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Sustainable Cryptocurrency Growth Impossible? Impact of Network Power Demand on Bitcoin Price

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Abstract
Due to the youth of the cryptocurrency sphere, the logic of interaction between investors, users and protocols is not always precisely defined. Analysis of the impact of ESG on cryptocurrencies proves that the demand for bitcoin network capacity (occupies the main market share) is the main factor in predicting the price of this cryptocurrency and the cryptocurrency market as a whole. The choice of the statistical method of analysis is determined by the purpose of statistically justified determination of the relationship of the data under consideration, and the reliability of the analysis is checked using Fischer and Student tests. In this paper, several innovations are proposed to solve the problem of energy dependence of cryptocurrencies: firstly, the analysis of cryptocurrencies in the paradigm of sustainable development (taking into account the consumption of a huge amount of energy for the functioning of cryptocurrency systems); secondly, feedback logic to explain the interaction of subjects, including the following parties: users, developers, network infrastructure and their interaction; thirdly, statistical analysis with the creation of artificial variables from real data and iterative improvement of the model. This paper proves that sustainable cryptocurrency growth is impossible when viewed from the perspective of "Green Economics" by Molly Scott Cato. The author's approach is relevant compared to other methods of linear transformations for creating artificial variables by selecting data using the VIF test. As a result, several versions of models were obtained using various combinations of the initially proposed factors, on the basis of which the nature of the greatest influence on the price of bitcoin was established in the form of technical factors and energy infrastructure needs.

Keywords: *cryptocurrency, investor behavior, bitcoin, data privacy, ESG factors, concept of green economy*

JEL: *E52, Q43*

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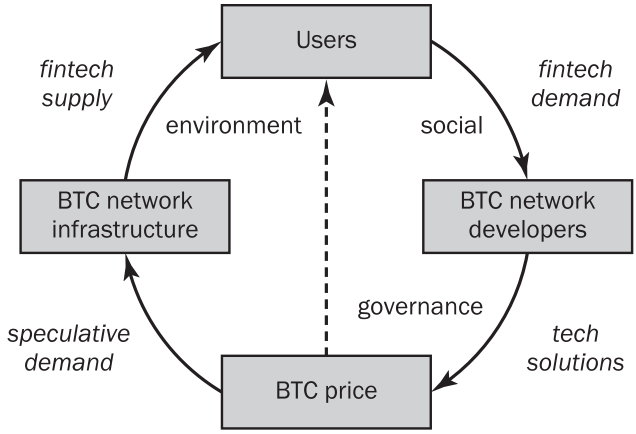
INTRODUCTION

Cryptocurrencies are a fairly new type of assets, and in terms of the principle of their structure and existence, they are radically different from financial market instruments in many ways [Kristoufek L., 2013; Khan Z.Y. et al., 2020]. So multiple methodologies for asset valuation, such as for stocks, have not yet been developed. This gap is gradually being filled, and sometimes new types of analysis are added, which are already adopted in traditional finance. This work is also aimed at transferring the methods of analyzing stock market assets to the crypto space, in particular, ESG factors will be considered in conjunction with the price of different cryptocurrencies such as BTC, TRX, SOL and MKR. Hence, the main hypothesis of the study is the existence of a statistically justified relationship between the prices of cryptocurrencies and ESG factors.

Due to the specifics of the cryptocurrency sphere, ESG factors are not considered as internal performance indicators or a company's strategies reflecting its impact on the environment, but rather as factors influencing the cryptocurrency system assessment and sustainability. Thus, the article statistically investigates a possible feedback loop of cryptocurrency use, considered on the example of BTC (Figure 1).

Figure 1

Loop of development and use of the BTC network



Source: developed by the authors.

On the outside, italics indicate the factors of influence of the previous cell on the next one. Inside the circle, the ESG components for the stages are assigned in regular font.

User needs shape the flow of tasks that blockchain developers solve. In general, modern theory of organizational development assumes that developers are trying to anticipate future needs. Besides, the idea of green economy assumes that sustainable cryptocurrency growth is impossible [Cato M., 2008].

In this article, the classic logic suggesting that demand gives rise to supply is retained, since, firstly, the main directions of the cryptosphere's development are derived from the problems of traditional finance, and, secondly, the threshold of entry into development is low, therefore the elasticity of product solutions in response to demand is extremely high. In this "external" implementation, the influence of the social factor will be considered.

