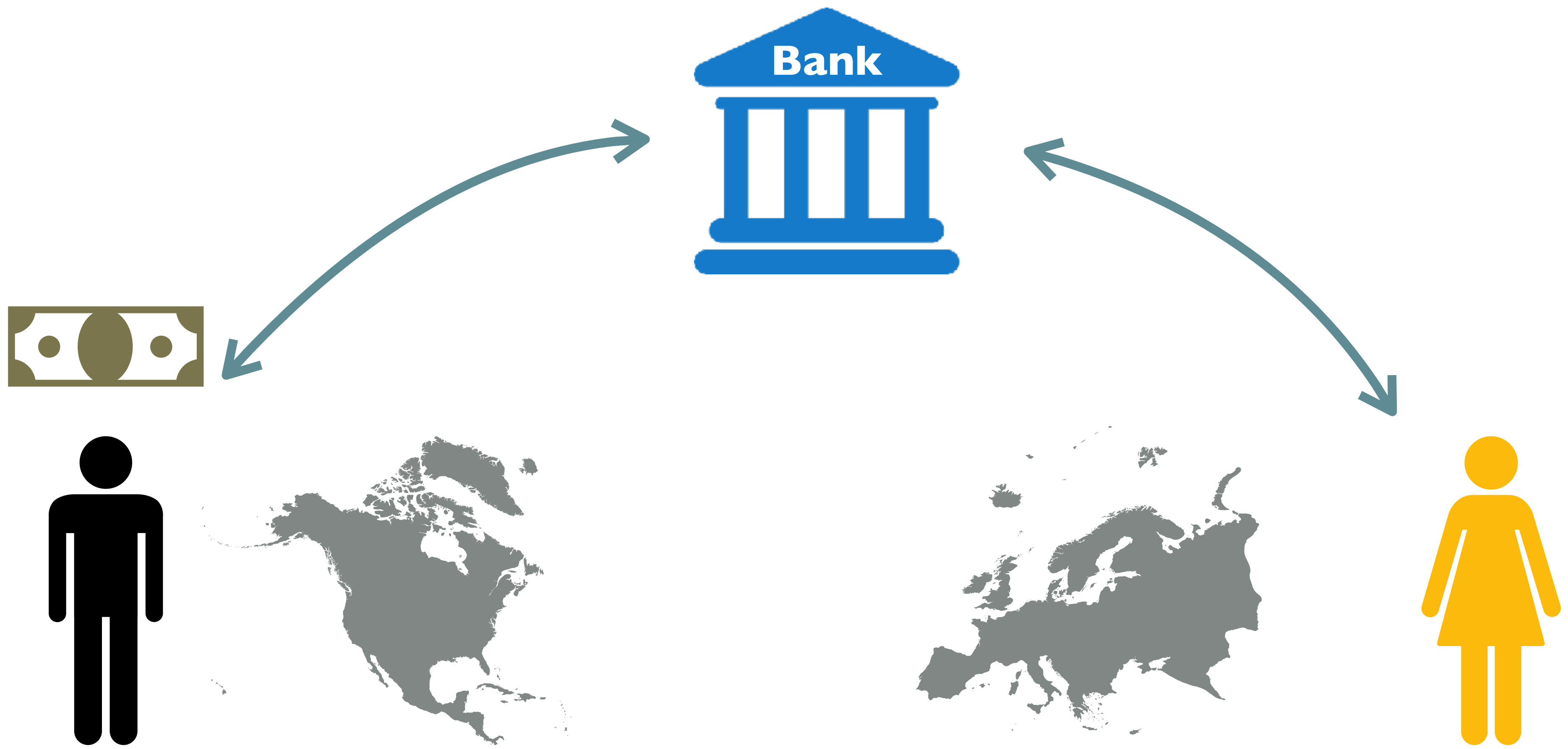
Ladislaus von Bortkiewicz Chair of Statistics
Humboldt-Universität zu Berlin
lvb.wiwi.hu-berlin.de

CRIX

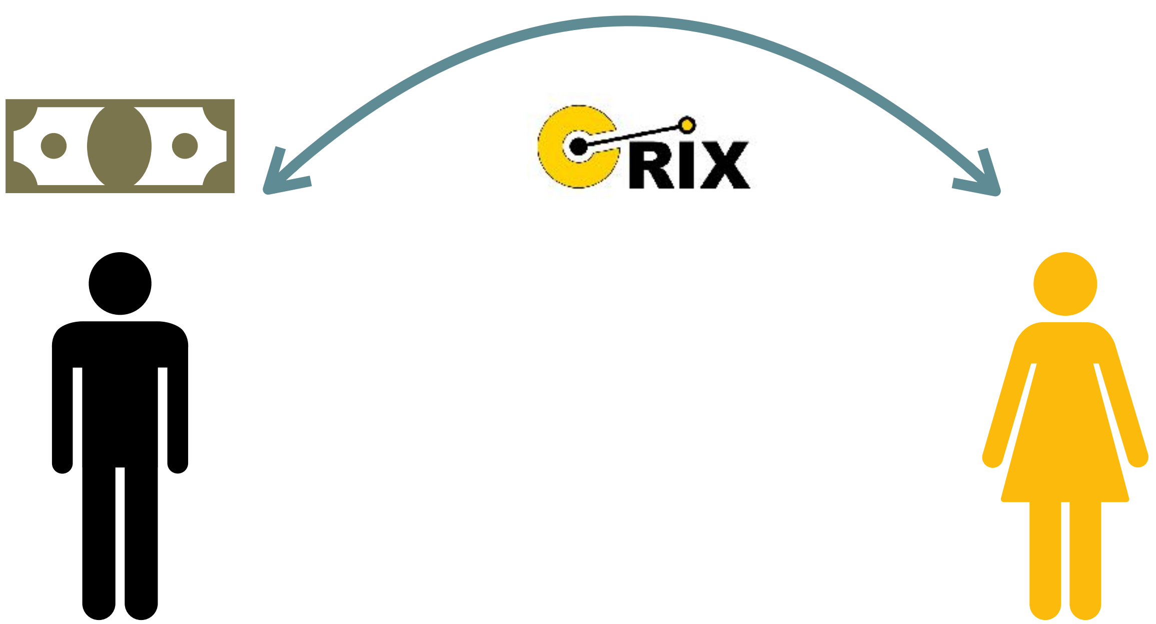
Chen Gauer Härdle Kolesnikova Petukhina Reule Spilak Trimborn Ünal

Hayek (1976) The Denationalization of Money.
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. (From Wikipedia)

Now



New



	USD	USD/EUR	EUR
USD	350,00 $	1,1372	307,77 €
USD	350,00 $	1,7047	205,31 €
P/L			-102,46 €

Verwendungszweck 1:		Interne Buchung
Verwendungszweck 2:		TRN/Re-Nr. 180607ABIB37267
Verwendungszweck 3:		TRN/MSG 180509ABSE34901
Verwendungszweck 4:	**HU Jerusalem**	USD 350,00
Verwendungszweck 5:		Kurs EUR/USD 1,185100
Verwendungszweck 6:		EUR 295,33
Verwendungszweck 7:		Verwendungszweck:
Verwendungszweck 8:		Gutschrift Ihres zum Inkass
Verwendungszweck 9:		o
Verwendungszweck 10:		eingereichten Auslandsschec
Verwendungszweck 11:		ks-
Verwendungszweck 12:		Nr. 467640275 ueber 350,00
Verwendungszweck 13:		USD
Verwendungszweck 14:		abzueglich Eigen- und Fremd
Verwendungszweck 15:		entgelt
Verwendungszweck 16:		Abrechnung:
Verwendungszweck 17:		Courtage
Verwendungszweck 18:		EUR 2,50
Verwendungszweck 19:		Scheckverkehr/Gutschr. n.E
Verwendungszweck 20:		EUR 25,00
Verwendungszweck 21:		Fremdentgelt Dokumenteninka
Verwendungszweck 22:		EUR 62,52
Verwendungszweck 23:	**HU Berlin**	Endbetrag
Verwendungszweck 24:		EUR 205,31
Verwendungszweck 25:		USt-IdNr.: DE 143589235
Verwendungszweck 26:		USt-befreite Finanzdienstl.

Berlin - Room 77

Hype, fools, gold or fact ?

Financial Inclusion

Homeostasis

Financial illiteracy
Corruption
Suboptimal governance
Inefficient monetary institutions
Insecurities about fiat currency (forgery …)

Mass-1st-World-Evolution

1970s: Mainframe
1980s: PC
1990s: Internet
2000s: Social Media
2010s: Blockchain

53% of the worlds' adult population is unbanked (2 455 million)
"Half the world is unbanked", McKinsey & Company

Smartphone ownership

 43% in 2013, 60% in 2018

 56% in 2013, 77% in 2018

 41% in 2013, 78% in 2018

 13% in 2013, 34% in 2017

Source: statista.com

Total Market Index (TMI)

Wilshire 5000 Total Market Index SP500 SP100
19951009 - 20141205

```r
library("rjson")
json_file = "http://data.thecrix.de/data/crix.json"
json_data = fromJSON(file=json_file)
x = as.data.frame(json_data)
n = dim(x)
b = seq(2, n[2], 2)
price = t( x[1, b] )
pdf(file = "CRIX_timeseries.pdf", width = 12, height = 12,
    onefile = FALSE, family = "Helvetica",
    title = "R Graphics Output", fonts = NULL,
    version = "1.4", paper = "special")
plot( price, type = "l" , lwd = 7)
dev.off()
```

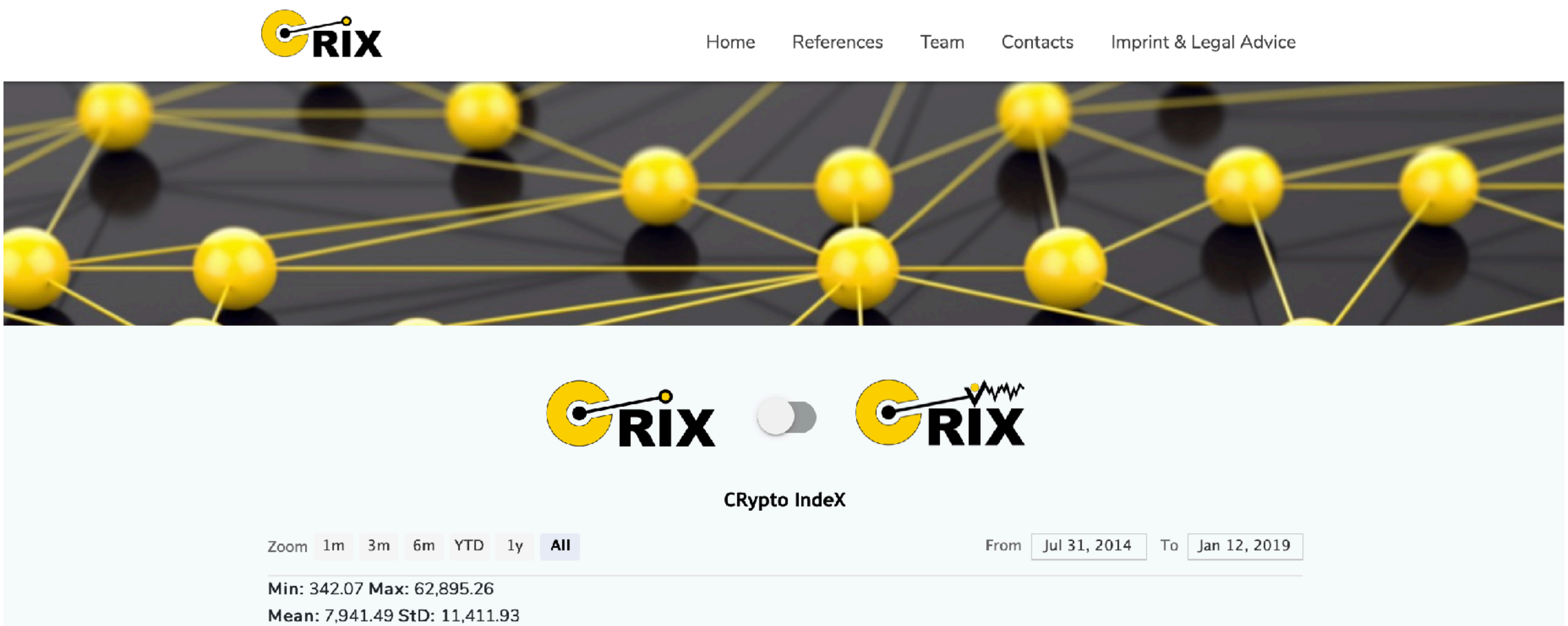
CRIX Code

Outline

1. Motivation ✔
2. Genesis
3. CRIX EtriX
4. VCRIX
5. OCRIX
6. CRIX Portfolii
7. Chance, Risk and Opportunities

crix.berlin, thecrix.de, crix.info

- CRIX CRyptocurrency IndeX
- benchmark for crypto currency (CC) dynamics
- a scalable index for investment



- market cap weighted index
- Dominance of BTC…
- reallocation: 3M evaluation of k = # constituents

CRIX Methodology

Laspeyres' Index:

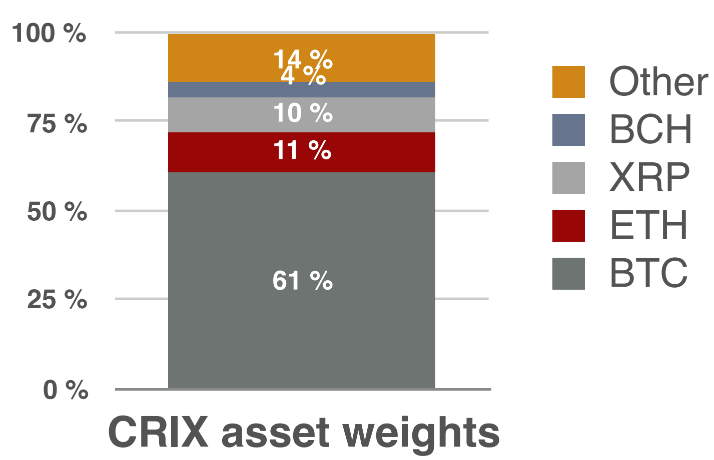
$$INDEX_t^{Laspeyres} = \frac{\sum_i P_{it} Q_{i0}}{\sum_i P_{i0} Q_{i0}}$$

$$INDEX_t^{CRIX} = \frac{\sum_i MV_{it}}{Divisor},$$

$$Divisor = \frac{\sum_i MV_{i0}}{1000}.$$

Only price changes cause a change in index development
Divisor ensures that changes in coin volume does not affect index price

