



# Rise of the Machines? Intraday High-Frequency Trading Patterns of Cryptocurrencies

Alla A. Petukhina <sup>\*</sup> <sup>\*2</sup>

Raphael C. G. Reule <sup>\*</sup>

Wolfgang Karl Härdle <sup>\*</sup> <sup>\*3</sup> <sup>\*4</sup> <sup>\*5</sup>



<sup>\*</sup> Humboldt-Universität zu Berlin, Germany

<sup>\*2</sup> Firamis GmbH, Germany

<sup>\*3</sup> Xiamen University, China

<sup>\*4</sup> Singapore Management University, Singapore

<sup>\*5</sup> Charles University, Czech Republic

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

# Rise of the Machines?

Intraday High-Frequency Trading Patterns of Cryptocurrencies

Alla A. Petukhina

Humboldt-Universität zu Berlin.

Firamis GmbH, Germany.

alla.petukhina[at]wiwi.hu-berlin.de

Raphael C. G. Reule

Humboldt-Universität zu Berlin.

irtg1792.wiwi[at]wiwi.hu-berlin.de

Wolfgang Karl Härdle

Humboldt-Universität zu Berlin.

Wang Yanan Institute for Studies in Economics, Xiamen University, China.

Sim Kee Boon Institute for Financial Economics, Singapore Management University, Singapore.

Faculty of Mathematics and Physics, Charles University, Czech Republic.

haerdle[at]wiwi.hu-berlin.de

July 17, 2019

## Abstract

This research analyses high-frequency data of the cryptocurrency market in regards to intraday trading patterns. We study trading quantitatives such as returns, traded volumes, volatility periodicity, and provide summary statistics of return correlations to CRIX (CRyptocurrency IndeX), as well as respective overall high-frequency based market statistics. Our results provide mandatory insight into a market, where the grand scale employment of automated trading algorithms and the extremely rapid execution of trades might seem to be a standard based on media reports. Our findings on intraday momentum of trading patterns lead to a new view on approaching the predictability of economic value in this new digital market.

JEL Classification: G02, G11, G12, G14, G15, G23.

Keywords: Cryptocurrency, High-Frequency Trading, Algorithmic Trading, Liquidity, Volatility, Price Impact, CRIX.

*The financial support of Czech Science Foundation under grant no. 19-28231X and the Firamis GmbH, Robert-Kempner-Ring 27, 61440 Oberursel (Taunus), as well as data support by dyos solutions GmbH, Oberwaldstr. 8, 10117 Berlin, is greatly acknowledged*

# 1 Motivation

High-frequency trading takes advantage of the incredible rise of computing power provided by the steady development of ever more capable structures. Algorithms are already mayor players on a variance of marketplaces and have proven to be more efficient than their human counterparts. By employing these so-called “algo’s”, positive effects can be exploited to their maximum and market inefficiencies can potentially be eliminated. However, just like every coin, there is a flipside, such as the negative impact on capital markets caused by technological inefficiencies (see also Emem, 2019). One of the most noted events of an early point of attack for these algorithms was the Flash Crash of 2010.

No matter what, the machines are here to stay and their influence will certainly increase even more with time - especially in regards to new emerging markets such as cryptocurrencies. The rising popularity and acceptance of this alternative value is asking for specialised strategies to maximise the potential return of investments (see Petukhina et al., 2018).

Yet, did the machines really venture in the realm of the machines, the digital world, or are they still with the world of the humans, the world of shares of oil and baby nutrition companies?

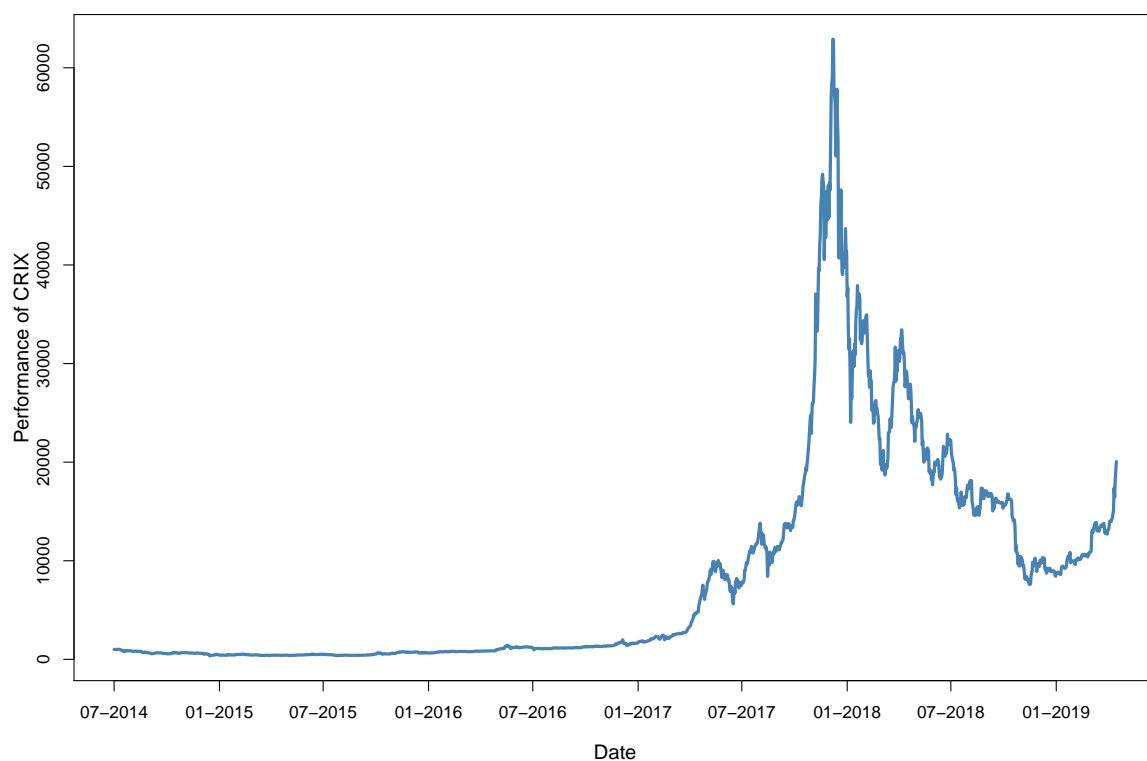


Figure 1: CRIX Time Series.



This is especially of interest, as the cryptocurrency market has greatly matured in the recent years and has attracted immense investments, not only by major players, but especially by individuals.

In this research, we are analysing high-frequency data (5-minute intervals) gained from the cryptocurrency market and see, if there is really a 24/7 algorithmic trading going on, or if there are still people sitting behind their computers creating and executing orders by hand after they have returned from their daily jobs.


Previous research outputs on this theme, such as Zhang Y. et al. (2018), have used time spans ranging from 1 hour to 12 hours. Their methods yielded results, which lead to different conclusions, yet opened up further thoughts towards factors such as trading patterns, variations in returns, volatility and trading volume. Zhang W. et al. (2018) are also looking at the same aspects as the previous research, with the additional finding of a power-law correlation between price and volume. Röschli et al. (2018) respectively build a uni- and multivariate analysis of quantitative facts to show off stylized facts of cryptocurrencies. Schnaubelt et al. (2018) analyzed limit order data from cryptocurrency exchanges. Besides their recovery of common qualitative facts, they find that these data exhibit many of the properties found for classic limit order exchanges, such as a symmetric average limit order book, autocorrelation of returns only at the tick level and the timing of large trades. Yet they find, that cryptocurrency exchanges exhibit a relatively shallow limit order book with quickly rising liquidity costs for larger volumes, many small trades and an extended distribution of limit order volume far beyond the current mid price.

As seen, previous research has not touched the problems at hand we will discuss in this research outlet. There are many papers with interesting approaches and solutions, but only for problems which are already known and have been rebrewn for some time now. Yet, with the advent and popular discussion of the employment of Long Short Term Memory Neural Networks and hence deep learning for finance. AI advisory, essentially based on the human factor of sentiment in the realm of cryptocurrencies (Chen C. et al., 2018), will play a major role in especially this completely digital market. This, as a circular argument, bring us once again to the fundamental idea of enforcing the understanding of market behaviour based on the time of the day and the agents acting in these markets that are predestined to be ruled by the machines.

The paper is structured by giving a brief general introduction and data source disclosure section, followed by a respective intraday data analysis, which is concluded by a section on Time-Of-Day effects and on the Proof-Of-Human.

All presented graphical and numerical examples shown are reproducible and can be found on  [www.quantlet.de](http://www.quantlet.de) (Borke & Härdle, 2018) and are indicated as  CCID.

## 2 High-Frequency Cryptocurrency Data

To understand the dynamics of this new high-frequency market, it is mandatory to investigate the statistical properties of various high-frequency variables, for example trading volume or volatility to find respective answers to questions like option pricing and forecasting. Preliminary research to visualize the cryptocurrency market was done by Trimborn and Härdle (2018) with the CRyptocurrency IndeX,  CRIX ([crix.berlin](http://crix.berlin)), in order to represent the performance of the cryptocurrency market with the help of the most mature and accepted cryptocurrencies, such as bitcoin (BTC), ethereum (ETH), or ripple (XRP) - see appendix section 6.1 for further used abbreviations.

We have chosen this data source, as the CRIX index family covers a range of cryptocurrencies based on different liquidity rules and various model selection criteria. CRIX represents the cryptocurrency market, but by its very nature is dominated by a few main players with BTC being the absolute market driver over time.

