The Effects of Central Bank Digital Currencies News on Financial Markets

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Abstract

Based on coverage of over 660m news stories from LexisNexis News & Business between 2015–2021, we provide two new indices around the growing area of Central Bank Digital Currency (CBDC): the CBDC Uncertainty Index (CBDCUI) and CBDC Attention Index (CBDCAI). We show that both indices spiked during news related to new developments in CBDC and in relation to digital currency news items. We demonstrate that CBDC indices have a significant negative relationship with the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index, and positive with the volatilities of cryptocurrency markets, foreign exchange markets, bond markets, VIX, and gold. Our results suggest that financial markets are more sensitive to CBDC Uncertainty than CBDC Attention as proxy by these indices. These findings contain useful insights to individual and institutional investors, and can guide policymakers, regulators, and the media on how CBDC evolved as a barometer in the new digital-currency era.

Keywords: CBDC; Uncertainty and attention index; Market effect; SVAR; DCC-GJR-GARCH
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1. Introduction

While our times are certainly changing, let us hope money remains with us. As a medium of exchange, money has evolved from shells, dogs teeth, knotted fabric, precious metals, banker's notes, cash to cryptocurrency [Davies, 2010]. While cryptocurrency is still a largely unregulated area, the introduction of the Central Bank Digital Currencies (CBDCs) will manifest the beginning of a new monetary era [Laboure et al., 2021]. Now, the Bahamas has already implemented CBDC in its territory, and China has recently completed two CBDC tests. The CBDC wallet app is now available in Suzhou, Xiongan, Shenzhen, and Chengdu, and the People's Bank of China and the Hong Kong Monetary Authority has begun 'technical testing' for cross-border use of e-CNY. Uruguay has also completed a CBDC pilot test. CBDC is a virtual form of a country's fiat currency issued by the central bank [Yao, 2018b]. CBDC was initially called a Digital Fiat Currency (DFC) [Krylov et al., 2018], which draws inspiration from famous crypto assets such as Bitcoin, Ethereum, Binance Coin, among others. In 2013, Shoaib et al. [2013] introduced the alternative terms of Official Digital Currency (ODC) and the Official Digital Currency System (ODCS).

A CBDC is of great importance over conventional cryptocurrencies and fiat currencies when studying. First, from the perspective of payment, it saves costs, prevents counterfeiting, and strengthens the authority of legal tender while enhancing the inclusive character of the payment system [Sun et al., 2017]. It also optimises the payment function of legal tender, reducing the reliance on payment services on business banks and private sectors, thereby decreasing the burden and pressure of supervision on the central bank [Qian, 2019]. Second, CBDCs can benefit to the monetary supervision and regulation. The structured currency circulation data allows total amount of money supply to be regulated precisely [Agarwal et al., 2021; Fernández-Villaverde et al., 2021]. This ameliorates the dilemmas facing modern monetary policies, such as inefficient policy transmissions, difficult regulation of conversion periods, the flow of money from the real economy to the virtual one, and the failed realisation of expected requirements by monetary policies. Moreover, capital flow information can be fully and quickly investigated, thereby aiding anti-corruption, anti-money laundering, anti-terrorist financing, and anti-tax evasion efforts [Tronnier, 2021; Dupuis et al., 2021]. Third, CBDCs have the potential to promote financial market stability by adjusting monetary, mitigating financial systemic risk, reducing shadow banking, among others [Larina and Akimov, 2020; Copeland, 2020; Zams et al., 2020].

While a CBDC could provide some benefits, it may also bring several significant challenges for society. First, CBDCs could exacerbate financial uncertainty during periods of economic stress [Ferrari et al., 2022; Sinelnikova-Muryleva, 2020]. Without effective regulations, individuals can hold CBDCs indefinitely. Therefore, in the event of a crisis, individuals or economic agents could try to substitute CBDCs for bank deposits, as they may be perceived as less risky [Williamson, 2021]. This behaviour may lead to bank runs and financial instability. Second, similar to the first point, CBDCs could have negative consequences for financial intermediation, aka the banking sector.

Banks play an important role in deposit management and payments. Now, some FinTech payment platforms have emerged that only focus on one function of money: payments. Meanwhile, other financial services are organised around the payment function, including features such as credit, fund management, and insurance (good examples of this kind of platform are Alipay and WeChat Wallet). These FinTech payment platforms connect consumers (borrowers, debtors, investors, among others) together, rather than the banks, so that banks can be replaced. CBDCs could have the same characteristic as these FinTech payment platforms because they also allow the general public easy access the central bank balance sheet. Therefore, some scholars worry that digital currency and digitalisation could cause an inversion of the currency financial intermediation system [Tronnier et al., 2020; Meaning et al., 2021]. Although Brunnermeier and Landau [2022] argue that CBDCs would only have small negative effects on the financial intermediation system because of the low circulation volume, the real effects of CBDCs on the banks' business model could only be proved with the development of CBDCs and would also vary depending on their liquidity. Third, CBDCs could pose risks to individual privacy [Fu et al., 2019; Tronnier, 2021]. The original intention of the CBDC design tries to strike a balance between the 'controllable anonymity' and 'anti-money laundering' [Turrin, 2021]. Therefore, CBDCs do not allow for anonymous transactions in the same way that cash can be spent anonymously [Lee et al., 2021]. Data privacy regulations could provide some protections, but these may be insufficient to eliminate public concerns over the risk of state surveillance [Borgonovo et al., 2021]. Fourth, as a kind of digital currency, CBDCs could bring about environmental issues [Laboure et al., 2021]. The production, deposit and transaction of CBDCs would likely consume a plethora of energy and emit a large amount of CO_2, leaving carbon footprints and causing increased environmental pollution. Finally, CBDCs could trigger a new round of trade wars between China and the United States [Waller, 2021; Goldman, 2022]. The Society for Worldwide Interbank Financial Telecommunications (SWIFT) system gives the United States a strong economic sanction capability. However, the digital renminbi supported by China's Cross-Border International Payments Systems (CIPS) can replace SWIFT and challenge the existing international payments system, which is dominated by the United Stated [Goldman, 2022]. This potential threat could trigger U.S. sanctions on Chinese banks by pressuring their transaction nodes, leading to a renewed U.S.-China trade war.

CBDCs' encouraging progress has generated extensive attention and discussions among academics and economists. The majority of available studies still concentrate on the fundamental qualitative analysis of CBDC and its technological innovations. The latest CBDC studies can be classified into five sub-groups. The first discusses (among other aspects) the definition, characteristics, classification, main models, and implications of the CBDC variants, as well as the potential advantages and risks of its introduction [Cunha et al., 2021; Kochergin, 2021]. The second focuses on the design theory, technology innovation, and model optimisation of CBDC [Qian, 2019; Lee et al., 2021]. The third examines its security and privacy [Borgonovo et al., 2021; Lee et al., 2021].

The fourth analyses CBDC's impacts on the monetary system and monetary policy [Davoodalhosseini, 2021; Meaning et al., 2021]. The fifth group investigates the relationships between CBDC and banking, including commercial and central banking [Fernández-Villaverde et al., 2021; Williamson, 2021]. Whereas only few studies investigate how current CBDCs' discussion among regulators and in the media affect behaviour of financial markets. Considering the process of CBDCs is at the early stages of development and adoption there is the lack of data or proxies which can reflect and stand for the CBDCs, thus hindering quantitative analyses of CBDC's effects on financial markets.

To fill this research gap and conduct a quantitative analysis of CBDC with financial markets, we developed and made available two CBDC indices – the CBDC Uncertainty (CBDCUI) and the CBDC Attention (CBDCAI), that can be used to track CBDCs' trends and variations. Our data covers the main period of CBDC development and the period of the most active discussion of this new asset in the media, i.e. from January 2015 to June 2021. Thus, we construct our indices use 663,881,640 news items collected from Lexis-Nexis News & Business. In this paper, we first to empirically examine the impact of CBDC news on the financial markets. Our sample includes the main cryptocurrency uncertainty indices, which are Cryptocurrency Policy Uncertainty Index (UCRY Policy or UCRYPo), Cryptocurrency Price Uncertainty Index (UCRY Price or UCRYPr), Cryptocurrency Environmental Attention Index (ICEA); Bitcoin as a proxy of cryptocurrency markets; the MSCI World Banks Index (MSCI WBI) and the FTSE World Government Bond Index (FTSE WGBI) to represent the commercial banking sectors, and the bond markets, separately. Furthermore, we selected EUR/USD, GBP/USD, RUB/USD, JPY/USD, and CNY/USD to represent the foreign exchange markets. To account for economic price and policy uncertainty we also included the The Cboe Volatility Index (VIX) and the United States Economic Policy Uncertainty Index (USEPU) in our sample. Finally, we chose the FTSE All-World Index (FTSE AWI) to represent the stock markets and gold as a safe-haven assets that often has been compared with Bitcoin.

We begin our empirical analysis with a vector autoregression (VAR) for testing the effectiveness and validity of the newly issued indices. Then, we apply a structural vector autoregression (SVAR) model to process a structural shock analysis of the effects of CBDCUI and CBDCAI on indices, as well as macro-level variables using impulse response function (IRF), forecast errors variance decomposition (FEVD), and historical decomposition (HD) tests. We further employ the dynamic conditional correlation (DCC-GJR-GARCH) model to investigate interconnections between indices and financial variables. Applications of SVAR and DCC-GJR-GARCH models to our set of variables, helps us to uncover how CBDC indices interact with these financial indicators providing novel empirical evidence on the CBDC news on financial markets.

This paper contributes to the existing literature in three main ways. First, based on news coverage from LexisNexis News & Business, we developed two new indices for CBDC between 2015–2021: the CBDCUI and CBDCAI, that can be used by investors, policy makers and financial regulators to monitor the impact of CBDC-related discussions on volatility of financial markets. Our indices capture CBDC trends and uncertainties as they are able to react to major relevant events. For example, our indices spiked near new CBDC announcements, digital currency flash-news, and main policy debates. Second, the paper reports that CBDCUI and CBDCAI indices had a significantly negative effect on the volatilities of the MSCI World Banks Index, USEPU, and FTSE All-World Index, where the volatilities of the financial variables reacted more strongly to shocks transmitted from the CBDCUI. Third, the paper presents the historical decomposition results, that show that the cumulative positive and negative effects of CBDCUI disturbances tend to be larger than those of the CBDCAI on the financial variables. Positive news items and government policy announcements can have a significant negative affect on the CBDCUI historical decomposition results, i.e. decreasing the uncertainty around CBDC introduction. Besides, we show that both CBDCUI and CBDCAI historical decomposition results significantly spiked near key CBDC progress news and significant events regarding digital currency.

Our paper offers useful proxies of CBDCs uncertainty and attention and a novel evidence for future quantitative studies into CBDCs. Moreover, this paper successfully links CBDCs to the financial markets and other volatility and uncertainty measures, that can originate another strand of CBDCs literature. The results provide novel useful insights for investors, policymakers, regulators, and media on how CBDCs evolved as a barometer in the new digital-currency era. For example, policymakers and regulators can adjust fiscal policy by referencing our CBDC indices. And the CBDC indices can guide investors to increase or reduce their financial assets' net long positions.

The remainder of this paper is structured as follows. section 2 outlines previous CBDCs literature. section 3 describes the construction of the indices and the data for the empirical analysis, while section 4 describes the econometric methods used. section 5 presents the empirical results and robustness tests. Finally, section 6 discussed the main findings of this research and its implications.

2. Literature review

A CBDC is a government credit-based digital currency, thereby reducing their risks. Therefore, some economic agents and individuals might prefer to transfer money from commercial banks to CBDCs during financial crises [Sinelnikova-Muryleva, 2020]. Many regulators and researchers regard a CBDC as a nationally issued 'stablecoin', and believe it can balance the banking system [Sissoko, 2020] and positively impacts financial stability [Larina and Akimov, 2020; Copeland, 2020; McLaughlin, 2021; Buckley et al., 2021]. Indeed, Zams et al. [2020], using an analytic network process and the Delphi method, demonstrated that the cash-like CBDCs model is the most suitable CBDCs design for Indonesia because it can improve financial inclusion and reduce shadow banking. Tong and Jiayou [2021] investigated the effects of the issuance of digital currency/electronic payment on economics based on a four-sector DSGE model, and conclude that CBDCs can mitigate the leverage ratio and the systemic financial risk. Barrdear and Kumhof [2021] examined the macroeconomic consequences of launching CBDCs by a DSGE model, and found that CBDCs issuance 30%'s GDP, against government bonds, could be permanently raised by 3%. Additionally, Fantacci and Gobbi [2021] focused on the geopolitical, strategic, and military impacts of CBDCs.

However, CBDCs are new research fields within digital currency and fintech domain, and a few paper available to date can be roughly allocated into five main sub-groups.

The first group discusses, among other aspects, the definition, characteristics, classification, main models, and implications of the CBDCs variants, and the potential advantages and risks of its introduction [Yao, 2018b; Masciandaro, 2018; Cunha et al., 2021; Kochergin, 2021; Li and Huang, 2021; Allen et al., 2022]. While the above mentioned researchers hold positive attitudes towards CBDCs, Kirkby [2018] criticised CBDCs as they would increase the central bank's costs for the whole money supply system.

The second group of studies focuses on the CBDCs' design theory, technological innovation, and model optimisation. Sun et al. [2017] proposed a multi-blockchain data centre model for CBDCs in order to help central banks manage the issuance of currency, prevent double-spending issues, and protect user privacy. Yao [2018a] conducted an experimental study on a Chinese prototype of a CBDC system. Qian [2019] introduced a CBDC issuance framework designed for forward contingencies in order to prevent the currency from circulating beyond the real economy. Wagner et al. [2021] discussed and proposed a potential blueprint for a digital euro and proved its possibility. Lee et al. [2021] proposed a blockchain-based settlement system using cross-chain atomic swaps that could be implemented for the CBDCs to manage settlement risks.

The third group illustrates CBDCs' security and privacy. Fu et al. [2019], Tronnier [2021] and Borgonovo et al. [2021] demonstrated the significance of anonymity for increasing the overall attraction of CBDCs' social medium payment. Lee et al. [2021] conducted a survey on security and privacy in blockchain-based CBDCs to address the remaining security and privacy research gaps, and a techno-legal taxonomy of methodologies was further proposed to balance CBDCs privacy and transparency without impeding accountability [Pocher and Veneris, 2021].

The fourth group analyses the impacts of CBDCs on monetary systems and policy. For instance, using a literature review, Tronnier et al. [2020] systematically revised CBDCs and further discussed their implications on economics, monetary policy, and legal issues. Meaning et al. [2021] discussed CBDCs' potential impact on monetary transmission mechanisms, and found that monetary policy can operate as it does now by adjusting the price or quantity of CBDCs. Shen and Hou [2021] applied a qualitative analysis of China's CBDCs and their impacts on monetary policy and payment competition, and argued that CBDCs have potential to transform the field completely rather than be a mere regulatory toolkit, especially when CBDCs will be adopted at a large-scale. To put it simply, some scholars hold positive views towards CBDCs on monetary policy. They have argued that CBDCs are useful complements to monetary and reserve policy [Davoodalhosseini, 2021], and that they have the potential power to strengthen the monetary transmission mechanism and bear interest [Stevens, 2021]. However, other studies have discussed CBDCs' monetary risks, for example, Viñuela et al. [2020] listed the sources of these risks, and presented both solutions and suggestions for further CBDCs research.

The fifth group investigates the relationships between CBDCs and banking, including commercial and central banking. Cukierman [2020] provided two proposals CBDCs' implementation, i.e the moderate and radical. The former suggests that only the banking sector can have access to deposits at central banks, while the latter suggests that the whole private sector could hold digital currency deposits at central banks. Cukierman supported the radical proposal due to its ability to condense the banking system and reduce the need for deposit insurance. Furthermore, some discussions have centred around the new role of central banks in the digital currency era. Some scholars believe that CBDCs can upset commercial banking because central banks are more stable and can play an essential role in reducing risks in economic transactions [Yamaoka, 2019; Zams et al., 2020; Sinelnikova-Muryleva, 2020]. This could possibly even lead to commercial banking panic [Williamson, 2021] or allow central banks to become deposit monopolists [Fernández-Villaverde et al., 2021].

None of these studies have linked CBDCs to financial markets. One possible reason for this research gap is the lack of a time series proxy that relates to the CBDCs. However, several scholars have shown that an index of news coverage frequency can serve as a proxy to reflect the uncertainty of one economic or financial objective (e.g., economic policy, cryptocurrency policy, or cryptocurrency price) [Baker et al., 2016, Huang and Luk, 2020; Lucey et al., 2021], or draw public attention to an economic or financial objective (e.g., cryptocurrency, cryptocurrency environmental, P2P lending) [He et al., 2021; Smales, 2022; Wang et al., 2022]. These papers further confirm that the uncertainty or attention indices mentioned above can act as validity and efficiency proxies by investigating their impacts on micro or macroeconomic variables. This research gap is the motivation behind our work to uncover the effects of CBDC news on financial markets. This is achieved by introducing new CBDC indices to capture existing trends and reflect the variations of CBDC uncertainty and attention by gathering a large amount of CBDC news items and analysing the interconnections between the CBDC indices and financial market variables using a variety of quantitative techniques.

This paper adds to the CBDCs literature in two main ways. First, it introduces new CBDCUI and the CBDCAI indices that can capture the uncertainty and attention around introduction and adoption of CBDCs, and can be used for further analysis of the impacts of CBDCs on various financial markets. These indices not only track current CBDCs' news trends, but also presents their variations over time and relationships with other uncertainty and attention measures. Second, this is the first paper to focus on the effects of CBDC news on financial markets using very large and comprehensive dataset. We have thoroughly investigated how CBDC news can impact cryptocurrency markets, commercial banking sectors, bond markets, foreign exchange markets, stock markets, uncertainty indices, and gold, and made our data available for replication.

3. Data

3.1. CBDC indices data collection

We conduct multiple search in LexisNexis News & Business using combinations of keywords relevant to CBDCs. There is no doubt that 'Central Bank Digital Currency' and 'CBDC' were set as our key search terms. Moreover, due to our identification of the strongest currencies (see the literature review, above), we considered what the official non-English terms for 'Central Bank Digital Currency' in these countries. The official language of the US, EU, and the UK is English[1]. Therefore, the aforementioned search terms have been translated to Chinese, Japanese, Russian to ensure comprehensive coverage of the stories in the main countries that are leading the CBDCs development. Furthermore, considering Spanish, Portuguese, French, and German are essential languages in the EU we also translated 'Central Bank Digital Currency' into these four languages. Additionally, as a CBDC is a type of digital currency, and some countries value a CBDC as a tool to counter cryptocurrencies. Therefore, we included 'Digital currency' as another key term. Once done, we searched for the most popular synonyms for digital currency, which we found to be 'digital money', 'electronic currency', 'electronic money', 'e-currency', and 'e-money'. Therefore, we also set these five synonyms as key search terms.

Knowing that USD, EUR, GBP, CHF, RUB, JPY, and CNY are heading towards CBDCs, we substituted the keywords 'currency' or 'money' with the official name of these currencies. For example, search terms for the currency of the United States also included 'digital dollar', 'electronic dollar', 'e-dollar', 'digital USD', 'electronic USD', and 'e-USD'. For countries where English is not the official language, we not only kept the English search terms, but also translate them into the particular official language. Considering that Germany and France have the EU's strongest economies, we also translated 'digital euro', 'electronic euro', and 'e-euro' into German and French. As we considered Switzerland an English speaking country, we applied 'digital Swiss franc', 'electronic Swiss franc', 'e-franc', 'digital CHF', 'electronic CHF', and 'e-CHF'. Compiling these key search terms together generated our search string for CBDCAI. Based on the CBDCAI's search term, we then added a new search term, 'uncert!', with the link of 'and', not 'or'. Therefore, we obtained a new search string for CBDCUI. Additionally, we set the option for Group Duplicate to MODERATE so as to avoid duplicate results as much as possible.[2] The search strings for CBDCUI and CBDCAI are as follows:

[1]Although the official languages in Switzerland are German, French, Italian, and Romansh, its population is relatively small, meaning that we consider Switzerland an English-speaking country

[2]Weekly values can be downloaded from: https://sites.google.com/view/cryptocurrency-indices/the-indices/cbdc-indices?authuser=0

(("Central Bank Digital Currency") OR ("CBDC") OR ("央行数字货币") OR ("Moneda digital del banco central") OR ("Moeda Digital do Banco Central") OR ("Национальная криптовалюта") OR ("中央銀行のデジタル通貨") OR ("Merkez Bankası Dijital Para Birimi") OR ("Monnaie numérique de la Banque centrale") OR ("Digitales Zentralbankgeld") OR ("Digital currency") OR ("Digital money") OR ("Electronic currency") OR ("Electronic money") OR ("E-currency") OR ("E-money") OR ("Digital dollar") OR ("Electronic dollar") OR ("E-dollar") OR ("Digital USD") OR ("Electronic USD") OR ("E-USD") OR ("Digital Euro") OR ("Electronic Euro") OR ("E-Euro") OR ("Digital EUR") OR ("Electronic EUR") OR ("E-EUR") OR ("Digital pound") OR ("Electronic pound") OR ("E-pound") OR ("Digital GBP") OR ("Electronic GBP") OR ("E-GBP") OR ("Digital RMB") OR ("Electronic RMB") OR ("E-RMB") OR ("Digital CNY") OR ("Electronic CNY") OR ("E-CNY") OR ("Digital CNH") OR ("Electronic CNH") OR ("E-CNH") OR ("Digital Renminbi") OR ("Electronic Renminbi") OR ("E-Renminbi") OR ("电子人民币") OR ("数字人民币") OR ("E-人民币") OR ("Digital ruble") OR ("Electronic ruble") OR ("Cryptoruble") OR ("Digital RUB") OR ("Electronic RUB") OR ("E-RUB") OR ("Цифровой рубль") OR ("криптору6ль") OR ("Digital Yen") OR ("Electronic Yen") OR ("E-Yen") OR ("Digital JPY") OR ("Electronic JPY") OR ("E-JPY") OR ("デジタル通貨") OR ("電子通貨") OR ("E-通貨") OR ("Euro numérique") OR ("Monnaie numérique") OR ("Digitaler Euro") OR ("Elektronischer Euro") OR ("E-Währung") OR ("Digital Swiss franc") OR ("Electronic Swiss franc") OR ("E-franc") OR ("Digital CHF") OR ("Electronic CHF") OR ("E-CHF")) and (uncert!)

Figure 1: CBDC uncertainty index search string

("Central Bank Digital Currency") OR ("CBDC") OR ("央行数字货币") OR ("Moneda digital del banco central") OR ("Moeda Digital do Banco Central") OR ("Национальная криптовалюта") OR ("中央銀行のデジタル通貨") OR ("Merkez Bankası Dijital Para Birimi") OR ("Monnaie numérique de la Banque centrale") OR ("Digitales Zentralbankgeld") OR ("Digital currency") OR ("Digital money") OR ("Electronic currency") OR ("Electronic money") OR ("E-currency") OR ("E-money") OR ("Digital dollar") OR ("Electronic dollar") OR ("E-dollar") OR ("Digital USD") OR ("Electronic USD") OR ("E-USD") OR ("Digital Euro") OR ("Electronic Euro") OR ("E-Euro") OR ("Digital EUR") OR ("Electronic EUR") OR ("E-EUR") OR ("Digital pound") OR ("Electronic pound") OR ("E-pound") OR ("Digital GBP") OR ("Electronic GBP") OR ("E-GBP") OR ("Digital RMB") OR ("Electronic RMB") OR ("E-RMB") OR ("Digital CNY") OR ("Electronic CNY") OR ("E-CNY") OR ("Digital CNH") OR ("Electronic CNH") OR ("E-CNH") OR ("Digital Renminbi") OR ("Electronic Renminbi") OR ("E-Renminbi") OR ("电子人民币") OR ("数字人民币") OR ("E-人民币") OR ("Digital ruble") OR ("Electronic ruble") OR ("Cryptoruble") OR ("Digital RUB") OR ("Electronic RUB") OR ("E-RUB") OR ("Цифровой рубль") OR ("криптору6ль") OR ("Digital Yen") OR ("Electronic Yen") OR ("E-Yen") OR ("Digital JPY") OR ("Electronic JPY") OR ("E-JPY") OR ("デジタル通貨") OR ("電子通貨") OR ("E-通貨") OR ("Euro numérique") OR ("Monnaie numérique") OR ("Digitaler Euro") OR ("Elektronischer Euro") OR ("E-Währung") OR ("Digital Swiss franc") OR ("Electronic Swiss franc") OR ("E-franc") OR ("Digital CHF") OR ("Electronic CHF") OR ("E-CHF")

Figure 2: CBDC attention index search string

We should also explain our decision to launch an extra CBDCUI, as well as the differences between 'volatility' and 'uncertainty'. We are living in a period of great uncertainty. Indeed, in recent years, various financial and political events have shaken the world. For example, the US financial crisis, the European sovereign debt crisis, terrorist attacks, Brexit, and the current global COVID-19 pandemic, to name but a few. This series of events has meant that uncertainty has become an important variable in modern economies. The CBDCUI not only helps us identify the uncertainty of CBDC itself, but also allow us to capture how these uncertainties can disrupt the modern economies. Uncertainty differs from volatility in the way it is designed and measured, and these have been analysed differently in the academic literature. In fact, volatility captures the variability in the price of financial assets. Therefore, it can be interpreted as a measure of 'the present'. Simply out, volatility is akin to a 'photographs' of the current situation. Uncertainty tries to capture 'the future' through studying economic, social, and political sentiment, that in our case, can be extracted from analysis of wide news coverage of CBDC.

3.2. CBDC indices' construction

Our method of CBDC indices' construction draws from the methods of Baker et al. [2016] and Huang and Luk [2020] and is in line with the methods of Lucey et al. [2021] and Wang et al. [2022], who created the cryptocurrency uncertainty indices and cryptocurrency environmental attention index.

However, considering the database used for the new indices' construction, our method differs from Baker et al. [2016], Huang and Luk [2020], Shen et al. [2019], He et al. [2021] and Smales [2022], who collected data only from American newspapers, Chinese newspapers, Twitter trends, Baidu trends, or Google trends for constructing their indices. In contrast, we choose LexisNexis News & Business, a comprehensive digital source, as our database because it provides access to a much larger volume of articles across various publication sources and over time (including, but not limited to, newswire feeds and media news transcripts) than Google, Twitter, Baidu and the other traditional trend search engines offer.

Moreover, we have to point out that one drawback of constructing an index based on any literature archive is that articles enter and leave the archive, so the overall volume of articles could vary across publication sources and time. This is why the standardisation and normalisation procedures should be processed according to the raw count data because it allows one to sort the data on the same scale.