Having an almost endless stream of technical requests from consumers as well as their own plans, both internal developers, e.g. bitcoin.org, and external independent programmers implement the component of the governance factor, which, according to the main hypothesis of this article, affects the price of the cryptocurrency.

In turn, the price of an asset has a dual effect through determining behavior of the users, both traders and individuals using BTC as a payment network; however, this aspect is beyond the scope of this study.

It puts pressure on the infrastructure through speculative demand, which, on the one hand, more strongly integrates the world of cryptocurrencies with reality, such as mining, crypto funds, etc., but at the same time complicates the use of the network by ordinary users, increasing the time and cost of transactions.

For a quantitative analysis of the logic of this chain, 5 factors were selected that potentially affect the price of cryptocurrencies and reflect the components of the ESG analysis. Also, for protocols, where possible, parameters were selected to assess the governance of the component. For the possibility of interpretation, the stability of the estimate and the completeness of statistical checks, a linear model in several variations is used. More data and methods are described in the corresponding section.

The article is further structured as follows: The section “Literature review” briefly describes previous research on the subject. The section “Methods” explains the approach to selecting and creating data and exploring models. The section “Results” presents the hypothesis testing results and the study of the feedback logic described above, and also summarizes the entire article. Finally, the section “Discussions” answers the question: Is sustainable cryptocurrency growth impossible?

LITERATURE REVIEW

In general, for a long time, the energy efficiency of cryptocurrencies and their environmental impact did not arouse serious interest, since the contribution to the problem at the global level was too small. Relatively recently, this kind of “green” concern has nevertheless appeared, since the energy consumption of BTC alone had become comparable to that of individual countries. This spurred interest in reorienting energy sources for cryptocurrencies to the green energy sphere [Memoria F., 2021; Shen D. et al., 2019; Cheung A. et al., 2015; Hafner C., 2020; Kaiser L. et al., 2020].

Also, for the protocols where the “governance” variable was implemented, one must note the absence of its significant impact on the price in the USD pair. The main hypotheses as to why this is the case are as follows. Investors look to evaluate fan communities for small-cap projects, large projects themselves can be benchmarks in terms of community activity. In the period under review, all 3 projects are quite large. It also proceeds from the fact that projects were already quite popular during the period under review, so there were no radical changes in the activity of developers and followers, but there were changes in the crypto industry itself, so prices changed more than fundamental factors [Bouri E. et al., 2019; Jacobs E., 2011; Schwarz N., 1990; Bouri E. et al., 2017; Sukamulja S. et al., 2018].

Since the first scientific work on cryptocurrencies in 2011, their development has gone far ahead and now the technology can be called a disruptive innovation. Their unprecedented growth is attracting increasing interest, and some even admit that they are being expelled by other types of assets; they are most often compared to fiat currencies. At the same time, there are often less enthusiastic opinions about the crypto area which is even regularly compared to “bubbles”. Many classical fundamental analysts adhere to this side, believing that crypto projects are not backed by anything at all, being a dangerous asset for investment [Vassiliadis S. et al., 2017; Jolliffe I.T. et al., 2016; Kasper J., 2017; Engelhardt M., 2017; Ciaian P. et al., 2016; Riek A. et al., 1995].

Due to the complex and unusual for the stock market fundamental analytics, cryptocurrencies are loved by behaviorists, since there are many studies in which there is a strong relationship between the prices of cryptocurrencies and sentiment, without fundamental factors [Feng L. et al., 2022; Sigler K., 2018; Cao G. et al., 2022; Nakamoto S., 2008].

In addition to the social effects of prices in the cryptosphere, many focus on price development and volatility in general. There are also those who compare DeFi with traditional assets such as currencies or commodities. One of the most productive approaches is the analysis of currency stability in developing countries and its comparison with cryptocurrencies [An J. at al., 2021; Mikhaylov A., 2021; Daniali S.M. et al., 2021; Kranina E.I., 2021].

If we generalize the above approaches, then the most common areas of analysis of crypto assets prices are behavioral and technical. The approach that will be considered in this paper is somewhat different from those indicated: a combination of value analysis of the blockchain, analysis in the ESG paradigm and the relationship of intrinsic value with reflection in price [Acemoglu D. et al., 2016; Adam A.M., 2020].

