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TESTING METHODS AND MODELS TO FORECAST CRYPTOCURRENCIES EXCHANGE RATE[1]

Stefan Simeonov[2], Theodor Todorov[3]
Daniel Nikolaev[4]

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Abstract

The course of cryptocurrencies forms by various factors which makes it difficult to apply fundamental methods for their forecasting. For these reasons technical analysis and various statistical models are used for short-term forex and financial market forecasting. In this study we test three models: the classical autoregression model (AR), the Box-Jenkins ARIMA, and the predictively modified model Frequency Analysis of the Volatility and Trend with movable calculation (FAVT-M). The five cryptocurrencies with the largest market capitalization as of July 10, 2019 are subject to test forecasting. The AR and ARIMA results report compromise confidence within the first 5 - 6 days, after which they show significant deviations from the actual course achieved. FAVT-M generates immediate signals for the reversal of the short-term trend, but at this stage they are not clear enough for its reliable independent application in forecasting cryptocurrencies.

Keywords: *cryptocurrencies, autoregression, ARMA, ARIMA, predictively modified frequency analysis of volatility and trend (FAVT+M).*
JEL Codes: *G17; C19; C58*

Introduction

Currency value is formed under the combined effect of multiple macroeconomic and political factors, which is the cause for their complicated and not vary accurate forecasting, especially in long term. On one side, there is a huge uncertainty in the evolution of the different factors and their complicated multiplicative and interference

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[1] Department of Finance, Tsenov Academy of Economics, Svishtov.
[2] Assoc. prof. Stefan Simeonov, PhD s.simeonov@uni-svishtov.bg (author of the methodology and empirical application of the FAVT-M)
[3] Theodor Todorov, PhD, +359884988069, tmtodorov@uni-svishtov.bg (author of methodical presentation and empirical application of AR).
[4] Daniel Nikolaev, PhD, +359893435185, dnikolaev@uni-svishtov.bg (author of methodical presentation and empirical application of ARIMA).

patterns. On the other, the fundamental analysis explains how given factor affects the value of given currency, but is not in the condition to give timely information for the upcoming change in the currency course. Under these objective circumstances the speculators of the FOREX base their strategies on a technical analysis that is more successful on reading short-term market signals due to the liquidity of the most converted currencies. Fin-tech and in particular the block-chain technologies introduce additional and even more difficult to predict determinants mainly related to the market actions of the the ones acquiring and using the respective cryptocurrency.

Considering that the main goal of the study is to analyze and test different quantitative statistical and econometric forecasting models applied in the forecast of cryptocurrencies. In order to determine the applicability of the given model we apply retrospective approach, in other words we forecast the value and return in historical sample and compare the results with the actual data for the cryptocurrency. In the process as byproduct we infer the predictability of the cryptocurrency itself.

1. Methodology of the study

1.1. Forecasting via auto-regressive method

As it is known the auto-regressive (AR) model is used to analyze and forecast returns and prices of financial instruments, which makes the AR modeling highly applicable in the investment management. An obligatory condition for the application of autoregressive models is that the time series is stationary. For that purpose we apply first the stationarity test of Dickey and Fuller (Dickey & Fuller, 1979). From methodological point of view, the auto-regressive model is a linear regression. Unlike the popular regression analysis, where the emphasis is put on a factors external for the studied value, in the AR models the factor is the historic values of the same variable. In this way the price predicts itself. The formula of the auto-regressive model has the following form (Bohte & Rossin, 2019):

$$P_t = \alpha + \varphi_1 P_{t-1} + \varphi_2 P_{t-2} + \varphi_p P_{p-t} + \varepsilon_t \quad (1.1)$$

where:

$P_t -$ forecast value;

α – constant;

φ–auto-regressive parameter.

The logical question here is what time lag should be included in the final equation of the forecast model. For the goals of the study (the five cryptocurrencies) we apply an

AR model with time lags of 1 to 10 days. We use the two criterions - Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), where the condition is to select the lowest value specification. Through the information criterions AIC and BIC we seek balance between reducing the standard error and reducing the number of degrees of freedom (Иванов & Овчинников, 2018). (It is a mandatory) condition for both criterions to have an identical sample of data. The (valuation) formula of Akaike Information Criterion is following (Akaike, 1974):

(1.2) AIC = N*LN(SS/N) + (2*df)

където:

AIC – Akaike Information Criterion;

N – number of observations;

SS – residual value of the squared deviation for the model;

Df – degrees of freedom.[1]

The formula for the calculation of the Bayesian Information Criterion (BIC) has the following form (Vrieze, 2012):

(1.3) BIC = N*LN (SS/N) + (df*LN(N))

където:

BIC– Bayesian Information Criterion;

N – number of observations;

SS – residual value of the squared deviation for the model;

Df – degrees of freedom.

Both information criterions have similar application for defining the final specification of ARIMA models to the Box-Jenkins methods using corelograms to derive the model specifics, described later.