For example, the CBDCUI scales the observed value of news articles in each week by the number of articles that meet the search string Figure 1 for the same week. The series is then standardised to obtain a time series dataset as the initial index. Lastly, the initial index is normalised by adding an average value of 100 to eliminate the potential negative impacts caused by the overall volume of articles varying across publication sources and time[3]. The final series after the normalisation can be valued as the CBDCUI. Repeating the standardisation and normalisation procedures by using the search string Figure 2 can construct the CBDCAI[4].

Based on the demonstrations mentioned above, the CBDCUI and CBDCAI can be calculated as in Equation 1 and Equation 2:

$$CBDCUI_t = (\frac{N_{1t} - \mu_1}{\sigma_1}) + 100, \tag{1}$$

where $CBDCUI_t$ is the value of the CBDCUI in the weeks t between January 2015 and June 2021, N_{1t} is the weekly observed value of news articles on LexisNexis concerning CBDC uncertainty, μ_1 is the mean of these same articles, and σ_1 is the standard deviation of such. Adding an average value of 100 to eliminate the potential negative impacts caused by the overall volume of articles varies across publication sources and time.

$$CBDCAI_t = (\frac{N_{2t} - \mu_2}{\sigma_2}) + 100, \tag{2}$$

where $CBDCAI_t$ is the value of the CBDCAI in the weeks t between January 2015 and June 2021, N_{2t} is the weekly observed value of LexisNexis news articles concerning the CBDC attention, μ_2 is the mean of these and, σ_2 is the standard deviation of such. Adding an average value of 100 to eliminate the potential negative impacts caused by the overall volume of articles varies across

[3] Applying an average value of 100 as the normalisation value is consistent with the other new digital currency indices, which are cryptocurrency policy uncertainty index, cryptocurrency price uncertainty index, cryptocurrency environmental attention index and NFTs attention index. These new digital currency indices can be found at https://sites.google.com/view/cryptocurrency-indices/home?authuser=0.

[4] More details about the methods of CBDC indices' construction can be found in Lucey et al. [2021] and Wang et al. [2022].

publication sources and time.

Based on our index construction method mentioned above, we do not need to distinguish and sort between the important news stories and the smaller ones when we construct our CBDC indices. Instead, we just need to count the weekly observed value of news articles from LexisNexis News & Business, regardless of where the keywords from Figure 1 or Figure 2 are located in an article's title, main content, comments or elsewhere. In other words, if the keywords from Figure 1 or Figure 2 show in one article's title, main content, comments or the other parts, we will collect it and record this article as one unit for constructing the CBDCUI or CBDCAI. Moreover, flash events are collected according to the frequency of articles that have a same topic. During the CBDC high uncertainty and attention periods, there are a plethora of articles discussing the same topic. The flash events can then be extracted from the heated discussion topics.

Figure 3 shows the weekly values for the derived indices based on 663,881,640 news items collected between January 2015 and June 2021. According to [Turrin, 2021], Ecuador was the first country to launch CBDCs, which it did in February 2015 to promote anti-dollarisation. This implementation is why we selected January 2015 as the beginning of our observation period. The weekly CBDCUI and CBDCAI indices were annotated in Figure 4 and display which events can drive spikes on the indices. The plot allowed us to clearly see how new CBDC developments could raise the indices, while they could also be stimulated by other significant events related to cryptocurrencies. We have listed all of the events captured by our indices in Appendix-A.

3.3. Financial market variable selection

To justify the selections of financial markets in our sample, we consider previous literature that reported which markets were susceptible to shocked transmitted from CBDCs, or reverse, were immunised from these shocks. According to the viewpoints expressed by the central banks around the world, a CBDC is a national tool to counter cryptocurrency volatility and uncertainty [Tronnier et al., 2020; Larina and Akimov, 2020; Lee et al., 2021; Koziuk, 2021]. We thus hypothesise that CBDCUI and CBDCAI may have significant effects on cryptocurrency markets. Specifically, we assume that debates around CBDCs may affect cryptocurrency price and policy uncertainty, therefore we decided to also include UCRY Policy and UCRY Price indices in our sample. It is important to assess how the new CBDC indices are related to other indices capture uncertainty of the cryptocurrency markets as a whole. ICEA can capture the public attention and concerns regarding the environment and cryptocurrency [Wang et al., 2022]. Both cryptocurrencies and CBDCs are a type of digital currency, and they will lead to environmental issues such as increased energy consumption and carbon emissions during their production and circulation [Chen et al., 2020; Su et al., 2020]. Moreover, Laboure et al. [2021] already pointed out the environmental implications of the introduction of CBDCs. The environmental concerns surrounding CBDCs require governments to make CBDCs sustainable; otherwise, the CBDCs might be seen as against environmental agendas.

These environmental concerns related to digital currencies could determine whether CBDCs are introduced in some countries or even decide the fate of CBDCs entirely. Investigating the interconnections between CBDCUI or CBDCAI and the ICEA could quantify the extent of CBDCs' impact on environmental concerns. The results could be a strong determinant in the increased debates on the necessity of regulation of CBDCs and proactive government intervention in the FinTech ecosystem. We also selected the most important cryptocurrency markets leader, i.e. Bitcoin, as one of our financial variables [Corbet et al., 2020b], since this digital asset attract the highest attention from media and general public [Su et al., 2020; Wu et al., 2021], and also often used a proxy of overall cryptocurrency market volatility [Le et al., 2021; Elsayed et al., 2022]. We omitted two composite cryptocurrency indices, the Bloomberg Galaxy Crypto Index (BGCI) and the Royalton CRIX Cypto Index (CRIX), because they only began in 2017 and 2018, respectively, and thus do not cover our entire research period. Moreover, we applied weekly data in this study, but the weekly available data of the BGCI and the CRIX are too short and may not be enough to run a successful and ideal advanced econometric model.

While the above studies would overwhelmingly suggest that introduction of CBDCs will affect commercial banks, there are insufficient quantitative analysis results that can prove this perspective. Therefore, we selected the MSCI World Banks Index[5] to represent the commercial banking sector, and investigated the impacts of CBDC indices on commercial banking. In addition, we chose the FTSE World Government Bond Index as a proxy for bond markets[6], since the bond market is a major segment of the financial system and a key player in monetary policy transmission mechanisms to other financial markets [Yan et al., 2018]. Barrdear and Kumhof [2021] have investigated the impacts of the CBDCs issuance on the GDP, compared with government bonds. It is a popular belief, that a CBDC is a simply digital version of a fiat currency, while many scholars consider it to be a 'national stablecoin'. Therefore, it is pertinent to examine its effects on the fiat currencies of countries that according to the literature are heading towards adopting the CBDCs, such as China, the US, the EU, the UK, Canada, Russia, and Japan [Alonso et al., 2021]. Moreover, Ciner et al. [2013]; Fatum et al. [2017]; Fong and Wong [2020] and Shehadeh et al. [2021] suggest that USD, EUR, GBP, RUB, JPY, and CNY are the strongest currencies in the world, and these countries (or blocs) are leading the CBDCs progress worldwide. We also set the F.X. Spot unit of all the currencies as USD, meaning that USD units per 1 of another currency [Aslam et al., 2020]. Therefore, the increase in the exchange rate implies the appreciation of the EUR/GBP/JPY/RUB/CNY against

[5]The MSCI World Banks Index is constructed on large and mid-capitalisation stocks across 23 developed market countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK, and the US). All stocks in the MSCI World Banks Index are classified in the Banks industry group.

[6]The FTSE World Government Bond Index is a broad benchmark for the global sovereign fixed income market. It measures the performance of fixed-rate, local currency, investment-grade sovereign bonds. The FTSE WGBI comprises sovereign debt from over 20 countries and is denominated in a variety of currencies.

the USD, and vice versa.

To analyse the relationship between our new CBDC indices and other popular global uncertainty measures we selected the VIX and the USEPU indices [Umar et al., 2021]. We did not choose the EPU (global) because it contains only monthly data. While in this paper, we utilise weekly data for all variables. The effects of CBDCUI and CBDCAI on stock markets is also captured by including the FTSE All-World Index in our analysis and we can assign the FTSE All-World Index to represent the all-world stock markets.[7] Lastly, we selected gold as our safe-haven [Baur and Lucey, 2010; Lucey et al., 2017], because our sample covers the period of COVID-19 pandemic [Yousfi et al., 2021], and safe-haven properties of gold has been often compared to the other assets [Thampanya et al., 2020; Le et al., 2021; Chemkha et al., 2021].

4. Methodology

The existing literature provides numerous examples of effective methodologies that can be used to capture the impact of Uncertainty and Attention indices on financial markets. The DCC-GARCH model, wavelet analysis, and the VAR model (SVAR structural shock analysis) are the three most popular and straightforward methodologies for analysing of the relationships between different financial variables. Applying the DCC-GARCH model, Akyildirim et al. [2020] analysed the relationship between the price volatility of cryptocurrencies and the implied volatilities of VIX and VSTOXX (EURO STOXX 50 indices Volatility Index). Çepni et al. [2021] investigated the time-varying comovements between Turkish sovereign yield curve factors and oil price shocks. Xie and Zhu [2021] examined the stabilisation effects of economic policy uncertainty (EPU) on gold futures market and spot market price volatility. Several recent studies have used wavelet-analysis to investigate the structure of financial indices' correlation with various financial asset classes. For instance, Conlon et al. [2018] used the continuous wavelet transformation to check the relationship between gold and inflation, as well as gold's ability to hedge against inflation dynamically. Sharif et al. [2020] analysed the connection between COVID-19, oil prices, stock markets, geopolitical risks, and EPU in the United States by applying the time-frequency coherence wavelet method. Moreover, Shahzad et al. [2021] examined the dynamics relationships between realised variances and semi-variances of the six strongest currencies by fitting wavelet squared coherence and wavelet cohesion. The VAR model, and its SVAR structural analysis tools, are widely used in issuing new financial indices. Baker et al. [2016] launched the EPU index and analysed its impact on economic activities (S&P 500 index, VIX, industrial production, and unemployment rate). Huang and Luk [2020] issued China Economic Policy Uncertainty Index (China's EPU) to examine the impact of its shocks on macroe-

[7] The FTSE All-World Index is an international equity index which tracks the market performance of large- and mid-capitalisation stocks of companies from developed and developing markets worldwide. The FTSE All-World Index includes roughly 3,900 stocks in approximately 50 countries.

conomic variables (equity price, deposit rate, unemployment rate, and output volume). Lucey et al. [2021] and Wang et al. [2022] built the UCRY Policy, UCRY Price and ICEA. Then, these studies performed the IRF, FEVD, and HD tests to further investigate the impacts of the three indices on financial and commodities assets. In this paper, we used the VAR model to check the effectiveness and validity of two new CBDC indices. Moreover, the SVAR model can investigate how CBDC indices can affect the financial variables and contribute to their variations. Furthermore, to determine the interconnections between CBDC indices and each financial variable, we employed the DCC-GARCH model as the most suitable and straightforward method for achieving this goal.

4.1. Structural shock model specification

The main uses of the VAR model are forecasting and structural analysis Lütkepohl [2005]. The standard VAR is a reduced form model, and can be expressed as Equation 3:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_{p-1} y_{t-(p-1)} + \Delta y_{t-p} + \Xi^{+} D_t + u_t, \tag{3}$$

where y_t is a $K \times 1$ dimensional vector of variables observed at time t. $A_1, A_2, \cdots, A_{p-1}, A_p$ are $K \times K$ coefficient matrices. D_t is a vector of deterministic terms, and Ξ^{+} is the coefficient matrices corresponding with D_t. u_t is a k-dimensional unobservable zero mean vector white noise process, and has covariance matrix Σ_u. u_t also denotes the reduced form disturbance.

In order to investigate the relationship between our indices and economic activities, we established a variable system based on the VAR model. The CBDCUI, the CBDCAI, the UCRY Policy, the UCRY Price, the ICEA, the MSCI World Banks Index, the FTSE World Government Bond Index, the VIX, the US EPU, the FTSE All-World Index, and the EUR/USD, GBP/USD, JPY/USD, RUB/USD, and CNY/USD exchange rates, as well as the price of gold and Bitcoin, were selected as the system variables. We ordered variables as indicated by Equation 4:

$$
\mathbf{Y}_t = \begin{bmatrix} CBDC1_t \\ CBDC2_t \\ UCRY\ Policy_t \\ UCRY\ Price_t \\ ICEA_t \\ MSCI\ World\ Banks\ Index_t \\ VIX_t \\ USEPU_t \\ FTSE\ All\ World\ Index_t \\ EUR/USD_t \\ GBP/USD_t \\ JPY/USD_t \\ RUB/USD_t \\ CNY/USD_t \\ Gold_t \\ Bitcoin_t \\ FTSE\ World\ Government\ Bond\ Index_t \end{bmatrix} \tag{4}
$$

where, CBDCUI or CBDCAI was ordered first and second because we believed that the UCRY Policy Index, UCRY Price Index, ICEA, MSCI World Banks Index, VIX, USEPU, FTSE All-World Index, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, Bitcoin and FTSE World Government Bond Index could react contemporaneously to uncertainty or attention shocks.

The standard VAR is a reduced form model designed for stationary data forms. If economic theory is used to provide links between forecast errors and fundamental structural shocks, the SVAR model can be used. Accordingly, structural shocks on the system variables y_t based on the VAR can be calculated as Equation 5:

$$
\bar{A}_0 y_t = \bar{A}_1 y_{t-1} + \bar{A}_2 y_{t-2} + \cdots + \bar{A}_{p-1} y_{t-(p-1)} + \bar{A}_p y_{t-p} + \bar{\Xi} D_t + \varepsilon_t, \tag{5}
$$

where ε_t is a $K \times 1$ dimensional vector white noise process with covariance matrix Σ_ε, also meaning structural shocks. $A_1, A_2, \cdots, A_{p-1}, A_p$ are $K \times K$ coefficient matrices. Pre-multiplying the Equation 3 by $\bar{A}_0^{-1}$ can link the reduced form disturbance (forecast errors) u_t to the underlying structural shocks ε_t. The normal distribution $(0, I_K)$ is subject to ε_t. Therefore, from this we can reach Equation 6:

$$
u_t = \bar{A}_0^{-1} \varepsilon_t, \tag{6}
$$

The SVAR model allows for three tools: the impulse response function (IRF), forecast error variance decomposition (FEVD), and historical decomposition (HD). These are used to capture the dynamic and instantaneous impacts of structural shocks within the variable system (see Equation 4). The three elements can be broadly defined as follows.

4.1.1. Impulse Response Function

When a VAR process is stationary, it can be said it has a moving-average (MA) representation. In the MA representation, the IRF can trace the marginal effect of a shock to one variable by counterfactual experiment. The MA representation can be expressed as Equation 7:

$$y_t = u_t + \sum_{i=1}^{\infty} \Phi_i u_{t-i}, \Phi_0 = I_k, \tag{7}$$

where u_t is a k-dimensional unobservable zero mean vector white noise process, and has covariance matrix Σ_u. $\Phi_i = JA^iJ'$ and $J = [I_k : 0 : 0 : \cdots : 0]$. A^i are summable.

4.1.2. Forecast Error Variance Decomposition

The forecast error variance of the k-th element of the forecast error vector can be denoted as Equation 8:

$$E(y_{j,t+h} - y_{j,t}(h))^2 = \sum_{j=1}^{K} (\theta^2_{jk,0} + \cdots + \theta^2_{jk,h-1}), \tag{8}$$

where $\theta^2_{jk,0} + \cdots + \theta^2_{jk,h-1}$ can represent the contribution of the j-th ε_t innovation to the h-step forecast error variance of variable k. $\frac{\theta^2_{jk,0}+\cdots+\theta^2_{jk,h-1}}{E(y_{j,t+h}-y_{j,t}(h))^2}$ can compute the contribution % of the j-th ε_t innovation to the h-step forecast error variance of variable k. $\omega_{kj,h}$ can decompose the contribution of the j-th ε_t innovation to the h-step forecast error variance of variable k.

4.1.3. Historical Decomposition

u_t can be decomposed into different structural components in the HD – much like what has been analysed above. Equation 7, the MA representation can be further denoted as Equation 9:

$$y_t = \sum_{i=1}^{t-1} \Phi_{i,t} u_{t-i} + \sum_{i=t}^{\infty} \Phi_{i,t} u_{t-i}, \tag{9}$$

where the time series can be decomposed into the estimate structural shocks ε from time 1 to time t, and the inestimable structural shocks ε preceding the dataset's start point.

In a stationary VAR process, the $\sum_{i=t}^{\infty} \Phi_{i,t} u_{t-i}$ can have a constantly diminishing impact on the y_t as time t increases, which can contribute to a reasonable approximation. This process can be denoted as Equation 10:

$$\hat{y}_t = \sum_{i=1}^{t-1} \Phi_{i,t} u_{t-i}, \tag{10}$$

Therefore, the HD is equal to the weighted sums, which can be measured as the contribution of shock j on variable k in the stationary VAR process. Consequently, the HD can be denoted as Equation 11:

$$\hat{y}_{kt}^{(j)} = \sum_{i=0}^{t-1} \Phi_{kj,t} u_{j,t} \tag{11}$$

Based on the prior ordering in the SVAR Cholesky decomposition, the relationship between reduced form residuals and structural shocks are shown in Equation 12:

$$\begin{bmatrix} u_t^{CBDC_1} \\ u_t^{CBDC_2} \\ u_t^{UCRY\ Policy} \\ u_t^{UCRY\ Price} \\ u_t^{ICEA} \\ u_t^{MSCI\ WBI} \\ u_t^{VIX} \\ u_t^{USEPU} \\ u_t^{FTSE\ AWI} \\ u_t^{EUR/USD} \\ u_t^{GBP/USD} \\ u_t^{JPY/USD} \\ u_t^{RUB/USD} \\ u_t^{CNY/USD} \\ u_t^{Gold} \\ u_t^{Bitcoin} \\ u_t^{FTSE\ WGBI} \end{bmatrix} = \begin{bmatrix} S_{11} & 0_{12} & 0_{13} & \dots & 0_{115} & 0_{116} & 0_{117} \\ S_{21} & S_{22} & 0_{23} & \dots & 0_{215} & 0_{216} & 0_{217} \\ S_{31} & S_{32} & S_{33} & \dots & 0_{315} & 0_{316} & 0_{317} \\ S_{41} & S_{42} & S_{43} & \dots & 0_{415} & 0_{416} & 0_{417} \\ S_{51} & S_{52} & S_{53} & \dots & 0_{515} & 0_{516} & 0_{517} \\ S_{61} & S_{62} & S_{63} & \dots & 0_{615} & 0_{616} & 0_{617} \\ S_{71} & S_{72} & S_{73} & \dots & 0_{715} & 0_{716} & 0_{717} \\ S_{81} & S_{82} & S_{83} & \dots & 0_{815} & 0_{816} & 0_{817} \\ S_{91} & S_{92} & S_{93} & \dots & 0_{915} & 0_{916} & 0_{917} \\ S_{101} & S_{102} & S_{103} & \dots & 0_{1015} & 0_{1016} & 0_{1017} \\ S_{111} & S_{112} & S_{113} & \dots & 0_{1115} & 0_{1116} & 0_{1117} \\ S_{121} & S_{122} & S_{123} & \dots & 0_{1215} & 0_{1216} & 0_{1217} \\ S_{131} & S_{132} & S_{133} & \dots & 0_{1315} & 0_{1316} & 0_{1317} \\ S_{141} & S_{142} & S_{143} & \dots & 0_{1415} & 0_{1416} & 0_{1417} \\ S_{151} & S_{152} & S_{153} & \dots & 0_{1515} & S_{1516} & S_{1517} \\ S_{161} & S_{162} & S_{163} & \dots & 0_{1615} & 0_{1616} & S_{1617} \\ S_{171} & S_{172} & S_{173} & \dots & S_{1715} & S_{1716} & S_{1717} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{CBDC_1} \\ \varepsilon_t^{CBDC_2} \\ \varepsilon_t^{UCRY\ Policy} \\ \varepsilon_t^{UCRY\ Price} \\ \varepsilon_t^{ICEA} \\ \varepsilon_t^{MSCI\ WBI} \\ \varepsilon_t^{VIX} \\ \varepsilon_t^{USEPU} \\ \varepsilon_t^{FTSE\ AWI} \\ \varepsilon_t^{EUR/USD} \\ \varepsilon_t^{GBP/USD} \\ \varepsilon_t^{JPY/USD} \\ \varepsilon_t^{RUB/USD} \\ \varepsilon_t^{CNY/USD} \\ \varepsilon_t^{Gold} \\ \varepsilon_t^{Bitcoin} \\ \varepsilon_t^{FTSE\ WGBI} \end{bmatrix} \tag{12}$$

where, u_t denotes the reduced form disturbances (forecast errors) at time t, ε_t denotes the structural shocks at time t.

This study adds 1 lag to the SVAR model and the three structural shock analysis tools. The optimal lag value of 1 for our variable system Equation 4 and SVAR model was selected based on the following procedures. First, we calculated the maximum lag value by applying the equation [Winker and Maringer, 2004] and [Lütkepohl, 2005]: $Lag.max = 10 \times ln(\frac{N}{m})$, where N is the number of observations and m is the number of series. This calculation result suggested a maximum lag value of 13. Second, we calculated the optimal lag value based on the AIC, HQ, SC and FPE information criteria from lag max = 1 to lag max = 13. The SVAR optimal lag calculation results are displayed in the Table 8, *Appendix B – Table*. Except for the AIC criteria in lag max = 13, 12 and 11 suggest 13, 12, 11 as the optimal lag, respectively. The other information criteria in each lag max value all suggest that 1 is the optimal lag. Third, we excluded 13, 12, 11 as the optimal lag by testing how stationary the SVAR model stayed. The results in the Table 9, *Appendix B – Table* show that the SVAR model cannot keep stationary when the lag is 13, 12, or 11, but the SVAR is a stationary model when the lag is 1[8]. Moreover, Lütkepohl [2005] suggests that a large lag should not be added into a variable system when one has a small number of observations and a comparatively large number of variables. Therefore, we decided to select 1 as the optimal lag value.

4.2. Dynamic conditional correlation model specification

The key preconditions to apply a GARCH model is that the time series data is stationary with ARCH effects. The results in Table 1 Panel C confirms that all the time series variables are stationarity in the continuously compounded returns. Moreover, Table 12 in *Appendix B - Table* indicates that all the variables have ARCH effects in 1, 2 and 3 orders. The above statistical evidence confirmed that the GARCH-type models were appropriate to use.

The DCC model, proposed by Engle [2002], enables the identification of the time-varying correlation among different variables. Many studies have applied multivariate GARCH-DCC models to estimate the DCCs [Celık, 2012; Jones and Olson, 2013; Ciner et al., 2013]. However, finding a suitable GARCH-type model is an extremely challenging task. There are five popular standard GARCH competing models in the digital currency field Chu et al. [2017]: SGARCH(p,q), EGARCH(p,q), IGARCH(p,q), APARCH(p,q) and GJR-GARCH(p,q). We fitted these five GARCH-type models by the method of maximum likelihood, and the discrimination among them is identified by the AIC, BIC, SC and HQ information criteria. The smaller the values of these criteria, the better the fit. Table 13, Table 14, Table 15 and Table 16 in *Appendix B - Table* give the GJR-GARCH model as the model with smallest values of AIC, BIC, SC and HQ for each variable.

The DCC-GJR-GARCH model is an innovative extension of the GARCH model, expanded by including an additional leverage term that detects asymmetries, and it can assess an asymmetric response to positive and negative shocks. The latest research suggests that the DCC-GJR-GARCH model outperforms other standard GARCH competing models in identifying financial variables' DCC [Laurent et al., 2012; Al Mamun et al., 2020; Corbet et al., 2021].

We first set $r_t = [r_{1,t}, \ldots, r_{n,t}]'$ and $\varepsilon_t = [\varepsilon_{1,t}, \ldots, \varepsilon_{n,t}]'$ as the $(n \times 1)$ vector of financial time series returns and the vector of return residuals, respectively. μ denotes a vector of constant with

[8] The SVAR optimal lag calculation criteria are also displayed in the *Appendix B – Table*.

length n. ψ represents the coefficient vector of the autoregressive terms. Second, set $h_{i,t}$ as the parallel conditional volatilities captured from the univariate GARCH process. Therefore, the mean equation with zero mean normally distributed return series can be given as Equation 13:

$$r_t = \mu + \psi r_{t-1} + \varepsilon_t, \varepsilon_t = z_t h_t, z_t \sim N(0,1). \tag{13}$$

Second, we set $I_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$, otherwise $I_{t-1} = 1$. Moreover, the asymmetric effect of positive and negative shocks are identified by λ (the leverage coefficient). Based on the GJR - GARCH (1,1) model, the conditional volatility $h^2_{i,t}$ can be expressed as Equation 14:

$$h^2_{i,t} = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \lambda\varepsilon^2_{t-1} I_{t-1}, \tag{14}$$

where, when $\lambda < 0$, the negative shocks can have a less of a significant effect on volatility than positive shocks, and when $\lambda > 0$, the positive shocks can have a less significant effect on volatility than negative ones. If parameters ω, α, β, and λ can satisfy the conditions of $\omega > 0$, α, β, $\lambda \geq 0$, and $\lambda + (\alpha+\beta)/2 < 1$, Equation 14 can always hold for a positive and stationarity volatility process [Glosten et al., 1993; Al Mamun et al., 2020].

Third, based on the constant conditional correlation model [Bollerslev, 1990], the constant conditional correlation H_t can be denoted as Equation 15:

$$H_t = D_t \times R \times D_t, \tag{15}$$

where, $D_t = diag\sqrt{h_{i,t}}$ and it is the diagonal matrix of the conditional variances, $R = [\rho_{ij}]$ is the $n \times n$ correlation matrix. Since $\varepsilon_t = D_t^{-1} r_t$, we can reach $E_{t-1}[\varepsilon_t] = 0$ and $R = E_{t-1}[\varepsilon_t \varepsilon_t'] = D_t^{-1} \times H_t \times D_t^{-1}$, where $E_t[\cdot]$ is the conditional expectation on $\varepsilon_t, \varepsilon_{t-1}, \ldots, \varepsilon_{t-n}$.

Based on the Equation 15, a simple estimate of R is the unconditional correlation matrix of the standardised residuals. When R is set as time-varying, we can reach a dynamic correlation model, which can be denoted as Equation 16:

$$H_t = D_t \times R_t \times D_t, \tag{16}$$

where, $R_t = [\rho_{ij,r}]$ is the $n \times n$ time-varying correlation matrix that is computed by the standardised residuals (i.e., $z_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$ computed from the univariate GARCH estimates).

