FRM financialriskmeter for cryptos

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FRM channels

FIRAMIS app HU Berlin app

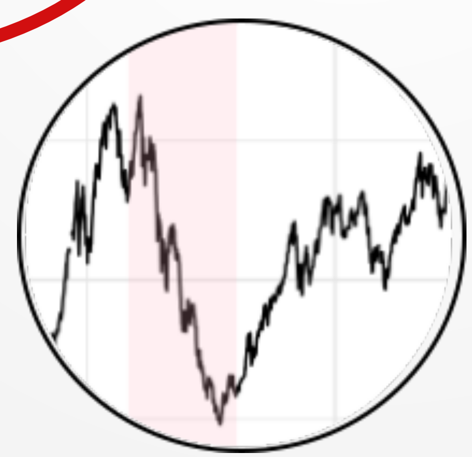
FRM@Americas

FRM@Asia

RIX

FRM@Crypto

FRM@Europe



FRM@iTraxx (CDS), FRM@EmergingMarkets, FRM@EuroRates, FRM@SP500

FRM

Objectives

- Apply FRM technology to the crypto market
- Examine sensitivity of FRM index to the set-up parameters
- FRM seems to work but it lacks the understanding why $\succ$

  Deep dive into the interpretations of penalisation parameter
- Graph/network view of the TE spillovers for crypto coins
- Test predictability power of FRM index

Quantile Lasso regression

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

penalise

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

- 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

No input standardisation: log return acts as centering, normalisation is skipped to preserve original variances.

Interpretation

λ in quantile Lasso regression

λ size of estimated LQR coefficients (Li and Zhu, 2008)