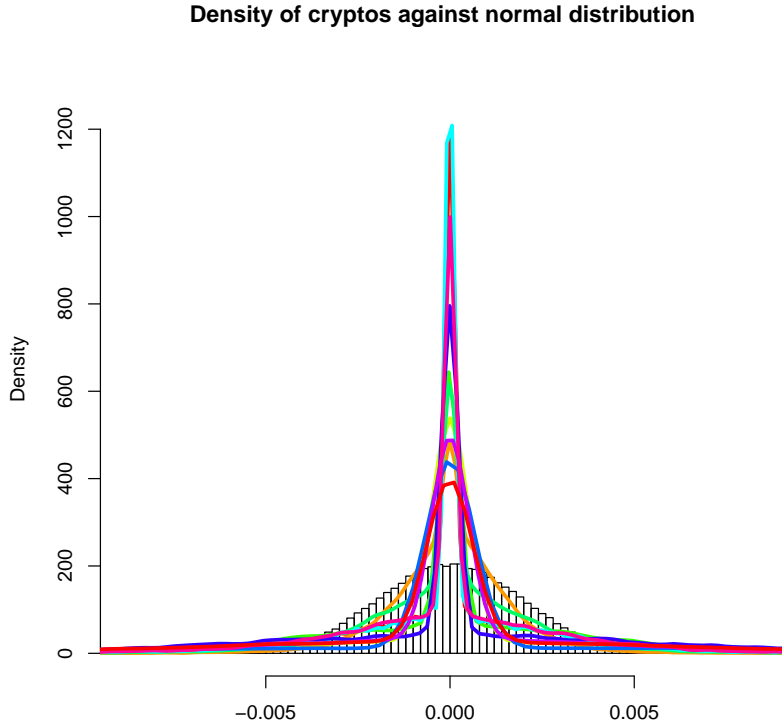
Furthermore, we used data provided by dyos solutions GmbH compiled from Bitfinex exchange. It is important to keep in mind, that the 5-minute data analysed in this research is gained from sources located in the *European markets* and therefore the time-of-day effects may look different for markets from the Americas or Asia.

Previous research on high-frequency data based on traditional data sources, such as for example the NYSE, has underlined data preparation issues and the specific statistical properties of various high-frequency variables, Hautsch (2011). As we are dealing with a subject, where individuals can act directly with the market without involving a middleman, the characteristics of our data observed on transaction level is thus are especially irregularly spaced in time and without interruption, see section 3.

In the following we provide an overview of the statistical intraday cryptocurrency market observations.

### 3 Intraday Data Analysis

As an introduction to the data analyzed in this brief research, we are providing some summary statistics regarding its statistical properties. Firstly, the trading data density of cryptocurrencies against the normal distribution of BTC is far from normally distributed, see figure 2. Hence the behaviour of agents in this market is far from what we would see in classic markets. This implies, that new rules are being employed, and therefore we have to rethink our common way on how to approach the quantitative analysis of markets in general.



Q

Figure 2: Density of intraday CCs returns. 01. July 2018 - 31. August 2018.

Secondly, using Generalized Additive Models (GAM), we gain interesting insights in to the trading activities in this 24/7 market. Cryptocurrencies are being traded without any forced break, as we know it from classic markets, for example, if the stock exchange closes for the night. In addition to this fact, we have to consider, that there is no centralized trading in act, and a plethora of service providers, so-called cryptocurrency exchanges. As we disclose the origin of our data, we underline, that caused by this very decentralized nature of cryptocurrency genesis and their respective trading, partially greatly diverging price data is available for each individual cryptocurrency. Again, this is caused by the decentralized root of individual, unsupervised and unregulated, places for exchange. There is no fixed price for BTC as we know it, for example, for exchange rates of USD-EUR.

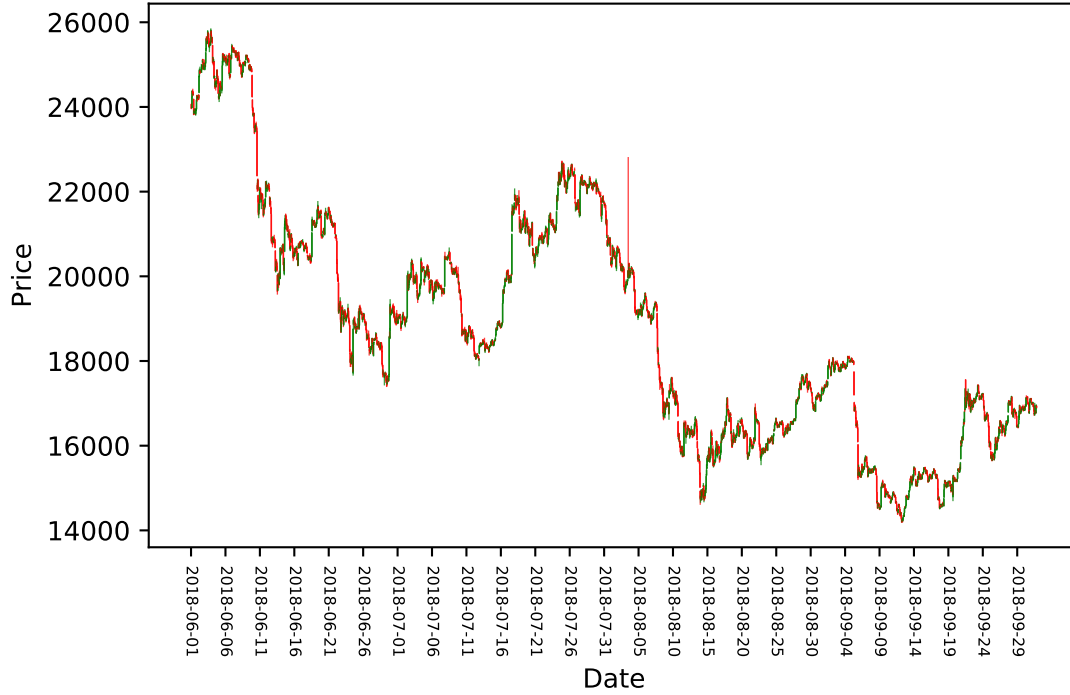


Figure 3: Candlestick chart of CRIX. 01. July 2018 - 29. September 2018.

In contrast to the CRIX candlestick chart which shows the overall index price movements - as it consists of a varying number of dynamically changing constituents - as presented in figure 3 where five minute high-frequency data is aggregated to 60 minutes, we present respective individual plots for each examined cryptocurrency, as shown in figure 4 to give an easier entry to understand this volatile market.

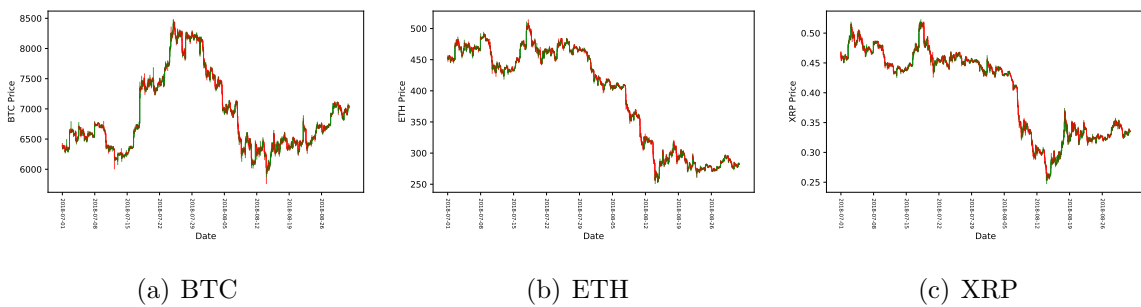


Figure 4: Chandlestick charts for individual price movements. 01. July 2018 - 31. August 2018.

Figure 5, shows the intraday 5-minutes returns for the period from the 01. July 2018 to the 31. August 2018. As indicated, overall returns across the board are very extreme - a phenomenon generally unknown to classic financial markets. In addition, we can observe an extreme activity cluster around the second half of August. We can link this activity to increased media outlets regarding cryptocurrencies: the more investors flooded

into this market, the higher the trading activity, fueled my sentiment, became - leading to partially absurd returns, positive as well as negative.

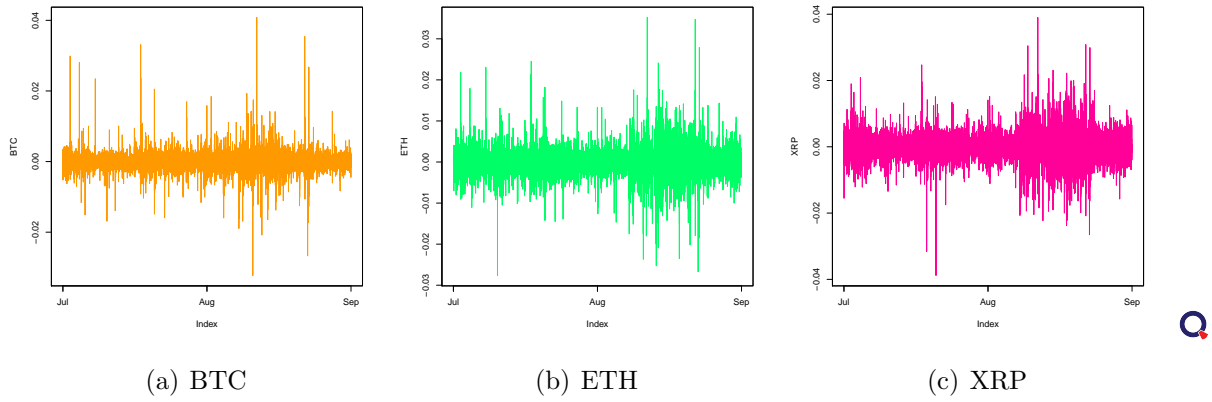


Figure 5: Intraday Returns (5 minutes). 01. July 2018 - 31. August 2018.

Figure 6 adds to this finding, presenting the overall volatility from beforehand stated period. Following for example Hussain (2011), intraday return volatility is calculated as absolute measure of returns. As we can see, the return activity cluster in August from figure 5 is mirrored in the volatility activity cluster in figure 4. Hence, we proof the beforehand stated claim of cryptocurrency activity being fueled by media outlets as well as sentiment, as being attested.