Moreover, based on the DCC model explanations in [Engle, 2002], we can further reach Equation 17, and Equation 18, and Equation 19:

$$R_t = (Q_t^*)^{-\frac{1}{2}} \times Q_t (Q_t^*)^{-\frac{1}{2}}, \tag{17}$$

$$Q_t = (1-\alpha-\beta)Q_s + \alpha Z_{t-1}Z_{t-1}^{'} + \beta Q_{t-1}, \tag{18}$$

$$(Q_t^*)^{-\frac{1}{2}} = diag\left[\frac{1}{\sqrt{Q_{11,t}}}, \ldots, \frac{1}{\sqrt{Q_{ij,t}}}\right], \tag{19}$$

where, $Q_t = (q_{ij,t})$ denotes the time-varying correlation matrix of Z_t, and $Q_t^* = diag(Q_t)$. Q_s denotes the $n \times n$ unconditional variance matrix of Z_t, and $Q_s = E\left[Z_t Z_t^{'}\right]$. α, and β are non-negative scalars as long as $\alpha + \beta < 1$.

Finally, we can give the element of the conditional correlation matrix $\rho_{ij,t}$ as Equation 20:

$$\rho_{ij,t} = \frac{q_{ij,t}}{q_{ii,t} \times q_{jj,t}} \tag{20}$$

5. Results

To investigate the indices' structural shocks on cryptocurrency, foreign exchange and stock markets as well as banking sectors, uncertainty indices and safe-haven gold, we applied the IRF, FEVD and HD tests derived from the SVAR model. By using the DCC-GJR-GARCH model, we can further examine the interconnections between CBDC indices and financial markets. We will discuss the results of these tests, including their potential underlying causes in full detail in the following subsections. We demonstrate that CBDC indices have a significant negative relationship with the volatilities of the MSCI World Banks Index, USEPU and the FTSE All-World Index, and a positive one with that of cryptocurrency markets, bond markets, foreign exchange markets, VIX and gold. Considering that the empirical findings from the two econometrics models are identical, we will not interpret them in each subsection for the sake of brevity. However, we will develop an independent subsection at the end of the current one to fully explain the empirical findings and further discuss the underlying excuses.

5.1. Descriptive statistic results

The time-varying of the dynamic returns for each variable can be seen in Figure 5. Table 1 shows the descriptive statistics for the variable system Equation 4. We opted for weekly data to process the empirical analysis. Following [Long et al., 2021], digital currency markets are enormously volatile, meaning that there are many outliers in the very short-term data period (1-min, 30-mins, or daily data). Weekly data is most suitable for analysing digital currency variables and effectively showcases the data's characteristics. We collected CBDCUI and CBDCAI from LexisNexis News & Business. UCRY Policy Index, UCRY Price Index, and ICEA were all collected from Cryptocurrency Indices[9]. We collected the MSCI World Banks Index, VIX, FTSE World Government Bond Index, FTSE All-World Index, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, and gold and Bitcoin prices from Thomson Reuters. USEPU[10] was collected from the EPU. Panel A presents the descriptive statistics for the raw data; panel B displays the descriptive statistics for the log return of the raw data; and panel C shows the descriptive statistics for the continuously compounded returns of the raw data. We calculated the continuously compounded returns as volatility by processing the first-difference in the logarithmic values of two consecutive prices, expressed as: $CCR_{i,t} = ln(P_{i,t}/P_{i,t-1}) \times 100$, where $CCR_{i,t}$ denotes continuously compounded returns for index i at time t, and P_{it} stands for the price of index i at time t.

As shown in Table 1, we will explain our raw data from the three perspectives of frequency distribution, central tendency, and dispersion. The indices had the same mean values – even when we expanded the decimal point to six. The value of CBDCUI's range was greater than the CBDCAI's, causing the former to have a lower minimum value and a higher maximum value than the latter. The standard deviation values of CBDCUI and CBDCAI were almost identical, and the differences in standard deviation were apparent when we set the decimal point to nine. The CBDCAI had higher skewness and kurtosis valued than the CBDCUI. Furthermore, the skewness and kurtosis values of these two variables were positive. These results indicate that an asymmetrical probability distribution of both indices (the mean was greater than the median, and the tail is on the right side), their being leptokurtic, and rejecting the normal distribution, which was confirmed by the Jarque-Bera tests. Based on the unit root test (ADF, KPSS, and PP) results, unit roots contained in all the (raw) variables were a non-stationary time series.

According to Lütkepohl [2005] and Durlauf and Blume [2010], a VAR model requires every variable running in the model to be stationary. Therefore, we calculated the log return to Equation 4. The results are shown in Table 1 in Panel B. Unfortunately, unit roots still existed in variable system Equation 4 confirmed by the ADF, PP, and KPSS tests. Therefore, we calculated the continuously compounded returns to Equation 4. The results are shown in Table 1 Panel C indicating the variables showed stationarity in the continuously compounded returns. Baker et al. [2016] used EPU raw data, the log of the S&P 500 Index, and the employment and industrial production log to process the IRF analysis. However, Lütkepohl [2005] and Corbet et al. [2021] indicated that continuously compounded return is more suitable than the log return for analysing the volatility characteristics. As such, we used the continuously compounded returns of Equation 4 to run the VAR and DCC-GARCH models.

[INSERT Table 1 HERE]

[9] https://sites.google.com/view/cryptocurrency-indices/home?authuser=0
[10] https://www.policyuncertainty.com/index.html

Table 2 unveils the Pearson correlation relationship between each variable. We can observe that the CBDCUI and CBDCAI indices positively correlated with the volatility of UCRY Policy, UCRY Price, and ICEA indices at the 1% significance level. When compared with CBDCAI, CBDCUI has a stronger positive correlation relationship with the volatility of UCRY Policy ($0.577 > 0.354$) and UCRY Price ($0.578 > 0.355$), but the correlation relationship is weaker with the volatility of ICEA ($0.412 < 0.536$). Furthermore, the CBDCAI and CBDCUI indices are also significantly positively correlated with the volatility of VIX, and all exchange rates EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, as well as with gold, Bitcoin, and the FTSE World Government Bond Index. However, we found negative correlation between both CBDC indices and the volatility of the MSCI World Banks Index, USEPU, and the FTSE All-World Index.

[INSERT Table 2 HERE]

5.2. CBDC shocks on the dynamics of financial variables volatility

In this subsection, we examine the effects of the indices' shocks on the financial variables' volatilities in Equation 4 from different time horizons. Figure 6 and Figure 7 show that the impulse response of financial variables in the structural CBDCUI is to continuously compound returns, as well as for CBDCAI shocks in short-, mid-, and long-term time horizons. 0–2, 2–4, 4–6, 6–8, 8–10, and >10 represent the very short-term, short-term, mid-term 1, mid-term 2, long-term, and very long-term, respectively.

As for CBDCUI shocks on the dynamics of financial variables' volatility, we can draw several inferences from Figure 6. First, we have empirically verified that CBDCUI shocks can significantly increase the volatilities of UCRY Policy, UCRY Price, ICEA, VIX, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, Bitcoin and the FTSE World Government Bond Index in the very short-term period. However, this increase tends to quickly drop to a negative value at the end of this period (expect for RUB/USD and CNY/USD). Moreover, CBDCUI shocks can significantly decrease the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index in the very short-term period – although this decrease tends to reverse rather rapidly (except for the MSCI World Banks Index). Second, CBDCUI shocks can slightly decrease the volatilities of UCRY Policy, UCRY Price, ICEA, the MSCI World Banks Index, VIX, USEPU, FTSE All World Index, EUR/USD, GBP/USD, JPY/USD, gold and the FTSE World Government Bond Index in the short-term, and maintains an increasing growth trend. Additionally, CBDCUI shocks can slightly increase the volatilities of RUB/USD, CNY/USD, and Bitcoin in the short-term period, and maintains a decreasing growth trend. Third, although CBDCUI can still slightly affect financial variables from the mid-term, the selected financial markets and indices' responses tend to quickly show a convergence trend.

Based on these three inferences mentioned above, we can draw two short conclusions that, CBDCUI shocks can significantly increase the volatilities of UCRY Policy, UCRY Price, ICEA, VIX,

EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, Bitcoin and the FTSE World Government Bond Index as a whole. Moreover, CBDCUI shocks can also significantly decrease the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index overall.

[INSERT Figure 6 HERE]

As for CBDCAI shocks, we can also draw several inferences from Figure 7. First, we empirically verified that CBDCAI shocks can significantly increase the volatilities of UCRY Policy, UCRY Price, ICEA, VIX, CNY/USD and the FTSE World Government Bond Index in the very short-term period. CBDCAI shocks on UCRY Policy, UCRY Price, and VIX show an increasing trend, whereas CBDCAI shocks on the ICEA, CNY/USD and the FTSE World Government Bond Index display a decreasing trend. CBDCAI shocks can significantly decrease the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index in the very short-term, which maintains an increasing trend. CBDCAI shocks can significantly increase, but also can slightly decrease (the initial significant increase is followed by a slight decrease), the volatilities of EUR/USD, GBP/USD, JPY/USD, RUB/USD, gold, and Bitcoin in the short-term. Additionally, for these financial variables, positive shocks tend to have a greater effect in the very short-term. Second, slightly negative shocks from the CBDCAI have a greater short-term effect for all of the variables. However, as for the variables which receive positive shocks from the CBDCAI at the very short-term period, the small negative shocks from CBDCAI at the short-term are not significant enough to contribute a significantly negative effect as a whole, the positive shock results are still dominant in the final results. Third, although the CBDCAI can still have positive or negative effects on financial variables at the mid- or long-term, the responses of the financial variables begin to converge from the former.

These three inferences illustrated above can lead to three short conclusions. First, the results of CBDCAI shocks on the dynamics of financial variables' volatility are the same as those relating to CBDCUI shocks. Second, CBDCAI shocks can significantly increase the volatilities of UCRY Policy, UCRY Price, ICEA, VIX, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, Bitcoin and the FTSE World Government Bond Index. Third, CBDCAI shocks can significantly decrease the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index.

[INSERT Figure 7 HERE]

5.3. Contributions of CBDC disturbances to the variation of financial variables' volatility

From Figure 8 and Table 3, we can see that a shock from the CBDCUI (100% to 85.0512%) could play a non-trivial role in explaining variations in the CBDCUI FEVD. CBDCAI (7.8467% to 9.0344%) was also a relatively significant variable in explaining variations in the CBDCUI FEVD. Considering the three cryptocurrency indices, the ICEA (2.4091% to 2.4482%) had a greater contribution to the CBDCUI's fluctuations. Therefore, a novel finding is cryptocurrency environmental attention contributed more to the CBDCUI variations than cryptocurrency policy uncertainty and cryptocurrency price uncertainty. As for the five foreign exchange rate variables, JPY/USD (0.8366% to 0.8724%) was the most important for CBDCUI variations. Banking sectors (i.e. MSCI WBI: 0.0322%), Stock markets (i.e. FTSE AWI: 0.2905%), Gold (0.03%), Bitcoin (0.1%) and bond markets (i.e. FTSE WGBI: 0.0215%) can only be used to explain a small part of the CBDCUI's variations.

From Figure 8 and Table 3, the dominant role that a shock from the CBDCAI (93.8919% to 94.8640%) could play in explaining variations in the CBDCAI FEVD. However, the CBDCUI's explanation power in the FEVD of CBDCAI was significantly lower than that of the CBDCAI. Due to the dominant role of the CBDCAI, and the lower importance of the CBDCUI's contributions in the FEVD of CBDCAI, the contributions from the other variables become more significant on the percentage level (despite each variable's contribution value being lower than those in the CBDCUI FEVD). For example, the contributions from the three cryptocurrencies have become more critical to the CBDCAI FEVD. Compared with the joint contributions of the ICEA with UCRY Policy and UCRY Price, ICEA (0.9651% to 1.2403%) still had the leading role. Compared with the three world indices, the MSCI World Banks Index was more relevant (0.3625% 0.3861%) than the FTSE All-World Index (0.0251%) and the FTSE World Government Bond Index (0.0954%) in explaining the CBDCAI's FEVD. Compared with the two uncertainty indices together, the VIX (0.5578% to 0.5678%) was relatively more important than the USEPU (0.0132% to 0.0854%) in explaining the FEVD of CBDCAI. Although JPY/USD (0.5152% to 0.5147%) was still important for the FEVD of CBDCAI among other foreign exchange rates, the RUB/USD (0.8386% to 0.8413%) had the greatest contribution to the CBDCAI's variations. Surprisingly, although China is leading the CBDC revolution, CNY/USD (0.0205% to 0.0588%) was relatively less important in explaining the variations in the CBDCAI FEVD. Compared with the role of Bitcoin in CBDCUI FEVD, Bitcoin is relatively more important (0.3250% to 0.3582%) in explaining the FEVD of CBDCAI. Moreover, we found that gold (4.25E-05) did not greatly contribute to the CBDCAI's variations.

[INSERT Table 3 HERE]

5.4. Cumulative contributions of CBDC disturbances to the financial variables' volatility

While Figure 8 and Table 3 assess the timing and magnitude of the indices' responses to a typical structural shock, they do not quantify how much of each shock explains the historical fluctuations in the CBDCUI and CBDCAI. Therefore, it is essential to investigate the historical evolution of both indices, and the contribution of each of the structural shocks to fluctuations in both, mainly following major historical episodes. Based on the HD method introduced in the previous section, Figure 9 and Figure 10 present the cumulative contributions of CBDCUI and CBDCAI disturbances to the volatilities of financial variables under dynamic economic environments. The contribution of CBDCUI shocks is given in the red, while the contribution of CBDCAI is presented in light blue.

Several conclusions can be drawn from Figure 9 and Figure 10. Firstly, we found that both the cumulative positive and negative effects of CBDCUI disturbances on financial variables were larger than those of the CBDCAI. The reasons seem abundantly clear: the uncertainty index fluctuates more than the attention index, and financial markets are also more sensitive to shocks from uncertainty indices. Our findings reconfirm those of [Lucey et al., 2021; Wang et al., 2022]. Secondly, the contributions of the estimated CBDCUI shocks to the evolution of the financial variables' volatilities changed over time, and we found that they tended to be larger between March 2015 to July 2015, February 2017 to December 2018, June 2019 to August 2019, and April 2020 to July 2021. Generally speaking, these positive or negative shocks appear perfectly reasonable. Indeed, in the first larger cluster period, we found that some good news about CBDC could have significantly negative shocks on the CBDCUI's HD results. For example, dollarisation and the launch of an electronic monetary system in Ecuador. Furthermore, new government CBDC regulations also negatively affected the CBDCUI's HD results. For example, the Chinese government revised its Anti-Money Laundering Law because digital currency makes Anti-Money Laundering enforcement challenging. Regarding the positive shocks in the first larger cluster, we clearly found that the new digital money process in commercial banks could have significant positive effects on the CBDCUI's HD results. For example, M-payment progresses in Brazil, Colombia, and Peru, and PayPal's announcement of their acquisition of Xoom.

It is worth noting that CBDC's progress in the UK may have significantly and positively affected the CBDCUI's HD results in the first larger cluster. In other words, between March 2015 to July 2015, the UK's new CBDC progress could have increased the CBDCUI. Analysing the second larger cluster period with the third and fourth also yielded several interesting findings. First, new CBDC developments (e.g., the digital-CAD, digital-EUR, digital-USD, etc,) significantly decreased CBDC uncertainties. However, it is also worth noting that the UK's CBDC performed differently, and thus increased CBDC uncertainty before the larger cluster in period four. Besides, perhaps because the Renminbi is not a free-float currency, it is hard to place it into the first portfolio position. Alternatively, many regulators and investors are concerned that the digital-RMB could challenge the USD's international hegemony. The new developments of digital-RMB could increase CBDC uncertainty, that is, until Hong Kong helps with its offshore digital-CNH test. Second, negative CBDC news can significantly increase CBDC uncertainties. For example, the Danish Central Bank's cancellation of its CBDC plans, the Deutsche Bundesbank's warning that there will be no CBDC in the Euro-zone, and the Deutsche Bundesbank and the Schweizerische Nationalbank's anti-CBDC plans. Furthermore, significant cryptocurrency events, as well as COVID-19, have seemingly increased CBDC uncertainties.

The contributions of the estimated CBDCAI shocks to the evolution of the financial variables' volatilities are changing over time, and we clearly noted the presence of four larger clusters between May 2016, December 2017, January 2018, June 2019 to July 2019, and March 2021 to July 2021.

We also successfully captured which significant events could cause these larger positive or negative shocks. These shocks match the expectations of the public to a certain extent. For example, digital-CAD, digital-USD, digital-RMB, and the Bahamas Sand Dollar prepaid card, as well as other forms of new CBDC progress, could significantly and positively affect the CBDCAI's HD results. However, during the 2021 cryptocurrency bull market, South Korea-based Shinhan Bank and the Central Bank of Russia's new CBDC announcements showed a significantly negative impact on the CBDCAI's HD results.

Furthermore, we can notice that certain significant events from the cryptocurrency market could also have significantly positive impacts on the CBDCAI's HD results. For example, Bitcoin's one-year bull market, and its record highs for both price and transaction values. In terms of the negative shocks, some negative CBDC news could have significantly negative impacts on CBDCAI's HD results. For instance, the Swiss town of Zug is planning to allow its residents to use Bitcoin to pay for municipal services; and the aforementioned plans of the Danish Central Bank, the Deutsche Bundesbank, and the Schweizerische National Bank. Additionally, potential CBDC concerns, such as how it cannot be applied to less developed areas due to poor internet connections. Moreover, due to its reliance on smart devices and technology, CBDC may not be ideally suited to the elderly. Other concerns include CBDC's energy consumption and environmental issues, and free-float concerns regarding the digital-RMB. More details about these events can be found in the Appendix-A.

[INSERT Figure 9 HERE]

[INSERT Figure 10 HERE]

5.5. Diagnostic tests for SVAR

We processed several diagnostic tests for the SVAR to check the validity of this model and to further confirm that lag 1 is the optimal lag. We tested the autocorrelation, heteroscedasticity and the properties of the residuals for the SVAR model. Autocorrelation and heteroscedasticity are tested by the portmanteau test (asymptotic) and ARCH (multivariate) tests, respectively. Using the Jarque–Bera test, skewness (multivariate) and kurtosis (multivariate) are examined to ensure normal distribution of the residuals. The stationarity of the residuals is investigated by the ARIMA test. The diagnostic test results are presented in Panel B (1) and (2) of the Table 8. As seen in the statistic results in Panel B (1), the p-values of the results of the diagnostic tests mentioned above are all greater than 0.05, which cannot reject the null hypothesis of no autocorrelation, no hypothesis and abnormal distribution of residuals, separately. Moreover, the best-match ARIMA(p,d,q) models for the 17 variables' residuals are all ARIMA(0,0,0), as shown in Panel B (2), indicating that the residuals' time series is stationary. In this way, we can infer that the SVAR model does not suffer autocorrelation and heteroscedasticity. Moreover, the residuals in the SVAR model are also normally distributed and stationary. Therefore, we can verify the correctness of the SVAR model and that lag 1 is the optimal lag.

5.6. Dynamic conditional correlations

Table 4 and Table 5 displays the bivariate DCC-GJR-GARCH (1,1) model results for CBDCUI/CBDCAI and each financial variable in Equation 4.

Regarding the interconnections between the CBDCUI and financial variables, as shown in Panel A of Table 4, the ARCH, GARCH and GJR parameters were statistically significant at the 10% level for all variables. These statistical results indicate that the application of the DCC-GJR-GARCH (1,1) models between CBDCUI and the other variables in Equation 4 is appropriate and reasonable. Panel B of Table 4 reveals the DCC between the CBDCUI's volatility and other financial variables. This allowed us to obtain three findings. First, the CBDCUI had a positive and statistically significant DCC with the volatility of UCRY Policy, UCRY Price, ICEA, VIX, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, Bitcoin and the FTSE World Government Bond Index in both the short- (a) and long-term (b). Second, the CBDCUI had a significantly small positive DCC with the volatility of the MSCI World Bank Index and FTSE All-World Index in the short-term, but a significantly negative DCC with both indices in the long-term. The value of b was significantly greater than a. Therefore, we can infer that the CBDCUI had a significantly negative DCC with the MSCI World Bank Index and FTSE All-World Index in general. Third, the CBDCUI had a significantly negative DCC with the volatility of USEPU in both the short- and long-term.

In terms of the interconnections between the CBDCAI and financial variables, as shown in Panel A of Table 5, the ARCH, GARCH and GJR parameters were statistically significant at the 10% level for all variables. These statistical results indicate that the application of the DCC-GJR-GARCH (1,1) models between CBDCAI and the other variables in Equation 4 is appropriate and reasonable. Panel B of Table 5 reveals the DCC between the CBDCAI and other financial variables, thus leading to three results. First, the CBDCAI had a significantly positive DCC with the volatility of UCRY Policy, UCRY Price, ICEA, VIX, GBP/USD and the FTSE World Government Bond Index in both the short- and long-term. Second, the CBDCAI had a significantly small negative DCC with the volatility of EUR/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin in the short-term, but has a significantly positive one in the long-term. Furthermore, the value of b was significantly greater than that of a. Therefore, we can infer that the CBDCAI has a significantly positive DCC with the volatility of EUR/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin in general. Third, the CBDCAI had a significantly negative DCC with the volatility of the MSCI World Banks Index, USEPU, and FTSE All-World Index in both short- and long-term, although the long-term effects were significantly stronger.

Regarding the CBDCUI and CBDCAI DCC results, it is worth noting that the volatilities of the same financial variables reacted differently to both indices. For example, compared with the CBDCUI, the volatility of the UCRY Policy had a stronger long- and short-term DCC relationship with the CBDCAI. Moreover, the volatility of the UCRY Price and ICEA had a stronger short-term DCC relationship with the CBDCAI. However, these stronger relationships did not exist in the long-term, and the volatility of the UCRY Price and ICEA were more sensitive to the CBDCUI in the long-term ($0.8457 > 0.8452$, $0.6829 > 0.000001$).

[INSERT Table 4 HERE]

[INSERT Table 5 HERE]

Figure 11 and Figure 12 displays the time-varying correlations between CBDCUI/CBDCAI and each financial variable in Equation 4.

As for the CBDCUI, the dynamic correlations between changes in the Bitcoin, CNY/USD, EUR/USD, gold, ICEA, RUB/USD, UCRY price, VIX and the FTSE World Government Bond Index were significantly positive across the entire research period. However, some details require further explanation. The maximum dynamic correlation value between the CBDCUI and Bitcoin, i.e., 0.2786, occurred on 2020-03-20, while the minimum value, i.e., 0.0318, occurred on 2021-04-30. The dynamic correlations between the CBDCUI and CNY/USD showed a significant increase trend after China's Central Bank began to both test and launch CBDC. Three peaks are visible in the dynamic correlation between the CBDCUI and EUR/USD. The first one is the cryptocurrency bear market and the China–US trade war of 2018–19. The second was due to Brexit in the second half of 2019, and the third occurred due to the cryptocurrency bull market in 2021. Regarding the CBDCUI and gold, there was a significant cliff-like drop in 2017–18, which may have been caused by the Federal Reserve's interest rate hike. The most volatile dynamic correlation relationships exist in the CBDCUI and VIX, which may explain why some refer to the VIX as a fear index. The dynamic correlation values between the CBDCUI and GBP/USD, CBDCUI and JPY/USD, CBDCUI and MSCI World Bank Index, and the CBDCUI and UCRY Policy were both significantly partially positive and negative[11]. From the negative dynamic correlation periods, we found that, generally speaking, the partial significantly positive dynamic correlations were the most significant relationships between the CBDCUI and the UCRY Policy, GBP/USD, and JPY/USD. Moreover, the partial significantly negative dynamic correlations were the foremost relationships between the CBDCUI and MSCI World Bank Index. We found the degrees of dynamic correlations between changes in the CBDCUI and USEPU, and the CBDCUI and FTSE All-World Index were negative throughout the entire research period, thereby providing the potential ability of the hedging strategy.

Regarding the CBDCAI, the degrees of dynamic correlations between changes in the CBDCAI and Bitcoin, CNY/USD, EUR/USD, GBP/USD, gold, ICEA, UCRY Policy, and VIX were positive and statistically significant throughout the whole research period. These empirical results

[11] For the sake of brevity, we list these negative dynamic correlation periods in the *Appendix-C*.

imply that one unit increase in CBDC attention can increase the volatilities of Bitcoin, CNY/USD, EUR/USD, GBP/USD, Gold, ICEA, UCRY Policy, and VIX. The dynamic correlation values between the CBDCAI and JPY/USD, the CBDCAI and RUB/USD, the CBDCAI and UCRY Price, and the CBDCAI and FTSE World Government Bond Index were both significantly partially positive and negative[12]. From the negative dynamic correlations periods, we found that, generally speaking, the partial significantly positive dynamic correlations to be the most important relationships between the CBDCAI and UCRY Price, RUB/USD, JPY/USD, and the FTSE World Government Bond Index. The degrees of dynamic correlations between changes in the CBDCAI and FTSE All-World Index, CBDCAI and MSCI World Banks Index, and CBDCAI and USEPU were negative throughout the whole research period, thus evidencing the potential availability of the hedging strategy.

[INSERT Figure 11 HERE]

[INSERT Figure 12 HERE]

5.7. Diagnostic tests for DCC-GJR-GARCH (1,1)

Following the guidance of Huber [2004], one efficient and robust GARCH-type-DCC (p,q) model should pass the following seven criteria: (1) the sum of the coefficient values of the ARCH (p) and GARCH (q) is greater than 0 and less than 1; (2) the significance level of these DCC parameters should less than 0.1; (3) the morphological parameter of the joint distribution should be significant; (4) DCC keeps a dynamic probability; (5) no ARCH effects in the residuals of the fitted DCC-GJR-GARCH (1, 1) models; (6) if we assume that the standardised errors follow a multivariate normal distribution in the DCC-GJR-GARCH (1,1) models, we should confirm that the residuals of the estimated models are normally distributed; (7) no serial correlation in the squared residuals. We processed diagnostic tests for the fitted DCC-GJR-GARCH (1,1) models by using the seven criteria mentioned above.

The diagnostic test results for each fitted DCC-GJR-GARCH (1,1) model are presented in Table 4 and Table 5. The sum of the coefficient values of the ARCH (1) and GARCH (1) for each fitted DCC-GJR-GARCH (1,1) model are all greater than 0 and less than 1. Parameters a and b represent the DCC short-run volatility impact and DCC long-run volatility impact, respectively. The p values of a and b are all significant in the 10% significance level. Parameter v stands for the joint distribution, and all the p values of v are significant in the 10% significance level. We applied the Engle and Sheppard method Engle and Granger [1987] to confirm that the DCC holds a dynamic probability. Based on the p values of the DCC probability, all the p values are less than 0.1, which can significantly reject the null hypothesis that the DCC holds a constant probability.

[12] For the sake of brevity, we list these negative dynamic correlation periods in the *Appendix-C*.

