ORIGINAL PAPER

DOI: 10.26794/2587-5671-2021-25-5-150-171
UDC 336.76,519.2(045)
JEL C22, C52, C58, E44, G12

Evolution of Bitcoin as a Financial Asset

K.D. Shilov[a] ✉, A.V. Zubarev[b]
Institute of Applied Economic Study, RANEPA, Moscow, Russia
[a] https://orcid.org/0000-0002-2149-3946; [b] https://orcid.org/0000-0003-2945-5271
✉ Corresponding author

ABSTRACT

The cryptocurrency market debate resumed in 2020 with renewed vigour as the price of Bitcoin surpassed late 2017 highs. This study **aims** to analyse possible factors of Bitcoin's pricing at various cryptocurrency market development stages — before the 2017 price bubble, after and during the COVID-19 pandemic. The main **method** of analysis is a generalized autoregressive conditional heteroskedasticity model with conditional generalized error distribution (GARCH-GED). Two groups of indicators are used as possible factors related to the Bitcoin dynamics. The first group consists of various quantitative indicators directly related to Bitcoin (the so-called internal factors) — the volume of exchange trade, the volume of transactions in the Bitcoin blockchain, the number of new and active wallets, hash rate, the sum of fees paid in the blockchain, as well as the dynamics of Google Trends search queries. The second group is the return on various financial assets — stock and bond indexes, commodities, and currency markets. The **results** of the analysis demonstrate the absence of a stable correlation between any of the factors under consideration and Bitcoin returns in all the periods that we focus on. In the period before the 2017 price bubble, the internal factors and Bitcoin returns showed generally co-directional dynamics, but the situation changed in 2018. In early 2021, the correlation between Bitcoin and traditional financial assets returns has increased significantly. We can **conclude** that Bitcoin is becoming a popular means of diversification as a high-risk asset, which, however, follows the pattern of a speculative bubble at the beginning of 2021. The increased demand for the need to invest in Bitcoin using various exchange-traded instruments (ETFs for cryptocurrencies) may soon lead to a further increase in the price of this cryptocurrency if such instruments are registered on the exchange.

Keywords: cryptocurrency; blockchain; Bitcoin; GARCH; financial markets; financial assets; COVID-19; Google Trends

For citation: **Shilov K.D., Zubarev A.V. Evolution of Bitcoin as a financial asset. *Finance: Theory and Practice.* 2021;25(4):150-171. DOI: 10.26794/2587-5671-2021-25-4-150-171**

INTRODUCTION

Cryptocurrencies represent an interesting phenomenon in the second decade of the 21st century. Since its inception and its first price offer in 2010 at 8 US cents, the price of the first and largest cryptocurrency in terms of capitalization, bitcoin, has skyrocketed to US$ 20,000 at the end of 2017 (which even then seemed as an exception) after which it will drop in price to US$ 3.3 thousand in the second half of 2018, and in March 2021 it will overcome the mark of US$ 60,000.

Other cryptocurrencies have experienced similar ups and downs. This volatility and the ability to generate hundreds of thousands of percent of profits have naturally attracted the attention of a large number of stock market participants, retail investors and economists. Debates about the nature and possible drivers of cryptocurrency pricing still continue, both in the corridors of hedge funds and central banks, and in academic journals.

In this article, we will try to contribute to the discussion of possible pricing factors for the largest cryptocurrency — Bitcoin. Specifically, we will examine how bitcoin profitability correlates with cryptocurrency-specific factors such as exchange trading volume, distributed ledger activity, number of active and new wallets/addresses, and commissions. Using the indicator of the dynamics of the popularity of search queries in the Google search engine (using the Google Trends service) for relevant keywords, we will assess how the profitability of cryptocurrencies depends on public attention to them.

Many researchers have tested the link between cryptocurrency profitability and traditional financial assets. For the most part, these works indicated its absence, which opened up the possibility of including a certain (usually small) share of cryptocurrencies in the investment portfolio in order to obtain a higher expected return at the same level of risk [1]. However, we assume that between the end of 2017 and the beginning of 2018, which many researchers define as a "bubble" [1], cryptocurrencies were an extremely *"marginal"* asset class with relatively low capitalization and popularity in narrow circles.

The sharp rise in cryptocurrency quotes in 2017 significantly fueled interest in this asset class, which contributed to the dissemination of information about it to a wider audience. Although the fall in 2018 was extremely painful for newcomers and there was less interest in the topic, the burst of the 2017 bubble significantly changed the cryptocurrency market. Moreover, the COVID-19 pandemic marked the beginning of a new stage in the evolution of the cryptocurrency market and led to significant changes in its characteristics. In particular, the cryptocurrency market has become more aligned with the stock market.

LITERATURE REVIEW

The technological base of any cryptocurrency is distributed ledger technology (DLT), one of the implementations of which is blockchain [2]. Each cryptocurrency has its own distributed ledger, and some of them are not even blockchains. Moreover, the cryptocurrencies themselves may differ in their functions and not all of them strive or can fulfill the role of a "new world currency" [3], and, therefore, the pricing mechanisms may differ.

A significant number of researchers model cryptocurrency (any) as a measure of payment within a certain service and platform and the growth in the price of such a cryptocurrency is provided due to various effects. Thus, M. Sockin and W. Xiong [4] model the price of a cryptocurrency as a means of payment on some decentralized platform for the exchange of goods and services, where platform users generate demand for tokens, but the growth of speculative demand for short-term transactions can unbalance the market.

J.S. Gans and H. Halaburda [5], based on a theoretical model of a digital currency serving a certain platform, concluded that the use or expansion of such a cryptocurrency outside the platform is unlikely.

B. Biais et al. [6] constructed a model of the equilibrium price of bitcoin, based on the possible advantages and costs of using it, with the help of which they demonstrated that the actions of regulators, leading to a decrease in costs or an increase in the benefits of using bitcoin as a means of payment, have a positive effect on the price cryptocurrencies.

L.W. Cong, Y. Li and N. Wang [7] have developed a dynamic pricing model for cryptocurrencies, which are means of payment within a certain platform. They demonstrated that an increase in the number of platform users, on the one hand, leads to an increase in demand for the platform's token for transactions, and on the other hand, to an increase in the expected return from price increases due to demand, which leads to endogenous risk in token returns and an explosive dynamics in prices.

The work of J. Chiu and T.V. Koeppl is devoted to the issue of bitcoin's competition with other payment systems [8], in which the authors showed that bitcoin can compete with traditional payment systems if the scalability problem is overcome and the transaction processing speed is increased.

One of the most significant works in terms of assessing the fair value of bitcoin and cryptocurrencies built on its source code is the work of A.S. Hayes [9], in which the author demonstrated that the value of the marginal cost of mining can be used as an estimate of the fundamental value.

Almost all cryptocurrencies (except for bitcoin and separate forks from other cryptocurrencies) appeared as a result of an initial coin offering (ICO) — a mechanism that allows creators to receive initial funds for the development of their platform from the general public in the early stages.

The theoretical work of C. Catalini and J.S. Gans [10] analyzed possible strategies of ICO initiators to achieve the maximum value of their tokens, and J. Chod and E. Lyanderes [11] analyzed the advantages and disadvantages of ICOs in comparison with venture investment.

The work of A. Simonov and V. Zyamalov [12] is devoted to an empirical analysis of long-term factors of profitability and survival of tokens after ICO [12], who, however, demonstrated that the main factor in the high profitability of ICOs is the general mood in the cryptocurrency market.

A large number of works are devoted to the study of cryptocurrencies as a new class of financial assets: to what their properties are closer — to stocks, currencies or commodities; how effective is their pricing; how they relate to markets for other assets.

The conceptual features of bitcoin, consisting in its limited supply and the need for its “extraction” (mining), led some researchers to the idea that the first cryptocurrency in its properties may be similar to gold (see, for example, [13]). However, further studies of this issue have demonstrated the controversy of this thesis. For example, D.G. Baur, T. Dimpfl and K. Kuck [14] authors using conditional heteroskedasticity models (GARCH) showed that the properties of a series of returns and volatility of bitcoin differ from the corresponding series for gold and stock indices.

Differences between Bitcoin and gold were also highlighted in the work of T. Klein, H. Pham Thu, T. Walther [15], in which the authors using models of asymmetric power GARCH (APGARCH), partially integrated APGARCH, as well as multivariate GARCH (BEKK–GARCH), showed that bitcoin cannot serve as a hedging tool, unlike gold, since the addition of bitcoin (or a portfolio of the largest cryptocurrencies, expressed through the CRIX index) leads to larger falls in the value of the portfolio during downturns in the markets.

S.J.H. Shahzad et al. [16] also demonstrated that bitcoin does not have a weak safe-haven property for developed and emerging (with the exception of China) markets.

On the other hand, A. Urquhart and H. Zhang [17] using asymmetric dynamic conditional correlation (ADCC-GARCH) models showed that bitcoin can be an instrument of short-term intraday hedging during increased volatility in some currency’s markets (Canadian dollar, euro, etc. British pound). The work of S.J.H. Shahzad et al. [18] analyzes the downside: can traditional currencies act as a hedge for the largest cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin). The authors showed that in the sample from 07.08.2015 to 31.07.2019, the Japanese yen was the best hedge for cryptocurrencies.

Cryptocurrencies, especially bitcoin, are often positioned as a means of payment. In the work of F. Glaser et al. [19], an attempt is made using empirical methods to answer the question of what bitcoin really is — a speculative asset or a means of payment? Using GARCH models, the authors analyzed daily bitcoin returns, as well as daily exchange and blockchain volumes, and concluded that speculation is the main motive for cryptocurrency buyers.

