Value at Risk implementation in business practice

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Abstract.

Value at Risk (VAR) is a frequently used risk measure. Its concept based on determination of maximal loss for predetermined level of certainty is easy to understand. It is often used by various corporate professionals to measure different risks in the company, but predominantly banking and investment sector is responsible for growth of this approach. The rapid growth of instruments in financial market, support growth of VAR estimation methods, as well as methods for proper validation of this models. Presented paper goes beyond traditional financial instruments and tries to assess usefulness of three different VAR estimation models in cryptocurrency market. The motivation behind this research is to determine whether Normal, Historical or EWMA approaches of VAR estimation can be used for determination of maximal loss in cryptocurrency market with 95% and 99% probability. The performance of these VAR model is measure by number of violations and four different backtests: Basel's Traffic light approach, Binomial test, POF test and TBF test. The results showed that performance of these VAR models differs based on the type of cryptocurrency and that VAR models perform differently at pre-COVID-19 and during COVID-19 period.

Keywords: Risk, VaR methodology, risk classification

JEL classification: *G24, G31*

1 Introduction

In the corporate environment there are several well-known concepts, which are used to measure risk. There is a beta which is used to measure volatility of systematic risks, r-squared for measurement of corelation between asset and benchmark, standard deviation as a measure of volatility and Sharpe ratio which measure performance adjusted for risks). (Likitratcharoen et al., 2018) Value at Risk concepts fall into that category. It was presented by J.P. Morgan in 1994 and became widely used methodology for determination of risks of various financial instruments such as stock, bond, options, futures. (Likitratcharoen et al., 2018). The concept behind VAR is easy to understand and can be applied to support investment decisions in almost all traditional financial instruments. The demand for cryptocurrencies increased so heavily, that there are considered by some authors as new class of investments products. (Corbet et al., 2018, Boako et al., 2019). Therefore, it is not surprise that there is a rapid increase of scientific studies which implement the time-tested concepts from traditional financial markets to cryptocurrency markets. Current studies covers topics like price determination (Kristoufek, 2015; Ciaian et al., 2018), information exchange between different cryptocurrencies and investments instruments (Corbet et al., 2018), technical issues connected to cryptocurrency environment (Dwyer, 2015; Bariviera et al., 2017a), cryptocurrency hedging strategies (Dyhrberg, 2016; Bouri et al., 2017), interconnection of returns and volumes of cryptocurrencies (e.g. Balciar et al., 2017), trading (Blau, 2017; Corbet et al., 2018), volatility (Katsiampa, 2017), Efficient market theory on cryptocurrency markets (e.g., Urquhart, 2016; Bariviera, 2017b; Nadarajah and Chu, 2017), and cost of cryptocurrencies transactions (Kim, 2017). (Boako et al., 2019) Current rapid growth of cryptocurrency market and use of cryptocurrencies as a part of corporate investment strategies open the question, whether VAR models can be usefully implemented in fintech sector. This paper tries to contribute to this scientific discussion by testing several VAR models on three major cryptocurrencies in pre-COVID-19 and during COVID-19 two years periods.

2 Methodology and data

This paper is focused on implementation of Value at risk methodology (VAR) in business practice to support decision making of investors regarding their positions in cryptocurrency market. The analyses conducted in this article tries to validate, whether VAR can be used to estimate losses from cryptocurrency trading based on some predefined level of confidence. In order to estimate VAR, we selected three frequently used methods: 1.VAR estimation using Normal distribution method. 2. VAR estimation using the Historical Simulation Method. 3. VAR using the Exponential Weighted Moving Average Method (EWMA). First model assume that the profits and losses are normally distributed. Second model represents nonparametric method, which is not so depended on distribution variables because it is based on quantiles. Based on this model present VAR is determined as the predefined th-quantile of last several returns determined by examination window. The last model is on the other hand based on assumption that not-so-distant past returns influence current return more that returns farer in the past, so the Exponential Weighted Moving Average is used for calculations of VAR. The examination window used in all three models is set to 250 days, based on assumption that general year has 250 trading days. For more information, please see Farid (2010). In term of level of confidence for VAR, we use two most frequently used levels of VAR: VAR 95% and VAR 99%. The sample data includes prices of three major (based on market capitalization) cryptocurrencies: Bitcoin, Ethereum and Lite coin. The dataset contains prices from 1.4.2017 to 2.8.2021 for all three cryptocurrencies. On the other hand, having in mind size of the rolling examination window and current market environment, the dataset was divided to two sub samples. For this subsamples VARs were calculated. First subsample represents pre-COVID-19 period. The first VARs calculated within this subsample have the date 1.1.2018 and the last VARs have the date 31.1.2019. The second period covers prices of cryptocurrencies within COVID-19 outbreak. The first VARs calculated within COVID-19 period have a date 1.1.2020 and last VARs have a date 2.8.2021. Both datasets include prices covering mentioned period plus prices of 250 days before first date. The descriptive statistics of datasets for every cryptocurrency and every sub-sample are presented in Table 1.