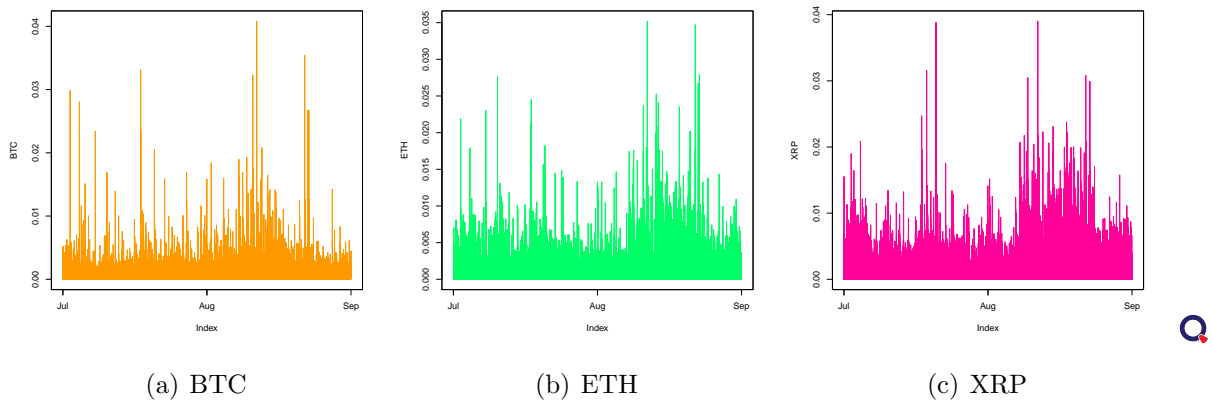


Figure 6: Intraday Volatility. 01. July 2018 - 31. August 2018.

Table 1 displays the estimated values of selected parameters for the cryptocurrency intraday trading for the given period of the 01. July 2018 to the 31. August 2018. The largest autocorrelation is for DASH (0.01), the smallest autocorrelation is for STR (-0.09).

While the first order autocorrelation of the returns of all cryptocurrencies are all close to zero and mostly negative, the autocorrelations of the squared and absolute returns of



all cryptocurrencies are positive and significantly larger than zero. Obviously there is a linear relationship in the absolute and squared values of the chronologically sequential returns. Since the autocorrelation is positive, it can be concluded, that small absolute returns are followed sequentially by small absolute returns and large absolute returns are followed by large ones again. This means, that there are quiet periods with small price changes and dynamic periods with large oscillations.

Furthermore, whereas the estimate for skewness are mostly close to zero, with the exception of BTC and ZEC, the estimate for excess kurtosis is in every case significantly larger than 3. The smallest estimated excess kurtosis is by STR (yet with an expressive  $\widehat{e.Kurt}$  of 8.12), and the largest by BTC ( $\widehat{e.Kurt} = 49.44$ ). These values show, that the tested constituents are far from normally distributed. Negative skewness signals about increasing the downside risk and is a consequence of asymmetric volatility models. Positively skewed distributions have a longer right tail, meaning for investors a greater chance of extremely positive outcomes. A well-known stylized fact about returns distributions highlights their leptokurtic nature: they have more mass around the centre and in the tails than a normal distribution. This phenomenon is known as kurtosis risk.

Table 1: Estimated first order autocorrelation of the returns,  $\hat{\rho}_1(ret_t)$ , the squared returns,  $\hat{\rho}_1(ret_t^2)$ , and the absolute returns,  $\hat{\rho}_1(|ret_t|)$ , as well as the estimated skewness,  $\hat{S}$ , the estimated excess kurtosis,  $\widehat{e.Kurt}$ , and the Jarque-Bera test statistic, JB, with the respective p-value for the overall summed intraday high-frequency data from the 01. July 2018 to the 31. August 2018.

	$\hat{\rho}_1(ret_t)$	$\hat{\rho}_1(ret_t^2)$	$\hat{\rho}_1( ret_t )$	$\hat{S}$	$\widehat{e.Kurt}$	JB	JB p-value
BCH	-0.01	0.12	0.20	0.49	13.69	140148.24	0.00
BTC	-0.05	0.13	0.24	1.30	49.44	1823779.80	0.00
DASH	0.01	0.17	0.20	0.73	28.98	626596.64	0.00
ETC	-0.06	0.26	0.26	0.70	26.07	507374.39	0.00
ETH	-0.01	0.18	0.27	0.17	16.34	198777.58	0.00
LTC	-0.01	0.11	0.19	0.44	14.91	166121.81	0.00
REP	-0.08	0.22	0.19	0.35	21.89	356937.91	0.00
STR	-0.09	0.12	0.18	0.28	8.12	49354.96	0.00
XMR	-0.07	0.13	0.14	0.03	10.51	82241.48	0.00
XRP	-0.05	0.17	0.25	0.11	11.44	97390.58	0.00
ZEC	-0.07	0.25	0.22	1.30	26.66	534032.89	0.00



The combined test of the normal distribution from Jarque and Bera (JB) can be derived as asymptotically  $\chi^2$  distribution with two degrees of freedom. The last column in table 1 shows, that in all cases the normal distribution hypothesis is clearly rejected. This is above all caused by the value of kurtosis, which is significantly larger than 3, caused by a very frequent appearance of outliers in this new market. The higher kurtosis, compared to a normal distribution, proves that these extreme points result in *leptokurtic* distributions and are an evidence of fat tails relative to the normal distribution's tail. However, as this asymmetry is common to financial markets, it is especially strong in the cryptocurrency markets with potentially extreme returns and a very pronounced volatility.

The following tables respectively show the individual correlation to CRIX, if the market is acting positively, table 2, or negatively, table 3. Extensive care should be put on our main actors - BTC, ETH and XRP - when studying these. As these enjoy a large market acceptance and hence are long-term drivers of the cryptocurrency market, we can once again, underline our findings given beforehand.

Table 2: Pairwise crypto-currency correlations of returns for positive market-movement days, as defined by returns on CRIX. 01. July 2018 - 31. August 2018.

UP	BCH	BTC	DASH	ETC	ETH	LTC	REP	STR	XMR	XRP	ZEC
BCH		0.50	0.23	0.33	0.47	0.46	0.13	0.29	0.25	0.37	0.23
BTC	0.50		0.27	0.36	0.55	0.49	0.18	0.34	0.30	0.40	0.27
DASH	0.23	0.27		0.17	0.22	0.22	0.10	0.17	0.17	0.22	0.14
ETC	0.33	0.36	0.17		0.37	0.31	0.11	0.21	0.17	0.28	0.14
ETH	0.47	0.55	0.22	0.37		0.47	0.16	0.30	0.27	0.42	0.22
LTC	0.46	0.49	0.22	0.31	0.47		0.17	0.26	0.25	0.39	0.23
REP	0.13	0.18	0.10	0.11	0.16	0.17		0.12	0.11	0.11	0.11
STR	0.29	0.34	0.17	0.21	0.30	0.26	0.12		0.18	0.27	0.19
XMR	0.25	0.30	0.17	0.17	0.27	0.25	0.11	0.18		0.20	0.15
XRP	0.37	0.40	0.22	0.28	0.42	0.39	0.11	0.27	0.20		0.19
ZEC	0.23	0.27	0.14	0.14	0.22	0.23	0.11	0.19	0.15	0.19	



We can observe, that the correlation to CRIX in both tables presents itself as clustered around well known cryptocurrencies, namely BTC, ETH, XRP, as well as BCH, ETC and. We can therefore interpret this activity in a way, which indicated these constituents as the market drivers. This finding also correlates with the long term trading activity registered on many online sources for these coins. We should note, without going into detail, that LTC and BCH are closely related to BTC, and that ETC is closely tied to the history

of ETH. XRP itself was able to carve out its very specific niche early enough for certain applications, especially in the banking sector - in contrast BTC can be seen as the genesis of a digital currency without any intrinsic value, whereas the ETH system enables many different applications, majorly through so-called “smart contracts”.

Table 3: Pairwise crypto-currency correlations of returns for negative market-movement days, as defined by returns on CRIX. 01. July 2018 - 31. August 2018.

<b>DOWN</b>	BCH	BTC	DASH	ETC	ETH	LTC	REP	STR	XMR	XRP	ZEC
BCH		0.48	0.21	0.32	0.47	0.43	0.15	0.27	0.23	0.37	0.22
BTC	0.48		0.26	0.36	0.52	0.45	0.19	0.33	0.30	0.41	0.24
DASH	0.21	0.26		0.15	0.22	0.21	0.11	0.16	0.18	0.18	0.14
ETC	0.32	0.36	0.15		0.36	0.30	0.14	0.21	0.18	0.30	0.16
ETH	0.47	0.52	0.22	0.36		0.42	0.16	0.29	0.23	0.40	0.21
LTC	0.43	0.45	0.21	0.30	0.42		0.16	0.26	0.24	0.35	0.19
REP	0.15	0.19	0.11	0.14	0.16	0.16		0.11	0.12	0.13	0.08
STR	0.27	0.33	0.16	0.21	0.29	0.26	0.11		0.16	0.26	0.16
XMR	0.23	0.30	0.18	0.18	0.23	0.24	0.12	0.16		0.20	0.15
XRP	0.37	0.41	0.18	0.30	0.40	0.35	0.13	0.26	0.20		0.17
ZEC	0.22	0.24	0.14	0.16	0.21	0.19	0.08	0.16	0.15	0.17	



### 3.1 Time-Of-Day Effects and Proof-Of-Human

Following we present our findings regarding the time-of-day trading, and hence support our hypothesis of mostly dealing with human agent initiated trades, which we want to coin as and “proof-of-human”. Additional information on information arrival, news sentiment, volatilities and jumps of intraday returns can also be taken from Qian et al. (2018).