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

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

Average penalty: indicator for tail risk, noise shaved off

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

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

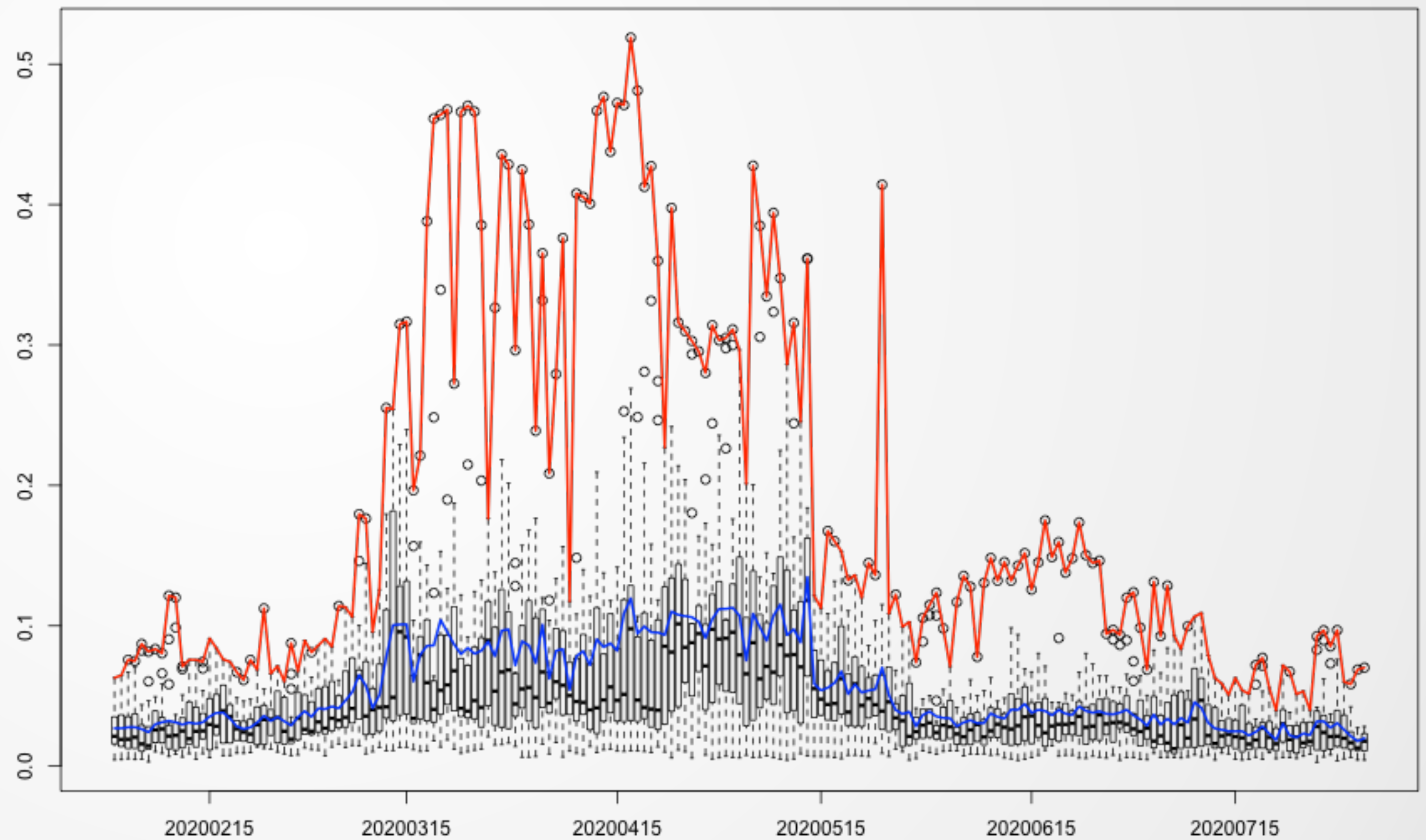
λ Selection

At each day obtain a *distribution* of λs with sample size J.

Allows one to identify tail event risk drivers.

Examine:

- Mean=FRM@crypto
- Median
- Quantiles
- Minimum
- Maximum



FRM@crypto data

- 15 largest cryptocurrencies
- 5 macro related variables
- Quantile level $\tau = 0.05, 0.10, 0.25, 0.50$
- Time window $s = 63, 21$
- Time frame: 2014–2021
- 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

