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Cryptocurrency Market Development: Hurst Method

A. Yu. Mikhailov
Financial University, Moscow, Russia
https://orcid.org/0000-0003-2478-0307

ABSTRACT

The aim of this work is to study the pricing in the cryptocurrency market and applying cryptocurrencies by the Bank of Russia for its monetary policy. The research **objectives** are to identify the cyclical nature of price dynamics, to study market maturity and potential risks that have a long-term positive relationship with the financial stability of the cryptocurrency market. The author uses the Hurst **method** with the Amihud illiquidity measure to study the resistance of four cryptocurrencies (Bitcoin, Litecoin, Ripple and Dash) and their evolution over the past five years. The study **results** in the author's conclusion that the cryptocurrency market has entered a new stage of development, which means a reduced possibility to have excess profits when investing in the most liquid cryptocurrencies in the future. However, buying new high-risk tools provides opportunities for speculative income. The author **concludes** that illiquid cryptocurrencies exhibit strong inverse anti-persistence in the form of a low Hurst exponent. A trend investing strategy may help obtain abnormal profits in the cryptocurrency market. The Bank of Russia could partially apply digital currency to implement monetary policy, which would soften the business cycle and control the inflation. If Russia accepts the law "On Digital Financial Assets" and legalizes cryptocurrencies after the economic crisis caused by the COVID-19 pandemic, the Bank of Russia might act as a lender of last resort and offer crypto loans.

Keywords: Bitcoin; Litecoin; Dash; Ripple; monetary policy; liquidity; volatility; profitability; Hurst method; crypto loans

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INTRODUCTION

The study and analysis of the cryptocurrency market is a relatively new area. A few works published in recent years have had the potential interest in this topic.

Many scientists have been studying Bitcoin from different angles ever since it appeared. In Russia, digital financial assets (crypto assets) have not yet become legal, since the State Duma adopted the draft law "On Digital Financial Assets", but subsequently it raised many questions in the Government of the Russian Federation*.

Due to the young age of blockchain technology, academic literature on this topic is still in its infancy. There are many studies on the security and technological aspects of cryptocurrencies that will not be discussed here.

One of the problems is that most articles contain information only about the most popular cryptocurrency — Bitcoin.

Cryptocurrency is a digital currency, whose creation and control is based on cryptographic methods. As a rule, cryptocurrency accounting is decentralized.

Some researchers claim that Bitcoin is just a bubble. The fundamental value of Bitcoin is difficult to reveal, and history shows that innovative assets are indeed more prone to bubbles.

The macroeconomic index and asset price index can affect the price of Bitcoin. Cryptocurrency can also get some value from network effects due to the size of the network where it is used. The ratio between the cost of the network and its size is super-linear meaning that the cost of the most popular cryptocurrency (Bitcoin) is much higher than other cryptocurrencies with fewer users, which is translated into the market capitalization. As computing power grows, the value of cryptocurrency should also increase.

Active trading in the cryptocurrency market started only in 2013. A key question to be analyzed is whether the behavior of crypto assets can be predicted. Forecasts of the cryptocurrency market parameters might be used as the basis for trading strategies aimed at profit earning in the cryptocurrency market.

* URL: http://duma.gov.ru/news/27027/.

LITERATURE REVIEW

The heterogeneous agent model of the Bitcoin market simulates many characteristics of the real market relatively accurately. It includes various trading strategies, the initial distribution of wealth under the Pareto law, a realistic mechanism for trading and price equalization based on the order book and an overall increase of Bitcoins over time due to mining.

Autocorrelation of raw returns is very low for all time periods, while autocorrelation of absolute incomes is much higher, which affirms the presence of volatility clustering [1].

R. Böhme, N. Christin, B. Edelman, T. Moore and A.M. Antonopoulos studied the profitability of Bitcoin production, its weaknesses and long-term financial stability [2, 3].

Cost models are proposed in terms of creation costs (technicality). Calculations and experiments revealed that the cost of business processes in Ethereum can be twice higher than in Amazon SWF [4, 5]. Given the high volatility of the exchange rate, a cost estimation model is important [6, 7].