The following figures employ the Generalized additive models (GAM) to observe daily and weekly patterns for intraday volatility and trading volume. For daily seasonality cubic regression spline is used, for weekly seasonality,  $P$ -splines is used, a number of knots are logically set to the number of unique values, i.e 62 for daily patterns and 7 for weekly. The summary statistics of GAM for all cryptocurrencies demonstrate a high significance of smooth terms combined with a quite low explanatory power (coefficients of determination are around 1%). Nevertheless, we can observe distinct intraday seasonality patterns.

Assuming, that the majority of employed persons do work from 09:00 to 17:00 o'clock in Europe, figures 7 and 8 present us with a very clear picture on returns and volume. A characteristic curve can be seen in the morning, after people wake up and before they go to work. Following that point, the respective curves growth rate shrinks significantly only to grow again around lunch break time - in contrast, classic markets are behaving quite differently. Each figure presents a peak around 17:00 o'clock, just when most people finish their daily routine jobs. Adding to this assumption is, that the curves are at their lowest when people are normally sleeping.

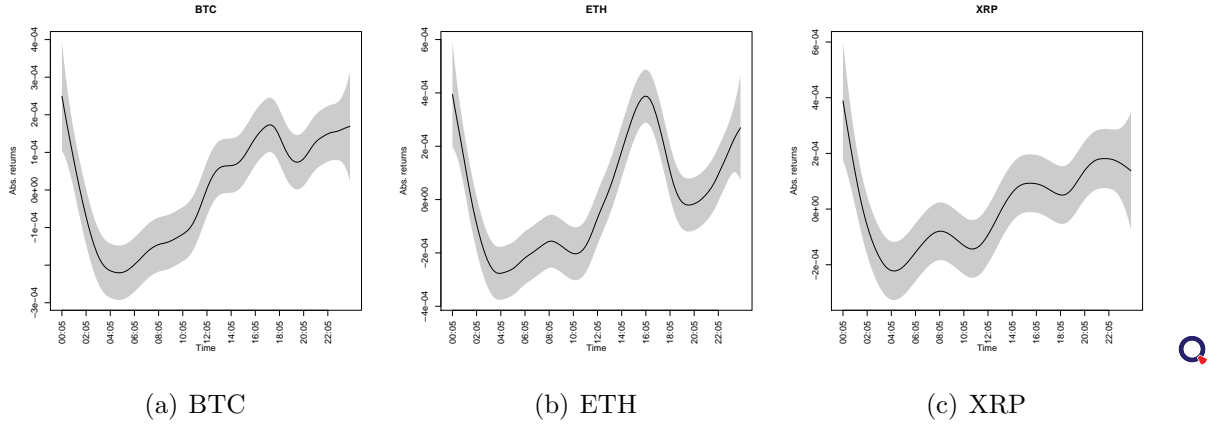


Figure 7: Daily seasonality: fit of Generalized Additive Model (5 min nodes) with cubic regression splines for absolute returns of cryptocurrencies (shaded regions represent confidence bands for smooths), 01. July 2018 - 31. August 2018.

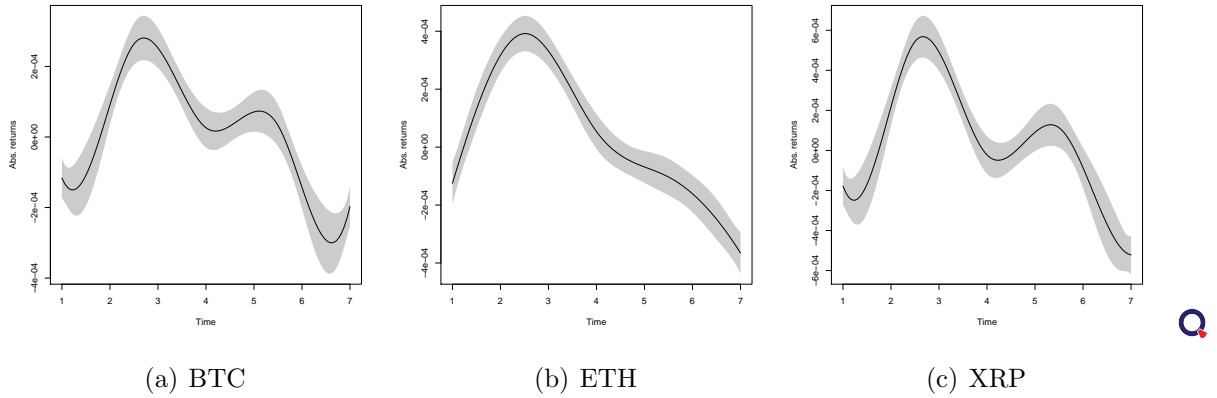


Figure 8: Weekly seasonality: fit of Generalized Additive Model with p-splines for absolute returns of cryptocurrencies (shaded regions represent confidence bands for smooths), 01. July 2018 - 31. August 2018.

Limited trade during regular working hours in Europe leads to the conclusion, that the majority of trades are not done by algorithms, which are active 24/7, but by human agents themselves making transactions and orders individually and by hand. These findings are similar across the board, see appendix section 6. While there is a plethora of well

working, open-source trading bots available for these markets, for example via Github (see also Nevskii, 2018), the trust in these, or the knowledge of how to employ them in this new market, is certainly low. This is especially surprising, as the possibility for arbitrage or mean reversion is obvious with multiple exchanges trading the same assets each with individually different prices, see section 3. The inherent possibility to take advantage of this inefficiency of the distributed trading, with near simultaneous transactions, leads to great opportunities for traders unseen in most traditional markets for most assets.

Yet, this has to be looked at with some caution, as figure 9 presents us a respective lower trading volume during the weekends compared to for example Thursdays or especially Fridays - one assumption from this could be taken from the immense influx of startups in this emerging market.

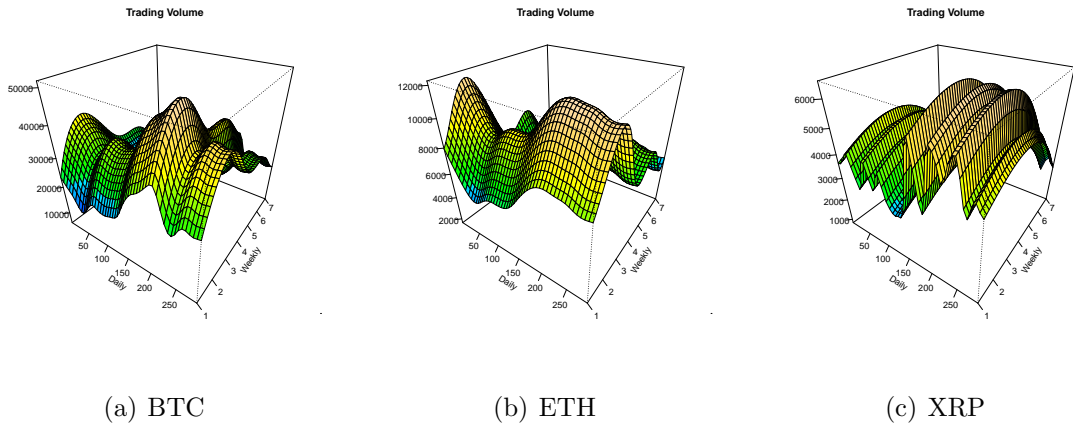


Figure 9: Daily and weekly seasonality: fit of Generalized Additive Model with cubic and p-splines for trading volume of cryptocurrencies (5 min nodes), 01. July 2018 - 31. August 2018. 01. July 2018 - 31. August 2018.

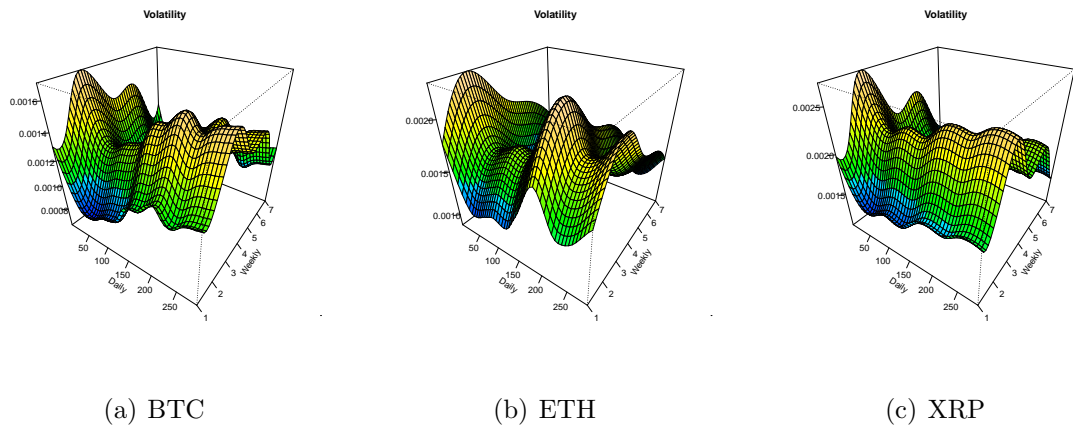


Figure 10: Daily and weekly seasonality: fit of Generalized Additive Model with cubic and p-splines for volatility of cryptocurrencies (5 min nodes), 01. July 2018 - 31. August 2018. 01. July 2018 - 31. August 2018.

To enable new industries using the blockchain technology, startups and commercial companies have been launching initial coin offerings (ICOs), similar to the initial public offerings (IPOs) of companies, to sell tokens in a transparent and decentralized manner and therefore creating a new method of raising funds without intermediaries. Some of these tokens are pegged to other (monetary) systems or even cryptocurrencies directly, as these have already gained a high market acceptance - especially the Ethereum ecosystem is facilitating this by providing excessive tools and documentaries, paired with a focused and growing community of developers, to create what they coined as “coloured coins”.

