Financial Risks of Business Management of Cryptocurrency Operations

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***Abstract* – Bitcoin is an asset with high risks, and a significant part of its volatility can be explained by the speculative component. Parametric variance-covariance (VaR) methods are not applicable for assessing the risks of bitcoin investment, since log returns are not distributed according to the normal law. Autoregressive risk assessment models (such as ARIMA-GARCH) for bitcoin volatility overestimate risks at times of sharp exchange rate changes and they underestimate them at times of less significant rate changes compared to historical volatility. The grid search for the smoothing parameter in the exponentially weighted moving average method is potentially interesting for modeling the risks of bitcoin investment. This makes it possible to fully take into account the autocorrelation of the bitcoin rate to the levels of previous periods and the volatility of the asset. As a conclusion, there are currently no econometric models that can explain and forecast the volatility of bitcoin in the medium and short term, considering the available factors in the market.**

***Keywords* – Financial risk, cryptocurrencies, business management, volatility, asset.**

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1. Introduction

Over the past decade, blockchain technologies and cryptocurrencies have been a new phenomenon in modern financial markets and have been the subject of close public attention. The great interest in cryptocurrencies is due to their differences from traditional payment methods, in particular: high anonymity of transactions, the absence of third parties and intermediaries in the process of making transactions, the speed of transfers, and low transaction costs.

However, the circulation of cryptocurrencies on the market is associated with a number of negative aspects, such as [1]: lack of legal regulation, uncertain legal status, the possibility of using cryptocurrencies to evade taxation, attractiveness for shadow, and criminal structures, etc.

Although virtual currencies are a new tool in the financial market and their adaptation to real social needs will take more than one year, there is no doubt that cryptocurrencies are the innovative future of the modern economy.

Bitcoin, which was created in 2009, became the first decentralized cryptocurrency [2]. Since then, Bitcoin has been the most famous, widely used, liquid and most significant of all existing virtual currencies in terms of market value, total market capitalization and the number of daily transactions.

The market value of all bitcoins exceeded 143.5 billion dollars [3]. On average, for the entire period of Bitcoin circulation on the market, about 190 thousand transactions with it were made daily, and accordingly about 8 thousand transactions with it were made hourly [3]. The economic indicators of Bitcoin circulation in the market, its key properties, and characteristics determine the growing interest in cryptocurrency not only from business structures, potential investors and common users, but also from the academic community.

Risk is not an objective fact that can be observed directly. The complexity of risk management is precisely in the fact that various relevant "risks" must be explained by the stakeholder. This risk structure is usually built with the help of quantitative models and observation techniques using the benefits and prices, which are usually based on the assets of the pricing model. Risk can be identified, understood, quantified, and monetized only through models and in the context of a specific set of benefits.

It is assumed that the risks of financial management have different forms. In the literature, the main financial risks faced by financial institutions are usually classified as market, credit, and operational risks [4]. The liquidity risk is often mentioned as a large separate category of risk. There are also other important non-financial risks, such as strategic and business risk. The main categories of financial risk can be further divided into narrower subcategories. It should be noted that the classifications of risks in the literature differ significantly [5].

The first and the simplest risk is the market risk. These are risks that are largely driven by market variables. The market risk can be subdivided into equity risk, interest rate risk, currency risk, and commodity risk. These risks may also have their own subcategories. Actually, there are two main ways to consider the market risk [6]: When considering the risk in currency terms, it is an absolute market risk, while when considering the risk in terms of closeness to the standard, it is a relative market risk.

It should also be noted that all the different types of market risk can be either directional or non-directional [7]. Directional risk refers to linear risks of changes in market prices or rates. Non-directional risk refers to non-linear risks, volatility risks (i.e. unexpected changes in volatility), and basis risks.

Credit risk is the risk underlying the default risk of counterparties ranging from retail customers to trade counterparties [8]. In other words, it is the risk of non-compliance with financial obligations due to delayed payment or insolvency. For example, if counterparty defaults for any reason, the financial institution suffers losses equal to the recovery value of the lost cash flows. This means only losses if the recovery value is positive. The loss itself is a function of the initial risk, i.e. the cash flows at risk, on the one hand, and the recovery rate, i.e. the proportion of the value that can be recovered, on the other.