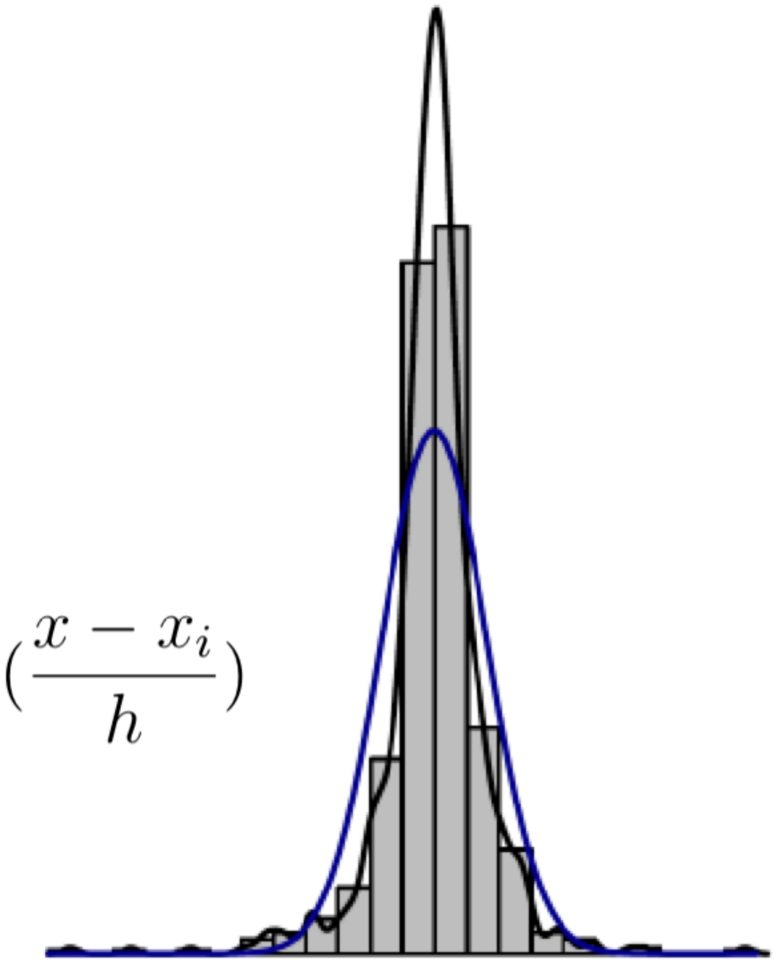
20181031 Underlying Crypto Assets and Weights



ca. 30 underlying cryptocurrencies
HF data available on crix.berlin
Constituent ranking every month

Source: CRIX

- CRIX AIC based selection of *k*
- KDE of difference *TMI - CRIX(k)*
- CRIX reflects 84% of the *TMI*

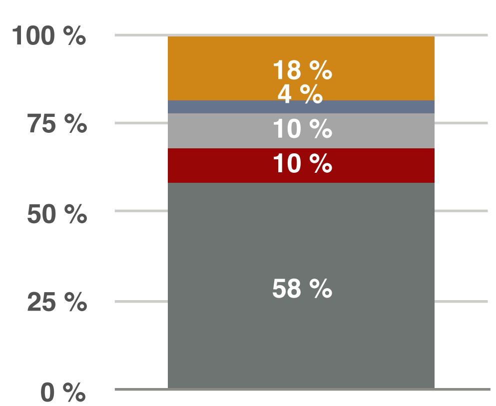


$$\widehat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n}\mathrm{Epa}\left(\frac{x-x_i}{h}\right)$$

1. Construct $\mathrm{TMI}_t(k_{max})$
2. Set $i = 1$
3. Construct $\mathrm{CRIX}(k_i, 1)$ and $\mathrm{CRIX}(k_i, \beta)$, $i = 1, 2, 3, \ldots,$ $k_1 < k_2 < k_3 < \cdots$
4. Compute $\varepsilon(k_i, \beta)_t$ and $\varepsilon(k_i, 1)_t$
5. Kernel density estimation for density $f(\varepsilon(k_i, \beta)_t)$ and $f(\varepsilon(k_i, 1)_t)$ with leave-one-out cross validation
6. Derive $AIC(k_i, \beta, s) = -2\log\prod_{t=1}^{n} f(\varepsilon(k_i, \beta)_t) + 2s$ and $AIC(k_i, 1, 0)$
7. If $AIC(k_i, \beta, s) < AIC(k_i, 1, 0)$: stop, else jump to 3. and $i = i + 1$

