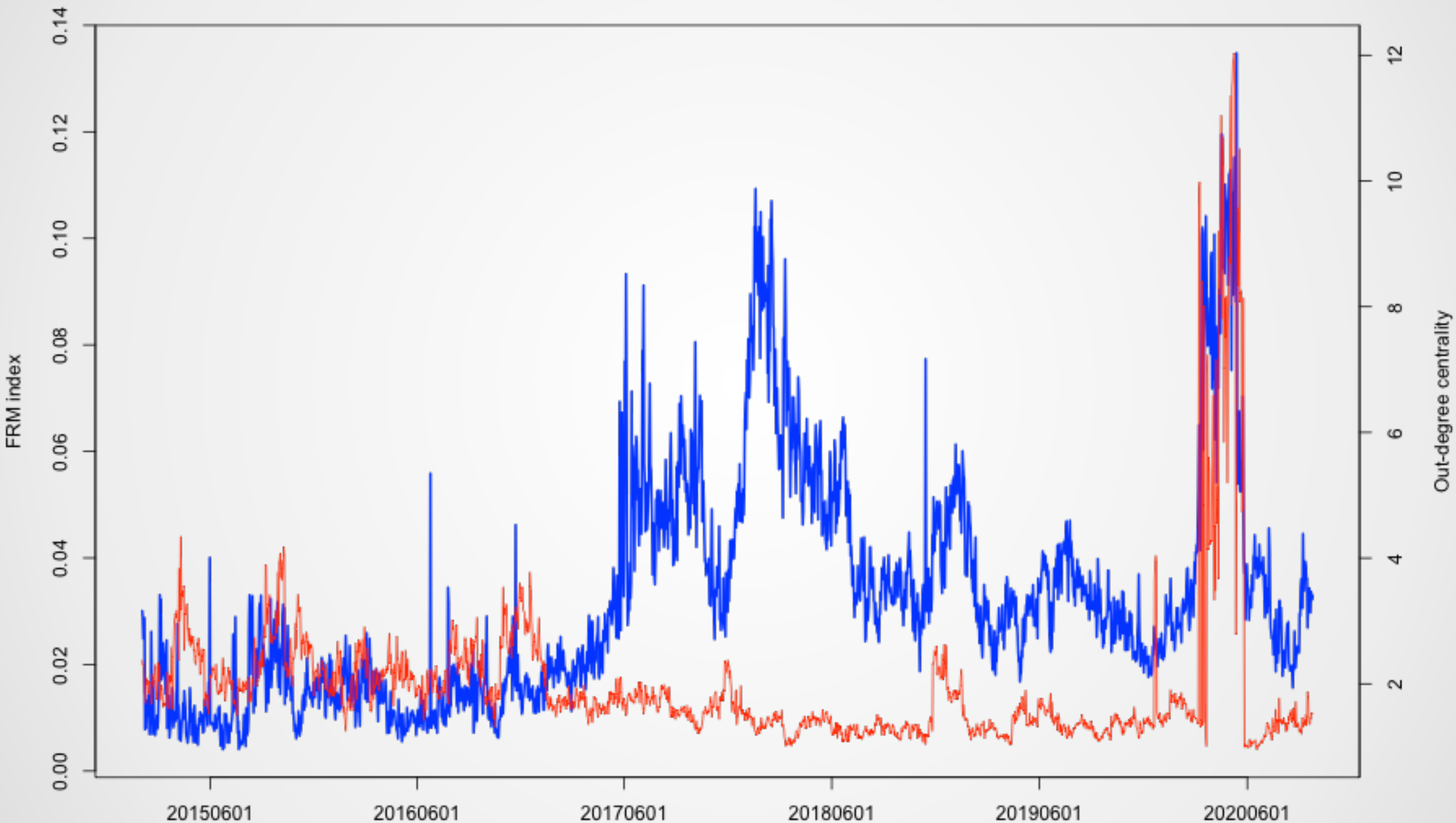


2. Freeman centralisation

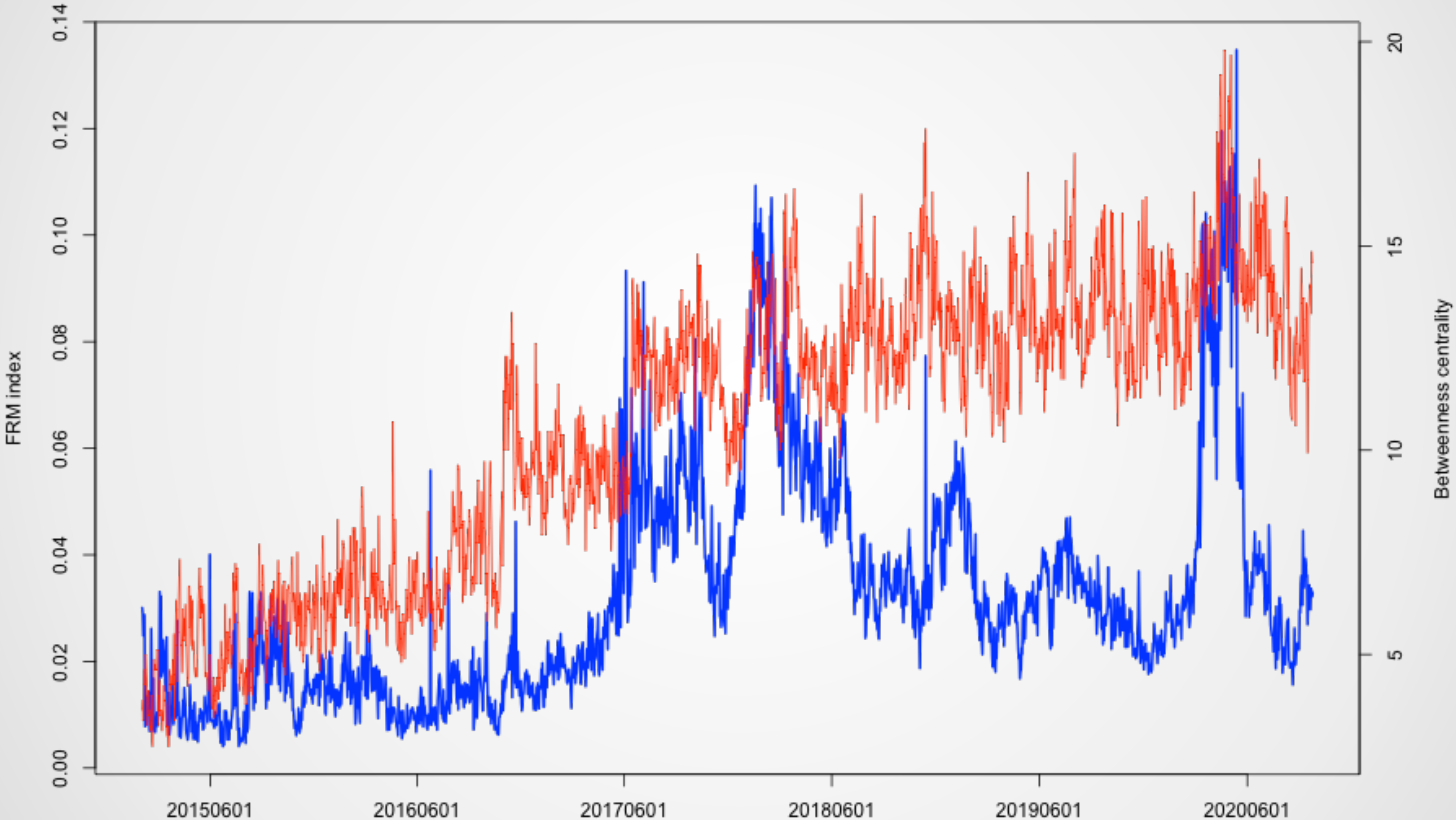
$$C = \frac{\sum_{i=1}^{M} [C(p_*) - C(p_i)]}{\max \sum_{i=1}^{M} [C(p_*) - C(p_i)]} \underset{\text{star}}{=} \frac{\sum_{i=1}^{M} [C(p_*) - C(p_i)]}{M^2 - 3M + 2}$$