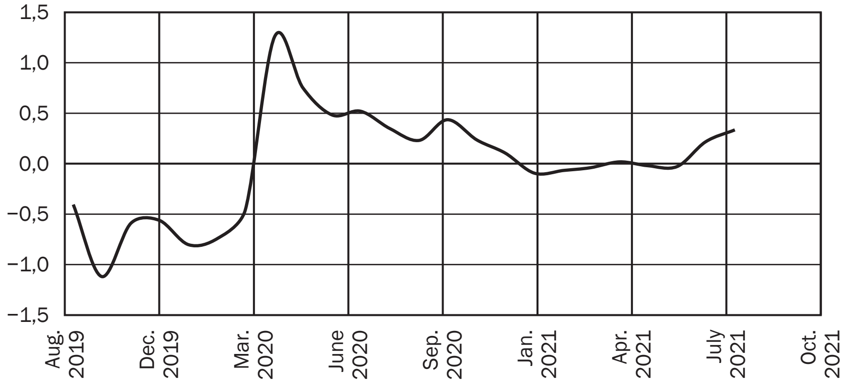
METHODS

In order to test the main hypothesis of the study, we needed data that correctly and with sufficient completeness reflect all 3 areas of the ESG asset analysis, and the asset price was chosen as a measure of reflecting the factors. Target variable is Price (y) — monthly closing prices of pairs against USD, taken as an average from CEX exchanges and DEX exchanges, where the volume of transactions is known, weighted by the trading volume on each [Akdere Ç. et al., 2018; Alam N. et al., 2019; Alber N., 2020; Al-Dmour H. et al., 2020; Ashley C. et al., 2015].

Synthetic currencies (x1) is a basket of twenty currency pairs of countries against the US dollar weighted by the crypto acceptance index from www.chainalysis.com (Figures 2–3).

Figure 2

Synthetic Currencies Index in 2019–2021. Basket of twenty currency pairs of countries against the US dollar weighted by the crypto acceptance index

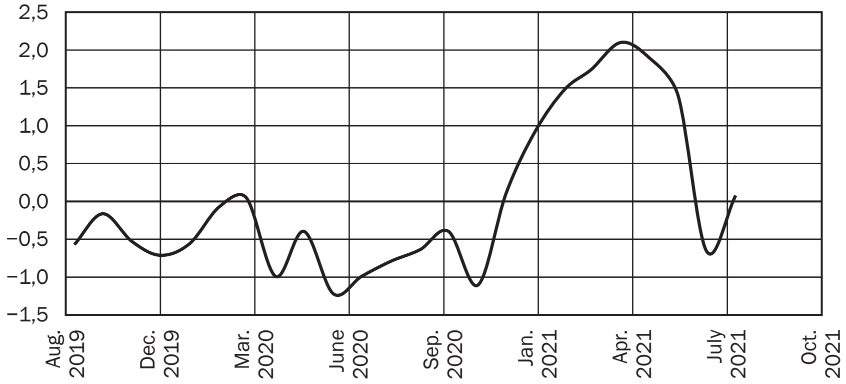


Source: developed by the authors on data of Chainalysis (www.chainalysis.com).

1. Volume (x2) — total trading volume, expressed in USD, from both types of exchanges. In fact, only investment-speculative cash flows are taken into account, excluding P2P transfers;
2. Total electricity consumption (x3) from the Cambridge Bitcoin Electricity Consumption Index.
3. Network power demand (x4) from the Cambridge Bitcoin Electricity Consumption Index.
4. Hashrate (x5) — the average monthly amount of used computing power on the network.
5. The "governance" block is not numeric for the general case of any cryptocurrency, so these factors vary between protocols.

Figure 3

Bitcoin network power Index in 2019–2021



Source: developed by the authors on data of Chainalysis (www.chainalysis.com).

BTC, since the largest cryptocurrency does not have a physical organization to manage it, and in a technical sense, community self-government is hidden inside the x3, x5, x2 metrics, which follows from the backpropagation loop logic.

SOL TRX, MKR — activity of developers on Github, number and speed of transactions adjusted for the number of validators, popularity of social networks, number of users, capitalization of the top 10 partner companies and the presence of the protocol in different countries (number of countries). A dummy variable has also been added to reflect the transition of the protocol to the DAO governance model.