Blockchain pursues a decentralized approach to building trust. This is a fundamental technology and platform for innovation, its value will grow in the future [8].

The vast majority of economic literature on Bitcoins and cryptocurrencies is devoted to the study of various factors that could explain the development of prices. Price determinants may be grouped and summarized as follows:

- market forces, i.e. supply and demand factors;
- macro-financial factors;
- interest of the public and investors;
- news coverage.

The main factors are attractiveness for investors, as well as public interest in the media. Examples of studies addressing these factors, as well as other price determinants of Bitcoin, are provided below.

The indicators of trading volumes and cryptocurrency volatility passed a number of tests, such as Dicky-Fuller (ADF) and CGCD tests [9, 10].

Investments in Bitcoin show very high volatility, but also very high returns. Moreover, for

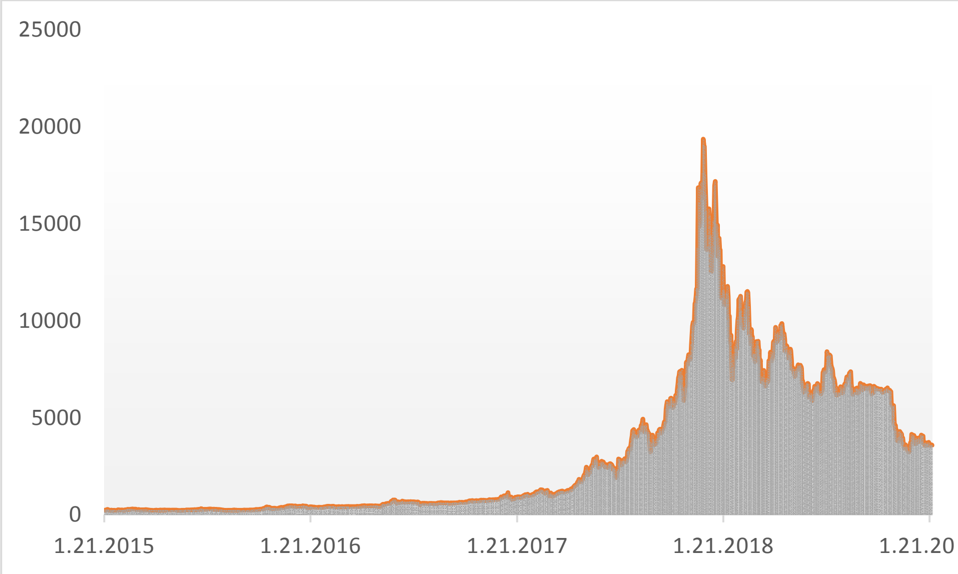

Fig. 1. **Bitcoin dynamics (BTC), US dollar**
Source: Thomson Reuters Datastream.