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

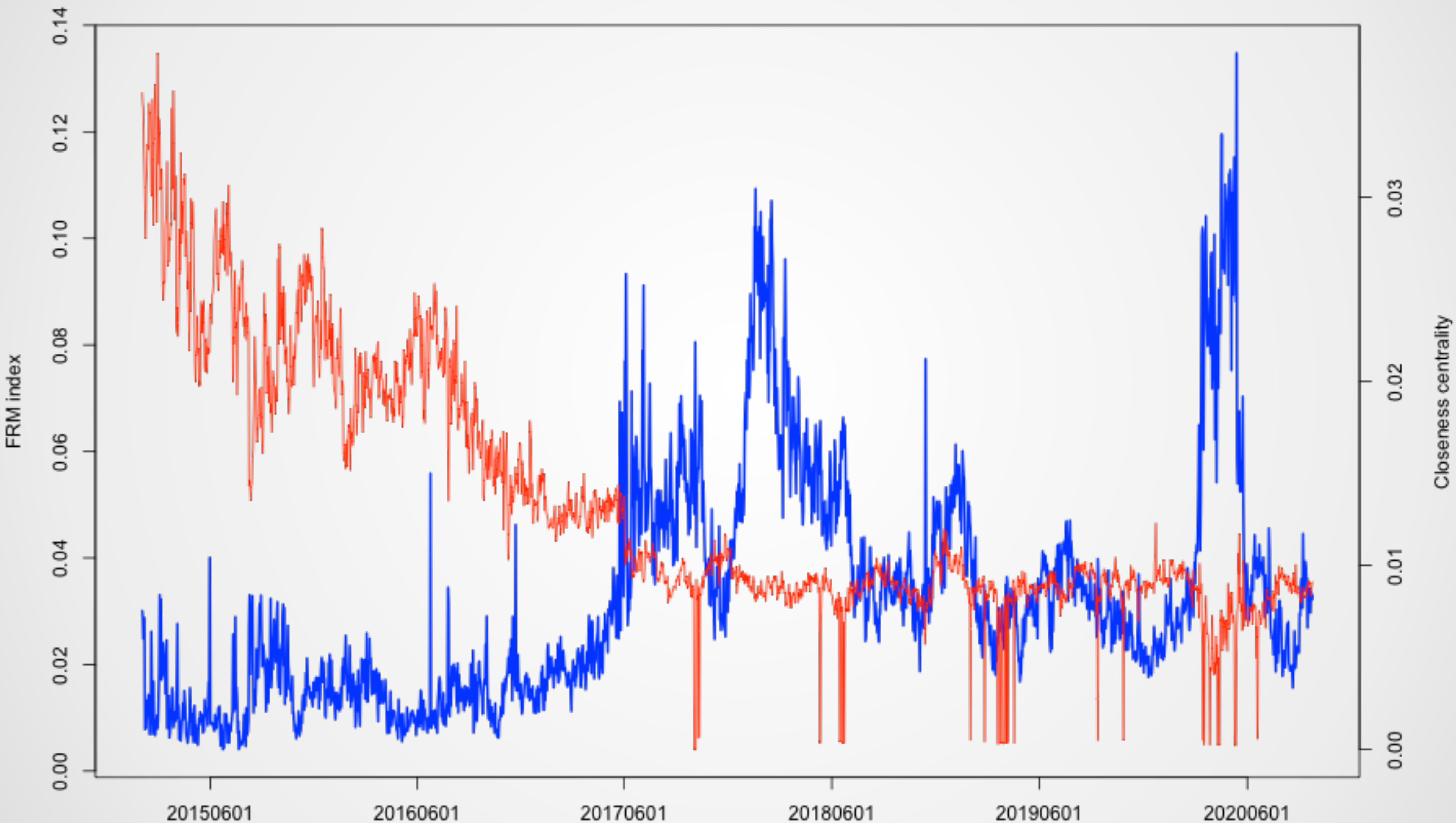
FRM@Crypto vs Average Degree Centrality



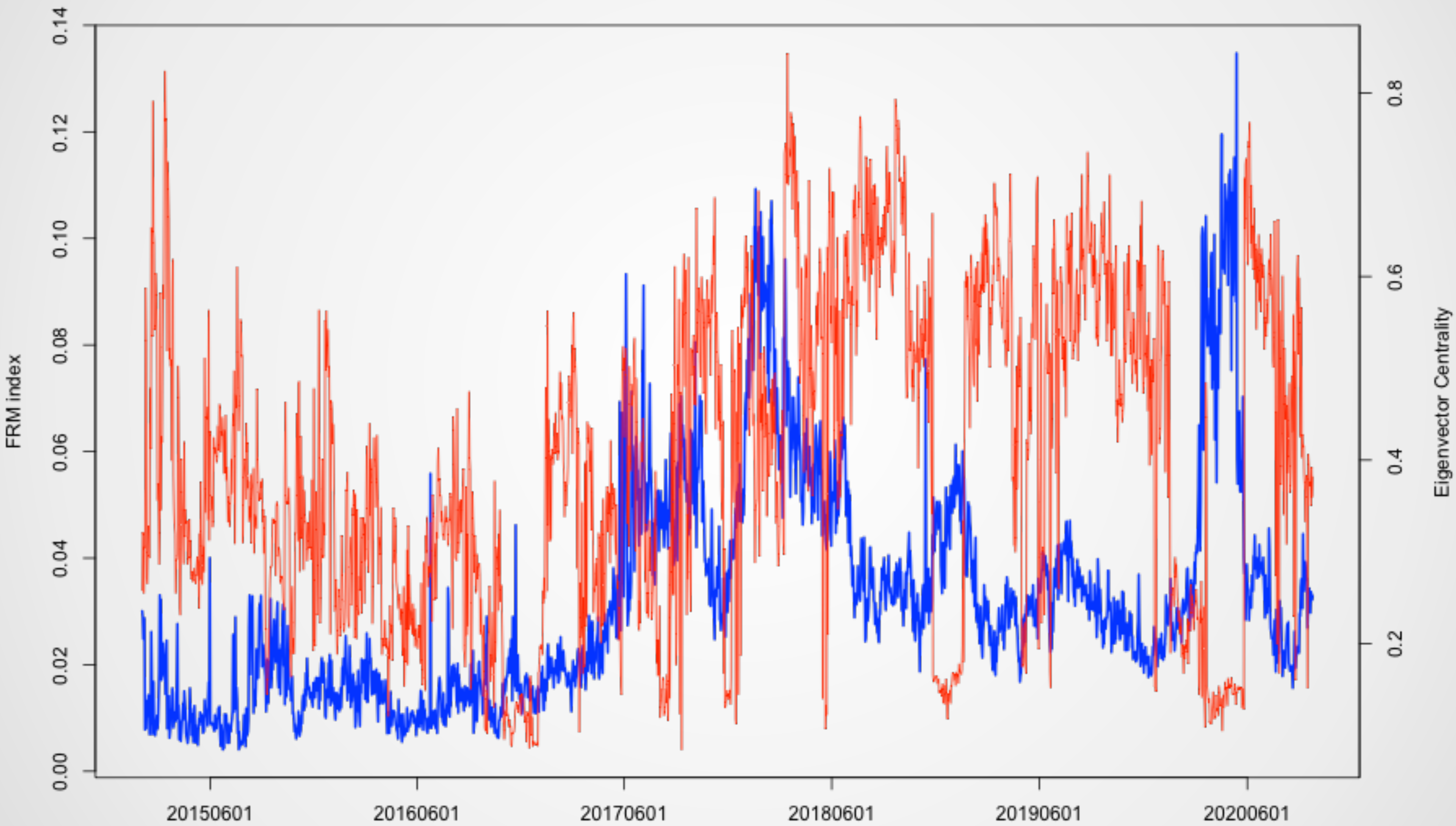
