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Dynamic Connectedness between Crypto and Conventional Financial Assets: Novel Findings from Russian Financial Market

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Abstract. In the dynamic landscape of the Russian digital economy and increasing financial openness, crypto assets have emerged as influential players in the financial market. The geopolitical and economic developments after a conflict with Ukraine have presented formidable challenges in the shape of financial and trade sanctions, coupled with the suspension from the SWIFT banking system, has plunged the Russian economy into a precarious situation. The current study delves into the network spillover effects between a prominent crypto asset and various financial assets including equity, exchange rates, crude oil, gold, and commodity futures using daily data from January 01, 2018, to August 31, 2023. The purpose of the study is to provide empirical and theoretical insights into countering the impact of sanctions on Russia, proposing a pragmatic solution for the Russian financial market. The research methodology involves the application of network spillover estimation and value-at-risk analysis. Notably, the findings expose a robust association between crypto and financial assets, where crypto assets play a pivotal role in transmitting risk within the financial landscape. While their impact on other financial assets remains relatively subdued, short-term correlations exhibit volatile fluctuations, often marked by sharp increases in downside risk. Theoretical implications follow the portfolio theory of asset pricing, with extreme risk spillover originating from long-run fluctuations in the crypto market, impacting market sentiment and elevating risk propagation in the Russian financial market. These results carry practical significance for payment and receipt processes, as well as trading activities with foreign countries, presenting essential insights for policymakers and investment decision-makers.

Key words: crypto assets; financial assets; Russian financial market; network spillover analysis.

JEL C31, G11, G12

1. Introduction

The Russian financial market faces a barrage of international economic and trade sanctions, originating from various countries and international bodies. These sanctions encompass various restrictive actions, including travel bans, asset freezes, and trade limitations. They target individuals, entities, and critical sectors like defense and energy, resulting in significant repercussions for Russia's economic landscape. The consequences are evident in the shape of the massive decline in foreign investment and restricted access to global financial markets.

However, Russia has responded with a strategic maneuver with a visionary economic policy of financial openness. In September (2022) the Russian Banking sector and Ministry of Finance agreed on cross-border payments in cryptocurrency. They aim to legitimize cryptocurrencies

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for payments, with major financial institutions supporting the use of crypto assets in international trade [1]. Among 14.6 million Russian crypto holders, Ethereum is popular (32 %), followed by Bitcoin (30.8 %). Altcoins like Ripple, Dogecoin, and Solana are owned by about one in five holders, showing growing diversity[1].

This new approach emphasizes trade openness, supported by financial asset mobilization, integration of crypto assets investments, and enticing trade concessions, particularly within financial, energy and technology sectors. This narrative holds profound implications for Russia economy which constrained by sanctions where the crypto assets offer an escape route for international trade and financial transactions.

In line with this financial openness, this study aims to assess asset price volatility and network risk spillover effects of a popular Russian-origin crypto asset on various Russian financial asset classes, including equities, exchange rates, crude oil futures, gold, and commodity futures. This assessment employs novel econometric techniques, focusing on the ongoing crisis between Russia and Ukraine in 2022.

As Russia's digital economy becomes increasingly integrated with various sectors, digital currency has become essential for ensuring efficient circulation and robust payment systems. In the global landscape of crypto assets numbers of digital currencies exist with total market capitalization exceeding $1.3 trillion.

Russia is positioning itself as a major player in the field cryptography, crypto mining and blockchain mining. Russia envisions a future where digital currency plays a pivotal role in driving economic growth and dynamism.

In addition, to compete the impact of economic and trade sanctions [2, 3] the new financial openness policy initiative further strengthened the imminent launch of Digital Rubles and remove bans on investments in popular Russian-based crypto assets like Ethereum (ETH).

As crypto transactions rise, nations consider banning crypto investments for financial stability [4]. Russia, despite recognizing digital currencies, forbids using them for payments. Some suggest regulated crypto exchanges for taxes and compliance. Russia plans a CBDC ruble and enforces strict rules on private crypto amidst sanctions. The goal is to facilitate seamless trade with partner nations and mitigate the potential impact of sanctions.

The literature gap and the problem which is faced to the existing economic condition where the previous studies have established correlations between crypto assets and various financial assets, primarily using Bitcoin as a representative of the crypto asset class only in normal economic condition.

However, there is a notable absence of specific research in the Russian financial market context that considers Russian-based crypto assets like Ethereum (ETH) in conjunction with equities, exchange rates, crude oil futures, gold, and commodity futures, especially during both normal, crisis and high market uncertainty and at the time of high geopolitical. The recent crisis of COVID-19 and Russia and Ukraine conflict (2022) has had a significant impact on Russia's financial market [1, 5]. Furthermore, the new financial openness policy (2022) has brought a hope to the financial market where the policy carries both short-term and long-term implications that encourages investment in crypto assets and strengthens their connection with other financial assets.

The purpose of the study is to provide empirical and theoretical insights into countering the impact of sanctions on Russia, proposing a pragmatic solution for the Russian financial market.

[1] https://bitcoinist.com/russia-approves-bitcoin-for-cross-border-payments/

Firstly, it examines both symmetric and asymmetric volatility spillover between Ethereum (ETH) and other various conventional financial assets from Moscow stock exchange (MOEX) such as equity, exchange rate, crude oil futures, gold, and commodity futures.

Secondly, the study explores the correlations among these underlying assets within the framework of the financial openness policy introduced in 2022, assessing the overall shifts of risk from crypto assets and other financial assets.

Thirdly, the study evaluates the magnitude of investment spillover from local financial assets to crypto assets during normal and crisis periods.

Lastly, the study examines key driving factors impacting crypto asset prices and their effects on local financial assets using Diebold and Yilmaz's risk spillover network and value-at-risk (VaR) analysis to measure portfolio investment's upside and downside risk.

This study provides the first quantitative analysis of the risk spillover of Ethereum (ETH) onto local financial assets, particularly during extreme risk scenarios. Additionally, it identifies the factors influencing the risk in the Russian financial market within the dynamic of crypto assets and other financial assets.

Based on the empirical analysis the study provides unique insights in the context of financial openness during crisis periods. The study observed investments shifts from traditional financial assets to crypto assets after proposing the new financial policy. Russia persists, navigating this evolving landscape through calculated after government interventions in the landscape of crypto assets the surge in cryptocurrency adoption has increased where 12.06 million Russians (9.05 % of the total population) now possess digital assets including the major share of Ethereum, which underscores the public embrace of new financial openness [6].

