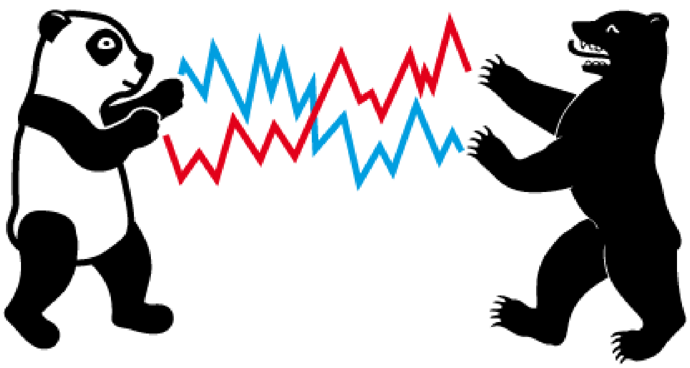
IRTG 1792 Discussion Paper 2020-028

Tail Risk Network Effects in the Cryptocurrency Market during the COVID-19 Crisis

Rui Ren *
Michael Althof *
Wolfgang Karl Härdle * *2 *3 *4



* Humboldt-Universität zu Berlin, Germany
*2 Singapore Management University, Singapore
*3 Charles University, Czech Republic
*4 National JiaoTong University, Taiwan

This research was supported by the Deutsche Forschungsgesellschaft 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

Tail Risk Network Effects in the Cryptocurrency Market during the COVID-19 Crisis

Rui Ren [*], **Michael Althof** [†], **Wolfgang Karl Härdle** [‡]

Abstract
Cryptocurrencies are gaining momentum in investor attention, are about to become a new asset class, and may provide a hedging alternative against the risk of devaluation of fiat currencies following the COVID-19 crisis. In order to provide a thorough understanding of this new asset class, risk indicators need to consider tail risk behaviour and the interdependencies between the cryptocurrencies not only for risk management but also for portfolio optimization. The tail risk network analysis framework proposed in the paper is able to identify individual risk characteristics and capture spillover effect in a network topology. Finally we construct tail event sensitive portfolios and consequently test the performance during an unforeseen COVID-19 pandemic.

Key words: Cryptocurrencies, Network Dynamics, Portfolio Optimization, Quantile Regression, Systemic Risk, Financial Risk Meter

1 Introduction

The economic fallout due to the COVID-19 pandemic demands exceptional fiscal and monetary stabilisation packages around the globe, leading to significant changes in government debt-to-gdp ratios and ever larger central bank balance sheets. Investors during such periods search for safe havens in the form of real assets, who's price will move together with a potential fiat currency. Gold is historically seen as such a safe haven asset. With the rise of the blockchain technology, cryptocurrencies may provide a hedging alternative against devaluation of fiat currencies. It is therefore of particular interest to analyse the behaviour of cryptocurrencies during such market turmoil. In order to provide a thorough understanding of this new asset class, risk management approaches need to consider tail risk behaviour in detail. In this paper, we put forward a tail risk analysis framework to

[*] IRTG 1792, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany
[†] IRTG 1792, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany
[‡] IRTG 1792, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany; School of Business, Singapore Management University, 50 Stamford Road, Singapore 178899; Faculty of Mathematics and Physics, Charles University, Ke Karlovu 3, 121 16 Prague, Czech Republic; Department of Information Management and Finance, National JiaoTong University, Taiwan

explore whether cryptocurrencies can help investors manage such risks and look at their behaviour during the the COVID-19 crisis.

Today we observe hundreds of cryptocurrencies that are all rooted in an idea on digital currencies, published 2008 by the author Satoshi Nakamoto (Nakamoto, 2008). The employed blockchain technology has spurred innumerable applications and has led via the now omnipresent cryptocurrencies to an alternative view on standard financial transactions. Digital coins are a peer-to-peer decentralised network, also called DAO (decentralised autonomous organisation), where the coin supply is set via algorithmic rules and the nodes of the network are maintained by "miners". These miners are rewarded via the DAO rules with a fraction of new coins. As with traditional financial systems, risks are also present in digital crypto networks (Catalini & Gans, 2016). Such risks may arise from sudden political interventions, cyberattacks, sentiment changes, a concentration on a too narrow set of exchanges and coins, and most importantly from sudden market stress such as the COVID-19 crisis. Many papers provide strong evidence of this heavy-tailed distributions of cryptocurrencies (Petukhina, Trimborn, Härdle, & Elendner, 2020). The combination of tail risk events and cryptocurrency markets make tail even network behaviour all the more important.

In light of this market structure, we propose an innovative framework to explore tail risk network effects in the cryptocurrency market during the COVID-19 crisis. The basic element of the framework is the Financial Risk Meter (FRM) technology (Mihoci, Althof, Chen, & Härdle, 2020) based on quantile lasso regression designed to identify systemic tail risks. The FRM is therefore geared to evaluate this new digital asset class' tail risk behaviour, where investors seek to mitigate network risk concentration. The FRM technology enables investors to measure inherent risks in the crypto coin ecosystem. As a comparison to standard markets of the Americas, Europe or Asia, we refer to the hu-berlin/frm, firamis/frm and the references therein. Next, we detect the interdependencies across digital coins and study spillover effects, which means identifying high or low joint tail event risks arising from single coins in the crypto universe. By a detailed study of the distribution of the individual coin's risk indicators we are able to identify high "co-stress" entities. Those coins with larger outdegree centrality impacting other nodes are "risk emitters". Risk receivers are then those "activated" via spill-over effetcs. By a simple sequence of boxplots over time we are able to study the entire chain of node dependencies. Last but not least, a portfolio construction method called tail event co-movement (TEC) portfolio approach is proposed, in order to help investors manage tail event co-movements. We investigate the performance using three rebalancing periods: daily, weekly and monthly based on a rolling window approach. The out-of-sample cumulative wealth performance is calculated to evaluate two TEC methods, and benchmarket against the classic Markowitz framework. During the period studied, TEC portfolios achieve better performance and prevent losses, implying that the FRM index' rich information is a very useful indicator for joint tail events and protection against the negative tail risks.

The codes are available at Quantlet. The rest of the paper is structured as follows: The tail risk network analysis framework is presented in Section 2. Economic interpretation and numerical implementation issues are discussed in Section 3 as well as empirical findings and portfolio constructions. Finally, Section 4 concludes and furthermore provides possible outlooks.

2 Tail Risk Network Analysis Framework

The tail risk network analysis framework is made up of three parts. The first section is denoted to the FRM method, from which one obtains FRM index measuring tail risks. Next, we concentrate on joint tail events across digital coins, study spillover effects and capture their dynamics as a system represented by a network. In order to help investors manage tail event co-movements (TEC), a portfolio construction method the TEC portfolio approach is proposed.

2.1 Financial risk meter

The basic element of FRM is the CoVaR (Adrian & Brunnermeier, 2016). CoVaR measures the stress level of a defined node in a network given that another node is at risk. FRM exploit this idea as well, but allows for all or a subset of nodes to be at risk, thereby measuring systemic risk. Systemic risk can be understood as a new class of risk, requiring specific risk management, and ideally in combination with the analysis of tail behaviour (Mieg, 2020). FRM is based on quantile lasso regression and the TENET ideas of Härdle, Wang, and Yu (2016).

Linear quantile lasso regression for log return series $X^k_{j,t}$ is given by

$$X^k_{j,t} = \alpha^k_j + A^k_{j,t}\beta^k_j + \varepsilon^k_{j,t} \tag{1}$$

with N crypto assets and m macroeconomic variables, $j \in \{1, 2, ..., N\}$, $A^k_{j,t} = [X^k_{-j,t}, M^k_{t-1}]$ representing a $p = N + m - 1$ dimensional vector of covariates, T denoting the total number of observations, $t \in \{1, ..., T\}$, k denoting the index of rolling windows, s representing the window size, $k \in \{1, ..., T - s + 1\}$, the vector β^k_j collecting p parameters.

The estimated coefficients are obtained by minimizing

$$\min_{\alpha^k_j, \beta^k_j} \left\{ \frac{1}{s} \sum_{t=k}^{s+k-1} \rho_\tau \left(X^k_{j,t} - \alpha^k_j - A^k_{j,t}\beta^k_j \right) + \lambda^k_j \left\| \beta^k_j \right\|_1 \right\} \tag{2}$$

with L_1-norm penalization Lasso parameter λ^k_j, loss function ρ_τ. The quantile loss function here is denoted as

$$\rho_\tau(u) = |\tau - \mathbf{I}\{u \leq 0\}||u| \tag{3}$$

given tail risk level τ. The quantile level τ represents the probability of tail events,

$$\tau = \mathrm{P}\left(X^k_{j,t} \leq q^k_{\tau,j} \right)$$

with $q^k_{\tau,j}$ quantile for company j at tail risk level τ at rolling window k.

λ^k_j is selected by minimizing Generalized Approximate Cross-Validation (GACV) criterion (Yuan, 2006)

$$\lambda^k_j = \arg\min GACV\left(\lambda^k_j\right) = \arg\min \frac{\sum_{t=k}^{s+k-1} \rho_\tau \left(X^k_{j,t} - \alpha^k_j - A^k_{j,t}\beta^k_j \right)}{s - df} \tag{4}$$

with df a measure of the effective dimensionality of the fitted model. Coefficients β_j^k depend on λ_j^k, so λ_j^k can be an indicator of tail risk. It also works for high dimensional cases when p is lager than s. FRM daily index is defined as,

$$\mathrm{FRM}_k = \frac{1}{N}\sum_{j=1}^{N} \lambda_j^k \tag{5}$$

The standard FRM index is the average of the penalty parameters of the Quantile Lasso Regression. The evolution of averaged λ_j^k represents the variation of the systemic tail risks (Härdle et al., 2016; Mihoci et al., 2020), thus FRM index measures joint tail events. We report these indices on above mentioned websites, since systemic risk indices are an important tool to communicate risks to the public, understand how risk is changing over time and support decision making (MacKenzie, 2014).