It should be noted that actual defaults are not the only source of credit risk. Other sources of credit risk come from anticipated or actual changes in the credit quality of counterparty, with the exception of actual default [9].

For example, downgrading agencies' credit ratings or deteriorating market perception can lead to losses in the market.

There are a number of specific forms of credit risk [10]. One subcategory includes sovereign, political, and state risks. Settlement risk is another type of credit risk. Settlement risk means the risk of loss if a bilateral payment transaction (for example, a foreign exchange transaction) cannot be completed. This happens when one party fails to fulfill obligations after the other has already fulfilled its obligations.

All forms generally address risks of loss in cross-border business related to the policies and decisions of a foreign government or foreign regulatory body (for example, in extreme cases, a sovereign debt default or the imposition of capital controls.

The third risk is liquidity risk. It can be divided into funding liquidity risk and asset liquidity risk [11]. Asset liquidity risk refers to the risk of losses arising from the inability to execute a transaction at current market prices due to the relative size of the position or temporary drying up of the markets. Being forced to sell under these circumstances can result in significant losses. Funding liquidity risk means the risk of losses if the institution is unable to meet its cash needs [12]. This can cause a variety of problems, such as failing to meet margin requirements or capital withdrawal requests, complying with collateral requirements or achieving debt rollovers. These problems may force the institution to liquidate assets.

Liquidity risk management is carried out by controlling the concentration and relative sizes of portfolios, in case of asset liquidity risk, and by diversification, securing credit lines or other backup financing and limiting cash flow gaps, in case of funding liquidity risk.

Operational risk is defined as the risk of loss due to inadequate or failed internal processes, people and systems or due to external events [13]. This definition includes legal risk but excludes strategic and reputational risks. They began to consider the category of operational risk relatively recently, comparing it with the types of risks described above. It was introduced to focus the attention of management on a wide range of various risks that could have been unknown or neglected earlier. The main ways to prevent operational risk include increasing the institution's resilience through contingency planning, adding system reserves, clearly separating different functional roles, and creating an effective management system [14].

Various other risk categories can be listed, with the most significant of them being reputational and strategic risks.

Reputational risk refers to the risk of losses that arise due to the deterioration of reputation [15]. The diminished reputation may be due to the perceived incompetence, negligence, or misconduct of the institution.

Strategic risk refers to potential losses arising from the strategic choices of top management [16].

The conditions of the international financial services industry began to undergo increasingly rapid changes, financial markets are becoming more complex and uncertain, which requires the introduction of new derivative financial instruments for risk management. Risk is not an objective fact. It can only be identified, understood, quantified and monetized using models.

In the section, a theoretical study of financial risks was carried out, the main financial risks were identified, each of them was discussed in detail and their analysis was made. While the main financial risks faced by financial institutions are usually classified as market, credit, operational and liquidity risks, it should also be noted that the risk classifications vary significantly in the literature. One of the most important risk categories includes reputational and strategic risks.

2. Methodology

Financial management publications identify two important aspects of risk, namely: volatility or variability of financial indicators and the sensitivity of performance criteria to its effects.

H. Markowitz suggested risk measurement through the volatility of a financial asset within the portfolio theory. As a rule, determining volatility begins with calculating the variance (spread of possible outcomes) of the return on a financial asset. Return is usually understood as the relative increase in the value of the financial asset, including interim payments on it.

The squared value of return variance or the standard deviation is known as volatility. The economic sense of volatility is to measure the risk of an asset through the spread of return values around its average level.

In practice, the distribution of returns is often estimated from historical data, with the assumption that observations are equally and independently distributed. Volatility can be calculated for various time intervals, such as hours, days, weeks, months, quarters, and years. In this regard, risk managers often face the issue of aggregation — the expression of volatility and returns for different periods. It should be noted that actually aggregation is carried out based on two strong assumptions. Asset prices change under the influence of news that can't be predicted. There is no correlation between asset prices at different time intervals. The second assumption is that the law of return distribution is maintained throughout the time interval.