The McLeod–Li test with 1 lag confirms no ARCH effects in the residuals of the fitted DCC-GJR-GARCH (1,1) models [McLeod and Li, 1983]. All the p-values of the McLeod–Li (1) test results are greater than 0.05, indicating that the null hypothesis of the McLeod–Li (1) test cannot be rejected, and there are no ARCH effects among 1 lag to note in the residuals of the fitted DCC-GJR-GARCH (1,1) models. The p values of the Jarque–Bera and Ljung–Box tests with 1 lag for residuals of each fitted DCC-GJR-GARCH (1,1) model are all greater than 0.05, which can confirm that the residuals of each estimated model are normally distributed with no autocorrelation in the squared residuals. Therefore, all the fitted DCC-GJR-GARCH (1,1) models can successfully pass the diagnostic tests, suggesting the correctness and robustness of the models. Moreover, these diagnostic tests can prove the GJR-GARCH (1,1) model can fit well to the estimated variables, and there is no need to further apply the higher-order moments within the GJR model.

5.8. A comprehensive interpretation of empirical findings

To start, we want to discuss the potential reasons why CBDC indices have a significant positive relationship with the volatility of cryptocurrency markets. It is clear that CBDCUI represents uncertainty, which has conduction effects on financial markets [Cao et al., 2017], so one variable's uncertainty may cause such in other variables. Thus, there exists a definite correlation between CBDCs and cryptocurrencies in terms of uncertainty. Second, upon examining the high CBDCUI periods in detail from Figure 4 and Figure 9, we find that the high CBDCUI values are aroused by unfavourable news regarding CBDC or cryptocurrency flash events. As we mentioned many times above, CBDCs can be viewed as 'cryptocurrency counters' launched by central banks [Turrin, 2021]. Consequently, the negative news for CBDC results is an acceptable signal for cryptocurrency. Under this condition, cryptocurrency investors could increase their transaction and speculation activities, which will raise uncertainty in relevant markets [Akyildirim et al., 2020; Smales, 2022]. For example, during cryptocurrency flash event periods (e.g., Bitcoin value record high and Bitcoin transaction volume record high). As a result, cryptocurrency markets experienced extreme volatility and uncertainty, and these fluctuations can be conducted to the CBDCs. This is also can explain why CBDCUI has a meaningful positive relationship with the volatility of cryptocurrency markets. Third, the reasons CBDCAI sport a substantial association with the cryptocurrency market's volatility are similar to those with CBDCUI. From Figure 4 and Figure 10, we can clearly observe that CBDCAI is occasionally dragged up by major cryptocurrency events. For example, during Bitcoin's one-year bull market, Bitcoin hit a record-high $63503 while volumes recorded 1.26358E+11, among others. Moreover, CBDC is a well-known fiat digital currency [Kirkby, 2018; Ferrari et al., 2022], which aims to be 'anti-cryptocurrency' [Brunnermeier and Landau, 2022]. Therefore, a heated discussion on or intensive attention of CBDCs will trigger the fluctuations in the cryptocurrency markets, same as the investor attention conduct mechanism in cryptocurrency market [Smales, 2022; Yan et al., 2022]. Fourth, we also desire to explain why CBDC indices can influence the volatility behind ICEA. This empirical finding is in line with the existing literature concerning the environmental issues of the CBDCs [Laboure et al., 2021]. Importantly, although the central banks launch CBDCs, they are still digital currencies. As such, CBDCs also will consume energy and thus pollute the environment. ICEA is an index that captures the cryptocurrency attention on environmental issues. Therefore, CBDC indices and ICEA volatility showcase a meaningful correlation with one another.

Now, we will explain why the CBDC indices have a significant positive relationship with the volatility of the foreign exchange markets. First, one possible explanation is that the rise in CBDC uncertainty and attention can motivate foreign exchange traders to reduce or increase their net long positions due to the 'stablecoin' characteristic of the CBDCs [Copeland, 2020; Fantacci and Gobbi, 2021; Brunnermeier and Landau, 2022], thus directly inducing fluctuations in the foreign exchange rate. Second, the essence of a CBDC is the fiat currency. With the development of CBDCs, the public has access both to cash and digital currency, which leads to increased supplies of both in general. The supply influx may lead to inflation. Although Chen and Siklos [2022] indicates that CBDCs need not produce higher inflation, this is only a simulation result based on the historical behaviour of the velocity of circulation. Undoubtedly, liquidity will increase by developing CBDCs, but excess supply will cause disruptions and major inflation [Brunnermeier and Landau, 2022]. Under this circumstance, increasing one country's inflation rate will increase the volatility of its currency exchange rate. Moreover, because of a conduction effect, the same will occur between one country's currency exchange rate and that of other currencies. Third, CBDCUI is an uncertainty index. High uncertainty maybe can cause high volatility. Fourth, from Figure 4 and Figure 10, we can see that excellent news about CBDCs spikes the high CBDC attention value (e.g., the CBDCs' new developments). As we mentioned, CBDCs can increase the liquidity of currencies, which also means the cost of currency circulation is reduced, and foreign exchange transactions will become easier to perform. Therefore, the cost of the foreign exchange speculation transactions will lower, and the foreign exchange speculation activities will also increase, bringing more fluctuations to foreign exchange markets. This is especially true for CNY due to the progress of cross-border transactions involving e-CNY. The exchange rates of CNY will definitely become more volatile.

Thirdly, we want to explain the relationships between CBDC and uncertainty indices (i.e., VIX and USEPU). Moreover, we will further elucidate on the inconsistency between the two sets of relationships. Our empirical findings indicate CBDC indices have a significant positive relationship with the volatility of VIX but conversely have a negative one with that of USEPU. These findings are consistent with the views of Larina and Akimov [2020], who believe that the CBDCs are conductive to reducing systemic financial risk, and also reconfirm the notions that CBDCs positively impact the consumer friendly [Larina and Akimov, 2020]; financial stability [Zams et al., 2020; Copeland, 2020; McLaughlin, 2021; Buckley et al., 2021]; welfare gains [Davoodalhosseini, 2021]; economic growth rate [Tong and Jiayou, 2021]; the ability of central bank's to stabilise the business cycle

[Barrdear and Kumhof, 2021]. First, one possible explanation behind the latter case concerns the 'stablecoin' characteristic of CBDCs because the substitution effect of the CBDCs on bank deposits is limited, and the overall economic effect is positive. Second, based on our unconditional correlation table Table 2 and the literature about USEPU and VIX, the USEPU and the VIX should express a positive relationship. In fact, the relationships between CBDC indices and USEPU, the relationships of CBDC indices and VIX are inconsistent in this study. The potential explanations could be that the VIX-EPU relationship is not always positive and is time-variant, and USEPU and VIX are more coherent to the developed market (i.e., France, Germany, Japan and the United Kingdom), which is confirmed by [Tiwari et al., 2019]. However, our CBDC indices boast wider coverage (e.g., China, Russia, Swiss, Spain, Portugal, etc.), also including some developing countries (e.g., Ukraine, Panama, Ecuador, etc.). These points potentially can explain the inconsistencies in the relationships between CBDC and uncertainty indices. Third, the likeliest reason for the significant positive relationship between CBDC indices and VIX is that the latter is related to the market's expectations for the volatility in the S&P 500 over the coming 30 transaction days, and the S&P 500 contains 500 large companies listed on stock exchanges in the USA. From the news our indices captured, we know that, although the e-USD is being tested, the progress remains slow. China and its e-CNY are leading in the CBDC [Turrin, 2021]. The new progress of e-CNY can spike both CBDCUI and CBDCAI. Moreover, many media, scholars and investors believe that e-CNY is challenging the hegemony of the USD and will supplant it as the most important currency used for international settlements [Fantacci and Gobbi, 2021]. This kind of viewpoint will shake the confidence of US financial markets and cause panic in the US stock market, especially for large companies with prominent international businesses.

Fourthly, we want to illustrate that why CBDC indices have a significant positive relationship with the safe-haven, gold. This empirical evidence confirms our concerns that CBDC may lead to inflation because favourable CBDC news spike CBDC indices in general, and gold is a safe haven against anti-inflation [Brunnermeier and Landau, 2022]. First, a widely discussed viewpoint now is that the CBDCs could serve as a stablecoin, and it is preferable to hold CBDCs as a safe-haven instead of the traditional safe-haven, gold in times of financial crisis [Copeland, 2020; Fantacci and Gobbi, 2021]. Second, with the increasing of CBDC uncertainties, speculation transaction activities concerning gold as a safe haven also will increase, thus causing gold price fluctuations. Third, the significant positive relationship between CBDCAI and gold can be similarly explained by the aforementioned gold speculation transactions. If some investors value CBDCs from an analyst perspective, they may also realise this phenomenon is a potential issue. They will increase their net long positions in gold, thus directly inducing fluctuations in gold prices.

Fifthly, CBDC indices have a significant negative impact on the volatility of the MSCI World Bank Index. This empirical finding reconfirms the notion of [Sissoko, 2020; Zams et al., 2020; Brunnermeier and Landau, 2022] that CBDCs can balance the banking system, reduce the shadow banking, and the magnitude of the disruption from the CBDCs to banks business model is small, but different from [Yamaoka, 2019; Zams et al., 2020; Sinelnikova-Muryleva, 2020; Williamson, 2021; Fernández-Villaverde et al., 2021; Viñuela et al., 2020; Chen and Siklos, 2022], who believe that CBDCs can upset commercial banking, the CBDCs may have significant negative consequences for the risk of structural bank disintermediation and systemic bank runs, and the central banks will become deposit monopolists by issuing CBDCs. [Barrdear and Kumhof, 2021] also suggests the risks to banks can be minimised through appropriate CBDCs issuance arrangements. The operating system of CBDCs could contribute a lot to this phenomenon. Currently, multiple countries have adopted the two-level operation system of CBDCs. For example, the People's Bank of China converts e-CNY to the designated operating institutions such as commercial banks or other commercial institutions and allows these institutions to convert e-CNY to the public instead of directly issuing and converting CBDCs to the public. The conversion of a CBDC adopts the conversion process of 1:1, which means commercial banks and other operating institutions must pay the central bank the reserve fund of 100%. The two-level operation system of CBDCs guarantees the reasonability of a CBDC issuances like the issuance of paper currencies, which will negatively influence the existing financial system and impact the real economy or financial stability such as increasing inflation rate, competing for commercial banks and traditional financial institutions and stimulating the speculative transactions of the financial market. Digital Currency/Electronic Payment (DC/EP) in China adopts the two-level operation mode to guarantee the excess issuance of CBDCs. When the currency production requirement meets verification rules, corresponding limit vouchers will be sent, which will neither negatively influence the inflation rate nor compete with the traditional business model of commercial banks.

Sixth, we seek to uncover the significant negative relationships between the FTSE All-World Index and CBDC indices. The characteristic of the CBDCs have the potential to promote financial stability can explain this empirical phenomenon [Zams et al., 2020; Copeland, 2020; McLaughlin, 2021; Buckley et al., 2021]. Moreover, this empirical proof is consistent with [Zams et al., 2020; Tong and Jiayou, 2021; Barrdear and Kumhof, 2021; Fantacci and Gobbi, 2021], who suggest that CBDCs can improve financial inclusion, mitigate systemic financial risk and raise GDP. In point three, we have demonstrated why the CBDC indices have a significant positive relationship with the volatility of the VIX. However, the FTSE All-World Index is also related to the stock market, and its volatility shows a significantly negative relationship with CBDC indices. To determine why the two stock market indices have adverse reactions to the shocks from the CBDCs, we need to differentiate between the scopes of the VIX and the FTSE All-World Index. VIX focuses on large companies in the U.S. financial market [Whaley, 2009], but the FTSE All-World Index is an international stock market index that covers over 3,100 companies in 47 countries. The markets represented by the FTSE All-World Index and the VIX differ, resulting in their different relationships with the CBDC indices.

Finally, CBDCUI and CBDCAI positively affect the FTSE World Government Bond Index, which can be explained by the following two points. First, CBDCs could cast doubt on the solvency of commercial banks, reshape the international monetary system, and cause negative interest rates [Brunnermeier and Landau, 2022]. Moreover, this finding echoes the latest study of [Ferrari et al., 2022], which indicates that a CBDC issued by one country could increase asymmetries in the international monetary system by having negative consequences on monetary policy autonomy and welfare in the other countries. These potential characteristics of CBDCs may destabilise the financial system. The lower the financial stability, the higher the volatility of bond markets, especially government bond markets [Acharya and Steffen, 2015]. Second, exchange rate mechanisms and exchange rate regimes also have a positive impact on the volatility of sovereign bond markets [Cappiello et al., 2006]. Since CBDC indices positively impact the exchange rate volatility of EUR/USD, GBP/USD, JPY/USD, RUB/USD and CNY/USD, they will certainly bring a positive shock to the volatility of the FTSE World Government Bond Index. Moreover, the positive relationships between CBDC indices and bond markets volatility can also be interpreted as public concern for CBDCs in the economy and society.

5.9. Robustness test

As we sought to identify the effects of CBDC indices on financial markets, we selected the SVAR and DCC-GJR-GARCH models as the two econometrics models that would most effectively help us achieved our research aim. In order to obtain a more rigorous conclusion, we considered it necessary to design and process several robustness tests. The core heart of the indices' effects on financial markets with SVAR and DCC-GJR-GARCH models is the relationships between the indices and the financial variables. From our empirical analysis, we concluded that both CBDC indices had a significantly negative relationship with the MSCI World Bank Index, USEPU, and FTSE All-World Index. Moreover, both CBDC indices had a significantly positive relationship with the other financial variables. Therefore, our robustness tests could focus on how to confirm these relationships between the CBDC indices and those financial variables.

Due to the limitation of the data period, we only selected Bitcoin as a proxy to represent the broader cryptocurrency market in the main empirical analysis. In the robustness test, we consider including a more comprehensive cryptocurrency proxy, CRIX [Trimborn and Härdle, 2018], to capture the cryptocurrency market. It allows close tracking of the evolution of the diverse, very volatile, and frequently changing cryptocurrency market with a small number of constituents (a minimum of five cryptocurrency assets, which are verified as investable). We collected the CRIX from S&P Global. CRIX is widely used as a broad cryptocurrency market indicator to investigate the relationships between the cryptocurrency market and other financial markets [Klein et al., 2018; Umar et al., 2021; Yan et al., 2022].

In order to evaluate the reliability of the empirical results, we first further analysed the relationship between CBDC indices risk and financial variables' volatility. Our hypothesis is as follows:

H_0: CBDC indices risk increases, financial variables' volatility also increases.

Or

H_0: CBDC indices risk increases, financial variables' volatility decreases.

To evaluate the significance of the relationship, we followed the methodologies of [Pástor and Veronesi, 2013; Demir et al., 2018, Al Mamun et al., 2020; Lang et al., 2021]. The regression model is as follows Equation 21:

$$FV_t = \beta_1 + \beta_2 CBDC_t + \beta_3 FV_{t-1} + \varepsilon_t, \tag{21}$$

where, FV denotes financial variable volatility, and $CBDC$ denotes the $CBDC$ uncertainty risk or the $CBDC$ attention risk, FV_{t-1} is designed to removing any serial correlation in FV_t. ε is the error term.

We tested this hypothesis as a null hypothesis of when $\beta_2 > 0$, indicates that the volatility of financial variables increases under more uncertainty or attention; when $\beta_2 < 0$, indicates that the volatility of financial variables increase when there is less uncertainty or attention.

First, FV and $CBDC$ are still calculated by the continuously compounded returns. The results are shown in Table 6 columns (1) and (2).

The results in columns (1) and (2) show the significance of the results at the 10% level. The β_2 values of the MSCI World Bank Index, USEPU, and FTSE All-World Index in the CBDCUI and CBDCAI were less than zero, thus implying that the volatility of these three financial variables had a negative relationship with the CBDCUI and CBDCAI. In other words, the volatility of the MSCI World Bank Index, USEPU, and the FTSE All-World Index decrease in the face of greater CBDC uncertainty or attention. The β_2 values of the other financial variables (except for the three just discussed) were greater than zero, thereby indicating a positive relationship between these financial variables and the CBDCUI or CBDCAI. These additional results accord with our former empirical analysis, thus proving our main findings' robustness.

Second, while we still followed the formula of Equation 21, we calculated the FV and $CBDC$ by the realised variance. For example, denoting the nearby weekly variable value at time t as S_t, the realised variance from time 1 to time T, denoted as $RV_{t,T}$, can be computed as: $RV_{t,T} = \frac{1}{T}\sum_{i=1}^{T}(r_{t+i} - \overline{r_{t+i}})^2$, where $r_{t+i} = 100 \times ln(S_{t+i}/S_{t+i-1})$ and $\overline{r_{t+i}} = 100 \times \overline{ln(S_{t+i}/S_{t+i-1})}$ are the one-period return and the average return for T periods. The results are shown in Table 6 columns (3) and (4).

From the results in columns (3) and (4), although we calculated all of the variables in a realised variance, the relationships between the financial variables and the CBDC indices (which we demonstrated in the former empirical analysis) still held in the Equation 21. Moreover, the MSCI World Banks Index, USEPU, and FTSE All-World Index showed a statistically significant negative relationship with the CBDCUI or CBDCAI at the 10% significance level. The statistically significant positive relationships between the other financial variables and CBDC indices were also still at the 10% level. The results from this Equation 21 further prove the robustness of our main empirical findings.

Secondly, the robustness test of our results can be confirmed using the methodology of Whaley [2009]. When $CBDC_t$ displayed a negative relationship with FV_t, we found that the changes in $CBDC_t$ rose at a higher absolute rate when the FV_t fell than when it increased. In other words, when $CBDC_t$ showed a positive relationship with FV_t, the changes in $CBDC_t$ rise at a higher absolute rate when the FV_t rises, than when the FV_t falls. The regression model is as follows Equation 22:

$$CBDC_t = \beta_1 + \beta_2 FV_t + \beta_3 FV_t^- + \varepsilon_t, \tag{22}$$

where $CBDC$ and FV are still calculated by the continuously compounded return and represent the rate of change of the CBDCUI, CBDCAI, and financial variables. FV^- denotes the rate of change of the financial variables conditional on the market going down, and zero otherwise. ε is the error term.

First, if CBDC has a positive relationship with FV, both of the slope coefficients of FV and FV^- would have to be greater than zero. The second condition is that the slope coefficient of FV is more significant than zero, and the slope coefficient of FV^- less than, but the coefficient value of FV would be greater than that of FV^-. If CBDC has a negative relationship with FV, both of the slope coefficients of FV and FV^- should be less than zero.

The results are shown in Table 6 columns (5) and (6). The results of the robustness test confirmed our empirical results reported earlier. Moreover, the results allow us to clearly observe that the CBDCUI and CBDCAI have a statistically significant and negative relationship with the MSCI World Banks Index, USEPU, and FTSE All-World Index. Additionally, the CBDCUI and CBDCAI have a statistically significant and positive relationship with the other variables. For example, if the USEPU rises by 100 basis points, the CBDCUI will fall by: $CBDCUI_t = -0.000,2 \times (0.01) = -0.000,2\%$, and if the USEPU falls by 100 basis points, the CBDCUI will rise by: $CBDCUI_t = -0.000,2 \times (-0.01) - 0.002,5(-0.01) = 0.000,002 + 0.000,025 = 0.000,027 = 0.0027\%$.

In the end, the statistical results regarding effects of the CBDC indices on the CRIX from column (1) to column (7) show that the CBDCUI and CBDCAI have a statistically significant and positive relationship with the CRIX, which indicates that the CBDCUI and CBDCAI can have a positive impact on the cryptocurrency market. Moreover, this finding can further confirm the positive relationship between the CBDC indices and Bitcoin, which has been proved above.

[INSERT Table 6 HERE]

6. Conclusions

This paper assesses the impact of CBDC news on financial markets using the over 660m news items collected from LexisNexis News & Business database. Specifically, we introduce two new measures of uncertainty and attention for CBDCs that can be used by cryptocurrency researchers, investors, and financial regulators in their subsequent work.

Our new CBDC Uncertainty Index and the CBDC Attention Index have been constructed and made available for the period from January 2015 to June 2021. We employ of empirical test to examine the behaviour of CBDC indexes in relation to cryptocurrency markets (i.e. UCRY indices, ICEA and Bitcoin), other popular uncertainty measures (i.e. VIX and USEPU), stock markets (i.e. FTSE All-World Index), banking sectors (i.e. MSCI World Bank Index), bond markets (i.e. FTSE World Government Bond Index), exchange rates (i.e. EUR/USD, GBP/USD, RUB/USD, JPY/USD, and CNY/USD) and gold during this period and capture the dynamics of these interrelationships.

Our empirical results suggest that CBDC indices have a significantly negative effect on the volatilities of the MSCI World Banks Index, USEPU, and FTSE All-World Index. However, CBDC indices have a significantly positive effect on the volatilities of UCRY Policy, UCRY Price, ICEA, and Bitcoin (cryptocurrency markets), FTSE World Government Bond Index (bond markets), EUR/USD, GBP/USD, RUB/USD, JPY/USD, and CNY/USD (foreign exchange markets), as well as VIX and gold. Furthermore, the volatilities of financial variables are more sensitive to CBDCUI when compared with reactions from CBDCAI shocks, highlighting the importance of CBDC uncertainty in this interconnected system. The HD results suggest that both cumulative positive and negative effects of CBDCUI's disturbances on financial variables are larger than those of CBDCAI disturbances. These results display that uncertainty around CBDC news plays more important role that just an attention to this new digital assets, which suggest that introduction of CBDC can bring significant changes to the economy. Our results show that good news and positive government policies can significantly negatively affect the CBDCUI HD results, by decreasing the uncertainty around these assets. However, the HD results for both the CBDCUI and CBDCAI show significant spikes near key CBDC innovations and important digital currency events. The results of the robustness test demonstrate the reliability and validity of our empirical findings.

In terms of methodology, our paper further contributes to the literature by showcasing how to make the most effective use of internet literature database archives to develop and issue new indices of interest to financial areas. This methodology can provide a new channel to more comprehensively understand broad financial developments by systematic online empirical inquiries.

While early research suggests that Bitcoin is by far the most influential cryptocurrency [Corbet et al., 2020a; Ma et al., 2020], the most recent evidence indicates that crypto-assets can be categorised as decentralised applications (dapps) and protocols [Huynh et al., 2020; Chang et al., 2020], and have become more attractive for investors than 'pure' cryptocurrencies [White et al., 2020]. This displays a shift in consumer and investor preferences from pioneer cryptocurrency towards more innovative, scalable, and versatile digital payment instruments and assets [Umar et al., 2021]. Thus, CBDC may become a competitive product for investors and cryptocurrency users, thereby bridging the gap between cryptocurrency and traditional markets for widespread use.

We believe it pertinent to mention several research pathways for future investigation. As another innovation of a central bank's financial system, CBDCs are aimed at the digitisation, decentration, and disintermediation of sovereign currency. From a global monetary perspective, applying these (central bank-endorsed) digital currencies is a new step towards modern society's digital transformation. As CBDCs continue progressing, the functions of sovereign currency will be enriched, and sovereign currency will be endowed with such new functions as value storage and measurement, and free convertibility instead of a single payment tool. As society increasingly accepts CBDCs, the global financial system will be changed dramatically and inevitably in multiple aspects, such as daily individual payment modes, the payment system of society as a whole, the structure of the commercial banking system, and even the operation of the capital market. Countries assuming the leading role regarding CBDCs can maintain effective competitive advantages during the digitisation of global currencies. While promoting the internationalisation of sovereign currency, CBDCs can improve the financial software power of various countries. In China especially, the RMB has been castigated due to its failure to freely circulate and be converted in the international market. As the progress of digital-RMB is pushed forward, the currency will operate more competitively at the levels of international or reserve currency. We thus expect to see significant local and international impacts of CBDCs on competition in the payments and fintech sector.

The role of CBDCs in the monetary system, its actual economic performance, and society's acceptance of it remain to be tested and observed. Therefore, CBDCs' problems require further investigation. First, we can further analyse the CBDCAI and CBDCUI with firm-level data. For example, we can investigate if our CBDC indices are associated with greater stock price volatility, poor financial statement performances in the financial services sector, or other policy-sensitive sectors, such as energy, technology, and real estate. Second, due to constraints regarding the scope of this paper, future studies could examine the effects of CBDCUI and CBDCAI on cryptocurrencies in greater detail. Considering the issue of the data period length, we did not include composite cryptocurrency indices into the main variable system. However, it would be interesting to also investigate the interconnections between the CBDC indices and the CRIX or BGCI by using the

VAR, DCC-GARCH or VAR spillover connectedness model. Besides, the predicted powers of CBDC indices can also be further developed. Third, it is worth understanding that cryptocurrencies can have a partial effect between CBDC indices and financial markets or the partial effects of CBDC indices on USEPU and VIX. Fourth, the construction of infrastructures supporting the progress of CBDCs, issuance and market supervision of CBDCs, and compliance and supervision of the financial institutions responsible should be explored further. Focusing on individual users is another potential research direction. What actual effects, advantages, and disadvantages will a CBDC be able to provide a country's different users? When other digital payment modes still occupy a large market share, can various governments' CBDCs research and efforts expect returns?

There is plenty of room for the development of CBDC in various countries, and there remains much progress to be made. However, digital currency is reshaping our payment system, payment modes, and new financial order. CBDC must be the main battlefield of various countries in the field of fintech. Besides, as money never sleeps, further research into the roles and advantages of CBDCs can only be beneficial.

Highlights

1). Two Central Bank Digital Currency (CBDC) indices are made available: CBDC Uncertainty and CBDC Attention indices.

2). The relationships between the CBDC indices and financial markets are investigated through the SVAR and DCC-GJR-GARCH models.

3). CBDC indices have a negative relationship with the volatilities of the banking sectors, stock markets, and USEPU.

4). CBDC indices have a positive relationship with the volatilities of cryptocurrency, foreign exchange, and bond markets, as well as VIX and Gold.

5). The relationships are accentuated to the CBDC Uncertainty Index and robust to several panel-pooled OLS models.

Declaration of Conflicts of Interest

No conflicts of interest to declare.

CRediT authorship contribution statement

Yizhi Wang: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualization, Project administration, funding acquisition, Writing - Review & Editing. **Brian M. Lucey:** Conceptualization, Supervision, Project administration, Resources, Writing - Review & Editing. **Samuel A. Vigne:** Conceptualization, Supervision, Project administration, Resources, Writing - Review & Editing. **Larisa Yarovaya:** Conceptualization, Supervision, Project administration, Resources, Writing - Review & Editing.

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Brian Lucey is Professor of International Finance and commodities. A graduate of TCD (BA, Economics, 1985), the National University of Ireland (MA, International Trade 1988) and Stirling (PhD, Finance , 2003), he has worked at Trinity Business School since 1992. Prior he worked as an economist at the Central Bank of Ireland and as an analyst at the Department of Health and Children.

Brian researches mainly in the areas of the financial economics of precious metals, and has attracted significant funding from industry over the years on this area. He also researches international finance, with an emphasis on financial integration, chairing the annual INFINITI Conference on International Financial Integration. He also edits two academic journals. He is editor in chief of International Review of Financial Analysis, and co-editor in chief of Finance Research Letters.