2.2 Tail-event driven network and centrality

The quantile lasso regression coefficients from equation (2) can be arranged into an adjacency matrix $A = \{\beta_{j,i}^k\}$ where $\beta_{j,j}^k = 0$ for every considered day. The adjacency matrix representation, in turn, allows us to consider the interaction between the selected cryptocurrencies in the spirit of graph theory. A $N \times N$ adjacency matrix for cryptocurrencies A_k at the kth rolling window can be denoted as,

$$A_k = \begin{pmatrix} \beta_{1,1}^k & \beta_{1,2}^k & \cdots & \beta_{1,N}^k \\ \beta_{2,1}^k & \beta_{2,2}^k & \cdots & \beta_{2,N}^k \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{N,1}^k & \beta_{N,2}^k & \cdots & \beta_{N,N}^k \end{pmatrix} \tag{6}$$

which represents total interdependencies across cryptocurrencies and allows to measure spillover effects and to capture their dynamics as a system represented by a network. The network refers to a directed graph, and in Section 3 we display the estimation results in a form of a weighted adjacency matrix. In graph theory, network centrality implies the structure of graph and identifies important vertices. Degree centrality is a natural measure of centrality, which is defined as,

$$D = \sum_{j=1}^{N}\sum_{i=1}^{N} \mathbf{1}(\beta_{j,i}^k) \tag{7}$$

$$\mathbf{1}(\beta_{j,i}^k) = \begin{cases} 1 & \text{if } \beta_{j,i}^k \neq 0 \\ 0 & \text{if } \beta_{j,i}^k = 0 \end{cases}$$

Degree centrality captures total connectedness in a graph. Indegree is the number of inflows meaning that how many other cryptocurrencies influence the node. Indegree of crypto j is,

$$Ind_j = \sum_{i=1}^{N} \mathbf{1}(\beta_{j,i}^k) \tag{8}$$

where crypto j can be regarded as a risk receiver in this situation. Similarly, outdegree is the number of out-going links implying that how many other cryptocurrencies the node affects. Outdgree of crypto i is,

$$Outd_i = \sum_{j=1}^{N} \mathbf{1}(\beta^k_{j,i}) \tag{9}$$

where crypto i can be treated as a risk emitter.

2.3 Tail-event co-movement portfolio construction

Here we present the TEC portfolio construction method that as any portfolio optimization balances the trade-off between tail risks and returns. The most popular or widely accepted approach is the Markowitz framework or mean-variance (MV) rule, which combines assets into an "efficient" portfolio providing risk-adjusted target returns (Härdle & Simar, 2019), more specifically, which minimizes risk measured by variance for a given level of returns. The MV technique is of course also a TEC method, but only for Gaussian variables, where the tail event indicator is the quantile, i.e. a multiple of the volatility. Consider now N assets with T returns given by an $(N \times T)$ matrix X, then MV portfolio can be denoted as,

$$\begin{aligned} \min_{w \in \mathbb{R}^p} \quad & w^\top \Sigma w \\ \text{s.t.} \quad & x^\top w \geq \mu \\ & w^\top \mathbf{1}_N = 1 \end{aligned} \tag{10}$$

with $w = (w_1, w_2, \ldots, w_N)^\top$ the weight on N assets, x the $(N \times 1)$ vector of mean returns, μ the target return, Σ the covariance matrix of the respective assets, $\mathbf{1}_N$ the vector with size N filled with ones. There is however strong evidence of heavy-tailed distributions of cryptocurrencies (Petukhina et al., 2020). So it is important to consider tail risks in crypto market.

The idea of a TEC portfolio is to minimize tail risk co-movement or joint tail events for a given level of returns. As λ_j can be treated as an indicator of tail risk for crypto j, it is natural to minimize the value for all cryptos, thus linear tail event co-movement (LTEC) portfolio method can be developed,

$$\begin{aligned} \min_{w \in \mathbb{R}^p} \quad & \lambda^\top w \\ \text{s.t.} \quad & x^\top w \geq \mu \\ & w^\top \mathbf{1}_N = 1 \end{aligned} \tag{11}$$

where $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_N)^\top$ denotes joint tail events. In this situation, optimizing tail risk portfolio turns to solving linear programming. On top of this, one might also minimizes the variance of λ, leading to quadratic tail event co-movement (QTEC) portfolio approach,

$$\begin{aligned} \min_{w \in \mathbb{R}^p} \quad & \gamma w^\top \Sigma_\lambda w + (1-\gamma)\lambda^\top w \\ \text{s.t.} \quad & x^\top w \geq \mu \\ & w^\top \mathbf{1}_N = 1 \end{aligned} \tag{12}$$

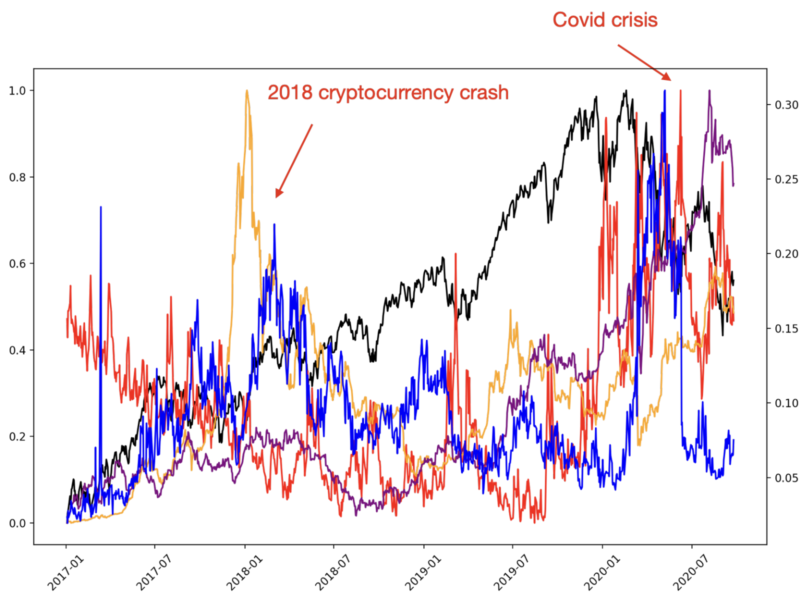


FIGURE 1: Flight to safety, normoalized SP500, VIX, CRIX, Gold denoting by left vertical axis, FRM denoting by right vertical axis

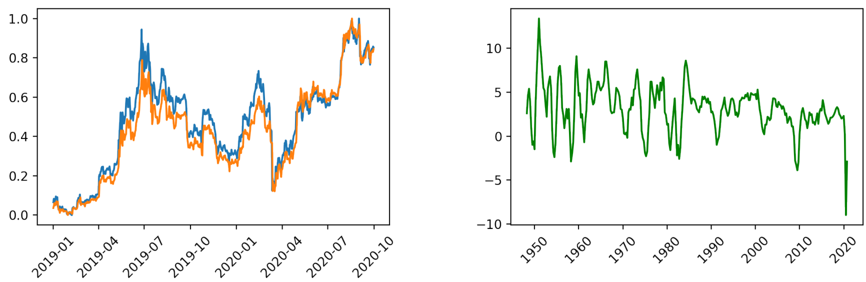
with Σ_λ the covariance matrix of λ and γ the scale parameter between 0 and 1. If $\gamma = 0$, a QTEC portfolio turns to a LTEC portfolio.

3 Empirical Results

3.1 Data description

We base our analysis on data loaded via the R package "crypto", which retrieves cryptocurrency market data such as price, market capitalisation and exchange information as taken from `https://coinmarketcap.com`. The macro economic risk variables are taken from Bloomberg. As macroeconomic risk variables M_t, we select U.S. one year government treasury bill yields, the Chicago Board Options VIX Index mesuring SP 500 Index option implied volatility, the CVIX Index as provided by Deutsche Bank and similar to the VIX measuring the implied volatility of currency markets, SP 500 equity index returns, and lastly the U.S. Dollar Index USDX as computed by Intercontinental Exchange (ICE) as the average of exchange rates between the USD and major world currencies.

The U.S. one year treasury rate indicates the deposit rate that can be earned for holding U.S. Dollars (rather then owning cryptocurrencies). The VIX and CVIX reflect the option market's perception of uncertainty in respectively U.S. Equity markets as well as global currency markets. The SP 500 Index returns reflect global risk aversion as one of the most liquid instruments to trade the most junior part of companies capital structure. The USDX reflects the global relative value of the U.S. Dollar versus other Central Bank issued fiat



(a) Normalized CRIX, Normalized market capitalization of 30 largest cryptocurrencies

(b) GDP growth rate year-on-year

FIGURE 2: CRIX index, Market Capitalisation of 30 largest cryptocurrencies and U.S. GDP growth rate

currencies.

As we will see later on, most of these macro economic risk measures, while important for FRM indices on "traditional asset classes", have less of an impact on cryptocurrencies across the multivariate return distribution at various quantile levels. Most predominantly, it is the VIX and CVIX which regularly have a certain influence, as will be discussed in more detail in the next subsections.

In Figure 1 we compare the performance of the cryptocurrency index CRIX (Trimborn & Härdle, 2018) , which aims to measure the cryptocurrency market's price performance, against more traditional asset classes such as Gold, SP 500 equity index, and the FRM for cryptocurrencies. Of particular note is the co-movement of the CRIX with SP 500 during stress scenarios, and increasingly over the more recent history the co-movement of the CRIX with the price of Gold. Cryptocurrencies appear to have reached a mature enough level to be accepted as an alternative to fiat currencies.

3.2 Corona-virus crisis

Whilst expectations of a pandemic spread of virus had been present and accounted for in government health care driven response mechanisms, the sudden spread of COVID-19 caught most economies off guard and ill-prepared in terms of rapid responses necessary to contain the contagion of a virus dispersion which follows a multiplicative process. Whereas the "usual" financial market crises, government debt crises, housing market and other crises investors have witnessed over the last decades usually have had some precursors giving some time for preparation to attentive investors and market regulators, or at least the necessary tools to central banks around the global to respond in time, the COVID-19 related market turmoil was altogether different. Contrary to a common misconception, the COVID-19 pandemic cannot be described as a so called "Black Swan Event" (Taleb, 2009), since such endemics and even pandemics had been prevalent in the past. In fact, major contagious diseases of history are listed by Cirillo and Taleb (2020) with more than 1000 victims, for a total of 72 observations since from 429BC. Since the year 2000 alone,

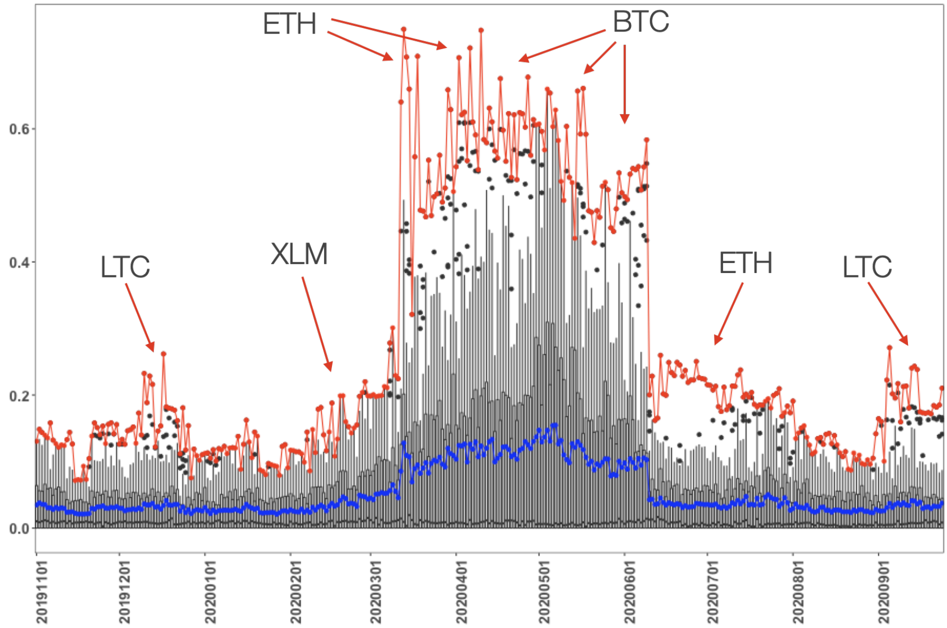


FIGURE 3: FRM distribution during the COVID-19 crisis for $\tau = 0.05$

there are 11 cases, so these contagious diseases, whilst infrequent, do appear from time to time. Most governmental health care departments have had emergency plans in place, an example of which is Germany's "Nationaler Pandemieplan" with its last pre-COVID-19 update in March 2017. But a spread as seen by the corona virus, amplified by the global airtravel networks, had hitherto not been appreciated as a real possibility.