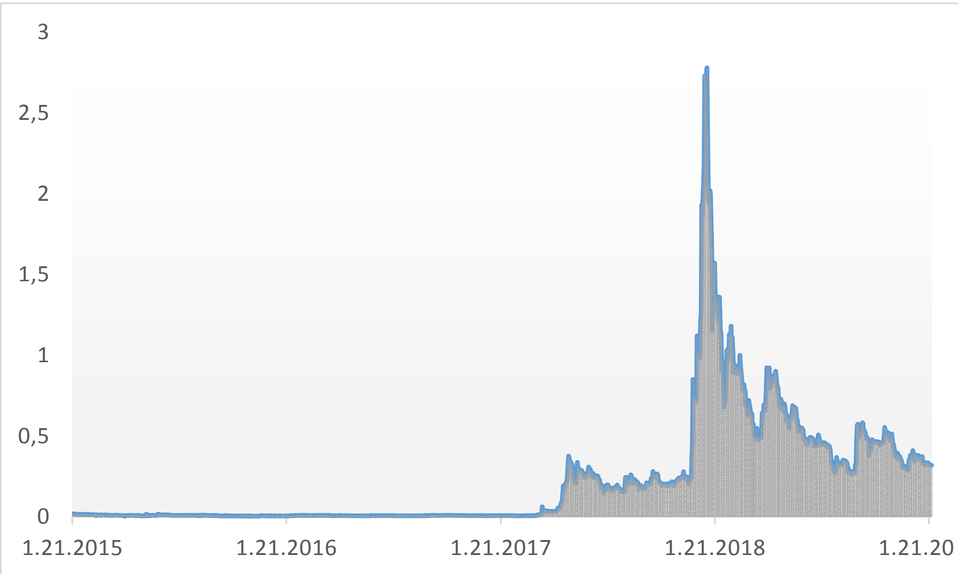

Fig. 2. **Ripple (XRP) dynamics, US dollar**
Source: Thomson Reuters Datastream.

holders of well-diversified portfolios, high risk is offset by a low correlation with other assets [11–13].

Financial intermediaries should modernize and optimize their activities based on the cryptocurrency study results [14, 15].

The results of the cryptocurrency market research confirm the hypotheses of negotiations and strategic trading [16].

It was found out that price constancy is of great importance for the future volatility of the two cryptocurrencies (*Fig. 1–4*). The conditional covariance of two cryptocurrencies significantly depends on previous news, which confirms the conclusions about the interconnectedness of cryptocurrencies [17].

Researchers identify a specific pricing mechanism: maximizing the profits of entrepreneurs who play a coordinating role in creating opportunities for using the new currency (within a small network) [18]. However, one must remember about the differences between virtual (centralized) and

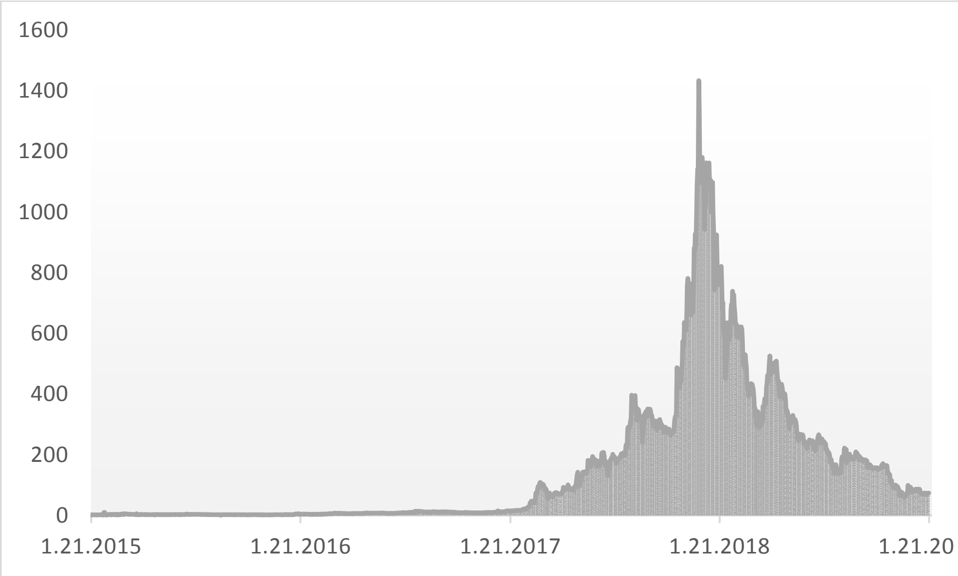

Fig. 3. **DASH dynamics, US dollar**

Source: Thomson Reuters Datastream.

