“Analysis of the impact of central bank digital currency on stock markets: Dynamics and implications”

AUTHORS	Serhiy Frolov Maksym Ivasenko Mariia V. Dykha Mykhaylo Heyenko Viktoriia Datsenko
ARTICLE INFO	Serhiy Frolov, Maksym Ivasenko, Mariia V. Dykha, Mykhaylo Heyenko and Viktoriia Datsenko (2023). Analysis of the impact of central bank digital currency on stock markets: Dynamics and implications. *Banks and Bank Systems*, *18*(4), 149-168. doi:10.21511/bbs.18(4).2023.14
DOI	http://dx.doi.org/10.21511/bbs.18(4).2023.14
RELEASED ON	Tuesday, 21 November 2023
RECEIVED ON	Friday, 15 September 2023
ACCEPTED ON	Saturday, 11 November 2023

JOURNAL	"Banks and Bank Systems"
ISSN PRINT	1816-7403
ISSN ONLINE	1991-7074
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
52	4	5

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Serhiy Frolov (Ukraine), **Maksym Ivasenko** (Ukraine), **Mariia Dykha** (Ukraine), **Mykhaylo Heyenko** (Ukraine), **Viktoriia Datsenko** (Ukraine)

ANALYSIS OF THE IMPACT OF CENTRAL BANK DIGITAL CURRENCY ON STOCK MARKETS: DYNAMICS AND IMPLICATIONS

Abstract

The purpose of the study is to explore the influence of central bank digital currency on stock markets. To realize the purpose, the TVP-VAR model was built, which determines the impact of volatility of the CBDC attention index (CBDCAI) on the volatility of stock market indices. The study uses a time-varying vector autoregressive model that analyzes weekly data from the first week of January 2015 to the first week of July 2023. The endogenous vector to be assessed by VAR contains CBDCAI and stock market indices of different countries (France: CAC 40, The United States of America: S&P 500, Germany: DAX 40, United Kingdom: FTSE 100, China: SSEC, The Netherlands AEX 25, Switzerland: SMI 20, Japan: Nikkei 225, India: NIFTY 50, Brazil: BVSP, South Korea: KOSPI). The results of the TVP-VAR model show that compared to stock market indices, CBDCAI appeared to be relatively independent and isolated. Interdependence and mutual influence between the digital currency market of central banks and stock markets were also revealed. In addition, CBDC functions primarily as a volatility absorber rather than a source of volatility. Despite the overall ability of the CBDC market to absorb fluctuations in volatility, it may also change its function with the widespread adoption of central bank digital currencies in many countries.

Received on: 15th of September, 2023
Accepted on: 11th of November, 2023
Published on: 21st of November, 2023

Serhiy Frolov, Doctor of Economics, Professor, Department of Finance of Business Entities and Insurance, Sumy National Agrarian University, Ukraine. (Corresponding author)

Maksym Ivasenko, Ph.D. Student (Economics), Department of Finance, Banking and Insurance, Sumy National Agrarian University, Ukraine.

Mariia Dykha, Doctor of Economics Sciences, Professor, Professor of the Department of Economics, Analytics, Modeling and Information Technologies in Business, Khmelnytskyi National University, Ukraine.

Mykhaylo Heyenko, Ph.D., Professor, Head of the Department of Finance, Banking and Insurance, Sumy National Agrarian University, Ukraine.

Viktoriia Datsenko, Ph.D., Senior Lecturer, Department of Marketing, University of Customs and Finance, Ukraine; Ph.D., Associate Professor, Dean of the Faculty of Economics, Business and International Relations, University of Customs and Finance, Ukraine.

Conflict of interest statement:
Author(s) reported no conflict of interest

Keywords central bank, digital currencies, stock markets, indices, TVP-VAR, volatility, attention index

JEL Classification C50, E58, G15, G17, G18

INTRODUCTION

The modern financial world is experiencing a period of stunning innovation and change. One of the important financial innovations is the introduction of central bank digital currencies (CBDCs). CBDC is created digitally and recorded in centralized or decentralized ledgers. It is expressed in the existing unit of account and can be exchanged for physical cash, money from commercial banks and other forms of money at the owner's request through authorized institutions. If CBDC is introduced, it will become legal tender, just like physical cash.

In recent years, central banks of various countries have been actively engaged in research and development in the field of central bank digital currency and are competing for leadership in this area. The launching of the world's first CBDC, known as "Sand Dollar", took place in the Bahamas in 2020, and this event officially marked a new era in the history of money. After its launch, the digital currency became very popular and generated a lot of interest (Skrynnyk & Lyeonov, 2022; Liu, 2023; Bublyk et al., 2023; Dubyna et al., 2023). As of September 2023, a significant increase in interest in the implementation of a central bank digital currency was recorded in the world. Currently, 130 countries, which together represent 98% of global GDP, are actively exploring the possibility of implementing CBDC (Atlantic Council, 2023).

There is currently considerable uncertainty in the financial industry about how exactly CBDCs affect stock markets and their volatility. Wang et al. (2022) studied the impact of the central bank digital currency attention index (CBDCAI) on financial markets. The results of this study showed a possible relationship between the volatility of the CBDAI and the volatility of the FTSE All World index.

The main innovation of the study is the use of quantitative analysis to study the impact of volatility of the CBDC attention index on the stock market volatility. A key question is whether CBDCs have the potential to change the markets' perception of news, affect the level of volatility and change the performance of stock markets. The next important question is to determine whether the CBDCAI is a source of stock market volatility or whether the index absorbs volatility. Therefore, the study aims to prove the hypothesis that there is a significant relationship between the volatility of the CBDCAI and the volatility of the stock market.

The problem requires a detailed analysis of the interaction between central bank digital currencies and stock markets to understand their impact on global financial stability and the ability of investors to make informed decisions.

1. LITERATURE REVIEW

The trends in recent years indicate an increase in interest in digital currencies, especially due to the attempt by private organizations to reproduce the characteristics of cash in a digital environment. Digital currencies exist in different formats and value propositions and can be used on a variety of platforms for real-time transactions.

Investigating this new phenomenon, the Committee on Payments and Market Infrastructures determined that digital currencies have certain characteristics of a currency, commodity, or asset. The use of digital currencies for retail payment services may be particularly important, as they can facilitate e-commerce, cross-border transactions, and P2P payments, making them faster and more accessible (World Bank Group, 2021).

As of September 2023, 64 countries are in the advanced research phase, meaning they are in the process of developing, piloting or even launching their CBDCs. In particular, 19 countries from the G20 are actively working on the development of CBDC, and among them 9 countries already have pilot projects in this area. Over the past six months, each of these G20 countries has taken a significant step forward and allocated new resources to implement these projects (Atlantic Council, 2023).

Fully launched digital currencies already exist in 11 countries. China, for example, has a CBDC pilot project that currently includes 260 million users and is being tested in more than 200 scenarios, including the use in public transportation, incentive payments and e-commerce (Atlantic Council, 2023).

Countries will implement different forms of central bank digital currency systems depending on their specific goals. These systems can be divided into two main categories: single ledger systems and distributed ledger systems. In systems with single ledger systems, the central bank and other government agencies are responsible for CBDC management. This model may have a single management system, but it also considers the difference between a central bank and a management account. In systems based on a distributed ledger, management is carried out jointly by several parties, which promotes transparency of operations and reduces the risk of digital attacks. Such systems use distributed accounts that do not disclose personal information to verify the identity of users (Liu, 2023). One important feature is that CBDC, as a central bank liability, can be considered risk-free and irrevocable (Boar & Wehrli, 2021).

CBDC systems can also be classified by the type of central bank control as direct or indirect. In a direct CBDC system, the central bank directly controls the issuance and management of CBDC. In the case of a non-direct CBDC system, partial authority may be delegated to intermediary agencies, but the management of intermediaries

http://dx.doi.org/10.21511/bbs.18(4).2023.14

remains with the central bank. These different approaches to the implementation of CBDC have their advantages and disadvantages and correspond to different goals and contexts that countries choose according to their needs and circumstances (Chu et al., 2022).

The implementation of CBDC will have a serious impact on countries' financial systems and will require careful monitoring and analysis. The future financial stability will require deep interaction between the financial system and digital technology systems. The stability of the financial system can be achieved by jointly ensuring the stability of financial institutions and the reliable functioning of the digital technology system on which financial institutions rely (Ozili, 2022b; Kerimov et al., 2023; Panigrahi, 2023).

Research has also indicated that the introduction of a central bank digital currency has the potential to affect financial markets and systems in different ways.

1) Li et al. (2022) indicate that the issuance of CBDC can have a positive impact on global financial systems as it helps to reduce the demand for cash and gives sovereign money a significant role in strengthening trust in payments by providing a reference value to private money.

2) Panetta et al. (2022) demonstrate that CBDC can improve capital allocation as it reduces transaction costs and facilitates access to payments. This can promote competition in banks' funding markets, as it reduces their market power.

3) Auer et al. (2022) indicate that CBDC can support banking intermediation. It can also provide an alternative to deposits, which limits the monopoly profits of banks and encourages them to increase lending.

4) Wang et al. (2022) discuss the possibility of coexistence of private and sovereign money thanks to CBDC in the digital world. This can underpin monetary and financial stability and promote efficiency and competition in payment markets.

Accordingly, the implementation of CBDC can have a significant impact on financial systems and markets, contributing to a variety of positive changes, improving trust in payments, capital allocation and competition in the banking sector.

There are several areas of research analyzing different aspects of CBDC, namely, description and general characteristics of CBDC, macroeconomic and monetary implications of CBDC, security and privacy issues of CBDC, model optimization and technological innovation of CBDC, interaction of commercial and central banks with CBDC (Koziuk, 2021; Kuznichenko, 2022).