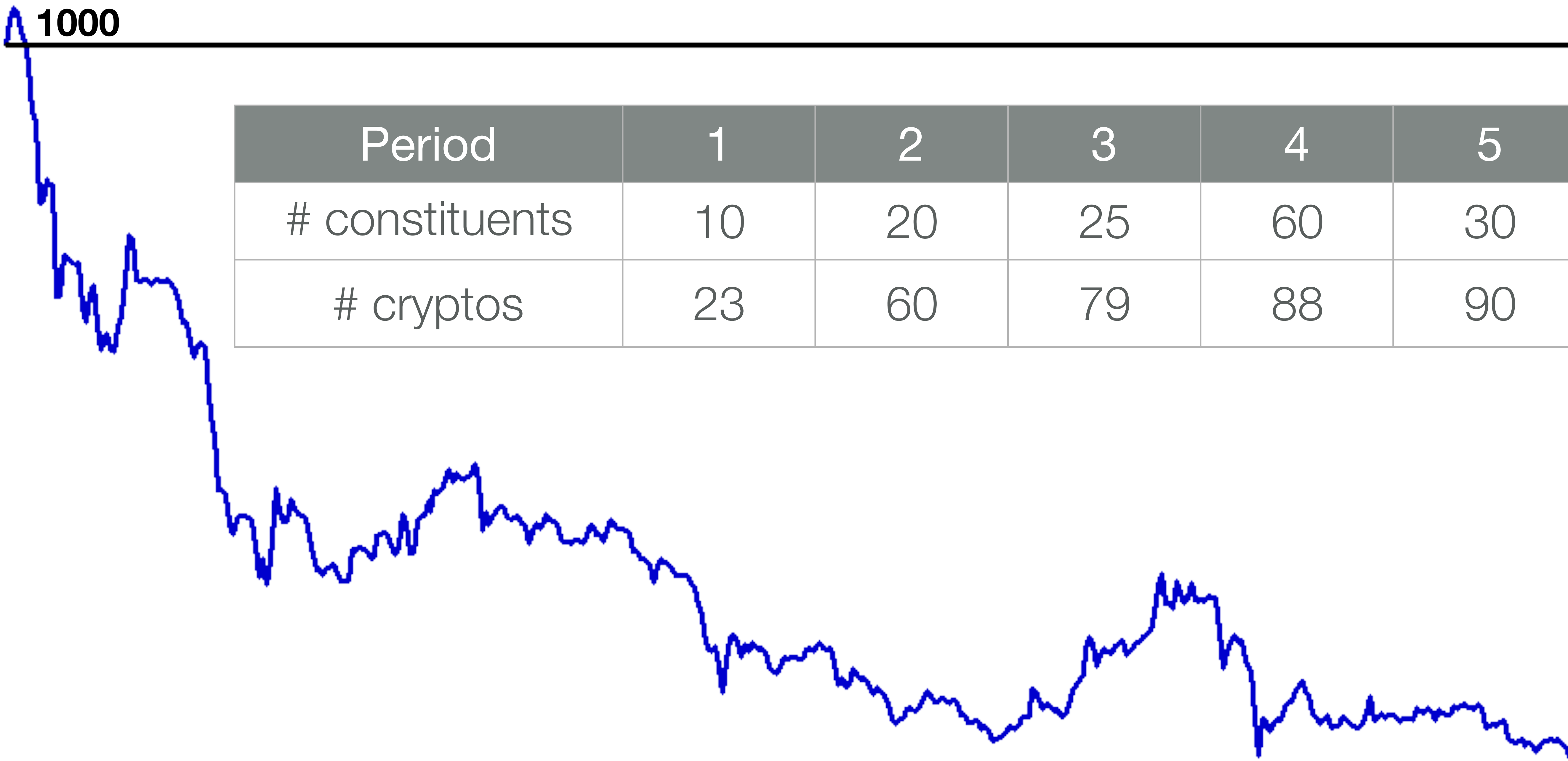
CRIX Methodology

20190131 Underlying Crypto Assets and Weights



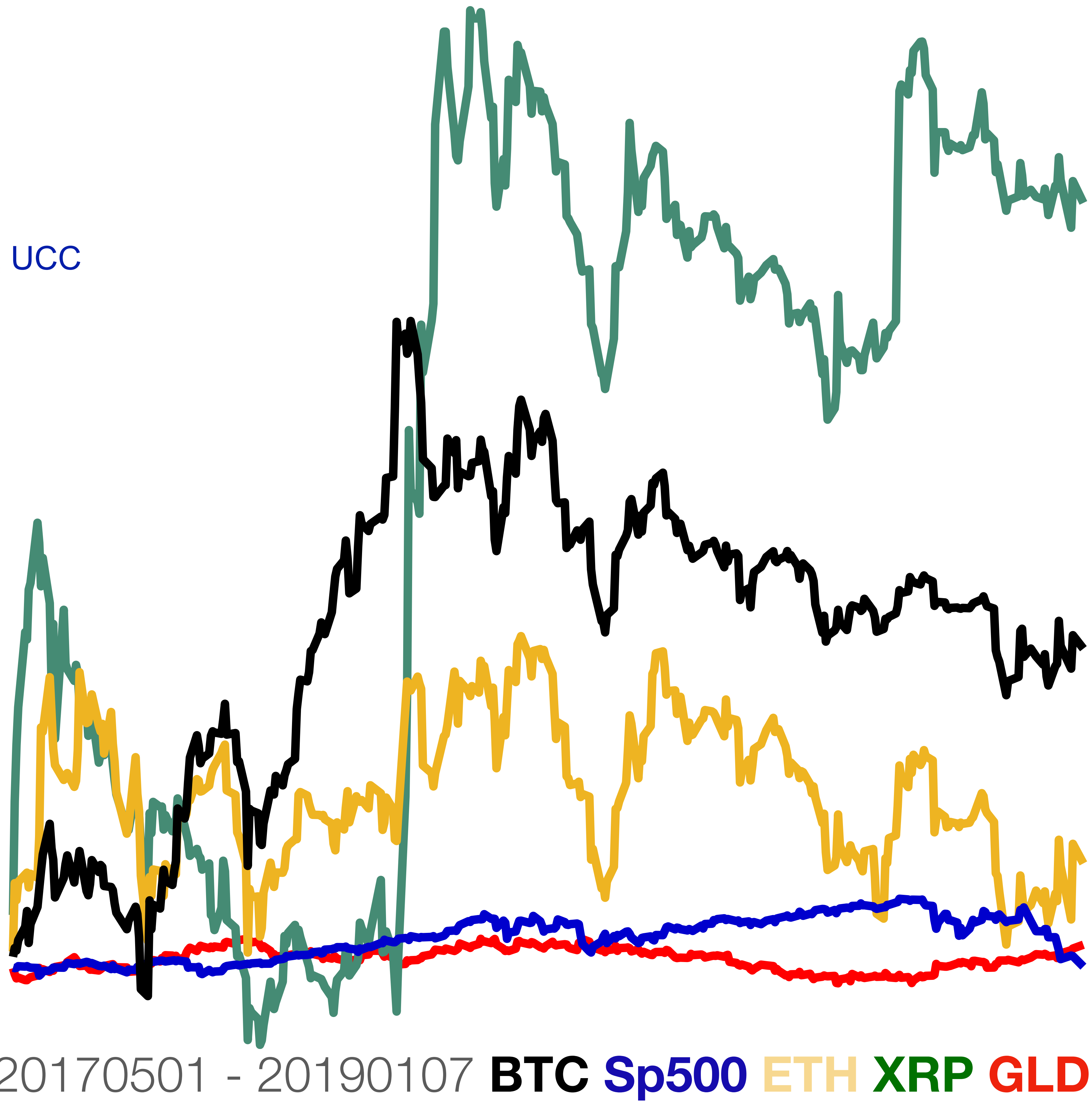
CRIX asset weights

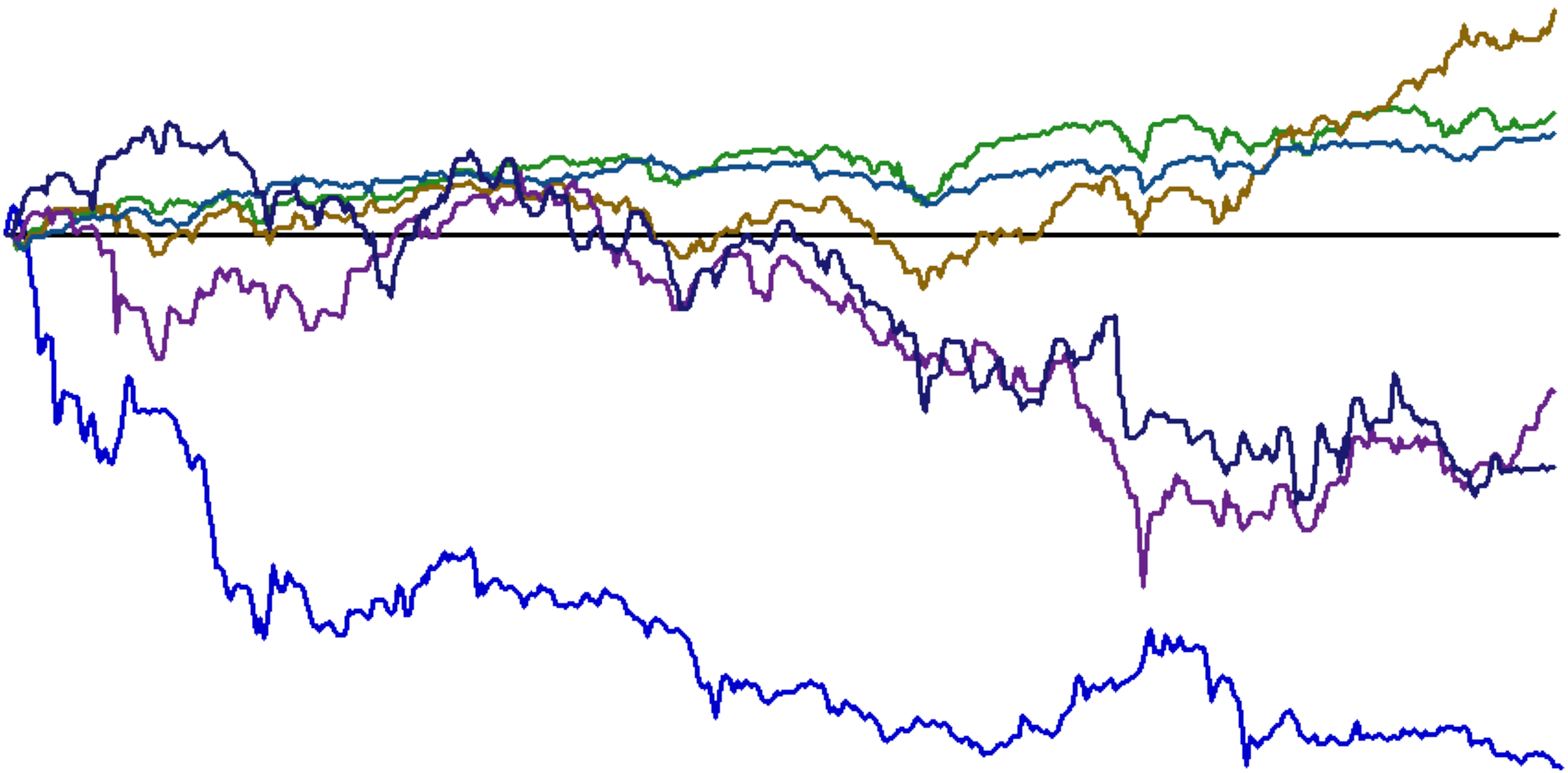
Source: CRIX



Period	1	2	3	4	5
# constituents	10	20	25	60	30
# cryptos	23	60	79	88	90

20140201 - 20150412


UCC
20170501 - 20190107 BTC Sp500 ETH XRP GLD

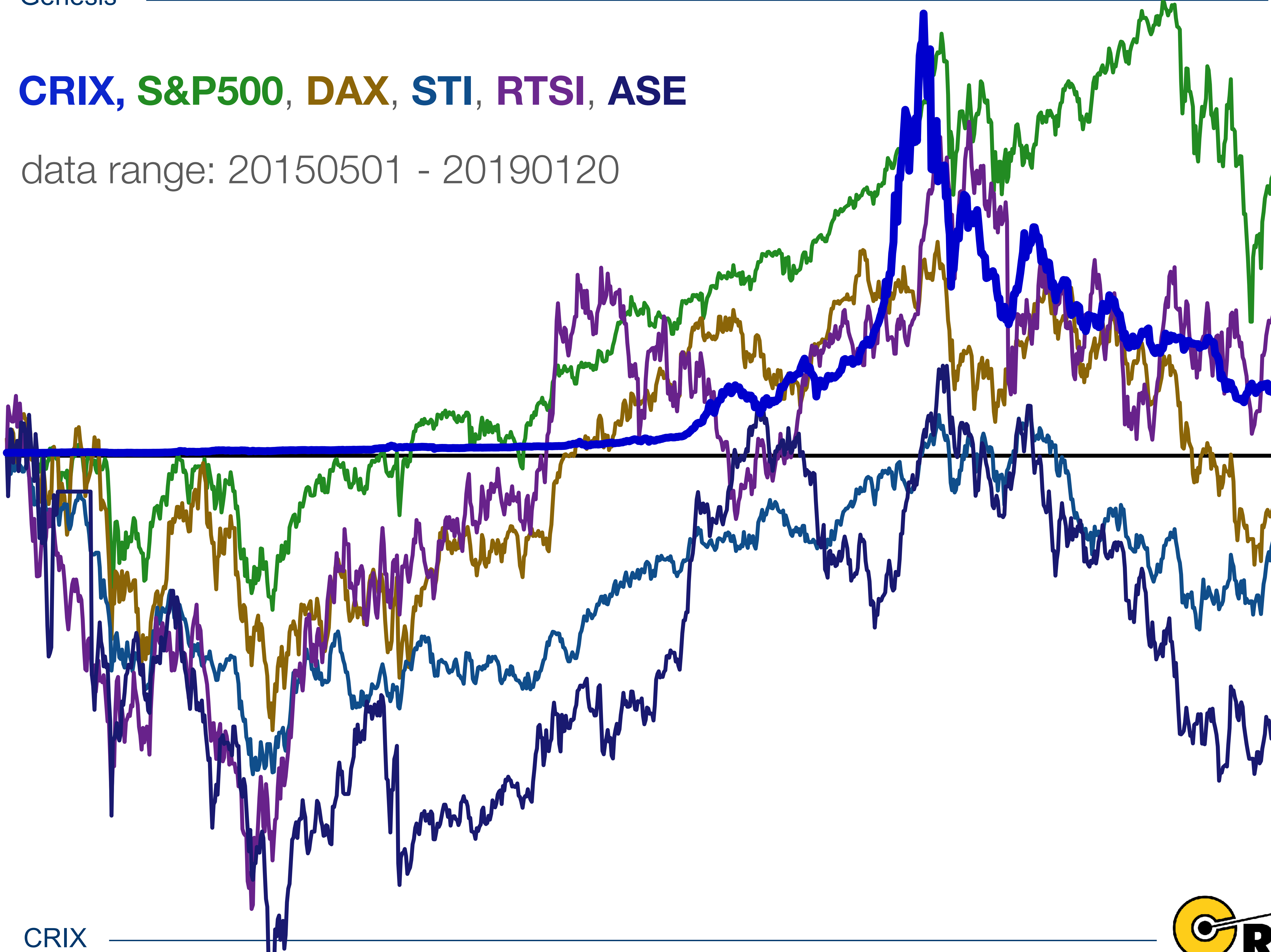


CRIX, S&P500, **DAX**, **STI** (Singapore), **RTSI** (Russia), **ASE** (Greece),

data range: 20140201 - 20150412

CRIX, S&P500, DAX, STI, RTSI, ASE

data range: 20150501 - 20190120



- CCs, Commodities, FX rate, Stocks (23 dimensions)
- Quantile (0.5, 1, 2.5, 5, 95, 97.5, 99, 99.5) %
- Expected Shortfall ES (0.5, 1, 2.5, 5, 95, 97.5, 99, 99.5) %
- Skew, Kurt, Var, stable, AR(1), Hurst Exponent
- Tail + Moment Factor

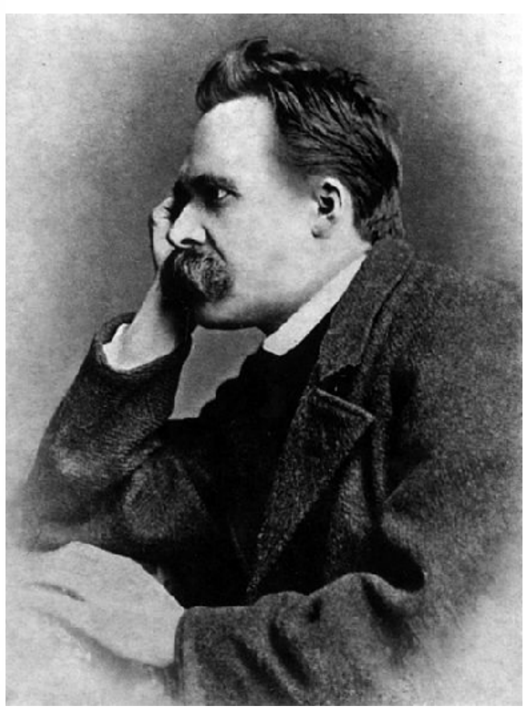

Also sprach Zarathustra.

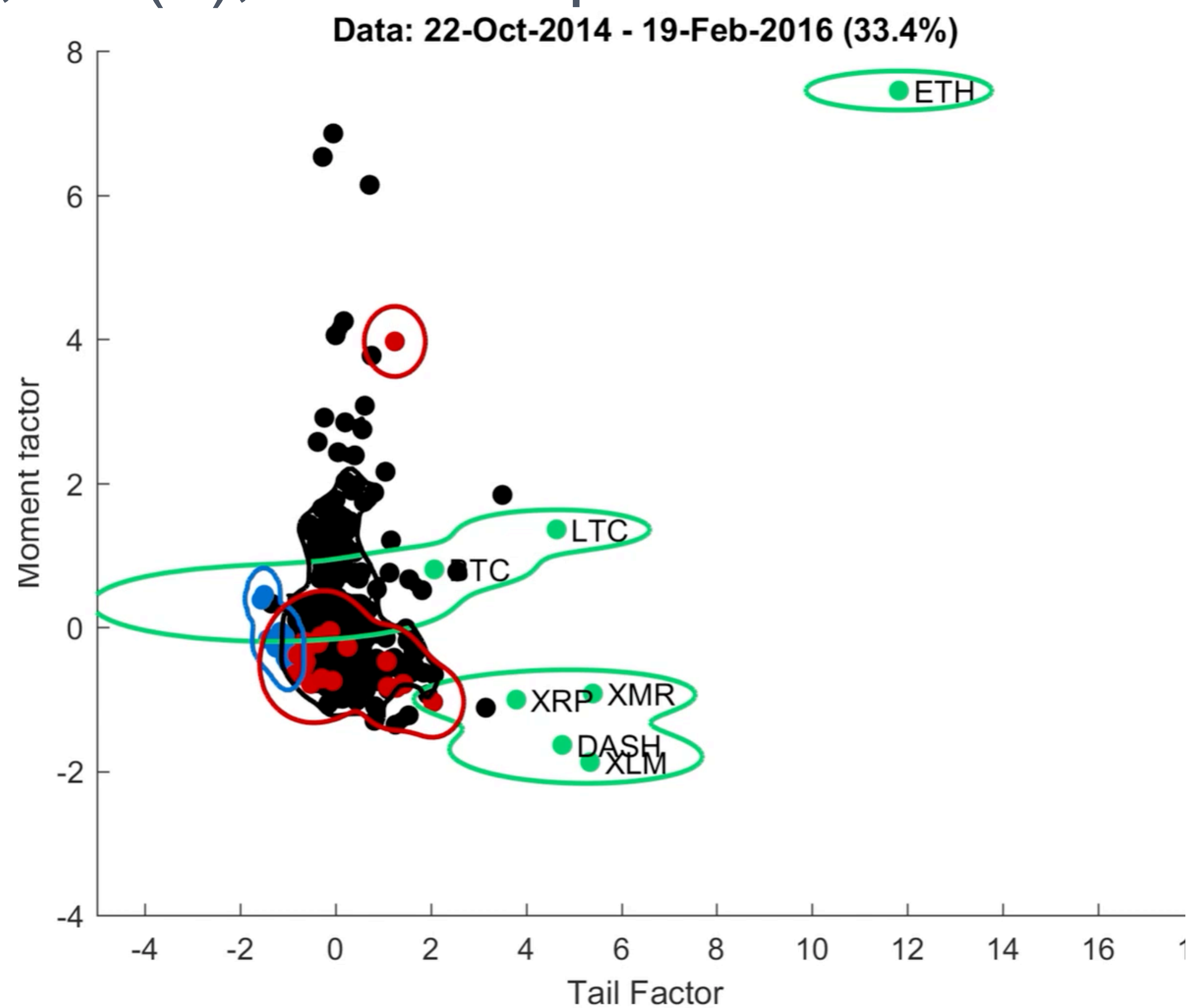
Ein Buch für Alle und Keinen.

Von Friedrich Nietzsche.

Chemnitz 1883.

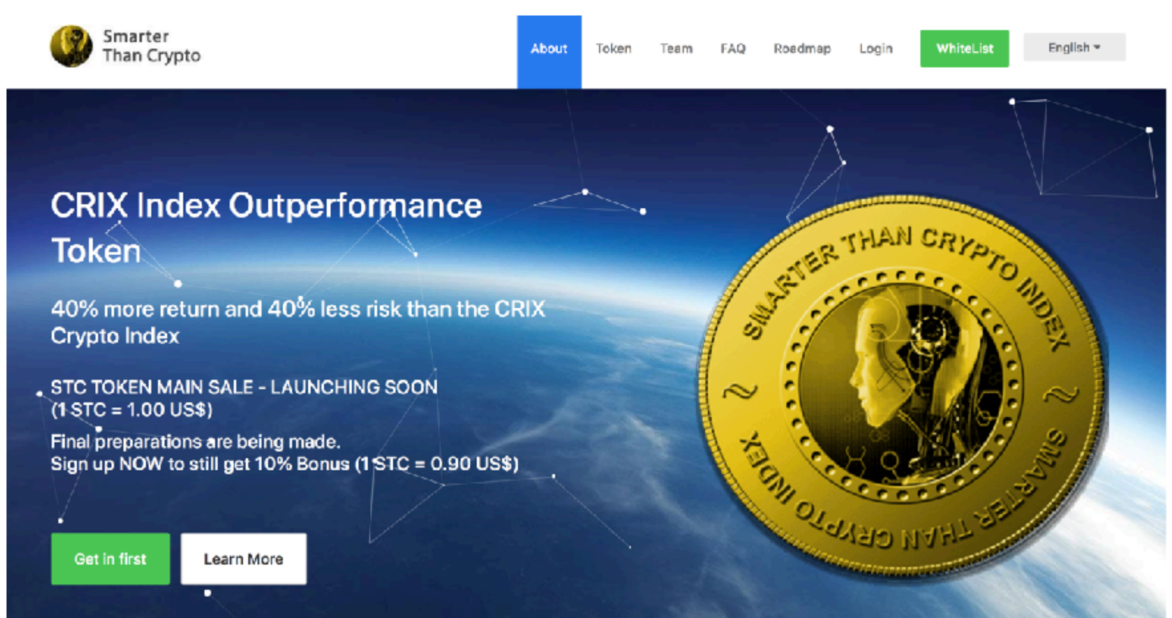
Verlag von Ernst Schmeitzner.