It should be noted right away that the variables of the governance section are numerous and slightly variable, therefore, in order not to overload the models with the number of variables, they were grouped into one statistical variable using the principal component method. This simplification does not allow us to draw a direct conclusion about the influence of any specific factor on token prices, but makes the model itself more statistically reliable and makes it possible to judge the relationship between yield dispersions and governance indicators.

In general, BTC is the most universal currency in terms of quantitative reflection of parameters, so the main modeling ideas will be demonstrated using the example of the BTC/USD pair, but the results of applying the same analysis for other protocols will also be covered.

Reflecting such diverse factors for ESG analysis in several variables is not an easy task. The limitation on the type of model and the number of variables was dictated by the desire to better understand the influence of the fundamental metrics of the BTC network on its price, and not learn how to predict it. To solve this technical problem, the following simplifications were made on the basis of the available data.

A month is a sufficient period of time to reflect the impact of the factors on the price. This assumption is necessary due to the imperfection of the cryptocurrency market and the small amount of historical data.

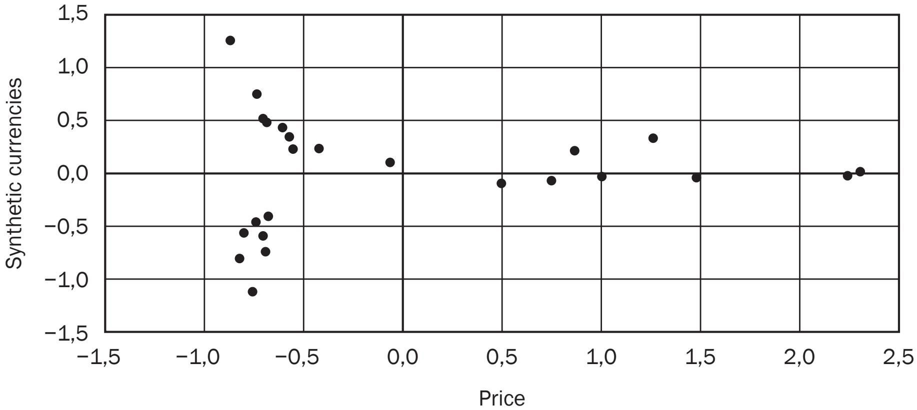
The public prices of the BTC/USD pair are generally about equal to the actual price of using the cryptocurrency by individuals.

RESULTS

Thus, the above variables were selected, and for comparability of the analysis, they were standardized. Data distributions by price are shown in the graphs (Figures 4–8).

Figure 4

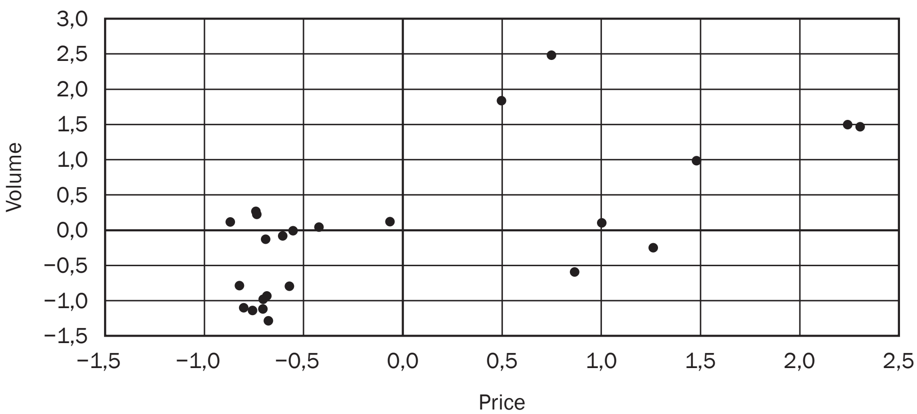
Data distributions by price for Synthetic currencies (x1)



Source: developed by the authors on data of Chainalysis (www.chainalysis.com).