Despite such plans in place, the outcome of contagious diseases from a public health care perspective but also from an economic perspective is difficult to estimate, since fatalities have a fat right tail in the underlying distribution (Cirillo & Taleb, 2020), which is an often underestimated tail event risk by most policy makers and economic agents alike. The reasonable approach is to implement a hard lockdown early on in the process, for a short period of time, cutting the pandemics spread at its roots. Its exponential growth turns to exponential decay as a result. However, this is often not easily implemented as populist moves are likely to appear and are difficult to incorporate in models. Taleb, Bar-Yam, and Cirillo (2020) give three key central measures to contain exponential growth patterns, focusing on the reduction of "super-spreader" events, monitoring and quarantines, and lastly "cheap measures with large payoffs in terms of the reduction of multiplicative events (e.g. facemasks)".

In contrast to past economic crises, usually with origins in financial markets, the COVID-19 impact was heavily impacting so called brick and mortar businesses primarily given that one third of the global population was in lockdown at some point. This entailed governments to implement sizeable fiscal packages resulting in double digit growth in some economies' debt to gdp ratio, the result of which is yet to be seen.

In a nutshell, the COVID-19 pandemic had investors face an unknown type of eco-

	BTC	INNBCL	ETH	XRP	BCH	BSV	LTC	EOS	BNB	TAGZ5	XTZ	XLM	LINK	ADA	XMR	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC		0.00	0.09			0.07		0.01	0.12		0.11		0.09		0.06						8	8	0	0.55
INNBCL			12.9			-6.3		-10.1	-7.4			15.9			-6.1	-4.71	1.85		3.71	-3.01	6	2	4	0.02
ETH		0.01			0.21	0.01	0.20	0.12	0.07		0.13		0.06	0.06	0.14						10	10	0	0.35
XRP		-0.01	0.25				0.01	0.02	0.13					0.36			0.00			0.01	6	5	1	0.06
BCH		-0.01	0.41			0.23		0.06	0.06	0.00	0.06		0.06								8	7	1	0.61
BSV		0.00			0.72			0.14		-0.03					0.24	0.01	0.03				5	3	2	0.09
LTC		0.00	0.18		0.09	0.06		0.28			0.02			0.20							7	7	0	0.31
EOS		0.00			0.33	0.14	0.15		0.04	0.01	-0.02	0.12		0.19							9	8	1	0.10
BNB	0.20		0.22		0.26	0.03					0.09		0.00		0.17					0.00	7	7	0	0.18
TAGZ5		0.00	0.45		0.42	-0.14					0.11		0.21				0.27				6	5	1	0.07
XTZ		-0.01	0.07			0.42							0.48								4	3	1	0.33
XLM		0.00		0.15	0.23			0.21	0.07				0.08								6	5	1	0.12
LINK	0.19					0.21			0.15	0.00	0.19			0.34							6	6	0	0.23
ADA					0.13		0.40	0.14	0.09		0.14		0.00		0.05						7	7	0	0.28
XMR			0.12		0.03			0.30	0.15		0.13			0.13							6	6	0	0.61
1YR		-0.01	1.88		-1.07	-0.45		-0.02		0.23	-0.95		0.29											
CVIX		-0.01		-0.08						-0.08	0.32		0.06		-0.26									
DXY		0.00		-0.04		-0.03				0.00	0.08													
SPX		0.00				-0.10				0.00			0.08											
VIX		0.01								0.11		-0.01	-0.14	-0.02										
B<>0	2	10	9	1	9	10	4	10	10	4	10	2	8	6	6	2	4	0	1	3				
B>0	2	5	9	1	9	8	4	9	9	3	9	2	8	6	5									
B<0	0	5	0	0	0	2	0	1	1	1	1	0	0	0	1									

FIGURE 4: Network on 20200429 for $\tau = 0.05$

nomic crisis in terms of length, policy responses (and effectiveness thereof), relapses into multiplicative contagious disease spread environments (further waves of infection), and where historical analysis becomes a less useful tool. After all, the economic impact and depth of recession was, literally shown on Figure 2 with US year on year GDP growth.

The investor in cryptocurrency markets therefore faced a duality of problems. First, the uncertainty around outcomes of the COVID-19 pandemic's on the global economy, and secondly, how cryptocurrencies will behave throughout such tail event risk scenarios. Importantly, the cryptocurrency market has grown strongly, depicted as circulating supply in U.S. Dollar terms, see Figure 2, attracting institutional investors who can also access the market via futures and options on Bitcoin on the Chicago Mercantile Exchange. A recent glance at it was detected by Forbes (Castillo, 2020), who went through 13F reports at the Securities and Exchange Commission of holdings in Grayscale Investment's Bitcoin Trust and showing wider use of cryptocurrencies in investment portfolio allocations. In fact, at the beginning of the COVID-19 pandemic related market turmoil, both Gold prices as well as CRIX Index prices fall together with the SP 500 Index, driven by the same initial flight to cash moves in Figure 1. But on the follow, as government fiscal and monetary stimulus measures to contain the economic crisis became evident, the CRIX index rebounds together with Gold prices in expectation of fiat currency devaluation. Periods of co-movements between the cryptocurrency prices and traditional asset classes have appeared over the past. For example, when the U.S. equity market dropped some ten percent in the follow-up of higher average hourly earnings reported by the Labor Department, the cryptocurrency market faced a similar drop (by around 35 percent), and rebounds to previous price levels in line with the recovery in equity market prices.

There are also periods, when cryptocurrency market prices fluctuate strongly based on factors idiosyncratic to the cryptocurrency market, which is still a relatively young market at risk of being manipulated by large scale flows. For example, large individual investor flows led to the significant rise in cryptocurrency prices in 2017 (Griffin & Shams, 2020) . Similarly, the sudden drop in September 2020 can be attributed to miners in Bitcoin were selling a significant amount of stock into the market, which led to an around 15 percent drop in Bitcoin prices, as apparent in data from data provider glassnode (Garner, 2020).

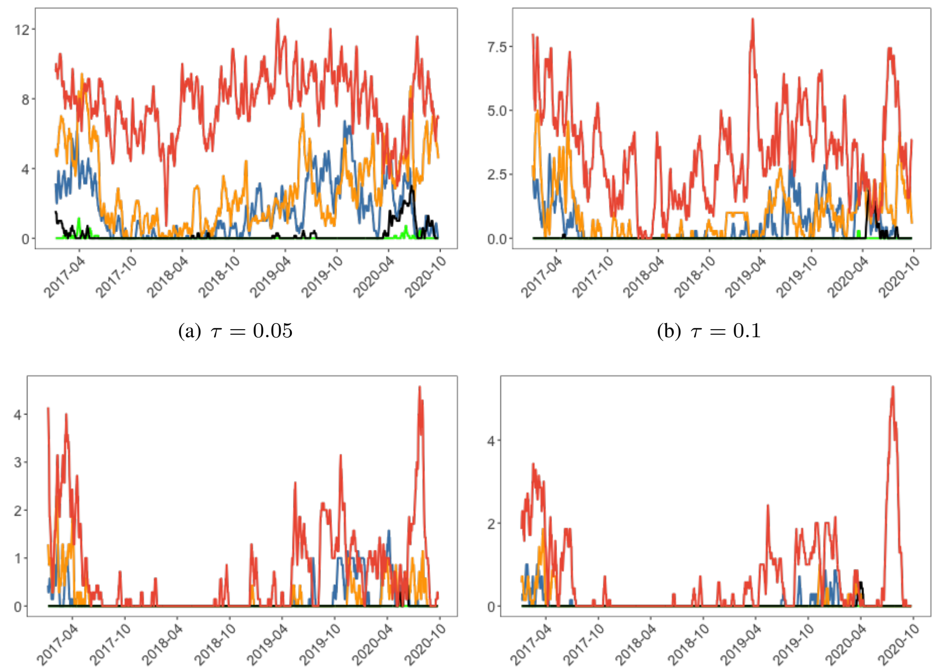
Faced with such an unpredictable market set-up, an investor should look at the entire return distribution paying particular attention to tail event risk. Figure 3 shows the box-plot of λ distribution across digital coins for tail risk level $\tau = 0.05$ on different days during the COVID-19 Crisis, where the blue line is the FRM index and the coin with the largest λ for each day is highlighted in red. As can be seen on Figure 3, large cryptocurrencies in terms of market capitalisation had the highest readings in individual λ_j^k, i.e. the most dominant cryptocurrencies had high co-stress in tail even risk scenarios, during the period of April to June 2020, specifically Bitcoin (BTC) and Ethereum (ETH) with the highest readings. A more detailed look will be taken in Section 3.3 in terms of network analysis, but to give some insight already, in Figure 4, estimated at a $\tau = 0.05$, BTC's returns are explained, in terms of marginal contribution, by several of the network's cryptocurrencies, specifically ETH, Bitcoin SV (BSV), Binance Coin (BNB), Tezos (XTZ), Chainlink (LINK), Monero (XMR) in the first row. However, BTC itself only influences only two coins (first column). In Figure 14, estimated at a $\tau = 0.10$, BTC's returns are best explained by seven cryptocurrencies, but itself shows no marginal return contribution to other coins. This contrasts with ETH, with high readings in April 2020, its returns explained by ten and eight currencies, respectively, but itself emitting risk to other cryptocurrencies, nine and eleven respectively for $\tau = 0.05$ and $\tau = 0.1$. Thus while both BTC and ETH exhibit high co-stress, ETH is more likely to create spill-over to the entire network. In the early September 2020 BTC sell-off, it was comparably smaller coins figuring as highest co-stress, Litecoin (LTC) as high co-stress cryptocurrencies. As outlined, one may detect network behaviour estimated over a recent time frame, so as to minimize spill-over effects within the cryptocurrencies held in a portfolio. Therefore, analysis of TECs in a network topology are key to correctly diversify within asset class risk concentrations. With the FRM technology, we can analysis in detail the network behaviour at various quantile levels and later on optimise portfolio positioning based on that analysis.