Research in this area is indeed limited, as CBDC is a relatively new phenomenon, information and data on its impact on financial markets is still limited. However, with the development of this field, more studies and analyses of the impact of CBDC on various segments of financial markets, including stock markets, are possible (Kuznichenko, 2022).

Wang et al. (2022) developed and presented new indices, such as CBDC Uncertainty Index (CBDCUI – Central Bank Digital Currency Uncertainty Index) and CBDC Attention Index (CBDCAI – Central Bank Digital Currency Attention Index), to study the impact of the central bank's digital currency on the financial markets. Their research used SVAR (structural vector autoregression) and DCC-GARCH (dynamic conditional correlation – generalized autoregressive conditional heteroskedasticity) models for analysis.

CBDC Uncertainty Index (CBDCUI) was created based on the number of CBDC-related words that appeared in the news using the LexisNexis News and Business database. This index measures the level of uncertainty or volatility associated with the introduction of CBDC into the market.

CBDC Attention Index (CBDCAI) also takes word count into account, but in this case, it measures the level of audience attention to CBDC information in the news and media.

Wang et al. (2022) show that the response of financial markets to central bank announcements regarding CBDC may be asymmetric, meaning that markets may react differently to positive and negative news or announcements regarding CBDC. This indicates that financial markets can be very sensitive to events related to central bank digital currencies, and their reactions can vary depending on the context and circumstances.

There is a group of studies that describe the main concepts, characteristics, and categories of CBDCs, possible advantages and disadvantages, as well as risks in case of adoption of a central bank digital currency by monetary authorities. CBDCs are seen as a new form of central bank money that can be issued in different systems for retail or wholesale payments, with the direct system model being the most attractive for retail payments and the universal digital currency model being the most suitable for wholesale payments, but difficult to implement by countries with underdeveloped financial market infrastructure (Kochergin, 2021). Williamson (2022) argues that allowing CBDCs to accrue interest is not always an advantage, as replacing physical currency with CBDCs does not expand the available options for equilibrium distributions. CBDC can have a positive impact on the general welfare by competing with private payment instruments and transferring safe assets from the private banking sector to what is effectively a narrow banking institution. This may be a more efficient way of using the common resources of reliable support, especially given certain problems related to incentives in private banking. In addition, the issuance of CBDC is believed to help solve the dilemmas of modern monetary policy, including the ineffectiveness of transmission policy, difficulties in countercyclical control, the flow of currency from the real economy to the virtual economy, and inadequate management of political expectations (Qian, 2019). Barrdear et al. (2021) argue that central bank digital currency issuance can reduce real interest rates, distortionary taxes and monetary transaction costs, and CBDC countercyclical policy rules can improve the central bank's ability to stabilize the business cycle, while risks for banks can be minimized with the help of appropriate emission mechanisms. It is also worth considering the conclusion (Bian et al., 2021) that the issuance of CBDC is a double-edged sword: the benefit of replacing physical cash with a more efficient payment system comes at the expense of the destruction of deposit base for commercial banks. Bindseil (2019) concluded that a well-regulated CBDC seems possible, but this does not mean that CBDC will not become a catalyst for change in the financial system. Lee et al. (2020) concluded that CBDC will be a major tool in the future digital economy, and countries familiar with the technology will have a competitive advantage.

Another group of studies deals with the theoretical and technological aspects of CBDC implementation. In particular, Han et al. (2021) propose the implementation of CBDC based on Cosmos blockchain (Cos-CBDC), which provides communication between blockchains using Inter-Blockchain Communication (IBC) protocol to ensure interoperability. Also, Sethaput and Innet (2023) claim that blockchain or distributed ledger technology can be used to implement CBDC in conducting and accounting for peer-to-peer transactions. With the emergence of private money such as cryptocurrencies and stablecoins, as well as the growing use of digital payments to combat the global spread of pandemic, CBDC is becoming an active area of research for central banks around the world.

Many of them have started their CBDC projects by building trial models based on distributed ledgers (PoCs) to scale up wholesale payment systems and explore possible applications such as delivery of goods (DvP) and international money transfers. Countries with large economies, such as the United States of America, are also actively exploring CBDC issues. For example, the People's Bank of China (PBoC) is already piloting its digital currency for retail payments. Central bank digital currency transaction accounting systems use blockchain to exchange information with the central bank. Public data on currency exchange between countries can provide information on the flow of money between those countries. The paper proposes a blockchain system and management method based on the ISO/IEC 11179 metadata exchange standard to exchange information between registered CBDCs and to record transactions between them.

One group of research concerns the security and privacy of CBDC implementation, conducting and tracking transactions, etc. Atako (2021) argues that a proper privacy system governing re-

http://dx.doi.org/10.21511/bbs.18(4).2023.14

tail CBDC records will reduce privacy risks and increase public confidence in the retail CBDC system. Bijlsma et al. (2021) suggests that central banks can drive consumer acceptance of CBDC through interest rates, a way to implement CBDC that considers society's needs for security and privacy and a clear message about what CBDC entails. Grothoff et al. (2021) conclude that a privacy-preserving and regulatory-compliant way of implementing CBDC can offer an appropriate balance between transaction privacy and legal compliance. Rybski (2023) recommends that central banks emphasize sustainability in their strategy. The general support for sustainable development, public safety, and privacy (as a positive factor) will contribute to the positive perception of the digital currency of the central bank by society. This is important because one of the key risk situations that central banks can face is the possibility of launching (retail) CBDC projects that fail to gain popularity among mass users (Passacantando, 2021). To avoid this risk, central banks should include in their strategy all aspects reviewed from the position of a broad understanding of sustainability. This includes minimizing energy consumption, ensuring social integration through the availability of CBDC to a wide range of users, significantly reducing the cost of money transfers and fighting financial crime.

Central banks' digital currency privacy will be tested through litigation. To facilitate this process, each CBDC project should be underpinned by a specific legal foundation so that courts can appropriately evaluate the invasion of privacy. With these factors in mind, central banks must adapt their strategy to develop CBDC projects that meet the requirements of sustainability, public security, and privacy. This approach will help reduce the environmental impact of CBDCs and gain social recognition for these projects (Rybski, 2023). CBDC security aspects are also important in implementing a central bank digital currency.

CBDC security expectations may include the following rules: currency may only be issued by a central bank or authorized persons; currency balances cannot be used twice, which prevents duplicated charges; participants cannot deny the authorship of their transactions, ensuring the reliability of the process; the central bank can enforce Know Your Customer (KYC), Antitrust and Anti-Terrorist Financing (AML/CTF), and Office of Foreign Assets Control (OFAC) sanctions (Truque & Hernandez, 2021).

Another group of studies concerns how the implementation of CBDC will affect the banking system and central banks. Research evidence suggests that CBDCs can improve payment functions and enhance financial stability, while potentially displacing bank deposits and affecting bank funding, but the impact on the banking system and central banks varies depending on implementation and control measures. Wholesale CBDCs, which are digital liabilities of central banks, can serve as a new payment instrument between financial institutions (Auer et al., 2020; Fakhrunnas & Anto, 2023).

This means that wholesale CBDCs can facilitate faster and more efficient inter-bank transactions, reducing reliance on traditional payment systems. On the other hand, retail CBDCs that are available to the general public could have broader implications. Also, CBDC issuance can have an important impact on central bank balance sheets depending on the modality of CBDC conversion (Kiff et al., 2020). This means that central banks may need to adjust their balance sheets and operations to accommodate the implementation of CBDC. Additionally, CBDCs can potentially increase financial accessibility by expanding banks' depositor base if additional competition forces banks to raise deposit rates (Ozili, 2022a). This can lead to a more inclusive banking system as more people will have access to banking services. CBDCs could also change the role of central banks in the financial system. They can give central banks more direct control over monetary policy and financial stability (Fung & Halaburda, 2016). With the help of CBDC, central banks can see transactions in real time and potentially implement more targeted and effective monetary policy. CBDC can also improve the efficiency and security of payments, reducing reliance on intermediaries and increasing the resilience of the financial system (Kshetri, 2021). However, the introduction of CBDCs can also present challenges and risks. For example, the impact of CBDC on private banks needs to be carefully assessed. An interest-bearing CBDC could potentially affect the profitability and business model of private banks, especially in the monopoly banking sector (Andolfatto, 2018). Central banks need to consider the potential consequences and develop appropriate policies to mitigate any negative effects on private banks.

CBDCs have the potential to transform the banking system and central banks. They can improve the efficiency and inclusiveness of the financial system, increase the effectiveness of monetary policy, and strengthen the stability of payments. However, implementing a CBDC also requires careful consideration of the impact on private banks and the necessary adjustments to central bank operations and balance sheets.

2. DATA DESCRIPTION AND METHODOLOGY

Weekly data from January 2015 to September 2023 was collected to analyze the impact of central bank digital currency attention index volatility on stock markets. This starting point in the analysis was chosen due to the availability of CBDCAI attention index, which was calculated (Wang et at, 2022) and is available on a weekly basis. We believe that using weekly data will increase the number of observations. In addition, the use of TVP-VAR model with a variable structure of the variance-covariance matrix will make it possible to consider the volatile nature of high-frequency financial variables, as indicated by Primiceri et al. (2005).

The next stage is to decide on the inclusion of stock market indices in the study, taking into account the main task of the study, namely the analysis of the impact of volatility of the central bank's digital currency attention index on the volatility of stock market indices. The selection of equity markets for inclusion in the analysis is based on the previous research that has shown which markets responded to CBDC-related disruptions and which remained resilient to these disruptions (Kuznichenko, 2022). It also focuses on the world's most influential indices, which reflect global stock markets and the world's largest economies. For example, Wang et al. (2022) examine the relationship between CBDC and the global stock market, in particular the FTSE All World index. Similarly, Van der Westhuizen et al. (2022) use the MSCI All World Index to predict volatility in global markets.