Since volatility changes in proportion to the square root of time and the expected return — in proportion to time, in the long term, risk managers focus on average returns, and in the short term, they focus on volatility.

A certain disadvantage of the return variance is that it equally considers deviations from the expected level, both upward and downward. Often, an investor who has bought a financial asset is only interested in a negative scenario associated with a decrease in profitability. In this case, the growth of profitability is not considered as a risk. Following this logic, H. Markowitz later suggested the semi-variance indicator as a measure of risk. When calculating this indicator, only asset returns that are less than the expected (average) one are considered [8]:

$$SV(X) = \mathrm{E}\left(\min\left(0, X - E(X)\right)^2\right) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\min\left(0, X - \mathrm{E}(X)\right)^2\right) \quad (1)$$

For the case of n=2, the lower partial moment coincides with the semi-variance. Using lower partial moments, as in the case of the semi-variance, does not imply consideration of upward deviations of returns from the average value. The degree 'n' in Formula (3) characterizes some subjectivity, because with its increase, possible losses are given more and more weight.

A linear measure of the spread of returns around its average value is the absolute deviation [10]:

$$AD(X) = \mathrm{E}\left(\left|X - E(X)\right|\right) = \frac{1}{N-1}\sum_{i=1}^{N}\left|X_i - \overline{X}\right| \quad (2)$$

It reflects the extent to which observed returns deviate from the average value.

It should be noted that all the above methods of risk assessment have both their advantages and disadvantages. The property of similarity with the variance of returns, which is considered among the main quantitative measures of risk, remains common to them. At the same time, using the variance as a measure of risk simultaneously with its definition leads to the paradox: on the one hand, the increased variance of the return on a financial asset indicates higher risks. In accordance with theoretical assumptions, a riskier asset is a more profitable asset. The growing number of profitable trades reduces the likelihood of adverse events (losses), which, on the other hand, already qualifies as risk reduction.

To resolve this paradox, Z-test [12] was suggested, which also has forecasting properties in risk assessment:

$$\varsigma = \frac{H-L}{L} \tag{3}$$

where H is the maximum transaction cost during the exchange session; L is the minimum transaction cost during the exchange session.

One of the common methods for assessing systematic market risk is the beta coefficient (β, beta), which evaluates the sensitivity of the stock risk in relation to the market as a whole [13]:

$$\beta_i = \frac{\mathrm{cov}_{im}}{\sigma_m^2} \tag{4}$$

where cov_{im} is the covariance between stock return and market return, σ_m^2 is the variance of market return.

This method is based on the capital asset valuation model. Its widespread application is explained by the use of historical data in the calculations. This makes it possible to consider the indicator as a forecasting tool.

The alternative arbitrage pricing model (ARM) does not provide for the division of risk by the sources of its occurrence or other criteria. As a result, market analysis models based on mathematical modeling are widely used. They are reduced to the detailed systematization of potential risk factors and determining the degree of their impact on profitability by calculating sensitivity coefficients using historical data.

In recent years, such tool as Value at Risk (VaR) has become increasingly popular in risk management [14]. It is an estimate of the amount, expressed in the base currency, that temporary losses expected during a given period will not exceed with a set probability. According to the definition of VaR, the result of using this method is the largest expected loss due to price fluctuations in financial markets. It is calculated taking into account a set time horizon with a certain level of confidence (probability of not exceeding it) and under given assumptions about the character of market behavior. Calculating VaR makes it possible to state: “We are α% sure that we will not lose more than q in the next N days” [15].

In the general case, for one asset subject to a single risk factor, VaR can be calculated using the Formula 5 [16]:

$$VaR = V\left(\mu_\tau \frac{T}{\tau} - k_{1-\alpha}\sigma_t\sqrt{\frac{T}{\tau}}\right) \tag{5}$$

where V — current cost of the position (the product of the price and the number of asset units; μ_τ — mathematical expectation of τ-day return (calculated based on historical data); T — time horizon; σ_τ — standard deviation of returns; $k_{1-\alpha}$ — quantile.