The public's acceptance of this policy acts as a shield against economic sanctions. The removal of the Russian banking system from SWIFT network has elevated the financial market risk in transformation of payments where the crypto assets are now used for cross-border transactions and attract foreign investments. Empirical evidence supports the significant increase in investment and its correlation with other assets in the Russian financial market [7–9].

The Society for Worldwide Interbank Financial Telecommunication (Swift), the global banking communication network, enables secure international money transfers among thousands of banks in 200+ countries. It became a tool in the Russia-Ukraine conflict as potential sanctions targeted Russia's Swift access. In response, Russia introduced SPFS, akin to Swift, but limited to certain trading partners like China, India, and neighboring nations.

These findings can assist fund managers and investors in formulating effective risk management strategies, optimizing financial investment portfolios, and encouraging the development of the Russian financial sector.

Our motivation for this study stems from recent policy changes in financial modernization where this study holds significant policy implications given Russia's status as a major producer of energy, minerals, commodities, and technology, understanding how policy changes affect correlation among the crypto and other financial assets. The study also provides practical policy insights for Russia's global trade partners, stock investors, and fund managers. Furthermore, the study enhances market risk monitoring by offering guidelines to mitigate financial market volatility through network spillover and VaR estimations.

This study is relevant in context of the rapidly evolving Russian digital economy and financial openness, crypto assets have gained significant influence in the financial market. In preview of the current geopolitical and economic developments, such as the conflict between Russia and a neighboring country that started in 2022, several challenges have arisen for Russia's growing economy [1].

With the Russian economy facing financial and trade sanctions, suspension from the SWIFT banking system for transferring financial funds, all these challenges pose dangerous economic matters that create a challenge for policymakers and market regulators to address this unresolved issue. In this context, this current study explores the network spillover effects between a prominent crypto asset and various financial assets, such as equity, exchange rate, crude oil futures, gold, and commodity futures in the Russian financial market.

The study employs network spillover and value-at-risk analysis by utilizing daily data from January 01, 2018, to August 31, 2023. In particular, the study examines the dynamic connections among the assets under normal and crisis conditions. The time span of the study makes the findings more important by providing a poly dimensional solution to stock market investors, traders, importers, and exporters in foreign countries' payment and receipts.

The hypothesis thesis statement of the study is to dig out the network spillover effects of crypto assets and their correlation with equity, exchange rate, crude oil, gold, and commodity markets in the Russian Financial Market during an economic crisis.

The structure of this study unfolds as the *second* section elucidates the review of literature, proposed hypothesis and *third* section provides the methodological contours such as data, models, and estimations with the framework for risk spillover network construction. While the *fourth* section discusses the empirical outcomes and discussion on the findings, and the *final* section provides the conclusion and policy recommendation.

2. Review of Literature

Crypto assets play a dual role, advancing the digital economy and gaining significance in global capital markets, especially in the post-Russian-Ukraine crisis era and amid the COVID-19 turmoil [25].

Crypto assets stand out in the financial landscape due to their unique qualities. It operates through a decentralized blockchain network, ensuring transaction security while bypassing intermediaries like banks, governments, and agencies [1].

The blockchain guarantees immutability and transparency. Crypto assets' limited supply further enhances its security. Within this complex environment of economic uncertainty and geopolitical risk, the expansion and influence of crypto assets have become profound. The removal of the ban on initial coin offerings and decentralized digital currency trading in Russia has accentuated the direct impact of crypto assets on the nation's economy and financial landscape [10]we implement the time and frequency connectedness time-varying parameter vector autoregression (TVP-VAR.

The growing demand for crypto asset trading has elevated it to a distinct currency category within the Russian financial sphere, countering economic adversities like sanctions. Globally, crypto assets have evolved into a burgeoning asset class, assuming a pivotal role in investment portfolios embraced by a wide range of investors [11, 12].

In the context of global portfolio strategy, a significant portion of crypto asset investment serves as both an innovative safeguard against the volatility of other financial asset valuations and a novel hedge against traditional financial assets such as equity, bonds, metals, and commodities [13].

Crypto assets are known for their high price volatility, presenting opportunities and risks. In this context the current study aimed the hypothesis that there is negative correlation and opposing connection among the crypto assets and equity indices. On this basis the study projected the first hypothesis as:

H1: There is network spillover effects crypto asset and equity in Russian Financial Market during economic Crisis.

This volatility is attributed to their relatively short history, limited adoption, and sensitivity to news events, making them prone to price fluctuations [14, 15]. Crypto assets exhibit various relationships with other financial assets. Research has explored the connection between crypto assets and exchange rate markets, yielding mixed findings.

Bouri et al. [16] suggests a positive correlation, implying that crypto assets may act as risk-on assets, moving in sync with forex market movements. Conversely, Dyhrberg [17] indicate negative correlations suggesting that crypto assets diversify forex portfolios.

In this context the current study aimed the hypothesis that there is negative correlation and opposing connection among the crypto assets and equity indices. On this basis the study projected the hypothesis as:

H2: There is network spillover effects crypto asset and exchange rate in Russian Financial Market during economic Crisis.

The relationship between crypto assets and crude oil future rates yielding mixed results some studies find a positive correlation as both assets are speculative in nature [18].

While other studies find an insignificant relationship, indicating limited linkage between crypto assets and traditional crude oil future rates [19]. Research on the relationship between crypto assets and commodities, gold and crude oil has produced mixed findings. Some studies suggest a positive correlation, implying that crypto assets exhibit safe-haven characteristics during economic uncertainty [20].

However, other research indicates weak relationships highlighting the distinct properties of crypto assets in comparison to crude oil future rates [21]. In this context the current study aimed the hypothesis that there is correlation and connection among the crypto assets and crude oil futures. On this basis the study projected the hypothesis as:

H3: There is network spillover effects crypto asset and crude oil futures in Russian Financial Market during economic Crisis.

A research gap exists regarding the economic viability of investing in crypto assets in comparisons with investment in gold during economic crises, particularly in the context of the Russian financial market. Some argue that crypto assets serve as hedges against traditional financial assets during economic turmoil due to their decentralized nature and potential independence from central bank policies [22].

In addition, crypto assets are seen as diversification tools for investment portfolios in matching to the gold as other studies [23] consider the gold as safe haven. During economic crises, the correlation between crypto assets and traditional assets are low potentially providing diversification benefits [18]. It is important to note that crypto asset markets experience higher liquidity compared to traditional financial markets during times of crisis. This liquidity can amplify price fluctuations and restrict the ability to buy or sell crypto assets at desired prices [1].