Besides the fact, that the legality of ICOs and potential responses from surveillance agencies, ICOs enable anyone within the community to participate in the investment, providing opportunities for small-scale investors. Hence the assumption would be, that these startups are working on their codes and maintain their ecosystem, whilst active trading - without the support of algorithms - only commences after this work has been done during the regular working hours.

With the cryptocurrency market being easy to join and to actively participate in, financial traders are becoming redundant - unless they provide specialized services. Making many transactions doesn't cost time to interact with a trader and money to pay this person, as one can do that by hand at home with very low transactions costs. This said, there is a big competition going on between the exchanges, who themselves may act as traders or brokers. The future has to tell, if through this competition the rise of the machines and the respective mass employment of algorithmic trading in this digital realm will become reality.

## 4 Closing remarks

We have shown, that meanwhile there are certainly grand-scale employers of algorithmic trading around in this new emerging market of cryptocurrencies, yet, based on the time-of-day effects and the evidence gained, we can conclude, that the impact of 24/7 algorithmic trading is rather negligible given the empirical facts we have at hand. This leads us to the conclusion, that even though this new digital market is predestined to be ruled by algorithms and specialised AI advisors, the digital realm of cryptocurrencies has yet to be conquered by the machines and is still firmly in the hands of free-time-/holiday-traders or could be even driven by respective start-up's.

## 5 References

- Bogousslavsky, V. 2016. “Infrequent Rebalancing, Return Autocorrelation, and Seasonality”. *The Journal of Finance*, Vol. LXXI, No. 6, December 2016.
- Borke, L., and W. Härdle 2018. “Q3-D3-LSA.” In Härdle, W., Lu, H., Shen, X. (Eds.). *Handbook of Big data Analytics*. Springer-Verlag Berlin Heidelberg. ISBN 978-3-319-18284-1, DOI: 10.1007/978-3-319-18284-1.
- Chen, K., Luo, P., Sun, B., and H. Wang. 2015. “Which stocks are profitable? A network method to investigate the effects of network structure on stock returns”. *Physica A* 436 (2015), pp. 224–2356.
- Chen, C. YH., R. Després, L. Guo, and T. Renault. 2018. “What makes cryptocurrencies special? Investor sentiment and price predictability in the absence of fundamental value.” IRTG 1792 Discussion Paper. ISSN: 2568-5619. Forthcoming.
- Cont, R. 2001. “Empirical properties of asset returns: stylized facts and statistical issues”. Institute of Physics Publishing. *Quantitative Finance Volume 1* (2001), pp. 223–236.
- Emem, M. (2019) “Wall Street Shenanigans: Rampant Trading Bots are Exploiting Crypto Exchanges.” CNN. Retrieved on the 28.06.2019 from <https://www.cnn.com/trading-bots-exploit-crypto-exchanges-dex/>.
- Gourieroux, C., Jasiak, J., and G. Le Fol. 1999. “Intraday market activity”. *Journal of Financial Markets* 2 (1999), pp. 193-226.
- Harju, K., and S. Hussain. 2011. “Intraday Seasonalities and Macroeconomic News Announcements”. *European Financial Management*, Vol. 17, No. 2, 2011, 367–390. DOI: 10.1111/j.1468-036X.2009.00512.x .
- Hautsch, N., 2011. *Econometrics of financial high-frequency data*. Springer Science & Business Media.
- Heston, S., Korajczyk, R., and R. Sadka. 2010. “Intraday Patterns in the Cross-section of Stock Returns”. *The Journal of Finance*, Vol. LXV, No. 4, August 2010.
- Hussein, S. 2011. “The Intraday Behaviour of Bid-Ask Spreads, Trading Volume and Return Volatility: Evidence from DAX30”. *International Journal of Economics and Finance* Vol. 3, No. 1; February 2011.
- Lee, J., Youna, J., and W. Chang. 2012. “Intraday volatility and network topological properties in the Korean stock market”. *Physica A* 391 (2012), pp. 1354–1360.
- Nevskii. 2018. “Crypto trading bots review 2019.” Medium. Retrieved on the 25.06.2019 from <https://medium.com/@vladnevskii/crypto-trading-bots-review-2018-312cf3e8145c>.
- Petukhina, A., Trimborn, S., Härdle, W., and H. Elendner. 2018. “Investing With Cryptocurrencies – Evaluating the Potential of Portfolio Allocation Strategies.” SSRN. Retrieved on the 12.03.2019 from [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3274193](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3274193).
- Schnaubelt, M., Rende, J., and C. Krauss. 2018. “Testing Stylized Facts of Bitcoin Limit Order Books”. *Journal of Risk and Financial Management*, 2019, 12, 25, doi:10.3390/jrfm12010025.
- Tilak, G., Szell, T., Chicheportiche, R., and A. Chakraborti. 2012. “Study of statistical correlations in intraday and daily financial return time series”. *Econophys-Kolkata VI*, Oct 2011, Kolkata, India. pp.77, 2012, DOI:10.1007/978-88-470-2553-0. HAL Id: hal-00827947.

<https://hal.archives-ouvertes.fr/hal-00827947>.

Trimborn, S., Härdle, W. 2018. “CRIX an Index for cryptocurrencies.” *Journal of Empirical Finance*.  
<https://doi.org/10.1016/j.jempfin.2018.08.004>.

Qian, Y., Tu, J., and W. Härdle. 2018. “Information Arrival, News Sentiment, Volatilities and Jumps of Intraday Returns.” IRTG 1792 Discussion Paper. ISSN: 2568-5619. Forthcoming.

Zhang, W., Wang, P., Li, X., and D. Shen. 2018. “Some stylized facts of the cryptocurrency market”. *Applied Economics*, 50:55, 5950-5965, DOI: 10.1080/00036846.2018.1488076.

Zhang, Y., Chan, S., Chu, J., and S. Nadarajah. 2018. “Stylised facts for high frequency cryptocurrency data”. *Physica A*, <https://doi.org/10.1016/j.physa.2018.09.042>.



## 6 Appendix

### 6.1 List of cryptocurrencies in this research

Abbrev.	CC	Website
BCH	Bitcoin Cash	bitcoincash.org
BTC (XBT)	Bitcoin	bitcoin.com, bitcoin.org
DASH	Dash	dash.org
ETC	Ethereum Classic	ethereumclassic.github.io
ETH	Ethereum	ethereum.org
LTC	Litecoin	litecoin.com, litecoin.org
REP	Augur	augur.net
STR	Stalker	staker.network
XMR	Monero	getmonero.org
XRP	Ripple	ripple.com
ZEC	Zcash	z.cash

### 6.2 Appendix-Statistics for BCH, ETC and LTC

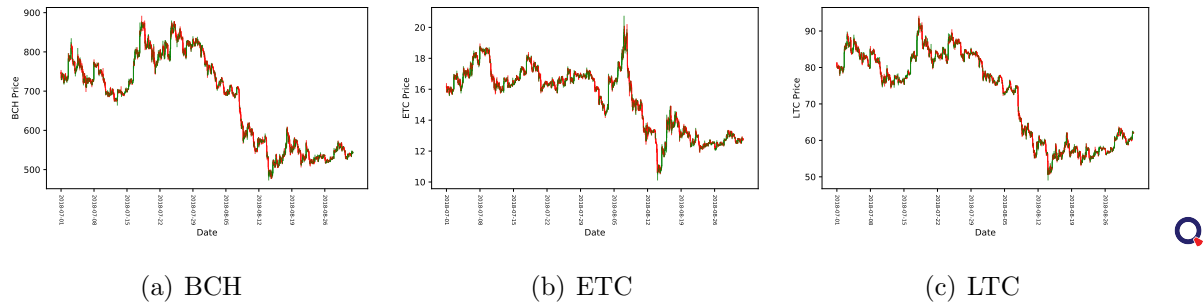


Figure 11: Candlestick charts for individual price movements. 01. July 2018 - 31. August 2018.

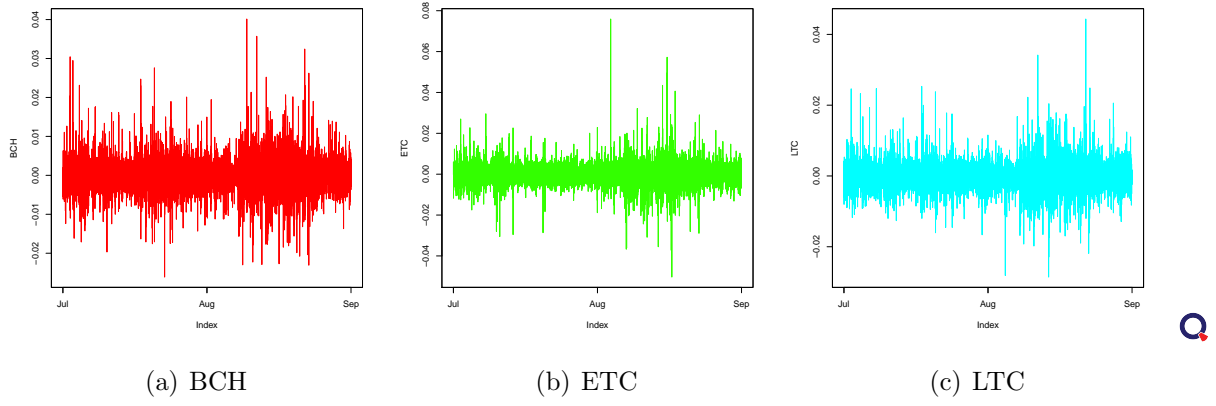


Figure 12: Intraday 5-minutes log-returns. 01. July 2018 - 31. August 2018.