FRM@Crypto vs Average Betweenness Centrality



FRM@Crypto vs Average Closeness Centrality



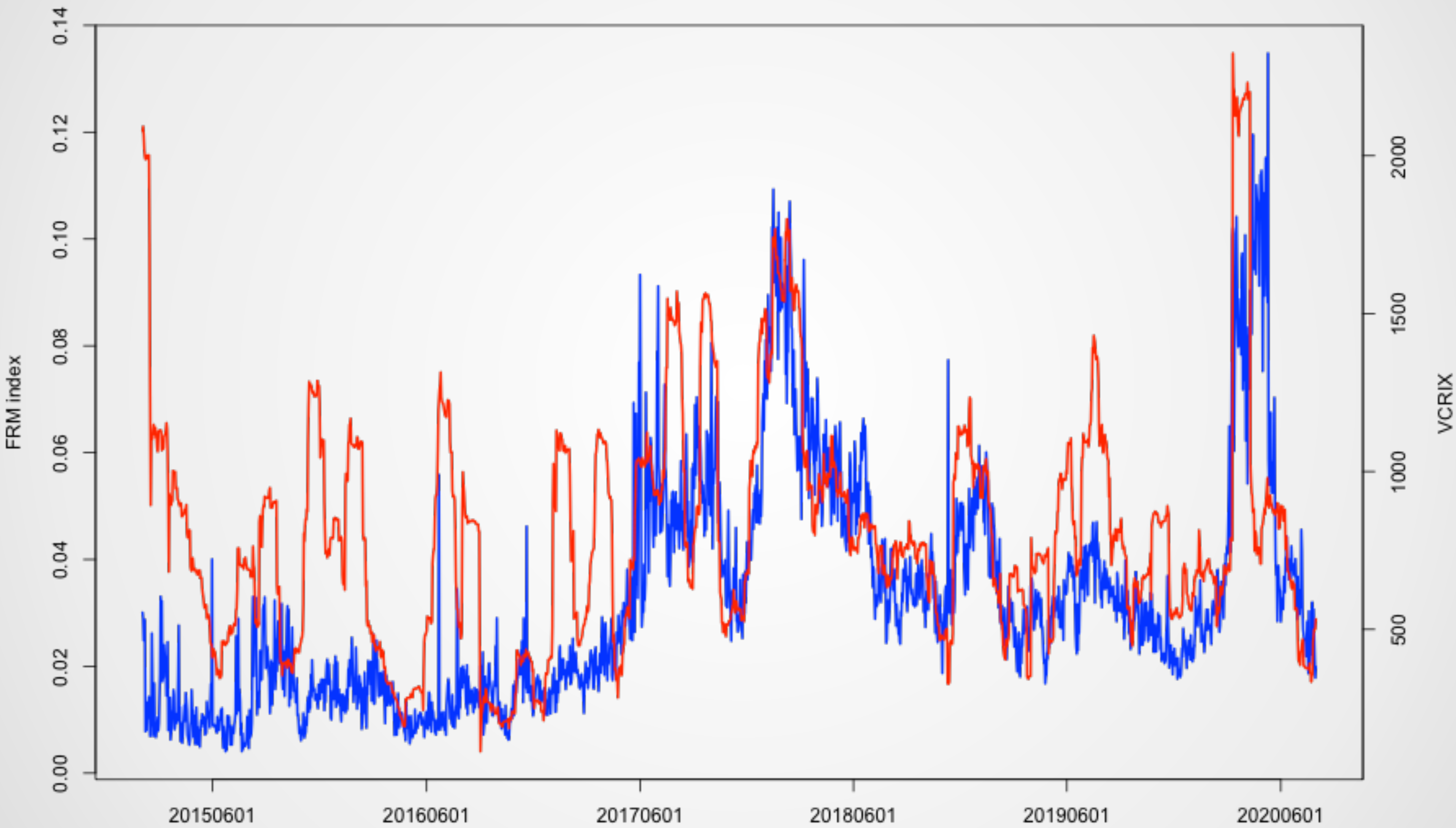
FRM@Crypto vs Average Eigenvector Centrality