He has published over 200 refereed papers in international finance, commodities, behavioural finance and financial management. A fellow of the University, Professor Lucey has been recognized as a Conference Ambassador by Fáilte Ireland, for his work in development of the INFINITI conference on International Finance.

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Before starting her academic career, Larisa was an elite Paralympic swimmer for over 16 years, and worked with charities and non-profit organisation supporting children with disabilities and their families in Moscow, Russia. Her interest in Finance developed during the time of the Global Financial Crisis of 2008 which severely hit the unstable Russian economy, especially impacting on people and families from less privileged backgrounds. She decided to study finance at the Management Faculty in the Finance University under the Government of the Russian Federation to understand how countries can become more resilient to financial crises. She received the Scholarship of the President of the Russian Federation for foreign education and continued her academic journey in Newcastle Business School, Northumbria University, UK, where she completed her PhD with the project entitled "Return and Volatility transmission in emerging and developed stock markets" under the supervision of Professor Janusz Brzeszczynski and Dr Chi Keung Marco Lau in 2016. Since then Larisa published more than 30 papers in top academic journals and became one of the most cited female authors in the Fintech and cryptocurrency research area.

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Yizhi Wang is holding a PhD full scholarship from China Scholarship Council (CSC) – Trinity College Dublin Joint Scholarship Programme.

Table 1: Descriptive statistics

	CBDCUI	CBDCAI	UCRYPo	UCRYPr	ICEA	MSCI WBI	VIX	USEPU	FTSE AWI	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin	FTSE WGBI
Panel A: price																	
Observation	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340
Mean	100.0000	100.0000	100.19	100.20	100.29	88.23	17.45	127.95	325.55	1.14	1.35	0.01	0.02	0.15	1384.81	8323.89	957.72
Min	99.12	99.44	99.02	99.03	99.40	56.19	9.14	35.15	235.71	1.04	1.17	0.01	0.01	0.14	1056.20	210.34	856.07
Max	106.16	106.02	108.26	109.18	112.00	114.62	66.04	601.16	477.60	1.25	1.59	0.01	0.02	0.16	2010.10	60204.96	1098.56
Range	7.04	6.58	9.23	10.15	12.60	58.43	56.90	566.01	241.89	0.20	0.42	0.001	0.01	0.02	953.90	59994.63	242.49
Std. Dev.	1.00	1.00	1.23	1.26	1.68	12.21	7.76	99.22	53.53	0.05	0.10	0.001	0.001	0.01	241.71	12156.80	62.90
MAD	0.50	0.29	0.46	0.48	0.58	11.20	4.51	39.93	53.91	0.05	0.08	0.001	0.001	0.01	130.91	7038.16	70.02
Skewness	3.00	3.95	2.78	3.07	3.94	−0.43	2.63	2.59	0.88	0.33	0.79	−0.47	0.22	0.23	1.03	2.67	0.46
Kurtosis	11.70	16.40	9.38	11.90	17.70	−0.45	10.63	7.16	0.48	−0.67	−0.38	−0.24	−0.26	−1.03	−0.20	7.12	−0.73
SE	0.05	0.05	0.07	0.07	0.09	0.66	0.42	5.38	2.90	0.001	0.01	0.001	0.001	0.001	13.11	659.30	3.41
J-B test	2482.9***	4755.8***	1707.8***	2577.1***	5387.9***	13.307***	2021***	1122.5***	47.539***	12.454***	37.628***	13.465***	3.5849	17.872***	61.496***	1137.9***	19.359***
ADF	−2.7817	−2.5028	−2.9183	−2.9066	−2.9971	−1.973	−3.8293**	−3.1866*	−1.7614	−2.516	−1.4776	−2.62	−3.3439*	−1.9712	−2.1804	−2.6065	−2.9232
KPSS	1.8065***	1.549***	1.9293***	2.056***	1.6208***	0.45627*	1.3422***	2.132***	4.3691***	1.2755***	2.3293***	2.3074***	2.0678***	1.9179***	4.2772***	2.7922***	4.6276***
PP	−48.75***	−17.008	−52.702	−46.594***	−11.743	−8.3806	−45.253***	−35.045***	−9.5526	−16.624	−6.6449	−15.1	−16.056	−4.6877	−8.3714	−7.8294	−13.548
Panel B: log return																	
Observation	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340
Mean	4.61	4.61	4.61	4.61	4.61	4.47	2.79	4.67	5.77	0.13	0.30	−4.71	−4.17	−1.90	7.22	8.02	6.86
Min	4.60	4.60	4.60	4.60	4.60	4.03	2.21	3.56	5.46	0.04	0.15	−4.83	−4.38	−1.97	6.96	5.35	6.75
Max	4.66	4.66	4.68	4.69	4.72	4.74	4.19	6.40	6.17	0.22	0.46	−4.61	−3.91	−1.81	7.61	11.01	7.00
Range	0.07	0.06	0.09	0.10	0.12	0.71	1.98	2.84	0.71	0.18	0.31	0.22	0.47	0.15	0.64	5.66	0.25
Std. Dev.	0.01	0.01	0.01	0.01	0.02	0.15	0.36	0.56	0.16	0.04	0.07	0.05	0.10	0.04	0.16	1.60	0.06
MAD	0.00	0.00	0.00	0.00	0.01	0.12	0.33	0.44	0.17	0.04	0.06	0.04	0.10	0.05	0.11	1.22	0.07
Skewness	2.94	3.91	2.72	2.99	3.84	−0.73	0.97	1.03	0.50	0.26	0.68	−0.58	−0.02	0.18	0.84	−0.22	0.35
Kurtosis	11.17	16.07	8.84	11.16	16.72	−0.08	1.11	0.87	−0.20	−0.70	−0.51	−0.16	−0.49	−1.06	−0.47	−1.13	−0.81
SE	0.001	0.001	0.001	0.001	0.001	0.01	0.02	0.03	0.01	0.001	0.001	0.001	0.01	0.001	0.01	0.09	0.001
J-B test	2287.2***	4582.7***	1548***	2304.3***	4861.3***	30.458***	72.197***	72.304***	14.563***	10.38***	30.283***	19.708***	3.1647	17.367***	43.413***	20.697***	16.209***
ADF	−2.7481	−2.4361	−2.9059	−2.9066	−2.9764	−2.1027	−3.4551**	−3.3427	−2.4057	−2.527	−1.4932	−2.5921	−3.216	−1.9756	−2.3738	−2.0129	−3.0199
KPSS	1.8263***	1.5654***	1.9409***	2.0727***	1.6474***	0.43944*	1.5168***	2.998***	4.5332***	1.2814***	2.2613***	2.373***	2.1086***	1.9105***	4.378***	5.0548***	4.6417***
PP	−48.518***	−16.703	−51.967***	−45.332***	−10.838	−9.2871	−41.388***	−69.578***	−14.076	−16.959	−6.9719	−14.908	−15.736	−4.661	−9.7523	−7.0336	−14.356
Panel C: continuously compounded returns																	
Observation	339	339	339	339	339	339	339	339	339	339	339	339	339	339	339	339	339
Mean	0.0063	0.0091	0.0058	0.0064	0.0164	0.04	−0.05	0.03	0.16	0.00	−0.03	0.02	−0.07	−0.01	0.12	1.44	0.04
Min	−1.83	−1.54	−3.58	−3.27	−2.37	−16.02	−55.62	−84.69	−13.30	−3.88	−8.10	−4.63	−8.90	−3.01	−9.74	−40.79	−3.81
Max	2.32	2.35	3.53	3.92	5.68	15.26	85.37	114.54	9.88	3.69	6.68	4.57	7.93	1.57	9.01	34.70	3.24
Range	4.14	3.89	7.10	7.19	8.05	31.28	140.99	199.23	23.19	7.58	14.78	9.20	16.83	4.57	18.75	75.49	7.05
Std. Dev.	0.48	0.30	0.61	0.58	0.44	3.31	17.09	28.11	2.26	1.18	1.42	1.17	2.15	0.59	2.06	10.69	0.86
MAD	0.32	0.10	0.44	0.32	0.08	2.37	12.88	24.02	1.47	1.06	1.37	0.93	1.67	0.49	1.65	7.28	0.73
Skewness	0.49	2.41	0.32	1.61	5.37	−0.35	0.84	0.38	−1.22	−0.26	−0.60	0.30	−0.72	−0.42	−0.10	−0.45	−0.37
Kurtosis	4.61	21.55	7.41	15.73	82.55	5.17	3.25	1.55	9.11	0.92	4.59	1.85	2.59	2.37	2.69	1.49	2.46
SE	0.03	0.02	0.03	0.03	0.02	0.18	0.93	1.53	0.12	0.06	0.08	0.06	0.12	0.03	0.11	0.58	0.05
J-B test	320.29***	6978.5***	794.3***	3692.9***	99083***	391.05***	193.08***	43.262***	1274.6***	16.377***	323.61***	54.847***	127.13***	91.052***	105.04***	44.051***	95.406***
ADF	−7.13***	−6.49***	−7.98***	−7.43***	−6.81***	−6.67***	−8.44***	−9.04***	−7.43***	−6.67***	−7.91***	−7.06***	−6.26***	−5.72***	−6.85***	−6.51***	−6.5432***
KPSS	0.022	0.089	0.0227	0.0234	0.149	0.084	0.024	0.026	0.125	0.11921	0.19924	0.083	0.035	0.246	0.094	0.075	0.0662
PP	−337.34***	−330.11***	−393.61***	−369.76***	−300.27***	−336.6***	−352.41***	−351.84***	−350.27***	−360.01***	−338.73***	−333.46***	−372.79***	−400.91***	−339.31***	−332.54***	−353.12***

Note:*p<0.1; **p<0.05; ***p<0.01

Table 2: Unconditional correlation of variables returns

	CBDCUI	CBDCAI	UCRYPo	UCRYPr	ICEA	MSCI WBI	VIX	USEPU	FTSE AWI	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin	FTSE WGBI
CBDCUI	1																
CBDCAI	0.565***	1															
UCRY Policy	0.577***	0.354***	1														
UCRY Price	0.558***	0.355***	0.903***	1													
ICEA	0.412***	0.536***	0.384***	0.390***	1												
MSCI World Banks Index	−0.015*	−0.047*	−0.044*	−0.012*	0.038*	1											
VIX	0.063*	0.075*	0.119**	0.130**	0.032*	−0.558***	1										
USEPU	−0.081*	−0.158**	0.094*	0.034*	−0.063*	−0.069*	0.082*	1									
FTSE All World Index	−0.021*	−0.031*	−0.101**	−0.071*	−0.015*	0.840***	−0.715***	−0.079*	1								
EUR/USD	0.049*	0.001*	0.053*	0.077*	0.022***	0.209*	0.031*	0.007*	0.231***	1							
GBP/USD	0.056*	0.068*	−0.028*	−0.024*	0.044*	0.426***	−0.134*	−0.040*	0.439***	0.574***	1						
JPY/USD	0.104**	0.031*	0.058*	0.076*	−0.011*	−0.244***	0.293***	0.094**	−0.089*	0.427***	0.114**	1					
RUB/USD	0.005*	0.020*	−0.031*	−0.035*	0.043*	0.383***	−0.313***	−0.068*	0.462***	0.124**	0.198***	0.081*	1				
CNY/USD	0.036*	0.015*	0.058*	0.070*	0.040*	0.162**	0.002*	0.019*	0.210***	0.361***	0.364***	0.220***	0.121*	1			
Gold	0.093**	0.010*	−0.038*	−0.029*	−0.022*	−0.012*	0.041*	0.045*	0.207***	0.393***	0.331***	0.543***	0.163**	0.251***	1		
Bitcoin	0.023*	0.021*	−0.056*	−0.048*	−0.028*	0.152**	−0.159**	−0.045*	0.168**	0.025*	0.049*	0.033*	0.108**	−0.025*	0.056*	1	
FTSE WGBI	0.059*	0.005*	−0.024*	0.003*	−0.051*	−0.092*	0.161**	0.019*	0.117*	0.633***	0.392***	0.751***	0.137*	0.296***	0.656***	0.052*	1

Note:*p<0.1; **p<0.05; ***p<0.01

Table 3: FEVD of variable system due to the CBDCUI and CBDCAI shocks

Panel A: CBDCUI shocks FEVD

Period	CBDCUI	CBDCAI	UCRY Policy	UCRY Price	ICEA	MSCI WBI	VIX	USEPU	FTSE AWI	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin	FTSE WGBI
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0.873979956	0.07846738	0.001496663	0.001844651	0.024090811	0.000203611	3.78E-06	0.000297256	0.002699565	0.001495986	0.002360862	0.008366141	0.001219922	0.002065292	6.90E-05	0.001217338	0.0001218
3	0.854600173	0.090435837	0.0044316	0.002347661	0.024326694	0.000283899	8.66E-06	0.000667154	0.002807125	0.001732437	0.003082989	0.008752332	0.0019327	0.002545808	0.000218449	0.001641437	0.000185045
4	0.851570744	0.090391836	0.005939381	0.003102635	0.024409359	0.000311848	4.26E-05	0.000675592	0.002879157	0.001782057	0.003259399	0.008728048	0.00222783	0.002569148	0.000283798	0.00163837	0.000188191
5	0.850722621	0.090339539	0.006272954	0.003345428	0.024481338	0.00031184	0.000100753	0.000679373	0.002901356	0.001823814	0.003265762	0.008720344	0.002262951	0.002577728	0.000329472	0.001657245	0.000207482
6	0.85054351	0.090344359	0.006310054	0.003392455	0.024481396	0.000318058	0.000125011	0.000682702	0.002904905	0.001829038	0.003265105	0.008721943	0.002263478	0.002588781	0.000347521	0.001667503	0.000214181
7	0.850516634	0.090344031	0.00631196	0.003399798	0.024481251	0.000321154	0.000129175	0.000683255	0.002904969	0.001829043	0.003265041	0.008723218	0.002263503	0.002591291	0.000351549	0.001669164	0.000214964
8	0.850512456	0.090343641	0.006311976	0.003400975	0.024482317	0.000321782	0.000129516	0.000683285	0.002904967	0.001829091	0.003265032	0.008723483	0.002263616	0.002591526	0.000352081	0.001669266	0.00021499
9	0.85051166	0.090343553	0.006311971	0.003401208	0.024482722	0.000321859	0.000129533	0.000683284	0.002904984	0.001829126	0.003265029	0.008723509	0.002263648	0.002591533	0.000352125	0.001669266	0.00021499
10	0.850511507	0.090343536	0.006311971	0.003401264	0.024482806	0.000321868	0.000129535	0.000683284	0.002904989	0.001829133	0.003265028	0.00872351	0.002263654	0.002591533	0.000352127	0.001669265	0.000214991

Panel B: CBDCAI shocks FEVD

Period	CBDCAI	CBDCUI	UCRY Policy	UCRY Price	ICEA	MSCI WBI	VIX	USEPU	FTSE AWI	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin	FTSE WGBI
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0.948640469	0.003687947	0.005916024	0.003804595	0.009650608	0.003625086	0.005578543	0.000132395	0.000251176	0.001527289	8.55E-05	0.005151805	0.008413023	0.000204582	2.50E-05	0.003250982	5.50E-05
3	0.93994376	0.004924018	0.006824692	0.004104308	0.01231671	0.003841894	0.005642791	0.000695599	0.000248548	0.003194334	9.35E-05	0.005133189	0.00837129	0.000397517	2.62E-05	0.003491917	0.000749703
4	0.939048189	0.004966926	0.00683459	0.004099166	0.012392858	0.003847147	0.005672115	0.000841025	0.000250012	0.003275832	0.00012652	0.005137899	0.008375937	0.000570173	3.95E-05	0.003577699	0.000944383
5	0.938943976	0.004970073	0.006839745	0.004105207	0.012397154	0.003859491	0.005677105	0.00085391	0.000250156	0.003275506	0.000131054	0.00514611	0.008384987	0.000587528	4.24E-05	0.003581923	0.000953721
6	0.938922872	0.004974669	0.006842558	0.004107717	0.012402616	0.003860467	0.005677214	0.000854087	0.000250854	0.003276833	0.000131274	0.005146986	0.008386207	0.000587615	4.24E-05	0.003581955	0.000953723
7	0.938919355	0.004975524	0.006842717	0.004108076	0.012403182	0.003860455	0.005677733	0.000854093	0.000251029	0.003277069	0.000131274	0.005146964	0.008386226	0.000587763	4.25E-05	0.003582208	0.000953867
8	0.938918975	0.004975571	0.006842717	0.0041081	0.012403176	0.003860486	0.005677827	0.000854094	0.000251037	0.003277072	0.000131275	0.005146978	0.008386223	0.000587812	4.25E-05	0.003582257	0.00095389
9	0.938918921	0.004975571	0.006842726	0.004108101	0.012403192	0.003860492	0.005677829	0.000854094	0.000251037	0.003277073	0.000131275	0.005146982	0.008386225	0.000587815	4.25E-05	0.003582259	0.00095389
10	0.93891891	0.004975571	0.006842727	0.004108101	0.012403199	0.003860492	0.005677829	0.000854094	0.000251038	0.003277074	0.000131275	0.005146983	0.008386226	0.000587815	4.25E-05	0.003582259	0.00095389

Table 4: Estimate from the CBDCUI GJR-GARCH-DCC model

Panel A (1): estimates of AR(1)-GARCH(1,1) model	CBDCUI	UCRY Policy	CBDCUI	UCRY Price	CBDCUI	ICEA	CBDCUI	MSCI World Banks Index	CBDCUI	VIX	CBDCUI	USEPU	CBDCUI	FTSE All World Index
Const.(v)	0.0048*	0.0094*	0.0027*	0.0054**	0.0042*	0.0016**	−0.0030*	−0.9474***	0.0031*	21.2874***	−0.0233*	−3.4476***	−0.0041*	−0.3035**
	(0.8677)	(1.9222)	(0.9759)	(1.923)	(0.7985)	(0.7124)	(−0.8779)	(−2.3587)	(0.9243)	(6.5871)	(−0.2637)	(−3.0515)	(−0.9847)	(−2.0948)
ARCH (1)	0.1852***	0.1755***	0.1065***	0.1177***	0.1693***	0.1502***	−0.2033***	−0.0171*	0.2076***	0.000092*	−0.0582*	−0.0272*	−0.2012***	−0.0689**
	(2.9619)	(3.9854)	(3.6433)	(2.8688)	(3.0564)	(2.7573)	(−3.0502)	(−0.3867)	(3.3069)	(0.0288)	(−0.2764)	(−0.3032)	(−3.2419)	(−0.9216)
GARCH (1)	0.7899***	0.7420***	0.8221***	0.8768***	0.8065***	0.7643***	0.8212***	0.7078***	0.8190***	0.9592***	0.9782***	0.7743***	0.7922***	0.6856***
	(7.3271)	(15.6031)	(11.9939)	(12.0024)	(8.1141)	(4.7883)	(10.0654)	(7.3188)	(10.4843)	(2113.9894)	(14.7319)	(2.7395)	(9.0582)	(11.5944)
GJR	0.0477*	−0.1237***	−0.0590**	−0.3015***	0.0464*	−0.4310***	−0.0511*	0.3539**	−0.0552*	−0.1345***	0.2923*	0.2626*	0.0113*	0.3890**
	(0.2631)	(−0.8861)	(−0.4398)	(−2.3607)	(0.2397)	(−3.0971)	(−0.3541)	(1.9956)	(−0.3857)	(−4.5559)	(0.6655)	(1.7554)	(0.0722)	(2.1039)
Panel B (1): DCC estimates														
a	0.1409*		0.0581*		0.0205*		0.0135*		0.000001*		−0.000001*		0.000001*	
	(1.7584)		(0.2856)		(0.4701)		(0.6689)		(1.3003)		(0.000002)		(0.000002)	
b	0.4720***		0.8457*		0.6829*		−0.9566***		0.3009*		−0.9078***		−0.9495***	
	(2.9921)		(0.6339)		(0.5171)		(10.54563)		(0.3059)		(8.7714)		(9.0846)	
V joint distribution	4.5734***		4.3269***		4.0000**		6.0310***		5.2892*		5.6025***		5.3985***	
DCC probability	3.7189*		6.3556**		1.0551*		1.0238*		4.0604*		7.7064**		1.1945*	
Panel C (1): diagnostic test results														
McLeod-Li_P-value (1)	0.1804 > 0.05	0.7371 > 0.05	0.8329 > 0.05	0.9437 > 0.05	0.7147 > 0.05	0.9566 > 0.05	0.8518 > 0.05	0.3505 > 0.05	0.3342 > 0.05	0.8411 > 0.05	0.4664 > 0.05	0.9368 > 0.05	0.4012 > 0.05	0.3065 > 0.05
Jarque-Bera	2.6598	4.2656	1.4566	5.2438	7.9927	7.0328	1.5172	5.2357	1.5241	2.7787	1.1455	7.5602	1.0929	1.6572
Ljung-Box (1)	3.4232	6.1564	5.8232	5.3688	7.1347	3.8588	5.9821	9.4327	5.8329	3.5654	3.8446	0.7547	3.705	6.4882
Panel A (2): estimates of AR(1)-GARCH(1,1) model														
	CBDCUI	EUR/USD	CBDCUI	GBP/USD	CBDCUI	JPY/USD	CBDCUI	RUB/USD	CBDCUI	CNY/USD	CBDCUI	Gold	CBDCUI	Bitcoin
Const.(v)	0.0033**	0.0638*	0.0277*	0.3203***	0.0044*	0.0395*	0.0042*	0.1507*	0.0035*	0.0187***	0.0045*	0.3254*	0.0042*	0.8772***
	(0.8943)	(1.1504)	(0.3692)	(2.5007)	(0.8349)	(1.4056)	(0.8676)	(1.6818)	(0.9418)	(8.2973)	(0.8976)	(1.0609)	(7.7588×10^{-1})	(4.2911×10^{2})
ARCH (1)	0.0973***	0.0764**	0.0305*	0.0986*	0.1836***	0.1018***	0.1878***	0.0061*	0.1793***	0.000001*	0.1914***	0.1959*	0.1753***	0.0671***
	(3.3401)	(1.2547)	(0.1998)	(0.6922)	(3.0963)	(2.6788)	(2.8232)	(0.1549)	(3.1339)	(0.0081)	(2.9448)	(1.8621)	(2.5477)	(7.0613×10^{2})
GARCH (1)	0.8195***	0.8466***	0.8742***	0.4535***	0.7891***	0.8585***	0.7969***	0.8592***	0.8149***	0.9635***	0.7916***	0.7989***	0.8069***	0.8816***
	(10.1700)	(9.5910)	(20.7864)	(2.6901)	(7.4884)	(17.5126)	(7.5917)	(14.4046)	(9.5409)	(4508.0829)	(7.5012)	(6.9123)	(7.4144)	(1.6031×10^{5})
GJR	−0.0356*	0.0426*	0.3234*	0.5766***	0.0526*	0.0218*	0.0287*	0.1657*	−0.0106*	−0.0363**	0.0321*	−0.1466*	0.0337*	−0.0993***
	(−0.2468)	(0.7341)	(1.1818)	(2.8659)	(0.3128)	(0.3181)	(0.1861)	(1.7291)	(−0.0814)	(−2.0156)	(0.1921)	(−1.2593)	(2.1941×10^{-1})	(-5.9355×10^{2})
Panel B (2): DCC estimates														
a	0.000001*		0.0082*		0.0193*		0.000001*		0.000001*		0.000001*		0.0146*	
	(0.000001)		(0.5754)		(0.4099)		(0.000003)		(0.000002)		(0.000002)		(3.6812×10^{-1})	
b	0.9305***		0.9907***		0.8528**		0.9284***		0.9449***		0.9208***		0.7588***	
	(13.2015)		(25.2558)		(2.3202)		(20.9329)		(7.7331)		(8.1857)		(2.4951)	
V joint distribution	10.1227***		10.2529***		9.6711***		6.4888***		5.7948***		6.9853***		4.7952***	
DCC probability	1.0143*		2.7122**		3.5886**		11.1605*		3.6006*		8.4513*		3.9446**	
Panel C (2): diagnostic test results														
McLeod-Li_P-value (1)	0.1447 > 0.05	0.4721 > 0.05	0.8301 > 0.05	0.0635 > 0.05	0.1228 > 0.05	0.0965 > 0.05	0.0827 > 0.05	0.1093 > 0.05	0.8647 > 0.05	0.8837 > 0.05	0.1276 > 0.05	0.1079 > 0.05	0.1842 > 0.05	0.4940 > 0.05
Jarque-Bera	1.6233	1.257	1.0333	2.9808	1.0826	5.1906	0.1140	0.1298	0.1365	1.1039	1.2008	1.2107	1.3363	4.4916
Ljung-Box (1)	6.4495	2.6392	0.3964	2.5867	3.7461	0.1595	0.3829	4.1799	5.6423×10^{-5}	2.9604×10^{-5}	3.7328	1.0619	8.3839	4.844
Panel A (3): estimates of AR(1)-GARCH(1,1) model														
	CBDCUI	FTSE World Government Bond Index												
Const.(v)	0.0044*	0.3504*												
	(0.9101)	(1.8085)												
ARCH (1)	0.1866***	0.2630***												
	(3.0656)	(1.6748)												
GARCH (1)	0.7918***	0.2620*												
	(7.9789)	(0.7923)												
GJR	0.0412*	0.0903*												
	(0.2530)	(0.5546)												
Panel B (3): DCC estimates														
a	0.00048*													
	(0.0193)													
b	0.9103***													
	(3.3685)													
V joint distribution	7.8098***													
DCC probability	14.4181***													
Panel C (3): diagnostic test results														
McLeod-Li_P-value (1)	0.2685 > 0.05	0.1051 > 0.05												
Jarque-Bera	0.1101	0.7513												
Ljung-Box (1)	0.3724	0.7982												

Note:*p<0.1; **p<0.05; ***p<0.01.