1.2. Methodology of ARIMA forecasting

In order to present the forecasting with ARIMA models additionally to the explanation of the autoregressive model (AR) we should focus attention to the moving averages (MA partition of the model). Modelling with moving averages is assuming that the factor which determines the future value of a variable is the average of its previous (historical) values. The order of the model is derived by the past periods used for the

[1] Degrees of freedom in this case show the type of regression compared to the number of included factors. It follows that in auto-regression the factors are the different lagged values of the first difference of the dependent variable.

average. Additionally, as the forecast is getting further (in the future) with respect to the current value, a greater portion of the forecast is based on prior forecasts. If we combine both, the AR and MA modeling we reach ARMA (Auto Regressive Moving Averages) and if the used data is non-stationary we integrate the time series. In the process of integration, we use for further calculation the differences between current and previous values ($\Delta y = y_t - y_{t-1}$) and we can use more than single integration if necessary. Then we derived the so called ARIMA model or Autoregressive Integrated Moving Averages. **Such a** model has tree specification – p, d and q. Each represents a different part of the modeling**:** p is the order of the AR model, q - the order of the MA model and d - the integration. (Thus, ARMA can be considered as a special case of ARIMA in which $d = 0$ or no data integrations.

One way to derive the p, d and q is to apply the Box-Jenkins method (Box & Jenkins, 1970). The first step is to define the required integration in order to force stationarity on our sample. We use the Dickey-Fuller test (Dickey & Fuller, 1979) to determine if stationarity is present again after each step of integration. Next step is the application of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) and more precisely their graphics. ACF is based on the correlation between different orders of AR or MA models to the base value of the variable, practically it measures the change of the correlation with the increase of lags. The PACF is a bit harder to present, as regression based on the same increasing lags, where we calculate the values of the Betas of the corresponding lag. In order to structure graphically PACF we use only the Betas with p-value below 5% or with less than 5% risk of error. Based on the graphics we determine the p and q and for this part of the method is said to be more art than science (Zaiontz, 2019a).

1.3. Stationarity testing (Dickey-Fuller)

Dickey-Fuller test (Dickey & Fuller, 1979) aims to determine if a data set is stationary by disproving the existence of unit root and if so, the data can not be accepted as stationary. The test is based on regression analysis and more precisely auto-regression. Depending on the data set we can apply one of three models:

(2.1) Without constant and trend: $\Delta y_t = \beta y_{t-1} + \varepsilon_t$;

(2.2) With constant and without trend: $\Delta y_t = \alpha + \beta y_{t-1} + \varepsilon_t$;

(2.3) With constant and trend: $\Delta y_t = \alpha + \beta y_{t-1} + \beta_t T + \varepsilon_t$.

where:

Δy_t –is the difference y_t-y_{t-1}, or the integrated value;

B –beta of the factor in the auto-regression;

ε_t– random drift;

α – constant;

βtT –trend component.

We determine the model due to the value of the derived beta coefficient. If the beta is negative we can accept the model and further analyse the data. After deriving negative value of the Beta coefficient we can use the t-statistics (tao) to examine if there is a stationarity. We use a function to derive the critical or theoretical value of tao below which we can accept the result and therefore the data are stationary. Additional information about the test and the function of critical tao (including table of tao values) can be found on (Zaiontz, 2019b).

1.4. Modified in forecasting application Frequency analysis of volatility and trend with moving calculation FAVT+M

The Frequency analysis of volatility and trend (FAVT) with moving calculation includes three coefficients:

(3.1) Coefficient of Dynamics (D): $Dinamix = \frac{Days_{Change}}{Days_{n-1}}$;

(3.2) Coefficient of the Average duration of unidirectional movement (AD_{UM}):

$$Averag\ Duration_{Unidirectional\ Movement} = \frac{Days_{n-1}}{Days_{Change}};$$

(3.3) Coefficient of the prevailing tendency(PT):

$$Prevailing\ Tendency = \frac{Days_{Increase}}{Days_{Decrease}}$$

As you can see, the first two coefficients have reciprocal calculation and complementary information significance. The D (dynamics) numerator and AD_{UM} denominator represent the number of changes in course direction of the instrument. FAVT was developed for stock exchange activity analysis and its methodology is presented in details in a 2016 monograph (Симеонов, 2016). In several previous studies, summarized in the above monograph, we apply empirically FAVT to analyze the main indicators of the Bulgarian Stock Exchange (Симеонов, Септември 2015), (Симеонов, Ноември 2015), (Симеонов, ноември 2016). In the study of 2017 we present methodologically and empirically the application of FAVT in assessing market risk for BSE-traded shares (Simeonov & Todorov, 2018). In the study of 2019 we develop methodologically the concept of predictive application of frequency analysis by movable calculation of the frequency coefficients (FAVT-M) and we test it empirically on major stock indices of several European stock exchanges (Симеонов, Тодоров, & Николаев, 2019). Encouraging results were achieved in the short-term forecast of more drastic changes in the trend of stock indices. Unlike stock indices, which are a composite measure and instrument, in individual investment instruments we expect better results than the foreseen application of the FAVT-M. Nor do we overlook the considerations set out in the introduction to the complexity of currency rates forecasting.