D. G. Baur, K. Hong, A. D. Lee came to similar conclusions [20], who demonstrated using information from the bitcoin blockchain that only a small part of cryptocurrency holders regularly performs any transactional transactions. Also, in this paper, the authors demonstrated that the returns on the largest cryptocurrency are not correlated with the returns on traditional financial assets (stocks, bonds, commodities, currencies).

The work of G. O. Krylova, A. Yu. Lisitsyn and L.I. Polyakov [21] demonstrated that the leading cryptocurrencies are characterized by significantly higher volatility than fiat currency rates, which indicates the premature definition of cryptocurrencies as a means of payment.

Y. Liu and A. Tsyvynkiy [22] carried out a large-scale study of possible factors that can predict the profitability of leading cryptocurrencies (Bitcoin, Ethereum, Ripple). In particular, the authors demonstrated that the profitability of cryptocurrencies can be largely explained by such cryptocurrency-specific factors as changes in the number of open wallets, active addresses, all and separate payment transactions on the blockchain. The authors did not find a significant correlation between the returns of cryptocurrencies and other financial assets, as well as the Fama-French factors, macroeconomic indicators. Momentum (momentum of price movement) and investor attention, expressed in terms of the relative frequency of searches in Google and Wikipedia, were the only indicators that significantly affect the future profitability of cryptocurrencies and to some extent can predict price movement. The presence of a two-way relationship between Google searches and bitcoin returns is also indicated by the results of the work of S. Dastgir et al. [23], obtained using the copula-based Granger causality test.

In another work, the same authors [24] attempted to construct factors specific to the cryptocurrency market, similar to the Fama-French market factors of and not only. By modeling portfolios that reflect certain factors, it has been demonstrated that only three factors — cryptocurrency market capitalization, size and momentum — can explain the expected return on a given asset class.

Many researchers are also involved in the analysis of cryptocurrency volatility. J. Chu et al. [25] reviewed 12 different GARCH model specifications for the 7 largest cryptocurrencies. The most suitable specifications turned out to be integrated GARCH (IGARCH) and asymmetric GARCH (GJR-GARCH), which indicates high stability of volatility (effect of infinite memory) in cryptocurrency returns, as well as an asymmetric response of volatility to yield shocks.

The study of the asymmetric reaction of the cryptocurrency market to news is devoted to the work of M. Malkina and V. Ovchinnikov [26], in which the authors using Markov-switching GARCH models and models of heterogeneous autocorrelation realized volatility (HAR-RV) have shown, the asymmetry effect depends on the phase (rising, falling) and the level of volatility (high, low) of the cryptocurrency market. The asymmetric influence of positive and negative news on bitcoin profitability was also demonstrated in the work of E.A. Fedorova, K.Z. Bechvaya and O. Yu. Rogov [27], and the authors showed that the influence of negative news is stronger.

In the work of H.A. Aalborg, P. Molnár, J.E. de Vries [28] using HAR-RV and panel regressions, a correlation was found between volatility and the volume of cryptocurrency exchange trades. The authors did not find a correlation between the returns of cryptocurrencies and traditional financial assets, as well as some macroeconomic factors. In a study by D. Bianchi [29], using panel regressions, it was also shown that the volatility of cryptocurrencies correlates with the volume of trade, which, in turn, can be predicted by past returns. In another work by the same author [30], it was shown that the factor of the joint influence of lags in the trading volume and profitability (i.e. the multiplication of these indicators) positively and significantly correlates with the future profitability of cryptocurrencies.

DATA AND METHODOLOGY

Data

The Cryptocompare website database is used as the main data source for the series of cryptocurrency prices in US dollars. S. Alexander and M. Dakos [31] in their study showed that the prices of this service are most suitable for research or practical use. This paper examines the factors of bitcoin pricing, but for comparison, we also use the price series of other major cryptocurrencies —Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), Cardano (ADA), Litecoin (LTC), Stellar (XLM). The sampling time interval is from 01.01.2013 to 31.01.2021. *Table 1* presents descriptive statistics of the logarithmic returns of cryptocurrencies.

Bubbles have been repeatedly detected in the dynamics of the cryptocurrency rate.[1] We will exclude from consideration the periods of bubbles in the cryptocurrency market, since they correspond to special (explosive) data generation processes, the study of which is beyond the scope of this work.

Many researchers have identified two large bubbles — at the end of 2013 and at the end of 2017. The exact dates of their start and end differ from study to study and depend on the tests with which they were carried out, the chosen window width, the method for calculating the critical values of statistics, etc.

In this work, we are guided by the results of other studies, however, we choose the specific boundaries of the periods in a certain averaged way. In *Fig. 1*, two periods of the bubble are painted over, which we will exclude from consideration — from 01.01.2013 to 01.04.2014 and from 01.05.2017 to 01.05.2018 results.

Thus, the period between the two highlighted bubbles (from 01.04.2014 to 01.05.2017) will be designated as the "formation period" of the market, when cryptocurrencies were known only in a relatively narrow circle, and the period after the bubble at the end of 2017 came the "period of maturity" when cryptocurrencies became known to the general public. Naturally, the period of the COVID-19 pandemic also belongs to the period of maturity, the beginning of which in this work we relate to the beginning of the fall in stock markets against its background, that is, from 01.03.2020. We consider the maturity period both in full and separately before the pandemic — from 01.05.2018 to 01.03.2020 — and during the pandemic — from 01.03.2020 to 31.01.2020.

In addition to direct daily close prices, the study uses a number of possible internal factors presented in *Table 2*.

All factors are considered the first difference of logarithms $\ln(x_t) - \ln(x_{t-1})$. Those indicators that are expressed in cryptocurrencies— trans, vol_b, fee_m and fee_t — are converted into US dollars by multiplying by the average the maximum and minimum values of the bitcoin rate per day.

The literature notes that one of the important factors in the pricing of cryptocurrencies is the interest of the general public. In this work, as a proxy variable of such interest, we use the dynamics of searches in Google, provided through the Google Trends service,[2] for keywords such as *bitcoin, blockchain*. The specificity of the indicator of the dynamics of the popularity of a particular search query in Google is that the search engine provides not absolute, but relative values of popularity for a selected period, but a value at the point (day/week/month) when the analyzed search query was most popular. is taken as 100, and the rest of the points are normalized relative to this maximum. Moreover, the dimension (minutes, hours, day, week, month) of a number of search query dynamics depends on the selected period for building the dynamics. Thus, when choosing a 7-day period, the service provides a breakdown by hours, a quarter (90 days) — by days, year — by weeks and, finally, by several years — by months.

To obtain the daily dynamics of search queries for the period from 01.01.2013 to 31.01.2021, for each query for the entire period, monthly series were first unloaded. Further, for each month, starting from January 2013, we sequentially unloaded daily data, divided it by 100 and multiplied by the values of the popularity dynamics of this query, obtained earlier for each month. *Fig. 2* shows the resulting series, and *Table 3* presents descriptive statistics for internal factors.

In this paper, as traditional financial assets, we use the values of the S&P500, MSCI All Countries World Index (MSCI ACWI), MSCI Emerging Markets Index (MSCI EM), MSCI

[1] For example, Li Z.-Z., Tao R., Su C.-W., Lobonţ O.-R. Does Bitcoin bubble burst? Quality & Quantity. 2019;53(1):91–105.

[2] URL: https://trends.google.com/ (accessed on 10.02.2021).

Table 1

Descriptive statistics of cryptocurrency returns

Cryptocurrency	First observation	Number of observations	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
BTC	01.01.2013	2954	0.0027	0.0590	−0.8488	1.4744	4.55	164.65
LTC	24.10.2013	2658	0.0013	0.0842	−0.9742	0.8941	0.39	43.47
XRP	21.01.2015	2204	0.0015	0.0865	−0.7791	1.0280	1.24	30.56
ETH	07.08.2015	2006	0.0031	0.0688	−1.2336	0.4362	−2.87	56.56
XLM	12.02.2016	1817	0.0027	0.0895	−0.9097	1.0526	1.48	24.72
BNB	24.08.2017	1258	0.0024	0.0668	−0.5664	0.4951	−0.08	11.46
ADA	01.10.2017	1220	0.0023	0.0762	−0.5389	0.8621	1.93	22.94

Source: authors' calculations based on the data from Cryptocompare.

Fig. 1. **Dynamics of logarithmic Bitcoin prices**

Source: authors' calculations based on the data from Cryptocompare.com.

Table 2

Internal factors of Bitcoin

Variable	Name in the source	Description	Source
vol_t	volumeto	The sum of all transactions for the cryptocurrency under consideration on all cryptocurrency exchanges in one day (US dollars)	Cryptocompare.com
new	new_addresses	The number of addresses (wallets) created on this day in the cryptocurrency blockchain	Cryptocompare.com
act	active_addresses	The number of addresses that made at least one transaction during the day	Cryptocompare.com
trans	average_transaction_value	Average size of transactions during the day expressed in native cryptocurrency (the main currency of the distributed ledger)	Cryptocompare.com
hash	hashrate	Average daily difficulty (hash) for the formation of a new block in the blockchain (terahashes per second, TH/s)	Cryptocompare.com
vol_b	TxTfrValAdjNtv	The number of cryptocurrency units moved between addresses per day	Coinmetrics.io
fee_m	FeeMeanNtv	Average daily transaction fees on the blockchain expressed in cryptocurrency units	Coinmetrics.io
fee_t	FeeTotNtv	The total amount of transaction fees per day expressed in cryptocurrency units	Coinmetrics.io

Source: Cryptocompare.com, Coinmetrics.io (accessed on 10.02.2021).

