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# Financial Fear Index in the Digital Financial Assets Market

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## ABSTRACT

The **relevance** of the research topic is due to the increasing role of non-traditional financial instruments that contribute to financial instability. Therefore, various indicators are required to reflect the situation in the digital financial assets market, the volatility quotes, and the level of investor confidence. The **aim** of the study is to develop and test on empirical data a generalized indicator of financial instability (financial fear index) in the digital financial assets market. The **novelty** of the research lies in the adaptation of the classic model of building the volatility index to the cryptocurrency market. The authors use statistical **methods** for collecting and processing data, analyzing time series, weighing, designing economic indicators. The paper summarizes the results of modern research on the correlation between digitalization and financial instability. The authors **conclude** that at certain short periods of 2020 the ruble-dollar volatility was comparable or even higher than the ruble-bitcoin one. In addition, there is much less fear and uncertainty in the cryptocurrency market today than there was at the end of 2018. The main **result** of the study is the financial fear index model based on the method of calculating the weighted average option price of the underlying asset and hedging of price risks. The model has been tested using data on the bid and ask prices of cryptocurrencies at a specific point in time. Estimates have been obtained indicating the growing instability in the digital financial asset market. The authors offer **recommendations** regarding the index threshold values, which indicate the level of investors' fear.

***Keywords:*** fear index; digital financial assets; cryptocurrency market; volatility; financial instability; option contracts

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## INTRODUCTION

The current stage of economic development is characterized by a global change in the proportions of development of the real and virtual sectors of the economy, structural changes in the financial sector, and, in general, a qualitative change in the financial component of the economy as an integral link between the processes of production and consumption. New technologies are being actively introduced to financial markets: big data [1, 2], quantum computing [3], the blockchain of financial transactions [4, 5], etc.

Business digitalization, on the one hand, can significantly improve the quality of life by increasing labor productivity, the quality and efficiency of decisions made, increasing the transparency of information processes, financial and business operations in various fields of activity. In [6] it is proved that considering the components of the digital potential of the city (information and communication infrastructure, digital government and e-business) makes it possible to more accurately assess its investment attractiveness. On the other hand, digitalization inevitably leads to the emergence of specific conditions for the implementation of financial and economic activities and qualitatively new scenarios for the development of the economy, the emergence of additional risks and threats. The paper presents the most complete list of risks and opportunities of the digital economy concerning the current stage of development of the Russian Federation [7].

It should be noted that the new course towards digitalization of the economy is taking place against the background of negative processes in the economy [8] and politics [9] associated with the impact of COVID-19. In an era of global instability, the most acute problem is the preservation and diversification of investment portfolios to avoid negative effective rates of return. In these conditions, the instruments of the modern digital economy look like an interesting alternative to traditional instruments, but not as a full-fledged replacement, but as a hedging instrument, an important addition to the risky part of any investment portfolio. At the same time, considering the social risks of investment, the main emphasis should be placed not on the highest profitability, but on maintaining the expected profitability.

This paper aims to present existing approaches to the construction of generalized indicators of financial market volatility and show their capabilities in relation to the digital financial asset market. Based on this, it is planned to develop and test on the example of the cryptocurrency market a universal indicator of financial instability (financial fear index), which is necessary for timely making adequate decisions, hedging investment risk in the absence of an exhaustive volume of statistical data on the situation on world markets. To build the indicator, a special adaptation of the existing stress meters of traditional financial assets to the specifics of the virtual market is required.

It is quite obvious that in the context of declining investor confidence in a number of traditional financial assets, the markets for modern digital financial instruments are very active. There are currently over 2,000 cryptocurrencies actively traded on unregulated or registered exchanges. In January 2016, the total capitalization of the cryptocurrency market was about $ 7.5 billion, and two years later it reached its maximum value — more than $ 750 billion (as of May 2020, the capitalization was about $ 250 billion) [10]. The daily trading volume of cryptocurrencies exceeds billions of dollars. According to the Skew analytical service, by June 2020, the value of open positions in bitcoin options on the Deribit exchange reached $ 1.1 billion, in contracts on Ethereum — $ 150 million.[1]

[1] $ 1 Billion Bitcoin & Ethereum Options To Be Exercised On Deribit. URL: https://forklog.com/na-deribit-ispolnyatsya-optsiony-na-bitkoin-i-ethereum-stoimostyu-v-1-mlrd/ (accessed on 07.02.2021).