3.3 Network analysis

As outlined in Section 2, the analysis of co-movements in tail event scenarios is possible through a deeper analysis of the τ dependent adjacency matrix containing by rows the coefficients β_j^k. In Figure 4 and 9 to 20 in the Appendix, we depict the adjacency matrices estimated at τ equal to 0.05, 0.10, 0.25 and 0.50, with dates 20200201 ahead of the COVID-19 market crisis, 20200429 at the highs of the crisis, and 20200630 at local lows in FRM Crypto index post crisis.

The rows show the respective β_j^k including macroeconomic risk variables. The columns show the marginal return contribution by respective cryptocurrencies and macroeconomic risk variables. For both rows and columns, we sum the non-zero, smaller and larger than zero β_j^k, and also the non-zero ones for macroeconomic risk variables. The last column shows the respective cryptocurrency's λ_j^k for reference.

Across all three dates, the following observation can be taken. Macroeconomic risk variables have a less significant marginal return contribution at τ of 0.5, but their contri-



(a) $\tau = 0.05$ (b) $\tau = 0.1$

(c) $\tau = 0.25$ (d) $\tau = 0.5$

FIGURE 5: Macro variables' marginal return contribution across time with 7-day moving average: VIX, CVIX,1 year U.S. T-Bill, U.S. Dollar Index, SP 500 Index

butions become more significant towards τ of 0.05 tail event risk market situations. The main concentration of macro economic risk variables influencing cryptocurrency returns stems from the VIX Index, representing market uncertainty in the near future. In Figure 5 we show the non-zero β_j^k for the five selected macro economic risk variables. While at the centre of the distribution risk measures such as the VIX index only have significant marginal return contributions during prolonged risk scenarios, the tail event market set up points to an almost constant contribution from the VIX index, increasingly impact from the currency risk measure CVIX, and an increasing impact from short rates as well as SP 500 returns. The contribution from the U.S Dollar index is mostly negligible judging by impacted cryptocurrencies. Thus, whilst cryptocurrencies might behave as a separate asset class during normal market circumstances, in tail events, their returns are heavily influenced by general market risk perception.

Secondly, as Figure 6 the network centrality graphs from the adjacency matrices show, estimated at τ of 0.5 down to 0.05, at the tail end of the return distribution, λ_j^k are less elevated and more β_j^k are non-zero. So while during non-distressed market scenarios it is sufficient to hold a few select cryptocurrencies - ideally the most liquid with least trading cost - in tail event risk scenarios, close attention needs to be paid on which cryptocurrency is a receiver and emitter of tail risk.

We sketched the analytical approach towards the end of Section 3.2. Again, the FRM's

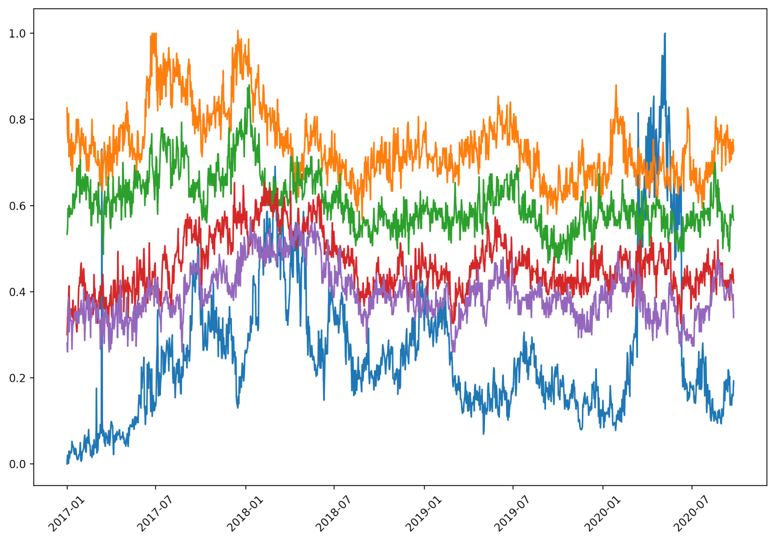
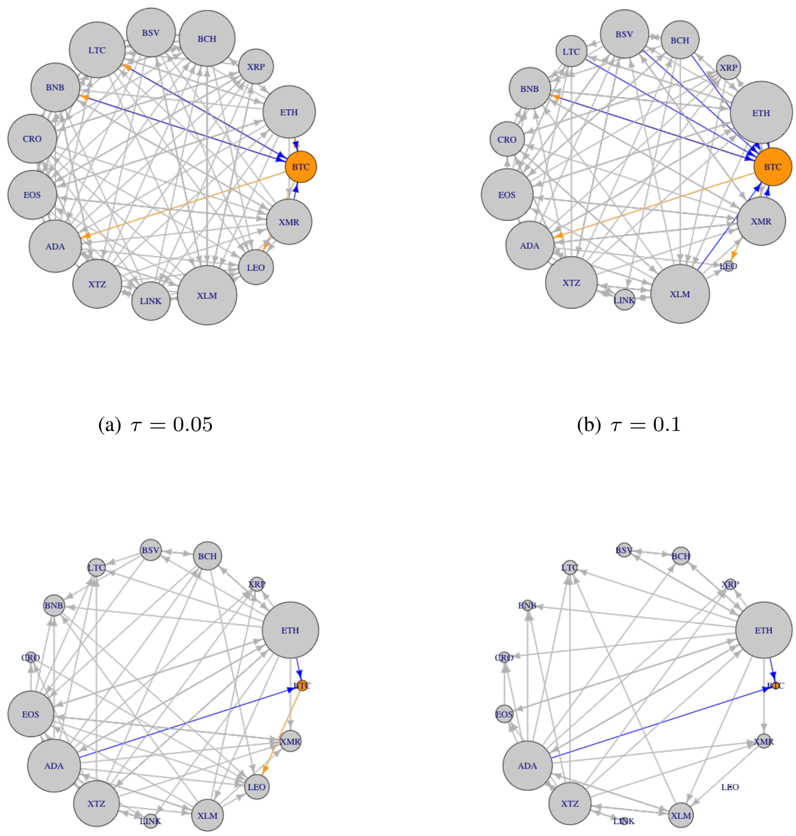


FIGURE 6: Network centrality index: τ=0.05, τ=0.10, τ=0.25, τ=0.50, FRM Crypto

key advantage lies on the one hand in the distribution of λ_j^k that make up this risk measure. We name those with high readings co-stress cryptocurrencies, driven by specific external factors, or other cryptocurrencies. Through detailed network analysis, we know the co-stress identify (ID), and can rapidly map out the spill-over channels. This can be done by detailed reading of adjacency matrices, and by visual representation, see Figure 7. We highlight BTC as an example. The edges are given by the betas in the network, and the size of the node represents the total degree centrality in this example. Despite it's market capitalisation, BTC is comparably less significant in terms of network centrality, and has a small λ_j^k reading, hence less spill-over risk in a tail event, for all τ. We can compare this to ETH, which has high centrality across all τ on 20200630, see Figure 17 to 20, as well as the highest λ_j^k. At $\tau = 0.05$, ETH's return is mostly explained by BCH, which in itself is explained by ETH, BSV and LTC. ETH's return impact ten other currencies, making ETH a risky holding: at risk of a spill-over, and at risk of impacting much of the network.

For obvious reasons, particular attention should be paid to cryptocurrencies exhibiting a range of negative β_j^k in tail event scenarios, in particular if they have low λ_j^k. LEO is one such example and represents a utility token within the iFinex ecosystem with specific usage geared towards cryptocurrency traders. Such portfolio diversifiers within tail event risk analysis could reduce tail risk exposure in a portfolio composition context.

Whether or not a currency is a risk receiver in such a scenario is encompassed in its λ_j^k value. A higher reading indicates spill-over risk, or co-stress, co-movements in a tail event scenario. Therefore, the central idea of an FRM technology based portfolio construction is to find the weight vector that minimizes the risk of spill-overs, i.e. minimizes λ^k.



(a) $\tau = 0.05$ (b) $\tau = 0.1$

(c) $\tau = 0.25$ (d) $\tau = 0.5$

FIGURE 7: Network graphs with the size of nodes representing total degree on 20200630

3.4 Portfolio Construction

As selecting portfolios is an inherent part of the decision-making process (Korotkov & Wu, 2020), three different portfolios are computed based on the MV rule, LTEC method and QTEC approach in this section, all applied to the cryptocurrency market. A rolling window approach referring to (10) (11) and (12) is applied for asset allocation, where $\gamma = 0.8$ for QTEC approach to get a relatively good performance. Specifically we choose the window size s equivalent to 90 days, which is consistent with the FRM calculation. We investigated the performance for three rebalancing periods p days: daily with $p = 1$, weekly with $p = 7$, monthly with $p = 30$. In each rebalancing period i, $k \in \{1, ..., \lfloor (T - s)/p + 1 \rfloor\}$, starting on date t, $t \in \{s + 1, ..., T\}$, the data in the previous s days are selected to estimate the parameters required to implement a particular strategy. We use these optimized weights in the rebalancing period $t+1$ to calculate the weighted return. This process is repeated by choosing the data of previous s days for the next period until the end of the dataset is reached. The outcome of this rolling-window approach is a series of $\lfloor (T-s)/p+1 \rfloor\}$ out-of-sample returns generated by three portfolio strategies.