The delta-normal method is quite easy to use. The cost of primary data collection and calculations is relatively low, and in most cases the method has acceptable calculation accuracy. But the method has these drawbacks:

– Inapplicability for non-linear instruments due to low calculation accuracy;

– Incompatibility of the distribution of most market assets with the normal law and, as a result, overestimation or underestimation of VaR;

– Disregard of possible large losses due to rare single events.

The Monte Carlo method is another method of complete evaluation within the framework of the VaR methodology. It is based on the simulation of a random process with given characteristics, for example, the mathematical expectation of returns and their variance [17]. Simulation has a pseudo-random nature, with any kind of distribution, and the number of scenarios analyzed can exceed tens of thousands. The further procedure for VaR calculation using the Monte Carlo method is similar to the method of historical simulation.

It should be noted that regardless of the group of approaches used to calculate VaR, this method involves the calculation of variance, standard deviations and other statistical parameters of historical returns discussed above.

In addition, an important characteristic of VaR models is lack of subadditivity, a property that assumes that the risk of a portfolio should not exceed the sum of the risks of its constituent assets. There are examples when the VaR of a portfolio is greater than the sum of the VaR of the assets it consists of, which is contrary to common sense.

A modification of VaR meeting the requirements of coherence and, in particular, subadditivity is an indicator of expected losses. The economic meaning of CVaR is the mathematical expectation of losses that are greater than VaR [18]:

$$CVaR_{1-\alpha}(X) = \mathrm{E}\left(X \middle| X > VaR_{1-\alpha}\right) \tag{6}$$

where (1-α) — confidence interval.

Apart from coherence, this risk measure is more appropriate in the case of heavy-tailed distributions.

The main disadvantage of all the above volatility-based risk assessment methods, is their heavy dependence on historical data, which often makes it difficult to forecast future volatility values [19]:

$$\sigma_t^2 = \alpha + \sum_{j=1}^{p} \beta_j \cdot r_{t-j} \tag{1}$$

where α — constant or base volatility considering long-run variance; β_j — observation weight determined j periods ago; p — number of observations; r_{t-j} — return of the j-th period.

The ARCH model is based on the idea of differences in conditional and unconditional moments of second order. Unlike constant unconditional variances and covariances, conditional moments can change over time and depend non-linearly on past states. Over the years, the standard model has undergone several modifications. MARCH, FARCH and TARCH models appeared. As a result of their evolution, a new class of methods for quantitative risk assessment has emerged, making possible to abandon assumptions about the independence of volatility in previous returns and consider autocorrelation in them [20]:

$$\sigma_t^2 = \alpha + \sum_{i=1}^{p} \beta_i \cdot \sigma_{t-i}^2 + \sum_{j=1}^{q} \gamma_j \cdot r_{t-j} \tag{8}$$

where p — number of observations of σ; q — number of observations of r; β_i — weight of observations made i periods ago; σ_{t-i}^2 — variance of previous periods.

A significant advantage of GARCH models is their ability to quickly respond to any market changes and recover after large fluctuations.

The model for calculating the exponentially weighted moving average (EWMA) has an approach similar to the ARCH and GARCH models for calculating volatility [21]:

$$\sigma_n^2 = \lambda \sigma_{n-1}^2 + (\lambda - 1) r_{n-1}^2 \tag{2}$$

where λ — constant from 0 to 1; r_{n-1}^2 — previous period return squared; σ_{n-1}^2 — variance of the previous period.

When a new element of the time series appears during the application of the exponentially weighted average method, the average value and variance are recalculated based on it.

All these models are centered around one of the two aspects of risk — volatility. Approaches to analyzing the sensitivity of performance criteria to their results are much less numerous in modern literature. Sensitivity analysis is usually limited to the identification of indicators that are measures of risk and help reveal the relationship between risk factors. These include: stocks, gaps, coefficients of liquidity and financial stability, coefficients of elasticity of economic indicators for certain factors, etc.