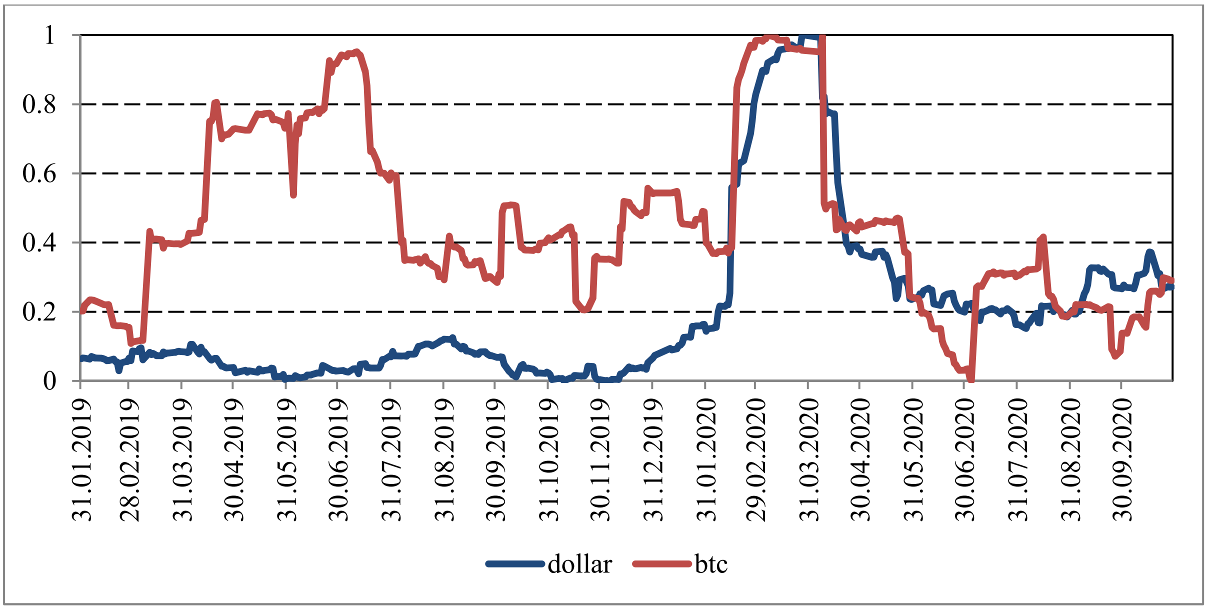


*Fig. 1.* **Volatility of the ruble against the dollar and bitcoin**

*Source:* calculated by the authors on the data of the ruble exchange rate to the dollar and bitcoin.

This suggests that the majority of players are betting on the further growth of the cryptocurrency market. At the same time, opinions are expressed about extremely high risks associated with the significant volatility of digital financial instruments as an inevitable attribute of the process of the formation of new markets [11]. There are even studies that compare cryptocurrencies to speculative bubbles similar to those found in traditional financial markets [12–14]. Indeed, in the cryptocurrency markets, at the moment of expiration of the nearest options, as a rule, there is increased volatility, especially when the expiration affects a large number of open positions (although most investors postpone open positions for a new period). However, we believe that the threat of serious consequences associated with the high volatility of digital assets is greatly exaggerated. This can be illustrated by a simple statistical example in relation to the Russian foreign exchange market, especially in light of the processes that took place in 2020, when the state allowed a significant depreciation of its own national currency. As the simplest indicator of volatility, the standard deviation of the ruble against the dollar and bitcoin can be used. To do this, we take a daily sample of quotes for the period from January 2019 to November 2020 and for each date, we calculate the spread of growth rates by 30 points (15 values before this date and 15 values after). To bring the indicators to a single scale (from 0 to 1), we will normalize and, as a result, we will get a graph of moving standard deviations (*Fig. 1*), by the peaks of which we can judge the high volatility of the ruble against the dollar and bitcoin. The figure shows that in 2019 the exchange rate of the ruble against bitcoin was more volatile than against the dollar. In 2020, the situation has changed. The behavior of the curves is largely similar, the volatility of the ruble against the dollar was even higher in certain periods (April, June, September–October). Overall, these dynamics are much less subject to fluctuations. For the cryptocurrency market, the beginning of the volatility compression phase is noticeable, which subsequently led to rapid growth in quotations by almost 200% at the beginning of 2021.

We also note that the thesis of a decrease in cryptocurrency volatility is confirmed by a number of studies. For example, in [15], using numerical methods for analyzing time series, it is shown that the cryptocurrency market has entered a new stage of development despite the presence of risks that have a long-term positive relationship with the level of financial stability. After 2018, there is still a decrease in the volatility of all liquid cryptocurrencies. This circumstance, according to the author, allows even partial use of digital currency in the monetary policy of the Central Bank of the Russian Federation.

The fundamental reasons for the instability of the Russian economy include not only the volatility of digital financial assets (in a certain way, private and insignificant instruments on a macroeconomic scale) but also the underdevelopment of market institutions and low management efficiency. Fluctuations in the global environment, in particular in world oil prices, also contribute to instability in Russia. However, in modern conditions it is difficult to assess this influence — the relationship between energy prices and the Russian ruble exchange rate, stock indices, and interest rates is contradictory. Correlation often changes from tight to weak, from direct to reverse, due to the actions of speculators, investor expectations, and, ultimately, market sentiment, which is constantly changing, resulting in new trends.

## BRIEF LITERATURE REVIEW

At present, quantitative methods for analyzing financial instability have been developed and are actively used. We refer to traditional and alternative estimates of the variation of the observed parameters of socio-economic development: macroeconomic indicators, industrial production, stock indices, exchange rates, etc. In particular, there is extensive experience in the development of various options for the index of financial instability. In Russian studies (for example, [16, 17]) this index was constructed by aggregating such indicators of financial and related markets as the volatility of stock indices and oil prices, exchange rate dynamics, yield spreads on government bonds, etc. In fact, in these and many other works, the financial instability index is the domestic alternative of the financial conditions index (FCI) or financial stress, widely known in foreign studies. Among the recent studies carried out by Russian scientists, one should highlight the work [18], which implements a number of alternative methods for constructing the index. In addition, we note the article [19], which also presents several specifications of the FCI of Russia. One of the results was the conclusion about the good predictive properties of this index concerning the 2014–2015 recession — the signal from it came two quarters before the start of a sharp drop in GDP.