Backtesting

- Assess model validity based on the usefulness of its predictions and not on the sophistication of the assumptions
- How well the risk measured by individual lambdas or their average reflects the short-time riskiness of cryptos
  - Riskiness benchmark: rolling historical volatility
  - Estimation window: 63 days

FRM@Crypto Index and VCRIX



Graphical backtest, $\tau = 5\,\%$

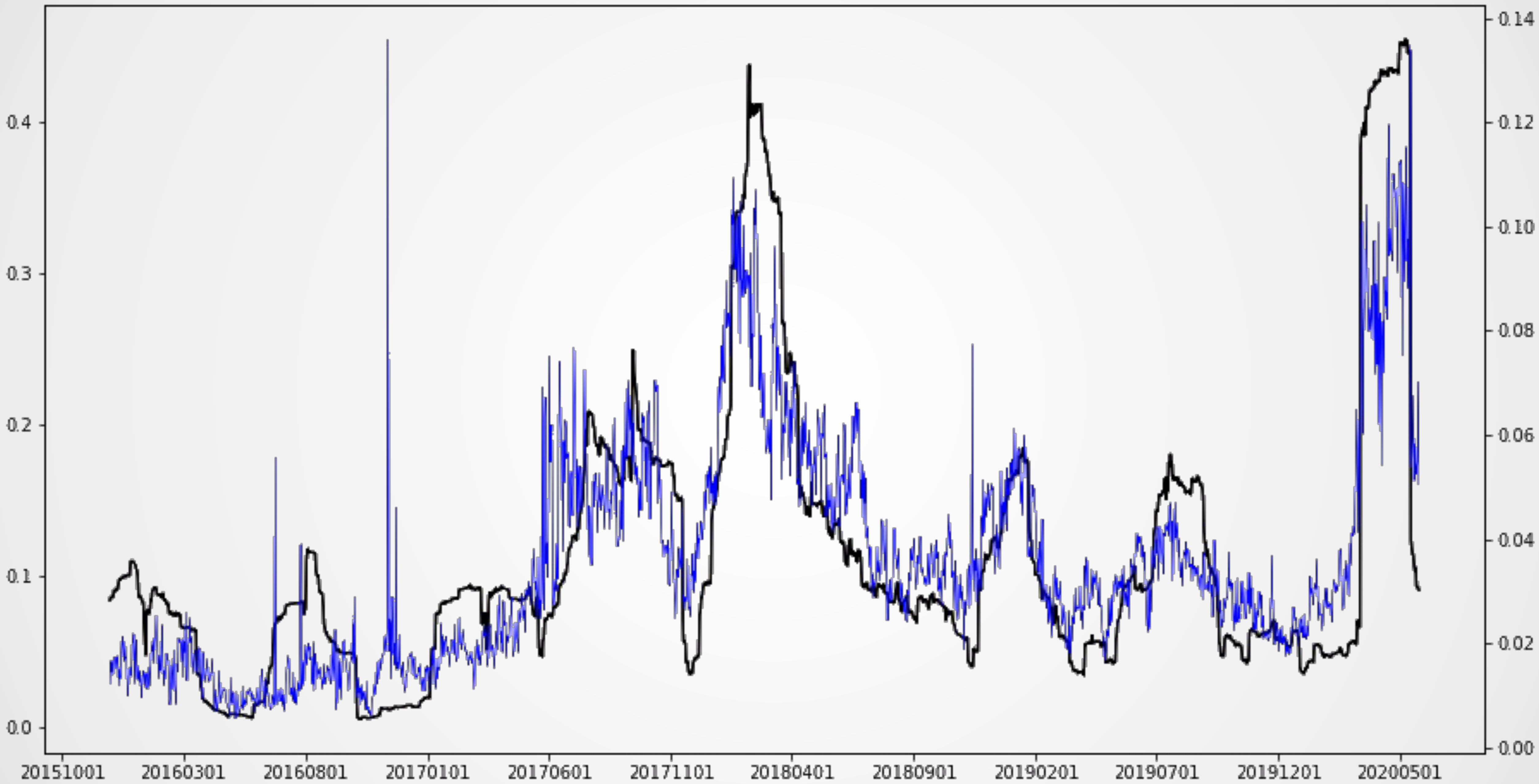


Figure: FRM@Crypto for $\tau = 5\,\%$ and CRIX rolling variance 20150404–20200525