We emphasize that the rolling calculation of the frequency coefficients is not related to averages, but to a moving (rolling) calculation period. The rolling calculation provides an opportunity to track the change in the coefficients with the introduction of each new (last) daily value. The choice of the base period is based on a preliminary analysis of the “average duration of unidirectional movement” ($AD_{\mathbf{UM}}$) of the studied instrument, in this case - cryptocurrency. The application of the forecasting model is facilitated by a duration of the calculation period close to the specified maximum unidirectional movement.[1] In this study we apply a 14-day basis for the mobile calculation of the frequency coefficients and the coefficient of variation that we use as standard in the FAVT. It should also be noted that the theoretical maxima and minima of the frequency coefficients are of greater importance for their analytical application and static calculation over a given period, for example in risk analysis. On the other hand, the interpretation of the predictive value of the frequency coefficients focuses on their variation and the accumulation of minima and maxima in their mobile calculations.

2. Object of empirical study

In our study we examine the five leading cryptocurrencies Bitcoin, Ethereum, XRP, Litecoinand Bitcoin Cash. The selection is made by the market capitalization (money mass) in USD, and we chose the top five by quantity for the 10.06.2019. The sample includes the daily values for the period 28.04.2013 through 10.07.2019.[2]

Table 1. Cryptocurrencies with greatest capitalization for 10.07.2019

N	Cryptocurrency	Market capitalization
1	Bitcoin	216.515.999.522
2	Ethereum	30.985.827.113
3	XRP	15.484.656.712
4	Bitcoin Cash	6.979.428.054
5	Litecoin	6.792.744.022

[1] Detailed arguments for the determination of the period for the chain calculation of the frequency coefficients are given in the study cited above by Simeonov, St., Todorov, T., and Nikolaev, D. E-Journal Dialogue 1, 2019.

[2] The date for the daily change of the value of the cryptocurrencies is accessible on https://coinmarketcap.com/currencies/bitcoin/historical-data/.

3. Forecasting the value of the selected cryptocurrencies

3.1. Application of Auto-Regressive model in forecasting the value of cryptocurrencies

The application of the AR model for each of the five chosen cryptocurrencies is with time lag of 1 to 10 days. The best predictive model for the analyzed currencies is determined with the information coefficients Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). From the application of both coefficients with 1 to 10 lags, the best forecast for the value of the cryptocurrencies is given by a single lag, or AR-1, the values are given in Table 2. The forecast period here is 30 days, from 11.07.2019 until 09.08.2019.

Table 2. Results from the application of AIC u BIC

Cryptocurrencies	Specification of the model	AIC	BIC
Bitcoin	AR (Pt - 1)	24865	24871
Ethereum	AR (Pt - 1)	8723	8729
XRP	AR (Pt - 1)	-13789	-13783
Litecoin	AR (Pt - 1)	7321	7326
Bitcoint Cash	AR (Pt - 1)	6606	6610

The graphical presentation of the results is given below with two lines: the first represents the foretasted values and the second is constructed from the factual values of the analyzed cryptocurrency.

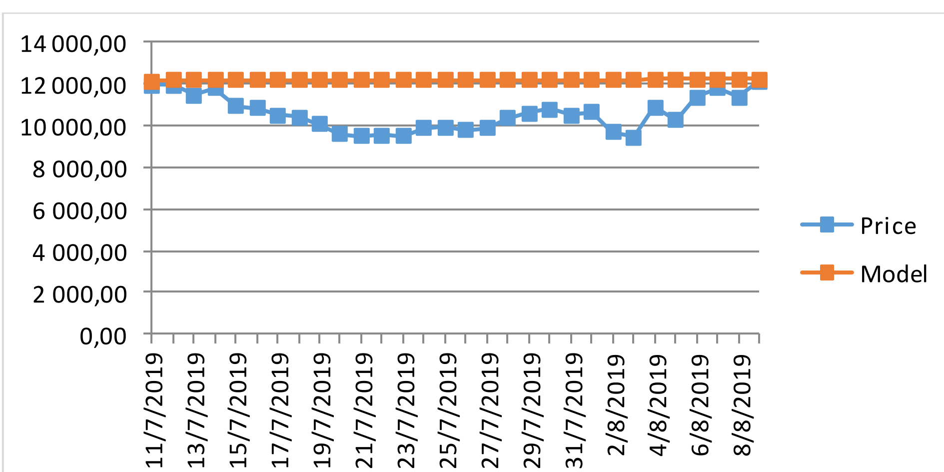

Figure 1.1. AR-1 forecast of Bitcoin

From figure 1.1. is visible that for the first few days of the forecast the results are consistent with the real data. The line presenting the foretasted data predict a near static values with insignificant increase of Bitcoin. The actual price of the currency doesn't confirm such a prediction. The historically calculated beta coefficient is above 1 and the fact that the previous prediction is a base for the present, describes a model with single direction which can not fit the factual values.