Back to Lasso Regression

FRM@crypto distribution

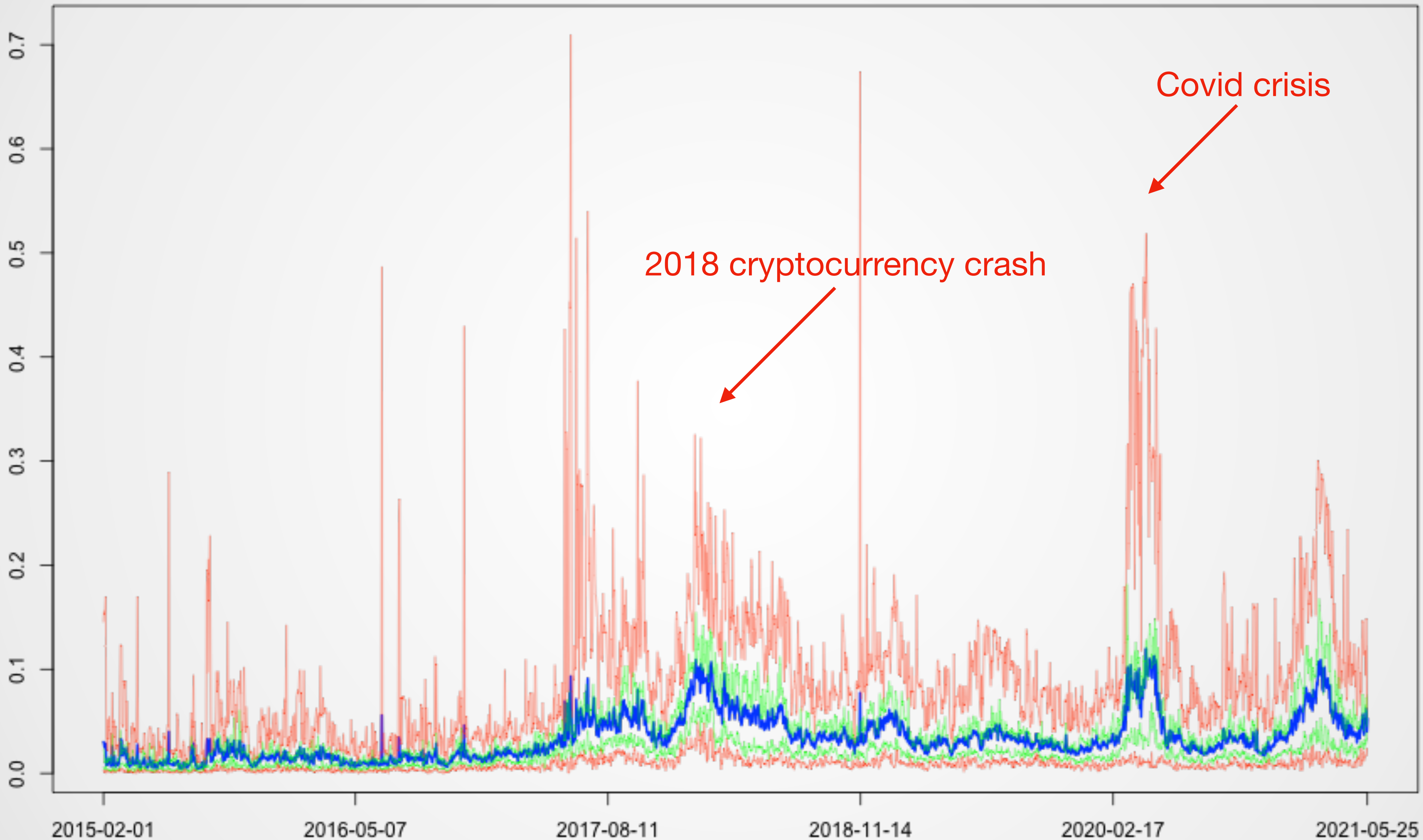


Figure: FRM@crypto index, max and min and 75 % and 25 % Quantiles for $\tau = 5\,\%$