Graphical backtest, $\tau = 10\,\%$

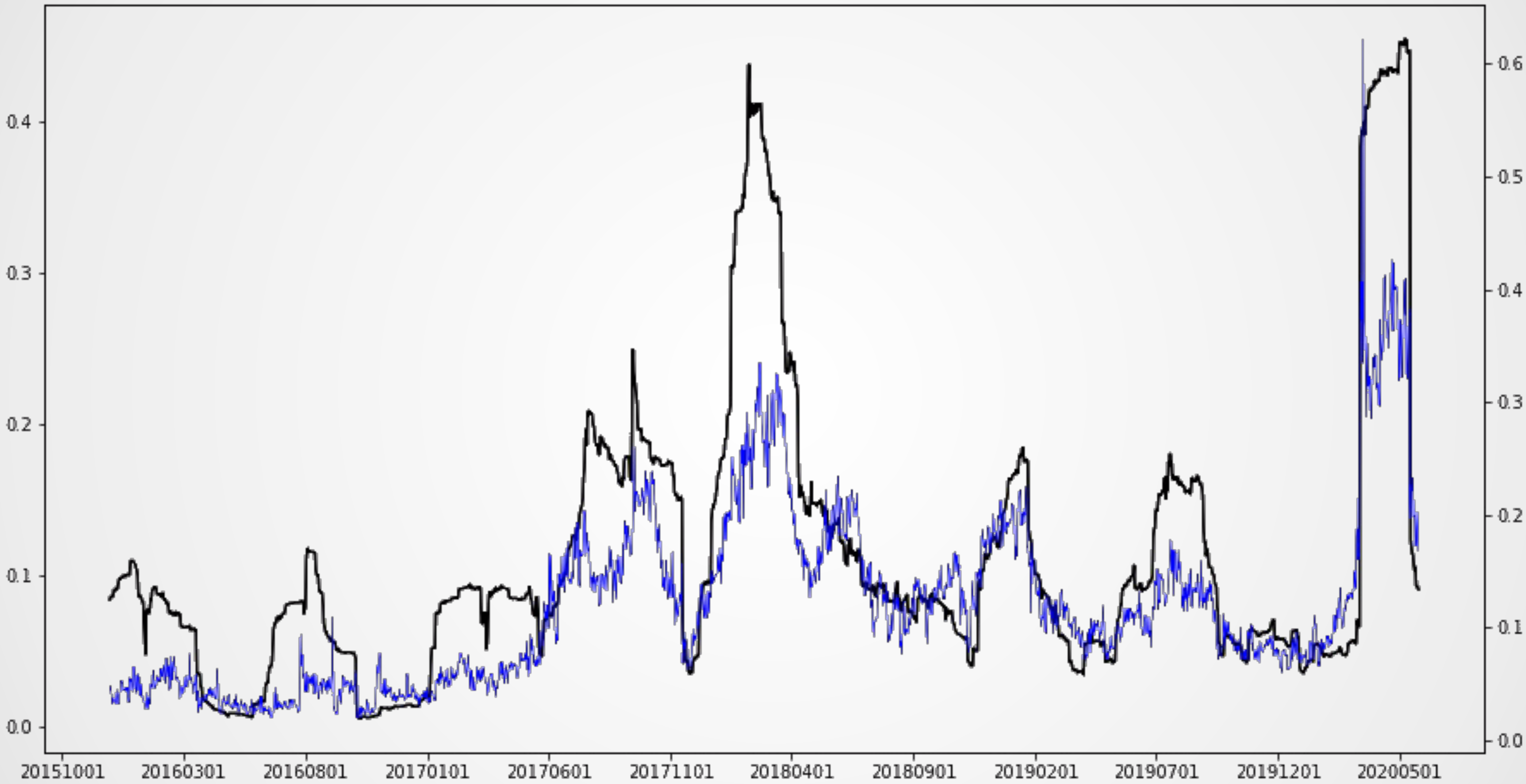


Figure: FRM@Crypto for $\tau = 10\,\%$ and CRIX rolling variance 20150404–20200525