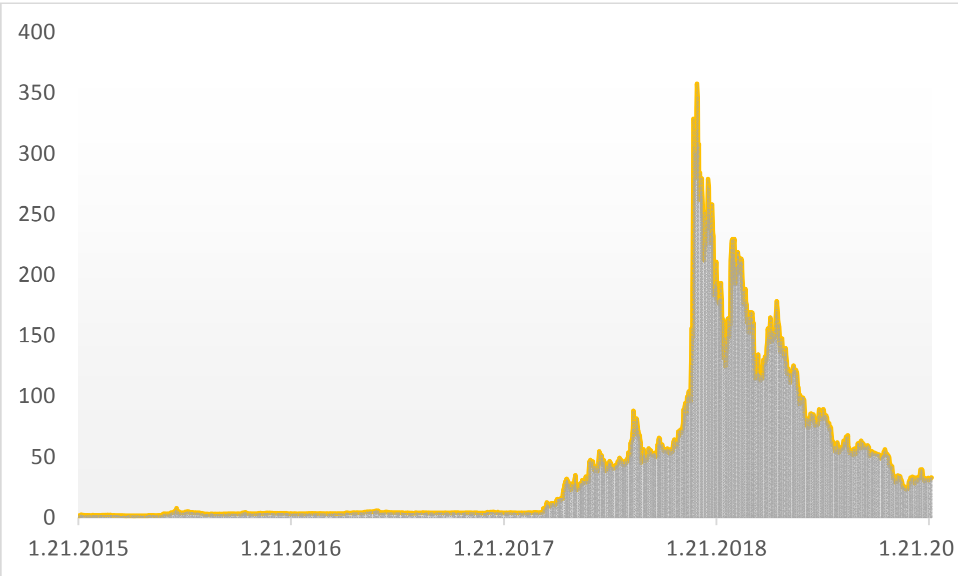

Fig. 4. **Litecoin (LTC) dynamics, US dollar**

Source: Thomson Reuters Datastream.

crypto (decentralized) currencies [19]. Bitcoin correlates with various financial and percentage drivers, however, none of the internal factors has a significant impact on the price [20, 21].

Controlling money supply and interest rates is becoming increasingly difficult. The role of central banks will have to be adapted to this new monetary system if cryptocurrencies are accepted as equivalent means of payment and financial assets with significant market capitalization [22, 23].

The legal and economic difficulties of cryptocurrency realization for international transfers were disclosed [24, 25].

Higher transaction costs in low-turnover markets affect the ability of traders to act quickly [26, 27].

In general, foreign researchers consider Bitcoin not as cash, but as an asset. Empirical studies show that economic factors such as CPI, DJIA, USDI and the Fed rate have a long-term negative effect on the Bitcoin price. This implies that Bitcoin can be a hedging tool against a decline in the US dollar [28, 29].

DATA AND METHODS

The framework of the study was the profitability analysis of various cryptocurrencies sorted by market liquidity. To study the market, the author used tests based on the application of the Amihud illiquidity ratio [30, 31].

We chose this approach due to its reliability and simplicity. It only requires daily market data, which is convenient when information about the market microstructure is not available. At the same time, complete data on market capitalization, necessary for the turnover-based indicators, are not required, which can be a problem for Altcoins.

The daily return on asset *i* on day *t* in US dollars is calculated by the formula

$$Rt = \ln(Pt) - \ln(Pt-1), \quad (1)$$

where $\ln(Pt)$ is the natural logarithm of the price P of time *t*.

The Amihud illiquidity ratio is defined as follows:

$$\mathrm{ILLIQ}_T^i = \frac{1}{D_T}\sum_{t=1}^{D_T}\frac{|R_t^i|}{P_t^i V_t^i}, \quad (2)$$

where D_T is the number of days traded per year T;

R_t^i US is the daily return on asset *i* on day *t* in US dollars;

V_t^i is the daily volume, traded asset *i* on day *t*;

P_t^i is the daily price of asset *i* on day *t* in US dollars.

This ratio provides an understanding of the relationship between volume and price changes.

To study the cryptocurrency market, one may use a set of statistical tests:

- the Ljung-Box test;
- the Bartels test, if the returns of the cryptocurrencies turn out to be independent;
- the Lo&McKinlay's test, to check if the standard deviation from √T scales.

To test the coefficient of variation, it is advisable to use the automatic dispersion test (AVR), proposed by researchers J. H. Bergstrand, J. J. Lewer and H. Van den Berg [32, 33] and the BDS test for time based dependence in a series with average *p* values in different specifications.