The out-of-sample cumulative wealth (CW) is used to evaluate each strategy j,

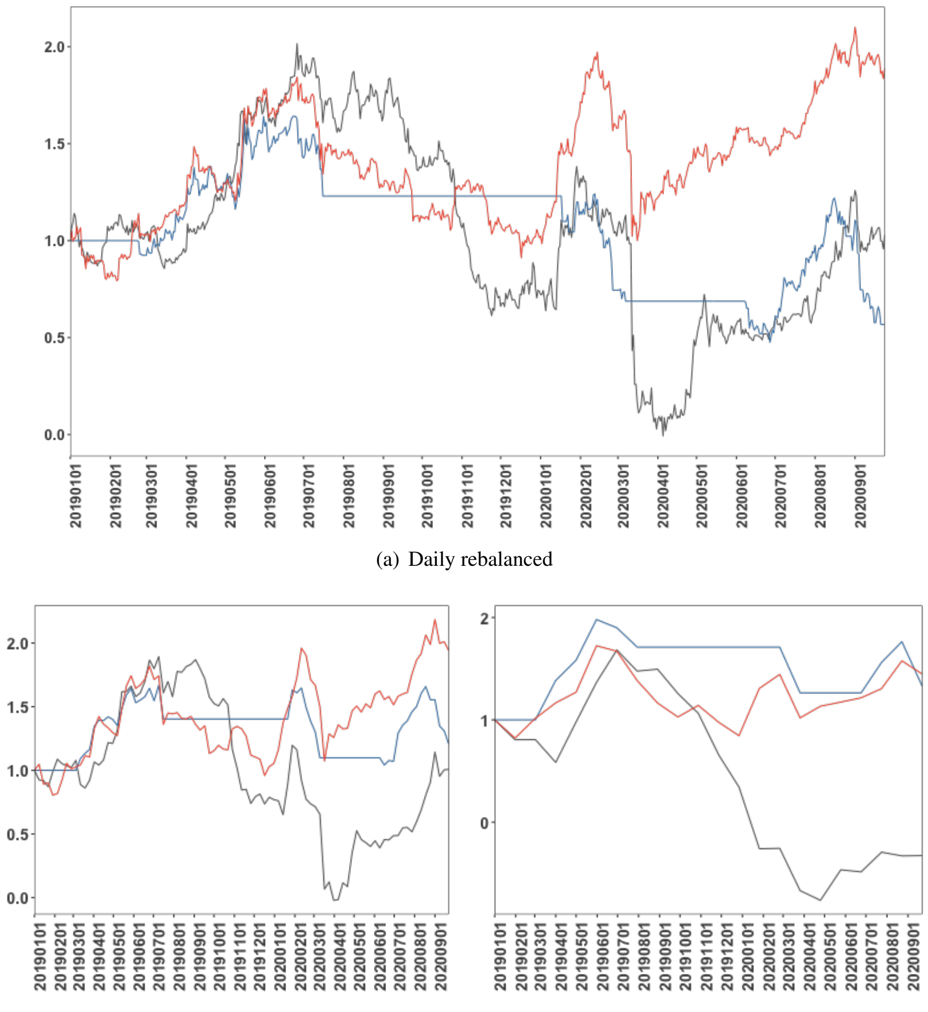
$$W_{j,t+1} = W_{j,t} + \hat{w}_{j,t}^{\top} X_{t+1} \tag{13}$$

where $W_{j,t}$ represents the out of sample cumulative return for strategy j on day t ($t \in \{1, ..., T\}$). The initial portfolio wealth is set to $W_1 = \$1$. Figure 8 shows the cumulative wealth dynamics for the three strategies for $\tau = 0.05$ from January 1st, 2019 to September 24th, 2020. The red line, blue line and black line represent QTEC, LTEC and MV approaches respectively. The cumulative wealth graph for the LTEC method does not change for some periods - leaving a straight line in the figure - since the linear programming does not always have solutions. We can see that the performance of the three strategies for daily rebalanced portfolios is similar from January 2019 to June 2019, followed by a decline until December 2019. MV decreased by 5.70% whereas QTEC declined by only 3.91%. The MV portfolio has an increasing trend in Janurary 2020 but plunges down to \$-0.05 in cumulative wealth in April 2020. Although QTEC bears losses from February to March 2020, the method rebounds quickly when it touches the initial wealth and then has a increasing trend till September ending at the wealth level \$1.81. QTEC is the only method not losing money in this scenario. As for weekly rebalancing, three strategies follow the same tendency as the daily rebalanced portfolios. However, MV rule hits \$-0.98 at the end of the period in September 2020 when it comes to monthly rebalancing situations, while QTEC and LTEC are still above the initial wealth level. Table 1 demonstrates the final wealth (FW) level of three methods for different tail risk level. The performance of the MV rule does not change over different τ because by construction it does not include hedge tail risks. LTEC at times outperforms the QTEC portfolio, but as it does not always yield solutions and further has tendencies to exhibit high portfolio concentration, LTEC appears a less appealing method for tail event risk sensitive portfolio construction.

Apart from cumulative wealth, we want to understand portfolio diversification effects, which is particularly important in tail event risk scenarios. Effective N measurement is one of allocation concentration methods(Strongin, Petsch, & Sharenow, 2000), which is defined as,

$$N_{Eff}\left(w_t\right) = \frac{1}{\sum_{j=1}^{N} \hat{w}_{j,t}^2} \tag{14}$$

for strategy j. If N_{Eff} is close to 1, the concentration is highest, i.e., the portfolio contains a single asset. Table 1 reports the average effective N measure for different strategies. As can be seen from Table 1, the LTEC portfolio is very concentrated while the other two are more diversified. The QTEC method is in general the best approaches amongst the three to help investors lose less and manage tail risks. It also implies that the FRM index underlying data is a good indicator for joint tail events and can be used to hedge against negative tail risks.



(a) Daily rebalanced

(b) weekly rebalanced

(c) monthly rebalanced

FIGURE 8: Cumulative wealth of MV, QTEC and LTEC during the COVID-19 crisis for $\tau = 0.05$.

4 Conclusions

In this paper we discussed the how tail event network risk behaviour can be estimated with quantile lasso regression applied to the example of cryptocurrencies - the FRM Crypto Index. We explained how this technology permits to understand tail event behaviour, relationships to macroeconomic risk variables in tail events, and resulting adjacency matrices which we also depicted as centrality graphs. We also notice that, similar to Gold prices, cryptocurrencies sold off at the start of the COVID-19 crisis as a preference for cash holdings dominated. But on the follow, as government fiscal and monetary stimulus measures to contain the economic crisis became evident, the CRIX index rebounds together with Gold prices in expectation of fiat currency devaluation. This suggests a certain maturity

TABLE 1
Portfolio Performance

	Daily		*Weekly*		*Monthly*	
$\tau = 0.05$	*FW*	*Effect N*	*FW*	*Effect N*	*FW*	*Effect N*
QTEC	1.81	6.63	1.74	6.61	1.62	6.48
LTEC	0.57	1.28	1.33	1.26	1.74	1.30
MV	0.99	0.30	1.15	0.29	-0.98	0.31
$\tau = 0.1$						
QTEC	1.35	7.83	1.25	7.81	1.34	7.74
LTEC	0.75	1.28	1.48	1.27	1.73	1.30
MV	0.99	0.30	1.15	0.29	-0.98	0.31
$\tau = 0.25$						
QTEC	1.45	8.14	1.42	8.10	1.45	8.32
LTEC	0.71	1.28	1.47	1.26	1.73	1.28
MV	0.99	0.30	1.15	0.29	-0.98	0.31
$\tau = 0.5$						
QTEC	1.37	8.75	1.33	8.81	1.28	8.99
LTEC	0.73	1.28	1.49	1.25	1.73	1.28
MV	0.99	0.30	1.15	0.29	-0.98	0.31

of the cryptocurrency markets, a contender to portfolio holdings in gold. The fat-tailed return distribution of cryptocurrencies might prevent investors to allocate part of their portfolio to cryptocurrency markets. For better risk perception, we construct and compare three portfolios over time. Against the classic mean-variance approach, we compare two portfolios based on risk measures obtained from the FRM technology. We aim to build portfolios of cryptocurrencies, whilst specifically minimizing the spill-over effect in tail events encapsulated in λ_j^k. We show that especially the QTEC approach yields significant outperformance in an out-of-sample setting without losing diversification, and can help investors mute exposure to negative tail risk such as stemming from the COVID-19 crisis.

Acknowledgements

This research has received funding from IRTG 1792 "High Dimensional Non Stationary Time Series" at Humboldt-Universität zu Berlin, the European Union's Framework Programme for Research and Innovation Horizon 2020 (2014-2020) under the Marie Skłodowska-Curie Grant Agreement No. 897277, the Czech Science Foundation under grant No. 19-28231X, COST Action 19130, supported by COST (European Cooperation in Science and Technology), and the European Union's Horizon 2020 research and innovation program "FIN-TECH: A Financial supervision and Technology compliance training programme" under the grant agreement No 825215 (Topic: ICT-35-2018, Type of action: CSA)

References

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *The American Economic Review*, *106*(7), 1705-41.

Castillo, M. (2020). 20 institutional bitcoin investors revealed, but soon the list may vanish. *Forbes*. Retrieved from `https://www.forbes.com/sites/michaeldelcastillo/2020/08/06/valuable-sec-data-on-20-institutional-bitcoin-investors-could-soon-disappear/?sh=278ecff91de2`

Catalini, C., & Gans, J. S. (2016). *Some simple economics of the blockchain* (Tech. Rep.). National Bureau of Economic Research.

Cirillo, P., & Taleb, N. N. (2020). Tail risk of contagious diseases. *Nature Physics*, 1–8.

Garner, C. (2020). 20 institutional bitcoin investors revealed, but soon the list may vanish. *Twitter*. Retrieved from `https://twitter.com/ColeGarnerBTC/status/1301985117473103872`

Griffin, J. M., & Shams, A. (2020). Is bitcoin really untethered? *The Journal of Finance*, *75*(4), 1913–1964.

Härdle, W. K., & Simar, L. (2019). Applications in finance. In *Applied multivariate statistical analysis 5th edition* (pp. 487–499). Springer.

Härdle, W. K., Wang, W., & Yu, L. (2016). TENET: Tail-Event driven NETwork risk. *Journal of Econometrics*, *192*(2), 499–513.

Korotkov, V., & Wu, D. (2020). Evaluating the quality of solutions in project portfolio selection. *Omega*, *91*, 102029.

MacKenzie, C. A. (2014). Summarizing risk using risk measures and risk indices. *Risk Analysis*, *34*(12), 2143–2162.

Mieg, H. A. (2020). Volatility as a transmitter of systemic risk: Is there a structural risk in finance? *Risk Analysis*.

Mihoci, A., Althof, M., Chen, C. Y.-H., & Härdle, W. K. (2020). FRM Financial Risk Meter. *The Econometrics of Networks (Advances in Econometrics)*, *42*, 335–368.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Bitcoin.–URL: https://bitcoin. org/bitcoin. pdf*.

Petukhina, A., Trimborn, S., Härdle, W. K., & Elendner, H. (2020). Investing with cryptocurrencies–evaluating the potential of portfolio allocation strategies. *Available at SSRN 3274193*. doi: http://dx.doi.org/10.2139/ssrn.3274193

Strongin, S., Petsch, M., & Sharenow, G. (2000). Beating benchmarks. *The Journal of Portfolio Management*, *26*(4), 11–27.