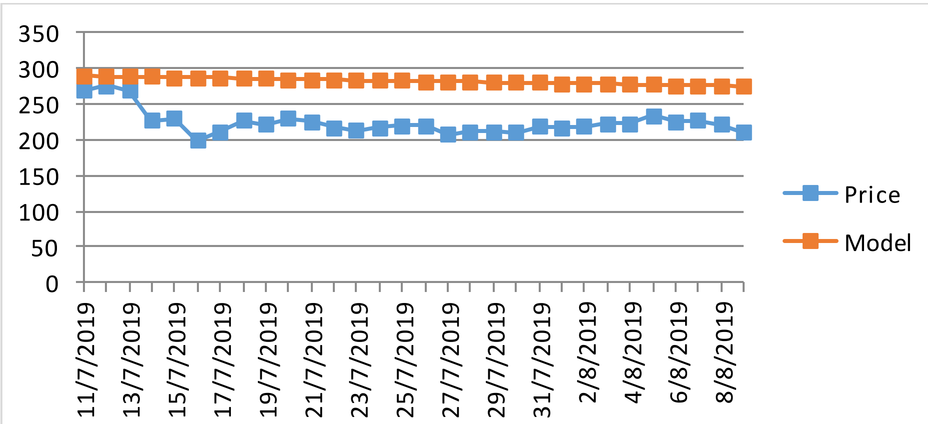

Figure 1.2. AR-1 forecast of Ethereum

The forecast values of AR-1 for Ethereumhave the greatest deviation from the actual results from all the analyzed currencies (Figure 1.2.). We can conclude that during the analyzed period the auto-regressive model does not fit the forecast requirements for Ethereum.

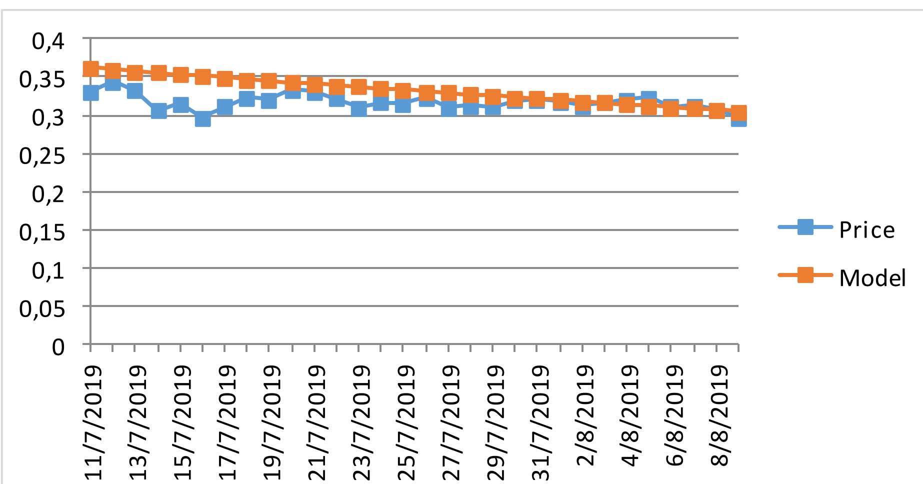

Figure 1.3. AR-1 forecast of XRP

The results reached by AR-1 for XRP are considerably different form Bitcoin and Ethereum (Figure 1.3.). The AR model registers the best forecasts in the end of the forecast horizon. The figure shows an accurate forecast in the longer-term prediction (20 – 30 days), while in the shorter (10 days) XRP is overpriced by the modeling. On the bases of statistical criterion average daily error (MAPE), calculated for 15 and 30 days, Litecoinhas the smallest values after XRP (Figure 1.4.).