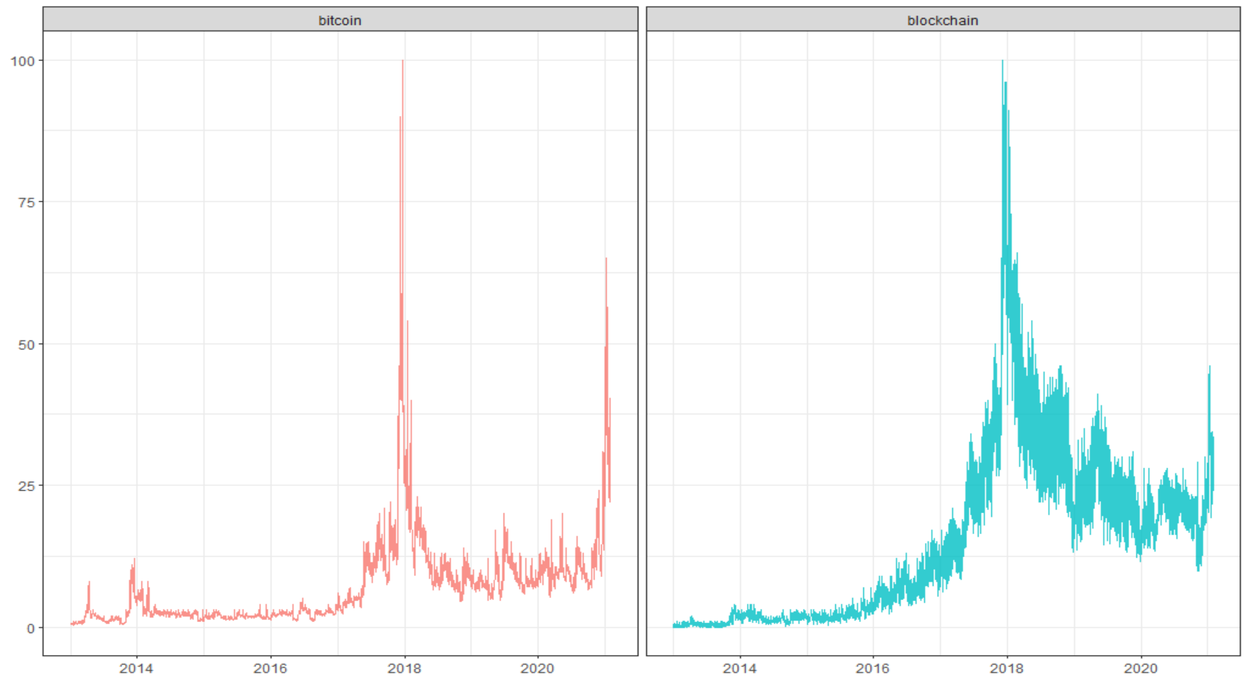

Fig. 2. **Leading search queries dynamics**

Source: authors' calculations based on the data from Google Trends. URL: https://trends.google.com/ (accessed on 10.02.2021).

Table 3

Descriptive statistics of internal factors (logarithmic differences)

Factor	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
vol_t	0.0028	0.5079	−2.3428	2.7154	0.27	1.09
vol_b	0.0026	0.2981	−1.3445	1.9035	0.31	1.63
new	0.0011	0.1356	−0.7108	0.8883	0.32	1.66
act	0.0011	0.1260	−0.4604	0.6470	0.47	1.14
trans	0.0020	0.3153	−2.8745	2.4190	0.19	7.58
hash	0.0052	0.1159	−0.4828	0.6042	0.14	0.75
fee_m	0.0025	0.2301	−2.1384	1.9287	0.35	17.03
fee_t	0.0032	0.2692	−2.2495	2.0513	0.24	9.93
"bitcoin"	0.0166	0.1891	−0.7308	2.5714	2.52	18.53
"blockchain"	0.1819	1.1610	−1.0000	9.7143	6.83	52.29

Source: authors' calculations based on the data from Cryptocompare.com, Coinmetrics.io, trends.google.com (accessed on 10.02.2021).
Note: Number of observations — 2954 from 01.01.2013 to 31.01.2021.

Emerging Markets Asia (MSCI EM-Asia), FTSE World Government Bond Index (the dynamics are taken through the dynamics of the price of shares of the exchange-traded fund IGOV), CBOE Volatility Index (VIX), as well as the US dollar index (DXY), prices for gold and Brent oil. All data is sourced from Yahoo. Finance,[3] except for MSCI indices, taken from Investing. com.[4] *Table 4* presents descriptive statistics of logarithmic returns of traditional financial assets.

METHODOLOGY

To analyze the relationship of certain variables with cryptocurrency returns, we use the conditional generalized heteroskedasticity GARCH (1,1) model. In general terms, the models look like this:

$$r_t = \mu + x_t'\theta + \varepsilon_t, \tag{1}$$

$$\varepsilon_t = \sqrt{h_t}\eta_t, \quad \eta_t \sim i.i.d.GED(0,1,\kappa), \tag{2}$$

$$h_t = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + x_t'c, \tag{3}$$

where r_t — logarithmic profitability of cryptocurrencies ($\ln\frac{p_t}{p_{t-1}}$); x_t' — a vector of independent variables.

The choice of models of this class is due to the presence of heteroskedasticity in the series of returns on financial assets and cryptocurrencies [32], which must be considered to obtain correct confidence intervals and inference (statistical conclusions). The use of inappropriate conditional distribution of errors, which are assumed to be normally distributed in the standard GARCH model, can also lead to incorrect estimates of the confidence intervals. In the academic literature devoted to the analysis of the dynamics of returns, the problem of the discrepancy between the distribution of returns on assets and the normal distribution has been

[3] URL: https://finance.yahoo.com/ (accessed on 10.02.2021).
[4] URL: https://www.investing.com/ (accessed on 10.02.2021).

Table 4

Descriptive statistics of traditional financial assets

Asset	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
brent	−0.00024	0.02055	−0.27976	0.27419	−0.66	39.22
dxy	0.00004	0.00346	−0.02399	0.02032	0.00	4.13
eurusd	−0.00003	0.00423	−0.02814	0.03126	0.02	6.02
gold	0.00003	0.00825	−0.09821	0.05778	−0.67	13.98
igov	0.00003	0.00386	−0.02325	0.02316	−0.15	4.33
msci_acwi	0.00022	0.00735	−0.09997	0.08059	−1.82	35.63
msci_em	−0.00013	0.01102	−0.10619	0.06015	−0.84	8.81
msci_em_asia	0.00017	0.00813	−0.05846	0.05625	−0.57	7.12
sp500	0.00032	0.00897	−0.12765	0.08968	−1.24	33.95
vix	0.00028	0.06715	−0.29983	0.76825	1.60	12.21

Source: authors' calculations based on the data from Yahoo.finance, Investing.com (accessed on 10.02.2021).

Note: Number of observations — 2954 from 01.01.2013 to 31.01.2021. Returns during weekends and holidays are stated as 0.

raised for a long time (see, for example, [33, 34]). In particular, it has been shown that the distribution of returns on financial assets has heavy tails and a higher kurtosis coefficient than the normal distribution [32]. In the tables with descriptive statistics above, you can see that redundant, i.e. more than 3, kurtosis (leptokurtosis) is present in the distributions of returns of all cryptocurrencies and financial assets. The order of the GARCH (*p, q*) с $p = q = 1$ was chosen on the ARCH LM test [35].

In the context of conditional heteroskedasticity models, this means that the distribution of innovations η_t will often also be far from normal. In this regard, there is a practice of using other distributions, for example, Student's *t*-distribution, generalized normal distribution, Pareto stable distribution, and others, as well as their "skewed" variants (see, for example, works [25, 36–38]).

In this paper, we use the Generalized Error Distribution (GED), which has an additional shape parameter κ. For $\kappa = 1$ GED corresponds to the Laplace distribution (double exponential), for $\kappa = 2$ GED — normal, and for $\kappa \to \infty$ — pointwise converges to a uniform distribution.

The models are estimated using the maximum likelihood method in the rugarch package written in R [39].[5] A number of tests are used to diagnose the quality of the evaluated models. The modernized Ljung-Box test [35] makes it possible to assess the adequacy of the mean equation (4). The null hypothesis of this test is that there is no autocorrelation in the residuals of the model. Pearson's test in the version of Vlaar and Palm [40] as a null hypothesis has the correspondence of the distribution of model errors to the selected conditional distribution (GED). Akaike Information Criterion (AIC) and

[5] R version 4.0.3, rugarch version — 1.4–4. The arguments to the ugarchfit function are used by default, except for solver = "hybrid".

Table 5

Correlation matrix of factors

BTC	r_t	vol_t	vol_b	new	act	trans	hash	fee_m	fee_t	"bitcoin"	"blockchain"
r_t		−0.05	0.10	0.03	0.01	0.09	−0.01	0.18	0.17	−0.03	0.02
vol_t	−0.05		0.49	0.34	0.29	0.24	0.01	0.17	0.29	0.41	0.07
vol_b	0.10	0.49		0.56	0.44	0.45	−0.04	0.30	0.50	0.32	0.10
new	0.03	0.34	0.56		0.77	0.17	0.18	0.13	0.48	0.27	0.09
act	0.01	0.29	0.44	0.77		0.14	0.23	0.20	0.45	0.24	0.08
trans	0.09	0.24	0.45	0.17	0.14		−0.13	0.17	0.19	0.16	0.03
hashrate	−0.01	0.01	−0.04	0.18	0.23	−0.13		−0.11	0.04	−0.01	0.02
fee_m	0.18	0.17	0.30	0.13	0.20	0.17	−0.11		0.89	0.18	0.07
fee_t	0.17	0.29	0.50	0.48	0.45	0.19	0.04	0.89		0.27	0.11
"bitcoin"	−0.03	0.41	0.32	0.27	0.24	0.16	−0.01	0.18	0.27		0.07
"blockchain"	0.02	0.07	0.10	0.09	0.08	0.03	0.02	0.07	0.11	0.07	

Source: authors' calculations based on the data from Cryptocompare.com, Coinmetrics.io, trends.google.com (accessed on 10.02.2021).