Visualising the active set: FRM@crypto the movie

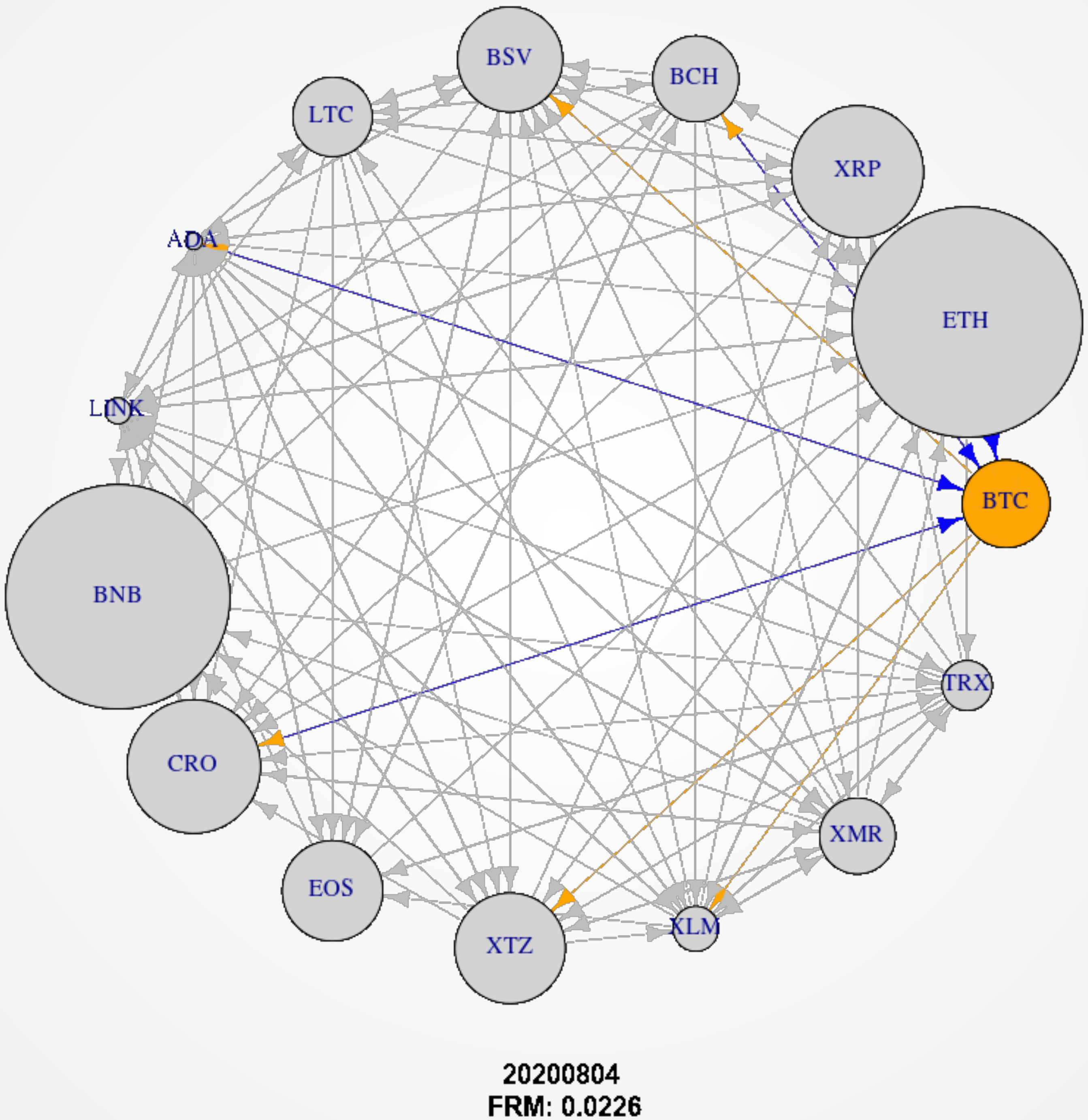
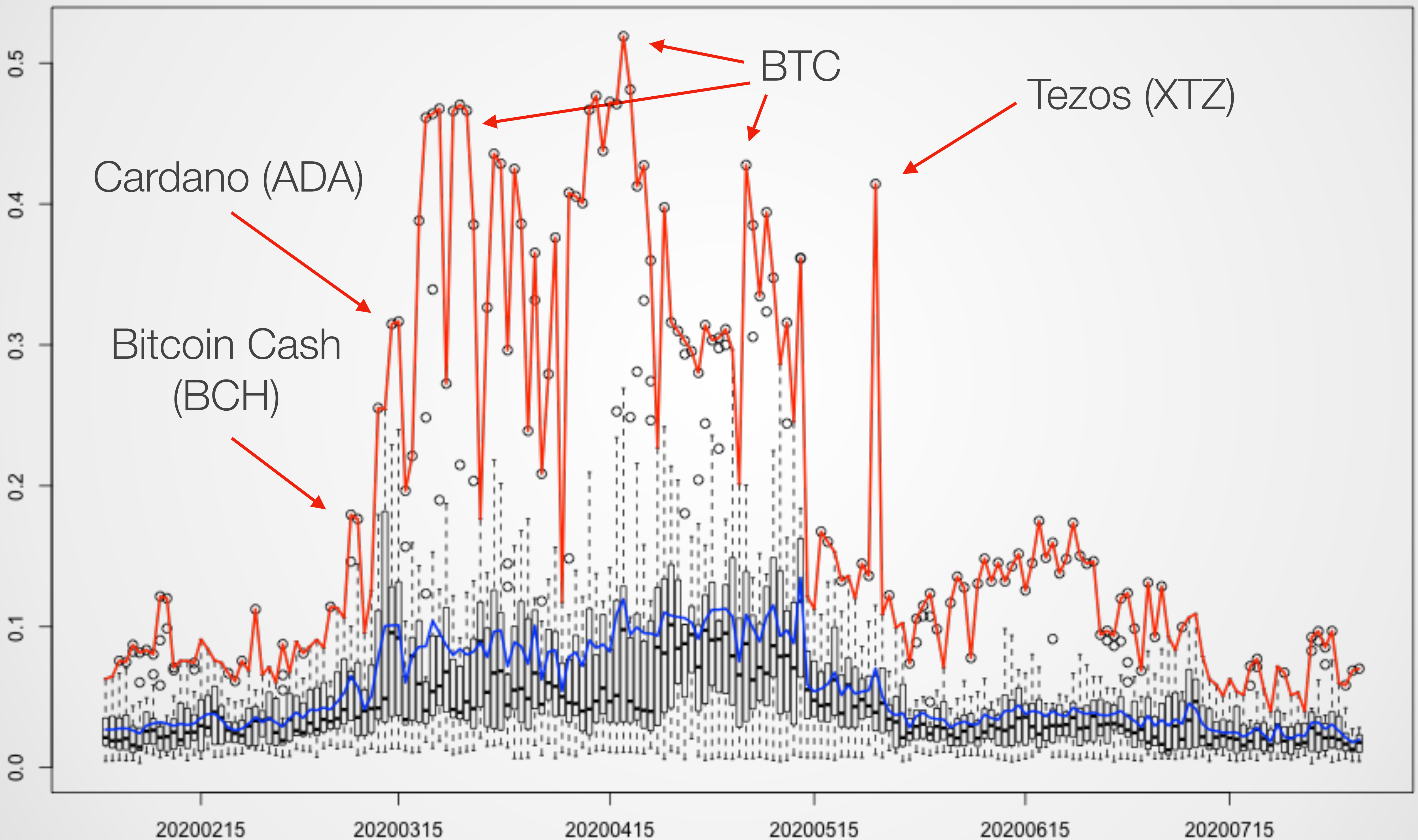
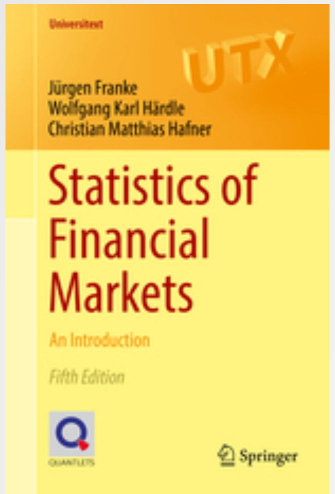