data range: 20141004 - 20181016 weekly data

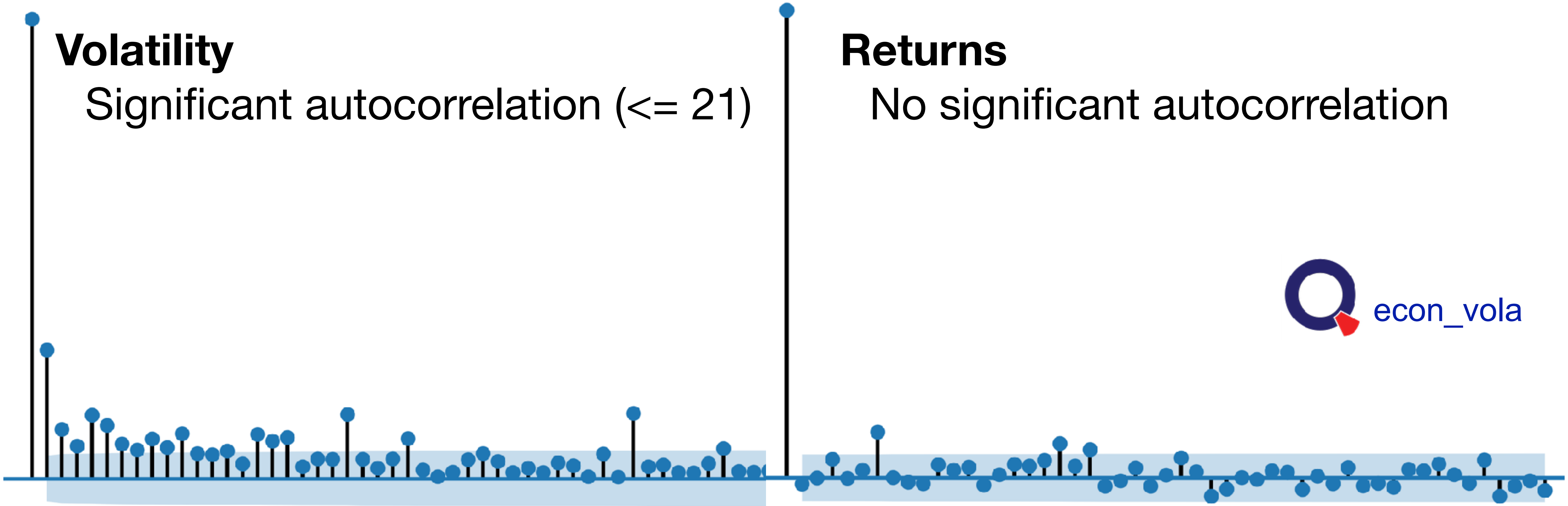
- CRIX EtriX (Chen S et al., 2017)
- CC based derivatives (e.g. XBT) emerge
- CRIX dynamics vital for pricing and risk management
- Emergence of VCRIX, the Vola of CRIX
- How does the crypto market stochastically evolve?



econ_vola

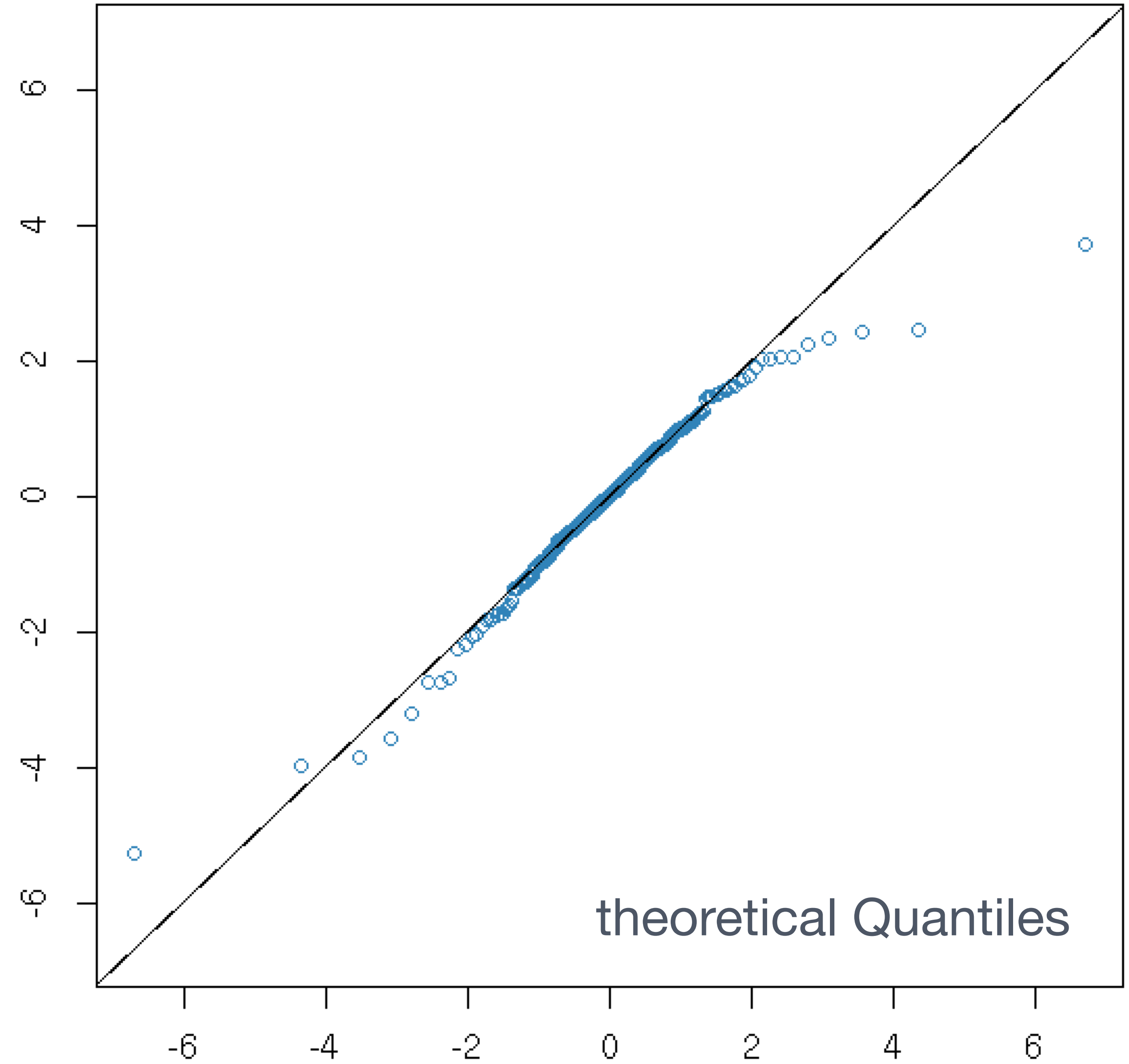
GARCH(1,1) model is sufficient in most cases,

$$\begin{aligned} \varepsilon_t &= Z_t \sigma_t, \quad Z_t \sim N(0,1) \\ \sigma_t^2 &= \omega + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 \end{aligned}$$

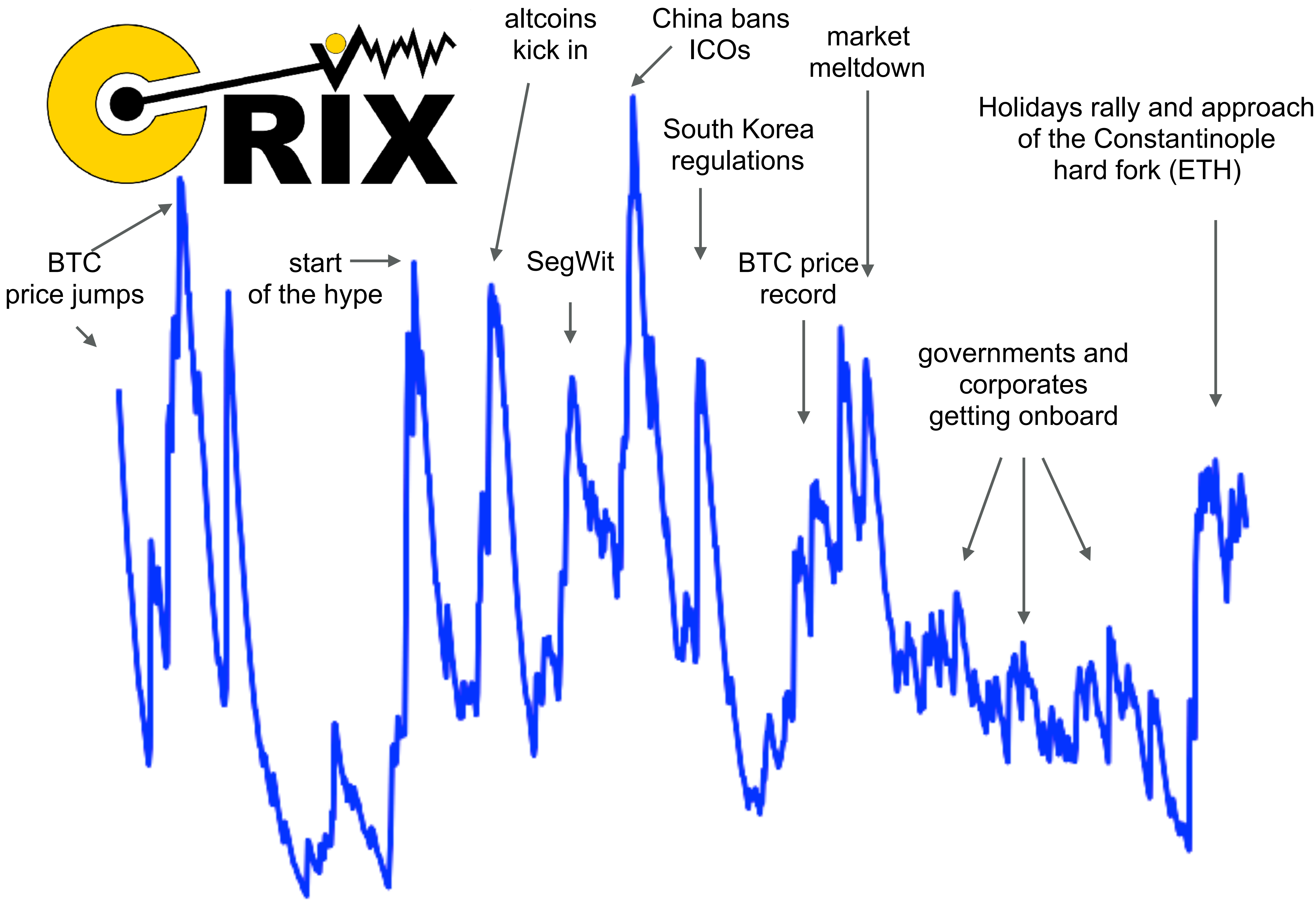


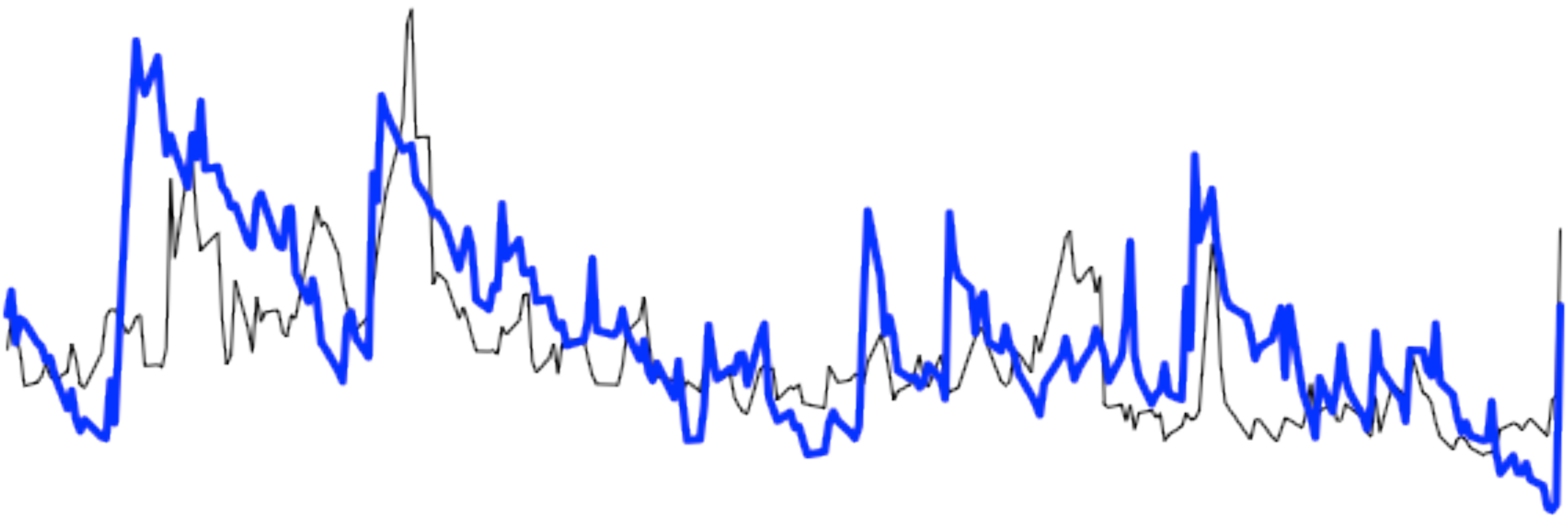
econ_vola

- ARIMA t-EGARCH model
- bad news on tail fits
- standard math finance ?



$$
\begin{aligned}
\varepsilon_t &= Z_t \sigma_t \\
Z_t &\sim N(0,1) \\
\log(\sigma_t^2) &= \omega + \sum_{i=1}^{p} \beta_i \log(\sigma_{t-i}^2) + \sum_{j=1}^{q} g_j\,(Z_{t-j})
\end{aligned}
$$


BTC
price jumps
start
of the hype
altcoins
kick in
SegWit
China bans
ICOs
South Korea
regulations
market
meltdown
BTC price
record
governments and
corporates
getting onboard
Holidays rally and approach
of the Constantinople
hard fork (ETH)