Figure 5

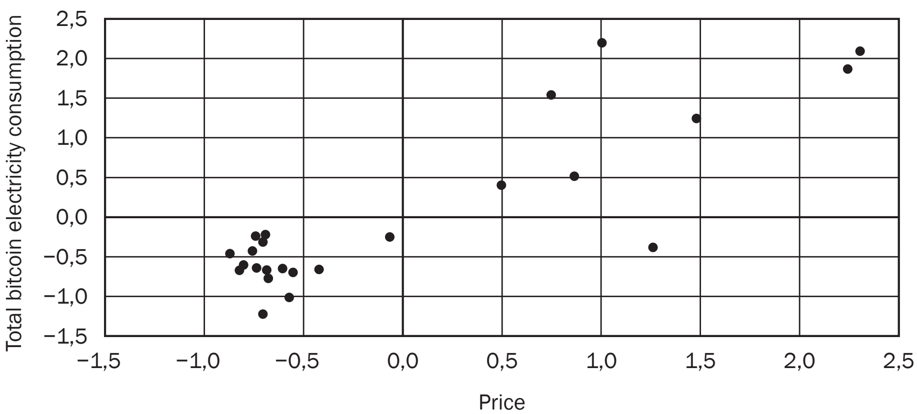
Data distributions by price for Volume (x2)



Source: developed by the authors on data of Chainalysis (www.chainalysis.com).

Figure 6

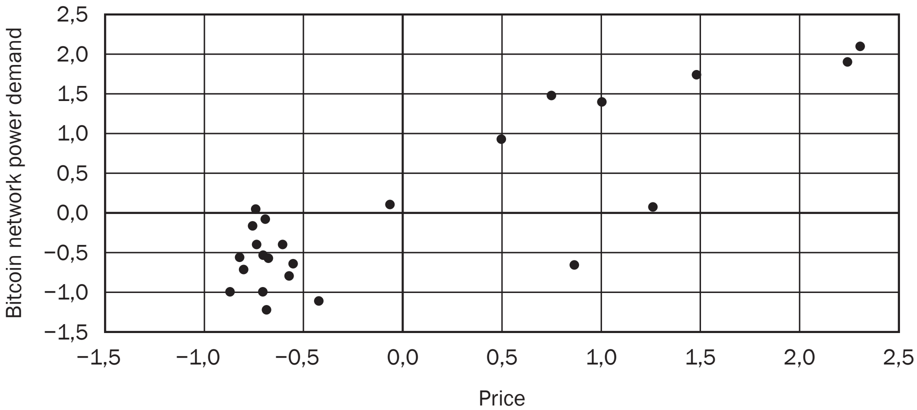
Data distributions by price for Total electricity consumption (x3)



Source: developed by the authors on data of Chainalysis (www.chainalysis.com).

Figure 7

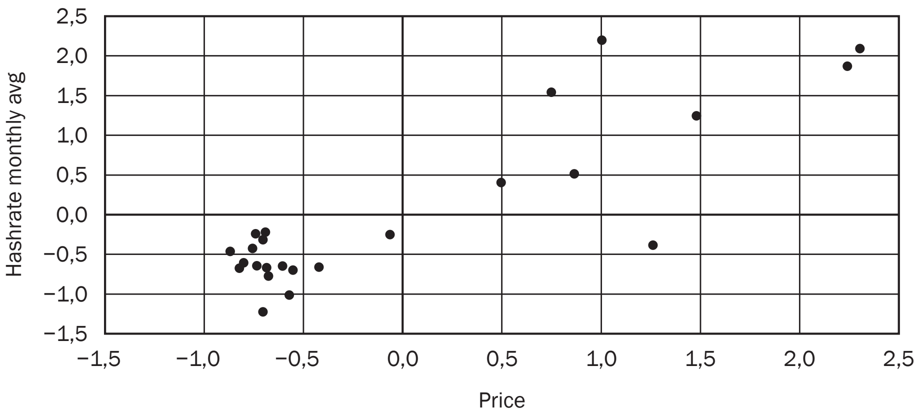
Data distributions by price for Network power demand (x4)



Source: developed by the authors on data of Chainalysis (www.chainalysis.com).

Figure 8

Data distributions by price for Hashrate (x5)



Source: developed by the authors on data of Chainalysis (www.chainalysis.com).

As can be seen, all distribution graphs have at least one significant part, similar to a linear dependence, therefore, the graphically selected method of multiple linear regression is justified. However, there are concerns that the variables may be correlated, therefore, a more accurate analysis and verification of the OLS assumptions are presented below (Tables 1–7).

Table 1

Descriptive statistics of the data

	Price	Synthetic currencies	Volume	Total bitcoin electricity consumption	Bitcoin network power demand	Hashrate monthly avg
AVG	0.00	0.00	0.00	0.00	0.00	0.00
SE	0.21	0.11	0.21	0.21	0.21	0.21
Median	−0.59	0.00	−0.04	−0.40	−0.40	−0.07
STD	1.00	0.54	1.00	1.00	1.0	1.00
VAR	1.04	0.29	1.04	1.04	1.04	1.04
Kurtosis	0.02	0.25	0.21	0.09	−0.42	−0.90
Skewness	1.14	0.00	0.88	1.18	0.94	0.39

Source: developed by the authors.