The R/S Hurst exponent helps research long-term memory profitability. Impulses appear in the time series of profitability, if the Hurst exponent is greater than 0.65, and the average reversal of the time series (or anti-persistence) appears when the Hurst exponent is less than 0.45.

Table 1 presents the average values for each of the five groups of cryptocurrencies. One can see the relationship between their liquidity and volatility. Group 1 — is the most liquid cryptocurrencies, group 5 — is the least liquid cryptocurrencies. At the same time, there is no evidence of a liquidity premium in cryptocurrencies. This is interesting and contradicts the features of traditional asset classes.

One may also note strong positive distortions and high levels of income kurtosis. Positive distortions in the price series may speak of a significant level of optimism among investors in a time of instability.

Table 2 shows the average value of *p* with the average Hurst exponent.

Cryptocurrencies with the lowest liquidity reject the null hypothesis of randomness in all tests. *p* average values increase in higher liquid quantiles.

Besides, the Hurst exponent proves persistence in illiquid markets (<0.5) confirming the results by C. Carrere, J. S. Silva and S. Tenreyro [34, 35].

The Hurst exponent lies in the interval [0,1] and is calculated by the formula

$$X_{k,a} = \sum_{i=1}^{k}\left(N_{i,a} - e_a\right). \quad (3)$$

Three categories of data series can be identified by *H* values:

- the series is anti-persistent, the results are negatively correlated ($0 \leqslant H < 0.5$);
- the series is random, the return is not correlated, the series has no memory ($H = 0.5$);
- the series is stable, the results are strongly correlated, the memory dynamics ($0.5 < H \leqslant 1$).

Table 1

Profitability of cryptocurrencies sorted by the Amihud illiquidity measure

Liquidity	Profitability statistics					
	Group	Amihud measure	Average	Standard deviation	Distortion	Kurtosis
High	1	< 0.00001	0.010	0.106	0.92S	11.422
	2	0.00011	0.010	0.160	1.167	13.162
	3	0.00101	0.009	0.234	0.90	17.409
	4	0.00900	0.009	0.22	0.742	20.276
Low	5	0.02581	0.010	0.366	0.101	10.829

Source: Thomson Reuters Datastream, calculated by the author.

Table 2

The Hurst exponent for cryptocurrencies sorted by the Amihud illiquidity measure: *p* average values

Liquidity			*p* average values					Hurst exponent
	Group	Amihud measure	Ljung-Box test	Runs test	Bartels test	AVR	BDS	
High	1	<0.00001	0.35	0.44	0.40	0.41	0.02	0.53
	2	0.00011	0.11	0.27	0.19	GL25	0.01	0.50
	3	0.00191	0.05	0.12	0.04	0LQ9	0.01	0.46
	4	0.00960	0.02	0.09	0.02	0103	0.02	0.44
Low	5	0.03531	0.01	0.04	0.01	OL02	0.01	0.41

Source: Thomson Reuters Datastream, calculated by the author.

Table 3

Results of *R/S* dynamic analysis (step = 50, data window = 300)

Log-yield	No conditions	Interception	Time
BITCOIN	0.992 (0.961. 1.040)	1.009 (0.983. 1.039)	1.009 (0.983. 1.039)
LITECOIN	1.005 (0.977. 1.038)	1.021 (0.994. 1.053)	1.021 (0.994. 1.053)
RIPPLE	1.028 (0.997. 1.064)	1.053 (1.023. 1.086)	1.053 (1.023. 1.087)
DASH	0.966 (0.933. 1.005)	0.985 (0.954. 1.022)	0.986 (0.954. 1.022)

Source: Thomson Reuters Datastream, calculated by the author.

Table 4

Top 10 cryptocurrencies by capitalization as of 02.01.2019

No.	Name	Capitalization	Price
1	Bitcoin	60 958 002 560	3480.60
2	XRP	12 605 993 911	0.306 242
3	Ethereum	11 147 795 484	106.51
4	EOS	2 112 336 072	2.33
5	Bitcoin Cash	2 045 890 560	116.26
6	Tether	2 030 218 013	1
7	Litecoin	1 957 580 695	32.48
8	TRON	1 739 274 086	0.026 089
9	Stellar	1 582 069 187	0.082 539
10	Bitcoin	1 130 006 345	64.21

Source: Thomson Reuters Datastream, calculated by the author.