Table 1: Overview of descriptive statistics of the research sample

		n	Mean	Median	St. Dev.	Var. coef.	Min.	Max.	Q1	Q3
Bitcoin Price	Pre-COVID-19	730	7463	7353	2532	0,34	3233	17172	6167	9142
	COVID-19	580	23315	11920	17440	0,75	4917	63558	9345	35917
Ethereum Price	Pre-COVID-19	730	331	211	261	0,79	84	1385	161	451
	COVID-19	580	963	402	951	0,99	110	4178	231	1792
Litecoin Price	Pre-COVID-19	730	87,45	72,78	50,78	0,58	23,12	278,92	53,20	117,16
	COVID-19	580	105,14	64,72	74,53	0,71	30,49	388,28	46,67	151,94

Source: author

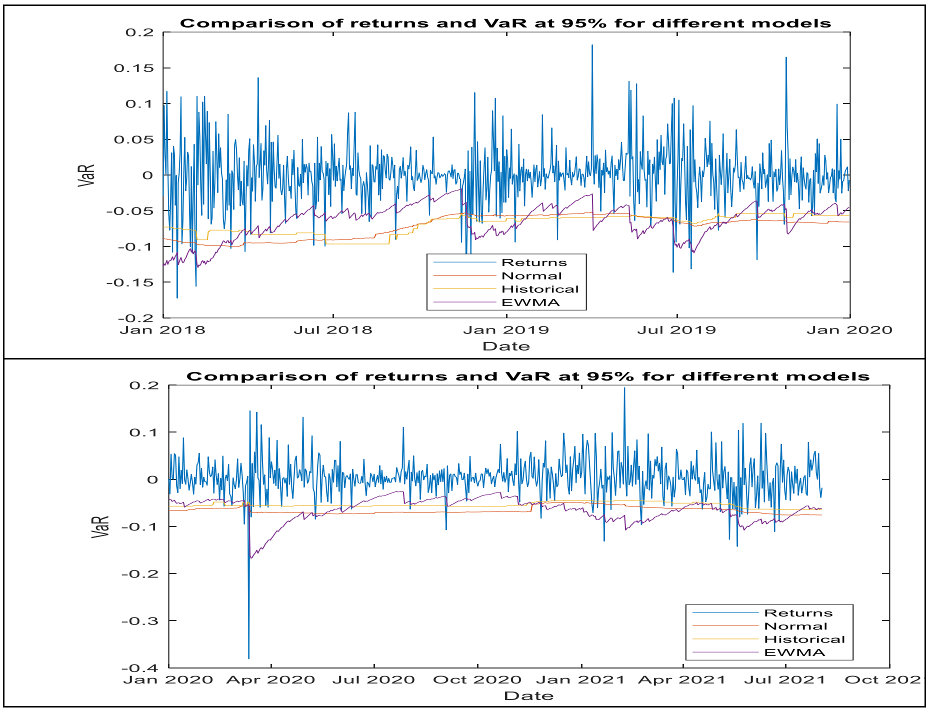
The VARs models are validated by several backtests. First one is Traffic light approach, which was established by Basel committee in 2013. For example, in case of 250 observations green zone allow less than five violations. Five to nine violations (for 250 observations) represent yellow zone and mean that model can be either precise or imprecise. The trust in model accuracy decreases, with the increasing number of violations. For 250 observations, the red zone is defined by more than 9 violations. (Roccioletti, 2015). Second backtesting test is based on Binomial distribution and it is used to test whether „the unconditional probability of a violation in the risk model, significantly differs from the conjectured probability. (Roccioletti, 2015) The third backtesting test is known as POF-test or as a Kupiec Test. The Proportion Of Failure test measures whether "there is a large discrepancy between the observed failure rate, ˆp and the theoretical failure rate p." (Roccioletti, 2015) The third backtesting approach is based on TBF test which is abbreviations for Time Between Failure. This test is also known as Mixed Kupiec Test. This test "measure time between exceptions, being able (at least potentially) to capture various form of dependence." (Roccioletti, 2015). For more information regarding all backtesting models, please see Roccioletti, (2015).