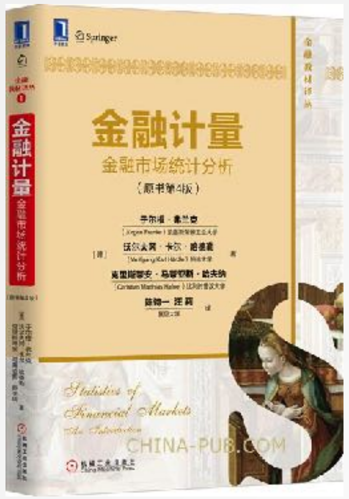
Figure: Network analysis for FRM@crypto from 4 August 2020 to 24 September 2020.
Size of the node corresponds to λ

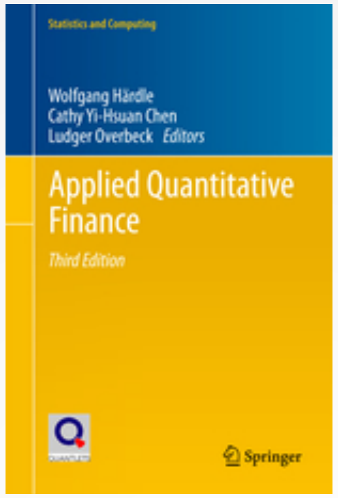
FRM@crypto distribution under Covid crisis