For the study, an empirical analysis will be conducted to examine the impact of CBDCAI volatility on international stock market indices (Appendix A, Table A1).

Stock exchange indices of countries where the state of CBDC launching is in different phases (research, pilot launching, launching) were selected for the study.

For the purpose of this analysis, the TVP-VAR model with stochastic volatility developed by Primiceri in 2005 (Primiceri, 2005) was used. This model was applied to weekly data from January 2015 to August 2023 to determine the impact of a central bank digital currency attention index on stock markets. The CBDCAI index, which was developed in 2022 (Wang et al., 2022), covers over 660 million news sources from LexisNexis News and Business that have been available since January 2015, when Ecuador first implemented its own CBDC.

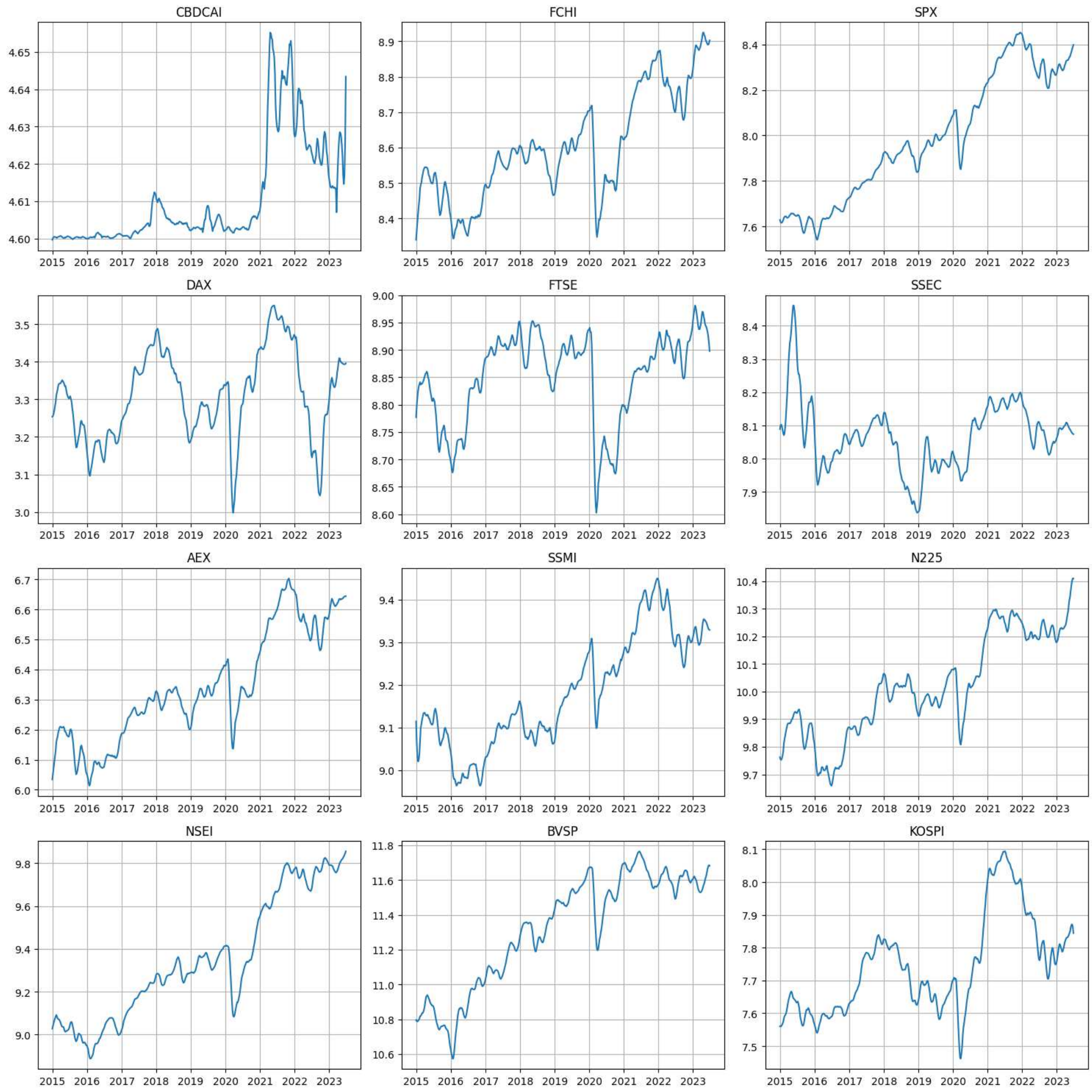
The TVP-VAR model has its advantages, especially compared to other nonlinear models. It makes it possible to consider the evolution of parameters and error terms over time, which makes it possible to record both gradual and unexpected changes in financial markets.

Except for CBDCAI, all data were obtained from Yahoo Finance Provider (Yahoo Finance Provider, 2023). Similar to Wang et al. (2022), Cholesky decomposition is used based on the recursive ordering of variables from the most exogenous to the most endogenous in VAR estimation. In this setup, the CBDC news attention index is ranked first, followed by stock market indices, respectively, as this study examines the impact of CBDC news on the stock market.

Therefore, when evaluating the TVP-VAR model, the following vector of endogenous variables is considered (Figure 1):

$$y_t^{'} = \begin{bmatrix} CBDCAI_t, FCHI_t, SPX_t, DAX_t, \\ FTSE_t, SSEC_t, AEX_t, SSMI_t, \\ N225_t, NSEI_t, BVSP_t, KOSPI_t \end{bmatrix}, \quad (1)$$

http://dx.doi.org/10.21511/bbs.18(4).2023.14



Note: Vertically: the value of the natural logarithm of the index value.

Figure 1. Dataset of input data

where $CBDCAI_t$ denotes the natural logarithm of CBDC news attention index calculated by Wang et al. (2022); $FCHI_t$ is the natural logarithm of the French stock market index, SPX_t is the natural logarithm of the US stock market index, DAX_t is the natural logarithm of the German stock market, $FTSE_t$ is the natural logarithm of the UK stock market, $SSEC_t$ is the natural logarithm of the Chinese stock market, AEX_t is the natural logarithm of the stock market in Netherlands, $SSMI_t$ is the natural logarithm of the Swiss stock market, $N225_t$ is the natural logarithm of the Japanese stock market, $NSEI_t$ is the natural logarithm of the stock market in India, $BVSP_t$ is the natural logarithm of the Brazilian stock market, $KOSPI_t$ is the natural logarithm of the South Korean stock market.

The next step is to transform the time-varying VAR parameter into its vector moving average. The purpose of this transformation is to calculate the impulse response function (IRF) and FEVD, which can be expressed according to Wang et al. (2022):

$$y_t = u_t + \sum_{i=1}^{\infty} \phi_i u_{t-i}, \quad \phi_0 = I_k, \tag{2}$$

where u_t is covariance matrix Σ_u of a k-dimensional unobservable process with zero mean vector white noise; $\phi_i = JA^iJ^i$ and $J = [I_k: 0: 0: ... 0]$; A^i – can be summed up.

Using TVP-VMA, *IRF* can identify a shock to a single variable and trace its marginal effect. Therefore, according to Wang (2022), IRF for each variable *j* on variable *i* can be calculated as follows:

$$IRF = \sum_{p=0}^{\infty} \left(e_i^{'} A_p \Sigma e_j\right)^2, \tag{3}$$

where e_i' and e_j are two fundamental ($N \times 1$) dimensional vectors, each with a unit *i* and *j*, respectively. ($A = K \times K_p$) is a matrix of coefficients for time-varying parameters. In time period ($t - p$), the response impulse equals the cumulative forecast error from the shock for variables *i* and *j*.

The next step of the study is to predict the error variance for the *k*-th element of the forecast error vector. For this purpose, Wang (2022) introduced the following formula:

$$\mathrm{E}\left(y_{j,t+h} - y_{j,t}(h)\right)^2 = \\ = \sum_{j=1}^{k}\left(\theta_{jk,0}^2 + \ldots + \theta_{jk,h-1}^2\right), \tag{4}$$

where $\theta_{jk,0}{}^2 + ... + \theta_{jk,h-1}{}^2 - j_{th}\varepsilon_t$ is the contribution of innovation to the variance of the h-step forecast error of variable *k*.

$\dfrac{\theta_{jk,0}^2 + \ldots + \theta_{jk,h-1}^2}{\mathrm{E}\left(y_{j,t+h} - y_{j,t}(h)\right)^2}$ – percentage contribution $j_{th}\varepsilon_t$ to the h-step variance of the forecast error of variable *k*.

$\omega_{kj,h} - j_{th}\varepsilon_t$ contribution of innovation to the error variance of the h-step *k*.

After clarifying the mathematical basis of volatility spread, the Total Spillover Connectivity Index (TSCI) can now be derived from the above equation based on FEVD (Wang, 2022).

$$TSCI(h) = \frac{\sum_{ij=1, i\neq j}^{N} \tilde{\theta}_{ij,t}(h)}{\sum_{ij=1}^{N} \tilde{\theta}_{ij,t}(h)} \cdot 100 = \\ = \frac{\sum_{ij=1, i\neq j}^{N} \tilde{\theta}_{ij,t}(h)}{N} \cdot 100. \tag{5}$$

The analysis of TSCI allows us to consider the dynamics of the relationship between different variables in the system. The paper examines the relationship between CBDCAI and stock markets, which were described earlier. This approach is similar to the one used in the analysis of systemic shocks. For example, unit "A" has the largest momentum and can transmit this momentum to nearby units. Then the impulses spread to neighboring units and so on. In the propagation process, high values can spread quickly, while low values can spread slowly and weaken (Kuznichenko, 2022).