Schwarz Criterion (BIC) are used to compare models with each other.

INTERNAL FACTORS OF BITCOIN PROFITABILITY

Let us now analyze the relationship between internal factors and bitcoin yields. *Table 5* shows the correlation matrix of the difference between the logarithms of the factors under consideration (bitcoin returns are denoted as r_t).

A significant positive correlation is observed between such similar indicators as an increase in the number of active (act) and new users (new), as well as the total and average size of commissions (fee_m, fee_t). To identify higher quality variables from each pair, GARCH models of bitcoin returns were analyzed separately using each indicator separately. Akaike and Schwartz's tests showed that models with the addition of fee_t and new to the mean equation improve model quality better than fee_m and act. Thus, further in this article, we will use in our models the indicator of the total amount of commission in the blockchain per day (fee_t) and the number of new users in the network (new).[6]

We alternately use all internal factors as independent variables in the mean equation.[7] We also add an indicator of trade volumes to the variance equation. The relationship between returns on financial assets, their volatility and volume are actively studied in the scientific literature (for example, [41]). Some cryptocurrency researchers have also found the impact of trading volume on cryptocurrency volatility.[8] Adding this indicator significantly improves the quality of the model.

Table 6 shows the results of evaluating the models of the influence of internal factors on the daily profitability of the bitcoin cryptocurrency in the period from April 01, 2014, to May 01, 2017. The table shows the coefficients of interest for the GARCH (1,1) — GED model, into which each factor was substituted alternately. In all the evaluated models, the shape coefficient (κ) is in the range from 0.98 to 1.11, which is evidence in favor of the heavy-tailed distribution in the residues. Pearson's test does not reject the null hypothesis that the theoretical distribution

[6] These and other intermediate calculations are available upon request from the authors.

[7] Adding multiple factors at once to the mean equation does not result in significant improvements in terms of model quality over single-factor models. These results are also available upon request.

[8] See, for example, [28, 30].

Table 6

The estimation results of GARCH(1,1)-GED models in the period from 01.04.2014 to 01.05.2017

Factor	Coefficients			LogL	AIC	BIC
	θ	c	κ			
vol_t	0.00591***	0.00064***	1.04088***	2692.86	−4.7664	−4.7352
fee_t	0.00926***	0.00047***	1.04674***	2690.48	−4.7622	−4.7309
trans	0.00142***	0.0005***	1.06456***	2690.28	−4.7618	−4.7306
vol_b	0.00324***	0.0006***	1.02174***	2689.77	−4.7609	−4.7297
new	*0.00744*	*0.0004***	*0.99467*	*2678.68*	*−4.7412*	*−4.71*
without factors		0.0004***	1.04896***	2675.33	−4.7371	−4.7103
“bitcoin”	−0.00156	0.00038***	1.01169***	2670.95	−4.7275	−4.6963
hashrate	0.0025*	0.00035***	0.99839***	2662.89	−4.7132	−4.682
“blockchain”	−0.00005	0.00026***	0.98802***	2652.16	−4.6942	−4.6629

Source: authors’ calculations based on the data from Cryptocompare.com, Coinmetrics.io, trends.google.com (accessed on 10.02.2021).

Note: Dependent variable – bitcoin logarithmic returns, θ – coefficient of factor in the mean equation, c – coefficient of trading exchange volume logarithmic difference in the volatility equation, κ – estimated shape parameter of GED distribution. Statistical significance is distinguished with asterisks, where *** – 1% level. μ, ω, α_1 and β_1 coefficient estimates are omitted for the reason of space economy. Models are presented in a descending order of LogL. The models with AIC and BIC lower than the model without factors are italicized. Number of observations – 1127.

matches the empirical distribution for the residuals of all models, therefore, the GED distribution is suitable. Also, the ARCH-LM and Ljung-Box tests do not reject their null hypotheses, which speaks in favor of the correct choice of the GARCH order and the absence of autocorrelation in the residuals, respectively.

In the period before the start of the 2017 bubble, the significant factors that had a co-directional movement with the returns of the bitcoin cryptocurrency were the trading volume (vol_t), the total amount of commissions for the movement of the cryptocurrency in the blockchain (fee_t), the average transaction volume in the blockchain (trans) and directly daily the volume of transactions on the blockchain (vol_b). Models that include these variables are also more preferable in terms of the Akaike and Schwarz criteria than the model without any factors included in the mean equation. The largest coefficient is observed with a fee_t of 0.00926. The direct calculation,[9] in this case, gives us the following interpretation: an increase in total daily commissions by 1 standard deviation relative to the average is associated with an increase in the price of bitcoin by almost 0.94%. It is noteworthy that the coefficients for search queries for the keywords “bitcoin” and “blockchain” turned out to be insignificant, as well as the complexity of mining (hash rate).

The relationship between the trading volume can be traced both with the returns of bitcoin — an increase in volumes by 1 standard deviation is associated with an increase in cryptocurrency by 0.01%,— and with volatility — the coefficient c_1 at vol_t in the dispersion equation turned out to be significant in all models with an average value around 0.0005.

In the period after the collapse of the bubble in the cryptocurrency market and before the start of the recession in the financial markets

[9] Hereinafter, it is calculated analytically depending on how many percent is one standard deviation of the value compared to the mean.

Table 7

The estimation results of GARCH(1,1)-GED models in the period from 01.05.2018 to 01.03.2020

Factor	Coefficients			LogL	AIC	BIC
	θ	c	κ			
blockchain	0.00141***	0.00107***	1.5123***	1505.5	–4.467	–4.42
vol_b	–0.00684***	0.00101***	1.42861***	1497.5	–4.443	–4.396
fee_t	0.0011**	0.00095***	1.45237***	1491.1	–4.424	–4.377
trans	–0.00514***	0.00082***	1.38016***	1486.3	–4.409	–4.362
vol_t	*–0.00213****	*0.00096****	*1.31626****	*1484.2*	*–4.403*	*–4.356*
bitcoin	*–0.00009*	*0.00095****	*1.30604****	*1483*	*–4.399*	*–4.352*
without factors		0.00073***	1.31361***	1482.2	–4.4	–4.36
new	–0.01826***	0.0008***	1.07529***	1479.4	–4.389	–4.342
hashrate	–0.01403**	0.00045***	1.2087**	1466.7	–4.351	–4.304

Source: authors' calculations based on the data from Cryptocompare.com, Coinmetrics.io, trends.google.com (accessed on 10.02.2021).

Note: Number of observations — 671. Detailed note can be found in *Table 6*.

against the backdrop of the COVID-19 pandemic (from May 01, 2018, to March 01, 2020), the simulation results are slightly different (*Table 7*).

Not all of the models built for this period are sufficiently adequate in terms of quality criteria. So, for models with the volume of transactions on the blockchain (vol_b) and search queries "blockchain", the null hypothesis of the Ljung-Box test is rejected at 10 and 5% levels, respectively, which indicates the presence of autocorrelation in the mean equation. The null hypothesis of the ARCH-LM test is rejected for higher-order lags (more than 5) for models with an average transaction volume on the blockchain (trans) and again for "blockchain" queries, which may indicate the need to select more complex variants of GARCH models to describe the dynamics of the considered variables. The null hypothesis of the Pearson's test is rejected for the model with network complexity (hashrate).

The first thing that can be paid attention to in comparison with the previous models is the increase in the coefficient with the GED distribution shape index to 1.3–1.5, which indicates a slight decrease in the severity of the distribution tails. In other words, relatively large negative or positive changes in the price of Bitcoin were observed less frequently during this period.

The second is a change in the signs of almost all significant coefficients in the model (except for fee_t and blockchain) under the analyzed factors. Now all the factors that had a positive association with Bitcoin returns have changed a sign or become insignificant. The change in signs may indicate the fact that after the bubble collapsed in 2017, investors became much more cautious and closed their positions at the first signs of a correction. This is evidenced by negative coefficients in terms of trading volume and volume in the blockchain — a fall in the price of bitcoin is accompanied by larger volumes than an increase.

Among the models with higher AIC and BIC model fitting criteria than the model without factors, the highest ratio in absolute terms is observed with the volume on the Bitcoin blockchain (vol_b) — an increase in this indicator by 1 standard deviation relative to the average is associated with a fall in the price of Bitcoin by 0.27%.

Let us now extend the considered period after the bubble to January 31, 2021 (*Table 8*),

Table 8

The estimation results of GARCH(1,1)-GED models in the period from 01.05.2018 to 31.01.2021

Factor	Coefficients			LogL	AIC	BIC
	θ	c	κ			
trans	0.00016***	0.00087***	1.23774***	2189.9	−4.336	−4.301
without factors		0.00083***	1.25033***	2181	−4.315	−4.286
vol_t	0.0021***	0.00084***	1.21561***	2178.9	−4.314	−4.28
blockchain	−0.00138	0.00097***	1.19162***	2148.8	−4.2538	−4.2197
fee_t	0.0013	0.00105**	1.23667***	2174.4	−4.305	−4.271
vol_b	−0.00206***	0.00085***	1.35423***	2171.6	−4.299	−4.265
new	−0.01653***	0.00081***	1.12956***	2163.6	−4.283	−4.249
bitcoin	0.02863**	0.00078***	1.21506***	2157	−4.27	−4.236
hashrate	−0.01883***	0.0005***	1.0885***	2148.8	−4.254	−4.22

Source: authors' calculations based on the data from Cryptocompare.com, Coinmetrics.io, trends.google.com (accessed on 10.02.2021).
Note: Number of observations — 1007. Detailed note can be found in *Table 6*.

i.e. we will include the period of the COVID-19 pandemic and the beginning of a new rally in the cryptocurrency market.