As predictors of global economic crises, various FCI types began to be developed back in the 1990s. (a detailed review of the world practice of their use is presented in [20]) and are still actively used. For example, in [21], using the FCI, a simulation of the distribution of future real growth of US GDP by quantiles was carried out depending on the current financial and economic conditions. The regression model showed asymmetry in quantiles, that is, the lower quantiles of the distribution show strong variations, while the upper ones are stable over time. Based on this methodology, South Korean researchers obtained similar results [22] — first, they proved the asymmetric influence of financial conditions on the future growth of the country's GDP using quantile regressions with only internal variables included in the index. They then extended their model to include variables that reflect fluctuations in the US financial markets. It is concluded that the deteriorating financial condition of the US economy makes further growth of Korean GDP more volatile (and this effect, according to the authors, began to be observed only after South Korea opened its financial market in 1998).

In general, indices of the FCI class use a “portfolio” approach in the sense that such indices are obtained by aggregating private or group variables using weighting methods, principal components, or dynamic factors. At the same time, quite often the volatility index (VIX), also called the “fear index”, is included in the FCI as one of the variables. For example, this was done back in 2009 when developing the KCFSI — the Kansas City Financial Stress Index [23]. However, the VIX is also used as an independent market indicator, which is calculated based on the volatility of the actual option prices on a particular stock index. Thus, the classic VIX, developed by the Chicago Board Options Exchange, is based on data on the prices of options on the S&P500 index with different expiration dates.[2] The Russian analogue (RVI) uses option prices on the RTS Index with a period of more than 30 days before expiration.[3] Note that the dynamics of the VIX and RVI indices reflect the influence of the American economy on the Russian markets. True, cross-border volatility indices are present with a certain time lag due to the rules of trading on exchanges. At the same time, the anonymity of bitcoin[4] is not a critical factor, which, in our opinion, significantly affects the volatility of quotes.

There are also many other indices (VIXY, VXEEM, VXGOG, etc.) — all of them are considered reliable market predictors and are used by market participants as an analytical tool before making investment decisions. In addition, VIX information is used in some models to improve the pricing of the options [24].

Numerous studies support the predictive power of the VIX. It is interesting to note that in [25] the high efficiency of this index was proved during the period of COVID-19. Using empirical data on 19 stock indices from different countries, the authors built and compared three models to predict financial market volatility during the pandemic. Various tests and evaluations have led us to conclude that the VIX model (more precisely, the HAR-RV–VIX model, which is a specification of the realized volatility autoregressive model) is better suited for most markets. However, there are works that criticize this index. In [26], it is argued that the correlation between the imputed (expected) volatility (which allows us to estimate the VIX, built in accordance with the Black-Scholes model) and the real (realized) market volatility is very weak.

In [27], it is concluded that, depending on the expectations of investors regarding the growth or decline in market returns, the VIX can give different estimates. In the case of positively biased expectations, the VIX usually overestimates market volatility, otherwise, it underestimates. Moreover, the higher the negative expectations of investors, the more the VIX underestimates volatility.

Volatility assessment using quantitative methods is also carried out in relation to the digital financial asset market. First of all, it should be noted the growing interest of researchers both in information technologies and in the economic aspects of the problem. Statistical and econometric methods are actively used to analyze cryptocurrency markets. Thus, in [28], bitcoin price drivers were analyzed using wavelet analysis methods, in [29], the advantages of cryptocurrency diversification in portfolios of various asset classes were assessed, in [30], evidence was found using VAR models, that the higher transactional activity of Bitcoin temporarily leads to its higher profitability.

[2] The Cboe Volatility Index. URL: https://www.cboe.com/indices/ (accessed on 07.02.2021).

[3] Russian volatility index. URL: https://www.moex.com/ru/index/RVI (accessed on 07.02.2021).

[4] The anonymity of cryptocurrencies is a controversial issue. Many consider anonymity to be a myth, since any transactions with cryptocurrency leave digital traces, which can be easily tracked by their participants via social networks, IP addresses, crypto wallets, etc. This opens the way for the transfer of data about market participants, see, for example, “One of the largest crypto exchanges will release customer data to the US authorities”. URL: https://ria.ru/20180225/1515243837.html (accessed on 28.02.2021).

In the literature, a significant amount of research on the digital financial assets market is devoted to their consideration as investment instruments. In this context, methods for assessing the profitability and volatility of cryptocurrencies are of great importance [31, 32]. However, considering the objectives of our work, index methods of assessment are of certain interest. Among them, one should highlight CRIX (CRyptocurrency IndeX) — one of the first indices proposed in [33]. It is based on the Laspeyres method, well-known in economic statistics, which makes it possible to assess the price dynamics of a portfolio of digital assets with fixed weights. This index became the basis for building a more advanced VCRIX (Volatility CRyptocurrency IndeX) — an index that uses the VIX methodology for imputed volatility and allows to predict the average annual volatility of cryptocurrencies for the next 30 days on a daily basis.

In [34] VCRIX is tested on empirical data for 2015–2019 — the index recorded all significant jumps in volatility associated with shocks in the cryptocurrency markets. For example, the authors managed to find significant amplitudes and high frequency of the index in 2017 — VCRIX showed values that were interpreted as expected daily volatility of 140%. This is due to major changes in cryptocurrency legislation in China, Korea, Japan, and the United States, as well as the debate over the adoption of Segregated Witness (SegWit), a protocol update designed to improve blockchain efficiency.

It should be noted that blockchain flaws affect volatility, but known vulnerabilities and types of attacks allow timely development and implementation of protection measures. In particular, it is a well-known fact that during a bitcoin transaction, after verification, a new block is formed in the chain, which contains information about this transaction. But verification requires computing power and some time. And only after that, the financial transaction is performed.

The essence of the vast majority of cryptocurrency attacks boils down to the following. An attacker with a relatively large amount of computational resources can create his own version of the chain without sending it for verification. Blockchain is an unauthorized fork into a real malicious chain that is not broadcast to the main network. The attacker performs some legal operation on the real chain without including information about it in a malicious fork that grows and outstrips the real blockchain in length. There is a kind of double payout, while the original amount of funds does not change.