The equations for calculating FEVD and TSCI provide an opportunity to determine the directional connectivity spillover (DCS). Directional spillover occurs when variable "*i*" receives information from all other variables in the system and simultaneously transmits information to all other variables in the system.

DCS can be described as TSCI decomposition process "from" or "to" a particular data source. There are four different ways to measure *DCS*:

1) DCS^f – connectivity from spillover;
2) DCS^t – connectivity to spillover;
3) DCS^n – connectivity to network spillover;
4) DCS^{np} – connectivity of pairwise directed spillover.

It should be noted that DCS^n between variables *i* and *j* measures the difference between the spillovers transmitted from *i* and *j* and the spillovers from *j* and *i*. A moving panel estimation regression methodology was applied to generate time-dependent schedules of these four DSC indicators to capture the dynamic relationships between all variables. Accordingly, the following formulas were used (Wang, 2022):

$$DSC_{i\leftarrow j,t}^{f}(h) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji,t}(h)}{\sum_{j,i=1}^{N} \tilde{\theta}_{ji,t}(h)} \cdot 100 = \\ = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji,t}(h)}{N} \cdot 100, \tag{6}$$

http://dx.doi.org/10.21511/bbs.18(4).2023.14

$$DSC^{t}_{i\leftarrow j,t}(h)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ij,t}(h)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij,t}(h)}\cdot 100= =\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ij,t}(h)}{N}\cdot 100, \tag{7}$$

$$DSC^{n}_{ij,t}(h)=DSC^{t}_{i\rightarrow j,t}(h)-DSC^{f}_{i\leftarrow j,t}(h)= =\left(\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ij,t}(h)}{N}-\frac{\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ji,t}(h)}{N}\right)\cdot 100, \tag{8}$$

$$DSC^{np}_{ij,t}(h)= =\left(\frac{\tilde{\theta}_{ij,t}(h)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij,t}(h)}-\frac{\tilde{\theta}_{ji,t}(h)}{\sum_{j,i=1}^{N}\tilde{\theta}_{ji,t}(h)}\right)\cdot 100= =\frac{\tilde{\theta}_{ij,t}(h)}{N}\cdot 100, \tag{9}$$

3. RESULTS

3.1. Descriptive analysis

The provided statistical data (Table 1) give an idea of the characteristics of various financial indicators. Each column represents a specific statistical indicator, and their combined analysis can help draw broader conclusions about the data set.

The mean values in the data set vary significantly, indicating different mean levels for each financial indicator. For example, the mean value for BVSP is significantly higher than other indices, suggesting a different scale for the Brazilian stock market index.

Standard deviations (Std) provide insight into the variance or variability of data. Indices such as FCHI and BVSP have relatively high standard deviations, indicating greater variability in these indices.

The range (the difference between the maximum and minimum values) is significant for some indices such as BVSP and N225. This indicates that these financial indicators have a wide range of values during the observation period.

Skewness measures the asymmetry of data distribution. Indices with positive skewness have a longer tail on the right side of the distribution, while columns with negative skewness have a longer tail on the left side. Notably, CBDCAI and SSEC exhibit positive skewness, while FCHI and BVSP exhibit negative skewness.

Kurtosis measures the granularity of distribution. Positive kurtosis indicates heavier tails, while negative kurtosis indicates lighter tails. SSEC has a significantly positive kurtosis, implying fat tails in its distribution.

The IQR is a measure of the spread of data between the 25th and 75th percentiles. Indices with a larger IQR have a larger distribution of data between the lower and upper quartiles. FCHI and BVSP have significantly higher IQRs, indicating a wider range of values in the middle 50% of the data.

The Jarque-Bera test assesses whether the data follows a normal distribution. A high Jarque-Bera statistic indicates a significant deviation from the norm. Indices with larger Jarque-Bera statistics, such as CBDCAI, SSEC, and BVSP, deviate more from a normal distribution.

It should be noted that all columns have the same number of records (count – 444), which indicates stable data availability.

Some financial indicators show significant differences in scale, variability, and form of distribution. For example, the BVSP stands out with a much higher mean, standard deviation and range compared to other stock market indices.

The next step analyzed the results (Table 2) of both the Augmented Dickey-Fuller (ADF) and Phillips-Perron stationarity tests for each index and CBDCAI.

The results show that the ADF test statistic is highly negative for all indices, indicating a strong rejection of the null hypothesis of non-stationarity. This is further supported by the corresponding P-values, which are extremely low for all columns.

The Phillips-Perron test statistic is also highly negative, confirming stationarity for all indices.

Banks and Bank Systems, Volume 18, Issue 4, 2023

Table 1. Descriptive data analysis

Variable	Mean	Std	Min	25%	50%	75%	Max	Range	Kurtosis	Skewness	Iqr	Jarque-Bera	Sum	Count
CBDCAI	100.552	1.498	99.442	99.591	99.850	100.898	109.584	10.142	4.261	1.983	1.307	626.811	44,645.078	444
FCHI	5,497.956	850.215	3,995.060	4,902.600	5,340.025	6,050.327	7,577.000	3,581.940	–0.556	0.571	1,147.728	29.866	2,441,092.563	444
SPX	3,048.011	833.866	1,864.780	2,313.305	2,843.730	3,865.703	4,766.180	2,901.400	–1.143	0.425	1,552.398	37.517	1,353,316.820	444
DAX	27.568	3.255	17.635	25.150	27.435	29.862	35.200	17.565	–0.445	0.120	4.712	4.731	12,240.238	444
FTSE	7,008.296	557.145	5,190.780	6,716.480	7,137.210	7,424.338	8,004.360	2,813.580	–0.158	–0.779	707.858	45.395	3,111,683.520	444
SSEC	3,212.544	350.422	2,493.896	2,987.310	3,202.951	3,382.648	5,166.350	2,672.454	4.948	1.371	395.338	592.017	1,426,369.570	444
AEX	577.194	109.107	391.860	494.997	550.615	671.890	821.800	429.940	–0.849	0.535	176.893	34.498	256,274.260	444
SSMI	9,801.165	1,298.653	7,593.200	8,816.735	9,475.335	10,840.402	12,875.660	5,282.460	–0.830	0.444	2,023.667	27.360	4,351,717.145	444
N225	22,762.315	4,145.854	14,952.020	19,561.526	22,185.955	26,858.570	33,706.078	18,754.059	–0.916	0.309	7,297.044	22.594	10,106,468.050	444
NSEI	11,946.269	3,505.023	6,980.950	8,835.100	10,898.200	15,166.300	19,189.051	12,208.101	–1.024	0.612	6,331.200	47.113	5,304,143.454	444
BVSP	86,245.579	25,062.784	38,031.000	62,881.500	90,917.000	108,205.250	130,126.000	92,095.000	–1.293	–0.233	45,323.750	34.973	38,293,037.000	444
KOSPI	2,333.683	364.372	1,566.150	2,045.135	2,248.210	2,485.400	3,302.840	1,736.690	0.164	0.958	440.265	68.463	1,036,155.158	444

http://dx.doi.org/10.21511/bbs.18(4).2023.14

These statistics are generally lower than the ADF statistics, which is consistent with the tendency of the Phillips-Perron test to produce more negative values.

The results of both tests converge, indicating that discretization successfully made all columns stationary. This means that trends and seasonality in the data have been removed and the data is now suitable for time series analysis. High absolute values of ADF and Phillips-Perron statistics in all columns indicate a robust degree of stationarity. This is particularly important for financial time series analysis as it allows for more robust modeling and forecasting (Wang, 2022).

Table 2. ADF and Philips-Perron stationarity tests

Variable	ADF	Phillips-Perron
CBDCAI	–11.760	–47.571
FCHI	–20.868	–21.042
SPX	–22.594	–23.167
DAX	–21.436	–21.491
FTSE	–21.376	–21.771
SSEC	–7.515	–19.517
AEX	–20.458	–20.679
SSMI	–11.162	–22.997
N225	–21.455	–21.622
NSEI	–8.661	–20.041
BVSP	–12.732	–20.320
KOSPI	–20.681	–20.687

3.2. Correlation analysis

The calculated Pearson correlation coefficients (Table 3) are unconditional, that is, they measure the linear relationship between pairs of indices without considering external factors or time dependencies. They represent a simple linear association between indices.

FCHI and SPX indices show a strong positive correlation of around 0.890, indicating that these two financial indicators tend to move positively together. AEX and SSMI show a strong positive correlation of approximately 0.944, indicating a similar movement pattern. N225 and NSEI also show a strong positive correlation of approximately 0.957.

CBDCAI and FCHI have a moderate positive correlation of approximately 0.730. SPX and DAX show a moderate positive correlation of approximately 0.553. KOSPI and FTSE show a moderate positive correlation of approximately 0.382.

There are a few cases of negative correlations, but they are generally weak. Notably, SSEC has a slight negative correlation with FTSE and BVSP. Some indices, such as SSEC and BVSP, show relatively low correlations with most other indices, suggesting weaker linear relationships.