Table 5: Estimate from the CBDCAI GJR-GARCH-DCC model

Panel A (1): estimates of AR(1)-GARCH(1,1) model														
	CBDCAI	UCRY Policy	CBDCAI	UCRY Price	CBDCAI	ICEA	CBDCAI	MSCI World Banks Index	CBDCAI	VIX	CBDCAI	USEPU	CBDCAI	FTSE All World Index
Const.(v)	0.0013*	0.0093*	0.0013*	0.0055*	0.0029*	0.0014*	−0.0017*	−0.7918**	0.0048*	3.2251***	−0.0163*	−3.2242***	−0.0016*	−0.3176*
	(1.9087)	(1.8120)	(1.5935)	(1.7201)	(1.0917)	(0.1321)	(−1.3207)	(−2.3191)	(0.0234)	(4.0131)	(−0.0859)	(−3.0266)	(−1.3712)	(−1.7539)
ARCH (1)	0.1288***	0.1548***	0.2231**	0.2113***	0.3094***	0.3906***	−0.5238***	−0.00059*	0.3263*	0.4947***	−0.4152*	−0.0231*	−0.4676***	−0.0886*
	(20.3448)	(3.7060)	(2.2679)	(3.3912)	(3.0216)	(3.0702)	(−2.8854)	(−0.0147)	(1.2392)	(3.4608)	(−1.4535)	(−0.2666)	(−2.6122)	(−0.9773)
GARCH (1)	0.7670***	0.7643***	0.7584***	0.7603***	0.5801***	0.5951*	0.7433***	0.7392***	0.9412***	0.4112***	0.9329***	0.5106***	0.7488***	0.6892***
	(20.0939)	(15.6031)	(20.6359)	(20.4433)	(5.2085)	(1.3843)	(19.9631)	(9.4292)	(27.2468)	(2.9420)	(30.0175)	(3.1421)	(14.3742)	(11.8936)
GJR	−0.5936***	−0.1434*	−0.5649**	−0.2231*	0.2189*	−0.3733*	−0.5361*	0.3787**	0.8831***	−0.1739*	1.0704***	0.2437*	−0.4348*	0.3278*
	(−25.0153)	(−1.7349)	(−2.2012)	(−1.6833)	(0.5515)	(−1.6126)	(−1.9006)	(2.2753)	(3.4623)	(−1.1930)	(3.4552)	(1.6828)	(−1.3385)	(1.7767)
Panel B (1): DCC estimates														
a	0.0467*		0.0732**		0.2322*		−0.000001*		0.000001*		−0.000001*		−0.000001*	
	(1.1837)		(2.2918)		(1.247532)		(0.0071)		(0.0285)		(0.0188)		(0.000006)	
b	0.8325***		0.8452***		0.000001*		−0.9042***		0.8930***		−0.8805***		−0.9217***	
	(4.0646)		(12.9301)		(0.0661)		(8.037396)		(3.6646)		(4.4211)		(10.1536)	
V joint distribution	6.4781***		4.6399***		3.4095***		4.3905***		6.0514***		9.3804***		8.9469***	
DCC probability	3.4955**		2.4237*		3.5039*		1.0565*		4.8980*		2.5105**		1.1679*	
Panel C (1): diagnostic test results														
McLeod-Li_P-value (1)	0.0504 > 0.05	0.9658 > 0.05	0.3437 > 0.05	0.8460 > 0.05	0.9071 > 0.05	0.9890 > 0.05	0.0577 > 0.05	0.2983 > 0.05	0.3903 > 0.05	0.9679 > 0.05	0.0686 > 0.05	0.8301 > 0.05	0.0091 > 0.05	0.1772 > 0.05
Jarque-Bera	0.1516	0.7987	2.0341	1.4345	0.9985	0.8086	1.0186	3.1173	0.7015	0.2709	0.9995	0.6371	0.7386	0.1802
Ljung-Box (1)	3.9336	4.7332	3.3573	4.1482	1.272	1.757	3.7117	3.8769	3.9879	1.815	0.3342	0.3082	0.3646	0.6259
Panel A (2): estimates of AR(1)-GARCH(1,1) model														
	CBDCAI	EUR/USD	CBDCAI	GBP/USD	CBDCAI	JPY/USD	CBDCAI	RUB/USD	CBDCAI	CNY/USD	CBDCAI	Gold	CBDCAI	Bitcoin
Const.(v)	0.0014*	0.0583*	0.0391*	0.3431**	0.0026*	0.0453*	0.0025*	0.1532*	0.0702*	0.0862***	0.0024*	0.2289*	0.0026*	0.9453***
	(1.2329)	(1.1390)	(0.2276)	(2.4791)	(0.9869)	(1.3657)	(0.9726)	(1.6683)	(3.9045×10^{-1})	(1.9338×10^{1})	(0.7893)	(0.7083)	(9.8787×10^{-1})	(1.0553×10^{2})
ARCH (1)	0.1119**	0.0757*	0.1789*	0.1084*	0.2883*	0.1014***	0.2829***	0.0074*	0.0261*	0.0216*	0.3085*	0.1709*	0.2891***	0.0555***
	(2.0227)	(1.4179)	(1.3574)	(0.7446)	(2.3987)	(2.6579)	(2.8084)	(0.1718)	(1.2410)	(9.7291×10^{-1})	(1.7366)	(1.3358)	(2.9371)	(2.9794×10^{2})
GARCH (1)	0.7551***	0.8549***	0.5393***	0.4265**	0.6581***	0.8581***	0.6490***	0.8516***	0.9295***	0.9259***	0.6657***	0.8301***	0.6658***	0.9003***
	(19.3449)	(10.7939)	(28.3969)	(2.3780)	(5.2388)	(15.0118)	(6.0123)	(13.2041)	(2.5945×10^{1})	(8.6684×10^{4})	(3.7912)	(6.1930)	(6.8731)	(1.4925×10^{4})
GJR	−0.5359*	0.0391*	0.8743***	0.5663***	0.1051*	0.0125*	0.1341*	0.1782*	0.8785***	−0.0861***	0.0496*	−0.1145*	0.0881*	−0.0935***
	(−1.9671)	(0.6952)	(4.1450)	(2.8378)	(0.2088)	(0.1796)	(0.3082)	(1.7084)	(4.0370)	(-2.7836×10^{1})	(0.0744)	(−0.8677)	(1.9239×10^{-1})	(-2.8211×10^{2})
Panel B (2): DCC estimates														
a	−0.000001*		0.000001*		−0.0095*		−0.0053*		−0.000002*		−0.000001*		−0.000001*	
	(0.000005)		(0.0359)		(0.8089)		(0.3851)		(9.1802×10^{-1})		(0.0178)		(0.0017)	
b	0.9244***		0.9369***		0.9799***		0.9062***		0.0808*		0.9058***		0.8068*	
	(9.5477)		(15.2649)		(27.4912)		(6.4818)		(5.0000×10^{-6})		(14.5571)		(0.2973)	
V joint distribution	5.1638***		5.4233***		4.5620***		4.3547***		4.3371***		4.4663***		6.6174***	
DCC probability	1.7567*		9.5174**		2.4577*		3.6097*		1.3021*		12.5413***		7.6275***	
Panel C (2): diagnostic test results														
McLeod-Li_P-value (1)	0.0622 > 0.05	0.3031 > 0.05	0.4749 > 0.05	0.4201 > 0.05	0.2259 > 0.05	0.1195 > 0.05	0.2915 > 0.05	0.1001 > 0.05	0.1697 > 0.05	0.8625	0.0580 > 0.05	0.0148 > 0.05	0.2631 > 0.05	0.4449 > 0.05
Jarque-Bera	0.1469	1.159	0.6080	0.2933	0.7164	0.4967	0.7329	1.3315	0.5617	0.9983	0.6816	0.1011	0.2034	0.9439
Ljung-Box (1)	3.9887	2.7279	5.9796	2.7408	3.3871	1.5461	0.3284	0.8889	0.0656	0.0192	0.3929	0.8558	3.3573	1.8929
Panel A (3): estimates of AR(1)-GARCH(1,1) model														
	CBDCAI	FTSE World Government Bond Index												
Const.(v)	0.0025*	0.4097* * *												
	(0.9742)	(2.6198)												
ARCH (1)	0.2828***	0.2558***												
	(2.6113)	(1.7066)												
GARCH (1)	0.6428***	0.1870*												
	(4.9617)	(0.7399)												
GJR	0.1467*	0.0796*												
	(0.3212)	(0.4851)												
Panel B (3): DCC estimates														
a	0.0105*													
	(0.2962)													
b	0.6995**													
	(1.3355)													
V joint distribution	4.5908***													
DCC probability	1.0167*													
Panel C (3): diagnostic test results														
McLeod-Li_P-value (1)	0.1633 > 0.05	0.0948 > 0.05												
Jarque-Bera	0.5184	0.7725												
Ljung-Box (1)	0.4844	0.8587												

Note:*p<0.1; **p<0.05; ***p<0.01.

Table 6: Uncertainty risk and volatility structure risk

	CBDC risk (CCR)		*CBDC risk (RV)*		*CBDC risk (R)*	
	CBDCUI	CBDCAI	CBDCUI	CBDCAI	CBDCUI	CBDCAI
	(1)	(2)	(3)	(4)	(5)	(6)
UCRY Policy	0.7003***	0.6334***	0.6094***	0.7315***	0.4520***	0.1773***
	(0.0529)	(0.0995)	(0.1293)	(0.1524)	0.0056***	−0.0073***
UCRY Price	0.6555***	0.6366***	0.5949***	0.6594***	0.4483***	0.1788***
	(0.0526)	(0.0963)	(0.1495)	(0.1837)	0.0316***	0.0096***
ICEA	0.3969***	0.7964***	0.7685***	0.7884***	0.4022***	3.747e-01***
	(0.0461)	(0.0681)	(0.1187)	(0.1384)	0.1423***	−4.096e-02***
MSCI WBI	−0.0985*	−0.5429*	−0.1455*	−0.6099*	−0.0132*	−0.0112*
	(0.3749)	(0.6023)	(0.6335)	(0.7801)	−0.0206*	−0.0130*
VIX	0.1592**	0.1531**	0.0473*	0.0943*	0.0004*	0.0004*
	(0.0538)	(0.0543)	(0.1177)	(0.1159)	0.0055*	0.0022*
USEPU	−0.2394**	−0.2406***	−3.2239*	−0.2895*	−0.0002*	−0.0011*
	(0.0528)	(0.0522)	(0.675)	(0.1164)	−0.0025*	−0.0012*
FTSE AWI	−0.0995**	−0.2132*	−0.0649*	−0.2601*	−0.0048*	−0.0031*
	(0.2567)	(0.4129)	(0.4390)	(0.5405)	−0.0005*	−0.0019*
EUR/USD	0.1238*	0.0216*	0.4218*	0.4018***	0.0423*	0.0018*
	(0.1323)	(0.2124)	(0.1013)	(0.1022)	0.0425*	0.0040*
GBP/USD	0.1800*	0.3351*	0.5098*	0.7419*	0.0201*	0.0121*
	(0.1607)	(0.2573)	(0.2653)	(0.3295)	0.0021*	0.0042*
JPY/USD	0.2524*	0.1240*	0.2555*	0.2731*	0.0203*	0.0044*
	(0.1316)	(0.2120)	(0.1116)	(0.1115)	0.0503*	0.0080*
RUB/USD	0.0281*	0.1526*	0.3585*	0.3608*	0.0196*	0.00682*
	(0.2429)	(0.3894)	(0.1012)	(0.1007)	0.0312*	−0.00665*
CNY/USD	0.0411*	0.0305*	0.0291*	0.1519*	0.0830*	0.0022*
	(0.0664)	(0.1064)	(0.1002)	(0.1229)	0.2111*	0.0187*
Gold	0.3893*	0.0704*	0.1704*	0.2555*	0.0022*	0.0028*
	(0.2329)	(0.3747)	(0.3618)	(0.1133)	0.0488*	0.0087*
Bitcoin	0.4789*	0.6257*	5.6714**	5.428*	0.0141***	0.0041*
	(1.2138)	(1.9506)	(1.8814)	(2.334)	0.0259***	0.0069*
FTSE WGBI	0.1049*	0.0174*	0.4623***	0.4603***	0.11161*	0.02549*
	(0.0968)	(0.1554)	(0.0484)	(0.0485)	−0.02526*	−0.01177*
CRIX	1.387**	0.793**	24.0391*	7.449*	0.01487*	0.0051*
	(1.196)	(1.792)	(1.4447)	(1.8108)	−0.01480*	−0.0029*

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

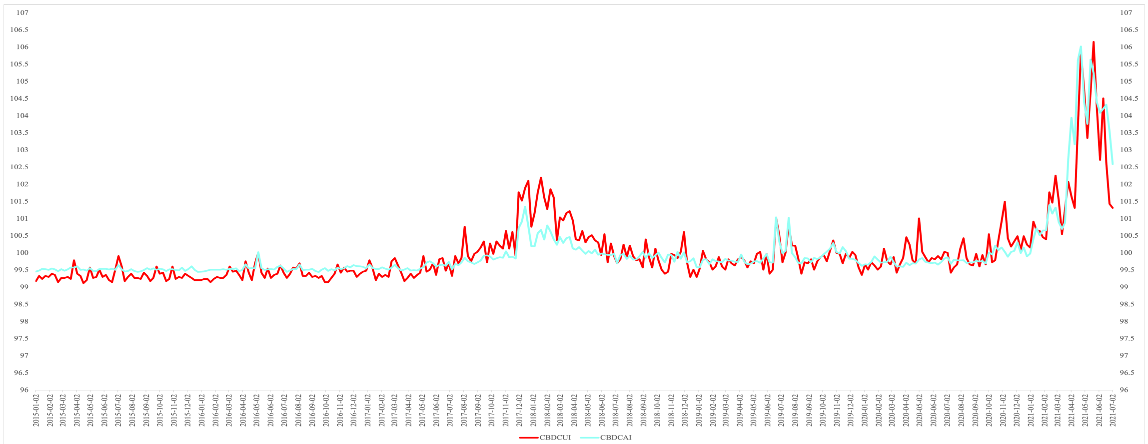


Figure 3: CBDCUI and CBDCAI

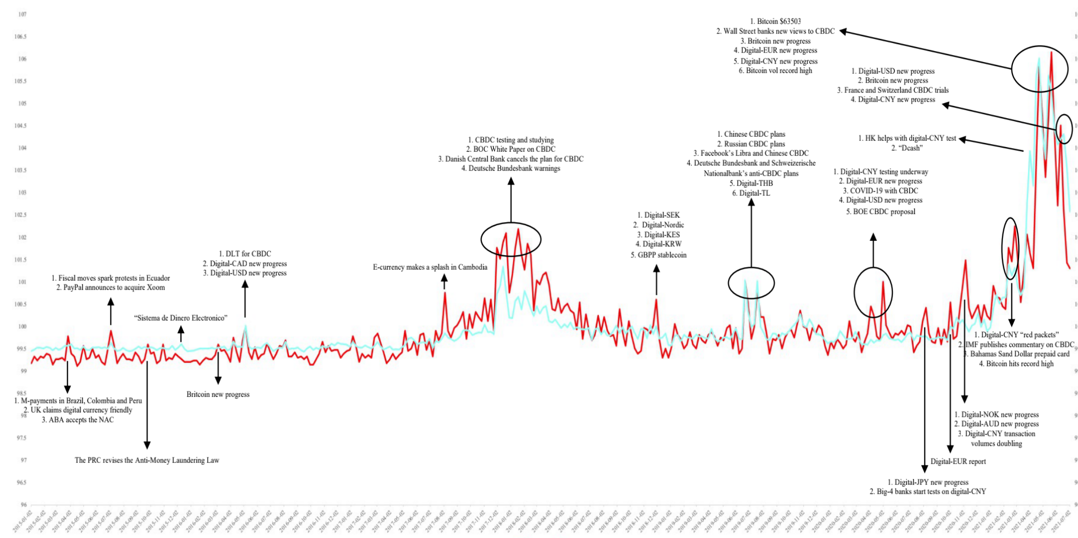
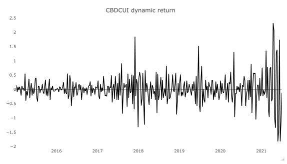
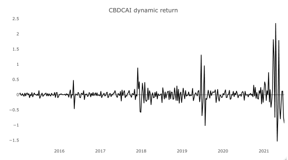


Figure 4: CBDC annotated indices

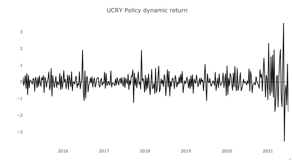
Figure 5: The dynamics of variables returns



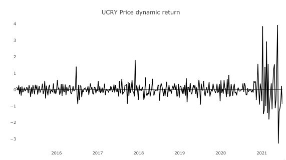
(a) CBDCUI



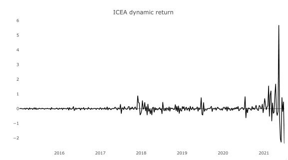
(b) CBDCAI



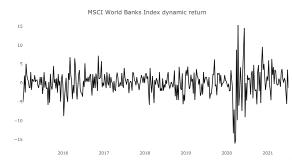
(c) UCRY Policy



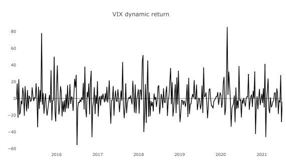
(d) UCRY Price



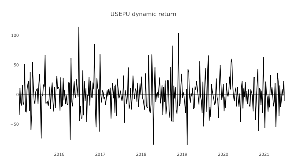
(e) ICEA



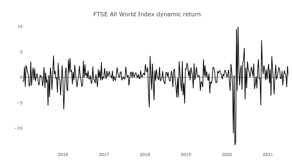
(f) MSCI World Banks Index



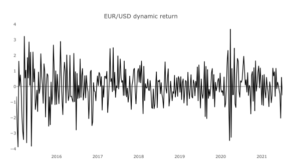
(g) VIX



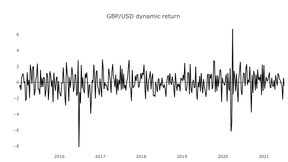
(h) USEPU



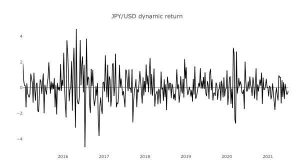
(i) FTSE All World Index



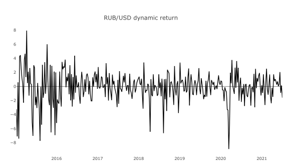
(j) EUR/USD



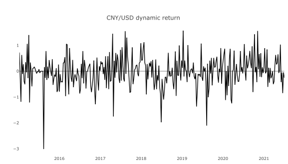
(k) GBP/USD



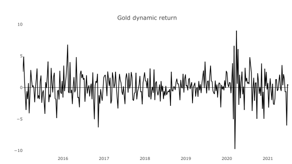
(l) JPY/USD



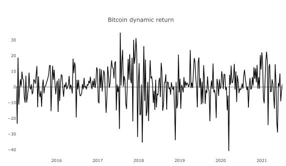
(m) RUB/USD



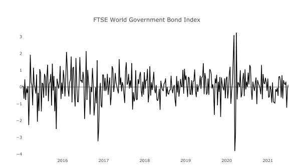
(n) CNY/USD



(o) Gold

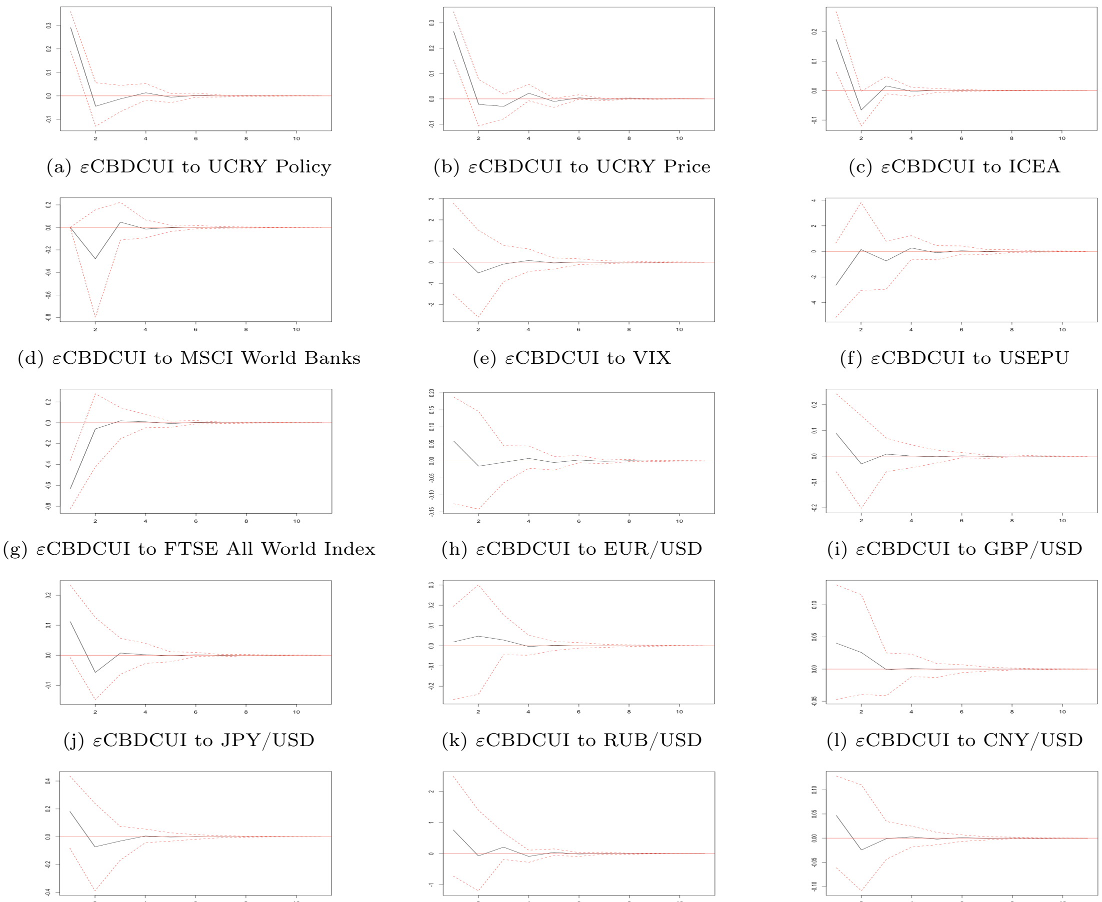


(p) Bitcoin



(q) FTSE World Government Bond Index

Figure 6: CBDCUI shocks to other variables



(a) εCBDCUI to UCRY Policy

(b) εCBDCUI to UCRY Price

(c) εCBDCUI to ICEA

(d) εCBDCUI to MSCI World Banks

(e) εCBDCUI to VIX

(f) εCBDCUI to USEPU

(g) εCBDCUI to FTSE All World Index

(h) εCBDCUI to EUR/USD

(i) εCBDCUI to GBP/USD

(j) εCBDCUI to JPY/USD

(k) εCBDCUI to RUB/USD

(l) εCBDCUI to CNY/USD

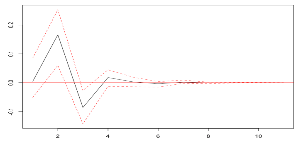
(m) εCBDCUI to Gold

(n) εCBDCUI to Bitcoin

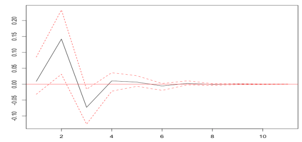
(o) εCBDCUI to FTSE WGBI

Notes: 99% Bootstrapping, 1000 runs.

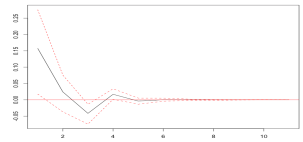
Figure 7: CBDCAI shocks to other variables



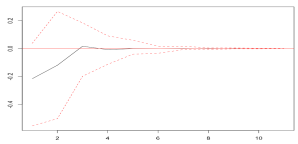
(a) εCBDCAI to UCRY Policy



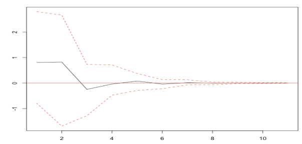
(b) εCBDCAI to UCRY Price



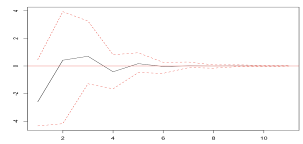
(c) εCBDCAI to ICEA



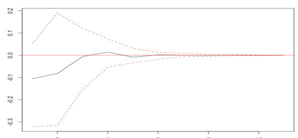
(d) εCBDCAI to MSCI World Banks



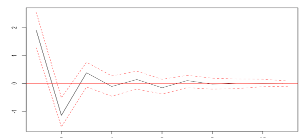
(e) εCBDCAI to VIX



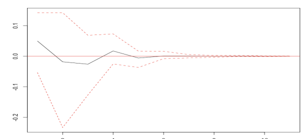
(f) εCBDCAI to USEPU



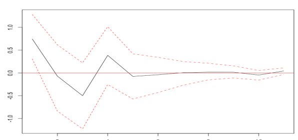
(g) εCBDCAI to FTSE All World Index



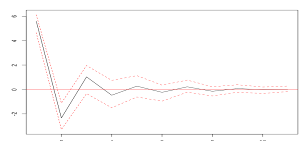
(h) εCBDCAI to EUR/USD



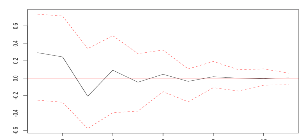
(i) εCBDCAI to GBP/USD



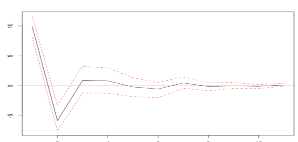
(j) εCBDCAI to JPY/USD



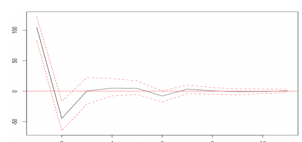
(k) εCBDCAI to RUB/USD



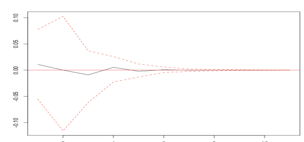
(l) εCBDCAI to CNY/USD



(m) εCBDCAI to Gold



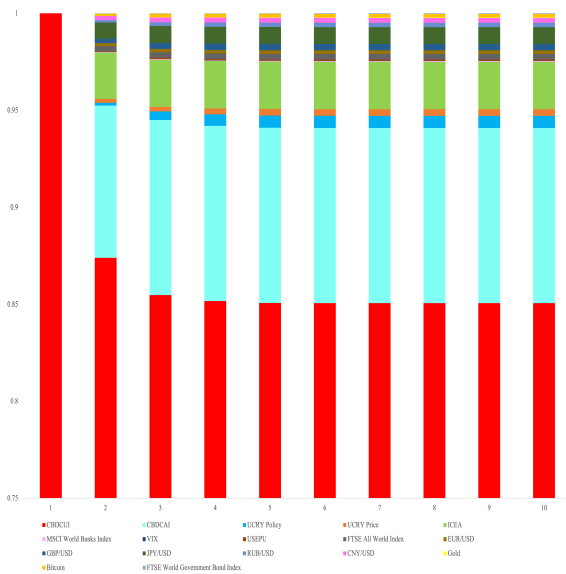
(n) εCBDCAI to Bitcoin



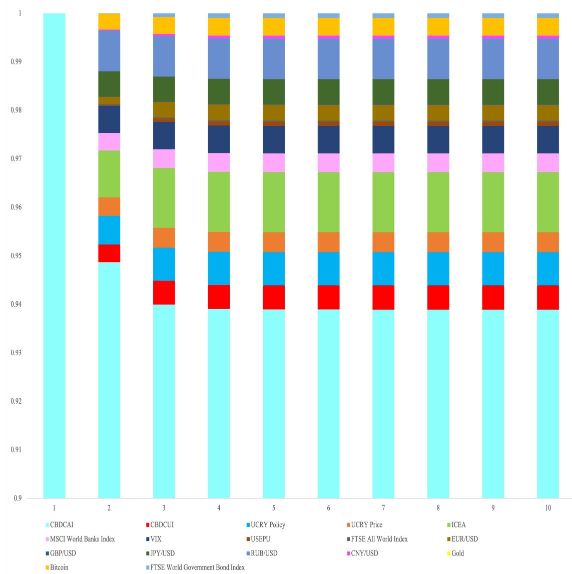
(o) εCBDCAI to FTSE WGBI

Notes: 99% Bootstrapping, 1000 runs.