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Note that the problem of vulnerability of all financial transactions is somewhat broader and concerns the necessary security measures when working with the blockchain. Similar risks are borne by the widespread introduction of neural network technologies into the work of the classical stock market. At the same time, the active use of blockchain and appropriate information protection measures will smooth out possible negative consequences and, accordingly, the contribution of this factor to fluctuations in cryptocurrency quotes.

In this context, assessments of the state's attempts to control the world cryptocurrency market are important. The necessary

[5] How to hack Bitcoin, attack 51. URL: https://altcoinlog.com/attack-cryptocurrency-51-procent/ (accessed on 28.02.2021).

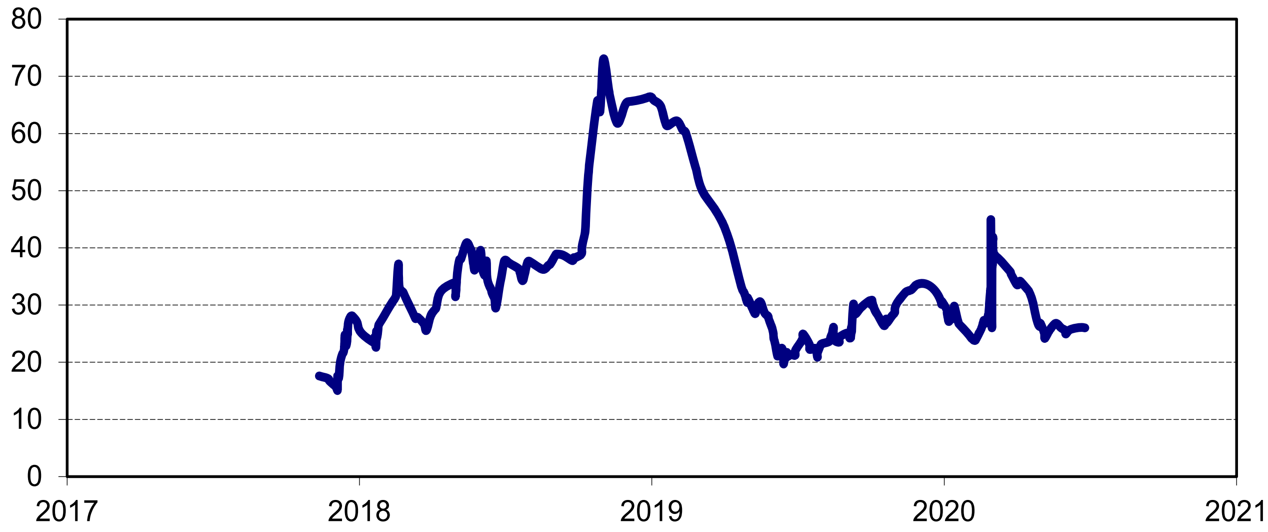


*Fig. 2.* **Dynamics of the financial fear index in the digital financial assets market**

*Source:* compiled by the authors.

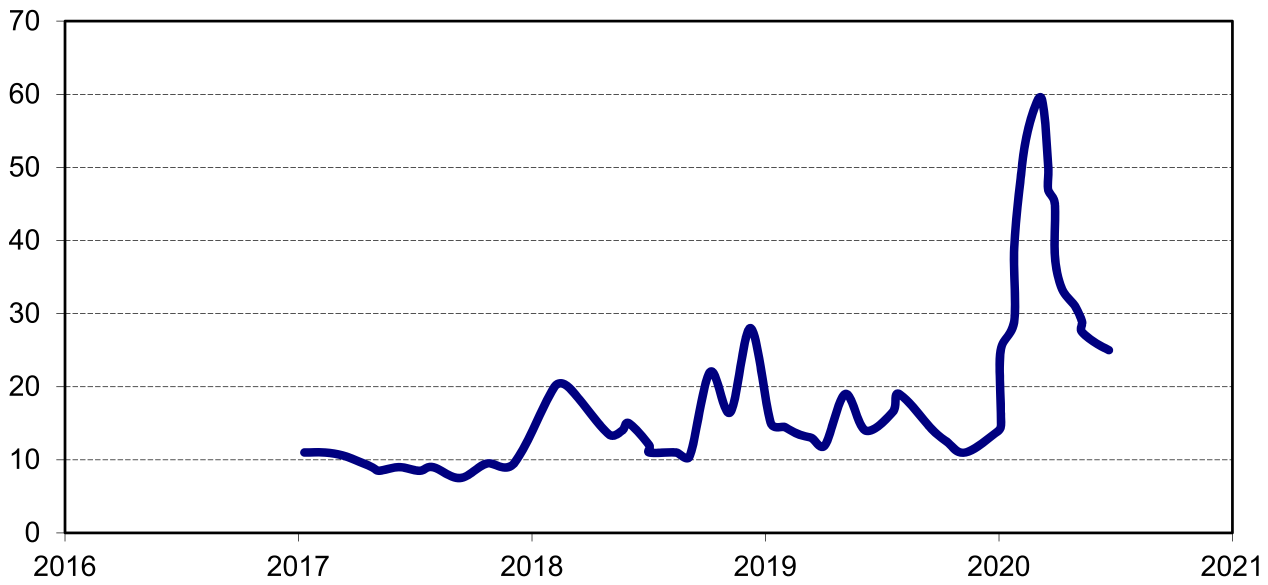


*Fig. 3.* **VIX dynamics**

*Source:* compiled by the authors based on data https://ru.tradingview.com/chart/?symbol=CBOE: VIX (accessed on 21.01.2021).