Crypto assets, particularly Ethereum, are well-known for their significant price volatility, attracting traders seeking opportunities but also carrying associated risks [24]. This volatility is a result of their volatility, limited adoption, and sensitivity to news events, leading to rapid price shifts [25]. In this context the current study aimed the hypothesis that there is negative correlation and opposing connection among the crypto assets and gold future. On this basis the study projected the hypothesis as:

H4: There is network spillover effects crypto asset and gold in Russian Financial Market during economic Crisis.

Numerous studies have explored the potential correlation, hedge and diversification properties utilizing various methodologies, researchers have collectively reached a consensus that crypto assets against commodity futures have a somehow connections with conventional assets it may relatively weak. In the estimations and econometric methods include all the analysis approaches to measure the risk and spillover estimation such as regression estimation analyses [26], vector autoregressive models [27], autoregressive distributed lag [28], unconditional connectedness in the time-frequency domain [29], wavelet coherence [30] directed acyclic graph approach [31], multivariate GARCH models [32] and univariate GARCH models [19].

The overall finding suggests significant advantages for diversifying portfolios and managing risks [16]. Another significant study [33] highlights the influence of macro-financial developments affect the crypto assets volatility in short-term pricing dynamics while this influence diminishes significantly over the long term.

Conlon & McGee [34] suggests that economic policy uncertainty mainly determines the volatility of crypto assets in comparison to the commodity futures. They argue that increasing economic policy uncertainties erode investor trust in the global financial system and traditional currencies, enhancing crypto assets attractiveness.

Taera et al. [35] recommend that both policymakers and investors carefully monitor the impact of economic policy uncertainties on crypto assets performance. In this context the current study aimed the hypothesis that there is negative correlation and opposing connection among the crypto assets and equity indices. On this basis the study projected the hypothesis as:

H5: There is network spillover effects crypto asset and commodity futures in Russian Financial Market during economic Crisis.

Investment in crypto assets is purely based upon the preferences of the investor here the modern portfolio theory proposed by Harry Markowitz's in 1952 [36] guides the rationality of investors and introduces the concept of portfolio construction. This study follows the modern portfolio and provides suggestions regarding the allocation of weights to different assets based on their associated risks and returns. In light of this theory, concepts such as hedging, and diversification emerge to manage risks associated with financial assets. Using advanced econometric estimations, this study offers systematic guidance on hedging and diversification among investments in crypto and other financial assets. Figure 1 illustrates the application phases of the theory for portfolio-based investments.

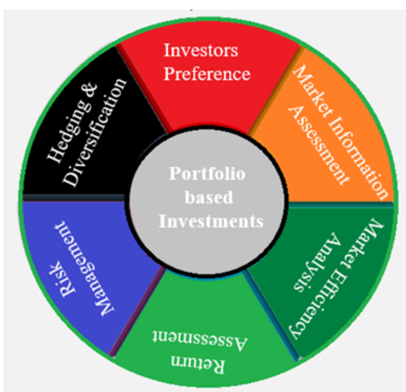

Figure 1. Theoretical Framework of the study

In conclusion, the crypto assets market is highly speculative and subject to regulatory changes, technological risks, and market sentiment. Therefore, this study provides suggestions based on statistical measurements to guide investors and fund managers in considering their risk tolerance and creating portfolios of crypto and financial assets before making investment decisions.

3. Methodology

Unveiling the latent potential of cryptocurrency assets in reshaping payment dynamics to counteract the impact of sanctions on the Russian economy is a critical pursuit. Delving into the intricate web of connections between crypto and traditional assets, employing cutting-edge econometric tools for nuanced analysis, stands as a pivotal endeavor in unraveling the authentic role of cryptocurrencies within the Russian financial framework.

The scrutiny of hedging strategies and risk diversification associated with both crypto and traditional assets promises valuable insights into the intricacies of risk transmission and potential avenues for hedging during periods of sanctions. This holds undeniable significance for investors and policymakers alike, especially in the midst of sanctions.

Numerous empirical models have been meticulously crafted to quantify the interplay of risk and return between these assets. Scholars widely favor the utilization of the GARCH process for volatility forecasting and network spillover estimation.

Hence, the empirical journey in this study embarks on a thorough exploration, commencing with a comprehensive overview of data sources and proceeding to the intricacies of estimation procedures. This includes forecasting through econometric models, simulation using GARCH, and the application of network spillover econometric estimation models.

3.1. Data

The study used daily closing price data gleaned from the esteemed crypto assets repository, Coin Market Cap (https://coinmarketcap.com), to underpin the crypto assets facet. In this context, Ethereum (ETH) was judiciously selected as the quintessential representative of the crypto asset's realm, driven by multifaceted rationales such as ETH's status as the second largest crypto assets.

Russian Vitalik Buterin created Ethereum (ETH), a notable crypto allowed for trading in Russia. ETH's blockchain aids transparent cross-border voting. In Russia, 40 % consider ETH and Bitcoin good for long-term investment. ETH is used for lodging, dining, cars, and furniture payments. Brand Analytics found ETH the most popular in Russian crypto in 2021.

The study's focus extends to encompass the MOEX Russia Index, meticulously handpicked to encapsulate the equity market milieu. Exploring the interaction of Bitcoin with the Russian stock market involves analyzing the MOEX Russia Index, which monitors the top 50 Russian companies across various sectors on the Moscow Stock Exchange.

This index, valued at 100 as its base, is capitalization weighted. The study also includes gold, using closing prices of spot-traded gold (GLD), and copper in RUB per gram from the FX and Precious Metals Market, along with the MOEX commodity future Index where we pick up the corn and soybean, and USD to RUB exchange rate. All data is sourced from the MOEX Russia Index for the other financial assets.

In pursuit of an all-encompassing examination, the study deftly integrated gold and copper futures (Ruble per gram) to deconstruct the dynamics within the metals and minerals arena. To holistically probe the energy sector, the study sought insight from the MOEX crude oil futures index.

Diversifying the purview, the study enlisted corn futures and soybean futures to illuminate the repercussions resonating from the commodity market. To empirically decipher the foreign exchange rate landscape (FRX), the USD/Rubles exchange rate emerged as a pivotal compass.

All these sector-specific indices, meticulously chosen, operate as quintessential conduits to epitomize the tapestry of broad financial assets. Deriving data for the designated variables, replete with significance, transpired from the annals of the Moscow stock exchange (MOEX), spanning the temporal swath from January 01, 2018, to August 31, 2023, thereby yielding a robust collection of 1306 observations. The motivation for the selection of this data time frame was to measure the impact of different crises and monitor policy changes on the financial market.