Corr(VCRIX_VIX, VIX) = 0.7

price (USD) Market Cap
20190121 - 20190128
coinmarketcap.com

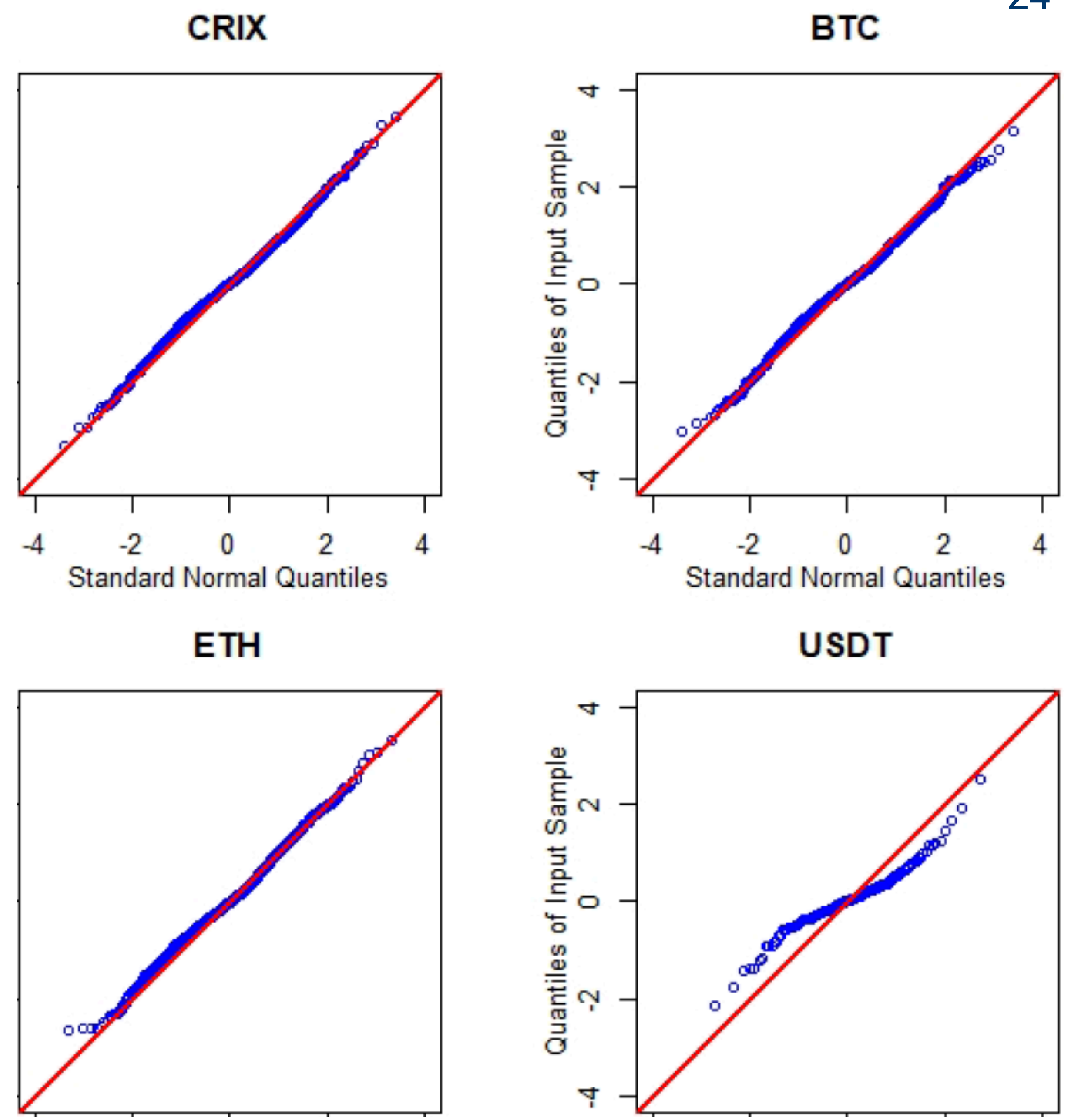
- Option Pricing on CRIX and CCs
- Stochastic Vola (SV) combined with Jump model
- VCRIX, a natural component

$$dlogY_t = \mu d_t + \sqrt{V_t} dW_{y,t} + Z_{y,t} dN_t$$

$$dV_t = k(\theta - V_t)dt + \sigma_V \sqrt{V_t} dW_{v,t} + Z_{v,t} dN_t$$

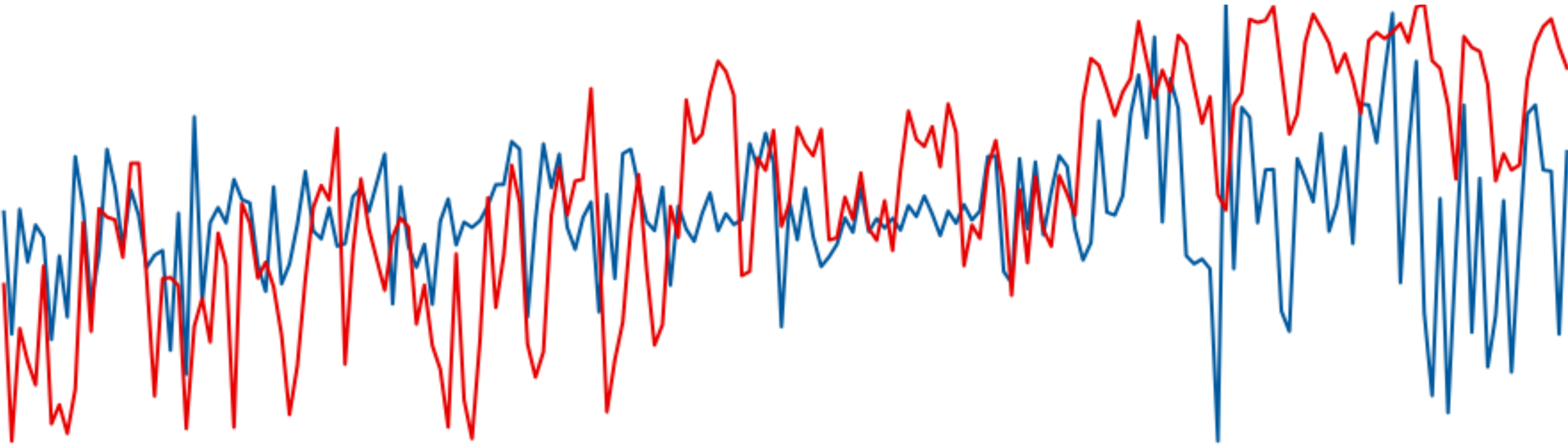
https://svcjoptionpricing.shinyapps.io/optionapp/

SVCJOptionApp



- SV Correlated Jump (CJ) model (Chen CYH et al., 2019)
- CJ makes the difference
- MCMC to calibrate SVCJ

CRIX and sentiments



Daily CRIX log-return, Daily stock twits sentiment
201407 - 201807

Després R, Chen CYH, Renault T (2019)

Term	Sentiment weight
🚀	0.90
hodl	0.54
hodl !	0.85
hackers	−0.74
miner	0.62
bitcoin 😂	−0.73
scam	−0.77
~~fucking~~ scam	−0.86

Crypto specific terms

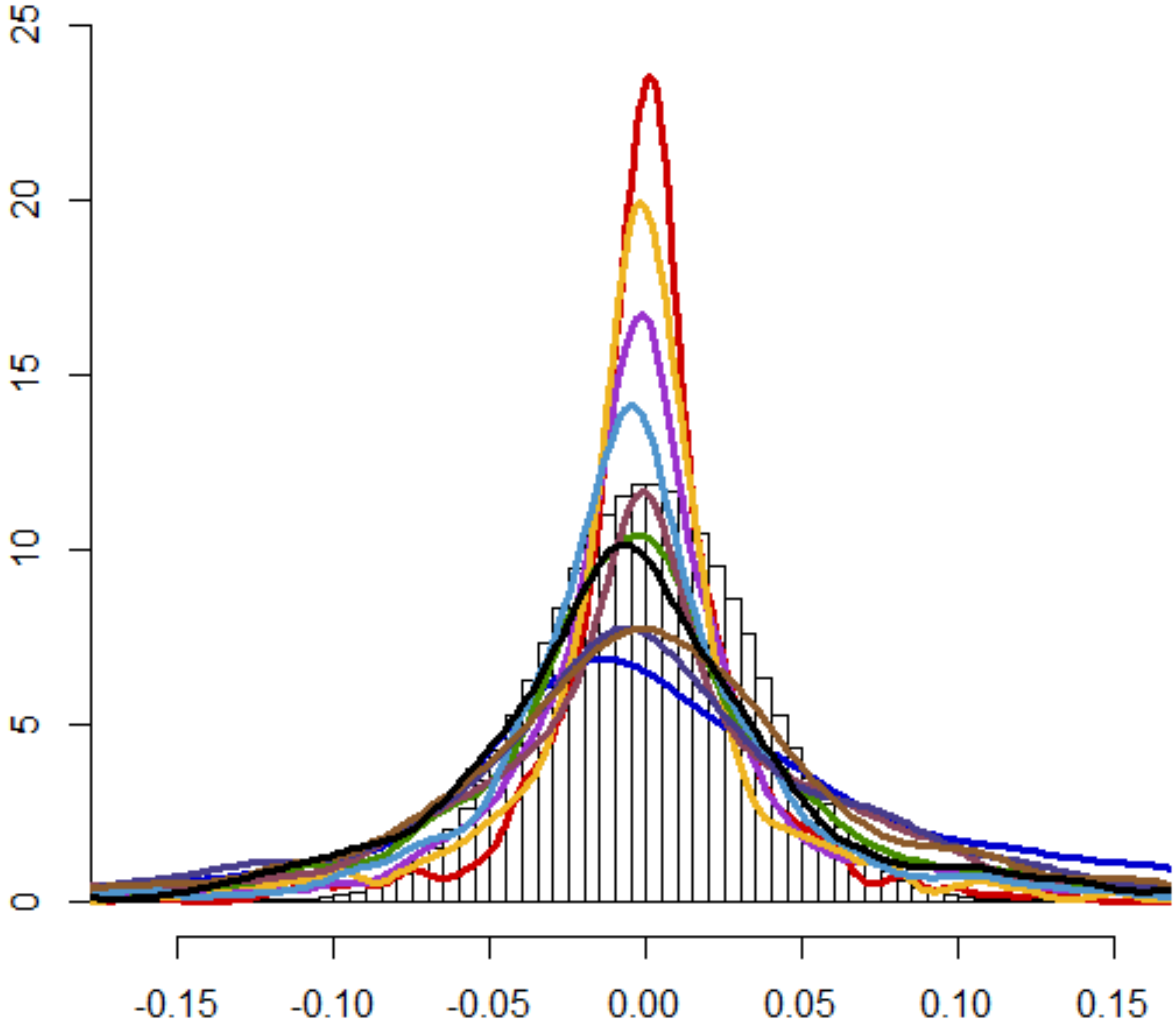
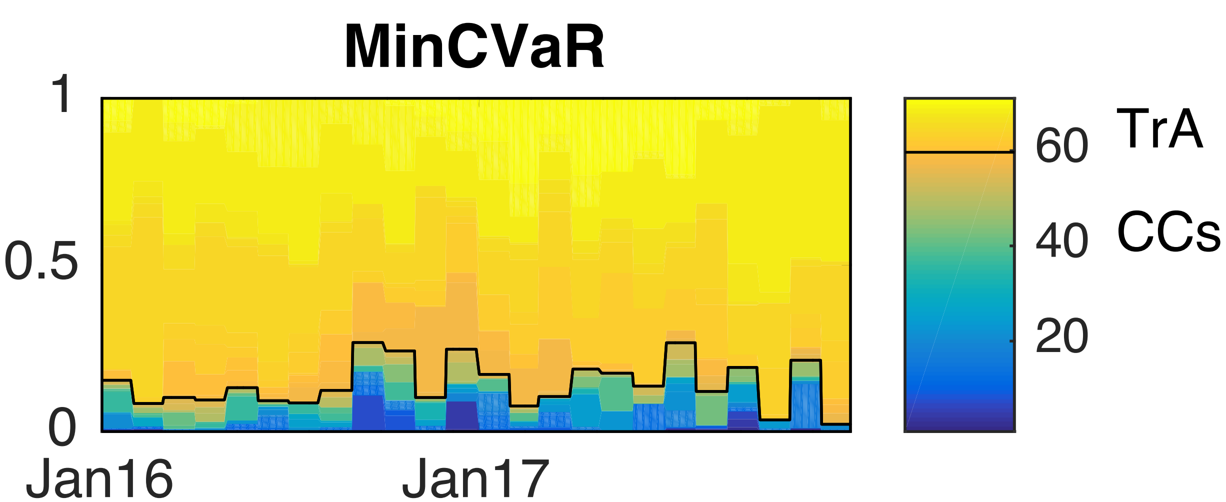


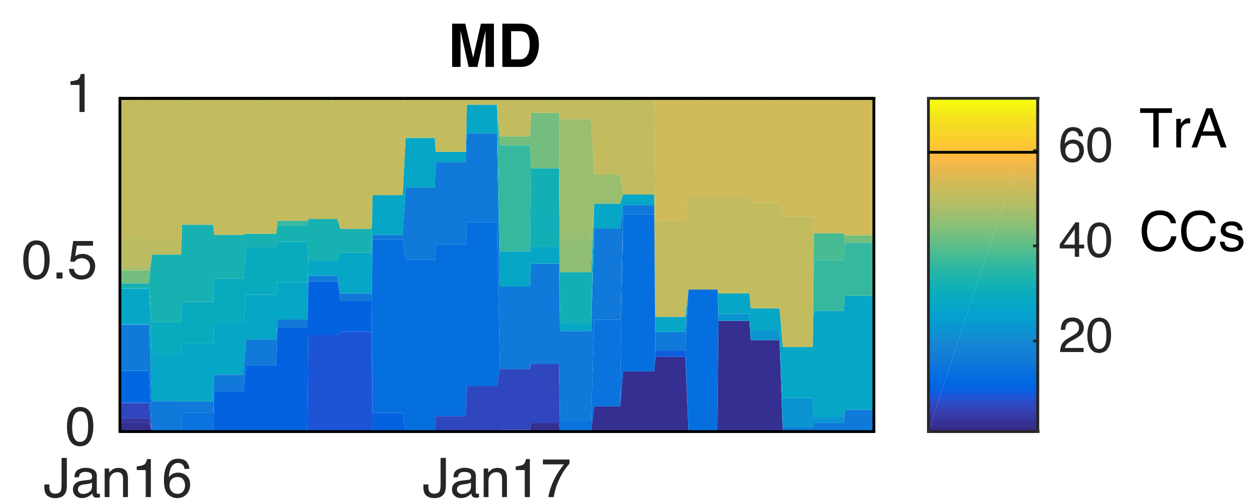
Figure 3: Density of Top-10 cryptos against normal distribution