Taleb, N. N. (2009). *The black swan*. Random House. Retrieved from `https://books.google.de/books?id=YdOYmYA2TJYC`

Taleb, N. N., Bar-Yam, Y., & Cirillo, P. (2020). On single point forecasts for fat-tailed variables. *International Journal of Forecasting*. doi: https://doi.org/10.1016/j.ijforecast.2020.08.008

Trimborn, S., & Härdle, W. K. (2018). CRIX an index for cryptocurrencies. *Journal of Empirical Finance*, *49*, 107–122.

Yuan, M. (2006). GACV for quantile smoothing splines. *Computational Statistics & Data Analysis*, *50*(3), 813–829.

5 Appendix

5.1 Abbreviations

Cryptos			
ADA	Cardano	ATOM	Cosmos
BCH	Bitcoin Cash	BNB	Binance Coin
BSV	Bitcoin SV	BTC	Bitcoin
CRO	Crypto.com Chain	EOS	EOS
ETH	Ethereum	LEO	LEO Token
LINK	Chainlink	LTC	Litecoin
NEO	NEO	TRX	TRON
USDC	USD Coin	USDT	Tether
XLM	Stellar	XMR	Monero
XRP	Ripple	XTZ	Tezos
Macroeconomic variables			
SPX	SP 500 Index		
VIX	CBOE Volatility Index		
1YR	U.S. one year government treasury bill yields		
CVIX	Implied volatility of currency markets by Deutsche Bank		
DXY	U.S. Dollar Index by Intercontinental Exchange		

5.2 Adjacency matrix

	BTC	ETH	XRP	BCH	BSV	LTC	EOS	BNB	ADA	ETC	XMR	TRX	XLM	XTZ	DASH	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC			0.21	0.12	0.00		0.10	0.06			0.09			0.06	0.02	-0.15					8	8	0	0.05
ETH				0.05		0.3	0.08	0.2	0.1	-0.03	0.06	0.1		0.01						-0.02	9	8	1	0.04
XRP				0.38	-0.02							0.12	0.20		0.03					0.07	5	4	1	0.05
BCH		0.11			0.23	0.24		0.11		0.06	0.16	0.01		-0.05	0.02		0.10				9	8	1	0.04
BSV	0.11			1.16			1.41			-0.30	-0.91		-0.95	0.07			0.37			-0.15	7	4	3	0.02
LTC		0.08	0.14	0.03	0.01		0.53		0.05	0.01		0.01			0.05						9	9	0	0.09
EOS		0.33			0.07	0.19		0.10	0.01			0.26		0.03						0.00	7	7	0	0.12
BNB				0.13	-0.04	0.20	0.07		0.03		0.05	0.21	0.08		0.08						9	8	1	0.10
ADA		0.18					0.21				0.13	0.30	0.10	0.02						-0.03	6	6	0	0.05
ETC		-0.42	-0.27	0.17	0.09		-0.22				0.62	0.26		0.22	0.38		0.04				9	6	3	0.02
XMR		0.05	0.00	0.01	-0.07			0.59		0.01		0.05		0.03	0.12						9	7	2	0.07
TRX			0.13	0.20	-0.03		0.18		0.31				0.12		0.13						7	6	1	0.06
XLM		0.03	0.28		0.01				0.16						0.13					-0.02	5	5	0	0.07
XTZ			0.19		0.02		0.08	0.44	0.32	0.07		-0.61	0.08		0.10		-0.11			0.13	9	8	1	0.02
DASH			0.06		0.30		0.17		-0.25		0.56		-0.39	0.12			0.50			0.05	7	5	2	0.02
1YR																								
CVIX	0.10				-0.03	0.13	0.06	0.45	-0.48	-0.01	0.03				-0.09									
DXY		0.00			0.00					0.00			0.00	0.00										
SPX													0.02	0.00										
VIX					0.04		0.20	0.20			-0.33		-0.08		-0.19									
B<>0	1	7	8	9	12	4	10	6	8	6	8	10	7	9	10	1	5	0	0	8				
B>0	1	6	6	9	8	4	9	6	7	4	7	9	5	8	10									
B<0	0	1	2	0	4	0	1	0	1	2	1	1	2	1	0									

FIGURE 9: Network on 20200201 for $\tau = 0.05$

	BTC	ETH	XRP	BCH	BSV	LTC	EOS	BNB	ADA	ETC	XMR	TRX	XLM	XTZ	DASH	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC				0.12			0.19								0.04						3	3	0	0.35
ETH				0.05		0.4	0.03	0.0	0.1			0.2		0.01	0.0						8	8	0	0.29
XRP				0.26	0.01				0.04			0.20			0.04					0.01	5	5	0	0.22
BCH					0.24	0.18		0.09			0.16	0.01			0.11						6	6	0	0.26
BSV				0.93			0.58						-0.40		-0.35					-0.08	4	2	2	0.07
LTC				0.01	0.04		0.54		0.01	0.03		0.07			0.05						7	7	0	0.37
EOS		0.19			0.08	0.46			0.02	0.02		0.14			0.03						7	7	0	0.31
BNB				0.04		0.33					0.18	0.01		0.03	0.12						6	6	0	0.27
ADA		0.27			0.00	0.05	0.07			0.01	0.00	0.18			0.09						8	8	0	0.20
ETC					0.00						0.07	0.11		0.07	0.44						5	5	0	0.13
XMR						0.10	0.05	0.39							0.08						4	4	0	0.28
TRX			0.01	0.12		0.24	0.09	0.16	0.18						0.05						7	7	0	0.18
XLM			0.29	0.01					0.17						0.15					-0.03	4	4	0	0.12
XTZ					0.01				0.23				0.24		0.09						4	4	0	0.07
DASH			0.15		0.23		0.21	0.17		0.00				0.01						0.13	6	6	0	0.06
1YR										0.08	-0.08						0.22			-0.13				
CVIX			-0.08					0.26							-0.07	0.80								
DXY		-0.01								0.01						0.06	-0.03							
SPX							0.00						0.00			0.07				-0.05				
VIX					0.02			0.23			-0.32		-0.08	0.02	-0.04		0.42		-0.24					
B<>0	0	2	3	8	8	7	8	5	7	4	4	8	2	4	14	0	0	0	0	4				
B>0	0	2	3	8	8	7	8	5	7	4	4	8	1	4	13									
B<0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1									

FIGURE 10: Network on 20200201 for $\tau = 0.1$

	BTC	ETH	XRP	BCH	BSV	LTC	EOS	BNB	ADA	ETC	XMR	TRX	XLM	XTZ	DASH	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC				0.13	0.02	0.04	0.03	0.15		0.00		0.05									7	6	1	0.58
ETH				0.12	0.01	0.1	0.15					0.0			0.0						6	6	0	0.63
XRP				0.11	0.02	0.12						0.14			0.03						5	5	0	0.55
BCH					0.26	0.16	0.01			0.04					0.05						5	5	0	0.67
BSV				0.53			0.42													-0.08	2	2	0	0.22
LTC				0.13	0.03		0.45								0.06						4	4	0	0.79
EOS				0.04	0.01	0.35			0.09			0.07									5	5	0	0.76
BNB				0.12		0.05			0.02		0.10	0.20			0.09						6	6	0	0.55
ADA							0.31					0.27			0.06						3	3	0	0.62
ETC				0.23								0.10			0.39						3	3	0	0.37
XMR				0.19			0.16	0.12	0.03						0.00						5	5	0	0.48
TRX				0.09	0.07	0.01	0.08		0.08	0.06					0.08						7	7	0	0.77
XLM				0.05			0.10					0.07			0.18						4	4	0	0.46
XTZ			0.33		-0.02		0.14								0.06						4	3	1	0.19
DASH					0.28	0.08					0.06										3	3	0	0.49
1YR																								
CVIX	0.10				-0.03	0.13	0.06	0.45	-0.48	-0.01	0.03				-0.09									
DXY		0.00			0.00					0.00			0.00	0.00										
SPX													0.02	0.00										
VIX					0.04		0.20	0.20			-0.33		-0.08		-0.19									
B<>0	0	0	1	11	9	8	10	2	4	3	2	8	0	0	11	0	0	0	0	1				
B>0	0	0	1	11	8	8	10	2	4	2	2	8	0	0	11									
B<0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0									

FIGURE 11: Network on 20200201 for $\tau = 0.25$

	BTC	ETH	XRP	BCH	BSV	LTC	EOS	BNB	ADA	ETC	XMR	TRX	XLM	XTZ	DASH	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC				0.09	0.02	0.06	0.05	0.07	0.00			0.07			0.01						8	8	0	0.91
ETH				0.07	0.03	0.1	0.15		0.0			0.0			0.0						7	7	0	0.99
XRP				0.05	0.05	0.03	0.07					0.10			0.02						6	6	0	0.93
BCH					0.28	0.08						0.06									3	3	0	0.97
BSV				0.36			0.35														2	2	0	0.60
LTC				0.22	0.08		0.08								0.04						4	4	0	1.11
EOS				0.10	0.10	0.19						0.13			0.03						5	5	0	0.91
BNB				0.16	0.02		0.06								0.05						4	4	0	0.98
ADA				0.02	0.04		0.16			0.03		0.21			0.06						6	6	0	0.83
ETC				0.04	0.12							0.07			0.31						4	4	0	0.66
XMR				0.16				0.19		0.04					0.05						4	4	0	0.60
TRX				0.20			0.10	0.03	0.05	0.05					0.05						6	6	0	0.86
XLM				0.07			0.16	0.12	0.06						0.06						5	5	0	0.41
XTZ			0.23				0.02		0.03		0.08				0.01						5	5	0	0.18
DASH				0.10	0.22			0.12		0.04		0.05									5	5	0	0.47
1YR					0.00					0.00	-0.08				0.00									
CVIX																								
DXY				0.00							0.00			0.00	0.00									
SPX																								
VIX																								
B<>0	0	0	1	13	10	5	10	5	5	4	1	8	0	0	12	0	0	0	0	0				
B>0	0	0	1	13	10	5	10	5	5	4	1	8	0	0	12									
B<0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0									

