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FUNDAMENTALS OF FORECASTING CRYPTOCURRENCY RATES

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Abstract

Since 2009, cryptocurrencies being a modern form of electronic means of payment have become widespread in the global financial market. In this regard, a study aimed to find an answer to the question: “Are cryptocurrencies a modern form of money?” was conducted. An analysis of the scientific works of leading economic schools has led to the conclusion that cryptocurrencies are a modern form of private money that performs the main monetary function being a means of payment, which corresponds to the idea of the Austrian economic school of full-fledged means of payment. The study attempts to predict the market rate of the three most popular cryptocurrencies at present being Bitcoin, Ethereum and Ripple due to the fact that modern cryptocurrencies demonstrate a high level of volatility in their market value, and reliable funds must maintain their purchasing power. The analysis of the cryptocurrency market with regard to the information efficiency has led to the conclusion that cryptocurrencies have been demonstrating instability of qualitative properties over the past five years. The authors proposed to improve the predictive characteristics of the HAR-RV model by additionally calculating the Shannon information entropy of the initial time series to level their insensitivity to unexpected information shocks in the cryptocurrency market being the main drawback of regression models. The study has proved that cryptocurrencies are a promising modern form of electronic money, their market rate is quite predictable, and the popularity of cryptocurrencies and their use in payment transactions will further increase.

Keywords: Heterogeneous market, realized volatility, Shannon entropy

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1. Introduction

Before considering the possibility of predicting the market rates of cryptocurrencies, it is necessary to clarify the meaning of the term "cryptocurrency". "Crypto" denotes secretive or secret, currency is a means of payment. Therefore, "cryptocurrency" is virtual electronic symbol of money. According to Masciandaro (2018), cryptocurrency is similar to traditional money in many ways. It provides an opportunity to pay for goods and services. Thus, what is cryptocurrency? Is it the currency of the future, or is it just a Ponzi scheme for the internet age? Dyhrberg (2015) found that bitcoin had similarities to gold and the dollar, and that it could be classified as something between a currency and a commodity. Bitcoin differs from gold due to its limited supply and from currency due to its decentralized nature. Many researchers argue that bitcoin behaves like a speculative investment, and they find a low correlation between bitcoin prices and traditional exchange rates. In "Is Bitcoin Money?" Bjerg (2015) states that bitcoin is commodity money without gold, paper money without government and credit money without debt. Bitcoin poses an ideological challenge to traditional forms of money, since it not only undermines the established belief in traditional money, but also reveals the forms of exploitation, risk and even violence inherent in the existing system of credit money legalized by the state (Ivanchenko, 2019). Bjerg (2015) paraphrased Winston Churchill's famous dictum about democracy: "Bitcoin is the worst form of money except for all others" (p. 54).

Table 1. Statistical characteristics of predictive HAR (3)-RV models for Bitcoin, Ethereum and Ripple, with dependent variable values calculated using the formula $RV_t^{(d)} = p_t^d - p_{t-1}^d$

Cryptocurrency	Alpha coefficient	Beta coefficient at variable $RV_t^{(d)}$	Beta coefficient at variable $RV_{t-1}^{(d)}$	Beta coefficient at variable $RV_t^{(w)}$	Beta coefficient at variable $RV_{t-1}^{(w)}$	Beta coefficient at variable $RV_t^{(m)}$	Beta coefficient at variable $RV_{t-1}^{(m)}$
Bitcoin	0	-0.11599	-0.15414	1.89232	-1.34383	7.03792	-6.59499
$R^2 = 0.69$		(-7.8)	(-10)	(31)	(-22)	(28)	(-26)
Ethereum	0	-0.31781	-0.19902	2.90088	-1.73884	0.00455	-0.00212
$R^2 = 0.57$		(-10)	(-6.3)	(29.7)	(-18.9)	(2.9)	(-1.57)
Ripple	0	-0.24105	-0.09855	2.52557	1.71526 (-	2.86780	-2.52587
$R^2 = 0.65$		(-8.8)	(-3.6)	(26)	19.5)	(8.3)	(-7.6)

Table 2. Statistical characteristics of predictive HAR (3)-RV models for Bitcoin, Ethereum and Ripple, with dependent variable values calculated using the formula $RV_t^{(d)} = \ln(p_t^d)$