CCSHistReturnsDensity

Asset allocation with Cryptos

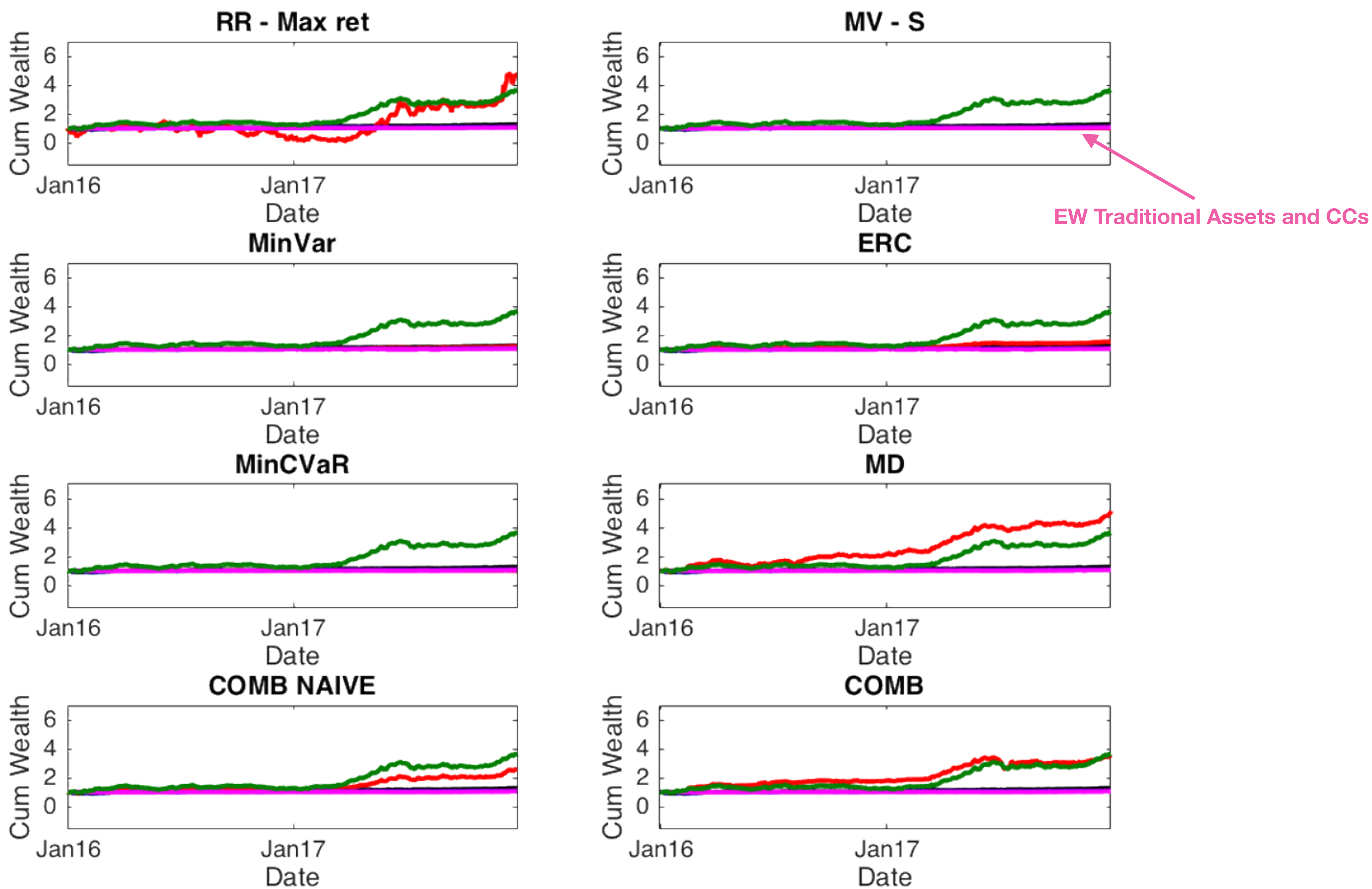
- Allocate cryptos ($n = 55$) and conventional assets ($m = 16$)
- Out-of-sample performance: 1 Y moving window, daily returns
- Monthly, weekly and daily rebalancing
- 7 individual optimisation strategies and 2 combinations of models
- Check performance under liquidity constraints (LIquidity Bounded Risk-return Optimisation - LIBRO)





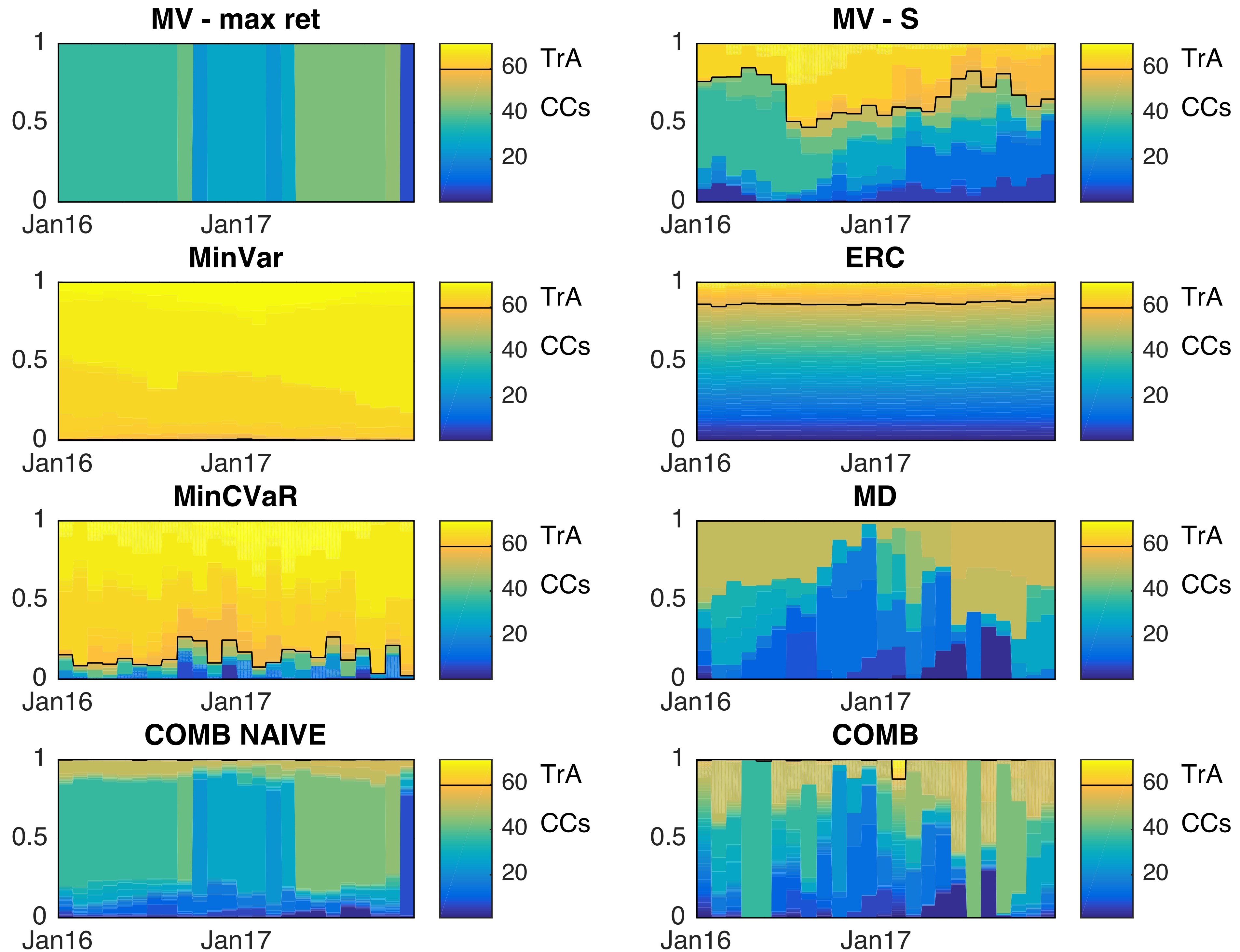
Asset allocation with Cryptos

Model	Reference	Abbreviation
Equally weighted	DeMiguel et al. (2009)	**EW**
	Risk-return-oriented strategies	
Mean – Var – max Sharpe	Jagannathan and Ma (2003)	MV – S
	Return-oriented strategies	
Risk – Return – max return	Markowitz (1952)	RR – max ret
	Risk-oriented strategies	
Mean – Var – min var	Merton (1980)	MinVar
Equal Risk Contribution ERC	Roncalli et al. (2010)	ERC
Mean – CVaR – min risk	Rockafellar and Uryasev (2000)	MinCVaR
Maximum Diversification	Rudin and Morgan (2006)	MD
	Combination of models	
Naïve Combination	Schanbacher (2015)	COMB NAÏVE
Combination bootstrap	Schanbacher (2014)	COMB



CCP Code

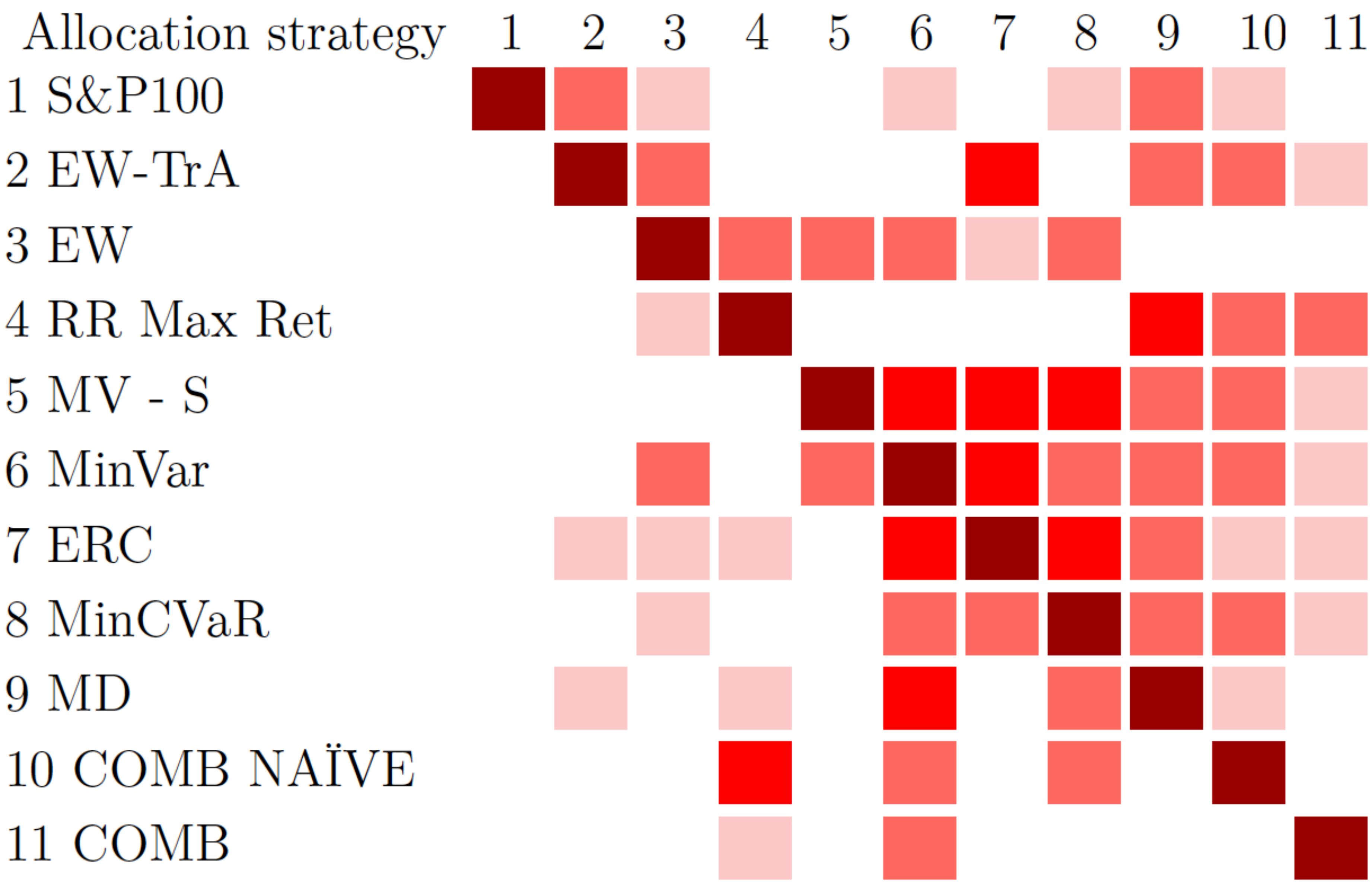
Performance of portfolii: S&P100, EW, EW–TrA, RR-Max ret–TrA and corresponding Allocation strategy
Data range: 20160101 to 20171231



![CCP Code] CCP Code

Change in the composition of portfolio
Data range: 20160101 to 20171231

Asset allocation with Cryptos

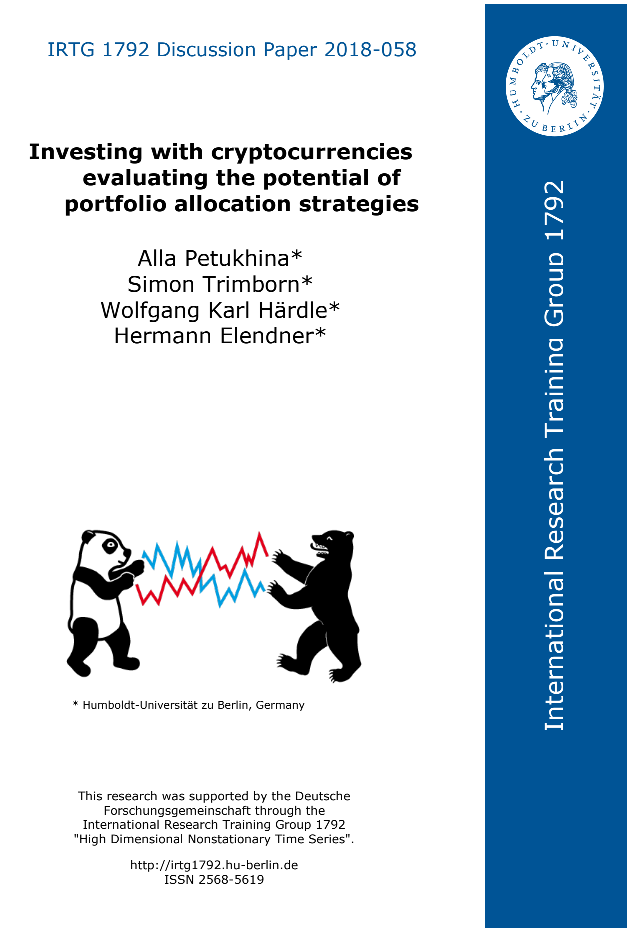


p-value of the difference between the Sharpe Ratio (lower triangle) and Certainty Equivalent (upper triangle) of all strategies with each other with significance codes 0.01, 0.05 and 0.1 (without liquidity constraints)

CCP Code

Asset allocation with Cryptos

- MD and Max Return strategies show the most promising results
- CC as portfolio components yield little variance reduction: application of CC in target return portfolio strategies
- The inclusion of CC is strongly related to investment objectives
- Combination of models outperforms individual ones
- Liquidity Bounded Risk-return Optimization (LIBRO) approach for CC portfolios:
  - improves risk-adjusted performance
  - strengthens diversification effects


IRTG 1792 Discussion Paper 2018-058

Investing with cryptocurrencies evaluating the potential of portfolio allocation strategies

Alla Petukhina*
Simon Trimborn*
Wolfgang Karl Härdle*
Hermann Elendner*

* Humboldt-Universität zu Berlin, Germany

This research was supported by the Deutsche Forschungsgemeinschaft through the International Research Training Group 1792 "High Dimensional Nonstationary Time Series".