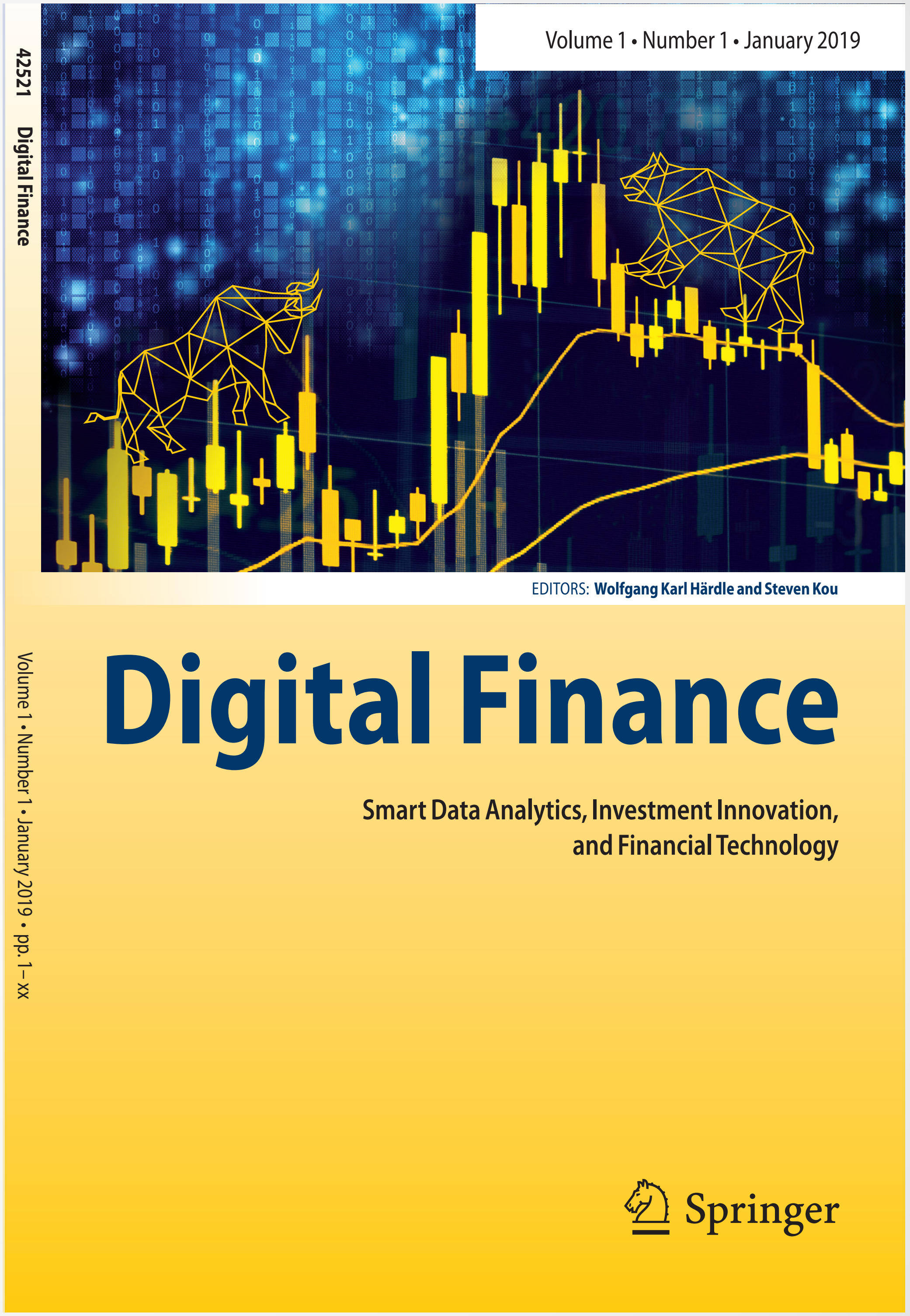
FRM in FinTech, Cryptos, ...







Vol 1. 2019 on Crypto Currencies

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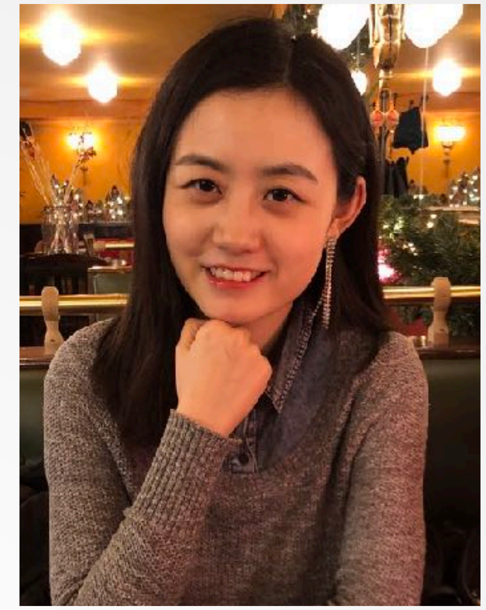
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Cryptocurrencies list (as per 24 May 2020)