Including a period of high volatility and extreme values as returns at the bitcoin price level degraded the quality of the models. Thus, the null hypothesis of the Ljung-Box test can be rejected at the 10% significance level for all models (except for the hashrate model) and most lags. Pearson's null hypothesis can also be rejected for almost all models, with the exception of models with the number of new users (new) and search terms "bitcoin".[10] The null hypothesis ARCH-LM is not rejected for all models; therefore, the conditional heteroskedasticity model from order (1.1) considers all heteroskedasticity in residuals.

From the point of view of the AIC and BIC criteria, only the model that considers the average transaction volume in the blockchain (trans) is slightly better than the model without factors. It is noteworthy that when adding a period from 01.03.2020, the coefficient for trans changed its sign from negative to positive. This may be due to the fact that during the new cycle of bitcoin price growth, investors who made investments at its peak in 2017 began to withdraw their funds. In 2017, it was difficult to enter fiat funds on cryptocurrency exchanges, so the purchase was mainly carried out through p2p (peer-to-peer) platforms, where purchase and sale transactions were concluded directly. Now these funds are in motion.

Also, we note that the popularity rate of the search query "bitcoin" became significant and reached the highest value among all previously evaluated models — 0.02863. That is, with an increase in the popularity of search queries by 1%, the price of bitcoin cryptocurrency grows by almost 0.03%, and with an increase in search queries by 1 standard deviation relative to the average, the price rises by 1.27%. It seems that this result is largely a direct consequence of the rise in bitcoin price: the higher the price became against the background of the recovery growth after the fall of the markets due to the pandemic, the more the media talked about it, which led to an increase in interest, which we see in popular Google Trends queries. The rise

[10] Using the normal, normal skew, Student's t-distribution and skewed Student's distribution, and skewed GED distribution, similar results are observed.

in interest leads to an inflow of investment in bitcoin, which reaches the next all-time high in prices, which leads to an increase in media mentions, etc. However, in terms of the AIC and BIC quality criteria, this model is worse than the model without factors.

Separately, we note that we were unable to find a stable short-term relationship between profitability and the dynamics of Google Trends search popularity using the chosen methodology. This result is somewhat different from the works in which a similar relationship was revealed (for example, [22, 23]), however, results similar to ours were obtained in the work of H.A. Aalborg, P. Molnár, J.E. de Vries [28]. The significance of the popularity ratio for the request "bitcoin" at a time when the largest cryptocurrency is experiencing a period of rapid growth again, may indicate a bubble in the cryptocurrency market. This is also evidenced by the fact that in recent years there have been no significant improvements or changes either in the technical part or in the regulatory part, therefore there are no fundamental reasons for such rapid growth.

The indicator characterizing the number of new wallets opened on the bitcoin blockchain (new) is also a kind of indicator of popularity, albeit somewhat noisy due to the fact that any user can open any number of wallets. In the period until 2017, the coefficient for this factor turned out to be insignificant, however, in subsequent periods, the increase in the number of wallets was associated with the fall in the price of bitcoin.

The results for such an indicator as to the difficulty of mining (hashrate) also coincide with the results of D. Fantazzini and N. Kolodin [42], who did not find a connection between the hashrate and the price of bitcoin in the period from 2016 to December 2017 and in the period from December 2017 year to February 2020 found a significant relationship, with the authors demonstrating bitcoin profitability as the hashrate Granger causes. S. Shanaev et al. [43] also found no significant relationship between bitcoin and hash rate in the sample from January 2014 to May 2019. Thus, our results, as well as the works listed above, cast doubt on the theory according to which the profitability of bitcoins is determined mainly at the cost of mining.

RELATIONSHIP WITH TRADITIONAL FINANCIAL ASSETS

We consider the relationship between the return on traditional financial assets and the return on bitcoin. It seems most obvious to demonstrate changes in this relationship using correlation matrices built for different periods.

In the period until May 2017 (*Fig. 3*), the profitability of those cryptocurrencies that already existed at that time (Bitcoin, Ethereum, Ripple, Litecoin, Stellar) had a relatively small correlation even among themselves and did not have a significant correlation with other market assets.

After the bubble burst in the cryptocurrency market (*Fig. 4*), we can observe how the returns of the largest cryptocurrencies, to which, compared to the previous period, Binance Coin (BNB) and Cardano (ADA) were added that appeared by that time, became extremely highly correlated. We can say that in the period from May 2018 to February 2020, cryptocurrencies formed as a separate class of financial assets. The dynamics of cryptocurrencies at this stage did not significantly correlate with any market assets, which made them an attractive tool for diversifying the investment portfolio.

The COVID-19 pandemic caused a significant downturn in financial markets, which also affected the cryptocurrency market. The correlation matrix, based on data covering all of 2020 and early 2021 (*Fig. 5*), shows an increase in the correlation between the returns of all major cryptocurrencies and market assets, in particular, the S&P 500 and MSCI World indices. Thus, cryptocurrencies failed to act as a short-term hedging instrument during the general recession.

Now we analyze the combined dynamics of bitcoin returns and various market factors using GARCH(1,1)-GED models. As in the

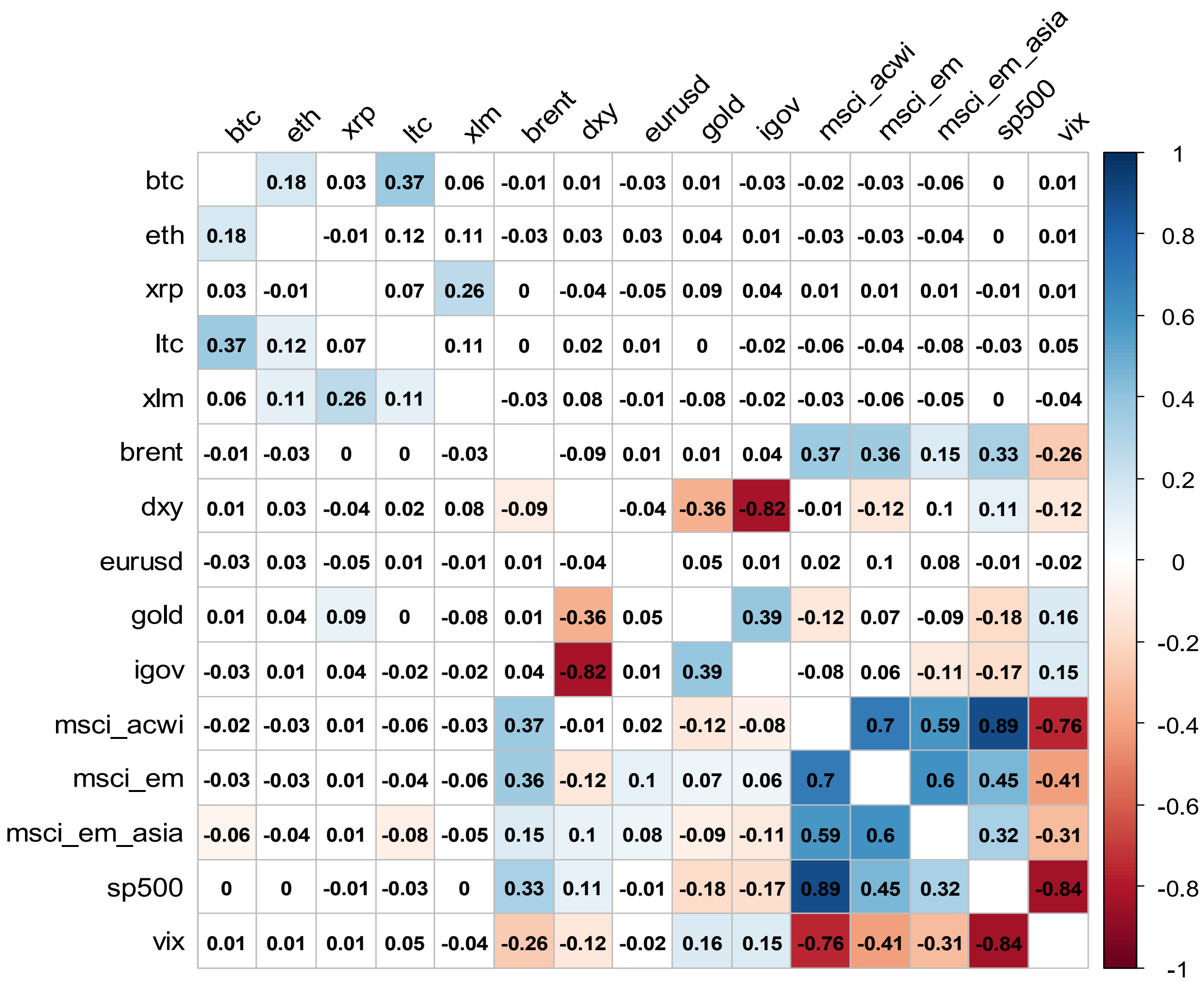

Fig. 3. **Correlation matrix of returns from 01.04.2014 to 01.05.2017**

Source: authors' calculations based on the data from Cryptocompare.com, Yahoo.finance, Investing.com (accessed on 10.02.2021).

previous section, we alternately replace in the equation of the average return of market assets, and in the equation of variance — the difference in the logarithms of the exchange trading volume of bitcoin on cryptocurrency exchanges, which significantly improves the model in terms of quality criteria.