3 The results of the research

As was mentioned in methodology, the research in this paper analyses use of three major Value at risk estimation techniques in cryptocurrency market. It has two parts. First part is focusing on estimation of VAR95 and VAR99 models and their efficiency in term of expected violations versus actual violations. The aim of provided analyses is to compare efficiencies of VAR models in pre-COVID-19 and during COVID-19 period. Second part of the research is dealing with the backtesting of estimated VAR models. Here also, the validity of the models are tested in pre-COVID-19 and during COVID-19 period.

First analysed cryptocurrency is Bitcoin. The analysis of the different approaches of VAR95's estimation in the periods before COVID-19 and during COVID-19 is presented in Figure 1.

Figure 1: Comparison of returns and VAR95s in per-COVID-19 and COVID-19 period for Bitcoin



Source: Authors

As can be seen on Figure 1, returns presented in COVID-19's sample are characterized by greater volatility (see variation coefficient) and bigger spikes (see max value) than the returns in post-COVID-19 sample. The VARs estimated by Normal and Historical approach are close to each other and VARs estimated by EWMA approach are more volatile. In order to measure the performance of VAR models, the Table 2 was created. It showed comparison between number of violations expected from VAR models and actual violations of VAR models. The Ratio lesser than one, means that number of actual violations is lower than number of violations predicted by VAR, and therefore VAR was able to predict maximal loss at predefined level of confidence.

Table 2: Overview of Bitcoin's VAR models violations in pre-COVID-19 and COVID-19 period

Bitcoin						
	Pre-COVID-19			COVID-19		
VaRID	Failures	Expected	Ratio	Failures	Expected	Ratio
Normal 95	34	36,50	0,9315	22	29	0,758621
Historical95	35	36,50	0,9589	36	29	1,241379
EWMA 95	34	36,50	0,9315	21	29	0,724138

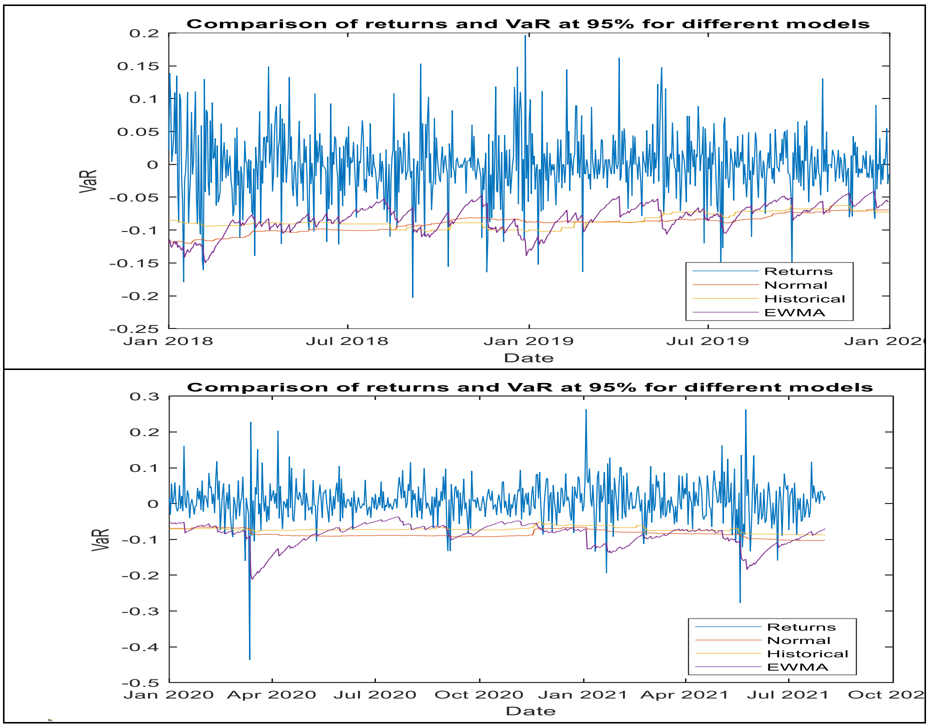
Normal 99	13	7,30	1,7808	9	5,8	1,551724
Historical99	7	7,30	0,9589	7	5,8	1,206897
EWMA 99	13	7,30	1,7808	7	5,8	1,206897