Figure 8: CBDC indices FEVD



(a) CBDCUI FEVD



(b) CBDCAI FEVD

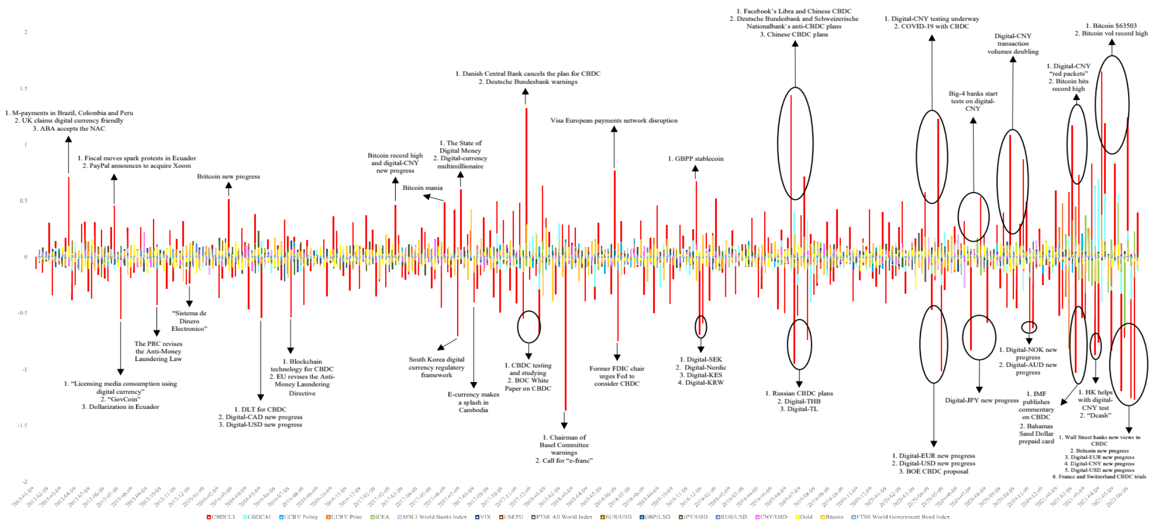


Figure 9: CBDCUI historical decomposition

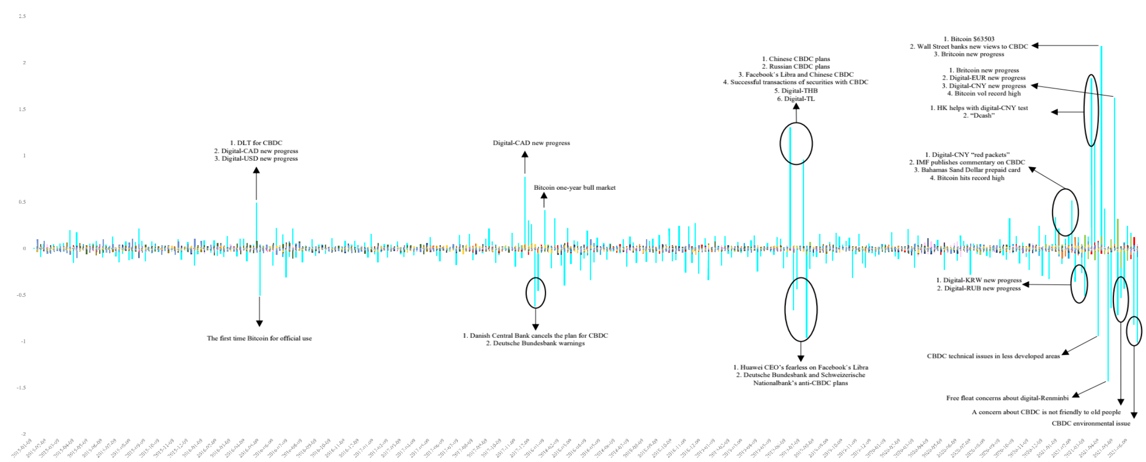
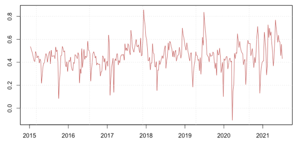
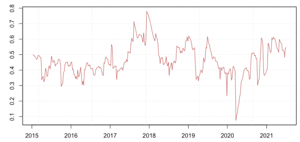


Figure 10: CBDCAI historical decomposition

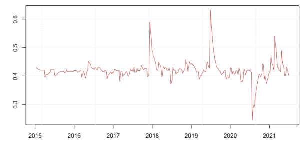
Figure 11: CBDCUI dynamic condition correlation



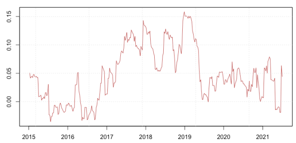
(a) UCRY Policy



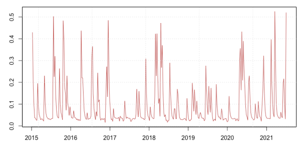
(b) UCRY Price



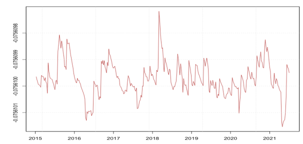
(c) ICEA



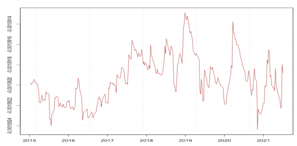
(d) MSCI World Banks Index



(e) VIX



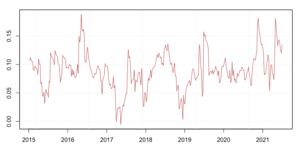
(f) USEPU



(g) FTSE All World Index

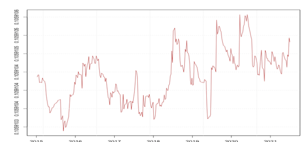
(h) EUR/USD

(i) GBP/USD

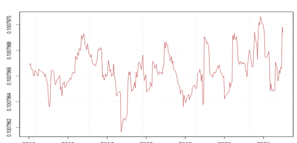


(j) JPY/USD

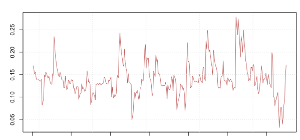
(k) RUB/USD



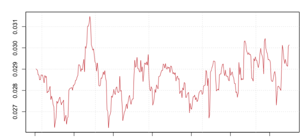
(l) CNY/USD



(m) Gold

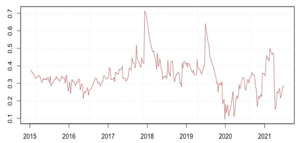


(n) Bitcoin

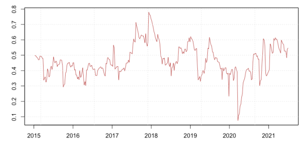


(o) FTSE World Government Bond Index

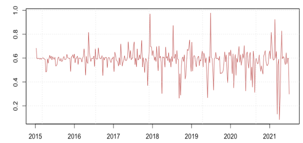
Figure 12: CBDCAI dynamic condition correlation



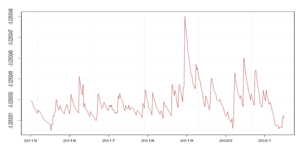
(a) UCRY Policy



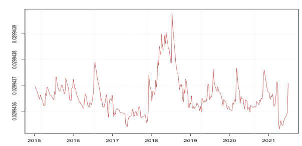
(b) UCRY Price



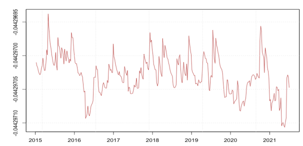
(c) ICEA



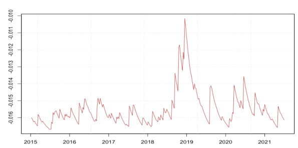
(d) MSCI World Banks Index



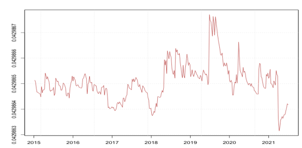
(e) VIX



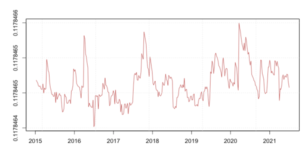
(f) USEPU



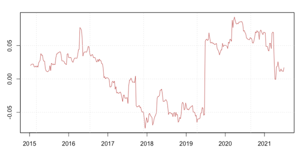
(g) FTSE All World Index



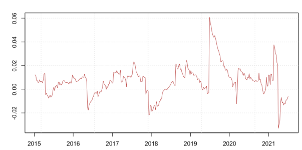
(h) EUR/USD



(i) GBP/USD



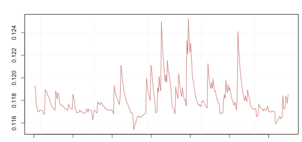
(j) JPY/USD



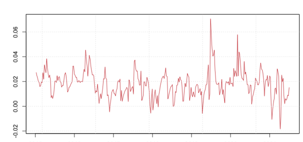
(k) RUB/USD

(l) CNY/USD

(m) Gold



(n) Bitcoin



(o) FTSE World Government Bond Index

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Appendix

Appendix A - Big events in annotated indices

- **23/03/2015 - 29/03/2015 (2015-03-27)**

  1). M-payments in Brazil, Colombia and Peru (23/03/2015).

  2). ABA accepts the NAC (23/03/2015). *Explanation: American Bankers Association accepts the National Atan Coin.*

  3). UK claims digital currency friendly (24/03/2015).

- **29/06/2015 - 05/07/2015 (2015-07-03)**

  1). Fiscal moves spark protests in Ecuador (01/07/2015). *Explanation: A new Electronic Currency System (ECS), the nationwide central bank digital currency progress have sent out danger signals to investors.*

  2). PayPal announces to acquire Xoom (02/07/2015).

- **13/07/2015 - 19/07/2015 (2015-07-17)**

  1). "GovCoin." (15/07/2015) *Explanation: UK intellectual property office grants trade mark "GovCoin" to GovCoin Limited.*

  2). "Licensing media consumption using digital currency." (16/07/2015) *Explanation: The United States Patent and Trademark office has granted a patent to WILDTANGENT, INC, titled as "Licensing media consumption using digital currency" .*

  3). Dollarization in Ecuador (17/07/2015) *Explanation: the dollarization of Ecuador process could come to an end within months, weeks or even days. Ecuador's government is trying to creating digital-currency to avoid to print cash. The use of digital-currency transactions has been imposed on private banks.*

- **28/09/2015 - 04/10/2015 (2015-10-02)**

  1). The PRC revises the Anti-Money Laundering Law (01/10/2015). *Explanation: Digital currency makes the Anti-Money Laundering enforcement gets tough.*

- **07/12/2015 - 13/12/2015 (2015-12-11)**

  1). "Sistema de Dinero Electronico" formally available (05/12/2015). *Explanation: Electronic money system was launched in Ecuador, making Ecuador becomes the first country with a state-run electronic payment system.*

- **29/02/2016 - 20/03/2016 (2016-03-04 to 2016-03-18)**

  1). Britcoin new progress (03/03/2016). *Explanation: Ben Broadent (Bank of England)'s speech about CBDC. In details, what is a CBDC? And what are the economic implications of introducing the CBDC.*

- **02/05/2016 - 08/05/2016 (2016-05-06)**

  1). DLT for CBDC (02/05/2016). *Explanation: Distributed ledger technology for CBDC.*

  2). Digital-CAD new progress & Digital-USD new progress (06/05/2016). *Explanation: Bank of Canada and the U.S. Treasury propose a project about launching dollars in digital.*

- **09/05/2016 - 15/05/2016 (2016-05-13)**

  1). First time Bitcoin for official use. *Explanation: Swiss town of Zug is planning to allow its residents to use Bitcoin to pay for municipal services.*

- **11/07/2016 - 17/07/2016 (2016-07-15)**

  1). EU revises the Anti-Money Laundering Directive (12/07/2016). *Explanation: EU brings virtual currency exchanges and wallet providers under the EU Anti-Money Laundering Directive.*

  2). Blockchain technology for CBDC (15/07/2016). *Explanation: The UK Parliament issued the news about the Economic Affairs Committee takes evidence from the Bank of England, Imperial College London, Z/Yen Group limited, among others for distributed ledger or blockchain technology for CBDC.*

- **20/02/2017 - 26/02/2017 (2017-02-24)**

  1). Bitcoin record high and digital-CNY new progress (25/02/2017). *Explanation: Bitcoin surges to record high ($1200) and China is developing digital-CNY.*

- **05/06/2017 - 11/06/2017 (2017-06-09)**

  1). Bitcoin mania (05/06/2017).

- **03/07/2017 - 09/07/2017 (2017-07-07)**

  1). South Korean digital currency regulatory framework (03/07/2017). *Explanation: Lawmakers of South Korea are preparing a set of bills to give cryptocurrencies legal grounds.*

- **10/07/2017 - 16/07/2017 (2017-07-14)**

1). The State of Digital Money (11/07/2017). *Explanation: Los Angeles' first global fintech and blockchain event.*

2). Digital-currency multimillionaire (16/07/2017). *Explanation: A secret cryptocurrency trader in Amyster turned $55 million of paper wealth into $283 million in just over a month.*

- **31/07/2017 - 06/08/2017 (2017-08-04)**

1). E-currency makes a splash in Cambodia (01/08/2017). *Explanation: the ASC group begins to use Aseancoin in the retail, e-commerce, tourism and import-export sectors all around Association of Southeast Asian Nations.*

- **27/11/2017 - 24/12/2017 (2017-12-01 to 2017-12-22)**

1). Digital-CAD new progress (2017-12-01). *Explanation: a research paper from the BOC points out that the Bank of Canada is considering the merits to creating the CBDC.*

2). Bank of Canada White Paper on CBDC (15/12/2017).

3). Danish Central Bank cancels the plan for CBDC (22/12/2017).

4). CBDC testing and studying (23/12/2017). *Explanation: a digital currency sponsored by the U.S. government and managed by the Federal Reserve is been studying. China's Central Bank is testing a digital currency. Bank of England, Bank of Canada, European Central Bank, Bank of Russia, Bank of Japan, Bank of Australia, among others are studying the Central Bank Digital Currency.*

4). Deutsche Bundesbank warnings (24/12/2017). *Explanation: Deutsche Bundesbank warns that there will be no CBDC in Euro-zone.*

- **08/01/2018 - 14/01/2018 (2018-01-12)**

1). Bitcoin one-year bull market. *Explanation: In January 2017, the price of Bitcoin was still under $1000, and 12 months later, the price of Bitcoin has risen to around $19600, increased by nearly 20 times.*

- **19/02/2018 - 25/02/2018 (2018-02-23)**

1). Chairman of Basel Committee warnings (19/02/2018). *Explanation: Stefan Ingves, the Chairman of Basel Committee warned banks to stay away from cryptocurrency.*

2). Call for "e-franc" (25/02/2018). *Explanation: the chairman of Switzerland's stock exchange urges that Switzerland should launch a cryptocurrency version of the Swiss franc.*

- **04/06/2018 - 10/06/2018 (2018-06-08)**

  1). Visa European payments network disruption (07/06/2018).

- **11/06/2018 - 17/06/2018 (2018-06-15)**

  1). Former FDIC Chair urges Fed to consider CBDC (11/06/2018). *Explanation: Sheila Blair, former chair of the US Federal Deposit Insurance Corporation (FDIC) urges the Federal Reserve to consider a CBDC.*

- **26/11/2018 - 02/12/2018 (2018-11-30)**

  1). Digital-SEK (26/11/2018). *Explanation: Sweden's Central Bank plans to launch CBDC to against cash usage declines.*

  2). Digital-KES (27/11/2018). *Explanation: Central Bank of Kenya is thinking to issue CBDC of Kenyan shilling.*

  3). GBPP Stablecoin (27/11/2018). *Explanation: the first digital pound sterling is mined, minted and used. London Block Exchange works with Alphapoint to create the first digital pound sterling, and the GBPP stablecoin is pegged to the value of pound sterling.*

  4). Digital-KRW (29/11/2018). *Explanation: Bank of Korea gave a presentation about CBDC on an international symposium held by the Financial Supervisory Service.*

  5). Digital-Nordic (30/11/2018). *Explanation: Nordic central banks are considering the CBDC because of the cyber security of digital payment.*

- **17/06/2019 - 21/07/2019 (2019-06-21 to 2019-07-19)**

  1). Chinese CBDC plans (10/06/2019). *Explanation: China's Central Bank publish the lastest plans for Chinese CBDC plan, and the cabinet gives approval to central bank to launch CBDC.*

  2). Russian CBDC plan (18/06/2019). *Explanation: The Central Bank of the Russian Federation is exploring its options when it begins to launching the CBDC.*

  3). Successful transactions of securities with CBDC (21/06/2019). *Explanation: Banque Internationale Luxembourg, LuxCSD and Seba Bank successfully tested use of CBDC for securities transactions.*

  4). Digital-CNY new progress (21/06/2019). *Explanation: Over 3,000 ATMs in Beijing now support CBDC withdrawals.*

5). Digital-THB (25/06/2019). *Explanation: Bank of Thailand is developing its own CBDC (Can not beat them, join them, can not beat the cryptocurrency, launch own digital currency).*

6). Deutsche Bundesbank and Schweizerische Nationalbank anti-CBDC plans (05/07/2019).

7). Facebook's Libra and Chinese CBDC (08/07/2019). *Explanation: the cryptocurrency plan of Facebook have forced China's Central Bank into stepping up research into launching Chinese CBDC.*

8). Digital-TL (11/07/2019). *Explanation: The Turkish Central Bank is planing to launch CBDC).*

- **22/07/2019 - 28/07/2019 (2019-07-26)**

1). Huawei CEO's fearless on Facebook's Libra. *Explanation: Ren, Zhengfei, the CEO of Huawei, has dismissed concerns that Facebook's Libra could dominate the world at the expense of China and its tech firms.*

- **30/03/2020 - 03/05/2020 (2020-04-03 to 2020-05-01)**

1). Digital-USD new progress (30/03/2020). *Explanation: (1) The Digital-Dollar project names 22 new advisory group members. And a partnership between Accenture and the Digital Dollar Foundation aims to promote establishment of a U.S. Central Bank Digital Currency. (2) Digital Dollar Project White Paper.*

2). BOE CBDC proposal (30/03/2020). *Explanation: Bank of England released a 57-page discussion paper about the opportunities, challenges and design of CBDC.*

3). Covid-19 with CBDC (08/04/2020). *COVID-19 has accelerated a move toward CBDC).*

4). Digital-CNY testing underway (21/04/2020). *Explanation: China has started testing the government-backed digital legal tender, CBDC wallet App available in Suzhou, Xiongan, Shenzhen and Chengdu these four cities..*

5). Digital-EUR new progress (02/05/2020). *Explanation: (1). The Banque de France plans to find cooperators to process the experiments in the use of a digital euro in interbank settlements. (2). The Dutch Central Bank intends to actively participate in any related policy discussions around a European CBDC in the future.*

- **03/08/2020 - 09/08/2020 (2020-08-07)**

1). Digital-JPY new progress (07/08/2020). *Explanation: The Bank of Japan has set up a new department to further promote digital Yen progress.*

2). Big-4 banks start tests on digital-CNY (07/08/2020). *Explanation: The Bank of China, China Construction Bank, Industrial and Commetrical Bank of China and Agricultural Bank of China, these big four state-owned commercial banks had started large-scale internal testing of digital-yuan..*

- **28/09/2020 - 04/10/2020 (2020-10-02)**

1). Digital-EUR report (02/10/2020). *Explanation: this report examines the issuance of the digital euro from the perspective of the Euro-system.*

- **02/11/2020 - 08/11/2020 (2020-11-06)**

1). Digital-CNY transaction volumes doubling (03/11/2020). *Explanation: China's CBDC testings has so far been smooth, with transaction volumes doubling over October, and the transactions hit $300 million.*

2). Digital-AUD new progress (04/11/2020). *Explanation: The National Australia Bank and the Commonwealth Bank of Australia will join forces to work with the Reserve Bank of Australia to develop CBDC. And Reserve Bank of Australia considering on Ethereum based digital currency.*

3). Digital-NOK new progress (06/11/2020). *Explanation: Norges Bank's presentation about CBDC and real-time digital payments.*

- **08/02/2021 - 28/02/2021 (2021-02-21 to 2021-02-26)**

1). Bahamas Sand Dollar Prepaid card (17/02/2021). *Explanation: Collaboration of MasterCard, Central Bank of the Bahamas and Island Pay issue the Bahamas Sand Dollar prepaid card, and can give people additional option to use the Bahamas Sand Dollar CBDC. This is the world's first CBDC-linked card.*

2). Digital-CNY "red packets" (18/02/2021). *Explanation: "Red packet" e-currency trials in Beijing, it is a catalyzator to hasten Asia e-currency race.*

3). IMF publishes commentary on CBDC (20/02/2021).

4). Bitcoin hits record high (21/02/2021). *Explanation: Bitcoin hit record high price $57,539.95 on 21/02/2021.*

- **08/03/2021 - 14/03/2021 (2021-03-12)**

1). Digital-KRW new progress. *Explanation: South Korea-based Shinhan Bank has said that it has built a platform for a potential South Korean CBDC.*

2). Digital-RUB new progress. *Explanation: Russian Central Bank Chairperson Elvira Nabiulline said on Association of Russian Banks that Central Bank of Russia will test digital ruble platform on 01/01/2022.*

- **29/03/2021 - 04/04/2021 (2021-04-02)**

1). Hong Kong helps with digital-CNY test (02/04/2021). *Explanation: The People's Bank of China and the Hong Kong Monetary Authority have begun "technical testing" for cross-border use of digital-RMB.*

2). Dcash (31/03/2021). *Explanation: 'Dcash', launched by the international fintech company, Bitt, in partnership with the Eastern Caribbean Central Bank (ECCB), became the world's first retail CBDC to be publicly issued within a formal currency union.*

- **05/04/2021 - 11/04/2021 (2021-04-09)**

1). CBDC technical issues in less developed areas.

- **19/04/2021 - 25/04/2021 (2021-04-23)**

1). Bitcoin $63503 (13/04/2021). *Explanation: Bitcoin hits the historical recording high $63503.*

2). Britcoin new progress (19/04/2021). *Explanation: The Bank of England and the Treasury will set up a new taskforce and joint together to explore the objectives of establishing a CBDC.*

3). Wall Street banks new views to CBDC (20/04/2021). *Explanation: Wall Street banks is warming up to the idea that CBDC as the next big financial disruptor.*

- **26/04/2021 - 02/05/2021 (2021-04-30)**

1). Free float concerns about digital-Renminbi. *Explanation: Some scholars worry about that RMB is not fully convertible, so taking a head position using RMB might be difficult.*

- **10/05/2021 - 23/05/2021 (2021-05-14 & 2021-05-21)**

1). Digital-CNY new progress (11/05/2021). *Explanation: (1). Digital-CNY trials has for the first time included a private bank, Zhejiang E-Commerce Co Ltd. (2). MYbanks joins Digital-RMB platform (12/05/2021)..*

2). Britcoin new progress (14/05/2021). *Explanation: Bank of England officially announces that Britcoin CBDC launch is 'probable'..*

3). Bitcoin vol record high (19/05/2021). *Explanation: Bitcoin transaction volumes hit the record high 1.26358E+11.*

4). Digital-EUR new progress (21/05/2021). *Explanation: The European Central Bank takes a new rush toward the digital-euro. In the coming weeks, The European Central Bank will announce whether it will issue a "digital euro" within the next four years. And many experts believe it will.*

5). CBDC is not friendly for old people (21/05/2021).

- **07/06/2021 - 13/06/2021 (2021-06-11)**

1). Britcoin new progress (07/06/2021). *Explanation: Bank of England publishes discussion paper on the CBDC-Britcoin.*

2). Digital-CNY new progress (08/06/2021). *Explanation: The second stage experiments of digital-RMB in Hong Kong starts, and Hong Kong is to test connecting digital-RMB with its domestic payment network.*

3). Digital-USD new progress (09/06/2021). *Explanation: Senate Banking, Housing and Urban Affairs Subcommittee on Economic Policy Hearing about Building a stronger financial system: opportunities of a CBDC.*

4). France and Switzerland CBDC trials (11/06/2021). *Explanation: two Central Banks of European in France and Switzerland have launched a joint CBDC cross-border trial.*

- **28/06/2021 - 04/07/2021 (2021-07-02)**

1). Digital currency environmental issue.