Graphical backtest, $\tau = 5\,\%$

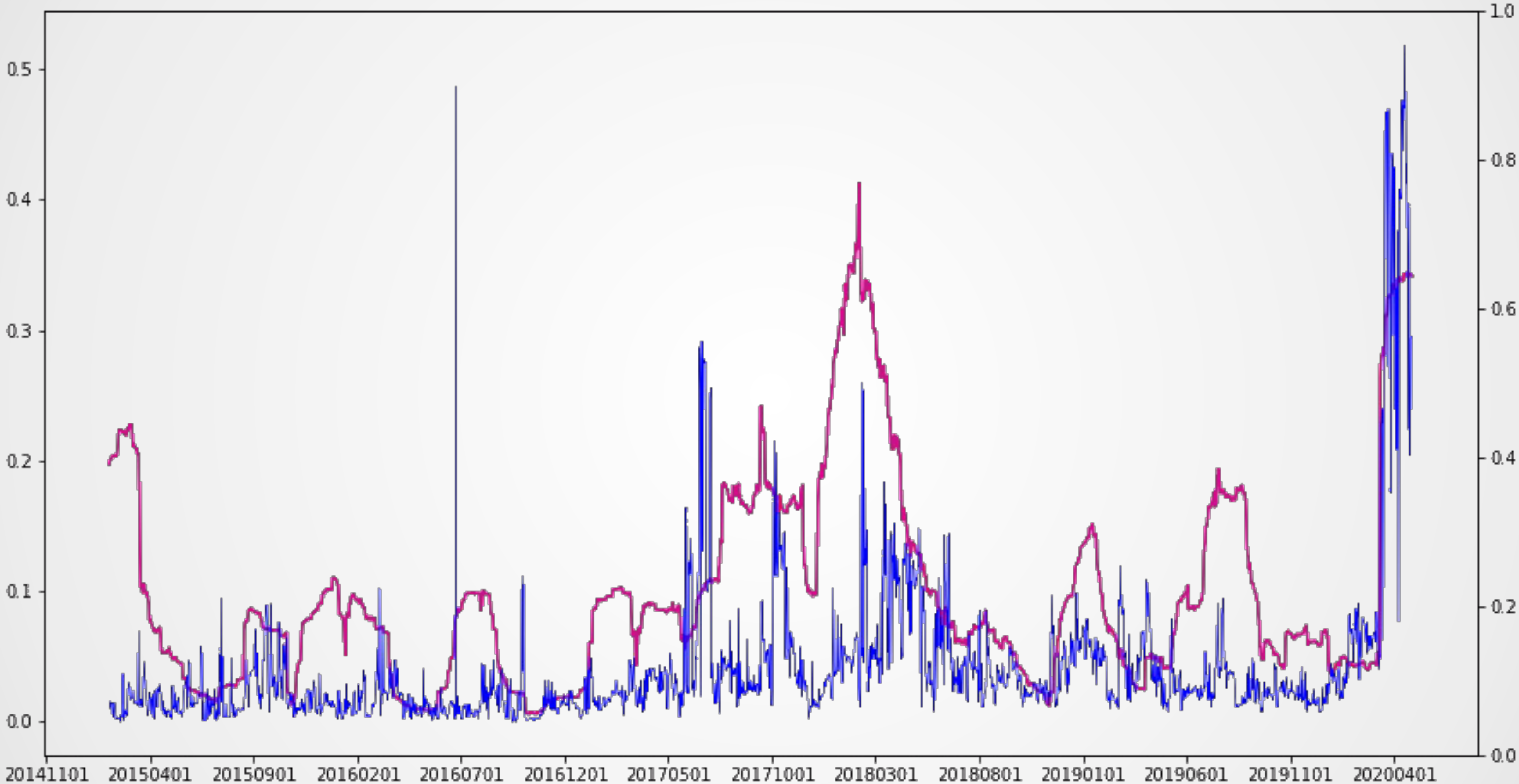


Figure: BTC lambda for $\tau = 5\,\%$ and BTC rolling variance 20150201–20200428

Graphical backtest, $\tau = 10\,\%$

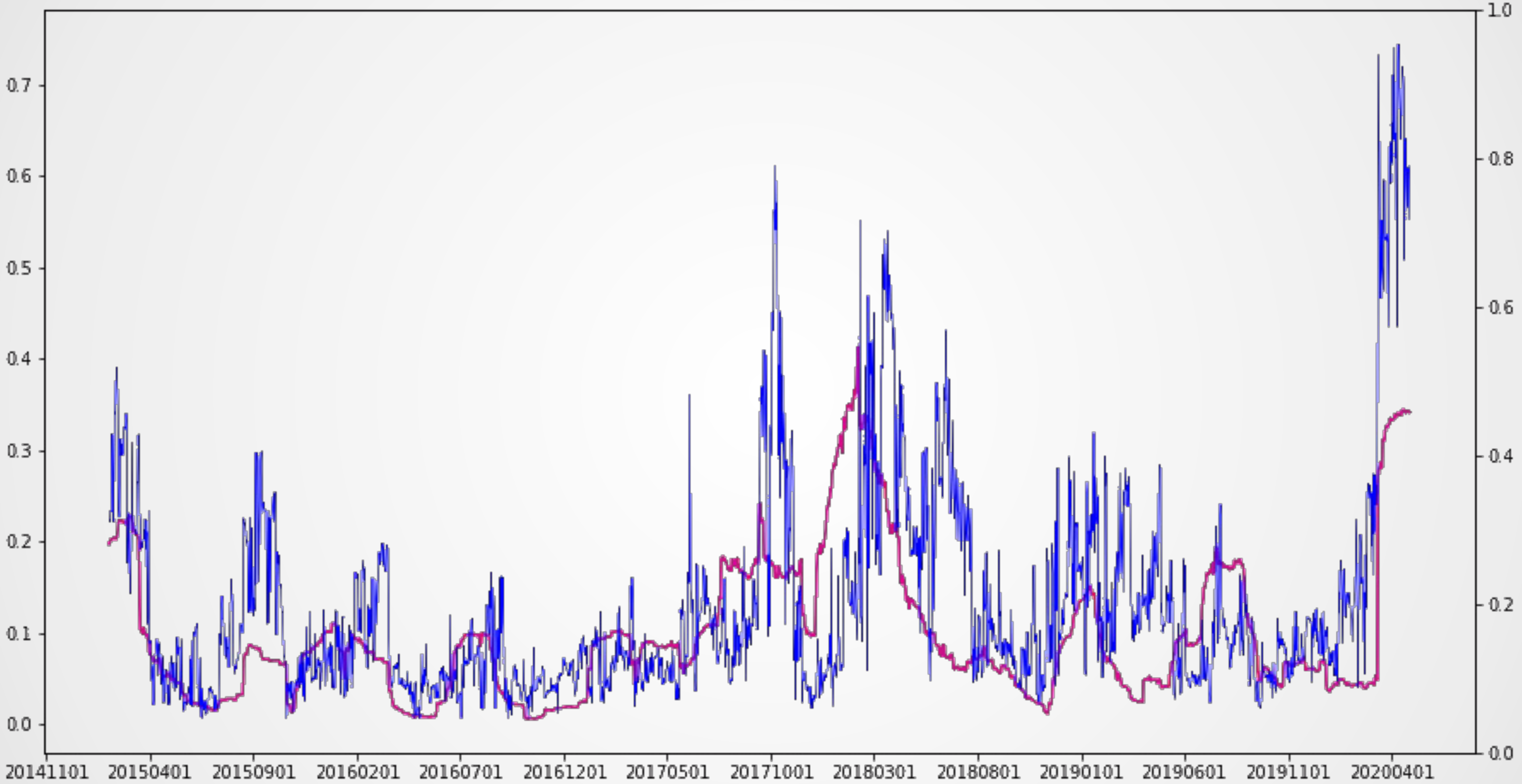


Figure: BTC lambda for $\tau = 10\,\%$ and BTC rolling variance 20150201–20200428