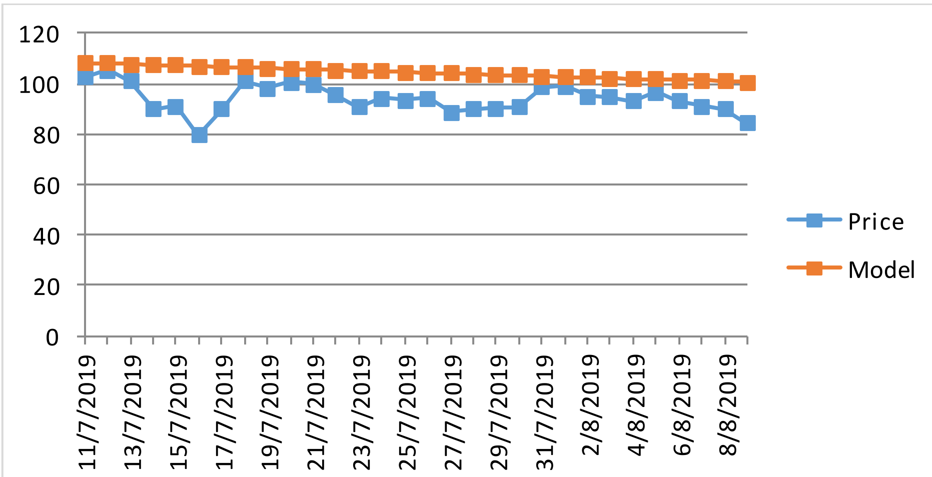

Figure 1.4. AR-1 forecast of Litecoin

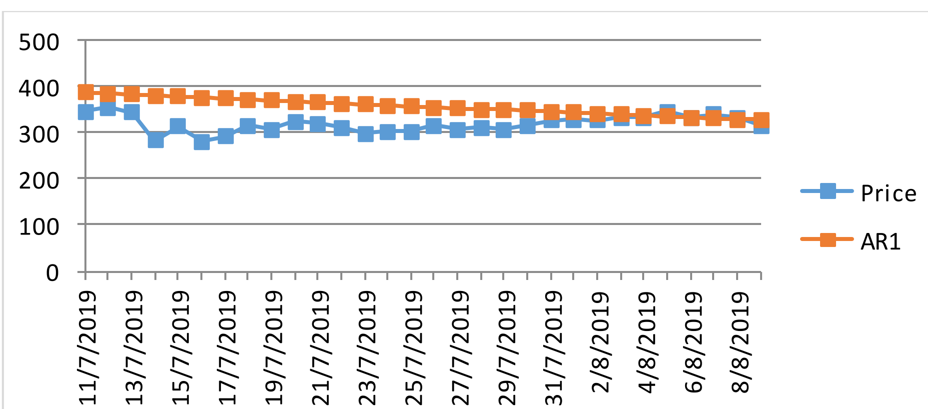

Figure 1.5. AR-1 forecast for Bitcoin Cash

The forecast with AR-1 for Bitcoin Cash is most reliable for the last 10 days of the forecasted 30 day period, same as the results for the cryptocurrency XRP (Figure 1.5).

Table 3. Average daily error AR-1 (%)

Days	Bitcoin	Ethereum	XRP	Litecoin	Bitcoin Cash
5	4,68	14,21	9,91	10,43	17,48
15	16,43	25,27	8,48	11,93	19,41
30	15,84	26,45	5,30	11,38	12,80

With the statistical value of average daily error we refine the results of the auto-regressive model for the five cryptocurrencies in three time frames of forecast – 5, 15 and 30 days (table 2). In the short-term (5 days) forecasts the lowest values for error are calculated for Bitcoin. The largest deviation for the same time frame are calculated for Bitcoin Cash. Mid-term – 15-daysforecast is most successful for the cryptocurrency XRP. The average daily error confirms the results from the figures above, where the best 30-day forecast is ascribed to XRP. The greatest deviation from the real data is measured for the Ethereum cryptocurrency. Of interest is the success of forecasting at different timescales. With the smallest average error of 4,7% are the results for short-term (5-days) forecasts, followed by the long-term 30-days forecast with 5,3% (XRP) and the final is the 15-days forecast with smallest deviation of 8,5% (XRP). The biggest errors are registered at the 30-day forecasts with 26,5% (Ethereum), followed by the 15-days 25,3% (Ethereum) and 17,5% (Bitcoin Cash) at the 5-day forecasting.

We can conclude that other forecasting tools are needed to evaluate and improve forecasting results.

3.2. Application of Box-Jenkins ARIMA in forecasting cryptocurrencies

For the Box-Jenkins forecasts we use reduced historical information or the time frame of the sample used for forecasting is two months - from 11 April to 11 July 2019. Because our forecast horizon is comparatively short, only one month and we use daily observations we can shorten our base data in order to capture the most recent changes in the variation. As such the application of the Box-Jenkins and the results of the PACF show us little room for interpretation as most currencies have no more than one acceptable value (under restriction of confidence range of up to 10%).

On the following graphic are presented the results from the application of ARIMA (1; 0; 9) for the forecast of Bitcoin. We use cumulative return to illustrate the results of the model. The forecast of Bitcoin illustrated by the graphic is of good consistency as we can determine even from the figure that the error is reasonable and additionally at the end of the forecast we observe a very little gap between the estimation and the actual values (Figure 2.1.).