Source: Authors

The Table 2 shows that in pre-COVID-19 period, the VAR at 95% has the ratio smaller than one for all three estimation methods and VAR at 99% have similar ratio at the same period only historical estimation method. The situation is different for VARs estimated during COVID period. Results shows that ratio smaller than one is presented only on VAR at 95% based on normal distribution or EMWA. These results suggest that only VAR95 estimated based on normal distribution and based on EWMA method have fewer violations that was predicted for both pre-COVID-19 and COVID-19 periods.

Second analysed cryptocurrency is Ethereum. The analysis of the different approaches of VAR95's estimation in the periods before COVID-19 and during COVID-19 is presented in Figure 2.

Figure 2: Comparison of returns and VAR95s in per-COVID-19 and COVID-19 period for Ethereum



Source: Authors

Similarly, to Bitcoin, also Ethereum's timeseries presented in Figure 2 behave differently when the pre-COVID-19 and COVID-19 periods are compared. Also, in this case the returns from COVID-19 period are characterized by greater volatility and have bigger spikes than the returns in pre-COVID-19 sample. Correspondingly, the VARs estimated by Normal and Historical methods are close to each other and more smother, than VARs estimated by EWMA approach, which are more volatile. The performance of VAR models is analysed based on results presented in the Table 3. This table compare number of violations expected from VAR models and actual violations of VAR models. If Ratio value is smaller than one, it means that the number of actual violations is smaller than number of violations predicted by VAR, and therefore VAR was able to predict maximal loss at predefined level of confidence for Ethereum cryptocurrency.

Table 3: Overview of Ethereum's VAR models violations in pre-COVID-19 and COVID-19 period

Ethereum						
	Pre-COVID-19			COVID-19		
VaRID	Failures	Expected	Ratio	Failures	Expected	Ratio
Normal 95	32	36,5	0,876712	26	29	0,896552
Historical 95	37	36,5	1,013699	35	29	1,206897
EWMA 95	40	36,5	1,09589	20	29	0,689655
Normal 99	10	7,3	1,369863	8	5,8	1,37931
Historical 99	7	7,3	0,958904	8	5,8	1,37931
EWMA 99	18	7,3	2,465753	7	5,8	1,206897

Source: Authors

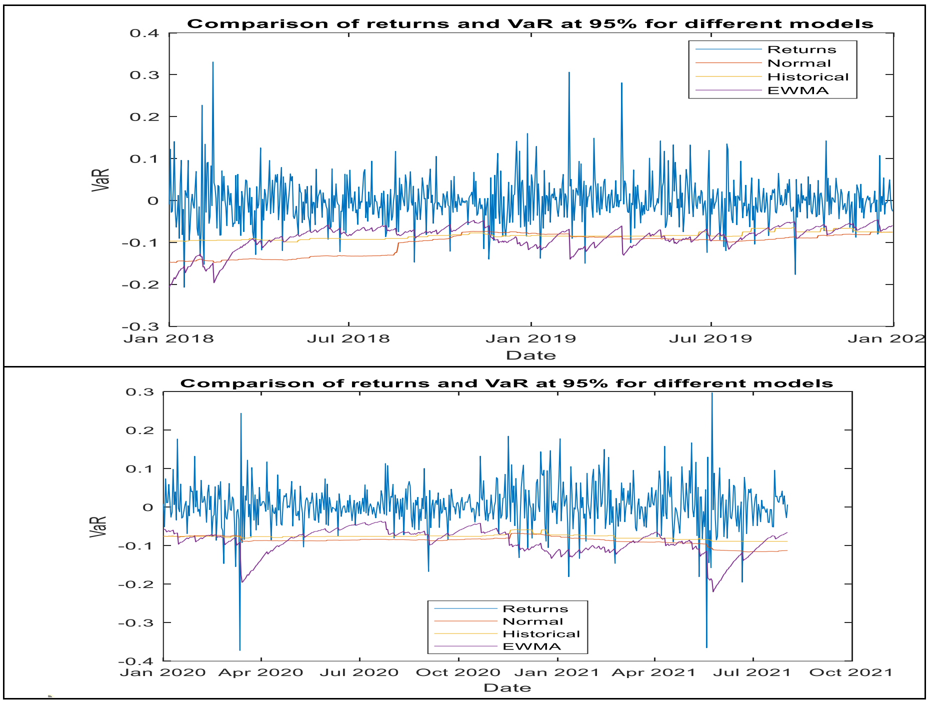
The Table 3 suggest that in pre-COVID-19 period, the VAR models at 95% has the ratio smaller than one only for normal estimation method and VAR models at 99% have similar ratio for the same period only for historical estimation method. The situation is different for VARs estimated during COVID period. Results shows that ratio smaller than one is presented for VAR at 95% in case of normal and EWMA estimation. These results suggest that only VAR95 estimated based on normal distribution has fewer violations that was predicted for pre-COVID-19 and COVID-19 periods.