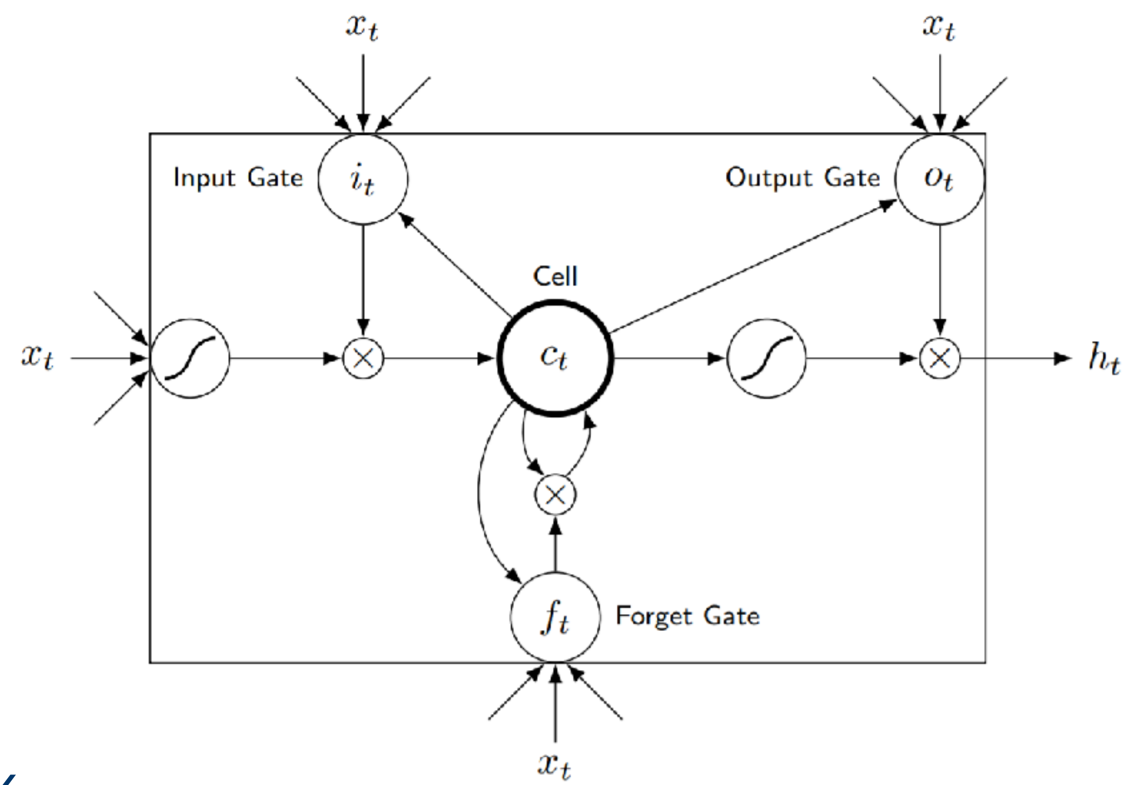
http://irtg1792.hu-berlin.de
ISSN 2568-5619

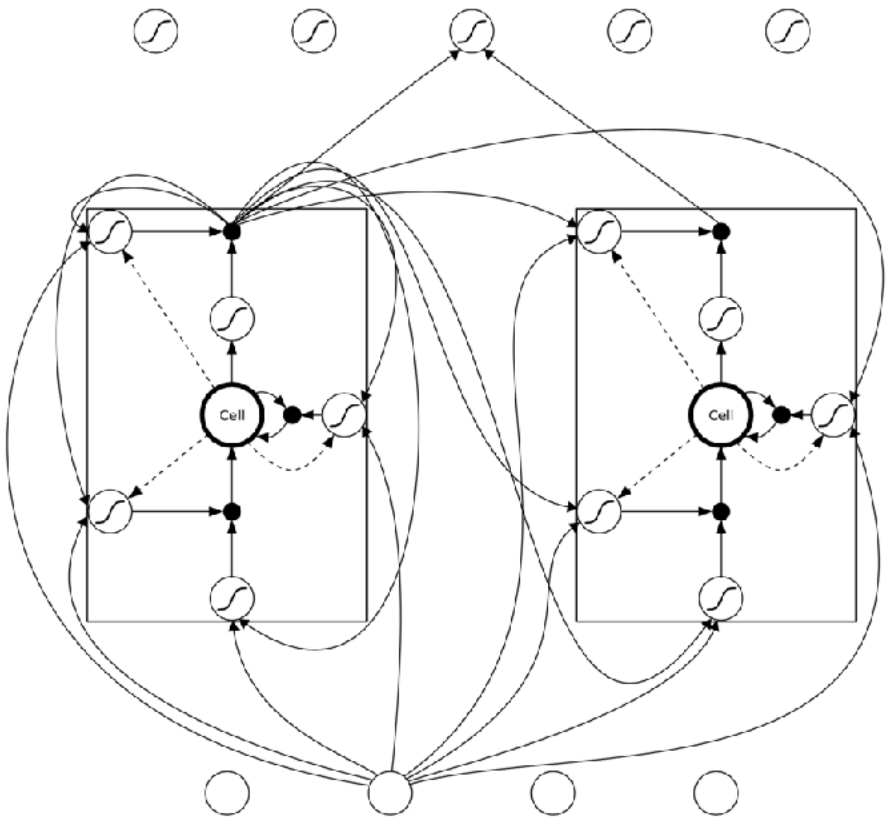
International Research Training Group 1792

Petukhina A, Trimborn S, Härdle WK, Elendner H (2018)
Investing with cryptocurrencies - evaluating the potential of portfolio allocation

Deep recurrent reinforcement learning for portfolio management

- Data driven: model free framework
- Fully automatised: deep learning
- Online learning: fast adaptation to market change
- Maximising return instead of minimising forecast error
- Limit liquidity risk: Select based on volume (usdt, btc, dash, xrp, eth, ltc, xmr, str)





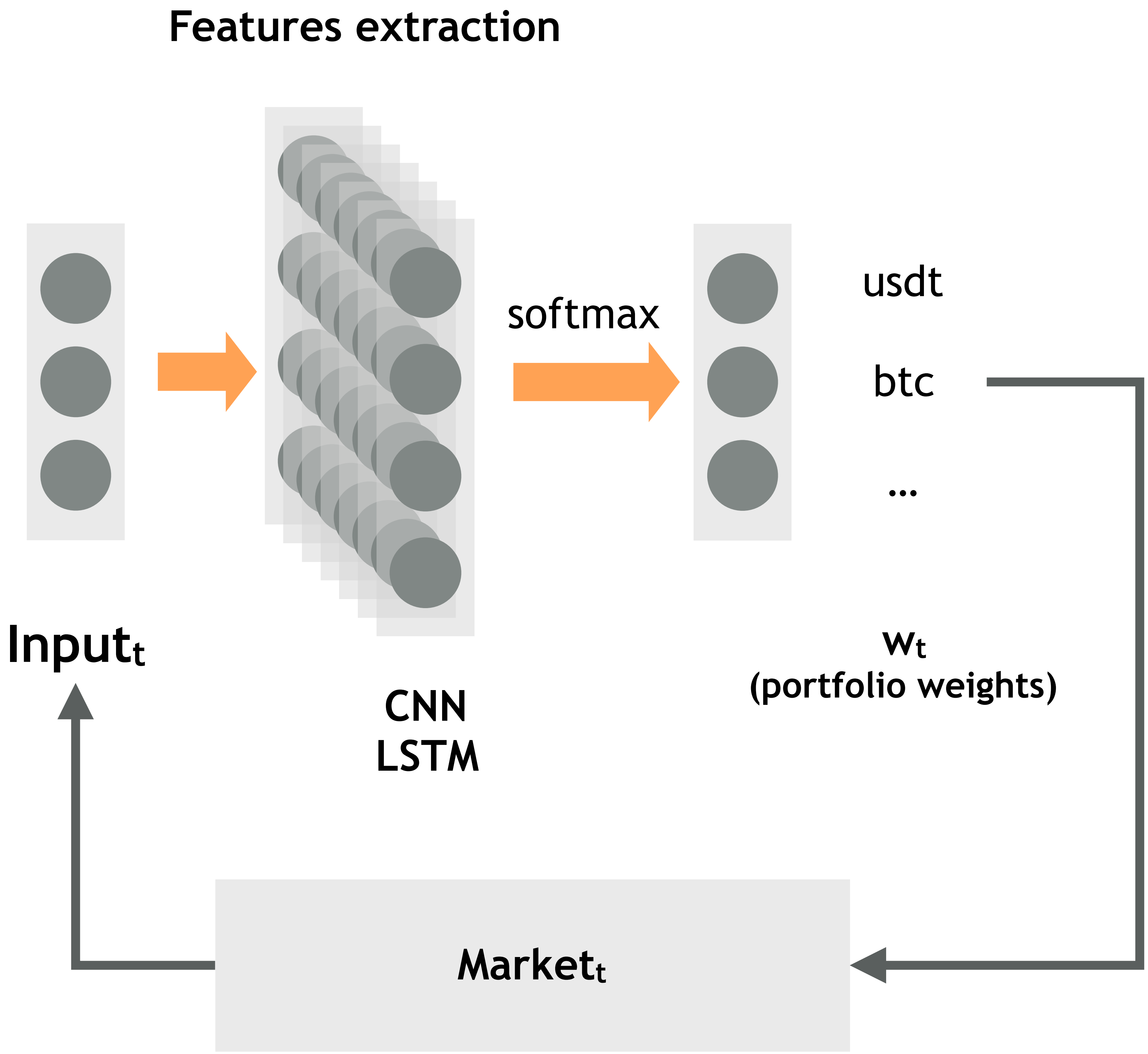
- Input: Price relative vector on look back period *l* of close, highest, lowest prices on a specified aggregation frequency
- Output: portfolio weights (trading actions) including risk free asset (cash)

$$(w_1, \dots, w_{n+1}) = f_\theta(X_t, \dots, X_{t-l})$$

$$\text{where } \sum_i w_i = 1 \text{ and } 0 \leq w_i \text{ (long only portfolio)}$$

- *w = (w_1,…,w_n+1)* maximise future returns at time *t+1*
- *X_t* is the input feature set at time *t*
- f_θ is a deep neural network (LSTM or CNN) with a softmax output layer

Policy network



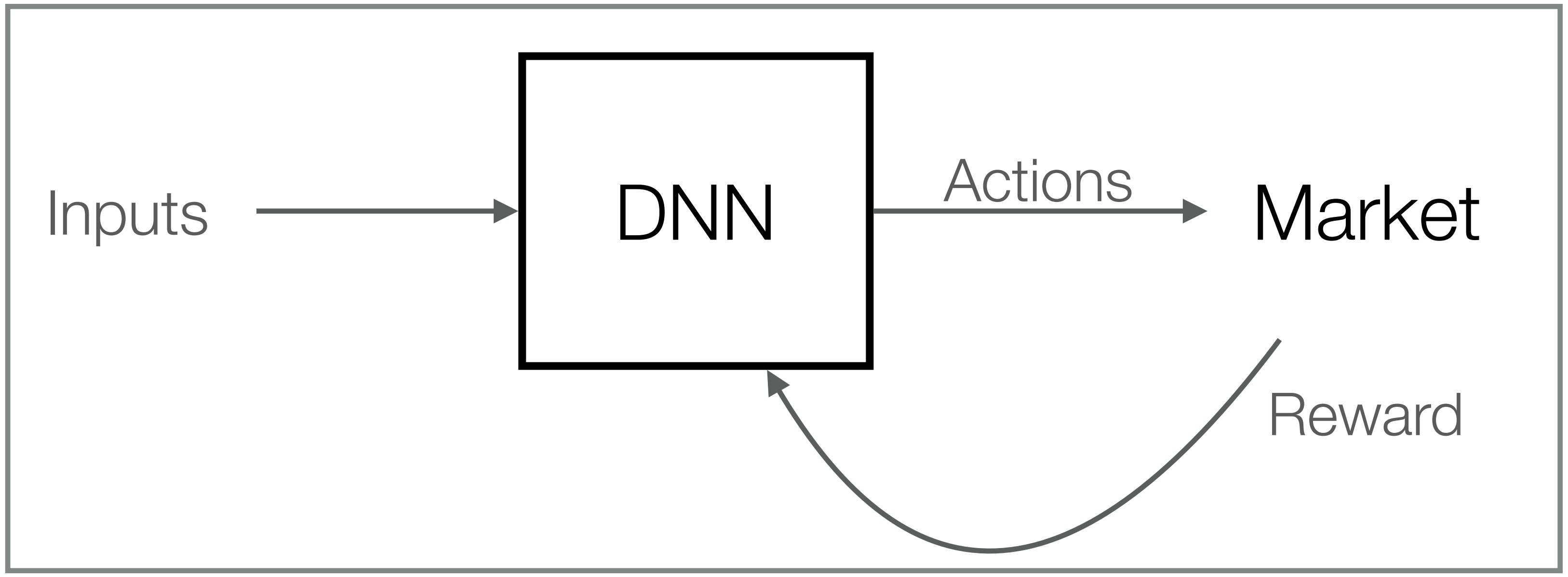
- Input: Price relative vector on lookback period l of close, highest, lowest prices on a specified aggregation frequency
- Output: portfolio weights (trading actions) including risk free asset (cash)

$$(w_1, \dots, w_{n+1}) = f_\theta(X_t, \dots, X_{t-l})$$

$$\text{where} \sum_i w_i = 1 \text{ and } 0 \le w_i \text{ (long only portfolio)}$$

- *w = (w_1,…,w_n+1)* maximise future returns at time *t+1*
- *X_t* is the input feature set at time *t*
- f_**θ** is a deep neural network (LSTM or CNN) with a softmax output layer

Policy gradient



- Learning through stochastic policy gradient:
- Goal: maximise portfolio value at each step (final portfolio value)
- Reward function: cumulated logarithmic return with transaction costs

$$J_{[0,t_f]}(f_\theta) = \frac{1}{t_f}\sum_{t=1}^{t_f+1} \log(\mu_t \frac{p_t}{p_{t-1}} w_{t-1})$$

p_t price vector, μ_t is the transaction costs

- Optimal policy f_**θ***: find optimal parameters **θ** that maximize reward
- Online stochastic policy gradient:

$$\theta \rightarrow \theta + \lambda \nabla_\theta J_{[0,t_f]}(f_\theta)$$

Transaction costs

- Assumptions: zero slippage, zero market impact (no implicit fee)