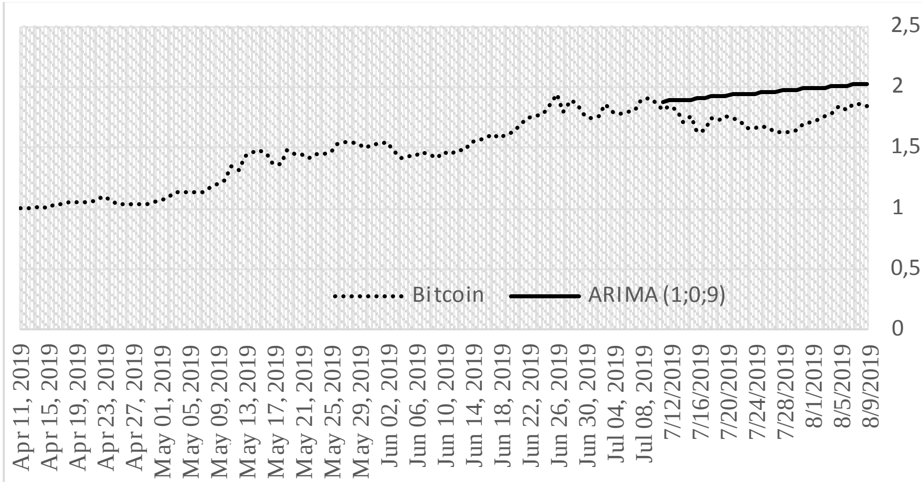

Figure 2.1. Box-Jenkins ARIMA forecast of Bitcoin

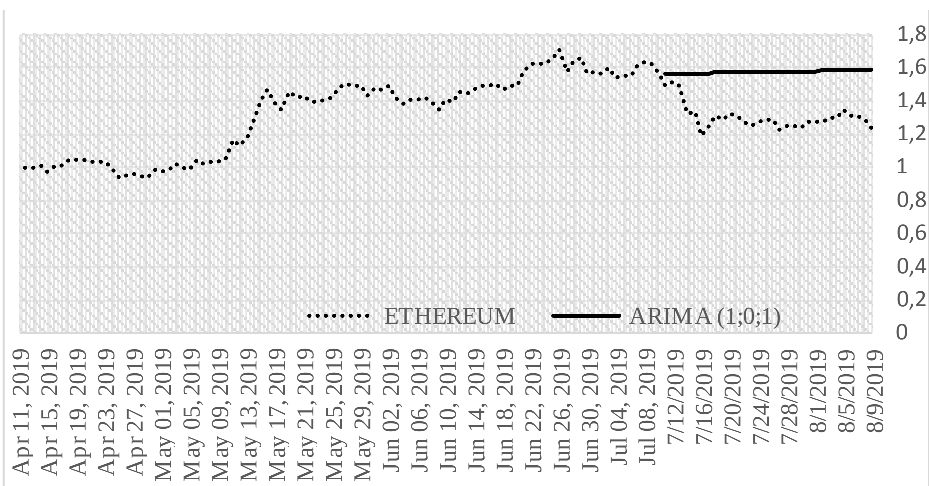

Figure 2.2. Box-Jenkins ARIMA forecast of Ethereum

The results indicate the forecast have a significant deviation from the observed values. We can see a great descent at the start of the forecast which can be accepted as random drift. Although the motion after that is parallel we can not estimate that the forecast is reliable enough due to the great differences between the forecast and actual returns.

Although there is a significantly greater descent in the estimation, we can accept the results for Ethereum as comparatively reliable due to the far lesser average daily deviations (Figure 2.2).

We can notice that there is a significant gap between the actual and the forecast values of XRP, where the forecasted rate is greatly underestimated (Figure 2.3).

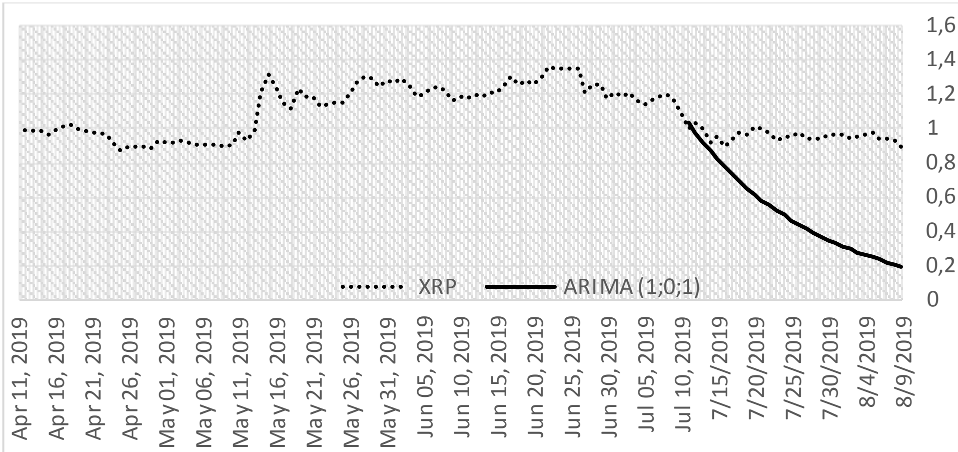

Figure 2.3. Box-Jenkins ARIMA forecast of XRP

From the graphic of Litecoin we can observe very similar condition as the forecasts for Ethereum. There is a sharp descent starting slightly before the forecast and although there are moments in which the values of the observation and forecasts get closer together there is a significant difference between the average return of the actual observations and the forecasts (Figure 2.4).