Last analysed cryptocurrency is Litecoin. The overview of the different approaches of VAR95's estimation in the periods before COVID-19 and during COVID-19 is presented in Figure 3.

Similarly, to Bitcoin, Ethereum also Litecoin behave differently when two testing periods are compared. The Litecoin return timeseries in COVID-19 period shows greater volatility and has bigger spikes than the returns in pre-COVID-19 sample.

Parallelly, the VARs estimated by Normal and Historical methods are close to each other and more smother, than VAR models estimated by EWMA approach. which are more volatile. The performance of VAR models is analysed based on results presented in the Table 4. The results compare number of violations expected from VAR models and actual violations of VAR models. If Ratio value is smaller than one, it means that the number of actual violations is smaller than number of violations predicted by VAR, and therefore VAR was able to predict maximal loss at predefined level of confidence for Litecoin cryptocurrency.

Figure 3: Comparison of returns and VAR95s in per-COVID-19 and COVID-19 period for Litecoin



Source: Authors

The results present in Table 4 shows that in pre-COVID-19 period, the VAR models at levels 95% and 99% has the ratio smaller than one for all estimated models except for VAR99 estimated by EWMA approach. For COVID-19 period, table shows that ratio smaller than one was determined for VAR at 95% in case of normal and EWMA estimation. The VAR models which have fewer violations than predicted, for both of examined periods are models estimated at 95% level using normal and EWMA approach.

Table 4: Overview of Litecoin's VAR models violations in pre-COVID-19 and COVID-19 period

Litecoin						
	Pre-COVID-19			COVID-19		
VaRID	Failures	Expected	Ratio	Failures	Expected	Ratio
Normal 95	24	36,5	0,657534	23	29	0,793103
Historical 95	36	36,5	0,986301	30	29	1,034483
EWMA 95	36	36,5	0,986301	22	29	0,758621
Normal 99	7	7,3	0,958904	14	5,8	2,413793
Historical 99	7	7,3	0,958904	12	5,8	2,068966
EWMA 99	11	7,3	1,506849	9	5,8	1,551724

Source: Authors

The second part of research is focused on backtesting of VAR models. We implement four frequently used tests to validate VAR models with different estimation techniques. First analysed cryptocurrency is Bitcoin. The results of the executed backtests are presented in table below. (Table 5)

Table 5: The results of Bitcoin's backtests in pre-COVID-19 and COVID-19 period

Bitcoin								
	Pre-COVID-19				COVID-19			
VaRID	TL	Bin	POF	TBF	TL	Bin	POF	TBF
Normal 95	'green'	'accept'	'accept'	'reject'	'green'	'accept'	'accept'	'reject'
Historical95	'green'	'accept'	'accept'	'reject'	'green'	'accept'	'accept'	'reject'
EWMA 95	'green'	'accept'	'accept'	'accept'	'green'	'accept'	'accept'	'accept'
Normal99	'yellow'	'reject'	'accept'	'reject'	'green'	'accept'	'accept'	'accept'
Historical 99	'green'	'accept'	'accept'	'accept'	'green'	'accept'	'accept'	'accept'
EWMA 99	'yellow'	'reject'	'accept'	'accept'	'green'	'accept'	'accept'	'accept'

Source: Authors

According to Table 5, comparing pre-COVID-19 period and COVID-19 period, results showed that VAR models have better backtests' results in second timeseries. n pre-COVID-19 period, the performed backtests together accepts only VAR95 model estimated by EWMA and Historical VAR99 model. On the other hand, in COVID-19 period, all tests except for the TBF, accept all examined VAR models. For the same period, the TBF tests rejects VAR95 models using normal and historical approach. Based on these results only VAR95 model estimated by EWMA and Historical VAR99 model were accepted by all backtests for both periods using Bitcoin timeseries.