3.3. Static general volatility correlation

When looking at the static total volatility correlation (Table 4), it is important to pay attention to the "From" values, which are given in the far right column of Table 4 ("From others" column). The "From" variables represent the effect of volatility transferred from the other 11 variables to each individual variable in the context of the forecast error variance. The "From" values range from 74.93% (FCHI) to 3.19% (CBDCAI). Most "From"

Table 3. Correlational data analysis

Variable	CBDCAI	FCHI	SPX	DAX	FTSE	SSEC	AEX	SSMI	N225	NSEI	BVSP	KOSPI
CBDCAI	1	–	–	–	–	–	–	–	–	–	–	–
FCHI	0.730	1	–	–	–	–	–	–	–	–	–	–
SPX	0.802	0.890	1	–	–	–	–	–	–	–	–	–
DAX	0.495	0.553	0.488	1	–	–	–	–	–	–	–	–
FTSE	0.294	0.632	0.357	0.422	1	–	–	–	–	–	–	–
SSEC	0.263	0.239	0.161	0.455	0.014	1	–	–	–	–	–	–
AEX	0.800	0.961	0.970	0.559	0.500	0.231	1	–	–	–	–	–
SSMI	0.769	0.888	0.952	0.509	0.335	0.295	0.944	1	–	–	–	–
N225	0.759	0.903	0.945	0.566	0.411	0.261	0.951	0.903	1	–	–	–
NSEI	0.769	0.928	0.957	0.392	0.468	0.137	0.964	0.902	0.932	1	–	–
BVSP	0.629	0.772	0.899	0.430	0.365	–0.009	0.849	0.846	0.859	0.845	1	–
KOSPI	0.768	0.720	0.803	0.810	0.341	0.382	0.808	0.760	0.824	0.721	0.690	1

Table 4. Statistical distribution of volatility

Variable	CBDCAI	FCHI	SPX	DAX	FTSE	SSEC	AEX	SSMI	N225	NSEI	BVSP	KOSPI	From others
CBDCAI	96.81	0.22	0.05	0.18	0.40	0.26	0.37	0.08	0.19	0.04	1.29	0.11	3.19
FCHI	0.23	25.07	1.70	8.06	39.04	1.01	12.29	5.21	3.07	2.26	0.75	1.31	74.93
SPX	0.04	3.37	36.24	10.88	21.22	0.32	5.92	3.34	2.76	5.98	5.09	4.85	63.76
DAX	0.06	10.10	8.08	31.71	24.15	0.79	5.94	2.87	3.15	3.46	4.75	4.94	68.29
FTSE	0.30	3.16	1.83	2.59	81.49	0.72	3.80	1.55	0.75	1.68	0.77	1.36	18.51
SSEC	0.84	1.19	0.07	0.03	4.44	87.22	1.75	0.37	0.25	0.26	1.38	2.20	12.78
AEX	0.13	12.27	3.10	4.55	38.67	0.81	26.50	6.12	3.33	2.54	0.42	1.55	73.50
SSMI	0.32	8.21	3.66	3.96	29.00	0.83	10.02	39.54	2.33	0.87	0.40	0.85	60.46
N225	0.07	5.75	4.23	6.64	16.32	0.60	6.28	3.04	43.09	4.24	2.22	7.51	56.91
NSEI	0.02	5.19	4.60	4.73	15.59	0.40	3.93	1.71	5.58	47.38	4.81	5.96	52.52
BVSP	0.03	2.45	4.91	6.84	12.57	1.30	2.28	0.94	3.03	6.23	56.11	3.31	43.89
KOSPI	0.07	3.49	4.30	6.97	22.12	1.44	3.73	1.67	6.22	5.28	2.89	41.82	58.18
Directional to others	2.12	55.40	36.52	55.43	233.52	8.48	56.31	26.89	30.66	32.83	24.77	33.96	586.91
Directional including own	98.94	80.47	72.77	87.14	305.02	95.70	82.81	66.43	73.76	80.30	80.88	75.78	TCI=48.91
NET Directional Connectedness	–1.06	–19.53	–27.23	–12.86	205.02	–4.30	–17.19	–33.57	–26.24	–19.70	–19.12	–24.22	–

indices exceed 50%, such as: SPX (63.76%), DAX (68.29%), FCHI (74.93%), AEX (73.50%), SSMI (60.46%), N225 (56.91%), NSEI (52.52%), KOSPI (58.18%). This is in line with the findings (Wang et al., 2022) that indicate the impact of global financial factors and uncertainty on stock markets. The "From" values for CBDCAI are the lowest, indicating that the impact of stock markets, global financial factors, and uncertainty on the CBDCAI index is limited.

Regarding the static relationship of total volatility spillover "To" shown in Table 4 (row "Directional to others"), "To" represents the relationship of total volatility spillover between the volatility of each variable and the volatility of other variables. In other words, it is the contribution of each variable to the expansion of the variance of the forecast error of other variables. "To" values range from 2.12% (*CBDCAI*) to 233.52% (*FTSE*). *FTSE* has the highest level of volatility (233.52%), followed by *AEX* (56.31%), *DAX* (55.43%) and *FCHI* (55.40%). Unsurprisingly, the "To" value for *CBDCAI* is the lowest.

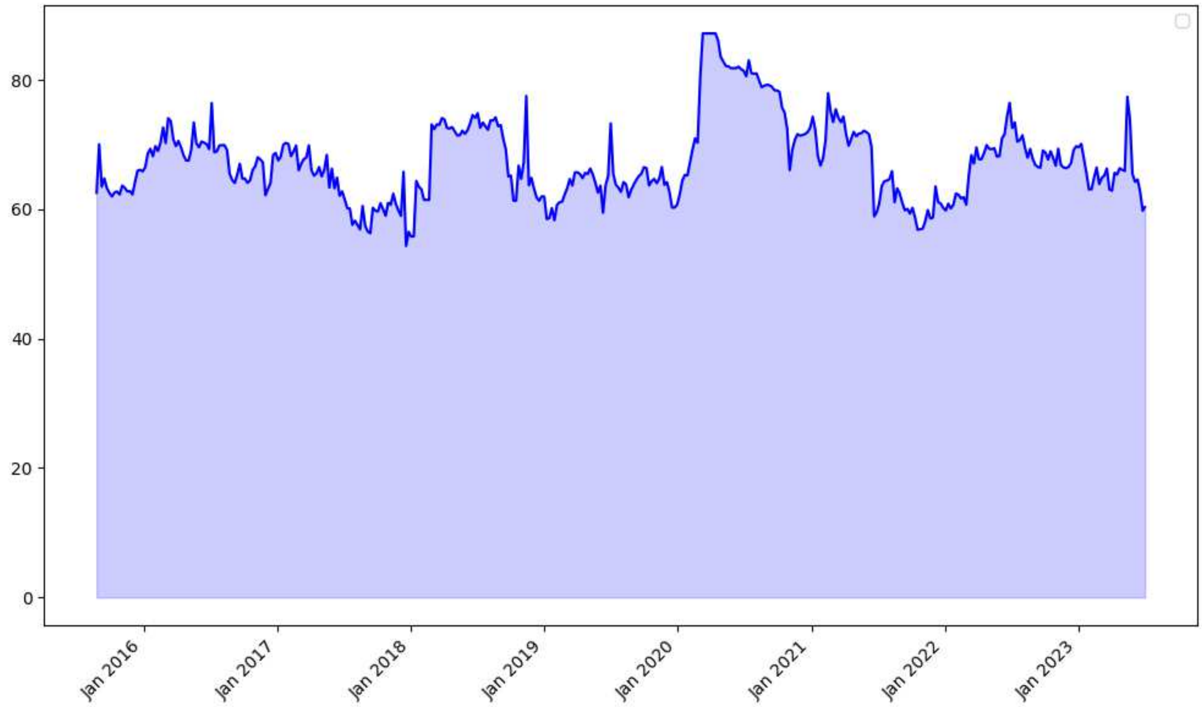
For the static net directional connectedness of total volatility spillover, which is also presented in Table 4 (row "Net directional Connectedness"), the net values indicate the difference between the static connection of total volatility spillover with others and the connection of static total volatility spillover from others. The "net" value for *CBDCAI* was negative at –1.06%, indicating that the impact of CBDCAI on the volatility of the other 11 variables is smaller than the impact of volatility of the other 11 variables on it. In other words, CBDCAI absorbs the impact of other indices, but has a limited effect on their volatility. Therefore, in stressful situations, *CBDCAI* can act as a spillover buffer. In comparison, *FTSE* is the most important source of volatility with 205.02% of total volatility.

The off-diagonal elements of the 12 x 12 matrix in Table 4 illustrate the static "Net" pairwise volatility relationship between the volatilities of the two variables. For example, the value 0.30% in row 5, column 2, represents the percentage of the variance expansion of the forecast error of *FTSE* volatility due to shocks from *CBDCAI*. Regarding the impact from *CBDCAI*, the correlation of static "Net" pairwise volatility between *CBDCA*I and other financial markets is low, ranging from 0.02% (*NSEI*) to 0.84% (*SSEC*). Most of *CBDCA*I's volatility is the result of domestic shocks (96.81%).

3.4. Dynamic spread of total volatility

The previous empirical analysis showed static connectivity based on the full sample of data. However, it is important to consider how this relationship may change over time in low-frequency data and how it may reflect the dynamic

http://dx.doi.org/10.21511/bbs.18(4).2023.14



Note: Vertically: the percentage value of connectedness shows the degree of interconnectedness for the entire system of variables.

Figure 2. Total volatility of the system

relationship between CBDCAI and other stock market indices. To do this, this section will determine the dynamic dependence of the spillover of total volatility using fixed sample data. Figure 2 shows how the assessment of the spillover effect changes over time. As indicated above and shown in Table 5, the static overall connectivity index is 48.91%. However, the actual total connectivity index (TCI) varies from 54.35% to 87.21% (Figure 2). That is why it is so important to take a close look at the TCI timeframe. CBDC timing methodology can also provide investors, stakeholders, and policymakers with useful information on volatility spillovers. This indicator reflects the degree of interrelationship for the entire system of variables. Using TVP-VAR, the figure illustrates how the relationship between volatility variables changes dynamically over time. The baseline variance schedule assumes a 52-week horizon (H = 52) for the sample period from January 2015 to July 2023.