3.2. Econometric Model Selection

To assess the impact of popular crypto assets Ethereum (ETH) price volatility on various Russian financial asset classes (equities, exchange rates, crude oil futures, gold, and commodity futures), this section establishes an economic framework through a network correlation model. The initial step before constructing the network involves quantifying the risk associated with each asset class.

In addition, this study examine the overall expected risks such as upside risk and downside risk faced to the investment in using the value-at-risk (*VaR*) methodology proposed by [37]. The estimation of upside risk and downside risk through *VaR* is outlined as follows:

$$VaR_{i,t}^{U,\alpha} = \mu_{it} + t_{\nu,\eta}^{-1}\, r(1-\alpha)\sigma_{it}, \qquad (1)$$

$$VaR_{i,t}^{D,\alpha} = \mu_{it} + t_{\nu,\eta}^{-1}\, r(1-\alpha)\sigma_{it}. \qquad (2)$$

Where the $VaR_{i,t}^{U}$ and $VaR_{i,t}^{D}$ represents the upside and downside risks respectively, μ_{it} and σ_{it} is the conditional mean, and standardized residual of the return series, where the $t_{\nu,\eta}^{-1}\, r(\alpha)$ represents the quantile of the distribution of biased students t-statistics at the α level.

3.3. GARCH (p, q) Model Estimation

The study employs several estimation models from the GARCH family under the assumption of Diebold & Yilmaz [38] estimations to predict the volatility, connectedness and marginal distributions of different types of assets returns individually.

The selection of the optimal marginal distribution model is based on criteria such as log-likelihood (LL) and Akaike Information Criterion (AIC). Specifically, in the mean equation, the asset's return adheres to the standard ARMA (m, n) distribution.

However, to capture the asymmetric and fat-tailed characteristics inherent in asset returns, we opt for the Skewed-t distribution for estimation. For the variance equation, this research utilizes the GJR-GARCH estimation model [39], AP-ARCH estimation model, and E-GARCH model [40].

These models are employed for conditional variance modeling, aiding in improved forecasting of volatility asymmetry attributed to the interplay among assets within the Russian financial market amid heightened economic uncertainty. For selection of the parameters, we estimate the GARCH (p, q) and E-GARCH (p, q) econometric models and presented are as follow:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, \qquad (3)$$

$$\ln \sigma_t^2 = \omega + \sum_{i=1}^{p} \left[\alpha_i \left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) + \gamma_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right] \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2. \qquad (4)$$

3.4. Network Spillover Estimation

From the GARCH estimation the study assesses the volatility and *VaR* of asset returns. Now this study employs the spillover network estimation model proposed by Diebold & Yilmaz [38] with the assumption that crypto assets have connection with other financial assets to quantify the extreme risk spillovers between the Ethereum (ETH) and large-scale Russian financial assets. This network model offers the advantage of a straightforward adaptation of the traditional variance decomposition method.

Moreover, the model facilitates the computation of asset variable volatility at varying time scales. Employing this estimation approach enables us to gauge the intensity of influence among market variables and the contribution of each variable's volatility in the financial market, aiding in the measurement of the spillover network at higher levels of extreme risk:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \left(\alpha_i + \gamma_i D_{t-i}\right) \varepsilon_{t-1}^2 + \\ + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2. \quad (5)$$

The estimation model [38] has found widespread application in studying information shocks and risk contagion within financial markets due to its straightforward calculation process and more intuitive representation:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p} \alpha_i \left(\left|\varepsilon_{t-i}\right| - \gamma_i \varepsilon_{t-i}\right)^\delta + \\ + \beta_j \sigma_{t-j}^\delta. \quad (6)$$

Given that the traditional Cholesky decomposition method is influenced by variable order, which could result in biased outcomes, this paper adopts the generalized variance decomposition method as an alternative to the traditional Cholesky decomposition approach [41]. Following the generalized variance decomposition method proposed by [39] are given as follow:

$$\theta_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\dot{e}_i A_h \sum e_i\right)^2}{\sum_{H=0}^{H-1} \left(\dot{e}_i A_h \sum \dot{A}_i e_h\right)}. \quad (7)$$

Among these variables, θ_{ij}^H denotes the variance contribution rate of variable *j* to variable *i* within the *Hth* step. The selection vector, denoted as "*e*," is structured such that only the *jth* element is assigned a value of 1, while the remaining elements are set to 0. The covariance matrix of the error term is represented by $\sum$, and "*A*" signifies the coefficient matrix for the h-order lag after the VAR model undergoes transformation into Vector Moving Average (VMA) form.

To ensure uniformity in the summation of each row within ∂", the row with a degree of 0° is normalized to generate a new variable:

$$\dot{\theta}_{ij}^H = \frac{\theta_{ij}^H}{\sum_{j=1}^{N} \theta_{ij}^H}. \quad (8)$$

Upon deriving the matrix of variance contribution rates, this study designates it as the risk spillover intensity from variable *j* to variable *i* during period *H* which helps to accurately measure the risk convergence at both ends of the portfolio such as upside and downside risk.

4. Results

4.1. Summary Statistics

Table 1 presents a statistical network summarizing returns from crypto assets and various financial assets. Ethereum (ETH) stands out with the highest mean return at 0.25, notably different from the returns of financial assets, which cluster around 0.05, except for crude oil futures, which exhibit an anomaly.

Most financial assets show positive average returns. In terms of extreme values and standard deviations, ETH's average return remains positive, while crude oil futures emerge as the second most volatile asset. This contrasts with other financial assets that display relatively lower volatility within the Russian financial landscape, especially during the period marked by economic uncertainty following the conflict with Ukraine (2022). The increased volatility in crude oil futures may be attributed to fluctuations in demand and supply during the conflict with Ukraine, leading to economic pressures on Russian crude oil.

Table 1 highlights a significant aspect, indicating that all return series have distinct peaks and tails. The JB statistic confirms the non-normal distribution observed in all variables. Additionally, the unit root test confirms that all return series exhibit stationary behavior.

4.2. Correlation Matrix

Table 2 presents a matrix that encapsulates extreme risk correlations between crypto assets and a wide range of financial assets, using comprehensive data from the entire sample period. The overall landscape of correlations, covering both downside and upside risk, reveals that more assets are correlated with each other at the downside risk level, while at the upside risk level, the study observed select assets that are correlated with each other. Specifically, Ethereum (ETH) is correlated with all other assets except for gold, corn, and soybeans.