Cryptocurrency	Alpha coefficient	Beta coefficient at variable $RV_t^{(d)}$	Beta coefficient at variable $RV_{t-1}^{(d)}$	Beta coefficient at variable $RV_t^{(w)}$	Beta coefficient at variable $RV_{t-1}^{(w)}$	Beta coefficient at variable $RV_t^{(m)}$	Beta coefficient at variable $RV_{t-1}^{(m)}$
Bitcoin	0	0.094325	-0.357670	2.560437	1.689907	3.952943	-3.560126
$R^2 = 0.99$		(5.8)	(-21)	(49)	(-40)	(22)	(-22)
Ethereum	0	-0.11001	-0.424905	3.71248	-2.25328	0.33736	-0.26178
$R^2 = 0.99$		(-3.4)	(-12)	(42)	(-39)	(4.5)	(-3.9)
Ripple	0	-0.04803	-0.39736	3.43538	2.18765	1.69246	-1.49533
$R^2 = 0.99$		(-1.6)	(-12)	(41)	(-39)	(9.2)	(-8.8)

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Table 3. Predicted and actually observed cryptocurrency values

Cryptocurrency	Dependent variable calculation method	Observed value dated 13.02.2020	Forecast value dated 13.02.2020	Percentage deviation
Bitcoin $R^2 = 0.99$	$RV_t^{(d)} = p_t^d - p_{t-1}^d$	10211	10263.84	0.51 %
	$RV_t^{(d)} = \ln(p_t^d)$	10211	10222.83	0.11 %
Ethereum $R^2 = 0.99$	$RV_t^{(d)} = p_t^d - p_{t-1}^d$	268,39	265.2	-1.19 %
	$RV_t^{(d)} = \ln(p_t^d)$	268,39	265.2	-1.18 %
Ripple $R^2 = 0.99$	$RV_t^{(d)} = p_t^d - p_{t-1}^d$	0.3285	0.3193	-2.8 %
	$RV_t^{(d)} = \ln(p_t^d)$	0.3285	0.3195	-2.7 %

2. Problem Statement

The Greater Fool Theory is well-known in the field of finance and economics. It claims that the price of an object is determined not by its intrinsic value but by the irrational beliefs and expectations of market players. The price can be accepted by a rational buyer who believes that there will be another buyer willing to buy the asset at a higher price. This scheme is based on speculation and the expectation that prices will continue to rise only because the asset price raised in the past.

According to the efficient market hypothesis, all useful information about an asset is contained in its current prices, and prices change only when investors receive new information about the asset. If this theory is correct, then past price changes do not provide useful information about future price changes. Proponents of the Greater Fool Theory and the efficient market hypothesis are of the opinion that investors consider fundamental information irrelevant.

Catania et al. (2019) explored the predictability of time series in Bitcoin, Litecoin, Ripple and Ethereum. The authors of this article compared the predictive characteristics of several one-dimensional and multidimensional models and found that achieving high accuracy in predicting the direction of changes in cryptocurrency prices was possible. Additionally, mexican researchers (Valencia et al., 2019) concluded that it was possible to predict the dynamics of cryptocurrency market prices. They compared the forecasting quality of four cryptocurrencies (Bitcoin, Ethereum, Ripple, and Litecoin) using three statistical methods: multi-layer perceptrons (MLP), support vectors (SVM – support vector machine), and random forest (RF). Valencia et al. (2019) concluded that the multilayer perceptron method showed the best prediction results. Bitcoin price movements were predicted using the MLP method with an accuracy of 74 %.

In practice, autoregressive distributed lag models (ARDL) are also used in forecasting the bitcoin rate. The considered models are characterized by the fact that the current value of the investigated time series depends both on the lagged values of this series and on the current and lagged values of other variables (Kjærland et al., 2018a, 2018b). The authors of these articles found that market prices for bitcoin correlate with market prices for oil and with the intensity of requests for information about cryptocurrencies on the Google search engine. In addition, the increased intensity of quantitative easing programs (QE) conducted by the central banks of the world's leading countries has a strong positive

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impact on the volatility of bitcoin returns (Corbet et al., 2017). Other macroeconomic variables including gold prices and hash rate are not significant for cryptocurrency dynamics.

3. Research Questions

The subject of the research is the cryptocurrency market; the economic nature of new digital payment instruments being not secure and having no people liable for them, which are generated privately using complex mathematical algorithms that have become quite widespread but are not officially recognized by the monetary authorities.