3. Results

The analysis of volatility using traditional risk models will consist of 2 main stages. At the first stage, using the Eviews and Excel econometric software packages, bitcoin volatility will be modeled and quantified according to historical parameters, Z score, GARCH and EWMA models, which are the most common risk assessment methods. Also, based on economic and mathematical models, there will be discovered the influence of individual factors on the volatility of bitcoin. At the second stage, the results of risk assessment of bitcoin investment will be compared using all the above methods.

One of the many reasons why bitcoin is considered a high-risk asset is its high volatility, as illustrated by historical data (Figure 1). To calculate the historical volatility, a 10-day period was used, since the cryptocurrency quickly and significantly responds to various market events and the actions of government regulators in relation to cryptocurrencies in general, and bitcoin in particular. Despite significant changes in the exchange rate of the cryptocurrency in 2017, higher volatility was recorded in April-June 2020, when the price of bitcoin suddenly increased by almost 7 times.

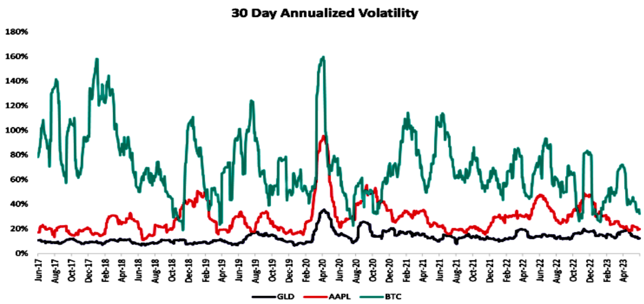

Figure 1. Historical volatility of bitcoin (BTC), gold (GLD), and Apple shares (AAPL) in 2017–2023 (based on Bitcoin is now more stable than [3]))

Quantifying the risk of bitcoin investment using Z-test does not allow drawing adequate conclusions when using a continuous data array for analysis, i.e. the one including extremely high and extremely low maximum and minimum prices per trading session. For example, on June 23, 2020, on the Bitstamp exchange, which data were used for modeling in the paper, the maximum price per trading session was USD 632.67, while the minimum price was only USD 1.5. Considering these data, Z score was 42078%, which greatly changed the general situation. We will remove this “spike" and look at the results of calculating Z score without it. When using the method without extremely high and low values of the time series, one can conclude that Z score quantitatively describes the risks associated with fluctuations in the bitcoin exchange rate quite well.

However, due to the high speculative component, here the order of quantitative risk indicators is many times higher than in the case of historical volatility. When assessing the risks of bitcoin investment based Z score, the results are likely to be inflated compared to other methods.

To model the log return of bitcoin using an autoregressive risk assessment model, the GARCH specification will be considered, which proved to be the best on the latest up-to-date data on the return of bitcoin in the study. It is the ARIMA(1) – GARCH(1.1) type model (Table 1). Using this model, one can forecast the next value of the time series based on past values, noise and variance.

Table 1. Results of the assessment of the autoregressive model for evaluating the volatility of bitcoin using the ARIMA(1) — type model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.23E-06	3.52E-06	0.633811	0.5262
AR(1)	0.205325	0.020834	9.855065	0.0000
MA(1)	-0.995293	0.001623	-613..2854	0.0000
	Variance Equation			
C	3.30E-05	1.93E-06	17.08090	0.0000
RESID(-1)^2	0.264588	0.015245	17.35541	0.0000
GARCH(-1)	0.751707	0.009698	77.51012	0.0000
R-squared	0.401039	Mean dependent var.		-1.26E-05
Adjusted R-squared	0.400519	S. D. dependent var.		0.054569
S. E. of regression	0.042250	Akaike info criterion		-4.146690
Sum squared resid.	4.112856	Schwarz criterion		-4.131752
Log likelihood	4789.207	Hannan-Quinn criter.		-4.149 1244
Durbin-Watson stat.	1.972548			
Inverted AR Roots	.21			
Inverted MA Roots	1.00			

This conclusion is also confirmed by the Ljung-Box Q-test. Its statistics for the considered series was 20.76.