regulatory measures in this area are contained in the FATF standards and recommendations,[6] as well as in a number of works on this issue (for example, in [35]). In particular, they highlight the need to introduce licensing mechanisms for services in the cryptocurrency industry, change legislation, establish thresholds for transactions, etc. In our opinion, the current regulatory policy in the digital asset market is a desire for a state monopoly on the emission of all means of payment, i.e. in fact, this is the way to the digitalization of national currencies in a non-cash form. In this situation, the blockchain is likely to become a link between national and global cryptocurrencies, as well as a

[6] FATF (2012–2020). International Standards on Combating Money Laundering and the Financing of Terrorism & Proliferation. FATF, Paris, France. URL: www.fatf-gafi.org/recommendations.html (accessed on 28.02.2021).

technological base for the functioning of not only the digital but also the real economy.

## FINANCIAL INSURANCE INDEX AS A GENERAL INDICATOR OF FINANCIAL INSTABILITY IN THE DIGITALIZATION OF FINANCIAL OPERATIONS

### Preliminary statistical analysis

Using the statistical data of the quotes of the underlying asset (bitcoin) and its derivative (bitcoin futures), we can approximately simulate the dynamics of our own indicator (index) of financial fear in the digital financial asset market — hereinafter we will use the abbreviation IFFD. This index model is constructed as the inverse of the derivative of the underlying asset, normalized to the standard deviation.

*Fig. 2* shows the dynamics of IFFD, where any point on the graph does not represent a discrete value, but a certain spread of numerical values that reach their maximum or minimum at the moment. It can be noted that the index in 2019 decreased to 30–40 points, which is approximately two times higher than the volatility indicators in the stock markets (*Fig. 3*). However, the cryptocurrency market has much less fear and uncertainty than there was at the end of 2018.

The level of financial instability of real and virtual financial assets is characterized by a negative correlation between indicators of price dynamics and the relative magnitude of volatility, especially during the crisis of 2014–2016, and the following crisis of 2020, which determines the level of investor confidence in real and digital financial assets. At the same time, the growth of the index of distrust in the financial sector differs significantly in the segments of digital and non-digital financial assets. There is a lag in the development of average rates of dynamics with a certain time lag.

This allows us to recommend the corresponding index as the most important leading indicator of financial instability and an effective tool for diversifying an investment portfolio to hedge risks.

If we compare the dynamics of IFFD and VIX, we can see that the crisis in 2019 affected investor confidence in the cryptocurrency market, while the crisis hit the stock market only a year later. In addition to quantitative assessments of levels, the nature of the risk of the virtual and real economies differs. This is due to the specifics of the manifestation of different types of interconnected crisis phenomena in the financial environment, the inertia of the corresponding processes in digital and traditional financial markets.

### Theoretical basis

To develop early warning systems for financial instability, an urgent indicator of financial instability is urgently needed, which quickly reflects the situation in the financial market, the degree of investor confidence, the level, dynamics, and relative magnitude of the volatility of the main quotes. Considering the above, we start developing our own indicator — the financial fear index. When calculating it, it is necessary to consider investors' demand for digital financial assets.

Anticipating our development, we note the discrepancies in understanding the essence of the term "volatility" and "fear of investors". Periods of turbulence in financial markets are usually preceded by a phase of declining short-term volatility. The uncertainty of the current state and the direction of further development of the economy raises concerns about the financial condition, volumes, structure of investments in financial assets, and the adoption of financial obligations. This fear gives impulses, shakes up and expands the sphere of volatility, causes an increase in the amplitude of price fluctuations, which, in turn, further intensifies investor fears and generates panic. Any slightest fluctuation in the market situation, sometimes for subjective but systemically significant reasons, can cause a snowball effect, become a turning point in a trend. There is a massive closure of the positions of market participants, a new trend is forming. Ultimately, everything is decided by expectations, moods, often associated with random factors indirectly related to the economy: speculative play, the interests of the political and business elites, the opposition of political forces, the influence of the international situation, local conflicts, natural disasters, man-made impacts and, finally, the spread of diseases. The latter directly affects the real sector of the economy, causing corresponding financial problems.

The financial fear index is a display of quantitative estimates of investors' forecasts regarding the volatility of the price of an underlying asset for a certain period. We take the VIX as a basis to develop our indicator, the underlying asset of which, as mentioned earlier, is an option on the US S&P500 index, which covers a large number of securities of various companies. A statistical regularity has been established, according to which the S&P500 indices and the VIX calculated on its basis have an inverse correlation, which is associated with financial fears of market participants caused by significant changes in quotations on the financial market. When volatility returns to normal, the market becomes more predictable, which leads to higher prices for financial instruments.

For the digital segment of the financial market, it is possible to use similar indicators, assessing the expected volatility similarly to the VIX indicator. We write about this in the review section. However, the presence of several indicators used for various segments of the financial market does not allow making operational financial decisions related to the diversification of an investment portfolio consisting of both traditional and digital financial assets.

## Methods

If we analyze in detail a sample of option contracts on the Deribit cryptocurrency exchange at certain points in time with expiration dates in the near future, then we can more accurately model the IFFD dynamics using the method of calculating the weighted average price of an option on the underlying asset and hedging the price risks. This approach is fully consistent with the classical methodology by analogy with the VIX.

Using the classic Black and Scholes model, we will quantify investor positions in digital financial assets. The value of the proposed IFFD will be determined as a weighted average forecast of the variance based on the prices of all options that investors are willing to pay for the right to buy or sell the underlying asset at a specified price, hedging the risks of sharp price fluctuations in the market.