Table 1. **Summary Statistics**

	ETH	X-rate	Equity	Crude oil	Gold	Copper	Corn	Soybeans
Mean	0.250	0.014	0.015	–0.076	0.083	0.014	0.064	0.044
Max	33.524	2.690	8.940	13.042	6.349	5.824	4.204	12.420
Min	–48.289	–1.224	–8.181	–9.064	–9.932	–6.328	–2.738	–5.630
Std. Dev.	5.563	0.273	1.390	2.384	1.020	0.872	0.797	1.195
Skewness	–0.627	0.548	–0.336	–0.389	–1.207	–1.248	1.542	2.053
Kurtosis	24.302	7.669	9.008	8.683	23.068	12.979	12.268	21.082
JB	0.001***	0.001**	0.001***	0.001***	0.001**	0.001**	0.001***	0.001**
ADF. St.	0.001***	0.001***	0.001***	0.001**	0.001***	0.001***	0.001**	0.001**
Sample Size	1306	1306	1306	1306	1306	1306	1306	1306

Note: Jarque Bera test and Augmented Dickey Fuller test p-values *** represents 1 % level of significance

Table 2. **Correlation Matrix (Full Sample)**

VaR^L	ETH	X-rate	Equity	Crude oil	Gold	Copper	Corn
X-rate	0.68	1					
Equity	0.67	0.61	1				
Crude oil	0.59	0.70	0.81	1			
Gold	0.28	0.01	0.13	0.38	1		
Copper	0.51	0.65	0.42	0.10	0.01	1	

End of table 2

VaR^L	ETH	X-rate	Equity	Crude oil	Gold	Copper	Corn
Corn	0.07	0.75	0.86	0.17	0.07	0.34	1
Soybeans	0.01	0.01	0.05	0.05	0.06	0.61	0.01
VaR^U	ETH	X-rate	Equity	Crude oil	Gold	Copper	Corn
X-rate	0.34	1					
Equity	0.01	0.10	1				
Crude oil	0.76	0.74	0.76	1			
Gold	0.18	0.03	0.58	0.16	1		
Copper	0.08	0.70	0.28	0.73	0.18	1	
Corn	0.01	0.12	0.45	0.05	0.01	0.08	1
Soybeans	0.07	0.15	0.06	0.08	0.81	0.24	0.40

Note: "VaRU" and "VaRL" indicate the extent to which the extreme risk VaR at upper side tiled risk and lower side respectively

Conversely, gold, corn, and soybeans exhibit lower correlations with other assets such as equity, exchange rates, and crude oil futures. The correlation patterns among assets at the upside risk are similar to those at the downside risk, highlighting discernible linkages characterizing extreme risk interactions between crypto assets and financial assets. The correlation matrix approves the projected hypothesis as proposed in the section literature review.

4.3. Risk spillovers Analysis

This section employs Diebold & Yilmaz's [38] spillover network analysis to construct an extreme risk correlation network between a popular crypto asset the Ethereum (ETH) and prominent financial assets in the Russian financial market.

The spillover network model reveals the intricate mechanisms underlying the transmission of volatility within the domain of both types of assets. To ensure robustness of the estimation model, the study employed the AIC and SC criteria as proposed by [41].

Similarly, VaR model is utilized to discern the interplay of volatility between crypto assets and the array of other underlying financial assets. Following the AIC and SC guidelines [37], the VAR model, equipped with a lag order of 1, is expertly harnessed. Subsequently, the generalized prediction variance is extrapolated with a forward projection spanning 10 steps lag order employing the construction of the variance decomposition matrix.

The process of constructing the VaR model involves the meticulous determination of the lag order through the prism of the AIC or SC criterion as outlined by [38]. Empirical evidence suggests that the lag order typically falls within the range of 1 to 3, with 1 being the most appropriate choice.

Therefore, the ultimate selection gravitates toward a lag order of 1, deviating from prior studies that often favored 10 for constructing the variance decomposition matrix. Primarily, it begins with the estimation of the marginal distributions of underlying asset return series. Subsequently, optimal marginal distribution models are selected for each return series based on the LL and AIC criteria. The selection process is meticulously documented, with the optimal marginal distribution models chronicled in Table 3.

Table 3. **Estimated results of the marginal distribution model of returns on crypto assets other financial assets**

	ETH	X-rate	Equity	Crude oil	Gold	Copper	Corn	Soybeans
Model	ARMA(2,2)-GARCH(2,1)	ARMA(1,1)-GARCH(1,1)	ARMA(2,2)-EGARCH(1,1)	ARMA(2,1)-EGARCH(2,2)	ARMA(1,2)-EGARCH(2,2)	ARMA(1,1)-EGARCH(2,2)	ARMA(1,1)-EGARCH(2,1)	ARMA(2,2)-EGARCH(1,1)
Obs.	1306	1306	1306	1306	1306	1306	1306	1306
μ	-0.08***	0.01	-0.06	-0.05***	0.01***	0.01***	0.03***	0.01***
	(–546.01)	(0.80)	(–5879.85)	(3854.81)	(11431.45)	(102.38)	(7345.70)	(3074.61)
AR (1)	1.25***	-0.12*	0.02***	-0.71***	0.54***	0.27***	0.12***	-0.64***
	(2748.57)	(–1.76)	(453.22)	(–6521.10)	(11433.62)	(7305.56)	(3133.62)	(–8685.1)
AR (2)	-0.36***		0.85***	0.12***				-0.58***
	(–1463.84)		(13195.84)	(4668.20)				(–7078.01)
MA (1)	-1.36***	0.11*	-0.02***	0.83***	-0.56***	-0.37***	-0.14***	0.65***
	(–5971.12)	(1.81)	(–4902.08)	(4788.40)	(–11503.08)	(–4455.05)	(–2607.53)	(7648.81)
MA (2)	0.23***	-0.12***	-0.99***		-0.01***			0.61***
	(1548.25)	(–1245.01)	(–3732.10)		(–123.62)			(7314.11)
ω	3.16***	0.00	-0.12***	0.10***	0.01***	-0.01***	-0.01***	-0.01***
	(2.81)	(0.71)	(1.70)	(5155.70)	(10714.02)	(–13.12)	(487.02)	(–3358.60)
α1	0.12***	0.04*	0.03***	-0.05***	0.11***	-0.06***	-0.14***	0.07***
	(3.27)	(1.61)	(2.40)	(–4624.5)	(7757.01)	(–1201.07)	(–7175.28)	(3260.5)
α2	0.01***			-0.13***	-0.01***	0.02***	0.21***	
	(2.78)			(–4752.00)	(–3535.53)	(1103.81)	(1555.15)	