In periods 2018–2019 and 2020–2021, a number of important events occurred that significantly affected the relationship between CBDC and stock exchange indices.

The peak was in 2018–2019: During these years the interest in CBDCs increased dramatically and many central banks began researching the possibility of implementing their own digital currencies. This has led to discussions and analysis in the global financial environment. Stock indices have become highly correlated as world events and news strongly influence stock markets. Various aspects of the economy and geopolitical events have affected stock market indices, and this has led to fluctuations and correlations between them. Decisions by central banks to implement CBDCs had the potential to bring major changes to the financial services and investment landscape.

The peak of 2020–2021: This period was marked by the global COVID-19 pandemic, which caused severe turbulence in global stock markets. Stock indices have suffered heavy losses due to the spread of the virus and the subsequent measures. But even after the recession, stock markets responded strongly to stimulus measures introduced by central banks and governments to keep the economy afloat. This has also affected the interest in CBDCs.

Therefore, in the periods of 2018–2019 and 2020–2021, the world of CBDC and the stock markets were strongly connected due to global financial and economic challenges, as well as the growing interest in digital central bank currencies.

3.5. Dynamic directional connectivity of volatility spillover

Figure 3 shows the relationship in volatility transmission, showing how volatility spreads among markets. The vast majority of volatility values for CBDCAI are negative, indicating that volatility is transmitted to the CBDC market more than from it. In other words, the CBDC market absorbs volatility. This is consistent with the results for the static volatility transmission relationship, suggesting the ability of the CBDC market to absorb volatility in general. Typically, equity markets spread the impact of volatility more than they absorb the impact. This is known from earlier studies (Bala & Takimoto, 2017; Natarajan et al., 2014).

Figure 3 shows that FTSE, NSEI, SSEC and BVSP are key sources of volatility in stock markets. On the other hand, SSEC and N225 appear to be volatility absorbers, similar to the CBDC attention

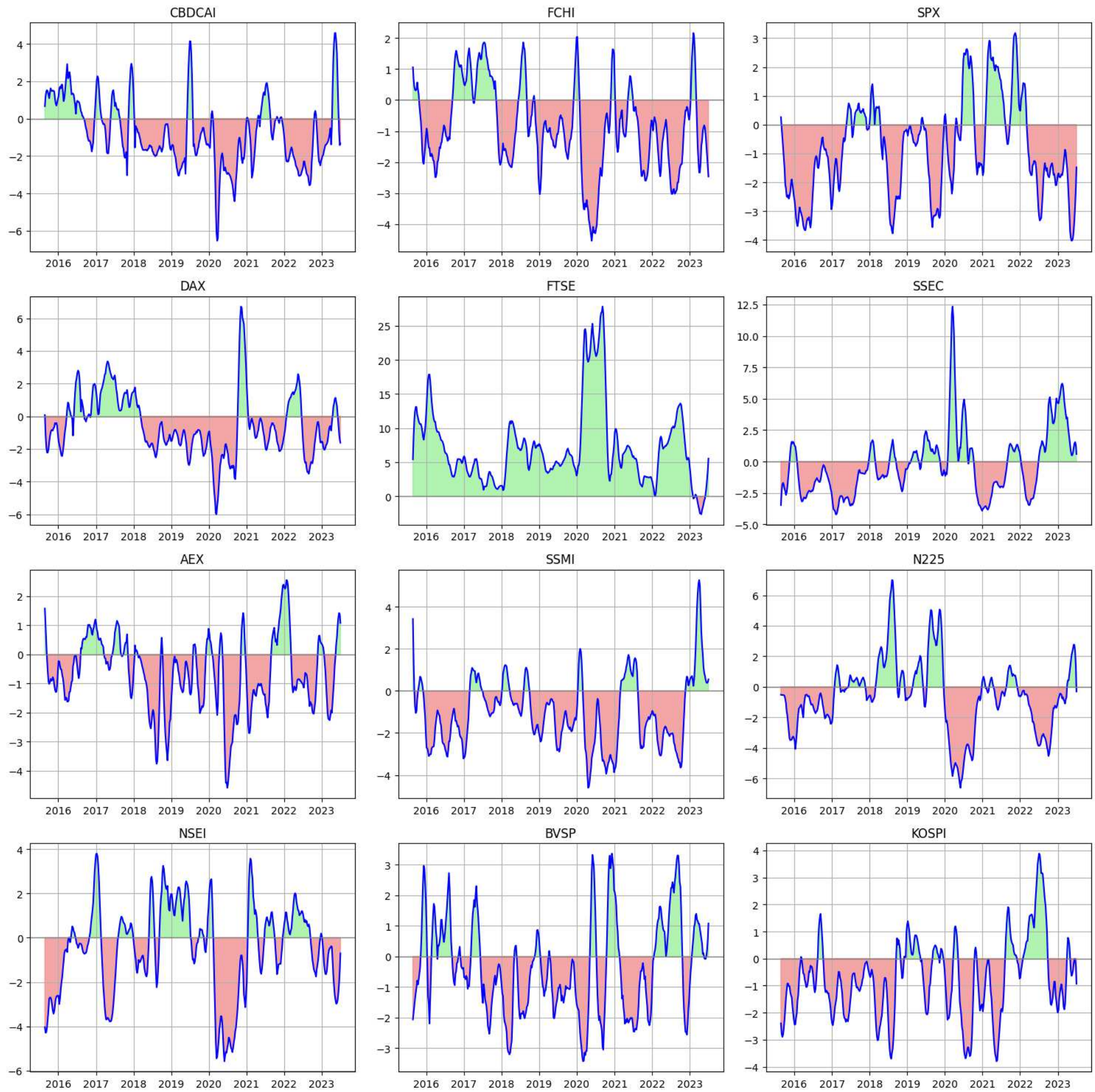
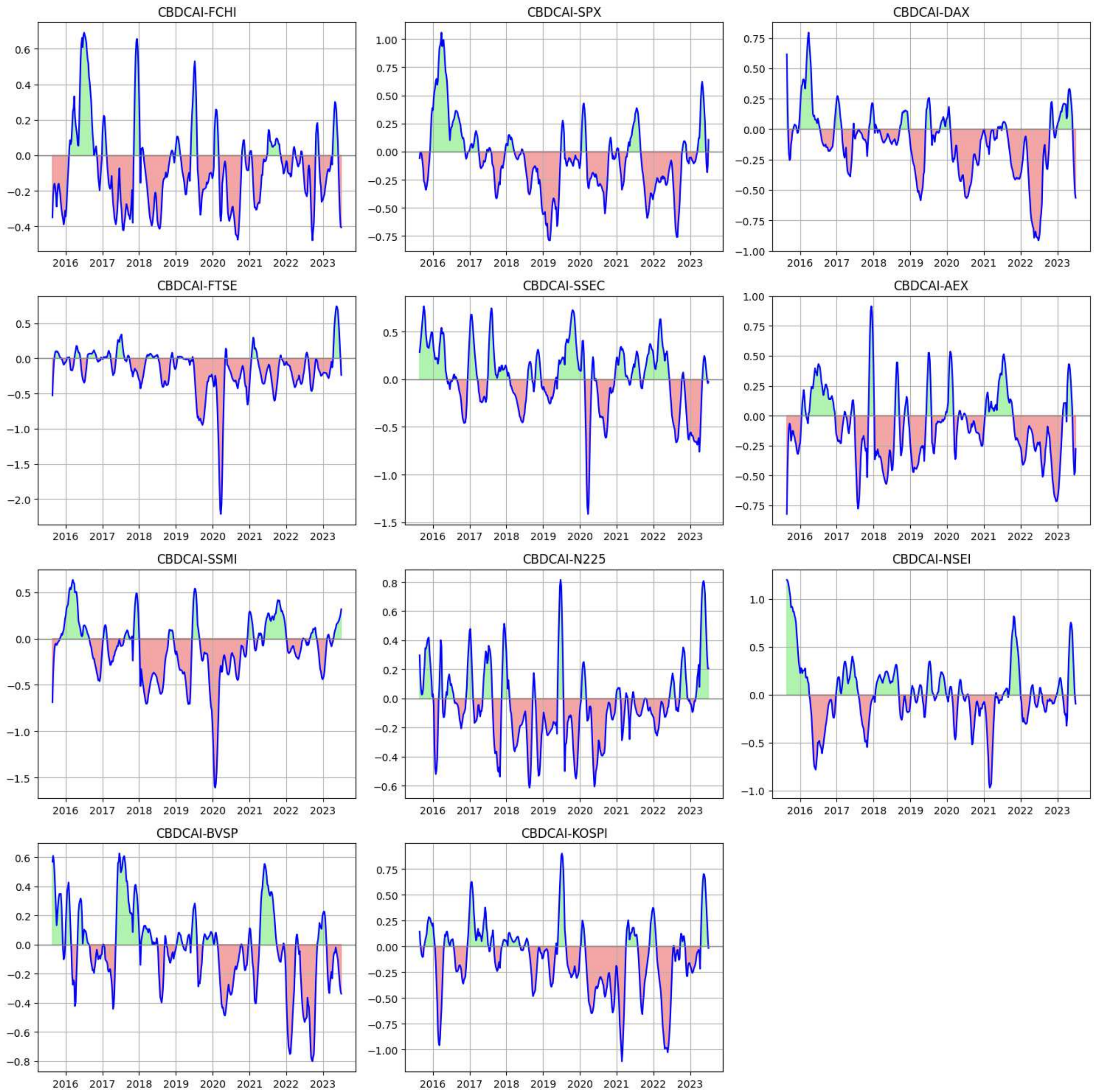


Figure 3. Spread of volatility among indices

Note: Negative values mean that the index accepts volatility, positive values – it is a source of volatility.

http://dx.doi.org/10.21511/bbs.18(4).2023.14



Note: Negative values mean that in the specified pair CBDCAI receives directional volatility spillovers, positive values – it is a source of directional volatility spillovers.