FIGURE 12: Network on 20200201 for $\tau = 0.5$

	BTC	INNBCL	ETH	XRP	BCH	BSV	LTC	EOS	BNB	TAGZ5	XTZ	XLM	LINK	ADA	XMR	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC		0.00	0.09			0.07		0.01	0.12		0.11		0.09		0.06						8	8	0	0.55
INNBCL			12.9			-6.3		-10.1	-7.4			15.9			-6.1	-4.71	1.85		3.71	-3.01	6	2	4	0.02
ETH		0.01			0.21	0.01	0.20	0.12	0.07		0.13		0.06	0.06	0.14						10	10	0	0.35
XRP		-0.01	0.25				0.01	0.02	0.13					0.36			0.00			0.01	6	5	1	0.06
BCH		-0.01	0.41			0.23		0.06	0.06	0.00	0.06		0.06								8	7	1	0.61
BSV		0.00			0.72			0.14		-0.03					0.24	0.01	0.03				5	3	2	0.09
LTC		0.00	0.18		0.09	0.06		0.28			0.02			0.20							7	7	0	0.31
EOS		0.00			0.33	0.14	0.15		0.04	0.01	-0.02	0.12		0.19							9	8	1	0.10
BNB	0.20		0.22		0.26	0.03					0.09		0.00		0.17					0.00	7	7	0	0.18
TAGZ5		0.00	0.45		0.42	-0.14					0.11		0.21				0.27				6	5	1	0.07
XTZ		-0.01	0.07			0.42							0.48								4	3	1	0.33
XLM		0.00		0.15	0.23			0.21	0.07				0.08								6	5	1	0.12
LINK	0.19					0.21			0.15	0.00	0.19			0.34							6	6	0	0.23
ADA					0.13		0.40	0.14	0.09		0.14		0.00		0.05						7	7	0	0.28
XMR			0.12		0.03			0.30	0.15		0.13			0.13							6	6	0	0.61
1YR		-0.01	1.88		-1.07	-0.45		-0.02		0.23	-0.95		0.29											
CVIX		-0.01		-0.08						-0.08	0.32		0.06		-0.26									
DXY		0.00		-0.04		-0.03				0.00	0.08													
SPX		0.00				-0.10				0.00			0.08											
VIX		0.01								0.11		-0.01	-0.14	-0.02										
B<>0	2	10	9	1	9	10	4	10	10	4	10	2	8	6	6	2	4	0	1	3				
B>0	2	5	9	1	9	8	4	9	9	3	9	2	8	6	5									
B<0	0	5	0	0	0	2	0	1	1	1	1	0	0	0	1									

FIGURE 13: Network on 20200429 for $\tau = 0.05$

	BTC	INNBCL	ETH	XRP	BCH	BSV	LTC	EOS	BNB	TAGZ5	XTZ	XLM	LINK	ADA	XMR	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC			0.05			0.04		0.13	0.07		0.10		0.10	0.04							7	7	0	0.66
INNBCL			11.6			0.0									-15.4				3.97	-0.61	3	1	2	0.05
ETH		0.01			0.31	0.05		0.15	0.04		0.17			0.04	0.05						8	8	0	0.98
XRP			0.12		0.10		0.01	0.14	0.01		0.12			0.21							7	7	0	0.70
BCH		0.00	0.33			0.16		0.22	0.01	0.01	0.05			0.02							8	7	1	0.79
BSV		0.00			0.68			0.30	0.02	-0.07	0.00				0.02		0.08				7	5	2	0.22
LTC		0.00	0.26		0.09	0.02		0.21			0.04			0.19							7	7	0	0.42
EOS		0.00	0.00		0.27	0.17	0.20		0.03	0.02				0.17	0.07						9	9	0	0.36
BNB		0.00	0.28		0.28	0.02					0.11		0.07								6	5	1	0.84
TAGZ5		0.00	0.21		0.28			0.06				0.11									5	4	1	0.26
XTZ		0.00	0.10		0.11	0.22							0.49								5	4	1	0.67
XLM					0.15			0.22	0.04		0.18										4	4	0	1.00
LINK		0.01				0.04					0.43			0.26							4	4	0	0.67
ADA		0.00	0.05		0.15		0.27	0.16			0.14		0.09		0.05						8	7	1	0.63
XMR			0.16					0.40			0.20										3	3	0	0.92
1YR		-0.01	0.44			-0.68				0.15														
CVIX		-0.01								-0.10	0.27		0.05	0.06	-0.31									
DXY		0.00		-0.06						0.01	0.06		-0.03											
SPX		0.00				-0.08							0.18		-0.14									
VIX		0.00																						
B<>0	0	10	11	0	10	9	3	10	7	3	11	1	4	7	5	0	1	0	1	1				
B>0	0	4	11	0	10	8	3	10	7	2	11	1	4	7	4									
B<0	0	6	0	0	0	1	0	0	0	1	0	0	0	0	1									

FIGURE 14: Network on 20200429 for $\tau = 0.1$

	BTC	INNBCL	ETH	XRP	BCH	BSV	LTC	EOS	BNB	TAGZ5	XTZ	XLM	LINK	ADA	XMR	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC						0.04			0.02	0.00	0.06		0.03	0.24							6	6	0	1.37
INNBCL			6.5			-0.9	-1.65				-3.11	4.1			-4.5		-0.66				6	2	4	0.08
ETH		0.00			0.18	0.09			0.01		0.20			0.13							6	6	0	1.48
XRP			0.13		0.13			0.02			0.06			0.22							5	5	0	1.32
BCH		0.00	0.07			0.11		0.33		0.02	0.07										6	5	1	1.42
BSV		0.00			0.56			0.00			0.00										4	3	1	1.52
LTC		0.00			0.07	0.07					0.11		0.02	0.22							6	6	0	1.61
EOS			0.07		0.08	0.21				0.01	0.02			0.21							6	6	0	1.46
BNB		0.00	0.08		0.09	0.09					0.26			0.06							6	5	1	1.49
TAGZ5			0.20		0.06						0.09										3	3	0	1.16
XTZ		0.00				0.09			0.17	0.01			0.39								5	4	1	1.33
XLM		0.00				0.00		0.12	0.15		0.18										5	4	1	1.52
LINK											0.38										1	1	0	1.27
ADA		0.00	0.14			0.04		0.03			0.27										5	4	1	1.60
XMR		0.00	0.07			0.11					0.20			0.14							5	4	1	1.41
1YR																								
CVIX		-0.01																						
DXY		0.00																						
SPX																								
VIX		0.01									0.03													
B<>0	0	9	8	0	7	11	1	5	4	4	14	1	3	7	1	0	1	0	0	0				
B>0	0	2	8	0	7	10	0	5	4	4	13	1	3	7	0									
B<0	0	7	0	0	0	1	1	0	0	0	1	0	0	0	1									

FIGURE 15: Network on 20200429 for $\tau = 0.25$

	BTC	INNBCL	ETH	XRP	BCH	BSV	LTC	EOS	BNB	TAGZ5	XTZ	XLM	LINK	ADA	XMR	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC						0.07				0.00	0.10			0.02							4	4	0	1.74
INNBCL																					0	0	0	0.62
ETH		0.00			0.26	0.07				0.02	0.18										5	5	0	1.54
XRP		0.00	0.13		0.15						0.03			0.02							5	5	0	1.55
BCH						0.32								0.13							2	2	0	1.67
BSV		0.00			0.57						0.03										3	2	1	1.64
LTC						0.00					0.15		0.03	0.05							4	4	0	1.84
EOS					0.13	0.17					0.04			0.00							4	4	0	1.60
BNB		0.00			0.21	0.04					0.16										4	3	1	1.56
TAGZ5		0.00	0.21		0.06						0.07										4	3	1	1.06
XTZ		-0.01	0.28							0.03			0.30								4	3	1	1.62
XLM		0.00	0.06								0.18										3	3	0	1.63
LINK		0.00									0.31										2	1	1	1.44
ADA		0.00			0.15						0.18										3	2	1	1.82
XMR		0.00				0.07				0.02	0.22										4	3	1	1.74
1YR																								
CVIX		-0.01																						
DXY		0.00								0.00														
SPX																								
VIX		0.00																						
B<>0	0	10	4	0	7	7	0	0	0	4	12	0	2	5	0	0	0	0	0	0				
B>0	0	3	4	0	7	7	0	0	0	4	12	0	2	5	0									
B<0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0									

FIGURE 16: Network on 20200429 for $\tau = 0.5$

	BTC	ETH	XRP	BCH	BSV	LTC	BNB	CRO	EOS	ADA	XTZ	LINK	XLM	LEO	XMR	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC		0.19				0.23	0.27								0.04					0.04	4	4	0	0.06
ETH	0.03			0.49		0.1			0.1		0.02										5	5	0	0.22
XRP								0.06	0.42	0.09	0.04		0.07							0.01	5	5	0	0.12
BCH		0.36			0.31	0.24	-0.08	0.02		0.04	0.13	-0.11	0.04							0.01	9	7	2	0.02
BSV		0.30		0.21		0.34	0.05						0.02		0.00		0.06				6	6	0	0.07
LTC	0.05	0.15	0.03	0.10	0.14			0.00	0.24	0.08					0.05						9	9	0	0.08
BNB	0.11	0.28		0.14				0.26		0.00	0.01	0.05			0.10					0.02	8	8	0	0.03
CRO			0.35		-0.01					0.00	0.27		0.20							-0.08	5	4	1	0.03
EOS		0.14	0.19	0.04	0.10	0.15	0.13			0.07			0.06		0.12						9	9	0	0.09
ADA	0.26	0.14			-0.04			-0.02			0.34		0.33		0.07					-0.01	7	5	2	0.04
XTZ					0.28		0.03	0.08				0.26	0.25							0.06	5	5	0	0.09
LINK		0.01	0.04					0.18	0.33		0.34		0.02							0.01	6	6	0	0.08
XLM		0.08	0.12	0.17	0.08	0.08				0.27		0.12								-0.01	7	7	0	0.03
LEO	-0.18			-0.23	-0.01	0.10		-0.04		0.14	-0.03	0.10	0.03		0.08		-0.15		-0.14	0.00	10	5	5	0.01
XMR		0.19					0.20	0.06	0.27		0.01		0.10								6	6	0	0.11
1YR	0.01	0.00	0.31	-0.35	-0.04		-0.01	0.08	-0.26		0.27		0.00	-0.18	0.04									
CVIX			-0.28		-0.21		-0.02	0.13	0.59	-0.07	-0.14				0.16									
DXY		-0.03	0.03					0.02	-0.02	0.02		-0.02	0.03		-0.05									
SPX					0.01			0.08		0.07		0.14	-0.10		-0.34									
VIX	0.15				-0.02					-0.17	-0.11		-0.12											
B<>0	5	10	5	7	8	7	6	9	5	8	9	5	10	0	7	0	2	0	1	10				
B>0	4	10	5	6	5	7	5	7	5	8	8	4	10	0	7									
B<0	1	0	0	1	3	0	1	2	0	0	1	1	0	0	0									