- Transaction costs come from commission rate per trade, *c*, from the exchange

- *c* depends on the exchange

- Explicit formula for μ_t:

$$\mu_t = c \sum_{i=1}^{n+1} | w'_{t,i} - w_{t,i} |$$

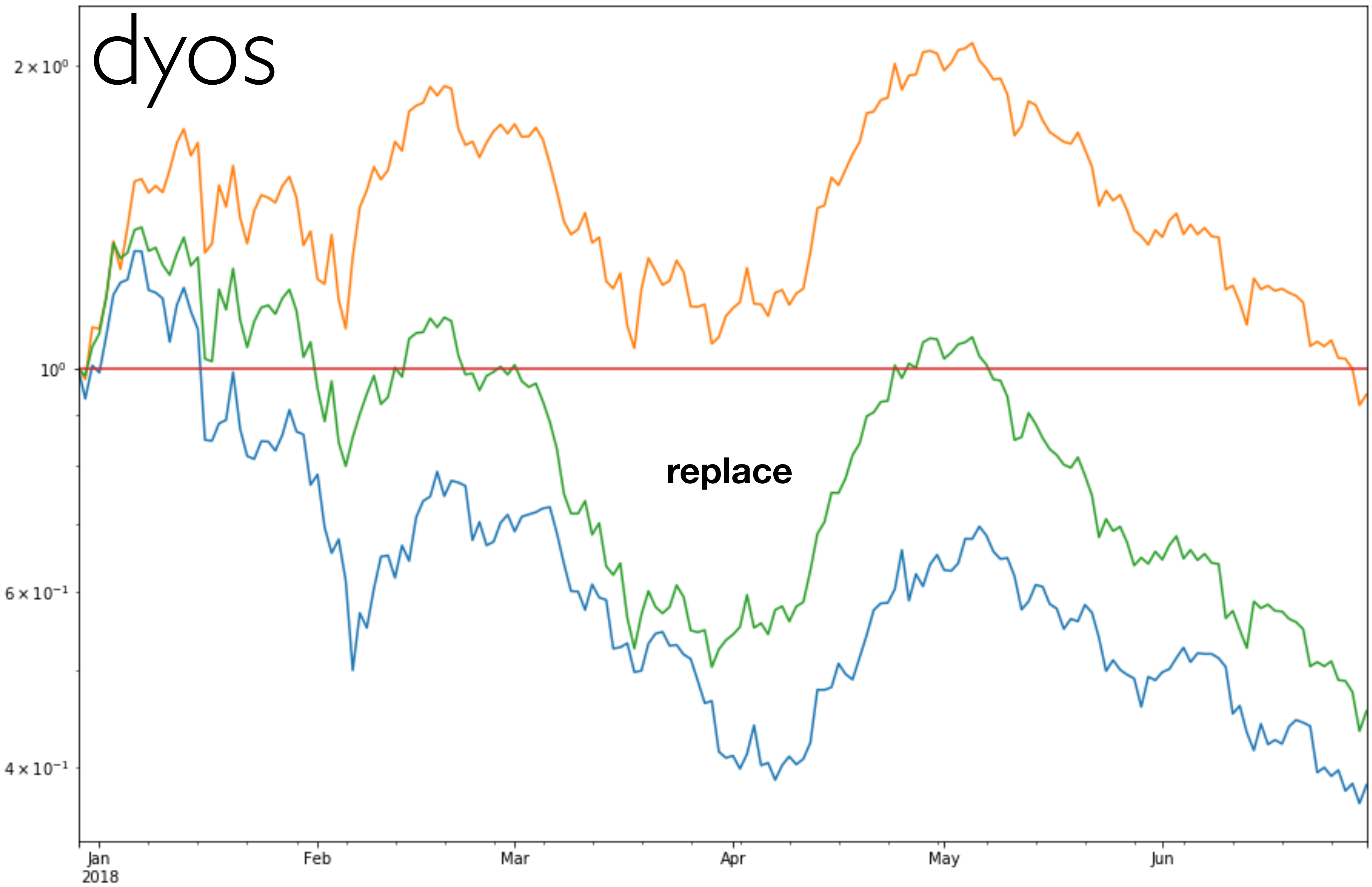
where w'_*t,i* is the weight of asset *i* before rebalancing

Results

- Data: 30 min prices from 2016-01-01 to 2018-06-30
- Test data 20 %: 2018-01-02 to 2018-06-30
- Horizon forecast: 30 min (next time step)
- Architecture
  - LSTM or CNN model (with one hidden layers)
  - Dropout layer
  - One softmax layer as output corresponding to next actions
- Benchmark: CRIX

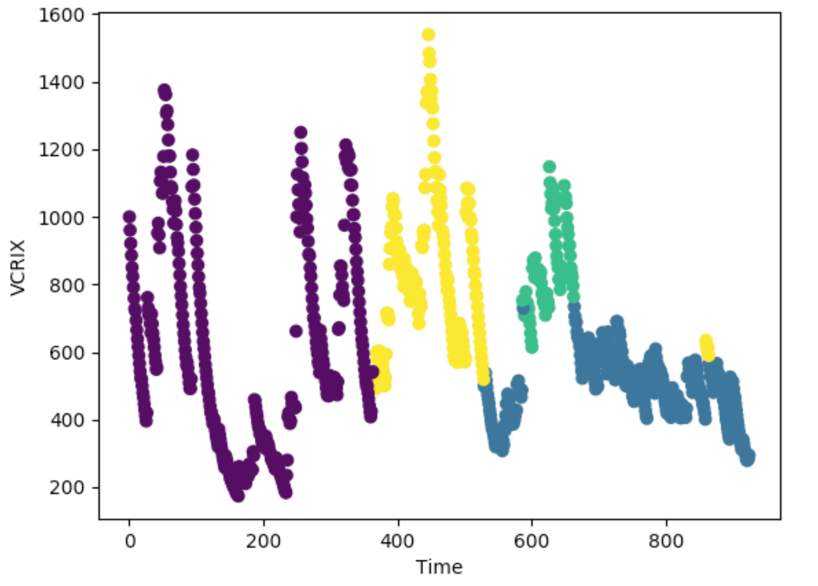
	Sharpe ratio	Sortino ratio	Max drawdown
CRIX	-1.08	-0.99	0.15
Long only	-0.88	-0.83	0.16
Long short	0.36	0.37	0.17

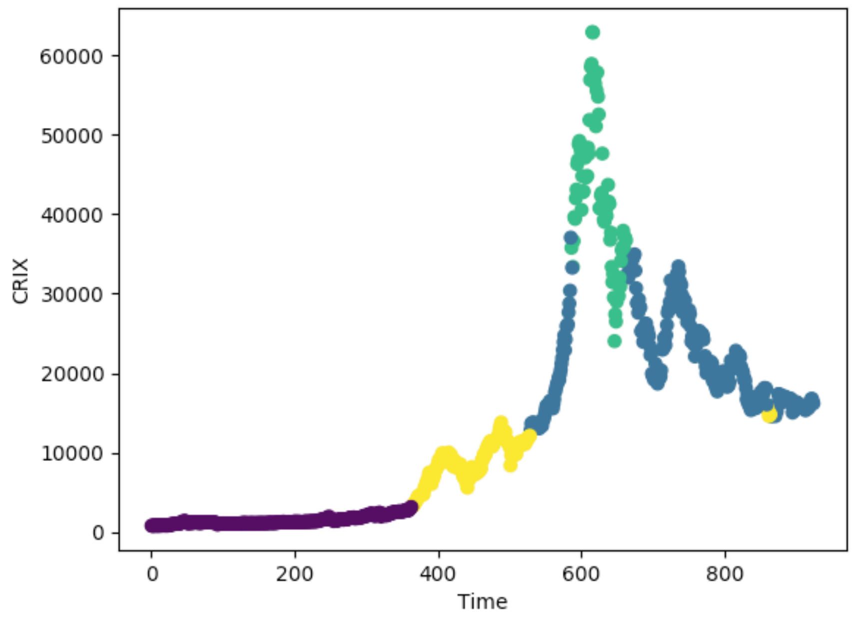
Risk measures for portfolii with **c=0.2%** and **c=0.1%** fee per trade

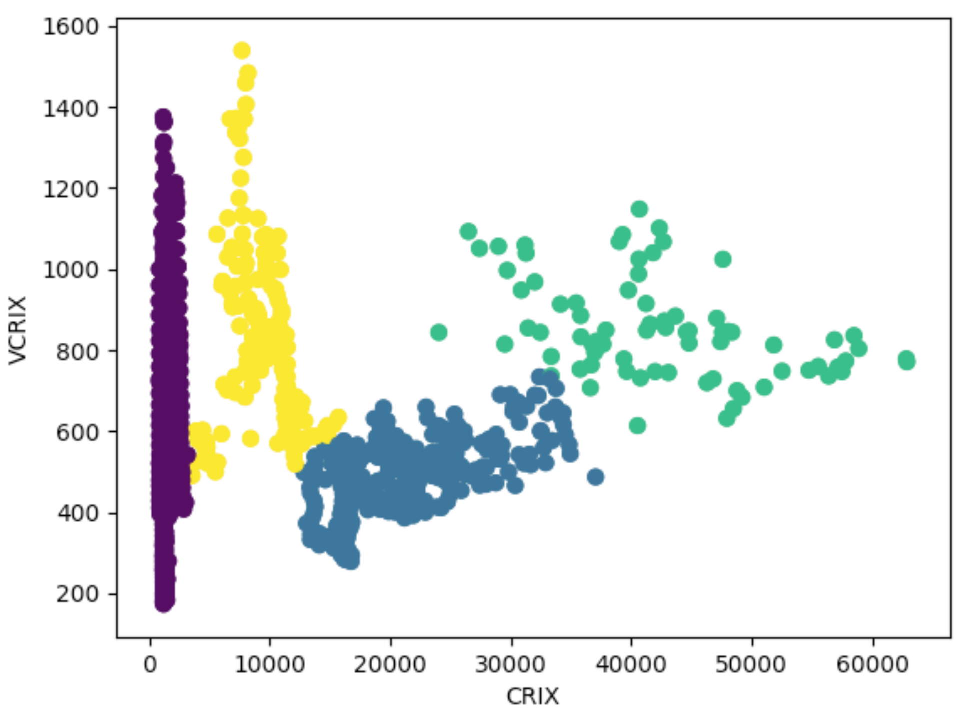


Cumulative returns of **CRIX**, RL agents for **long-short, long-only** strategies based on CNN predictions with **c = 0.2%** per trade (Bitfinex exchange)

Variational Bayes

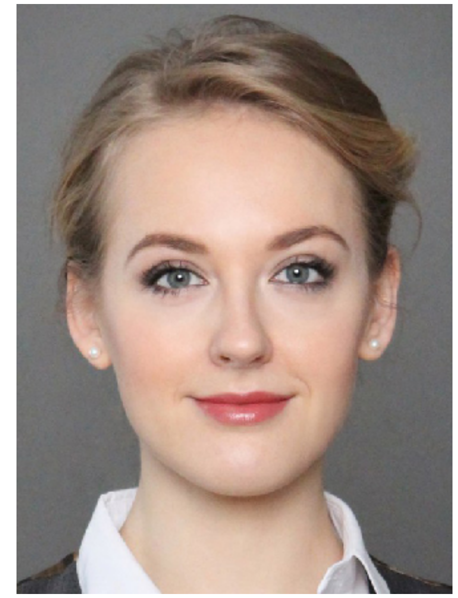
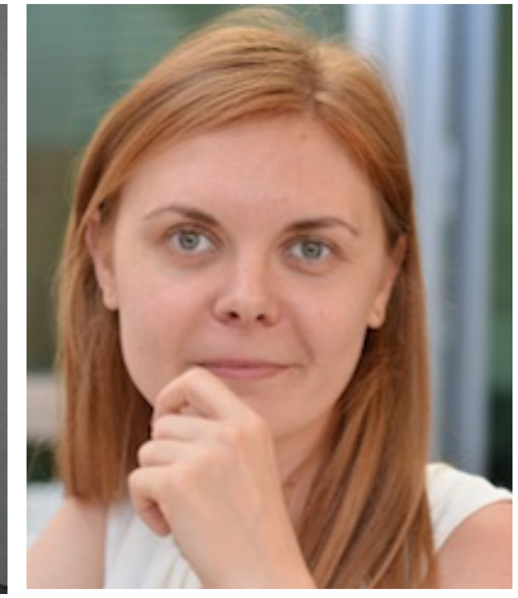






Industry Advisors





Chen Gauer Härdle Kolesnikova Petukhina Reule Spilak Trimborn Ünal

References

Back A (2002) Hashcash - A Denial of Service Counter-Measure. Retrieved on the 24.12.2017 from http://www.hashcash.org/papers/hashcash.pdf .

Chen S, Chen CYH, Härdle W, Lee TM, Ong B (2017) A first econometric analysis of the CRIX family. Handbook of Blockchain, Digital Finance and Inclusion, Vol 1, Cryptocurrency, FinTech, InsurTech, and Regulation. LEE KCD, Deng CR, eds. ISBN: 9780128104415, Academic Press, Elsevier .

Chen, K., Lei, J. (2017) Network cross-validation for determining the number of communities in network data. Journal of the American Statistical Association, Volume 113, 2018 - Issue 521, pp. 241-251.

Chen CYH, Härdle WK, Hou AJ, Wang W (2018a) Pricing Cryptocurrency options: the case of CRIX and Bitcoin. Journal of Financial Econometrics. Revised and Resubmit.

Chen, Y., Trimborn, S., Zhang, J.(2018b) Discover Regional and Size Effects in Global Bitcoin Blockchain via Sparse-Group Network AutoRegressive Modeling. SSRN. Retrieved on the 17.10.2018 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3245031.

Dwork C, Naor M (1992) Pricing via Processing or Combatting Junk Mail. Annual International Cryptology Conference. CRYPTO 1992: Advances in Cryptology — CRYPTO' 92, pp. 139-147.

Guo L, Li X (2017) Risk Analysis of Cryptocurrency as an Alternative Asset Class. In Härdle, W., Chen, C., Overbeck, L. (Eds.). Applied Quantitative Finance. Third edition. Springer-Verlag Berlin Heidelberg. ISBN 978-3-662-54485-3, e-ISBN 978-3-662-54486-0 (516 p), DOI:10.1007/978-3-662-54486-0 .

Guo L, Tao Y, Härdle WK (2019) Understanding Latent Group Structure of Cryptocurrencies Market: A Dynamic Network Perspective. Retrieved on the 25.05.2018 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3178672

References

Trimborn S, Härdle WK (2018) CRIX an Index for cryptocurrencies, Empirical Finance, 49, 107-122
https://doi.org/10.1016/j.jempfin.2018.08.004

Appendix: Investment universe

- 16 traditional assets
    - Equity indices: S&P100, FTSE100, SSE, NIKKEI225, SX5E
    - 10 Years government bonds: EU, UK, JP, CN, USA
    - Real estate & commodities: GOLD, MSCI ACWI COMMOD PRODUCERS, FTSE EPRA (NAREIT DEV REITS)
    - FIAT: EUR, GBP, CNY, YEN
- 55 crypto-currencies (97%/ 61% of Entire Market Cap)
- Sources: thecrix.de, Bloomberg
- Time span 2015-01-01 to 2017-12-31 (781 trading days/24 moving windows)

Petukhina A, Trimborn S, Härdle WK, Elendner H (2018)
Investing with cryptocurrencies - evaluating the potential of portfolio allocation

Why LSTM?

- Recurrent neural network for time series
- Address the vanishing gradient problem of simple RNN
- Learns long term dependencies thanks to gates operations
- Learns to forget
- Success in speech and handwriting recognition, NLP
- Should perform better than vanilla RNN, CNN
- Pbl: difficulty of hyper-parameters tuning