End of table 3

	ETH	X-rate	Equity	Crude oil	Gold	Copper	Corn	Soybeans
Model	ARMA(2,2)-GARCH(2,1)	ARMA(1,1)-GARCH(1,1)	ARMA(2,2)-EGARCH(1,1)	ARMA(2,1)-EGARCH(2,2)	ARMA(1,2)-EGARCH(2,2)	ARMA(1,1)-EGARCH(2,2)	ARMA(1,1)-EGARCH(2,1)	ARMA(2,2)-EGARCH(1,1)
β1	0.61***	0.81***	0.72***	-0.03***	1.01***	-0.01***	0.088***	0.88***
	(9.17)	(15.71)	(32.46)	(–7387.4)	(15107.62)	(–1567.20)	(10180.52)	(10423.21)
β2				0.89**	-0.01***	0.85***		
				(6268.80)	(–8155.65)	(581101)		
ϒ1				0.12***		0.01***	0.10***	-0.06***
				(1681.00)		(1024.72)	(7003.06)	(–6968.8)
ϒ2				-0.01***	0.76***	0.04***	-0.05***	
				(–1144.80)	(13020.35)	(2701)	(–7138.74)	
skew		1.03***				10.0***	1.01***	
		(17.69)			()	(1457)	(1248.65)	
Sharpe		2.03***			2.10***	2.02***	1.65***	1.65***
		(6.02)			(14011.21)	(823.50)	(8206.01)	(8663.71)
LL	-1653.31	-09.25	-1909.03	-1181.36	-463.36	-606.05	-423.56	-816.33
AIC	4.74	0.05	3.20	3.11	1.80	2.25	1.65	2.60

Note: t-statistics are given in parentheses *** represents 1 % level of significance·

The findings conspicuously reveal that the return series of all underlying assets exhibit distinctive attributes of asymmetric volatility, notably captured by the GARCH model. This distinct volatility profile is most pronounced within Ethereum (ETH) and the USD/RUB exchange rate, while other assets also experience heightened volatility over the study timeframe.

From Table 3 from total 1306 observations, the study observed massive increase in the spillover during the crisis period especially during the crisis with Ukraine where the tension intensified across all the underline assets which show the upsurge in the risk associated to the Russian financial market. In addition, the new policy regarding financial openness and removal of ban from the investment in crypto assets clearly shows that the investment shifts from conventional financial assets into the crypto assets. This overarching trend within the new financial policy and financial asset landscape underscores the substantial positive impact brought about by the ongoing Russia-Ukraine crisis (2022) upon the Russian economy.

To assess the overall portfolio risk in terms of both downside and upside risk, the study employed the estimation of Value at Risk (VaR) for both Ethereum (ETH) and other financial assets. The return series was analyzed, and corresponding statistical summaries are presented in Table 4. When examining the absolute values of these results, it becomes apparent that the average thresholds, volatility ranges, and magnitudes of volatility for both upside and downside risks are fundamentally similar for identical financial assets [38].

Table 4. **Values at Risk (VaR) estimation at Downside Risk and Upside risk**

VaR^L	ETH	X-rate	Equity	Crude oil	Gold	Copper	Corn	Soybeans
Avg.	–5.502	–0.283	–1.013	–3.312	–1.007	–1.301	–0.805	–1.454
Max.	–3.037	–0.171	–1.341	–1.377	–0.150	–0.504	–0.413	–0.611
Min.	–19.211	–0.703	–3.184	–8.434	–25.431	–4.083	–1.865	–1.638
Std. Div.	1.42	0.060	0.211	1.122	1.415	0.323	0.121	0.457
VaR^U								
Avg.	6.225	0.311	1.003	2.162	1.023	1.251	1.024	1.461
Max.	21.77	0.717	2.358	8.007	24.885	3.155	1.837	1.725
Min.	4.231	0.2.7	1.514	1.384	0.157	0.554	0.045	0.617
Std. Div.	1.576	0.058	0.301	1.006	1.408	0.351	0.201	0.373

Note: VaRL and VaRU represent the downside risk and upside risk.

In contrast, there has been a decline in demand for crude oil futures and gold, driven by various factors including international sanctions and the removal of the Russian banking network from the SWIFT system. These transformative shifts in the international landscape have tangible repercussions on the Russian financial terrain. This analysis highlights an increase in volatility for copper futures and crude oil futures following the critical event in February 2022, which corresponds with the Russia-Ukraine crisis (Table 4).

Furthermore, all financial assets, except corn futures, exhibit greater susceptibility to extreme price surges. However, when examining downside and upside risk correlation networks concerning the upside risk greater variability emerges. In the downside risk, soybean futures are the primary conduit for risk spillover, with Ethereum (ETH) ranking third.

In the upside risk domain, Ethereum (ETH) surpasses its downside counterpart, assuming a more prominent role in risk transmission. These findings underscore the significant impact of crypto assets on financial assets, particularly during extreme price surges.

Analyzing net spillovers in extreme risk across various financial assets, except exchange rates, reveals consistent positioning in both downside and upside risk correlation networks. Ethereum (ETH), stock markets, corn, and soybean futures play dominant roles in steering risk transmission within the Russian financial landscape. Ethereum (ETH) notably holds a top-tier position in terms of net spillover levels in both downside and upside risk correlation networks, emphasizing the substantial influence of global crypto asset price changes on corresponding shifts in financial asset prices.

In contrast, crude oil, gold, and copper futures play relatively passive roles in the Russian financial environment regarding extreme risk transmission between crypto assets and financial assets. The comprehensive analysis conducted on the full sample provides a panoramic view of prolonged dynamics characterizing extreme risk spillovers between crypto assets and financial assets within the Russian financial market.

However, considering the dynamic nature of short-term risk spillovers amid high economic uncertainty and economic sanctions on Russia, this study extends its scope to include a rolling window of 60 trading days (equivalent to the preceding 3 months) to dynamically unravel the risk spillover relationship between crypto assets and a array of financial assets.

In Figure 2, the dynamic trajectory of the comprehensive correlation encompassing downside risk and upside risk between crypto assets and other financial assets is illustrated.

Notably, this graph exhibits marked fluctuations in the overall correlation between crypto assets and financial assets in terms of both downside risk and upside risk. This correlation predominantly oscillates within the range of 30 % to 50 %, indicating a high-level extreme risk correlation. However, an intriguing nuance is the differing trends in overall correlation between downside risk and upside risk, with the former displaying greater volatility, especially up until February (2022).