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

▶ Back to Lasso

β_j selection

- Rewrite (2) as

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

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

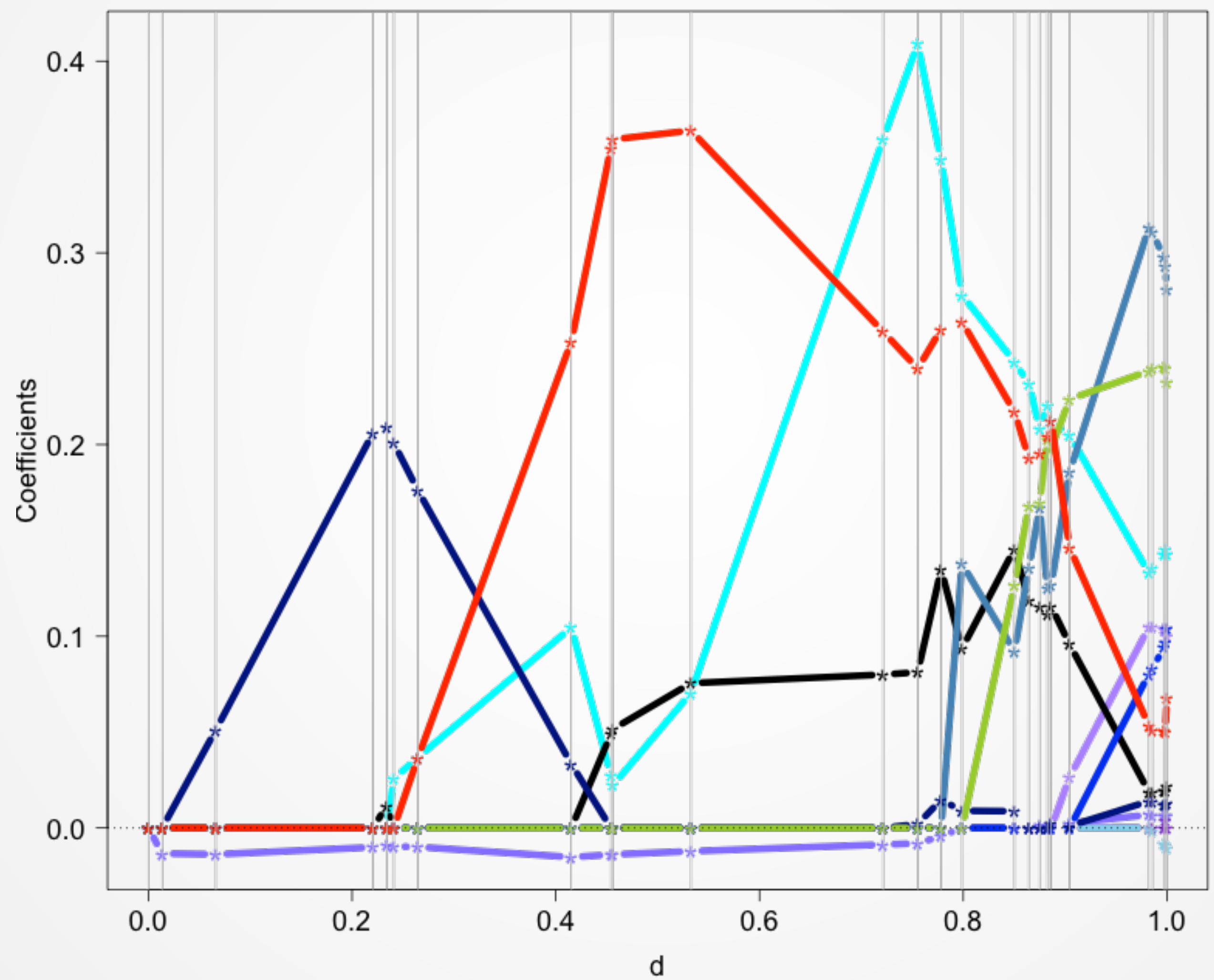
where d, regularisation parameter, plays the same role as λ

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