FIGURE 17: Network on 20200630 for $\tau = 0.05$

	BTC	ETH	XRP	BCH	BSV	LTC	BNB	CRO	EOS	ADA	XTZ	LINK	XLM	LEO	XMR	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC		0.23		0.02	0.00	0.08	0.21						0.06		0.05					0.04	7	6	1	0.18
ETH	0.14			0.27		0.1	0.11		0.0	0.03	0.03				0.1					0.02	8	8	0	0.27
XRP		0.07						0.03	0.28	0.09	0.09										5	5	0	0.33
BCH		0.25			0.26				0.16		0.14										4	4	0	0.32
BSV		0.27		0.43					0.00	0.00	0.00		0.03		0.07						7	7	0	0.23
LTC		0.25			0.15				0.22	0.07	0.03										5	5	0	0.38
BNB	0.11	0.33		0.18	0.02			0.03	0.04		0.00		0.04		0.03					0.03	9	8	1	0.11
CRO			0.34			0.00			0.03		0.22		0.11		0.10					-0.06	6	6	0	0.07
EOS		0.25		0.03	0.07	0.26				0.09			0.01		0.13						7	7	0	0.29
ADA	0.15	0.24									0.22		0.29		0.11					-0.02	5	5	0	0.12
XTZ					0.29			0.18				0.29	0.22							0.04	4	4	0	0.16
LINK				0.21			0.00			0.01	0.38		0.04							0.01	5	5	0	0.17
XLM		0.09	0.03	0.24				0.02		0.29	0.04	0.09									7	7	0	0.18
LEO	-0.15									0.07			0.04				-0.06			0.02	3	2	1	0.05
XMR		0.15			0.02		0.06		0.19	0.03	0.11		0.23								7	7	0	0.23
1YR				-0.03			0.13		-0.28	0.09		0.07	0.00											
CVIX					-0.11			0.09	0.16	-0.06		-0.09			0.10									
DXY	0.02				-0.02			0.01	-0.01				0.02											
SPX		-0.07																						
VIX	0.27		-0.42	-0.20		0.69		0.26				0.16	-0.53											
B<>0	4	10	2	7	7	4	4	4	8	9	11	2	10	0	7	0	1	0	0	8				
B>0	3	10	2	7	6	4	4	4	8	9	10	2	10	0	7									
B<0	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0									

FIGURE 18: Network on 20200630 for $\tau = 0.1$

	BTC	ETH	XRP	BCH	BSV	LTC	BNB	CRO	EOS	ADA	XTZ	LINK	XLM	LEO	XMR	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC		0.30								0.03										0.01	2	2	0	0.70
ETH				0.14					0.2	0.17	0.08										4	4	0	0.72
XRP		0.13								0.07	0.14		0.02								4	4	0	0.67
BCH		0.09			0.30					0.12	0.10										4	4	0	0.78
BSV		0.41		0.07																	2	2	0	0.75
LTC		0.29			0.06				0.18	0.09	0.04										5	5	0	0.60
BNB		0.42			0.05				0.09	0.09			0.00								5	5	0	0.67
CRO									0.20		0.19										2	2	0	0.40
EOS		0.09		0.20	0.03					0.07	0.15		0.06		0.01						7	7	0	0.62
ADA		0.46									0.15		0.16								3	3	0	0.49
XTZ		0.17								0.13		0.37									3	3	0	0.64
LINK		0.02								0.12	0.43									0.06	3	3	0	0.43
XLM		0.11								0.32	0.16										3	3	0	0.52
LEO	-0.08			-0.12			-0.01	0.01	0.08	0.04			0.03				-0.07				7	4	3	0.04
XMR		0.10							0.30	0.07	0.11		0.04								5	5	0	0.47
1YR									-0.02	0.01														
CVIX								0.18	0.14	-0.04		-0.05												
DXY										0.00			0.01		0.01									
SPX																								
VIX												0.24												
B<>0	1	12	0	4	4	0	1	1	6	12	10	1	6	0	1	0	1	0	0	2				
B>0	0	12	0	3	4	0	0	1	6	12	10	1	6	0	1									
B<0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0									

FIGURE 19: Network on 20200630 for $\tau = 0.25$

	BTC	ETH	XRP	BCH	BSV	LTC	BNB	CRO	EOS	ADA	XTZ	LINK	XLM	LEO	XMR	1YR	CVIX	DXY	SPX	VIX	B<>0	B>0	B<0	L_j
BTC		0.22								0.09											2	2	0	0.87
ETH				0.03	0.01				0.0	0.22	0.22									0.00	5	5	0	0.90
XRP		0.19								0.12	0.02										3	3	0	0.91
BCH		0.34			0.13					0.09										0.00	3	3	0	0.94
BSV		0.28		0.16																	2	2	0	0.79
LTC		0.16								0.14	0.09		0.00								4	4	0	0.87
BNB		0.47								0.03	0.05										3	3	0	0.80
CRO		0.09							0.05	0.27											3	3	0	0.59
EOS		0.20								0.08	0.03										3	3	0	0.86
ADA		0.33									0.19		0.21								3	3	0	0.77
XTZ		0.06								0.17		0.47									3	3	0	0.74
LINK											0.37									0.03	1	1	0	0.82
XLM		0.08								0.34	0.13				0.05						4	4	0	0.54
LEO																					0	0	0	0.38
XMR		0.38								0.06	0.00									0.00	3	3	0	0.74
1YR									-0.03	0.00														
CVIX																								
DXY													0.00		0.03									
SPX																								
VIX																								
B<>0	0	12	0	2	2	0	0	0	2	11	9	1	2	0	1	0	0	0	0	4				
B>0	0	12	0	2	2	0	0	0	2	11	9	1	2	0	1									
B<0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0									

FIGURE 20: Network on 20200630 for $\tau = 0.5$

IRTG 1792 Discussion Paper Series 2020

For a complete list of Discussion Papers published, please visit http://irtg1792.hu-berlin.de.

001 "Estimation and Determinants of Chinese Banks' Total Factor Efficiency: A New Vision Based on Unbalanced Development of Chinese Banks and Their Overall Risk" by Shiyi Chen, Wolfgang K. Härdle, Li Wang, January 2020.

002 "Service Data Analytics and Business Intelligence" by Desheng Dang Wu, Wolfgang Karl Härdle, January 2020.

003 "Structured climate financing: valuation of CDOs on inhomogeneous asset pools" by Natalie Packham, February 2020.

004 "Factorisable Multitask Quantile Regression" by Shih-Kang Chao, Wolfgang K. Härdle, Ming Yuan, February 2020.

005 "Targeting Cutsomers Under Response-Dependent Costs" by Johannes Haupt, Stefan Lessmann, March 2020.

006 "Forex exchange rate forecasting using deep recurrent neural networks" by Alexander Jakob Dautel, Wolfgang Karl Härdle, Stefan Lessmann, Hsin-Vonn Seow, March 2020.

007 "Deep Learning application for fraud detection in financial statements" by Patricia Craja, Alisa Kim, Stefan Lessmann, May 2020.

008 "Simultaneous Inference of the Partially Linear Model with a Multivariate Unknown Function" by Kun Ho Kim, Shih-Kang Chao, Wolfgang K. Härdle, May 2020.

009 "CRIX an Index for cryptocurrencies" by Simon Trimborn, Wolfgang Karl Härdle, May 2020.

010 "Kernel Estimation: the Equivalent Spline Smoothing Method" by Wolfgang K. Härdle, Michael Nussbaum, May 2020.

011 "The Effect of Control Measures on COVID-19 Transmission and Work Resumption: International Evidence" by Lina Meng, Yinggang Zhou, Ruige Zhang, Zhen Ye, Senmao Xia, Giovanni Cerulli, Carter Casady, Wolfgang K. Härdle, May 2020.

012 "On Cointegration and Cryptocurrency Dynamics" by Georg Keilbar, Yanfen Zhang, May 2020.

013 "A Machine Learning Based Regulatory Risk Index for Cryptocurrencies" by Xinwen Ni, Wolfgang Karl Härdle, Taojun Xie, August 2020.

014 "Cross-Fitting and Averaging for Machine Learning Estimation of Heterogeneous Treatment Effects" by Daniel Jacob, August 2020.

015 "Tail-risk protection: Machine Learning meets modern Econometrics" by Bruno Spilak, Wolfgang Karl Härdle, October 2020.

016 "A data-driven P-spline smoother and the P-Spline-GARCH models" by Yuanhua Feng, Wolfgang Karl Härdle, October 2020.

017 "Using generalized estimating equations to estimate nonlinear models with spatial data" by Cuicui Lu, Weining Wang, Jeffrey M. Wooldridge, October 2020.

018 "A supreme test for periodic explosive GARCH" by Stefan Richter, Weining Wang, Wei Biao Wu, October 2020.

019 "Inference of breakpoints in high-dimensional time series" by Likai Chen, Weining Wang, Wei Biao Wu, October 2020.

IRTG 1792, Spandauer Strasse 1, D-10178 Berlin
http://irtg1792.hu-berlin.de

This research was supported by the Deutsche Forschungsgemeinschaft through the IRTG 1792.

IRTG 1792 Discussion Paper Series 2020

For a complete list of Discussion Papers published, please visit http://irtg1792.hu-berlin.de.

020 "Long- and Short-Run Components of Factor Betas: Implications for Stock Pricing" by Hossein Asgharian, Charlotte Christiansen, Ai Jun Hou, Weining Wang, October 2020.

021 "Improved Estimation of Dynamic Models of Conditional Means and Variances" by Weining Wang, Jeffrey M. Wooldridge, Mengshan Xu, October 2020.

022 "Tail Event Driven Factor Augmented Dynamic Model" by Weining Wang, Lining Yu, Bingling Wang, October 2020.

023 "The common and speci
fic components of infl ation expectation across European countries" by Shi Chen, Wolfgang Karl Härdle, Weining Wang, October 2020.

024 "Dynamic Spatial Network Quantile Autoregression" by Xiu Xu, Weining Wang, Yongcheol Shin, October 2020.

025 "Non-Parametric Estimation of Spot Covariance Matrix with High-Frequency Data" by Konul Mustafayeva, Weining Wang, October 2020.

026 "Data Analytics Driven Controlling: bridging statistical modeling and managerial intuition" by Kainat Khowaja, Danial Saef, Sergej Sizov, Wolfgang Karl Härdle, November 2020.

027 "Blockchain mechanism and distributional characteristics of cryptos" by Min-Bin Lin, Kainat Khowaja, Cathy Yi-Hsuan Chen, Wolfgang Karl Härdle, November 2020.

028 "Tail Risk Network Effects in the Cryptocurrency Market during the COVID-19 Crisis" by Rui Ren, Michael Althof, Wolfgang Karl Härdle, December 2020.

IRTG 1792, Spandauer Strasse 1, D-10178 Berlin
http://irtg1792.hu-berlin.de

This research was supported by the Deutsche Forschungsgemeinschaft through the IRTG 1792.