The IFFD model will be as follows:

$$I = 100 \cdot \sqrt{\frac{2}{T} \sum \frac{\Delta p_{ex}}{p_{ex.i}^{2}} \cdot \bar{p}_{opt.i} - \frac{1}{T}\left(\frac{p_a + p_{opt}}{p_{ex.0}} - 1\right)^2},$$

where $T$ — the time in fractions from the calendar year until the exercise of a certain series of the option; $p_{ex.i}$ — the specific exercise price of the option from the aggregate; $\Delta p_{ex}$ — the average absolute change in the option strike price, calculated as the arithmetic average of the absolute change in the next and previous strike price; $p_{ex.0}$ — the closest exercise price of the option to the expected one at the time of exercise, which at each particular moment is considered relative to the set of exercise prices set in the current contracts; $p_a$ — the actual current price of the underlying asset on the market; $\bar{p}_{opt.i}$ — the average value between the purchase and sell prices of a particular option (option price).

As for the price of each option ($p_{opt}$), it depends solely on the expected probability of the price movement of the underlying asset, starting from the current price level relative to the option strike price during the next calendar month remaining until the expiration date. For example, the price of a call option would be determined as the difference between the current price and the

Table 1

**Data for options with various expiration dates (June 27, 2020) as of June 26, 2020**

| Buy option (call option) | | | Strike price, dollar | Option to sell (put option) | | |
|---|---|---|---|---|---|---|
| Bid price, dollar | | Volume of bids, btc. | | Bid price, dollar | | Volume of bids, btc. |
| purchase | sale | | | purchase | sale | |
| 677.85 | 1005.25 | 0 | 8375 | 0 | 13.83 | 22 |
| 553.35 | 885.36 | 0 | 8500 | 9.22 | 13.83 | 44088 |
| 433.46 | 765.47 | 0 | 8625 | 9.22 | 18.44 | 43832 |
| 313.57 | 645.58 | 0.1 | 8750 | 13.84 | 23.07 | 44102 |
| 355.26 | 382.94 | 43831 | 8875 | 23.07 | 32.3 | 43866 |
| 230.67 | 267.57 | 43866 | 9000 | 32.3 | 41.53 | 43886 |
| 143.08 | 166.16 | 43840 | 9125 | 64.57 | 73.8 | 31 |
| 78.41 | 87.64 | 43851 | 9250 | 106.12 | 124.58 | 56.1 |
| 27.69 | 41.53 | 52 | 9375 | 156.91 | 295.36 | 43933 |
| 18.45 | 23.07 | 118 | 9500 | 276.88 | 406.09 | 43831 |
| 13.83 | 18.45 | 90 | 9625 | 396.93 | 498.47 | 0.1 |
| 4.61 | 18.45 | 9 | 9750 | 498.02 | 0 | 0 |
| 0 | 13.83 | 43985 | 9875 | 0 | 0 | 0 |
| 0 | 18.45 | 35.4 | 10000 | 0 | 0 | 0 |
| 0 | 13.83 | 43895 | 10125 | 0 | 0 | 0 |

*Source:* compiled by the authors based on data https://www.deribit.com/main#/futures (accessed on 21.01.2021).

risk-weighted discounted strike price, that is, as follows:

$$p_{opt} = p_a \cdot p(EO) - p_{ex} \cdot p^{-r_f \cdot T} \cdot p(NO),$$

where $p(EO)$ — the probability of exceeding the spot price of the underlying asset (distributed approximately according to the normal law with zero mean and standard deviation equal to one) of the strike price, that is, the probability of the call option being exercised; $p(NO)$ — the probability that the spot price of the underlying asset will not be exceeded by the strike price, that is, the probability that the call option will not be exercised (risk hedging ratio); $r_f$ — risk-free interest rate (taken equal to 4.5% per annum); $T$ — the time until the option is exercised in years (taken equal to 1/12).

The numerical values of risk factors, that is, the odds of exercising an option and not exercising an option, are calculated as follows:

$$EO = \frac{\ln\left(\frac{p_a}{p_{ex}}\right) + r_f \cdot T + \frac{\sigma^2 \cdot T}{2}}{\sigma^2 \cdot \sqrt{T}},$$

$$NO = EO - \sigma \cdot \sqrt{T},$$

where $\sigma$ — the theoretical standard deviation (in fractions of a unit) in annual terms (taken as 0.4, based on data on option prices).

The price of a put option is determined using a similar formula with the opposite sign, adjusting the risk factors multipliers, respectively, by $1-p(EO)$ and $1-p(NO)$.

To obtain a generalized indicator, it is necessary to weigh the numerical values of the indicator according to the number of days before the expiration of each of the series in annual terms. For this purpose, we will determine the 30-day weighted average ($I_T$) using the formula:

$$I_T = \sqrt{\frac{T_{365}}{T_{30}}\left(T_1 I_1^2\left(\frac{T_2-T_{30}}{T_2-T_1}\right)+T_2 I_2^2\left(\frac{T_{30}-T_1}{T_2-T_1}\right)\right)},$$

where $T_{365}$, $T_{30}$ — time in fractions of the calendar year; $T_1$, $T_2$ — time until the date of execution of the next and subsequent series of option contracts for shares of a calendar year; $I_1$, $I_2$ — IFFD volatility assessment of the next and subsequent series of option contracts.