Graphical backtest, $\tau = 5\,\%$

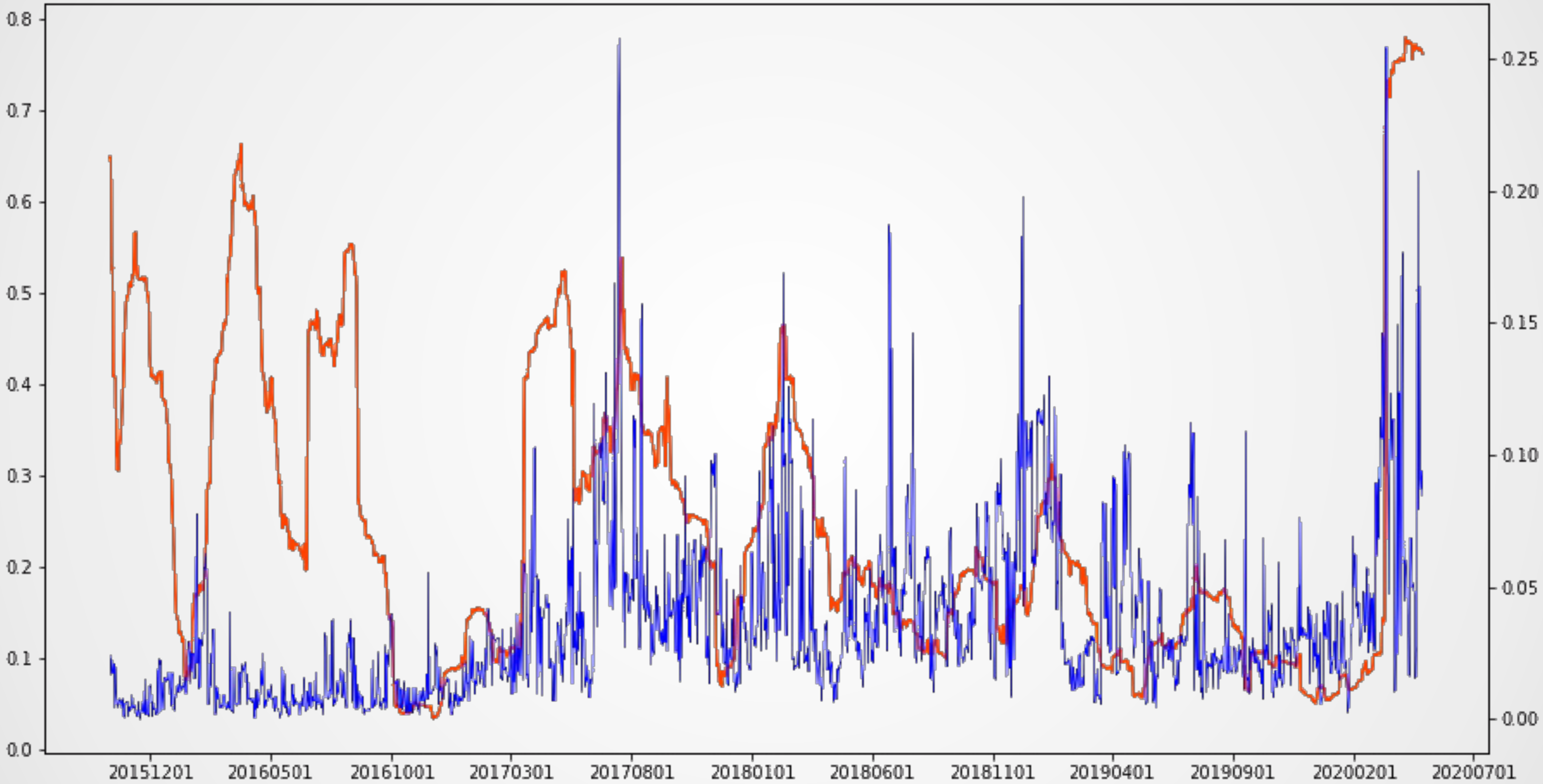


Figure: ETH lambdas for $\tau = 5\,\%$ and ETH rolling variance 20151011–20200428

Graphical backtest, $\tau = 10\,\%$

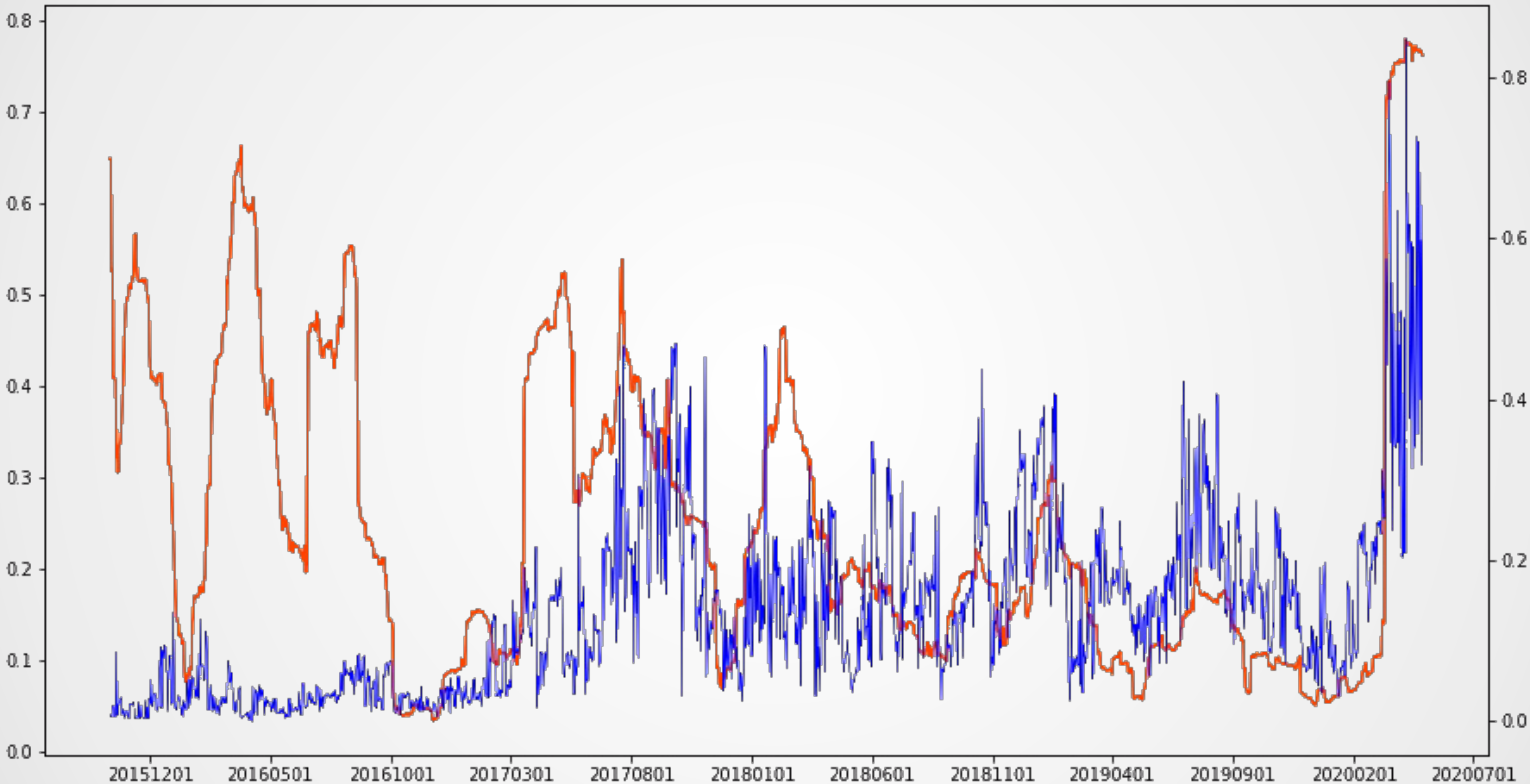


Figure: ETH lambdas for $\tau = 10\,\%$ and ETH rolling variance 20151011–20200428

Crypto Returns and the Pricing Kernel

According to the basic pricing equation

$$\mathrm{E}_t^{\mathbb{P}}[m_{t+1}R_{i,t+1}] = 1 \tag{4}$$

m_t *marginal rate of substitution,* $R_{i,t}$ return of i-th crypto.