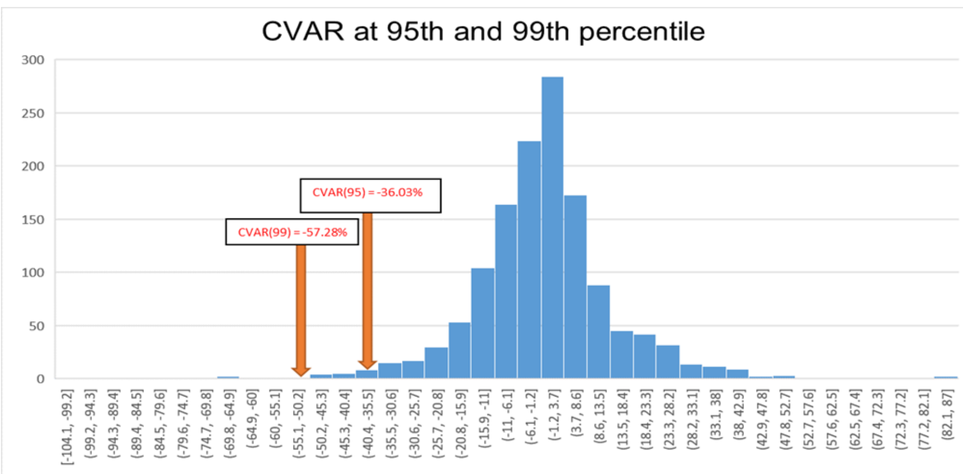

Figure 2. Overall correlation between downside and upside risk

During this period, the overall correlation of downside risk experiences recurrent fluctuations, while the correlation relating to upside risk remains relatively consistent, hovering around 35 % for most of the observed timeline. Additionally, the data reveals that the overall correlation of downside risk exhibits a higher frequency of abrupt shifts compared to the pattern observed in the realm of upside risk. This disparity underscores a notable difference in the dynamic behavior of the overall correlation encompassing downside risk and upside risk, indicating a substantial disconnect between the two from a dynamic standpoint.

Figure 3 reveals two notable surges in spillover levels around the event day of the crisis where the initial surge primarily affects downside risk, driven by increased spillover of volatility in global financial stress and market volatility.

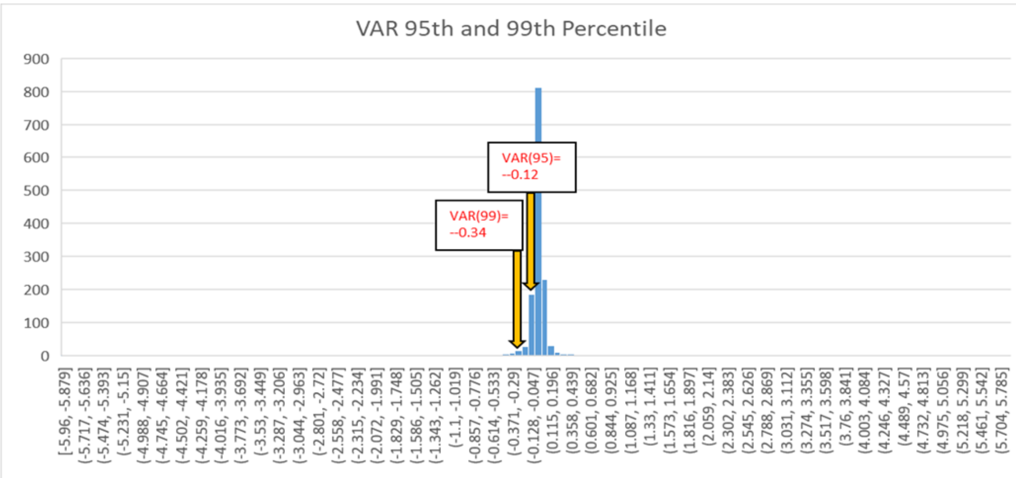

Figure 3. Downside and upside risk spillover effect from crypto other financial assets

In contrast, the subsequent surge during the 2022 crisis between Russia and Ukraine is mainly due to amplified spillover from volatility in commodity markets, influencing upside risk in the Russian financial market. These increases in spillover levels during the crisis can be attributed to consistent factors, including heightened global financial stress, market volatility, and increased network spillover levels, as well as volatility in stock markets.

Similarly, the findings depict the dynamic trajectory of net downside risk and upside risk spillover from crypto assets to financial assets. Over the observed timeline, these spillover levels show an oscillating pattern, except for a unique period before February 2022 when they deviated from the norm.

Generally, net downside risk and upside risk spillover from crypto assets to financial assets exhibit opposing trajectories, with spillover levels mostly around a neutral value of 0, except for a significant surge during the Ukraine crisis. This surge corresponds to a dramatic short-term fluctuation, with net downside and upside risk spillovers increasing by approximately 29 % and 35 %, respectively, due to the crisis's impact.

This trend aligns with prior studies including [34, 42], which found that crypto assets during COVID-19 and the other financial assets from MOEX do not function as safe-haven assets during economic crises.

5. Discussion

This comprehensive study meticulously explores the intricate relationships between cryptocurrency and traditional financial assets, including equities, gold, crude oil, commodities, and forex, within the context of the Russian financial market.

The investigation spans both normal economic conditions and crisis periods, providing valuable insights into the dynamic nature of these connections. A noteworthy observation arises from the analysis of increased volatility in crude oil futures, a phenomenon attributed to the geopolitical conflict with Ukraine. Fluctuations in demand and supply during this period exerted economic pressures on Russian crude oil.

The summary statistics offer a deeper understanding, revealing distinct peaks and tails in return series, supported by statistical tests indicating non-normal distribution and the presence of stationary behavior. Delving into the correlation among assets, a nuanced pattern emerges. Which insights the acceptance of the proposed hypothesis.

The findings are similar with the results in the same economic dynamics [42]. The downside risk level shows a higher correlation among various assets, while at the upside risk level, the study identifies specific assets correlated with each other. Ethereum (ETH) stands out, correlated with all assets except gold, corn, and soybeans.

The research employs the sophisticated Diebold & Yilmaz spillover network analysis methodology, unraveling intricate mechanisms governing the transmission of volatility between Ethereum (ETH) and key financial assets in the Russian market.

The findings not only highlight the presence of asymmetric volatility, especially in Ethereum (ETH) and the USD/RUB exchange rate, but also underscore a shifting trend toward crypto assets following recent financial openness policies. That accepts the proposed hypothesis there is network spillover effects crypto asset and exchange rate in Russian financial market during economic crisis. The findings are aligned with the results with [43].

During crisis periods, the study observes consistent downside risk correlations across financial assets, with Ethereum (ETH) playing a pivotal role in risk transmission. The impact of extreme price surges in commodity market is explored, revealing that Ethereum (ETH) assumes prominence in both downside and upside risk correlation networks.