## Data and results

We used the prices of options contracts as the initial statistics. The bid prices for the purchase and sale of cryptocurrency at the time of calculation were taken as a basis, i.e. as of June 26, 2020 — a total of 15 bid positions of the assets being valued. We will show the formation of the price of a specific option using the example of a buy option. We will proceed from the investor's average market assessment of the development of the market situation, which is expressed in the distribution of bid prices for purchase and sale.

Thus, the current price of the underlying asset was \$ 9230. Taking the approximate strike price of the option in July 2020 to buy at \$ 9410, we first determine the arguments of the factor function:

$$EO = \frac{\ln\left(\frac{9230}{9410}\right)+0.045\cdot 1/12+\frac{0.4^2\cdot 1/12}{2}}{0.4^2\cdot\sqrt{1/12}} = -0.077,$$

$$NO = EO - 0.4\cdot\sqrt{1/12} = -0.192.$$

To determine probabilities $p(EO)$ and $p(NO)$ we use the standard spreadsheet function NORM.ST.DIST($x$), which returns the standard normal cumulative distribution, has a mean of zero and a standard deviation of one:

$$p(EO) = 0.469 \text{ and } p(NO) = 0.424.$$

Thus,

$$p_{opt} = 9230\cdot 0.469 - 9410\cdot e^{-0.045\cdot(1/12)}\cdot 0.424 = 358.6 \ US\ dollars$$

The index was calculated based on the two closest series of call options and put options with different expiration dates, June 27 and July 31, respectively, in USD as of June 26, 2020, at the current price of the underlying asset of \$ 9230.

The use of sample data at the moment is associated with the objective lack of historical information about the dynamics of all parameters of options transactions. The calculations use sample data provided by the trading system under study. However, they correlate quite well with data from other trading systems, since it is a well-known fact that there are arbitrage transactions that quickly equalize prices between different markets and maintain their equilibrium. It should be noted that despite the possibility of using the information on the real quotes of the underlying asset, a feature of our study is the use of a data array at the time of calculation (as of June 26, 2020) due to the lack of up-to-date historical information on the distribution of order prices, order volumes regarding execution prices. This is due to the desire of the authors to focus not on real transactions reflecting the results of the operation of market pricing mechanisms, but on the expectations of investors hidden behind these figures. Initial data is continuously generated by traders in real-time based on their own views on the development of the situation, forecasts, expectations, beliefs, sentiments, fear, greed, etc., cannot be calculated.

We also note that any investor acts in the absence of comprehensive information about

*Table 2*

**Results of calculations of components of the financial fear index**

| $p_{ex.i}$ | $p^2_{ex.i}$ | $p_{opt.i}$ (call) | $p_{opt.i}$ (put) | $\Delta p_{ex} \times p_{opt.i}/p^2_{ex.i}$ (call) | $\Delta p_{ex} \times p_{opt.i}/p^2_{ex.i}$ (put) |
|---|---|---|---|---|---|
| 8375 | 70 140 625 | 841.55 | 6.915 | | 0.000012323 |
| 8500 | 72 250 000 | 719.355 | 11.525 | | 0.000019939 |
| 8625 | 74 390 625 | 599.465 | 13.83 | | 0.000023239 |
| 8750 | 76 562 500 | 479.575 | 18.455 | | 0.000030131 |
| 8875 | 78 765 625 | 369.1 | 27.685 | | 0.000043936 |
| 9000 | 81 000 000 | 249.12 | 36.915 | | 0.000056968 |
| 9125 | 83 265 625 | 154.62 | 69.185 | | 0.000103862 |
| **9250** | **85 562 500** | **83.025** | **115.35** | | 0.000168517 |
| 9375 | 87 890 625 | 34.61 | 226.135 | 0.000049223 | |
| 9500 | 90 250 000 | 20.76 | 341.485 | 0.000028753 | |
| 9625 | 92 640 625 | 16.14 | 447.7 | 0.000021778 | |
| 9750 | 95 062 500 | 11.53 | 249.01 | 0.000015161 | |
| 9875 | 97 515 625 | 6.915 | 0 | 0 | |
| 10000 | 100 000 000 | 9.225 | 0 | 0 | |
| 10125 | 102 515 625 | 6.915 | 0 | 0 | |
| Total | | | | 0.000114915 | 0.000446591 |

*Source:* authors' calculations.

all transactions made on various trading floors, relying only on certain indicators (moving averages, indices of relative strength, divergence, and convergence, etc.), selected data on the situation on the exchange markets. Investment decisions in such conditions are made impulsively. However, in general, such sample data and estimates obtained in the course of calculations are unbiased (for example, the average prices of options contracts) and with a certain degree of a probability represent the entire population. Thus, there is no systematic error in our calculations, which allows us to consider the accepted accuracy of calculations as satisfactory.

As an example, we will give the initial data (*Table 1*) and show the calculation in relation to only one date — June 27.

For settlements on options with an exercise date of June 27, we will use *Table 2*. We select for settlements contracts concentrated around the base execution price, i.e. closest to the one expected at the time of execution. In our case, it is equal to $ 9250. As a rule, it corresponds to the minimum absolute difference between the prices of options to purchase and sell. Next, we discard the non-monetary call and put contracts, respectively, below and above the base execution price. We also discard contracts with zero bid prices, purchase and sell volumes.

The formula is used to calculate the first series options expiring after 1 day as of June 26, 2020:

$$I_1 = 100 \times \sqrt{\frac{2}{1/365}(0.000114915 + 0.000446591) - \frac{1}{1/365}\left(\frac{9230 + \frac{83.025 + 115.35}{2}}{9250} - 1\right)^2} = 61.899.$$

We performed similar calculations for a series of options with a strike date of July 31, which is 35 days later than June 26, 2020. As a result, we get $I_2 = 68.826$.