Figure 4. Pairwise directional volatility spillover of the CBDCAI index

index. However, in 2017 CBDCAI changed from a volatility absorber to a volatility transmitter. This may be due to the global discussions regarding the implementation of CBDC. But as shown in Figure 3, usually CBDC acts as a volatility absorber.

3.6. Net pairwise volatility spillover

The values in Figure 4 are "net" pairwise directional volatility spillovers that represent the difference between the relationship of the static total directional volatility spillover to others and the relationship of the static total directional volatility spillover from others.

Variations in the net directional effects of volatility are observed over the covered period. The values show some fluctuations, indicating changing levels of correlation between CBDCAI and other indices. Negative values in the table indicate that CBDCAI tends to receive more directional volatility spillovers from other indices, while positive values indicate that CBDCAI is a source of directional volatility spillovers to other indices. This targeted information is critical to risk assessment. The results show that most indices are transmitters of volatility for CBDCAI volatility.

It should also be noted that the data reflect the dynamic nature of financial markets. For example, there are negative spillovers from most indices to CBDCAI in the initial period. However, this pattern changes over time and some indices become sources of volatility.

CBDCAI's net volatility values highlight the degree of correlation with traditional stock markets. It has become more interconnected with certain markets over time, while becoming disconnected from others.

The analysis of this data can help investors and financial analysts assess the risks and potential effects of the connection between the CBDC market and traditional stock markets. Positive values can mean that shocks in the CBDC market can affect traditional markets, and vice versa.

CONCLUSIONS

Several key conclusions can be made based on the analysis. First, the interdependence and mutual influence between the digital currency market of central banks and the stock markets was revealed. Second, even with this interaction, the CBDC market typically operates relatively independently from other stock markets. Third, CBDCAI assumes the influence of other indices, but has a limited effect on their volatility. Over time, CBDCAI has been seen to become more interconnected with certain markets while becoming disconnected from others. Fourth, despite the general ability of the CBDC market to absorb fluctuations in volatility, it may also change its function with the widespread adoption of central bank digital currencies in many countries.

The analysis of the resulting data can help investors and financial analysts to assess the risks and potential effects of the connection between the CBDC market and traditional stock markets. Moreover, investors can use the obtained results to improve risk management and optimize their investment portfolios. In addition, for regulators and policymakers, this document also offers several advantages. For example, it can help them get more information on the impact of CBDC news on stock markets.

There are several limitations to the study. First, because CBDCs are still in their early stages of development, the availability of data is limited. Second, the analysis is limited to the impact of CBDC news on the stock market only. The final results will become more accurate once CBDC is widely implemented. Third, much of the existing research on CBDC is theoretical, making it difficult to compare the results of this study with previous studies. Finally, once the majority of central banks have adopted CBDC, it will be possible to conduct additional research to assess the impact of CBDC on monetary policy mechanisms and various financial markets. Therefore, this topic remains relevant for future scientific research. It should be noted that in the future, we could also explore the relationship of CBDCAI volatility with the volatility of cryptocurrencies, fiat currencies, or try using different econometric models.

AUTHOR CONTRIBUTIONS

Conceptualization: Serhiy Frolov, Mykhaylo Heyenko.
Data curation: Mariia Dykha.
Formal analysis: Serhiy Frolov, Viktoriia Datsenko.
Funding acquisition: Mariia Dykha, Viktoriia Datsenko.
Investigation: Maksym Ivasenko, Mariia Dykha.
Methodology: Serhiy Frolov, Maksym Ivasenko, Mykhaylo Heyenko.
Project administration: Serhiy Frolov, Mykhaylo Heyenko.
Resources: Maksym Ivasenko, Mariia Dykha, Viktoriia Datsenko.

http://dx.doi.org/10.21511/bbs.18(4).2023.14

Software: Maksym Ivasenko.
Supervision: Serhiy Frolov, Viktoriia Datsenko.
Validation: Serhiy Frolov, Maksym Ivasenko, Mykhaylo Heyenko.
Visualization: Maksym Ivasenko, Mariia Dykha, Viktoriia Datsenko.
Writing – original draft: Maksym Ivasenko, Mykhaylo Heyenko.
Writing – reviewing & editing: Serhiy Frolov, Mariia Dykha, Mykhaylo Heyenko, Viktoriia Datsenko.

REFERENCES

1. Ahmad, S., Khan, N., Shah, M., & Khan, M. (2022). An analysis of the dynamic linkages of Pakistani stock market with the world's leading stock markets. *Journal of Management Practices Humanities and Social Sciences, 6*(5), 22-33. https://doi.org/10.33152/jmphss-6.5.3
2. Andolfatto, D. (2018). *Assessing the impact of central bank digital currency on private banks* (Working Paper No. 2018-026). Federal Reserve Bank of St. Louis W. https://doi.org/10.20955/wp.2018.026
3. Atako, N. (2021). Privacy Beyond Possession: Solving the Access Conundrum in Digital Dollars. *Vanderbilt Journal of Entertainment & Technology Law, 23*(4), 821-854. https://doi.org/10.2139/ssrn.3798838
4. Atlantic Council. (2023). *Central Bank Digital Currency (CBDC).* Retrieved from https://www.atlanticcouncil.org/cbdctracker/
5. Auer, R., Cornelli, G., & Frost, J. (2020). *Rise of the central bank digital currencies: drivers, approaches and technologies* (CESifo Working Paper No. 8655). https://doi.org/10.2139/ssrn.3724070
6. Auer, R., Frost, J., Gambacorta, L., Monnet, C., Rice, T., & Shin, H. S. (2022). Central Bank Digital Currencies: Motives, Economic Implications, and the Research Frontier. *Annual Review of Economics, 14,* 697-721. https://doi.org/10.1146/annurev-economics-051420-020324
7. Bala, D. A., & Takimoto, T. (2017). Stock markets volatility spillovers during financial crises: A DCC-MGARCH with skewed-t density approach. *Borsa Istanbul Review, 17*(1), 25-48. https://doi.org/10.1016/j.bir.2017.02.002
8. Barrdear, J., & Kumhof, M. (2021). The macroeconomics of central bank digital currencies. *Journal of Economic Dynamics and Control, 142,* 104148. https://doi.org/10.1016/J.JEDC.2021.104148
9. Bian, W., Ji, Y., & Wang, P. (2021). The crowding-out effect of central bank digital currencies: A simple and generalizable payment portfolio model. *Finance Research Letters, 43,* 102010. https://doi.org/10.1016/J.FRL.2021.102010
10. Bijlsma, M., Cruijsen, C., Jonker, N., & Reijerink, J. (2021). *What triggers consumer adoption of CBDC?* (De Nederlandsche Bank Working Paper No. 709). https://doi.org/10.2139/SSRN.3836440
11. Bindseil, U. (2019). Central Bank Digital Currency: Financial System Implications and Control. *International Journal of Political Economy, 48*(4), 303-335. https://doi.org/10.1080/08911916.2019.1693160
12. Boar, C., & Wehrli, A. (2021). *Ready, steady, go? – Results of the third BIS survey on central bank digital currency* (Working Paper No. 114). Bank for International Settlements. Retrieved from https://www.bis.org/publ/bppdf/bispap114.pdf
13. Bublyk, Y., Borzenko, O., & Hlazova, A. (2023). Cryptocurrency energy consumption: Analysis, global trends and interaction. *Environmental Economics, 14*(2), 49-59. https://doi.org/10.21511/ee.14(2).2023.04
14. Chen, H., & Bondt, W. (2004). Style momentum within the S&P-500 index. *Journal of Empirical Finance, 11*(4), 483-507. https://doi.org/10.1016/j.jempfin.2004.04.005
15. Chu, Y., Lee, J., Kim, S., Kim, H., Yoon, Y., & Chung, H. (2022). Review of offline payment function of CBDC considering security requirements. *Applied Sciences, 12*(9), 4488. https://doi.org/10.3390/app12094488
16. Dubyna, M., Popelo, O., Zhavoronok, A., Lopashchuk, I., & Fedyshyn, M. (2023). Development of the credit market of Ukraine under macroeconomic instability. *Public and Municipal Finance, 12*(1), 33-47. https://doi.org/10.21511/pmf.12(1).2023.04
17. Fakhrunnas, F., & Anto, M. B. H. (2023). Assessing the Islamic banking contribution to financial stability in Indonesia: A non-linear approach. *Banks and Bank Systems, 18*(1), 150-162. https://doi.org/10.21511/bbs.18(1).2023.13
18. Fung, B., & Halaburda, H. (2016). Central bank digital currencies: a framework for assessing why and how. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.2994052
19. Grothoff, C., & Moser, T. (2021). How to issue a privacy-preserving central bank digital currency? *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.3965050
20. Han, J., Kim, J., Youn, A., Lee, J., Chun, Y., Woo, J., & Hong, J. W.-K. (2021). Cos-CBDC: Design and Implementation of CBDC on Cosmos Blockchain. *2021 22nd Asia-Pacific Network Operations and Management Symposium (APNOMS)* (pp. 303-308). Tainan, Taiwan. https://doi.org/10.23919/APNOMS52696.2021.9562672
21. Kerimov, A., Babayev, A., Dudchenko, V., Samusevych, Y., & Tumpach, M. (2023). Banking

system stability in crisis periods: The impact of the banking regulator independence. *Banks and Bank Systems, 18*(3), 221-234. https://doi.org/10.21511/bbs.18(3).2023.18