That accepts the proposed hypothesis there is network spillover effects crypto asset and commodity future in Russian financial market during economic crisis. The findings are aligned with the results with [20]. This indicates the substantial influence of global crypto asset price changes on corresponding shifts in financial asset prices within the Russian financial landscape.

In a departure from global trends, the research reveals a unique dynamic in the Russian financial market where crypto assets challenge their traditional safe-haven status. Policy changes, influenced by challenges and sanctions, lead to a more permissive regulatory stance on crypto assets, strategically stimulating economic growth amid the Ukraine conflict.

The study adopts a comprehensive approach, considering prolonged dynamics and incorporating a rolling window to capture short-term risk spillovers, ensuring a nuanced understanding of the evolving economic landscape.

6. Conclusion

This study delves into an intricate analysis of network correlations between the volatility of crypto assets and their potential influence on conventional assets within the Russian financial market, particularly during periods of stability and crisis.

Additionally, the study examines the impact of financial regulations pertaining to investments in crypto assets, analyzing how policy amendments counteract the effects of trade and banking sanctions during crises.

Specifically, the study explores the repercussions of the ongoing crisis between Russia and Ukraine (2022) on the volatilities of the prominent and popular crypto asset, Ethereum (ETH), and various financial assets including equities, exchange rates, crude oil futures, gold, and commodity futures trading in Moscow stock exchange (MOEX). The selection of Ethereum (ETH) as the focal point of this study stems from its legal recognition by the Russian government, allowing for tradable investments.

Consequently, there has been a substantial increase in investments in crypto assets following the implementation of these new policies. Due to this financial openness, ETH holds a significant position within Russia, being a Russian-based digital coin renowned for its enhanced security compared to other crypto assets, notably Bitcoin.

Furthermore, this study examines overall portfolio risk encompassing both downside and upside risk, utilizing the estimation of value-at-risk (VaR) for both Ethereum (ETH) and other financial assets. To establish an extreme risk spillover network connectedness across ETH and other financial assets, the paper adopts a correlation network approach of Diebold & Yilmaz.

This study follows the modern portfolio proposed by Harry Markowitz's (1952) and provides suggestions regarding the allocation of weights to different assets based on their associated risks and returns. In light of this theory, concepts such as hedging, and diversification emerge to manage risks associated with financial assets.

In addition, the practical findings illuminate significant insights into the factors influencing risk within the Russian financial market. The results indicate the presence of substantial extreme risk correlations, both in the short and long term, between crypto assets and other financial assets.

Crypto assets, particularly ETH, emerge as dominant entities in risk transmission within the Russian financial market during periods of geopolitical turmoil. Extreme fluctuations in returns significantly affect extreme changes in financial assets, especially during instances of extreme price increases across the broader economy. However, crypto assets demonstrate relatively lower susceptibility to the ongoing crisis compared to financial assets, as evidenced by significant fluctuations in returns.

In the Russian financial market, the impact of extreme changes in returns on crypto assets does not exhibit strong hedging potential, especially when compared to gold futures. Notably, crude oil futures emerge as the primary source of risk for both crypto assets and financial assets within the studied timeframe.

In the short term, a high level of extreme risk correlation is observed between the underline assets, with a particular emphasis on the correlation between downside and upside risk. This correlation, however, exhibits significant asymmetry, characterized by volatility in downside risks and the prevalence of substantial instantaneous increases compared with upside risk.

Moreover, in the short term, the level of risk spillover between the crypto and financial assets displays relatively lower correlation, with only crude oil futures and exchange rates exhibiting notable correlations with ETH. This co-movement of crypto assets and other financial assets underscores the significant impact of the crisis between Russia and Ukraine (2022) on the risk in the Russian financial market, with market volatility emerging as the predominant influence on the Russian economy's context. During the crisis and after the implementation of the financial openness policy, crypto assets wield considerable influence within the Russian financial market, and the impact of extreme price volatility on financial assets cannot be disregarded.

This study underscores the imperative of incorporating extreme fluctuations in crypto asset returns into the realm of risk management for the financial market. Caution towards the stability of the financial market is warranted during periods of extreme increases in crypto asset returns, given the dynamic nature of connectivity. Timely adjustments aligned with regulatory strategies are necessary to mitigate the risks to the Russian financial market stemming from the volatility of global digital currencies and financial assets, particularly in times of emergencies such as the crisis between Russia and Ukraine.

This study provides empirical evidence of the risk associations between crypto and other financial assets. Nevertheless, during the course of this research study, certain limitations were encountered, including the inclusion of only ETH and main indices from MOEX to represent the Russian financial market.

For future research directions, it is suggested that various types of crypto assets should be incorporated and combined with main and sectorial indices to examine the overall impact of crypto assets more comprehensively on financial assets using a multifaceted network framework.

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Динамическая связь между криптовалютами и обычными финансовыми активами: новые выводы с российского финансового рынка

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Аннотация. В динамичном ландшафте российской цифровой экономики и растущей финансовой открытости криптоактивы стали влиятельными игроками на финансовом рынке. Геополитические и экономические события после конфликта с Украиной создали огромные вызовы в виде финансовых и торговых санкций в сочетании с приостановкой подключения к банковской системе SWIFT, что ввергло российскую экономику в опасное положение. Текущее исследование углубляется в побочные эффекты сети между известными криптоактивами и различными финансовыми активами, включая акции, обменные курсы, сырую нефть, золото и товарные фьючерсы, используя ежедневные данные с 1 января 2018 г. по 31 августа 2023 г. Цель исследования — дать эмпирические и теоретические представления о противодействии влиянию санкций на Россию, предложив прагматичное решение для российского финансового рынка. Методология исследования предполагает применение оценки сетевых вторичных эффектов и анализа стоимости актива, находящегося в зоне риска. Примечательно, что результаты показывают устойчивую связь между криптовалютами и финансовыми активами, где криптоактивы играют ключевую роль в передаче риска в финансовом ландшафте. В то время как их влияние на другие финансовые активы остается относительно незначительным, краткосрочные корреляции демонстрируют волатильные колебания, часто отмеченные резким увеличением риска ухудшения. Теоретические выводы следуют портфельной теории ценообразования активов, при этом экстремальные побочные эффекты риска возникают из-за долгосрочных колебаний на рынке криптовалют, влияя на рыночные настроения и повышая распространение риска на российском финансовом рынке. Наши результаты имеют практическое значение для анализа процессов оплаты и получения, а также для торговой деятельности с зарубежными странами, предоставляя важную информацию для политиков и лиц, принимающих инвестиционные решения.

Ключевые слова: криптоактивы; финансовые активы; российский финансовый рынок; анализ вторичных эффектов сети.

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ДЛЯ ЦИТИРОВАНИЯ

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