As mentioned above, the data had been standardized before the model was created, so almost everywhere the average is zero and the standard deviation is one, except for the basket of synthetic currencies. When compiling it, the data were first standardized, and then weighted by the cryptocurrency popularity index. Double standardization was not applied in order to preserve the uniformity of linear data transformations.

After the specified manipulations of data preparation, we got the OLS model:

$$\hat{y}_i = 0.34x1i - 0.4x2i + 0.55x3i + 0.47x4i + 0.32x5i \quad (1)$$

In general, a positive relationship of most of the selected factors was expected, but a negative correlation with trading volume contradicts the general theoretical views, so it is worth delving deeper into the study of the equation.

The model itself is generally significant according to the F-criterion, and explains the variability of the data much better than a naive solution.

Table 2

Descriptive statistics of the base model

Parameter	Coefficient
R	0.84
R-adj	0.79
F	18.75
MAE	0.28

Source: developed by the authors.

Since the main statistical hypothesis of the article is to verify the existence of a connection between the selected indicators and the BTC price, it is worth evaluating the classic statistics of the model's coefficients.

Table 3

Statistical check of coefficients of the base model

Parameter	SE	t-value	p-value	Lower 95%	Upper 95%
Synthetic currencies	0.24	1.44	0.17	−0.16	0.84
Volume	0.20	−1.98	0.06	−0.82	0.02
Total bitcoin electricity consumption	0.25	2.16	0.04	0.01	1.08
Bitcoin network power demand	0.33	1.40	0.18	−0.24	1.17
Hashrate monthly avg	0.20	1.64	0.12	−0.09	0.74

Source: developed by the authors.

Since, with the general significance of the model, of all the initial factors only x4 is significant, it is highly likely that the data do not comply with the Gauss-Markov assumptions, which needs to be verified.

Table 4

Heteroscedasticity check

Parameter	Glaser	Spearman's
Synthetic currencies	2.00	−1.96
Volume	−0.75	−2.35
Total bitcoin electricity consumption	1.09	−2.31
Bitcoin network power demand	0.23	−1.31
Hashrate monthly avg	−0.63	−2.50

Source: developed by the authors.

For t-critical = 2.10, we find that heteroscedasticity is not detected.

Autocorrelation was also checked by two methods. According to the Durbin-Watson test DW = 1.47, the result belongs to the zone of uncertainty. No autocorrelation was found using the series method.

As the Farrar-Glober test revealed, there is multicollinearity in the model. For further research and the veracity of the results of the model, a refinement was carried out using the results of variance inflation factor.

Table 5

VIF test for base model

Coefficient	VIF
Synthetic currencies	1.70
Volume	4.36
Total bitcoin electricity consumption	6.85
Bitcoin network power demand	11.91
Hashrate monthly avg	4.16

Source: developed by the authors.

Using the simple enumeration method, the best configuration of the model by VIF is as follows:

$$\hat{y}_i = 0.69x3 + 0.28x5 \quad (2)$$

Since, with this type of the model, the Gauss-Markov prerequisites are now fulfilled, it can be considered as the final one for the selected data. For a more substantiated answer, it is worth assessing the significance of the model and its performance indicators.

Table 6

Descriptive statistics of the base model

Parameter	Coefficient
R	0.79
R-adjusted	0.77
F	39.92

Source: developed by the authors.

On the F-measure, the model is unconditionally significant (F-critical = 2.74). In addition, with a 2.5-fold decrease in the number of variables, the adjusted R2 indicates a deterioration in the explanation of data variability by only 2%. The problem of the insignificance of the coefficients has also been fixed.

Table 7

Statistical check of coefficients of the base model

Parameter	SE	t-value	p-value	Lower 95%	Upper 95%
Total bitcoin electricity consumption	0.12	5.58	0.00	0.43	0.95
Hashrate monthly	0.12	2.26	0.03	0.02	0.54

Source: developed by the authors.