Table 9 presents the results of assessing the models of the influence of market factors on the daily profitability of the bitcoin cryptocurrency in the period from April 1, 2014, to May 1, 2017.

For all evaluated models, the null hypotheses of the Ljung-Box, ARCH-LM, and Pearson's tests are rejected, indicating that there is no unaccounted-for autocorrelation in the mean equation, an appropriate order of GARCH model, and a consistency of the conditional distribution to the actual.

The inclusion of one of three market factors — the S&P 500 index yields, the euro/dollar exchange rate and Brent oil — improves the quality of the model in terms of the Akaike and Schwartz criteria compared to the model without factors. The coefficients for all three factors are significant and positive, but they are not very large — a 1% increase in the S&P 500 or Brent is associated with an increase in bitcoin by only 0.043–0.044%. However, the S&P 500 index yield model is the best in terms of the AIC and BIC criteria, even compared to the models with intrinsic factors discussed in the previous section.

It is worth noting the significant and negative sign of the index of the stock market of

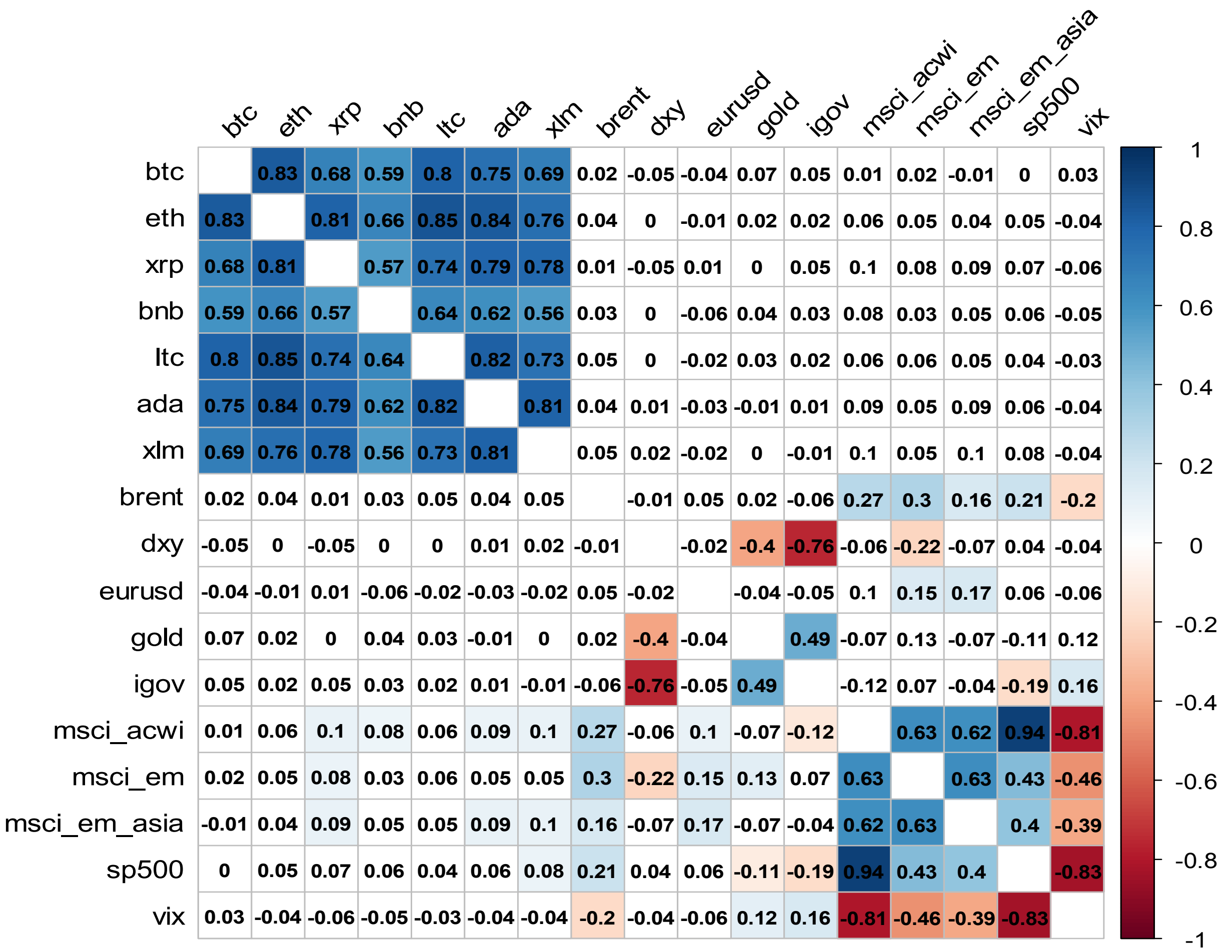

Fig. 4. **Correlation matrix of returns from 01.05.2018 to 01.03.2020**

Source: authors' calculations based on the data from Cryptocompare.com, Yahoo.finance, Investing.com (accessed on 10.02.2021).

developing countries in Asia (MSCI EM ASIA) — a decrease in this index by 1% was associated with a rise in bitcoin by 0.38%. We note the positive ratios for gold and the volatility index. To some extent, these results can be interpreted as the presence of "protective properties" in bitcoin, which are most pronounced in relation to the market of developing countries in Asia.

In the period from May 2018 to March 2020, a different situation is observed (*Table 10*). The null hypothesis of the Ljung-Box tests rejects at the 10% significance level for the gold and developing country index (MSCI EM) models. For the S&P 500 model, the null hypothesis of this test is rejected even at the 5% level, and the null hypothesis of the ARCH-LM test is also rejected. For the model with gold, the null hypothesis of the Pearson test is also rejected.

Compared to the previous period, the yields of the S&P 500, Brent oil and the volatility index (VIX) became insignificant, while the emerging market index (MSCI EM ASIA) changed sign. Also noteworthy is the high positive and significant ratio of the non-US investment grade government bond index (IGOV), which was negligible in the previous period. The positive index for the emerging market index (MSCI EM) and the negative coefficient for the US dollar index (DXY) also became significant.

Model results for this period appear mixed, reflecting general investor uncertainty about the outlook for the largest cryptocurrency after the 2017–2018 bubble crash. Nevertheless, with a certain degree of confidence, we can say about the lack of co-directionality of bitcoin's movement with the US stock market (S&P

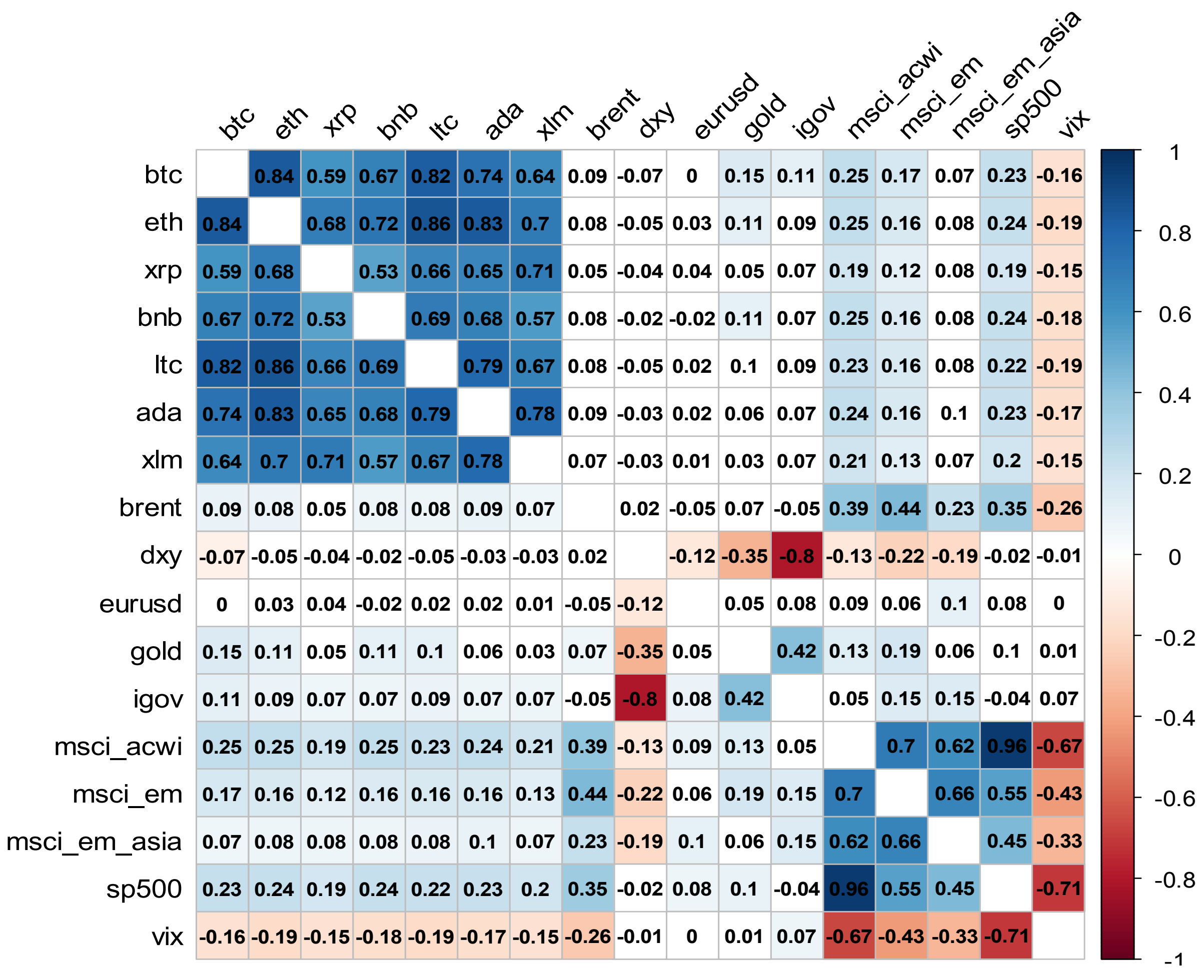

Fig. 5. **Correlation matrix of returns from 01.05.2018 to 31.01.2021**

Source: authors' calculations based on the data from Cryptocompare.com, Yahoo.finance, Investing.com (accessed on 10.02.2021).