We weigh the obtained numerical values of the indicator by the number of days before the expiration of each of the series in annual terms and obtain a 30-day weighted average:

$$I_T = \sqrt{\frac{365}{30}\left(\frac{1}{365}\cdot 61.899^2\cdot\left(\frac{35-30}{35-1}\right)+ \atop +\frac{35}{365}\cdot 68.826^2\cdot\left(\frac{30-1}{35-1}\right)\right)} = 68.788.$$

## Discussion

The proposed indicator quantifies the spread of option prices on the underlying asset and is interpreted as follows. The IFFD is measured as a percentage of the expected change in the price of the underlying asset during the next calendar year. For our calculation, it is expected that the quotes of the underlying asset will change in the direction of a decrease or increase by 68.8%. Then, with a probability of 0.954, it can be argued that the expected level of quotes during the next calendar month will be within the confidence interval from the current level within two standard deviations, i.e. plus or minus $2\times\frac{0.68788}{\sqrt{12}} = 0.39714$ or 39.7%. However, it is known that the Student's $t$-test for a small sample imposes more stringent restrictions on variation, given the nature of the distribution. This is because sample variance is a biased quantification of the total variance. Therefore, it is necessary to additionally consider such a distribution parameter as the number of degrees of freedom of the sample variance. Then, with a probability of 0.954, it can be argued that the expected level of quotes during the next calendar month will be within the confidence interval from the current level within 2.145 standard deviations, i.e. plus or minus 0.428, or 42.8%.

We offer the following recommendations on the threshold values of the index in relation to the digital financial asset market:

1. Below 30% — low volatility indicates good investor sentiment, however, the lower this value, the greater the likelihood of a trend reversal.
2. 30–50% — average value, normal state, but this value does not allow giving specific signals to open or close positions.
3. 50–70% — a serious increase in the degree of volatility, signaling the emerging crisis phenomena and the corresponding fluctuations in exchange quotations.
4. Above 70% — panic begins in the market, which leads to a collapse of stock prices.

The obtained assessment of our indicator at the level of 68.8% exceeded the value of the criterion of 50%, which indicates the growing instability in the segment of digital financial assets. Note that very often phases of turbulence, characterized by multiple growths of quotations, are preceded by a certain period of decrease in volatility when the corresponding assets are distributed or accumulated. We have identified such periods in 2020 — the volatility of bitcoin was comparable to the volatility of the ruble (*Fig. 1*). However, such periods are inevitably followed by a surge in volatility — our forecast based on data on prices for options contracts in June 2020 turned out to be correct, since at the beginning of 2021 the cryptocurrency market showed very high volatility.

The proposed indicator of investor confidence in financial assets can be successfully used in various spheres of economic activity that have embarked on the path of digitalization, and serve as a leading indicator of negative impulses and imbalances in development.

In the future, this model can be improved both by clarifying the nature of the relationship between the components of the financial market and by expert assessments. The generalized financial fear index can be formed from the corresponding financial fear indices for segments of the financial market. The construction of such a model will make it possible to draw even more accurate conclusions regarding the dynamics of the main parameters of economic development.

## CONCLUSIONS

The conducted research allows us to formulate several conclusions. The digital transformation of the economy is taking place in an environment of financial instability. In this situation, modern digital economy instruments as a hedging method can act as an alternative to traditional instruments.

Today, we are seeing increased investor interest in digital financial assets — with a total market capitalization of hundreds of billions of dollars. At the same time, one of the results of our research was the confirmation of the hypothesis about the presence of phases with relatively low risks of volatility in the cryptocurrency market. Using the methods of statistical analysis, it was shown that in certain short periods of 2020, the volatility of the ruble to the dollar is comparable or even higher than to bitcoin. However, the volatility reduction is always followed by a surge in volatility, which was especially clearly demonstrated by the bitcoin quotes in 2021.

Analysis of modern scientific publications allows us to conclude that there are a large number of developments that quantitatively assess financial instability. A special place here is occupied by indices of financial condition (financial stress) obtained by aggregating private or group variables and serving as good predictors of instability and crises. These indicators are being actively used in the digital financial asset market — they allow to record surges in volatility associated with shocks in the cryptocurrency markets. The generalization of these indicators made it possible to model the dynamics of the own index, obtained as the reciprocal of the underlying asset and normalized to the standard deviation.

The main result of the study was the model of the financial fear index in the digital financial asset market. This model is based on the method of calculating the weighted average price of the underlying asset option and hedging the risks of sharp price fluctuations in the market. This approach is fully consistent with the “classic” Black and Scholes model used to develop the famous VIX volatility indicator.

The IFFD model was tested on statistical data on the prices of option contracts. We considered the bid prices for purchasing, selling cryptocurrency not in dynamics, but on a certain date — this is due to the lack of up-to-date historical information on the distribution of bid prices and volumes concerning execution prices. The result was the calculation of the index and its interpretation. Threshold values of the index are proposed, which can be used to determine the level of fear of investors in the digital financial asset market. The estimates obtained (calculations were made based on data as of June 2020) gave a signal of increasing market volatility, which was confirmed by a sharp increase in price volatility in early 2021.

The developed model can be used in real financial transactions in order to make the right investment decision in a timely manner in conditions of uncertainty, lack of comprehensive information, insider information, etc. The practical value of the index is explained by its ability to signal the overheating of the digital segment of the financial market, which requires the immediate closure of long positions, the possible opening of short positions. This allows us to recommend the index as a leading indicator of financial instability in order to reduce investment risks.

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