After evaluating the quality of the model, one should consider the results of volatility modeling based on it. According to the distribution of residuals and the forecasted volatility, it is obvious that the model makes it possible to accurately forecast future volatility values even considering possible sharp spikes in the log return of bitcoin.

Applying the methods of exponentially weighted moving average (EWMA) to the time series of log return and historical volatility involves using the constant λ ranging from 0 to 1, which acts as a smoothing parameter. Let's consider the results of volatility modeling for various values of the parameter, such as 0.85, 0.91 and 0.99, which are among the most frequently encountered values in the literature. Matching the results of volatility modeling using the EWMA method with different smoothing parameters makes it possible to make a choice in favor of the first method with λ=0.85, since, to a greater extent (i.e. with a greater weight), it allows considering the values of cryptocurrency returns of past periods.

During modeling, the event (binary) control variable was also included in the set of regressors. It takes the value 1 if that day an event occurred on the market that could affect the rate of cryptocurrencies, and it takes the value 0 if there was no such event. The events considered in the control variable included both systemic updates to bitcoin protocols and political decisions regarding the bitcoin market, as well as messages and statements from government regulators.

Evaluation of variable correlations allows to speak about the interchangeability of Google, a variable responsible for the intensity of search queries, and Pageviews, a variable that illustrates the number of bitcoin page views on Wikipedia.

Evaluating bitcoin volatility models (Table 2) gives conflicting results. Evaluating the model based on an extended data set suggests that, apart from the constant, the determining factors of volatility include the price of one ounce of gold and the Shanghai Stock Exchange Composite Index.

Table 2. Results of evaluating models of the dependence of the bitcoin price volatility

Variable	**Model including Google variable**	**Model including Page views variable**
Constant	0.2718 (0.0036)	-0.58479 (0.0047)
Bitcoin price for the past day	0.9999 (0.1382)	1.0000 (0.0000)
Bitcoin client downloads	1.0000 (0.0000)	-0.00015 (0.0396)
Log price of 1 ounce of gold	-0.0159 (0.0668)	-0.0017 (0.9153)
Google Tends Index for the past day	0.00096 (0.0000)	–
Log hashrate (for the past period)	-0.000276 (0.6677)	0.00671 (0.2706)
Log of the total cost of all transactions	-0.000468 (0.7345)	0.01132 (0.0000)
Bitcoin page views on Wikipedia	–	1.0000 (0.6654)
Log of the Shanghai Exchange Composite Index	-0.0148 (0.0078)	0.0538 (0.0001)
Event control	Yes	Yes
Method	OLS	OLS
Observation number	755	344

And both macroeconomic indicators have the same effect on bitcoin volatility. As they increase, the volatility of cryptocurrency returns decreases. Volatility is also positively and significantly affected by indicators of the bitcoin popularity: Google Trends Index, which indicates the intensity of search queries related to bitcoin, increase the volatility of the cryptocurrency, which confirms the findings of earlier studies.

As a whole, in terms of explanatory properties, comparing the two models allows making a choice in favor of the second model, since the adjusted coefficient of determination of the model is 0.43. Also, it should be noted that both models are generally significant, and their probability value is zero.

4. Discussion

The works on modeling the dynamics of the bitcoin price have a special place in the literature. In most studies devoted to this subject, the method of time series analysis is used, and cross-sectional analysis is less popular. Despite the spread of the first method, time series analysis methods can give uninformative and misleading results, given that the time interval for consideration is small, cryptocurrencies are a relatively young phenomenon on the market, and they are highly speculative and volatile. However, for generality of the results obtained, we will consider both approaches.