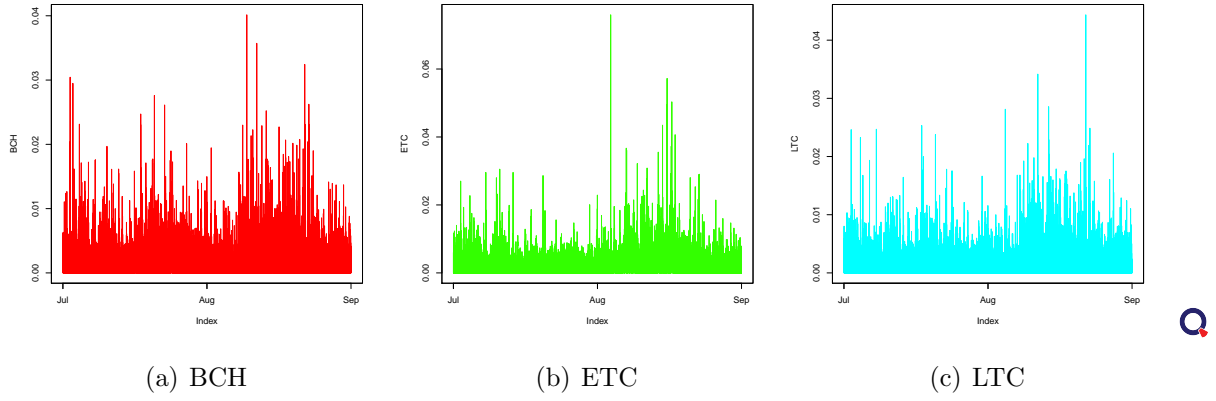


Figure 13: Intraday volatility (absolute values of 5-minutes log-returns) . 01. July 2018 - 31. August 2018.

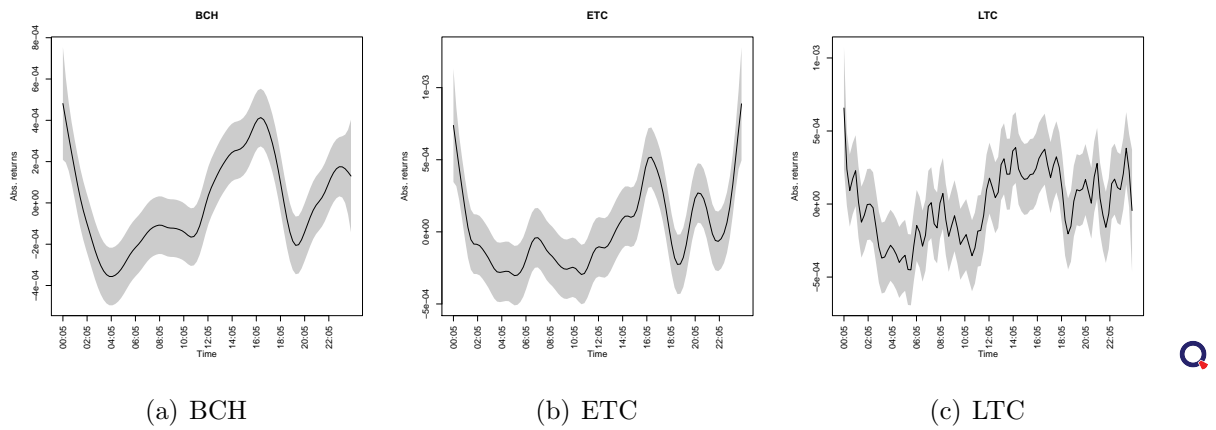


Figure 14: Generalized additive model of volatility. 01. July 2018 - 31. August 2018.

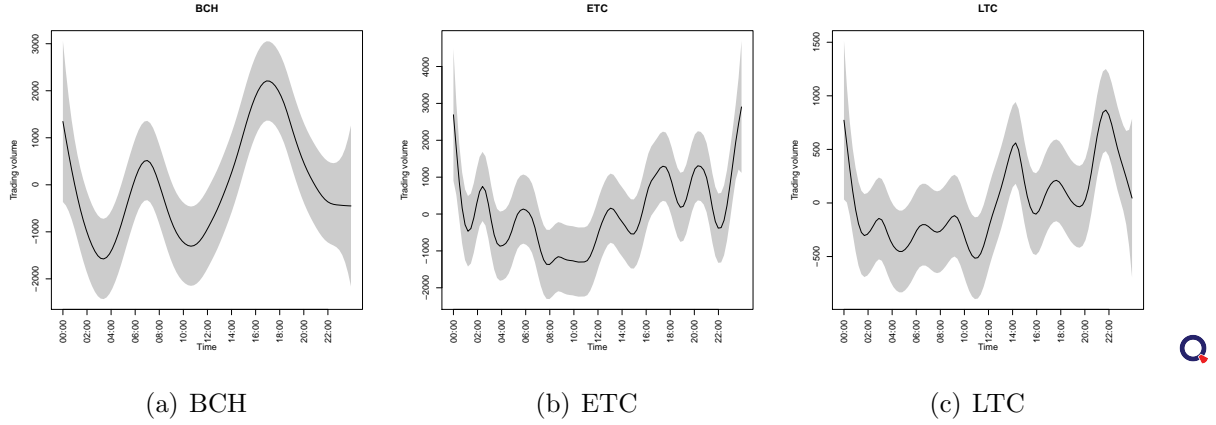


Figure 15: Generalized Additive Model of trading volume of cryptocurrencies. 01. July 2018 - 31. August 2018.

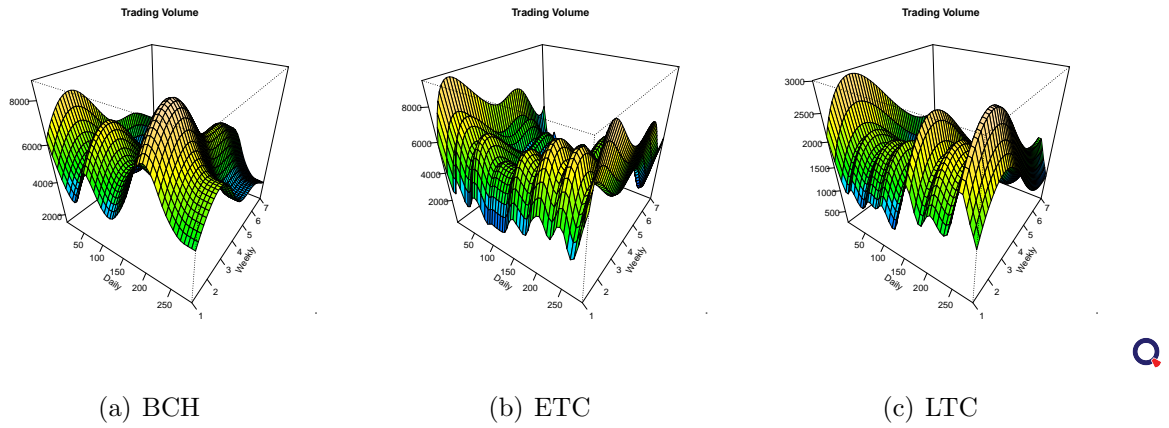


Figure 16: Daily and weekly seasonality: fit of Generalized Additive Model with cubic and p-splines for trading volume of cryptocurrencies (5 min nodes), 01. July 2018 - 31. August 2018. 01. July 2018 - 31. August 2018.

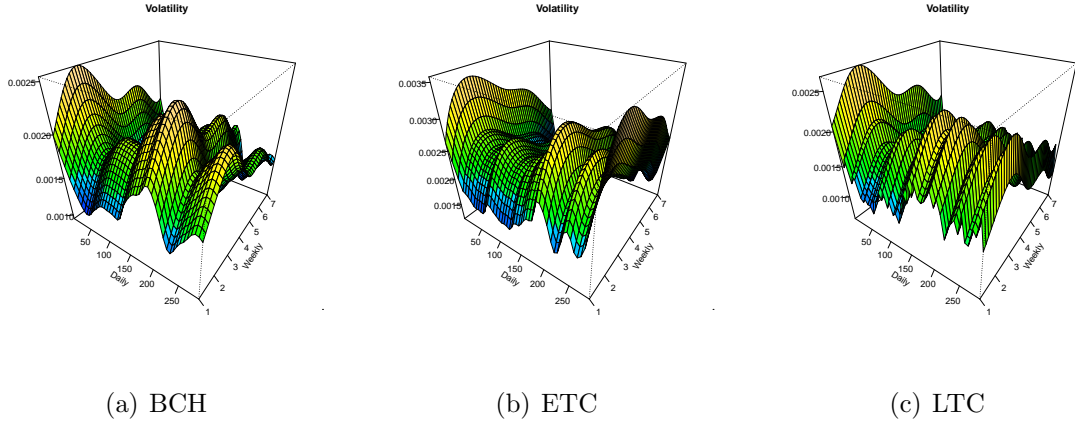


Figure 17: Daily and weekly seasonality: fit of Generalized Additive Model with cubic and p-splines for volatility of cryptocurrencies (5 min nodes), 01. July 2018 - 31. August 2018. 01. July 2018 - 31. August 2018.

### 6.3 Appendix-Statistics for DASH, REP and STR

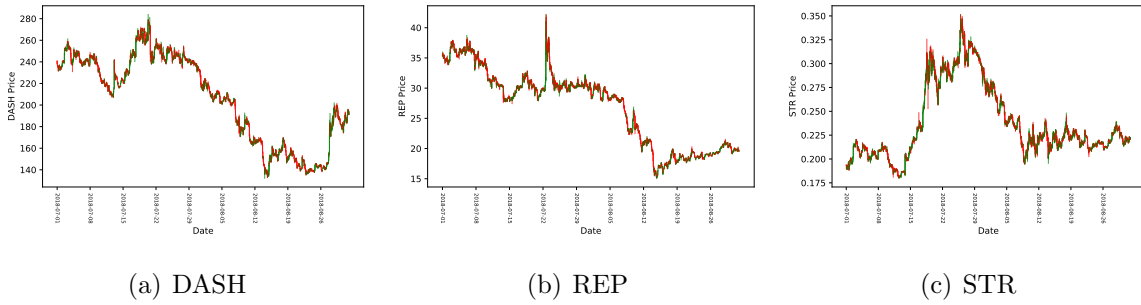


Figure 18: Candlestick charts for individual price movements (60-minutes intervals). 01. July 2018 - 31. August 2018.