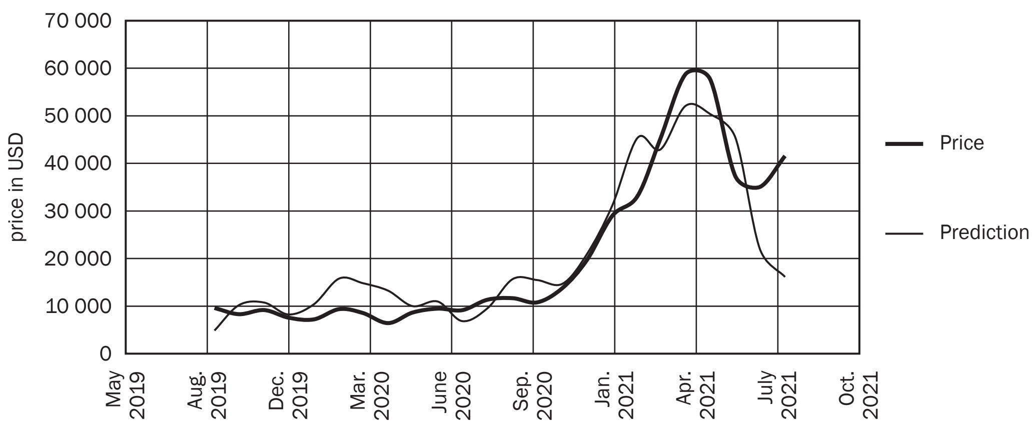
Both by the Student's test and by the 5% confidence level for the p-value, both remaining factors are significant in explaining changes in BTC prices. The results of the statistical study can be summarized as follows: not all of the initially selected factors have a significant impact on changes in crypto/USD prices. The final proposed model satisfies the OLS prerequisites; statistical tests prove the value of the research.

As mentioned above, a similar analysis was performed for other protocols as well, but with the addition of a dummy variable to reflect data from the governance section. The hypothesis of a statistically significant relationship was not confirmed. The economic conclusions that can be drawn from the available data will be given in the next section.

The obvious general conclusion for all projects from the resulting model is that there is a direct positive relationship between total electricity consumption, hashrate monthly average and asset prices. The result of the model's forecasts for BTC for the entire period considered is shown below (Figure 9).

Figure 9

Comparison of BTC/USD model forecast and reality



Source: developed by the authors on data of Chainalysis (www.chainalysis.com).

For the full-fledged medium-term trading, the accuracy of such a model is insufficient, but it should be noted that it reflects global trends correctly. Given the changes in the model, it can be said that the initial hypothesis is not fully confirmed within the selected data dimensions. Thus, the influence of the considered data of the "environment" block was almost completely confirmed, but the selected indicators to reflect the assessment of the "social" factor do not have a significant impact on the asset prices. There could be several reasons for this.

The selected data are not suitable for the correct representation of the stated hypothesis and the logic of the relationship of indicators. Then two hypotheses can be put forward: the use of cryptocurrencies as payment instruments has a significant impact on their price; spot trading activity of the BTC/USD pair has a significant impact on the price of the asset in question.

Bitcoin power demand was strongly correlated with the metrics of actual electricity consumption and used computing power, but it explained the change in the data a little worse, so it was excluded from the analysis. Hence, it can be assumed that the cryptocurrency market is not yet sufficiently formed and estimates of actual consumption manage to form the basis of the price, while demand estimates do not yet play the same role as in the classical stock market.

For countries where the use of cryptocurrencies is a necessity for accessing global cash flows, the situation of regulatory restrictions on the circulation of digital assets is often inherent, therefore, most of this demand can be masked through "more anonymous" protocols, which means that other protocols should be used to analyze such phenomena. Overall, bitcoin is not a representative asset of the cryptosphere, therefore, for specific areas of analysis, it is worth using protocols with the appropriate focus.

As a result, we can say that on the selected data, the investment attractiveness of an asset is only determined by the "environmental" component of the ESG framework. This is largely due to the technological component of the protocols of cryptocurrencies, because the fundamental component of cryptocurrencies is inextricably linked to the computing resources of the network involved, which exists at the expense of electricity. It was also found that the power consumption of the BTC network has a more significant impact on its price than the computing power involved.

DISCUSSION: SUSTAINABLE CRYPTOCURRENCY GROWTH IS IMPOSSIBLE?