22. Kiff, J., Alwazir, J., Davidovic, S., Farias, A., Khan, A., Khiaonarong, T., Malaika, M., Monroe, H., Sugimoto, N., Tourpe, H., & Zhou, P. (2020). *A survey of research on retail central bank digital currency* (IMF Working Paper No. WP/20/104). https://doi.org/10.5089/9781513547787.001

23. Koçak, E., Bulut, U., & Menegaki, A. (2021). The resilience of green firms in the twirl of covid-19: evidence from S&P500 carbon efficiency index with a Fourier approach. *Business Strategy and the Environment, 31*(1), 32-45. https://doi.org/10.1002/bse.2872

24. Kochergin, D. (2021). Central Banks Digital Currencies: World Experience. *World Economy and International Relations, 65*(5), 68-77. https://doi.org/10.20542/0131-2227-2021-65-5-68-77

25. Koziuk, V. (2021). Confidence in digital money: Are central banks more trusted than age is matter? *Investment Management and Financial Innovations, 18*(1), 12-32. https://doi.org/10.21511/imfi.18(1).2021.02

26. Kshetri, N. (2021). The economics of central bank digital currency [Computing's Economics]. *Computer, 54*(6), 53-58. https://doi.org/10.1109/mc.2021.3070091

27. Kuznichenko, P. (2022). *Volatility Spillovers Across CBDC Attention and Stock Market Volatility*. SSRN. http://dx.doi.org/10.2139/ssrn.4152316

28. Lee, D., Yan, L., & Wang, Y. (2020). A global perspective on central bank digital currency. *China Economic Journal, 14*(1), 52-66. https://doi.org/10.1080/17538963.2020.1870279

29. Lee, Y. (2022). Representative bias and pairs trade: evidence from S&P 500 and Russell 2000 indexes. *Sage Open, 12*(3), 215824402211203. https://doi.org/10.1177/21582440221120361

30. Li, Z., Yang, C., & Huang, Z. (2022). How does the fintech sector react to signals from central bank digital currencies? *Finance Research Letters, 50,* 103308. https://doi.org/10.1016/j.frl.2022.103308

31. Liu, J. (2023). CBDC Application Analysis and Prospects. *BCP Business & Management, 45,* 82-87. http://dx.doi.org/10.54691/bcpbm.v45i.4866

32. Natarajan, V. K., Singh, A. R., & Priya, N. C. (2014). Examining mean-volatility spillovers across national stock markets. *Journal of Economics Finance and Administrative Science, 19*(36), 55-62. https://doi.org/10.1016/j.jefas.2014.01.001

33. Ozili, P. (2022a). Central bank digital currency in Nigeria: opportunities and risks. In S. Grima, E. Özen, and H. Boz (Eds), *The New Digital Era: Digitalisation, Emerging Risks and Opportunities* (*Contemporary Studies in Economic and Financial Analysis, Vol. 109A*) (pp. 125-133). Emerald Publishing Limited, Bingley. https://doi.org/10.1108/s1569-37592022000109a008

34. Ozili, P. (2022b). CBDC, Fintech and cryptocurrency for financial Inclusion and financial stability. *Digital Policy, Regulation and Governance, 25*(1), 40-57. https://doi.org/10.1108/DPRG-04-2022-0033

35. Panetta, F., Mehl, A., Neumann, C. M., & Jamet, J.-F. (2022). *Monetary policy and financial stability implications of central bank digital currencies*. London: Centre for Economic Policy Research (CEPR). Retrieved from https://cepr.org/voxeu/columns/monetary-policy-and-financial-stability-implications-central-bank-digital-currencies

36. Panigrahi, S. (2023). Are cryptocurrencies a threat to financial stability and economic growth of India? Evidence from the cointegration approach. *Investment Management and Financial Innovations, 20*(2), 307-320. https://doi.org/10.21511/imfi.20(2).2023.26

37. Passacantando F. (2021). The Digital Euro: Challenges and Opportunities. In N. Bilotta, F. Botti (Eds.), *The (Near) Future of Central Bank Digital Currencies. Risks and Opportunities for the Global Economy and Society* (pp. 113-130). Retrieved from https://library.oapen.org/viewer/web/viewer.html?file=/bitstream/handle/20.500.12657/47398/9783034342919.pdf

38. Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies, 72*(3), 821-852. https://doi.org/10.1111/j.1467-937X.2005.00353.x

39. Qian, Y. (2019). Central Bank Digital Currency: optimization of the currency system and its issuance design. *China Economic Journal, 12*(1), 1-15. https://doi.org/10.1080/17538963.2018.1560526

40. Rai, S., Miller, J., & Balakrishnan, P. (2020). Evolutionary disruption of S&P 500 trading concentration: an intriguing tale of a financial innovation. *Plos One, 15*(3), e0230393. https://doi.org/10.1371/journal.pone.0230393

41. Rybski, R. (2023). Sustainability, Public Security, and Privacy Concerns regarding Central Bank Digital Currency (CBDC). In P. Łasak and J. Williams (Eds), *Digital transformation and the economics of banking: economic, institutional, and social dimensions*. Taylor & Francis. Retrieved from https://library.oapen.org/viewer/web/viewer.html?file=/bitstream/handle/20.500.12657/76546/9781003340454_10.4324_9781003340454-10.pdf

42. Sethaput, V., & Innet, S. (2023). Blockchain application for central bank digital currencies (CBDC). *Cluster Comput, 26,* 2183-2197. https://doi.org/10.1007/s10586-022-03962-z

43. Skrynnyk, O., & Lyeonov, S. (2022). Emerging trends and research focal points of information technologies for financial control and accounting at the state and corporate level: Bibliometric research and visualization. *Accounting and Financial Control, 4*(1), 49-62. https://doi.org/10.21511/afc.04(1).2023.05

44. Slimane, F., Mehanaoui, M., & Kazi, I. (2013). How does the financial crisis affect volatility behavior and transmission among European stock markets? *International Journal of Financial Studies, 1*(3), 81-101. https://doi.org/10.3390/ijfs1030081

45. Stoll, H., & Whaley, R. (1990). The dynamics of stock index and stock index futures returns. *Journal of Financial and Quantitative Analysis, 25*(4), 441. https://doi.org/10.2307/2331010

46. Truque, D., & Hernandez, J. (2021). *Central Bank Digital Currency (CBDC) Security and Privacy.* Satoshi Capital Advisors. https://doi.org/10.13140/RG.2.2.29364.37769

47. Van der Westhuizen, C., Van Eyden, R., & Aye, G. C. (2022). Contagion across financial markets during Covid-19: A look at volatility spillovers between the stock and foreign exchange markets in South Africa. *Annals of Financial Economics, 17*(1), 2250002. https://doi.org/10.1142/S2010495222500026

48. Wang Y., Lucey B. M., Vigne, S. A., & Yarovaya, L. (2022). The Effects of Central Bank Digital Currencies News on Financial Markets. *Technological Forecasting and Social Change, 180,* 121715. https://doi.org/10.1016/j.techfore.2022.121715

49. Wang, Y. (2022). Volatility spillovers across NFTs news attention and financial markets. *International Review of Financial Analysis, 83,* 102313. https://doi.org/10.1016/j.irfa.2022.102313

50. Williamson, S. (2022). Central Bank Digital Currency: Welfare and Policy Implications. *Journal of Political Economy, 130*(11), 2829-2861. https://doi.org/10.1086/720457

51. World Bank Group. (2021). *Central Bank Digital Currency. Background Technical Note.* Retrieved from https://documents1.worldbank.org/curated/en/603451638869243764/pdf/Central-Bank-Digital-Currency-Background-Technical-Note.pdf

52. Yahoo Finance Provider. (2023). Retrieved from https://finance.yahoo.com/

APPENDIX A

Table A1. Stock market indices used in the model

No.	Country	Stock market index	Description
1	France	CAC 40 (FCHI)	The index represents the performance of 40 largest companies that are most actively traded on the Euronext Paris exchange (Ahmad et al., 2022)
2	United States	Standard and Poor's 500 (SPX)	One of the most followed stock market indices in the world, it represents the performance of 500 companies with high capitalization listed on US stock exchanges (Lee, 2022)
3	Germany	DAX 30 (DAX)	The index reflects the performance of 30 largest and most liquid companies listed on the Frankfurt Stock Exchange (Slimane et al., 2013)
4	United Kingdome	Financial Times 100 (FTSE)	The index reflects the performance of 100 largest companies registered on the London Stock Exchange (Ahmad et al., 2022)
5	China	SSE Composite Index (SSEC)	The index represents the performance of all shares listed on the Shanghai Stock Exchange (Stoll & Whaley, 1990)
6	Netherlands	AEX	The index represents the performance of 25 largest and most actively traded companies registered on Euronext Amsterdam (Chen & Bondt, 2004)
7	Switzerland	Swiss Market Index (SSMI)	The index represents the performance of 20 largest and most liquid companies listed on the SIX 8Swiss Exchange (Koçak et al., 2021)
8	Japan	Nikkei Stock Average (N225)	The index represents the performance of 225 the largest and most actively traded companies registered on the Tokyo Stock Exchange (Slimane et al., 2013)
9	India	NIFTY 50 (NSEI)	The index represents the performance of 50 largest and most active companies traded on the National Stock Exchange of India
10	Brazil	Ibovespa (BVSP)	The index represents the most actively traded shares listed on B3 stock exchange (formerly BM&FBOVESPA)
11	South Korea	KOSPI (Korea Composite Stock Price Index)	The index represents the South Korean stock market and serves to measure the movement of share prices in the South Korean stock market

http://dx.doi.org/10.21511/bbs.18(4).2023.14