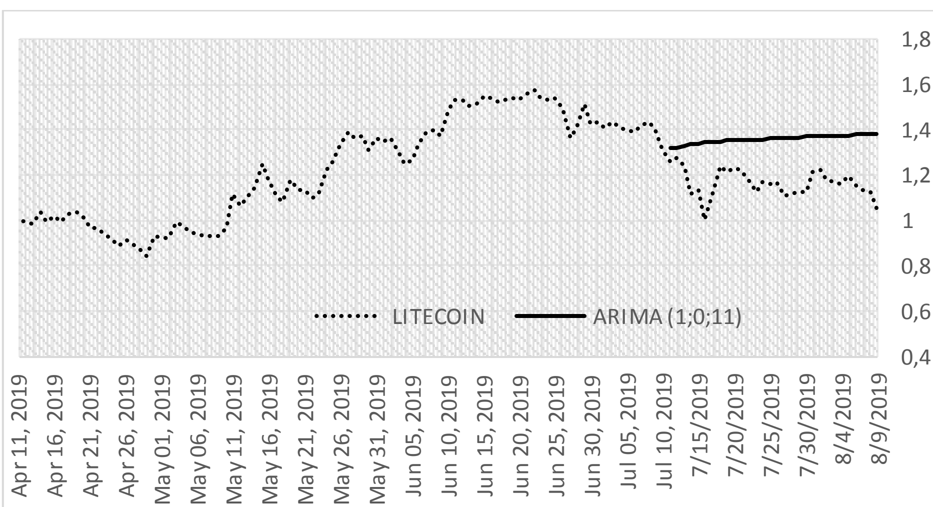

Figure 2.4. Box-Jenkins ARIMA forecast of Litecoin

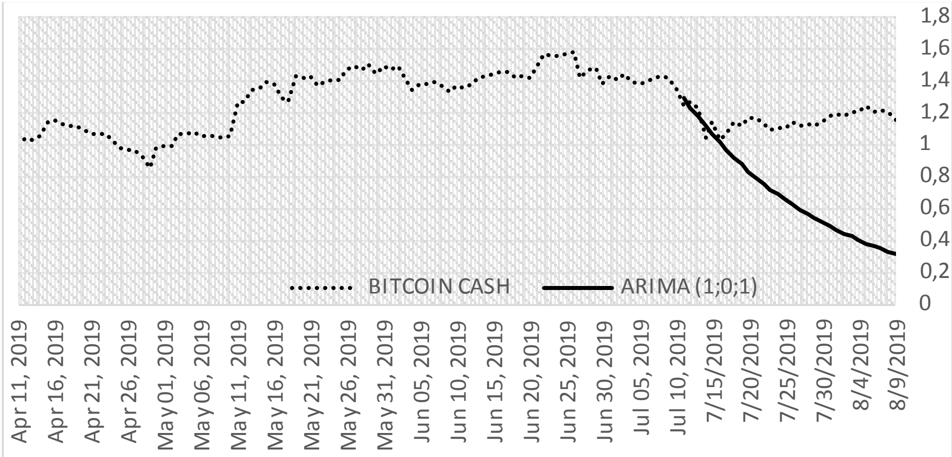

Figure 2.5. Box-Jenkins ARIMA forecast of Bitcoin Cash

On figure 2.5. the results are very similar to those of XRP, we expect far greater reduction in value then the observed, but it is a reduction in value still. In other words we expect a loss of value, but our estimation is far greater then the actual but in such conditions the actual daily average drift is not that great.

Additionally we analyze the errors from the predictions of ARIMA based on Box-Jenkins and the calculated results are presented in Table 4.

Table 4. Average daily error Box-Jenkins ARIMA forecasts (%)

Forecasting term	Bitcoin (1, 0, 9)	Ethereum (1, 0, 1)	XRP (1, 0, 1)	Litecoin (1, 0,1 1)	Bitcoin Cash (1, 0, 1)
5 day	4,42	5,55	4,86*	5,87	8,44
15 day	2,53	3,38	6,04*	4,58	6,76*
30 day	1,95*	2,57	5,57*	3,59	5,85*

Firstly we want to draw attention in the values marked by *, as those are the differences in which there is aliment between the direction of the average return of the factual values and the forecasts. As we can see in 3 out of 5 forecasts the estimated direction of the return is correct. Additionally we can observe in almost all forecasts (except XRP) that with the increase of the retrospectively observed results the average error is reduced as the random drifts become more insignificant. This can make us believe that although not perfectly and with great deviations the values of the crypto currencies are predictable to a degree. As the nature of the data is probabilistic it is expected to have a random drift but from the observed data it is more likely that a 30 day forecast by ARIMA applied with the Box-Jenkins method will be beneficial and will yield positive results.

3.3. FAVT-M testing for cryptocurrency forecasting

We present here the results from Frequency analysis of the volatility and trend with moving calculation only for Bitcoin, due to volume restrictions. We use historical daily values for a period from 01.01.2019 to the end of July 2019. In order to have visual comparability between the lines of the frequency coefficients and the variation coefficient with the line of Bitcoin the figure 3.1. we present the values of Bitcoin divided by 3000. We use 14 day period as a base for the moving calculation of the variables. Line of the Coefficient of the prevailing tendency (PT) illustrates the dominant direction of change which due to the magnitude of the deviations may fit the trend line, without it being expected. The interpretation of that dependent variable requires special attention. In general, the clumps of sharp edges and plateaus shows the most notable periods of defined trend and by definition of the concept it should be the harbinger of short-term corrections. The high values of the coefficient of average duration of the unchanged motion (AD_{UM}) demonstrates the longer (few days long) expectations. Coefficient of dynamics (D)is reciprocal to AD_{UM} and by definition the high values of D signal that soon there will be change in the trend.