500) and with the VIX volatility index, which is the exact opposite of the S&P 500 in terms of the dynamics of profitability (as can be seen from the correlation matrices above). Now let's look at the results, including the period of the COVID-19 pandemic in the model (*Table 11*).

The extreme volatility of financial asset returns affected the quality of the models. Despite the rejection of the null hypothesis of the ARCH-LM test for all models, the null hypothesis of the Lyng-Box test is rejected at normal significance levels almost everywhere (the only exception is the model with the euro-dollar pair). Pearson's null hypothesis is not rejected for the US dollar index (DXY), bond index (IGOV), emerging market indices (MSCI EM), and global stock market (MSCI ACWI) models. The model with the last index is also the best among the others in *Table 11*.

When we include the COVID-19 pandemic period, we can observe how bitcoin returns show a positive and significant relationship with global stock markets (MSCI ACWI, MSCI EM, and S&P 500) and a significant negative relationship with those assets that showed the opposite dynamics — US dollar indices (DXY) and volatility (VIX). In other words, it can be argued that Bitcoin dynamics in the period after March 2020 was characterized by a unidirectional movement with the general market situation.

CONCLUSIONS

In this article, we attempted to identify various factors, the dynamics of which are associated with the profitability of the first and largest cryptocurrency in terms of capitalization — bitcoin. Unlike other studies that conduct

Table 9

The estimation results of GARCH(1,1)-GED models in the period from 01.04.2014 to 01.05.2017

Market factor	Coefficients			LogL	AIC	BIC
	θ	*c*	κ			
sp500	0.04257***	0.00058***	1.13723***	2695.35	−4.7708	−4.7396
eurusd	0.17948***	0.00048***	1.04244***	2680.23	−4.744	−4.7127
brent	0.04397***	0.00043***	1.02758***	2678.92	−4.7417	−4.7104
without factors		0.0004***	1.04896***	2675.33	−4.7371	−4.7103
igov	0.00521	0.00039***	1.07534***	2672.64	−4.7305	−4.6993
msci_em_asia	−0.38475***	0.00061***	1.03255***	2670.82	−4.7273	−4.696
vix	0.00633***	0.0004***	1.01608***	2669.29	−4.7246	−4.6933
dxy	−0.01932	0.00038***	1.00402***	2666.98	−4.7205	−4.6892
gold	0.11313***	0.0004***	1.00725***	2665.44	−4.7177	−4.6865
msci_em	0.01697	0.00024***	0.92895***	2641.34	−4.675	−4.6437
msci_acwi	−0.1337***	0	0.8013***	2588.3	−4.5808	−4.5496

Source: authors' calculations based on the data from Cryptocompare.com, Yahoo.Finance, Investing.com (accessed on 10.02.2021).
Note: Number of observations — 1127. Detailed note can be found in *Table 6*.

Table 10

The estimation results of GARCH(1,1)-GED models in the period from 01.05.2018 to 01.03.2020

Market factor	Coefficients			LogL	AIC	BIC
	θ	*c*	κ			
gold	0.33708***	0.00079***	1.33132***	1489.76	−4.4196	−4.3725
sp500	0.02126	0.00074***	1.38253***	1488.3	−4.4152	−4.3682
brent	−0.00753	0.00101***	1.41934***	1487.59	−4.4131	−4.366
msci_em	*0.29278****	*0.00079****	*1.32554****	*1484.7*	*−4.4045*	*−4.3574*
vix	*−0.01825*	*0.00095*	*1.34834*	*1484.64*	*−4.4043*	*−4.3572*
igov	*0.78065****	*0.00071****	*1.29811****	*1483.67*	*−4.4014*	*−4.3544*
without factors		0.00073***	1.31361***	1482.24	−4.4001	−4.3598
dxy	−0.5581***	0.0007***	1.24822***	1481.67	−4.3955	−4.3484
msci_em_asia	0.20601***	0.00067***	1.28699***	1479.67	−4.3895	−4.3424
eurusd	0.4884***	0	0.85611***	1395.87	−4.1397	−4.0927
msci_acwi	0.34154***	0	0.82817***	1395.01	−4.1372	−4.0901

Source: authors' calculations based on the data from Cryptocompare.com, Yahoo.Finance, Investing.com (accessed on 10.02.2021).
Note: Number of observations — 671. Detailed note can be found in *Table 6*.

Table 11

The estimation results of GARCH(1,1)-GED models in the period from 01.05.2018 to 31.01.2021

Market factor	Coefficients			LogL	AIC	BIC
	θ	c	κ			
msci_acwi	0.48536***	0.00077	1.31236	2186.2	−4.328	−4.294
gold	0.40108***	0.00081***	1.16489***	2185.6	−4.327	−4.293
vix	−0.04124***	0.00081***	1.2485***	2183.6	−4.323	−4.289
msci_em	0.32014***	0.00087***	1.18084***	2183.4	−4.323	−4.288
msci_em_asia	*−0.03771*	*0.00086*	*1.18964*	*2181.7*	*−4.319*	*−4.285*
without factors		0.00083***	1.25033***	2181	−4.315	−4.286
sp500	0.31468***	0.00087***	1.21611***	2178.7	−4.313	−4.279
igov	1.04893***	0.00069***	1.23309***	2178.6	−4.313	−4.279
brent	0.03565	0.0007	1.21103***	2173.2	−4.302	−4.268
dxy	−0.76362***	0.00082***	1.14819***	2164.4	−4.285	−4.251
eurusd	−0.01119***	0	0.84322***	2061.1	−4.08	−4.046

Source: authors' calculations based on the data from Cryptocompare.com, Yahoo.Finance, Investing.com (accessed on 10.02.2021).
Note: Number of observations — 1007. Detailed note can be found in *Table 6*.

econometric and statistical analysis for the entire available period, we excluded from consideration the periods of two known bubbles in the dynamics of the price of bitcoin — at the end of 2013 and in 2017–2018, and also analyzed the period separately without considering the COVID-19 pandemic and with it. Considering the presence of heavy tails and unstable variance in the yield distribution of the bitcoin, we used conditional heteroskedasticity models with generalized normal distribution (GED) errors as the main method.

Our analysis allows us to draw the following conclusions. First, the dynamics of bitcoin have no connection with the indicators of complexity (hashrate), and therefore, with mining. If there was a connection, then an increase in the complexity of mining would lead to an increase in the price, but in the period until 2017 this was not observed, and after that, it was rather the opposite.

Second, we did not find a significant relationship between the dynamics of popular search queries and the dynamics of bitcoin in the period before the 2017 bubble. A possible explanation for this is precisely the fact that we excluded the period of the bubble. The graphs clearly show that the peak of popularity was during the period of the bubble. The inclusion of the COVID-19 pandemic period in the analysis also revealed a significant correlation between the dynamics of search queries and the profitability of bitcoin. It seems that this result may be an indirect sign that currently (as of the first half of 2021) we are witnessing another bubble.

Third, an analysis of the relationship between the profitability of bitcoin and other traditional assets revealed that this cryptocurrency is gradually becoming a part of the modern space of financial instruments. During a downturn in the markets, bitcoin, like any high-risk asset, fell more than the stock market, followed by an increase that many times exceeded the growth of other financial assets.

Thus, the results of our analysis demonstrate the absence of a stable relationship between bitcoin yields over the entire period under consideration (from 2014 to the beginning of 2021), both with internal factors related directly to the numerical indicators of the cryptocurrency blockchain and the dynamics of its popularity and with a number of traditional financial assets. However, there has been a recent trend in the perception of cryptocurrencies by investors, and bitcoin in particular, as a specific financial asset with a high degree of risk, which is a rather attractive means of diversification. The demand for cryptocurrencies from market players is growing, which is reflected, for example, in the rapid growth of assets under the management of the Grayscale Bitcoin Trust, whose shares are traded on the OTC market. Investors expect the launch of exchange-traded funds (ETFs) from major financial institutions as Fidelity and VanEck, which will allow them to add cryptocurrency to their investment portfolios in a completely legal, transparent manner and with low fees. The launch of such ETFs could contribute to further growth in cryptocurrency prices.

ACKNOWLEDGEMENT

The article was written on the basis of the RANEPA state assignment research programme. RANEPA, Moscow, Russia.