Rejeb *et al.* published the best known paper where cross-sectional data analysis methods are used to study the price dynamics of altcoins in general and bitcoin in particular [22]. The authors suggest and then, using econometric methods, test a model of the dependence of the natural logarithm of altcoin market prices, expressed in bitcoins, on 5 variables, such as: natural logarithm of processing power (gigahash per second); natural logarithm of the number of altcoins mined per minute; the share of already mined coins in their total number; binary variable for the applied mining algorithm (SHA-256 or Scrypt); the number of calendar days from the moment the cryptocurrency was created until September 18, 2014. The studies led to several important conclusions. The authors demonstrate a positive direct relationship between the increase in computing power required for the currency mining, and its (cryptocurrency) price.

Also, some authors found that the number of altcoins mined per minute is negatively related to the coin price, as scarcity per mined block has a higher perceived value [23]. The author explains this fact by the possibility of dividing the altcoin into an infinitely small number of units (now it is up to 8 decimal places, but the value can be increased). The relationship between the price of altcoin and the period of its existence on the market was also not found. This may be due to the relatively short history of the coin on the market.

The main idea of the study is a multivariate approach that takes into account the speculative component of the cryptocurrency price [24]. The authors suggested that both the phases of bubbles and the phases of the decline in the bitcoin price can be explained by fluctuations in investor interest in it [24].

As a result of evaluating vector autoregression models for weekly and daily bitcoin prices, a bidirectional mutual effect of search queries on prices and vice versa was found [25]. Such a market is favorable for the formation of new bubbles.

Based on the analysis results of a first-order 4D vector autoregression model with first differences, Nica *et al.* [26], [27] discovered these two positive relationships: "social cycle" and "user acquisition cycle". The social cycle suggests that the growth in bitcoin popularity leads to increased number of search queries and higher social media activity. As a result, new users buy bitcoin, causing an increase in prices and sales of cryptocurrency.

The second trend, the user acquisition cycle, demonstrates that new users download bitcoin clients after receiving information about bitcoin and the technological aspects of the system. An interesting finding of the study is the negative relationship between the number of Google search queries and bitcoin prices. For example, based on daytime data, Gil-Cordero and some other authors [28] showed that 3 of the 4 biggest price drops were preceded by increased Google search activity the day before. As a possible explanation, one can consider a higher sensitivity of search activity to negative events than that of the cryptocurrency price, so the authors suggest that search peaks be perceived as indicators of a subsequent price drop.

Another group of scientists [29] extended the first-order vector autoregression model by including additional social signals and an algorithmic trading mechanism based on this model, taking into account the risks and costs of trading. The authors considered these additional variables: daily closing prices of bitcoin; daily data on the volume of bitcoin exchange for other currencies in the 80 largest online markets; daily number of blockchain transactions; the number of downloads of the most popular bitcoin client; normalized volume of search queries for bitcoin in Google Trends; the number of unique Twitter posts about bitcoin per day; the average daily valency of tweets about bitcoin determined using vocabulary techniques that allow one to quantify the degree of pleasure or displeasure related to emotional experience; daily polarization of opinions about bitcoin on Twitter as a geometric mean of daily coefficients reflecting the number of positive and negative words in relation to bitcoin calculated using the psycholinguistic method of linguistic research and word count.

The statistical relationship between macroeconomic indicators and prices per unit of cryptocurrency is described in more detail in the paper of [30], [31]. The article also argues that bitcoin can no longer be perceived as a unit isolated from the global financial system and can be considered as an asset for portfolio investment with weak diversification.

5. Conclusion

Examining both the results of an empirical study on a cryptocurrency's log return distribution and volatility models built using historical data variance, Z-tests, autoregressive risk assessment, and exponentially weighted moving averages enables us to reach the following conclusions.

Risk assessment methodology based on Z-test is not relevant for bitcoin due to high price fluctuations in trading sessions during the day. These significantly overestimate the risks and sometimes make their assessment absolutely inadequate.

Evaluation of sensitivity parameters in this market and the Monte Carlo method are of scientific interest for risk assessment using traditional methods.

The Monte Carlo method was not used in this paper due to the high costs of computational and time resources.

The factors driving bitcoin price dynamics, their effect on the price (whether up or down), and their relative importance change over time.

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