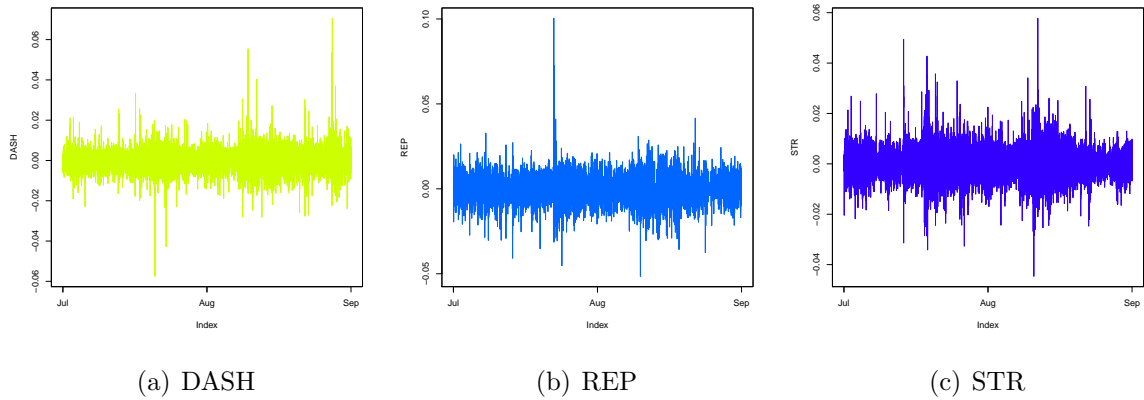


Figure 19: Intraday log-returns (5-minutes). 01. July 2018 - 31. August 2018.

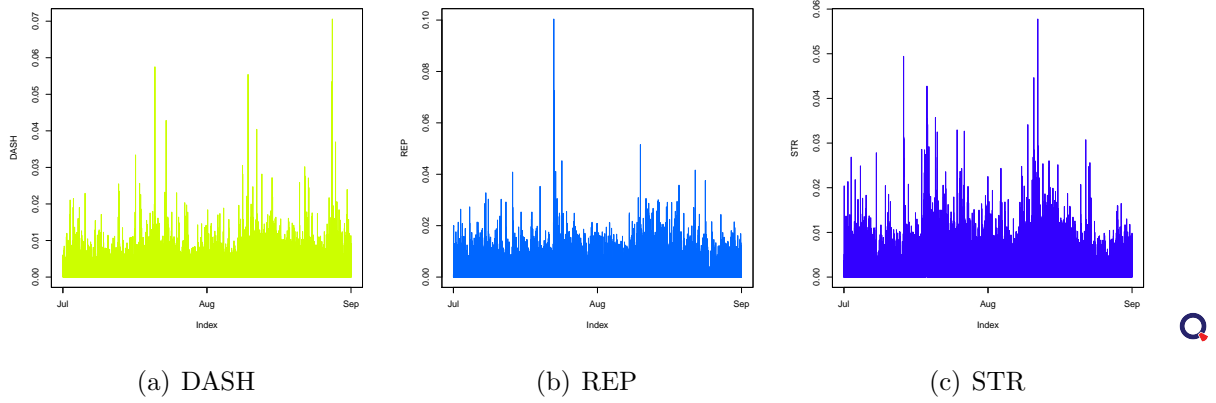


Figure 20: Intraday volatility (absolute 5-minutes log-returns). 01. July 2018 - 31. August 2018.

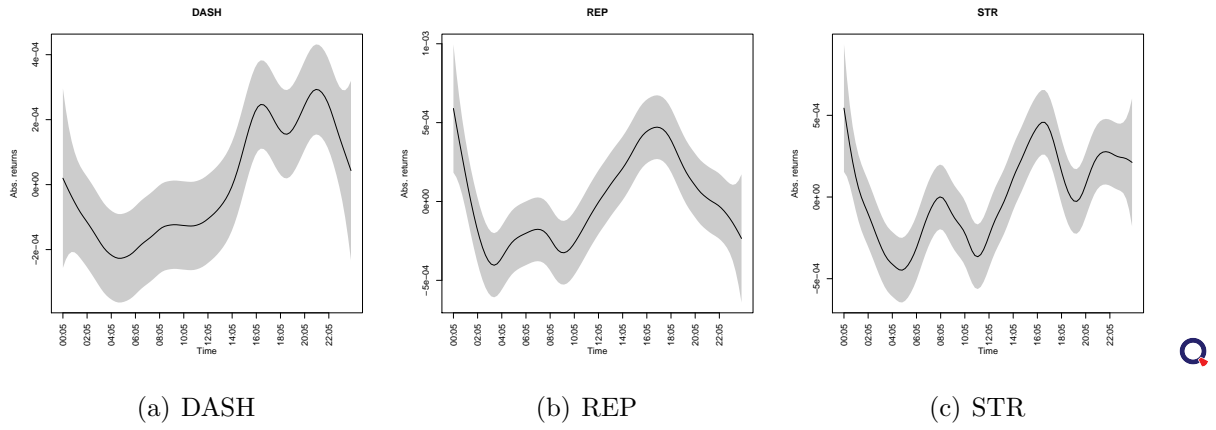


Figure 21: Generalized Additive Model of volatility of cryptocurrencies. 01. July 2018 - 31. August 2018.

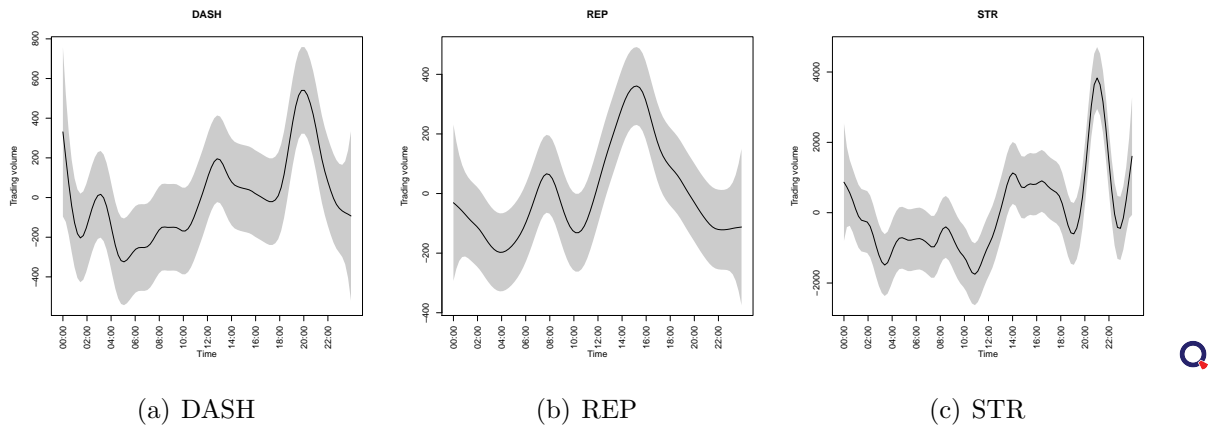
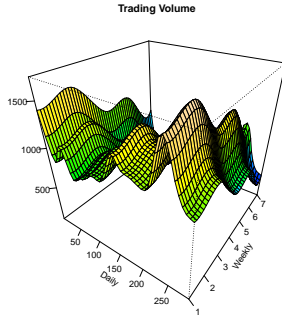
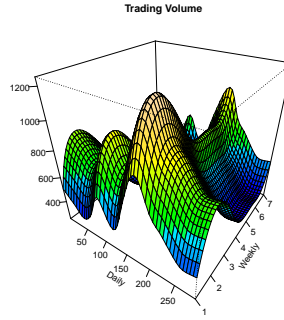


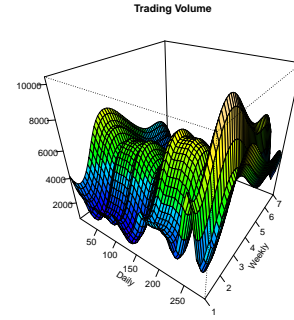
Figure 22: Generalized Additive Model of intraday trading volume of cryptocurrencies. 01. July 2018 - 31. August 2018.



(a) DASH

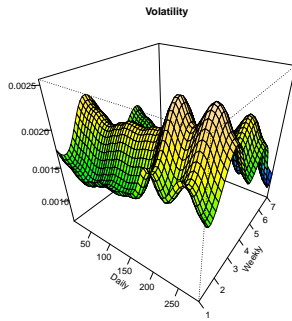


(b) REP

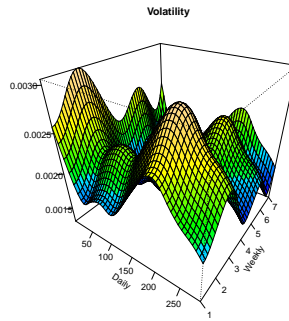


(c) STR

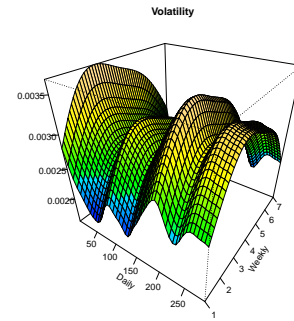
Figure 23: Daily and weekly seasonality: fit of Generalized Additive Model with cubic and p-splines for trading volume of cryptocurrencies (5 min nodes), 01. July 2018 - 31. August 2018. 01. July 2018 - 31. August 2018.