RESULTS

The study revealed that Altcoins demonstrate cyclicality, as speculators affect the level of pessimism. However, in the higher liquidity quintiles, the Hurst exponent is close to random walk (0.5) [36].

Most studies of financial stability focus on cryptocurrencies as an investment asset. Most Bitcoins are owned by investors and are not considered a means of payment. After skyrocketing of prices in 2017–2018, it became clear that there is a bubble in the cryptocurrency market. In 2018, it was actively deflating, and Bitcoin lost about 85% of its maximum historical value.

Typically, a bubble is defined as a positive deviation from the fundamental asset value. The question boils down to the fact that recent price gains have been driven by expectations of future price gains and, therefore, could be subjected to a sudden reversal. Asset price bubbles are often tied to technological change and an uncertain future. However, deflating these bubbles does not necessarily lead to problems of financial stability. For example, the dotcom bubble burst in 2000 with limited consequences.

In the cryptocurrency market, the bubble is also deflated. This fact is confirmed by the results of the *R/S* dynamic analysis (*Table 3*) and a decrease in the overall market capitalization (*Table 4*).

The asset class, which is only about $60 billion (as of February 1, 2019), is probably too small to be significant for financial markets. Risks to the financial stability of crypto assets, now or in the near future, are likely to be concentrated in countries where they are in great demand. In cases when a significant and rapid decline in the value of the currency may lead to widespread losses or even panic, it is difficult to understand how these losses will be transferred to the main financial intermediaries in the economy.

Similar problems arise when the central bank must provide the lender with last resort in foreign currency. In this situation, the major central banks could create currency swap mechanisms to facilitate such operations. In the case of digital currency, however, there is no counterparty for the central bank to create a swap line together.

The central bank could be well placed to act as a lender of last resort to banks, although this is limited by its need to maintain an adequate supply of digital currency to repay bank deposits it received.

A complete transition to digital currency is convenient, although, by all accounts, implausible. The situation will be somewhat similar to the one as if the entire global economy was fully converted into dollars.

In this case, the central bank could not stabilize the macroeconomics. Moreover, since the supply of digital currency is fixed, economic and financial volatility could increase.

If monetary policy could completely switch to digital currency, it would be possible to cancel the zero lower bound at nominal interest rates.

If the amount of digital currency is fixed, the real value of each currency unit will increase with the economic growth.

In other words, if the prices of goods in foreign currency fall, deflation occurs, which, as a rule, is associated with an inefficient economy. In this case, enterprises and households usually put expenses aside, since in the future prices will be lower than at present.

The deterrent effects of deflation are primarily due to the fact that nominal interest rates usually cannot be negative. Their zero border is explained by the fact that the currency always provides a zero rate of return. In the digital currency world, interest rate caps can be cancelled.

Anyway, the problem of deflation seems to be partially solved, allowing the amount of digital currency to grow with the economy. Despite this, the amount of digital currency will not be able to move up and down with seasonal demand, and also partially respond to other external shocks of the economy.

Partial use of digital currency by the economy would be more realistic. The central bank could then soften the business cycle and control the inflation rate in the currency, though with less accuracy.

Some recent monetary policy debates concern the central bank's digital currencies. The central bank's single digital currency can take the form of a token, similar to digital cash.

If monetary policy could completely switch to digital currency, it would be possible to cancel the zero lower bound at nominal interest rates. The central bank could pay a negative interest rate to banks, making its policy rate as low as necessary to achieve economic incentives.

Economic crises of the XX century were associated with the distorting effect of monetary policy pursued by governments, and not with the so-called market failures.

However, the central bank would not have to cease operations immediately. In competition with commercial banks and other private money producers, it will have a strong incentive to provide citizens with a stable currency.