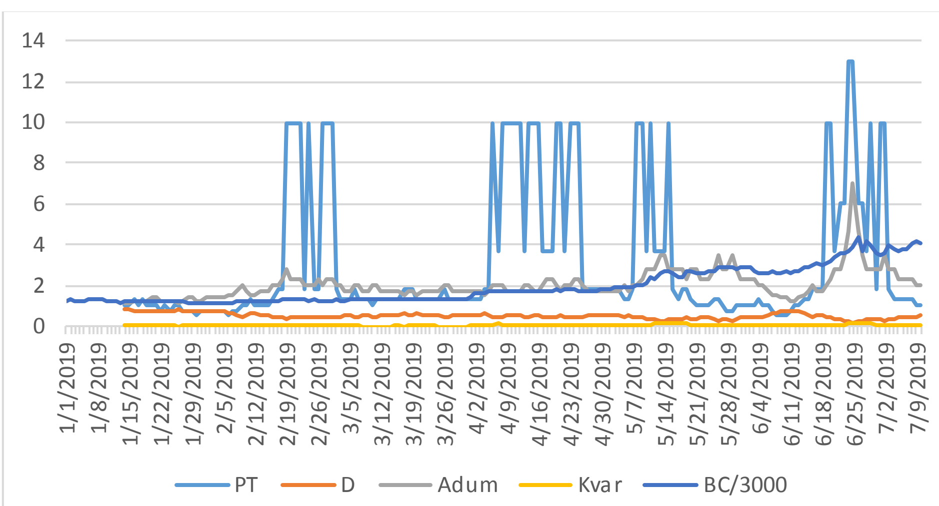

Figure 3.1. FAVT+M forecast of Bitcoin

Table 5. Sample form the FAVT-M for Bitcoin

Date	Bitcoin	Change	PT	D	AD_{UM}	Kvar
23.6.2019	10855,37	153,68	6	0,29	3,50	0,1076
24.6.2019	11011,10	155,73	13	0,21	4,67	0,1157
25.6.2019	11790,92	779,82	13	0,14	7,00	0,1358
26.6.2019	**13016,23**	1225,31	6	0,21	4,67	0,1269
27.6.2019	11182,81	-1833,42	6	0,29	3,50	0,1288
28.6.2019	12407,33	1224,52	3,67	0,36	2,80	0,1235
29.6.2019	11959,37	-447,96	10	0,36	2,80	0,1136
30.6.2019	10817,16	-1142,21	1,8	0,36	2,80	0,1060
1.7.2019	10583,13	-234,03	10	0,36	2,80	0,0938

Table 6. Coefficient of correlation between Frequency coefficients and the lagged return of Bitcoin

Lag	PT	D	ADum	Kvar
0	**17,11%**	**-56,89%**	**63,74%**	**63,85%**
-1	16,79%	-57,02%	62,82%	64,48%
-2	15,37%	-56,14%	61,04%	64,39%
-3	17,06%	-55,09%	59,30%	63,59%
-4	14,16%	-53,73%	56,93%	62,24%
-5	15,48%	-52,58%	54,96%	60,40%
-6	17,26%	-52,31%	55,05%	58,07%
-7	13,54%	-50,82%	53,51%	55,22%
-8	10,28%	-49,36%	52,31%	52,27%
-9	7,48%	-47,01%	49,89%	49,40%
-10	4,89%	-44,92%	47,79%	46,83%
-11	2,12%	-42,56%	45,04%	44,75%
-12	0,07%	-40,42%	42,24%	43,32%
-13	-2,36%	-37,75%	39,42%	42,05%
-14	-3,96%	-33,54%	36,89%	40,97%

Under closer observation of figure 3.1. and the sample of table 5. we can spot a stable increase of the value of Bitcoin through the second and third periods of 10 days of 2019 is combined with decrease of the Coefficient of Dynamics ***(D)***, accordingly also with noticeable growth and spikes of ***AD_{UM}*** and increase in the Coefficient of Variation ***(Kvar)***. On June 26, 2019, sharp and dynamic adjustments to the Bitcoin exchange rate began. In the previous few days clearly show the achieved theoretical maximums of ***PT*** (prevailing tendency), the low values of***D***, the high value of ***AD_{UM}*** as well as the achieved growth of ***Kvar.*** While on June, 26 Bitcoin is still growing and reaching its maximum for the time frame, the three frequency coefficients and the variation coefficient are already reversing.

The correlation between the frequency coefficients and the value of Bitcoin is significantly low. The coefficient of average duration of unchanged motion and the coefficient of variation have normal straight interdependence. As a result, the coefficient of dynamics has reverse correlation. Coefficient of persistent trend has straight but vary weak correlation. The lagged values from 1 to 14 days demonstrates reduction in the degree of correlation which strengthens the previous analytical comments and reinforces the results from previous forecasting of stock exchange indexes. Whereby we establish forecast signals derived from FAVT+M with a horizon up to several days.

Conclusion

The results of the empirical forecast tests of the five most active cryptocurrencies can be summarized in the following conclusions:

- Despite the partial similarities between factual market data and forecast results given by the three approaches, the predictions are inadequate and can not be considered an effective way to forecast cryptocurrencies.
- The forecasts with the classical auto-regressive models give partially good results in short-term forecast of 5-day followed by a 30-day period or the longest period available. Within the monthly forecast all five cryptocurrencies overvalues the factual currency rates.
- Unlike the previous model the ARIMA is used to forecast returns. The empirical testing of Box-Jenkins method has promising forecasts for the some of the cryptocurrencies, but the results are not reliable enough, especially for giving exact values of expected return.
- The modification in the forecast model FAVT (frequency analysis of the volatility and trend) with moving calculation applied for Bitcoin allows the predictions of signals, but at this stage they are not good enough for reliable by himself forecasting.

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