(a) DASH



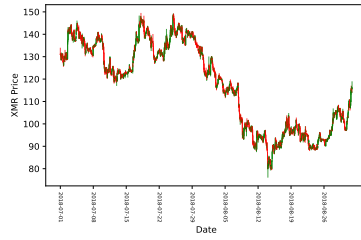
(b) REP



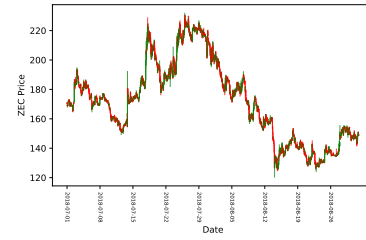
(c) STR

Figure 24: Daily and weekly seasonality: fit of Generalized Additive Model with cubic and p-splines for volatility of cryptocurrencies (5 min nodes), 01. July 2018 - 31. August 2018. 01. July 2018 - 31. August 2018.

## 6.4 Appendix-Statistics for XMR and ZEC

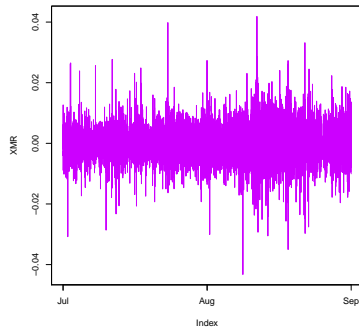


(a) XMR

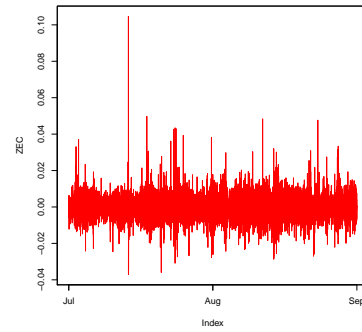


(b) ZEC

Figure 25: Chandlestick charts for individual price movements. 01. July 2018 - 31. August 2018.

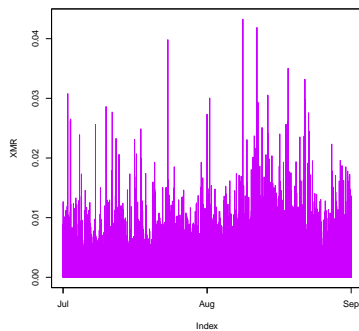


(a) XMR

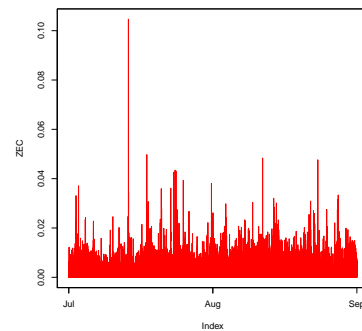


(b) ZEC

Figure 26: GAM Intraday Returns. 01. July 2018 - 31. August 2018.

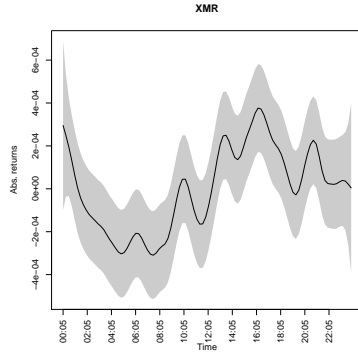


(a) XMR

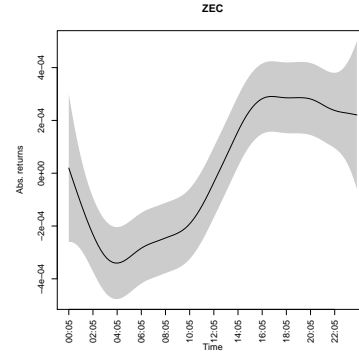


(b) ZEC

Figure 27: Intraday Volatility. 01. July 2018 - 31. August 2018.

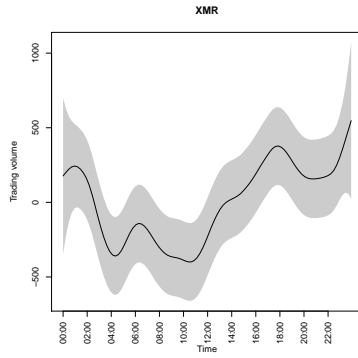


(a) XMR

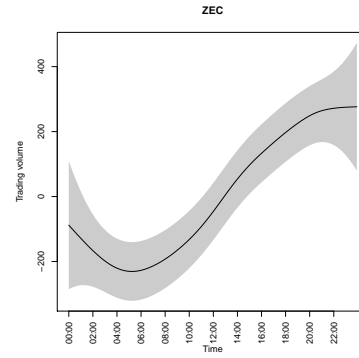


(b) ZEC

Figure 28: Generalized Additive Model of volatility of cryptocurrencies. 01. July 2018 - 31. August 2018.

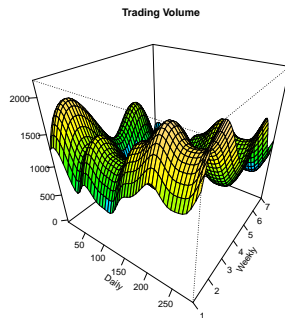


(a) XMR

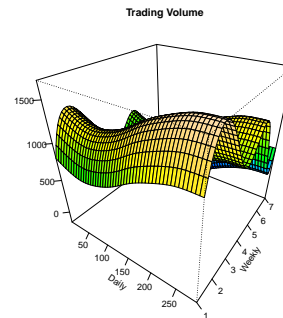


(b) ZEC

Figure 29: Generalized Additive Model of the 62 intraday trading volume of cryptocurrencies. 01. July 2018 - 31. August 2018.



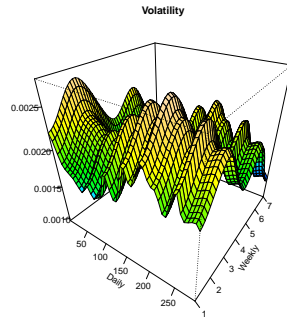
(a) XMR



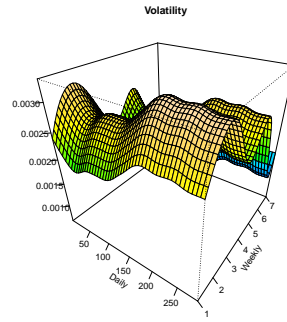
(b) ZEC

Figure 30: Daily and weekly seasonality: fit of Generalized Additive Model with cubic and p-splines for trading volume of cryptocurrencies (5 min nodes), 01. July 2018 - 31. August 2018. 01. July 2018 - 31. August 2018.





(a) XMR



(b) ZEC



Figure 31: Daily and weekly seasonality: fit of Generalized Additive Model with cubic and p-splines for volatility of cryptocurrencies (5 min nodes), 01. July 2018 - 31. August 2018. 01. July 2018 - 31. August 2018.

# IRTG 1792 Discussion Paper Series 2019



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

- 001 "Cooling Measures and Housing Wealth: Evidence from Singapore" by Wolfgang Karl Härdle, Rainer Schulz, Taojun Xie, January 2019.
- 002 "Information Arrival, News Sentiment, Volatilities and Jumps of Intraday Returns" by Ya Qian, Jun Tu, Wolfgang Karl Härdle, January 2019.
- 003 "Estimating low sampling frequency risk measure by high-frequency data" by Niels Wesselhöfft, Wolfgang K. Härdle, January 2019.
- 004 "Constrained Kelly portfolios under alpha-stable laws" by Niels Wesselhöfft, Wolfgang K. Härdle, January 2019.
- 005 "Usage Continuance in Software-as-a-Service" by Elias Baumann, Jana Kern, Stefan Lessmann, February 2019.
- 006 "Adaptive Nonparametric Community Detection" by Larisa Adamyan, Kirill Efimov, Vladimir Spokoiny, February 2019.
- 007 "Localizing Multivariate CAViaR" by Yegor Klochkov, Wolfgang K. Härdle, Xiu Xu, March 2019.
- 008 "Forex Exchange Rate Forecasting Using Deep Recurrent Neural Networks" by Alexander J. Dautel, Wolfgang K. Härdle, Stefan Lessmann, Hsin-Vonn Seow, March 2019.
- 009 "Dynamic Network Perspective of Cryptocurrencies" by Li Guo, Yubo Tao, Wolfgang K. Härdle, April 2019.
- 010 "Understanding the Role of Housing in Inequality and Social Mobility" by Yang Tang, Xinwen Ni, April 2019.
- 011 "The role of medical expenses in the saving decision of elderly: a life cycle model" by Xinwen Ni, April 2019.
- 012 "Voting for Health Insurance Policy: the U.S. versus Europe" by Xinwen Ni, April 2019.
- 013 "Inference of Break-Points in High-Dimensional Time Series" by Likai Chen, Weining Wang, Wei Biao Wu, May 2019.
- 014 "Forecasting in Blockchain-based Local Energy Markets" by Michael Kostmann, Wolfgang K. Härdle, June 2019.
- 015 "Media-expressed tone, Option Characteristics, and Stock Return Predictability" by Cathy Yi-Hsuan Chen, Matthias R. Fengler, Wolfgang K. Härdle, Yanchu Liu, June 2019.
- 016 "What makes cryptocurrencies special? Investor sentiment and return predictability during the bubble" by Cathy Yi-Hsuan Chen, Roméo Després, Li Guo, Thomas Renault, June 2019.
- 017 "Portmanteau Test and Simultaneous Inference for Serial Covariances" by Han Xiao, Wei Biao Wu, July 2019.
- 018 "Phenotypic convergence of cryptocurrencies" by Daniel Traian Pele, Niels Wesselhöfft, Wolfgang K. Härdle, Michalis Kolossiatis, Yannis Yatracos, July 2019.
- 019 "Modelling Systemic Risk Using Neural Network Quantile Regression" by Georg Keilbar, Weining Wang, July 2019.

**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 2019



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

- 020 "Rise of the Machines? Intraday High-Frequency Trading Patterns of Cryptocurrencies" by Alla A. Petukhina, Raphael C. G. Reule, Wolfgang Karl Härdle, July 2019.

**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.