Considering log returns $r_{i,t} = \log(R_{i,t}) \approx R_{i,t} - 1$

$$\mathrm{E}_t^{\mathbb{P}}[(1 + r_{i,t+1})\, m_{t+1}] \approx 1 \tag{5}$$

Substituting in (4) risk-free rate $R_{i,t} = R^f$

$$\mathrm{E}_t^{\mathbb{P}}[m_{t+1}] = 1 \tag{6}$$

Link to Sharpe Ratio

Combining (5) and (6)

$$\mathrm{E}_t^{\mathbb{P}}[m_{t+1} r_{i,t+1}] \approx 0 \tag{7}$$

Hence, the Sharpe ratio of $r_{i,t}$ is bounded by $\sigma(m_t)$

$$(7) \quad <> \quad \underbrace{\mathrm{E}_t^{\mathbb{P}}[m_{t+1}]}_{=1} \, \mathrm{E}_t^{\mathbb{P}}[r_{i,t+1}] + \mathrm{Cov}_t^{\mathbb{P}}[m_{t+1} r_{i,t+1}] \approx 0$$

$$<> \quad \mathrm{E}_t^{\mathbb{P}}[r_{i,t+1}] \approx -\underbrace{\mathrm{Corr}_t^{\mathbb{P}}[m_{t+1} r_{i,t+1}]}_{\in[-1,1]} \, \sigma(m_{t+1}) \, \sigma(r_{i,t+1})$$

$$> \quad \left| \mathrm{E}_t^{\mathbb{P}}[r_{i,t+1}] \right| \leq \sigma(m_{t+1}) \, \sigma(r_{i,t+1}) \tag{8}$$

Role of Lambda as Penalisation Parameter

An analogous inequality to (8) holds for the empirical distribution

$$\left| \widehat{\mathrm{E}}_t^{\mathbb{P}}[r_{i,t+1}] \right| \leq \sigma(\widehat{m}_{t+1})\, \hat{\sigma}(r_{i,t+1})$$

$$\succ \quad \left| \mathrm{E}_t^{\mathbb{P}}[r_{i,t+1}] \right| - \left| \widehat{\mathrm{E}}_t^{\mathbb{P}}[r_{i,t+1}] \right| \leq \sigma(m_{t+1})\, \sigma(r_{i,t+1}) - \sigma(\widehat{m}_{t+1})\, \hat{\sigma}(r_{i,t+1}) \qquad (9)$$

Due to persistency of volatility of returns $\hat{\sigma}(r_{i,t+1}) \approx \sigma(r_{i,t+1})$

$\lambda_{i,t}$ chosen with CV tries to minimise the LHS $\succ$

$$\lambda_{i,t} \propto \sigma(\widehat{m}_{t+1}) - \sigma(m_{t+1})$$

FRM in FinTech, Cryptos, …

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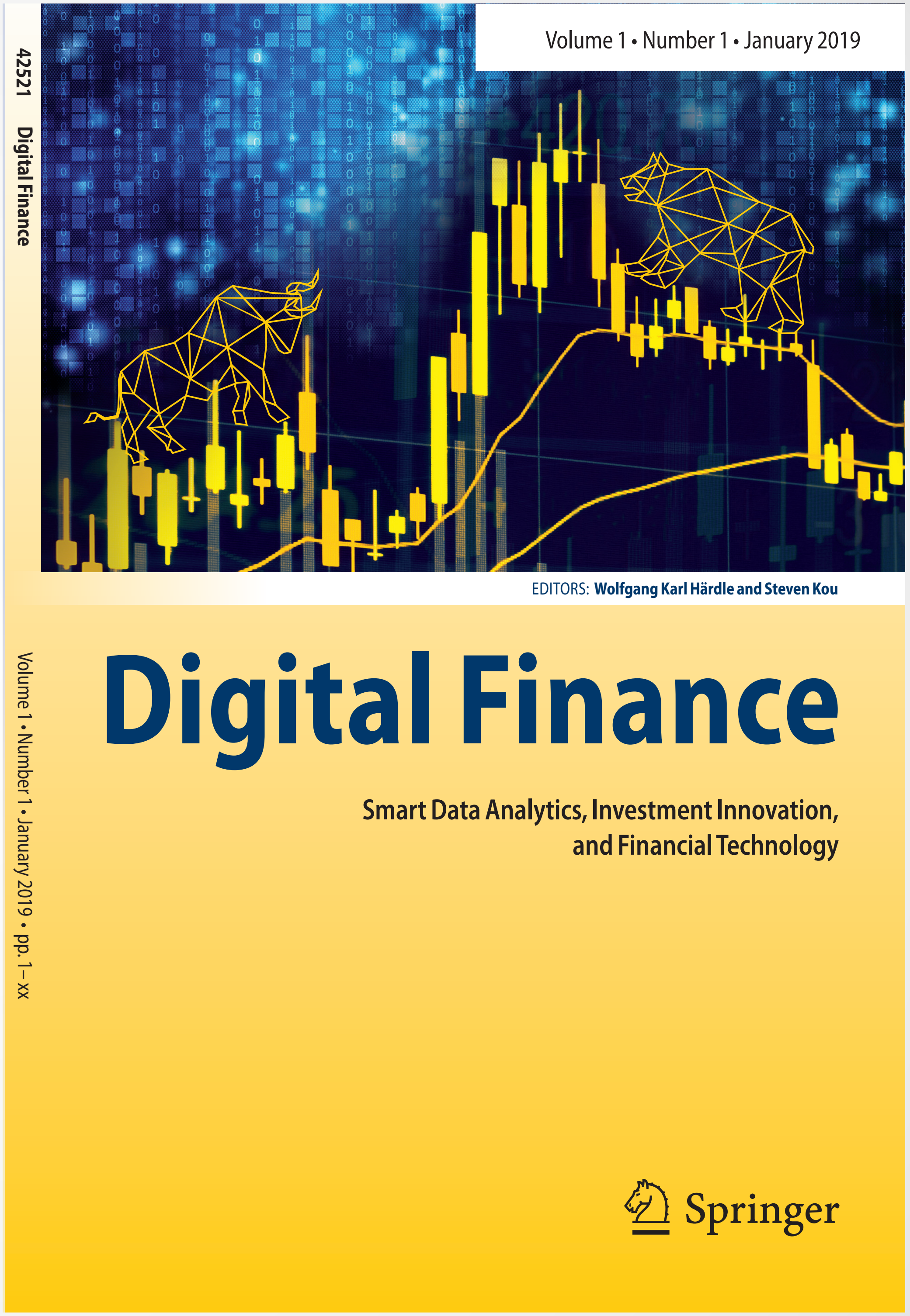


Michael Althof


Vanessa Guarino


Wolfgang K Härdle


Rui REN


Anna Shchekina


Alla Petukhina


Ang LI


Souhir Ben Amor


Alex Truesdale


Ilyas Agakishiev

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FRM financialriskmeter for Cryptos

Michael Althof

Vanessa Guarino

Rui Ren

Anna Shchekina

Humboldt-Universität zu Berlin
lvb.wiwi.hu-berlin.de
Charles University, WISE XMU, NCTU 玉山学者

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