Cryptocurrency monitoring relies heavily on public aggregated data from third parties. Most of the aggregated information is available on public websites. For example, indicators for blockchain networks, market capitalization estimates, prices and volumes of trade, as well as funds collected in initial coin offerings (ICOs). These sources vary depending on the methodologies used, coverage and access to basic source information.

The processing of baseline information (when available) is ambiguous due to the absence (only partial) of regulation related to various participants in the value chain of crypto assets that operate in an environment without borders.

Nevertheless, data processing allows some quality control of the data. Besides public sources, statistical and control reporting mechanisms usually do not cover cryptocurrencies.

Building a cryptocurrency monitoring structure on this basis requires careful processing of available data and a phased approach to filling current gaps.

Monitoring needs will be reviewed periodically to ensure that the monitoring structure is still relevant and monitoring efforts remain proportionate to the potential risks associated with changing market sizes and price changes of individual cryptocurrencies, as well as the links between cryptocurrencies and the financial system.

After the all-time maximum capitalization of 650 billion euros in January 2018, and the following savage correction, the market capitalization of cryptocurrencies decreased to 96 billion euros in January 2019. It moved in tandem with asset prices, as evidenced by the price of Bitcoin, whose correlation with the general market capitalization is 95%. In relative terms, the market capitalization of cryptocurrencies is 4% of the market capitalization of the stock, and is 1% of GDP in the Euro area.

This cryptocurrency bubble is smaller than the peak of the two main past bubbles — dotcoms and subprime mortgage-backed securities. Compared to money aggregates, the value of cryptocurrencies is 1.2% of M1 in the Euro area and 0.8% of money aggregates M3. Bitcoin keeps leading in the field of crypto assets in terms of market capitalization, user base and popularity.

Although over the past two years, Bitcoin has lost some positions compared to other cryptocurrencies due to increased competition and uncertainty about the success of the various business models underlying behind, its market share has recovered during 2018 and is currently 54%.

For comparison, at the peak of the dotcom bubble, the NASDAQ Composite was four times higher than three years ago. Over the past two years, the historical volatility of cryptocurrencies has overshadowed not only the volatility of diversified European stock and bond markets, but also the volatility of oil and gold prices, highlighting the market risk that cryptocurrency investors are exposed to.

Compared to the beginning of 2018, when some cryptocurrencies had price peaks, volatility decreased. It is interesting to note that Bitcoin is not so volatile as other cryptocurrencies, which potentially reflects a wider investor base and a relatively longer lifespan as an asset.

CONCLUSIONS

As you can see, the perseverance changes over time and fluctuates around the average. The temporary variation is especially evident in the case of Litecoin, whose indicator has significantly decreased: from 0.70 in 2015 to 0.40 in 2018. This indicates the adaptability of the market: after 2–3 years, it became more liquid, and the number of participants and trade volumes have increased.

A monetary system based on digital currency may seem attractive, as it provides an opportunity to limit the role of the central bank. Higher transaction costs in the markets affect the ability of traders to act quickly, which leads to market failures.

As a result, the study revealed that illiquid cryptocurrencies exhibit strong inverse anti-persistence in the form of a low Hurst exponent.

The study revealed the cyclical dynamics of cryptocurrency prices. We studied the level of market formation and proved that the cryptocurrency market has moved to a new development stage confirmed by a decrease in the volatility of all liquid cryptocurrencies. We identified potential risks that have a long-term positive relationship with the financial stability of the cryptocurrency market.

It is concluded that the partial use of digital currency would be realistic when implementing monetary policy by the Bank of Russia, which could thus mitigate the business cycle and control inflation.

If Russia accepts the law ‘’On Digital Financial Assets’’ and legalizes cryptocurrencies after the economic crisis caused by the COVID-19 pandemic, the Bank of Russia might act as a lender of last resort and offer crypto loans.

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ABOUT THE AUTHOR

Aleksei Yu. Mikhailov — Cand. Sci. (Econ.), Deputy Director Research Center of Monetary Relations, Financial University, Moscow, Russia
AYUMihajlov@fa.ru

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