Next cryptocurrency that was backtested is Ethereum. The results of the backtests are presented in table below. (Table 6)

Table 6: The results of Ethereum's backtests in pre-COVID-19 and COVID-19 period

Ethereum								
	Pre-COVID-19				COVID-19			
VaRID	TL	Bin	POF	TBF	TL	Bin	POF	TBF
Normal95	'green'	'accept'	'accept'	'accept'	'green'	'accept'	'accept'	'reject'
Historical 95	'green'	'accept'	'accept'	'accept'	'green'	'accept'	'accept'	'reject'
EWMA 95	'green'	'accept'	'accept'	'reject'	'green'	'accept'	'accept'	'accept'
Normal 99	**'green'**	**'accept'**	**'accept'**	**'accept'**	**'green'**	**'accept'**	**'accept'**	**'accept'**
Historical 99	**'green'**	**'accept'**	**'accept'**	**'accept'**	**'green'**	**'accept'**	**'accept'**	**'accept'**
EWMA 99	'yellow'	'reject'	'reject'	'reject'	'green'	'accept'	'accept'	'accept'

Source: Authors

Based on the results of Table 6, similarly to Bitcoin's results also Ethereum backtests' results from COVID-19 period are better than results analysing pre-COVID-19 period. In pre-COVID-19 period, the performed backtests together accepts all VAR models estimated by normal and historical approach. On the other hand, in COVID-19 period, parallelly to Bitcoin's results all tests except for the TBF, accept all examined VAR models. For the same period, the TBF tests rejects same two models it was when Bitcoin was tested. The models were theVAR95 using normal and historical approach. Based on these results only VAR99 model estimated by normal and historical approach were accepted by all backtests for both periods using Ethereum timeseries.

The last backtested cryptocurrency was Litecoin. The results of the backtests are presented in table below. (Table 7)

Table 7: The results of Litecoin's backtests in pre-COVID-19 and COVID-19 period

Litecoin								
	Pre-COVID-19				COVID-19			
VaRID	TL	Bin	POF	TBF	TL	Bin	POF	TBF
Normal 95	'green'	'reject'	'reject'	'reject'	'green'	'accept'	'accept'	'reject'
Historical 95	'green'	'accept'	'accept'	'reject'	'green'	'accept'	'accept'	'reject'
EWMA 95	'green'	'accept'	'accept'	'reject'	'green'	'accept'	'accept'	'accept'
Normal 99	'green'	'accept'	'accept'	'accept'	'yellow'	'reject'	'reject'	'reject'
Historical 99	'green'	'accept'	'accept'	'accept'	'yellow'	'reject'	'reject'	'reject'
EWMA 99	'green'	'accept'	'accept'	'reject'	'green'	'accept'	'accept'	'accept'

Source: Authors

As can be seen on Table 7, backtests results of Litecoin timeseries are slightly different that Bitcoin's or Ethereum's results. In pre-COVID-19 period, the performed backtests together accepts only VAR models at 99% level estimated by normal and historical approach. Analysing COVID-19 timeseries, the results showed that only VAR models estimated by EWMA approach are accepted by all used backtesting methods. These results suggests that, in case of Litecoin none of tested VAR models were accepted by all backtests conjointly in tested both periods.

4 The conclusions

Presented paper deal with implementation of Value at Risk methodology in business practice. The motivation behind this research is to determine whether Normal, Historical or EWMA approaches of VAR estimation can be used for determination of maximal loss in cryptocurrency market with 95% and 99% probability. Results showed that performance of these VAR models differs based on the type of cryptocurrency and that VAR models behave differently at pre-COVID-19 and during COVID-19 period. From all tested VAR models only VAR at level 95% estimated by normal approach has fewer violations (failures) than expected for all three examined currencies in both tested periods. In case of Bitcoin and Ethereum this type of VAR model was also accepted by all used backtests except for TBF test which is dealing with Time Between Failure. On the other hand, for Bitcoin and Ethereum we find some VAR models which are accepted by all used backtest (even by TBF test) for both examined periods. However, these models are different for Bitcoin and different for Ethereum and they had higher number of violations than was expected in one of the tested periods. In term of Litecoin no suitable model which was accepted by all backtests in both periods was found.

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