1. The issue of regarding cryptocurrencies the means of payment is being resolved.
2. The possibility of predicting the market value of cryptocurrencies aimed to increase trust in them on the part of users and investors is being clarified.

4. Purpose of the Study

The purpose of the study is to answer to the questions: “Do cryptocurrencies perform monetary functions?”, and “Do we predict their market rate?”

5. Research Methods

The main obstacle to the widespread distribution of cryptocurrencies in the global payment system is the instability of their exchange rate. In the middle of the 20th century the Austrian economist F. von Hayek brilliantly foresaw this scenario with alternative currencies. He stated that the main thing that an issuer of a competitive currency could attract its customers with was a guarantee that its value would remain stable (or would change in a predictable way) (Hayek, 1996). The rate of cryptocurrencies will be instable in the future until they are widely used as a means of payment. Therefore, we will try to find out how accurately it is possible to predict the rate of cryptocurrencies using the heterogeneous autoregressive model of realized volatility HAR-RV in the short term.

The economic nature of the HAR-RV model resides in the fact that different market players take actions based on different time horizons. These market players can be expected to react to and have influence on various time components of market volatility. It has been found that volatility over longer periods of time has a stronger effect on volatility over shorter periods of time in comparison with the opposite situation. The model is a cascade of volatilities from high frequencies (days) to low frequencies (months). In economic terms, the nature of the model is that short-term traders take both long-term and short-term volatility into account in their trading decisions. However, short-term volatility matters less to long-term traders. The following ratios can be written for the weekly $\boldsymbol{RV_t^{(w)}}$ and monthly $\boldsymbol{RV_t^{(m)}}$ realized volatility using the value of the daily realized volatility $\boldsymbol{RV_t^{(d)}}$:

$$\boldsymbol{RV_t^{(w)} = \frac{1}{5}(RV_{t-1}^{(d)} + RV_{t-2}^{(d)} + \cdots + RV_{t-5}^{(d)})} \quad (1),$$

$$\boldsymbol{RV_t^{(m)} = \frac{1}{22}(RV_{t-1}^{(d)} + RV_{t-2}^{(d)} + \cdots + RV_{t-22}^{(d)})} \quad (2).$$

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Then, as Corsi (2009) argues, we get a very simple convolution of time series in the proposed cascade model:

$$\boldsymbol{RV_{t+1d}^{(d)}} = \alpha + \boldsymbol{\beta^{(d)} RV_t^{(d)}} + \boldsymbol{\beta^{(w)} RV_t^{(w)}} + \boldsymbol{\beta^{(m)} RV_t^{(m)}} + \boldsymbol{w_{t+1d}} \qquad (3).$$

Equation (3) has a simple autoregressive structure of realized volatility. However, it enables to take into account volatilities realized at different time intervals. This model can be denoted as HAR(3)-RV.

6. Findings

Before constructing the regression equation (3) on real data, let us check the initial time series for stationarity. The calculations were performed using the statistical program Eviews-6.0. The Dickey-Fuller test for checking the stationarity of the analyzed time series $\mathrm{RV_t^{(d)}}$=$\mathrm{p_t^d} - \mathrm{p_{t-1}^d}$, where $\mathrm{p_t^d}$ is the market price of the cryptocurrency on a certain day, has showed that these rows are stationary. The calculated Dickey-Fuller statistics equals –20.5, –12.7, –9.2 for Bitcoin, Ethereum and Ripple, respectively. The critical value of this statistic is –3.43 for a 1 % significance level. Let us slightly complicate model (9) to improve the forecast accuracy by adding lagged values for one period of time for each variable to the right side of this equation. The calculation results are shown in Table 01.

Table 01 shows that the values of the coefficients of determination for the predictive equations of all three cryptocurrencies are not very high despite the fact that Student's t-statistics (numbers in parentheses) of almost all beta coefficients in these regression equations are significant. Therefore, let us once again construct predictive equations for the market prices of cryptocurrencies using model (3) for the logarithmic values of the initial time series in accordance with the methodology proposed in (Pele & Mazurencu-Marinescu-Pele, 2019). The statistical characteristics of the obtained models are presented in Table 02.