REFERENCES

1. Stolbov M.I. The 10th anniversary of the cryptocurrency market: Its current state and prospects. *Voprosy ekonomiki*. 2019;(5):136–148. (In Russ.). DOI: 10.32609/0042–8736–2019–5–136–148
2. Shilov K.D., Zubarev A.V. Blockchain and distributed ledgers as a type of database. *Innovatsii = Innovations*. 2018;12:77–87. (In Russ.).
3. Sinel'nikova-Muryleva E.V., Shilov K.D., Zubarev A.V. The essence of cryptocurrencies: Descriptive and comparative analysis. *Finansy: teoriya i praktika = Finance: Theory and Practice*. 2019;23(6):36–49. (In Russ.). DOI: 10.26794/2587–5671–2019–23–6–36–49
4. Sockin M., Xiong W. A model of cryptocurrencies. NBER Working Paper. 2020;(26816). DOI: 10.3386/w26816
5. Gans J.S., Halaburda H. Some economics of private digital currency. In: Goldfarb A., Greenstein S.M., Tucker C.E., eds. Economic analysis of the digital economy. Chicago, IL: University of Chicago Press; 2015:257–276. DOI: 10.7208/chicago/9780226206981.003.0009
6. Biais B., Bisiere C., Bouvard M., Casamatta C., Menkveld A.J. Equilibrium Bitcoin pricing. *SSRN Electronic Journal*. 2020. DOI: 10.2139/ssrn.3261063
7. Cong L.W., Li Y., Wang N. Tokenomics: Dynamic adoption and valuation. *The Review of Financial Studies*. 2021;34(3):1105–1155. DOI: 10.1093/rfs/hhaa089
8. Chiu J., Koeppl T.V. The economics of cryptocurrencies — Bitcoin and beyond. *SSRN Electronic Journal*. 2017. DOI: 10.2139/ssrn3048124
9. Hayes A.S. Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics* 2017;34(7):1308–1321. DOI: 10.1016/j.tele.2016.05.005
10. Catalini C., Gans J.S. Initial coin offerings and the value of crypto tokens. NBER Working Paper. 2018;(24418). DOI: 10.3386/w24418
11. Chod J., Lyandres E. A theory of ICOs: Diversification, agency, and information asymmetry. *Management Science*. 2021. In press. DOI: 10.1287/mnsc.2020.3754
12. Simonov A., Zyamalov V. Long run return and survival factors of ICO. *Ekonomicheskii zhurnal Vysshei shkoly ekonomiki = The HSE Economic Journal*. 2019;23(4):585–604. (In Russ.). DOI: 10.17323/1813–8691–2019–23–4–585–604
13. Dyhrberg A.H. Bitcoin, gold and the dollar — A GARCH volatility analysis. *Finance Research Letters*. 2016;16:85–92. DOI: 10.1016/j.frl.2015.10.008

14. Baur D.G., Dimpfl T., Kuck K. Bitcoin, gold and the US dollar — A replication and extension. *Finance Research Letters*. 2018;25:103–110. DOI: 10.1016/j.frl.2017.10.012
15. Klein T., Pham Thu H., Walther T. Bitcoin is not the New Gold — A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*. 2018;59:105–116. DOI: 10.1016/j.irfa.2018.07.010
16. Shahzad S.J.H., Bouri E., Roubaud D., Kristoufek L., Lucey B. Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis*. 2019;63:322–330. DOI: 10.1016/j.irfa.2019.01.002
17. Urquhart A., Zhang H. Is Bitcoin a hedge or safe haven for currencies? An intraday analysis. *International Review of Financial Analysis*. 2019;63:49–57. DOI: 10.1016/j.irfa.2019.02.009
18. Shahzad S.J.H., Balli F., Naeem M.A., Hasan M., Arif M. Do conventional currencies hedge cryptocurrencies? *The Quarterly Review of Economics and Finance.* 2021. In press. DOI: 10.1016/j.qref.2021.01.008
19. Glaser F., Zimmermann K., Haferkorn M., Weber M.C., Siering M. Bitcoin — Asset or currency? Revealing users' hidden intentions. In: Proc. 22nd European conf. on information systems (ECIS-2014). (Tel Aviv, June 9–11, 2014). Frankfurt am Main: Goethe University; 2014. URL: https://www.researchgate.net/publication/286338705_Bitcoin_-_Asset_or_currency_Revealing_users'_hidden_intentions
20. Baur D.G., Hong K., Lee A.D. Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*. 2018;54:177–189. DOI: 10.1016/j.intfin.2017.12.004
21. Krylov G.O., Lisitsyn A. Yu., Polyakov L.I. Comparative analysis of volatility of cryptocurrencies and fiat money. *Finansy: teoriya i praktika = Finance: Theory and Practice.* 2018;22(2):66–89. (In Russ.). DOI: 10.26794/2587–5671–2018–22–2–66–89
22. Liu Y., Tsyvinski A. Risks and returns of cryptocurrency. *The Review of Financial Studies.* 2021;34(6):2689–2727. DOI: 10.1093/rfs/hhaa113
23. Dastgir S., Demir E., Downing G., Gozgor G., Lau C.K.M. The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the Copula-based Granger causality test. *Finance Research Letters*. 2019;28:160–164. DOI: 10.1016/j.frl.2018.04.019
24. Liu Y., Tsyvinski A., Wu X. Common risk factors in cryptocurrency. NBER Working Paper. 2019;(25882). DOI: 10.3386/w25882
25. Chu J., Chan S., Nadarajah S., Osterrieder J. GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management*. 2017;10(4):17. DOI: 10.3390/jrfm10040017
26. Malkina M. Yu., Ovchinnikov V.N. Cryptocurrency market: Overreaction to news and herd instincts. *Ekonomicheskaya politika = Economic Policy*. 2020;15(3):74–105. (In Russ.). DOI: 10.18288/1994–5124–2020–3–74–105
27. Fedorova E.A., Bechvaya K.Z., Rogov O. Yu. The influence of the tonality of news on the exchange rate of Bitcoin. *Finansy: teoriya i praktika = Finance: Theory and Practice*. 2018;22(4):104–113. (In Russ.). DOI: 10.26794/2587–5671–2018–22–4–104–113
28. Aalborg H.A., Molnár P., de Vries J.E. What can explain the price, volatility and trading volume of Bitcoin? *Finance Research Letters*. 2019;29:255–265. DOI: 10.1016/j.frl.2018.08.010
29. Bianchi D. Cryptocurrencies as an asset class? An empirical assessment. *The Journal of Alternative Investments*. 2020;23(2):162–179. DOI: 10.3905/jai.2020.1.105
30. Bianchi D., Dickerson A. Trading volume in cryptocurrency markets. *SSRN Electronic Journal*. 2019. DOI: 10.2139/ssrn.3239670
31. Alexander C., Dakos M. A critical investigation of cryptocurrency data and analysis. *Quantitative Finance*. 2020;20(2):173–188. DOI: 10.1080/14697688.2019.1641347
32. Enders W. Modeling volatility. In: Enders W. Applied econometric time series. 4th ed. Hoboken, NJ: John Wiley & Sons, Inc.; 2015:118–180.
33. Fama E.F. The behavior of stock-market prices. *The Journal of Business*. 1965;38(1):34–105. URL: http://www.e-m-h.org/Fama65.pdf
34. Mandelbrot B.B. The variation of certain speculative prices. In: Mandelbrot B.B. Fractals and scaling in finance: Discontinuity, concentration, risk. New York: Springer-Verlag; 1997:371–418.

35. Fisher T.J., Gallagher C.M. New weighted portmanteau statistics for time series goodness of fit testing. *Journal of the American Statistical Association*. 2012;107(498):777–787. DOI: 10.1080/01621459.2012.688465
36. Nelson D.B. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*. 1991;59(2):347–370. DOI: 10.2307/2938260
37. Curto J.D., Pinto J.C., Tavares G.N. Modeling stock markets' volatility using GARCH models with Normal, Student's *t* and stable Paretian distributions. *Statistical Papers*. 2009;50(2):311–321. DOI: 10.1007/s00362–007–0080–5
38. Alberg D., Shalit H., Yosef R. Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics*. 2008;18(15):1201–1208. DOI: 10.1080/09603100701604225
39. Ghalanos A. Package 'rugarch': Univariate GARCH models. R package version 1.4–4. 2020. URL: https://cran.r-project.org/web/packages/rugarch/rugarch.pdf
40. Vlaar P.J.G., Palm F.C. The message in weekly exchange rates in the European monetary system: Mean reversion, conditional heteroscedasticity, and jumps. *Journal of Business & Economic Statistics*. 1993;11(3):351–360. DOI: 10.1080/07350015.1993.10509963
41. Andersen T.G. Return volatility and trading volume: An information flow interpretation of stochastic volatility. *The Journal of Finance*. 1996;51(1):169–204. DOI: 10.1111/j.1540–6261.1996.tb05206.x
42. Fantazzini D., Kolodin N. Does the hashrate affect the Bitcoin price? *Journal of Risk and Financial Management*. 2020;13(11):263. DOI: 10.3390/jrfm13110263
43. Shanaev S., Sharma S., Shuraeva A., Ghimire B. The marginal cost of mining, Metcalfe's law and cryptocurrency value formation: Causal inferences from the instrumental variable approach. *SSRN Electronic Journal*. 2019. DOI: 10.2139/ssrn.3432431

ABOUT THE AUTHORS

Kirill D. Shilov — Researcher, Institute of Applied Economic Research, Russian Presidential Academy of National Economy and Public Administration (RANEPA), Moscow, Russia
shilov-kd@ranepa.ru

Andrei V. Zubarev — Can. Sci. (Econ.), Senior Researcher, Institute of Applied Economic Research, Russian Presidential Academy of National Economy and Public Administration (RANEPA), Moscow, Russia
texxik@gmail.com

The article was submitted on 07.05.2021; revised on 21.05.2021 and accepted for publication on 27.08.2021.
The authors read and approved the final version of the manuscript.