Just at about the same time, there was an increased interest among researchers in developing the topic of sustainable growth of cryptocurrency [Atalay E. et al., 2011; Barrales-Molina V. et al., 2014; Bedendo M. et al., 2009; Buhalis D. et al., 2015; Carins J.E. et al., 2014]. Many studies argue that developing countries are the leaders in the adoption of renewable energy transition. To complete the picture, it also seems useful to consider the conditional target audience of each of the phenomena — cryptocurrencies and green energy. In relation to developed countries, this is a relatively young, solvent segment [Carvalho V. et al., 2013; Chang Y.T. et al., 2015; Chen K., 2018].

Several important conclusions can be drawn from these factors. Firstly, in view of the popularity of cryptocurrencies as a business in developed countries, its reorientation can organically occur due to the transition of the countries themselves to renewable energy. Secondly, the high marginality of the cryptocurrency business, combined with an increased interest in sustainable development among young people with an above-average income, can also initiate a transition to a new energy industry from within the sphere itself [Cooke P., 2020; Dabrowski S. et al., 2019].

The legal aspect of the fusion of cryptocurrencies and the ESG agenda remains the most controversial. While some developed countries already have an example of acceptance and legal reorientation to the ESG agenda, the legal status of cryptocurrencies remains uncertain [Faems D. et al., 2010; Fang X. et al., 2014; Fernadez A. et al., 2015, Ghosh A. et al., 2014].

One possible way to solve both problems could be to consider consolidation of cryptocurrencies as a financial instrument, but with some technical limitations that determine the energy efficiency of the protocols.

Thus, the main arguments for the potential sustainable development of cryptocurrencies are the possibility of simultaneous economic and environmental regulation and the main developers' interest in improving the stability of the sphere. The arguments against increasing the sustainable development of cryptocurrencies include the interest of some participants in the effectiveness of cryptocurrencies in the criminal sphere, and the problems of switching to lightweight blockchains [Podmetina D. et al., 2012; Sisodiya S.R. et al., 2013; Tiniç M. et al., 2021].

CONCLUSIONS

A positive result of the study can be considered evidence of the connection between the price of popular cryptocurrencies and some of the factors of the ESG framework.

The weaknesses of the analysis presented are in the choice of data: there is no single correct system for selecting factors, and the relative simplicity of the model is a conscious choice to allow interpretation rather than a biased verification of the existence of a connection, since complex models, such as neural networks and other machine learning algorithms, depend on the "black box" problem and may just remember the data, but not find a valid relationship between the parameters.

The following ideas may be useful for future research: Review of the project from its inception to the present. Introduction of displacement dummy variables to account for structural changes or the use of non-linear models; Search for behavioral aspects of pricing.

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Устойчивый рост криптовалют невозможен? Влияние спроса на мощности сети на цену биткоина

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Аннотация
Из-за молодости криптовалютной сферы логика взаимодействия между инвесторами, пользователями и протоколами не всегда точно определена. Анализ влияния ESG на криптовалюты доказывает, что спрос на мощности сети биткойн (занимает основную долю на рынке) является главным фактором прогнозирования цены этой криптовалюты и рынка криптовалют в целом. Выбор статистического метода анализа обусловлен целью статистически обоснованного определения взаимосвязи рассматриваемых данных, а надежность анализа проверяется с помощью тестов Фишера и Стьюдента.
В данной работе для решения проблемы энергозависимости криптовалют предлагается несколько инноваций: во-первых, анализ криптовалют в парадигме устойчивого развития (с учетом потребления огромного количества энергии для функционирования криптовалютных систем); во-вторых, логика обратной связи для объяснения взаимодействия субъектов, включая следующие стороны: пользователи, разработчики, сетевая инфраструктура и их взаимодействие; в-третьих, статистический анализ с созданием искусственных переменных из реальных данных и итеративным улучшением модели.
В статье сделан вывод, что устойчивый рост криптовалют невозможен с точки зрения концепции зеленой экономики Молли Скот-Като. Авторский подход актуален по сравнению с иными методами линейных преобразований для создания искусственных переменных путем отбора данных с применением теста VIF. В результате было получено несколько версий моделей с использованием различных комбинаций первоначально предложенных факторов, на основе которых был установлен характер наибольшего влияния на цену биткоина в виде технических факторов и энергетических потребностей инфраструктуры.

Ключевые слова: *криптовалюта, поведение инвесторов, биткойн, конфиденциальность данных, факторы ESG, концепция зеленой экономики*

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