The values of determination coefficients of the predictive equations for all three cryptocurrencies turned out to be high. The beta coefficient with the daily variable $\mathrm{RV_t^{(d)}}$ turned out to be statistically insignificant only for the Ripple cryptocurrency. Consequently, the main postulate of the heterogeneous theory being "traders who carry out cryptocurrency transactions on different time horizons with different speed of investment decisions have a significant impact on the pricing process of these digital assets" is confirmed. Table 3 shows the values of the actually observed prices of cryptocurrencies on the day that was not included in the training dataset, and the market prices of cryptocurrencies predicted using model (3).

Table 3 shows that the accuracy of price predictions for all three cryptocurrencies is quite high. The forecast was made one day ahead, while the situation in the global cryptocurrency market remained calm. Even if the coefficient of determination is 99 % (Table 02), then the model will provide a significantly inaccurate forecast every hundred days. Within a year, there will be 3 or 4 such errors. These are the days when there is a strong surge in volatility in the cryptocurrency market if the market receives unexpected positive or negative information.

A way out of this situation was found. After reviewing the foreign literature on forecasting the prices of financial assets, it was found that the growth of the Shannon information entropy calculated with

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regards to the analyzed time series can predict the moments of sharp volatility of its levels. Therefore, we propose to perform calculations of Shannon information entropy for the investigated time series of cryptocurrency market prices. This will eliminate the main drawback of the predictive model of the heterogeneous market (3) being the inability to predict unexpected shocks in the cryptocurrency market. Let us calculate the Shannon information entropy using formula (4). For this, first, using the formula $r_{t,v}$ = log $P_{t,v}$ – log $P_{t,v-1}$, calculate their daily profitability $r_{t,v}$, compose a time series of ones and zeros $S_{t,v}$. Next, we find the weekly probability p_t for each day t of units appearing in the series $S_{t,v}$ over the past five working days using the formula $p_t = \frac{m_t}{5}$, where m_t is the number of units in the current week.

$$S_t(X) = - \sum_{i=1}^{5} p_{i,t} \cdot log_2(p_{i,t}) \qquad (4),$$

A series of values of information entropy formed in this way indicates a decrease or increase in market prices of cryptocurrencies in advance, since the dynamics of market quotations of cryptocurrencies in a hidden form contains insider information about the further behavior of cryptocurrencies, which large institutional investors in this market are acknowledged about.

7. Conclusion

Having analyzed the Russian and foreign scientific literature on the issue and circulation of cryptocurrencies, it was concluded that these modern electronic means of payment can be considered money. Karl Marx argued that money should have five functions: a medium of exchange, a means of payment, a store of value, a measure of value, world money. However, the subsequent development of economic theory allows a smaller number of monetary functions in money. According to neoclassical theory, money can have three functions: a medium of exchange, a measure of value, a store of value. In accordance with the Austrian school of economics, money can even have one function, specifically, a medium of exchange. Considering that cryptocurrencies perfectly perform this function, it can be concluded that these assets based on blockchain technology have a great future in the field of world money circulation. Central banks of various countries are ambivalent about the prospect of expanding cryptocurrency circulation among legal entities and individuals. The central banks of Switzerland, Sweden, Great Britain and Japan have officially allowed the circulation of cryptocurrencies in their jurisdictions. The central banks of Russia and China prohibit the use of cryptocurrencies in payment transactions. Their fears are understandable. As cryptocurrencies are issued uncontrollably by individuals, there is no safety for cryptocurrencies while transactions involving these assets are often used in shady businesses. However, technological progress develops. Thus, cryptocurrency must be controlled by central banks to increase the transparency of digital payment transactions.

The study found that a short-term forecast of the dynamics of market prices of cryptocurrencies is possible one or two days in advance, which is very important when recognizing cryptocurrencies as independent and full-fledged means of payment. The testing of the intraday, daily, weekly and monthly dynamics of the market prices of bitcoin, ethereum and ripple revealed the information heterogeneity of these financial instruments. Therefore, a heterogeneous autoregressive model of realized volatility was chosen as a predictive model, since it can provide the best predictive results in an information-heterogeneous market for an asset. Thus, it became possible to obtain fairly accurate forecast results of the market prices of the analyzed cryptocurrencies. Consequently, at the present stage of their development, cryptocurrencies perform monetary functions even without official recognition from the mega-regulator. Now and in the future their role in the economy will only increase.

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