Appendix B - Table

Table 7: The negative dynamic correlation periods in the CBDC indices and financial variables

CBDCUI & Financial variables	Time period	CBDCAI & Financial variables	Time period
CBDCUI & GBP/USD	2015-07-03 to 2016-03-25	**CBDCAI & JPY/USD**	2017-01-13 to 2017-07-28
	2016-04-15 to 2017-09-15		2017-08-11 to 2017-09-08
	2019-06-14 to 2019-06-21		2017-09-22 to 2019-06-21
CBDCUI & MSCI WBI	2015-07-10 to 2016-03-04		2021-04-09 to 2021-04-16
	2016-04-29 to 2016-09-30	**CBDCAI & RUB/USD**	2015-04-17 to 2015-06-26
	2019-08-09		2015-07-10
	2020-12-11		2016-05-13 to 2016-09-23
	2021-04-30 to 2021-06-18		2016-11-04
CBDCUI & JPY/USD	2017-03-31		2017-11-10 to 2018-04-27
	2017-05-12		2018-05-18 to 2018-05-25
CBDCUI & UCRYPo	2020-03-20		2019-04-26
			2019-06-07 to 2019-06-21
			2020-03-06 to 2020-03-13
			2020-11-06 to 2020-12-04
			2020-04-02 to 2021-07-02
		CBDCAI & UCRYPr	2020-03-20
			2020-10-23
		CBDCAI & FTSE WGBI	2016-11-25
			2017-12-15
			2018-01-05
			2018-02-23
			2018-07-13
			2019-04-12
			2021-01-22 to 2021-01-29
			2021-04-09 to 2021-04-16

Table 8: SVAR optimal lag calculation and diagnostic test results

Panel A (1): SVAR optimal lag calculation results						
	lag max=13	lag max=12	lag max=11	lag max=10	lag max=9	lag max=8
AIC(n)	13	12	11	1	1	1
HQ(n)	1	1	1	1	1	1
SC(n)	1	1	1	1	1	1
FPE(n)	1	1	1	1	1	1
Panel A (2): SVAR optimal lag calculation results						
	lag max=7	lag max=6	lag max=5	lag max=4	lag max=3	lag max=2
AIC(n)	1	1	1	1	1	1
HQ(n)	1	1	1	1	1	1
SC(n)	1	1	1	1	1	1
FPE(n)	1	1	1	1	1	1
Panel A (3): SVAR optimal lag calculation results						
	lag max=1					
AIC(n)	1					
HQ(n)	1					
SC(n)	1					
FPE(n)	1					
Panel B (1): SVAR diagnostic test results						
	Autocorrelation	Heteroscedasticity	Normal distribution			
Portmanteau test (asymptotic)	60.798					
ARCH (multivariate)		26329				
Jarque-Bera test			57233			
Skewness (multivariate)			1459			
Kurtosis (multivariate)			55774			
Panel B (2): SVAR diagnostic test results						
	CBDCUI	**CBDCAI**	**UCRY Policy**	**UCRY Price**	**ICEA**	**MSCI World Bank Index**
ARIMA(p,d,q)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)
	VIX	**USEPU**	**FTSE All World Index**	**EUR/USD**	**GBP/USD**	**JPY/USD**
ARIMA(p,d,q)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)
	RUB/USD	**CNY/USD**	**Gold**	**Bitcoin**	**FTSE World Bank Index**	
ARIMA(p,d,q)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)	ARIMA(0,0,0)	

Notes: *p<0.1; **p<0.05; ***p<0.01.
Portmanteau test (asymptotic) tests for autocorrelation. ARCH (multivariate) examines the heteroscedasticity.
Jarque-Bera test, skewness (multivariate) and kurtosis (multivariate) investigates the normal distribution of the residuals.
ARIMA test detects the stationary property of the residuals.

Table 9: SVAR stationary test results

Panel A: lag = 1									
0.43339025	0.40103622	0.35739782	0.35739782	0.33678955	0.33678955	0.28040093	0.28040093	0.20960593	0.20960593
0.18534036	0.17590883	0.17590883	0.11187534	0.11187534	0.09602493	0.09602493			
Panel B: lag = 11									
1.0626308	1.0626308	1.0477280	1.0477280	0.9967779	0.9967779	0.9966858	0.9966858	0.9934265	0.9934265
0.9855301	0.9855301	0.9855177	0.9855177	0.9823259	0.9823259	0.9816757	0.9816757	0.9773306	0.9773306
0.9662268	0.9662268	0.9650655	0.9650655	0.9617585	0.9617585	0.9589159	0.9589159	0.9566369	0.9566369
0.9566146	0.9566146	0.9551385	0.9551385	0.9540229	0.9540229	0.9527343	0.9527343	0.9512787	0.9512787
0.9511361	0.9511361	0.9494771	0.9494771	0.9475306	0.9475306	0.9454159	0.9454159	0.9416422	0.9416422
0.9388607	0.9382693	0.9382693	0.9355511	0.9355511	0.9354032	0.9354032	0.9345113	0.9345113	0.9345017
0.9345017	0.9343431	0.9343431	0.9324365	0.9324365	0.9318819	0.9318819	0.9318705	0.9318705	0.9316112
0.9316112	0.9271749	0.9271749	0.9257596	0.9257596	0.9252973	0.9252973	0.9248595	0.9248595	0.9230105
0.9230105	0.9214961	0.9214961	0.9210916	0.9210916	0.9206875	0.9206875	0.9195477	0.9195477	0.9190009
0.9190009	0.9183191	0.9183191	0.9176708	0.9176708	0.9171782	0.9171782	0.9163064	0.9163064	0.9159635
0.9159635	0.9152966	0.9152966	0.9149638	0.9149638	0.9145136	0.9145136	0.9131954	0.9131954	0.9119801
0.9119801	0.9113989	0.9113989	0.9108363	0.9108363	0.9087380	0.9087380	0.9072714	0.9072714	0.9051846
0.9051846	0.9032133	0.9032133	0.9016401	0.9016401	0.8983769	0.8983769	0.8971456	0.8971456	0.8967732
0.8967732	0.8944260	0.8944260	0.8920923	0.8920923	0.8907755	0.8907755	0.8881035	0.8861473	0.8803714
0.8803714	0.8790250	0.8790250	0.8714777	0.8714777	0.8681207	0.8681207	0.8623371	0.8623371	0.8569263
0.8569263	0.8542542	0.8542542	0.8530951	0.8445511	0.8445511	0.8363759	0.8363759	0.8337704	0.8337704
0.8219375	0.8219375	0.8190283	0.8190283	0.8174261	0.8174261	0.8056541	0.8056541	0.7863461	0.7863461
0.7771035	0.7771035	0.7592535	0.7592535	0.6916011	0.6916011	0.6909626	0.6909626	0.6269823	0.6269823
0.6018190	0.6018190	0.5366766	0.4604166	0.4604166	0.2650298	0.2650298			
Panel B: lag = 12									
1.0692721	1.0692721	1.0479791	1.0479791	1.0127661	1.0127661	1.0071390	1.0071390	0.9994340	0.9994340
0.9972357	0.9972357	0.9917537	0.9917537	0.9880777	0.9880777	0.9854073	0.9854073	0.9831043	0.9831043
0.9733102	0.9733102	0.9730303	0.9730303	0.9699824	0.9699824	0.9692017	0.9692017	0.9690887	0.9690887
0.9690575	0.9690575	0.9665838	0.9665838	0.9663045	0.9663045	0.9646449	0.9646449	0.9642430	0.9642430
0.9622168	0.9622168	0.9584299	0.9584299	0.9557876	0.9557876	0.9549043	0.9549043	0.9534340	0.9534340
0.9521581	0.9521581	0.9515492	0.9515492	0.9514725	0.9514725	0.9489688	0.9489688	0.9483764	0.9483764
0.9478416	0.9478416	0.9478208	0.9478208	0.9476316	0.9476316	0.9471321	0.9471321	0.9454357	0.9454357
0.9451474	0.9451474	0.9443143	0.9443143	0.9440328	0.9440328	0.9424881	0.9424881	0.9423777	0.9423777
0.9421368	0.9421368	0.9406066	0.9406066	0.9392456	0.9392456	0.9369675	0.9369675	0.9366846	0.9366846
0.9365431	0.9365431	0.9355346	0.9355346	0.9345062	0.9343123	0.9343123	0.9332733	0.9332733	0.9325329
0.9325329	0.9297648	0.9297648	0.9251661	0.9251661	0.9242737	0.9242737	0.9235828	0.9235828	0.9226230
0.9226230	0.9217563	0.9217563	0.9212035	0.9212035	0.9210401	0.9210401	0.9178952	0.9178952	0.9176051
0.9176051	0.9175646	0.9175646	0.9094094	0.9094094	0.9076621	0.9076621	0.9067346	0.9067346	0.9062449
0.9062449	0.9058348	0.9058348	0.9058276	0.9058276	0.9020215	0.9020215	0.9007341	0.9007341	0.8995925
0.8995925	0.8975175	0.8975175	0.8967814	0.8967814	0.8962136	0.8962136	0.8932653	0.8932653	0.8919239
0.8919239	0.8912290	0.8912290	0.8907098	0.8907098	0.8892957	0.8892957	0.8862659	0.8862659	0.8852197
0.8852197	0.8838815	0.8838815	0.8829566	0.8829566	0.8780702	0.8780702	0.8778946	0.8778946	0.8730989
0.8730989	0.8655382	0.8407097	0.8407097	0.8372654	0.8372654	0.8335346	0.8335346	0.8318033	0.8318033
0.8191835	0.8191835	0.8185088	0.8185088	0.8157835	0.8157835	0.8120816	0.8120816	0.8102164	0.8102164
0.7532686	0.7532686	0.6590117	0.6590117	0.5936493	0.4370524	0.3808283	0.3808283	0.3403902	0.3403902
0.3324544	0.3324544	0.3042311	0.0880327						
Panel B: lag = 13									
1.08079651	1.08079651	1.05277286	1.05277286	1.02574642	1.02574642	1.02201397	1.02201397	1.00918356	1.00918356
1.00830681	1.00830681	1.00258545	1.00258545	0.99993082	0.99993082	0.99828206	0.99828206	0.99690832	0.99690832
0.98795723	0.98795723	0.98606582	0.98606582	0.98211813	0.98211813	0.98129502	0.98129502	0.97589092	0.97589092
0.97271447	0.97271447	0.97121679	0.97121679	0.97015381	0.97015381	0.96799468	0.96799468	0.96776894	0.96776894
0.96773548	0.96773548	0.96743883	0.96743883	0.96452746	0.96452746	0.96444397	0.96444397	0.96363322	0.96363322
0.96312747	0.96312747	0.96121910	0.96121910	0.96033324	0.96033324	0.96003727	0.96003727	0.95877533	0.95877533
0.95845444	0.95845444	0.95654931	0.95654931	0.95632280	0.95632280	0.95520970	0.95520970	0.95481234	0.95481234
0.95455164	0.95455164	0.95427086	0.95427086	0.95332853	0.95332853	0.95318110	0.95318110	0.95115687	0.95115687
0.95038997	0.95038997	0.95018586	0.95018586	0.94980732	0.94980732	0.94827701	0.94827701	0.94712449	0.94712449
0.94690987	0.94690987	0.94677823	0.94677823	0.94572472	0.94535278	0.94535278	0.94514437	0.94514437	0.94444826
0.94444826	0.94326054	0.94326054	0.94312437	0.94312437	0.94278238	0.94278238	0.94092301	0.94092301	0.94005740
0.94005740	0.93962665	0.93962665	0.93939154	0.93939154	0.93880128	0.93880128	0.93801427	0.93801427	0.93662231
0.93662231	0.93611079	0.93611079	0.93544416	0.93544416	0.93444024	0.93444024	0.93379336	0.93379336	0.93318596
0.93318596	0.93071486	0.93071486	0.92996406	0.92996406	0.92835493	0.92835493	0.92833365	0.92833365	0.92798452
0.92798452	0.92694052	0.92694052	0.92601931	0.92601931	0.92587238	0.92587238	0.92426223	0.92426223	0.92020826
0.92020826	0.91823800	0.91823800	0.91711539	0.91711539	0.91706001	0.91706001	0.91251199	0.91251199	0.91121012
0.91121012	0.90866618	0.90866618	0.90745772	0.90745772	0.90349062	0.90349062	0.89728675	0.89728675	0.89681609
0.89681609	0.89317347	0.89317347	0.89128595	0.89128595	0.89051934	0.89051934	0.88674028	0.88674028	0.88648894
0.88648894	0.88343736	0.88343736	0.88117329	0.88117329	0.87504033	0.87504033	0.86991612	0.86991612	0.85184079
0.85184079	0.84638441	0.84638441	0.83586632	0.83586632	0.83544710	0.83544710	0.80825590	0.80825590	0.80284388
0.80284388	0.80016600	0.80016600	0.79805552	0.79805552	0.77706191	0.77706191	0.77674594	0.77674594	0.74719710
0.71065329	0.71065329	0.69123325	0.69123325	0.61819128	0.61819128	0.50233710	0.50233710	0.41145848	0.41145848
0.08803656									

Table 10: SVAR optimal lag calculation criteria (1)

Lag max = 13								
	1	2	3	4	5	6	7	8
AIC(n)	7.1483	7.2868	7.3456	7.3988	7.6133	7.8013	7.6772	7.5974
HQ(n)	8.5668	10.0449	11.4434	12.8363	14.3905	15.9182	17.1337	18.3936
SC(n)	10.7028	14.1985	17.6144	21.0247	24.5962	28.1413	31.3743	34.6516
FPE(n)	1274.3396	1481.6475	1623.4400	1824.8461	2516.1362	3575.3178	3997.2043	5118.9926
	9	10	11	12	13			
AIC(n)	7.8459	7.2113	6.8053	6.1426	4.6754			
HQ(n)	19.9818	20.6869	21.6205	22.2975	22.1699			
SC(n)	38.2572	40.9798	43.9308	46.6252	48.5151			
FPE(n)	10213.6519	9747.7599	14078.3623	20025.1389	17571.2484			
Lag max = 12								
	1	2	3	4	5	6	7	8
AIC(n)	7.1295	7.2636	7.3239	7.3738	7.5856	7.7731	7.6630	7.6003
HQ(n)	8.5446	10.0153	11.4120	12.7985	14.3468	15.8708	17.0973	18.3710
SC(n)	10.6761	14.1597	17.5695	20.9690	24.5303	28.0674	31.3068	34.5936
FPE(n)	1250.5989	1447.5312	1587.8582	1778.0184	2442.3489	3463.4084	3917.6939	5085.9929
	9	10	11	12				
AIC(n)	7.8547	7.2109	6.8094	6.1419				
HQ(n)	19.9619	20.6548	21.5897	22.2588				
SC(n)	38.1976	40.9034	43.8513	46.5335				
FPE(n)	10160.5989	9545.5491	13722.3073	19179.2235				
Lag max = 11								
	1	2	3	4	5	6	7	8
AIC(n)	7.1202	7.2562	7.3154	7.3618	7.5735	7.7614	7.6629	7.5799
HQ(n)	8.5320	10.0013	11.3939	12.7736	14.3188	15.8400	17.0750	18.3253
SC(n)	10.6588	14.1368	17.5380	20.9264	24.4802	28.0100	31.2537	34.5126
FPE(n)	1239.0616	1436.6499	1573.8272	1754.9352	2408.3007	3410.7337	3894.4533	4937.6258
	9	10	11					
AIC(n)	7.8201	7.1819	6.7757					
HQ(n)	19.8989	20.5941	21.5211					
SC(n)	38.0949	40.7987	43.7344					
FPE(n)	9680.1171	9086.1669	12883.9164					
Lag max = 10								
AIC(n)	7.1103	7.2374	7.2909	7.3403	7.5548	7.7365	7.6481	7.5851
HQ(n)	8.5188	9.9761	11.3598	12.7395	14.2843	15.7962	17.0380	18.3053
SC(n)	10.6409	14.1026	17.4906	20.8745	24.4236	27.9398	31.1859	34.4575
FPE(n)	1226.8064	1409.7365	1535.0295	1715.8552	2358.9883	3315.0542	3814.5749	4918.7681
	9	10						
AIC(n)	7.8100	7.1913						
HQ(n)	19.8605	20.5719						
SC(n)	38.0169	40.7327						
FPE(n)	9452.8966	8988.9134						
Lag max = 9								
	1	2	3	4	5	6	7	8
AIC(n)	7.1083	7.2279	7.2833	7.3294	7.5469	7.7481	7.6661	7.5898
HQ(n)	8.5135	9.9602	11.3427	12.7159	14.2607	15.7889	17.0340	18.2849
SC(n)	10.6311	14.0778	17.4602	20.8335	24.3781	27.9063	31.1514	34.4022
FPE(n)	1224.3200	1396.1812	1522.7426	1695.6430	2335.8997	3342.0060	3861.5644	4897.6894
	9							
AIC(n)	7.8302							
HQ(n)	19.8524							
SC(n)	37.9697							
FPE(n)	9516.3813							
Lag max = 8								
	1	2	3	4	5	6	7	8
AIC(n)	7.1263	7.2406	7.2942	7.3391	7.5512	7.7395	7.6402	7.5422
HQ(n)	8.5282	9.9665	11.3441	12.7131	14.2492	15.7615	16.9863	18.2123
SC(n)	10.6413	14.0752	17.4485	20.8131	24.3448	27.8528	31.0732	34.2948
FPE(n)	1246.5799	1413.8811	1538.8156	1710.5023	2341.1906	3301.9935	3741.6611	4628.6341

Table 11: SVAR optimal lag calculation criteria (2)

Lag max = 7							
	1	2	3	4	5	6	7
AIC(n)	7.1174	7.2207	7.2779	7.3303	7.5359	7.7039	7.6142
HQ(n)	8.5160	9.9402	11.3184	12.6917	14.2183	15.7073	16.9385
SC(n)	10.6245	14.0401	17.4096	20.7743	24.2923	27.7726	30.9952
FPE(n)	1235.4159	1385.7890	1513.3511	1693.7885	2301.3159	3175.9308	3625.3067
Lag max = 6							
	1	2	3	4	5	6	
AIC(n)	7.0872	7.1855	7.2552	7.3035	7.5259	7.6684	
HQ(n)	8.4826	9.8987	11.2863	12.6525	14.1929	15.6531	
SC(n)	10.5866	13.9898	17.3645	20.7177	24.2452	27.6926	
FPE(n)	1198.7548	1337.6903	1478.8132	1647.4476	2274.2655	3054.6347	
Lag max = 5							
	1	2	3	4	5		
AIC(n)	7.0726	7.1835	7.2731	7.3072	7.5216		
HQ(n)	8.4647	9.8905	11.2949	12.6439	14.1731		
SC(n)	10.5642	13.9728	17.3601	20.6919	24.2039		
FPE(n)	1181.2554	1334.9066	1504.8965	1652.1029	2260.0905		
Lag max = 4							
	1	2	3	4			
AIC(n)	7.0619	7.1669	7.2506	7.2969			
HQ(n)	8.4509	9.8676	11.2632	12.6212			
SC(n)	10.5459	13.9412	17.3154	20.6520			
FPE(n)	1168.8174	1312.7693	1470.9322	1633.5009			
Lag max = 3							
	1	2	3				
AIC(n)	7.0666	7.1589	7.2407				
HQ(n)	8.4523	9.8535	11.2439				
SC(n)	10.5429	13.9185	17.2833				
FPE(n)	1174.1801	1302.2939	1455.8068				
Lag max = 2							
	1	2					
AIC(n)	7.1052	7.2215					
HQ(n)	8.4878	9.9098					
SC(n)	10.5739	13.9661					
FPE(n)	1220.3938	1386.0852					
Lag max = 1							
	1						
AIC(n)	7.1722						
HQ(n)	8.5516						
SC(n)	10.6333						
FPE(n)	1304.9024						

Table 12: ARCH test results

Panel A (1): ARCH LM test results								
	CBDCUI	CBDCAI	UCRYPo	UCRYPr	ICEA	MSCI WBI	VIX	USEPU
ARCH (1)	101.1***	12.825***	76.698***	57.917***	42.304***	85.994***	35.552***	28.52***
ARCH (2)	103.79***	81.565***	77.213***	57.828***	58.616***	94.616***	39.163***	34.37***
ARCH (3)	111.78***	101***	84.319***	60.496***	132.08***	108.81***	59.307***	44.657***
Panel A (2): ARCH LM test results								
	FTSE.AWI	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin
ARCH (1)	65.298***	27.788***	24.996***	17.653***	7.7402***	24.148***	8.6592***	5.8392***
ARCH (2)	91.569***	30.267***	30.663***	23.779***	24.116***	44.83***	54.364***	16.479***
ARCH (3)	94.209***	32.741***	31.96***	28.84***	25.117***	45.14***	55.625***	18.058***
Panel A (3): ARCH LM test results								
	FTSE.WGBI							
ARCH (1)	72.181***							
ARCH (2)	76.453***							
ARCH (3)	81.246***							

Notes: *p<0.1; **p<0.05; ***p<0.01.

Table 13: Discrimination among the GARCH-type models (1)

Panel A (1): GARCH-type models for CBDCUI							
		SGARCH	EGARCH	IGARCH	APARCH	Discrimination	GJRGARCH
UCRYPo							
	AIC	1.5625	1.5623	1.5625	1.5635	>	1.5622
	BIC	1.8895	1.8228	1.8569	1.8356	>	1.8218
	SC	1.5554	1.5538	1.5567	1.5635	>	1.5538
	HQ	1.6670	1.6658	1.6680	1.6659	>	1.6657
UCRYPr							
	AIC	1.1016	1.1052	1.0899	1.1096	>	1.0892
	BIC	1.4138	1.4099	1.4195	1.4069	>	1.3939
	SC	1.0917	1.0937	1.0814	1.0864	>	1.0777
	HQ	1.2141	1.2266	1.2133	1.2119	>	1.2106
ICEA							
	AIC	−0.73181	−0.73243	−0.74415	−0.74499	>	−0.74563
	BIC	−0.44065	−0.43771	−0.43457	−0.41769	>	−0.44090
	SC	−0.74172	−0.74392	−0.75260	−0.75614	>	−0.75711
	HQ	−0.61937	−0.61610	−0.61071	−0.61456	>	−0.62419
MSCI World Banks Index							
	AIC	5.5973	5.5836	5.5937	5.5988	>	5.5821
	BIC	5.8895	5.8884	5.8953	5.8961	>	5.8868
	SC	5.5874	5.5722	5.5852	5.5757	>	5.5706
	HQ	5.7098	5.7051	5.7071	5.7093	>	5.7035
VIX							
	AIC	9.1167	9.1088	9.1050	9.1030	>	9.1017
	BIC	9.4088	9.4135	9.4146	9.4081	>	9.4065
	SC	9.1068	9.0973	9.0965	9.0976	>	9.0902
	HQ	9.2291	9.2302	9.2284	9.2312	>	9.2232
USEPU							
	AIC	10.080	10.070	10.059	10.418	>	10.057
	BIC	10.339	10.307	10.373	10.700	>	10.316
	SC	10.071	10.063	10.053	10.408	>	10.048
	HQ	10.183	10.165	10.164	10.531	>	10.160
FTSE All World Index							
	AIC	4.7216	4.7103	4.7097	5.0249	>	4.6941
	BIC	4.9586	4.9699	4.9641	5.3071	>	4.9537
	SC	4.7145	4.7018	4.7038	5.0150	>	4.6857
	HQ	4.8160	4.8137	4.7976	5.1374	>	4.7951
EUR/USD							
	AIC	3.7989	3.7997	3.7917	3.7840	>	3.7368
	BIC	4.1036	4.1045	4.0738	4.0641	>	4.0436
	SC	3.7874	3.7883	3.7818	3.7756	>	3.7236
	HQ	3.9203	3.9212	3.9041	3.8875	>	3.8672
GBP/USD							
	AIC	4.1801	4.1801	4.1597	4.1990	>	4.1348
	BIC	4.4396	4.3967	4.4170	4.4396	>	4.4134
	SC	4.1716	4.1716	4.1526	4.1932	>	4.1249
	HQ	4.2835	4.2541	4.2835	4.2845	>	4.2472
JPY/USD							
	AIC	3.7297	3.7429	3.7429	3.7283	>	3.7202
	BIC	3.9667	4.0058	4.0024	3.9774	>	3.9346
	SC	3.7226	3.7378	3.7344	3.7273	>	3.7143
	HQ	3.8241	3.8497	3.8463	3.8314	>	3.8056
RUB/USD							
	AIC	4.8659	4.8638	4.8652	5.2130	>	4.8580
	BIC	5.1029	5.1234	5.1248	5.4951	>	5.0724
	SC	4.8588	4.8553	4.8568	5.2030	>	4.8521
	HQ	4.9603	4.9672	4.9687	5.3254	>	4.9434
CNY/USD							
	AIC	2.4001	2.4045	2.3880	2.4119	>	2.3705
	BIC	2.6823	2.7092	2.7166	2.6978	>	2.6476
	SC	2.3902	2.3930	2.3795	2.4004	>	2.3574
	HQ	2.5125	2.5259	2.5333	2.5010	>	2.4914

Table 14: Discrimination among the GARCH-type models (2)

Panel A (2): GARCH-type models for CBDCUI							
		SGARCH	EGARCH	IGARCH	APARCH	Discrimination	GJRGARCH
Gold							
	AIC	4.9124	4.9219	4.9234	4.915	>	4.9023
	BIC	5.1494	5.1815	5.1830	5.1577	>	5.1168
	SC	4.9053	4.9135	4.9150	4.9076	>	4.8965
	HQ	5.0069	5.0254	5.0269	5.0118	>	4.9878
Bitcoin							
	AIC	8.1124	8.1246	8.1004	8.1069	>	8.0901
	BIC	8.3494	8.3842	8.3497	8.3495	>	8.3148
	SC	8.1053	8.1162	8.0945	8.0994	>	8.0817
	HQ	8.2068	8.2280	8.1936	8.2036	>	8.1858
FTSE World Government Bond Index							
	AIC	3.1561	3.1586	3.1544	3.1528	>	3.1422
	BIC	3.3792	3.4182	3.4157	3.3955	>	3.3688
	SC	3.1477	3.1502	3.1485	3.1454	>	3.1351
	HQ	3.2398	3.2621	3.2596	3.2496	>	3.2367

Table 15: Discrimination among the GARCH-type models (3)

Panel B (1): GARCH-type models for CBDCAI							
		SGARCH	EGARCH	IGARCH	APARCH	Discrimination	GJRGARCH
UCRYPo							
	AIC	−0.1957	−0.1434	−0.1625	−0.1789	>	−0.2139
	BIC	0.0865	0.1613	0.1422	0.1089	>	0.0456
	SC	−0.2056	−0.1549	−0.1740	−0.1892	>	−0.2224
	HQ	−0.0832	−0.0219	−0.0411	−0.0642	>	−0.1105
UCRYPr							
	AIC	−0.5828	−0.5238	−0.5522	−0.5454	>	−0.5948
	BIC	−0.3007	−0.2191	−0.2474	−0.2181	>	−0.3352
	SC	−0.5927	−0.5353	−0.5636	−0.5585	>	−0.6032
	HQ	−0.4704	−0.4023	−0.4307	−0.4149	>	−0.4913
ICEA							
	AIC	−2.8596	−2.8584	−2.8470	228.89	>	−2.8721
	BIC	−2.5774	−2.5537	−2.5422	229.22	>	−2.6126
	SC	−2.8695	−2.8699	−2.8584	228.88	>	−2.8806
	HQ	−2.7471	−2.7370	−2.7255	229.03	>	−2.7687
MSCI World Banks Index							
	AIC	3.8452	3.8606	3.8267	3.8303	>	3.8145
	BIC	4.0822	4.0741	4.1202	4.1125	>	4.0411
	SC	3.8381	3.8521	3.8209	3.8204	>	3.8060
	HQ	3.9397	3.9179	3.9640	3.9428	>	3.9122
VIX							
	AIC	7.2956	7.3110	7.2957	7.3339	>	7.2835
	BIC	7.5326	7.5706	7.5553	7.6160	>	7.4980
	SC	7.2885	7.3026	7.2872	7.3239	>	7.2777
	HQ	7.3901	7.4145	7.3991	7.4463	>	7.3690
USEPU							
	AIC	8.2987	8.3802	8.3021	8.3048	>	8.2858
	BIC	8.5357	8.6398	8.5617	8.5869	>	8.5003
	SC	8.2916	8.3717	8.2937	8.2948	>	8.2800
	HQ	8.3932	8.4836	8.4056	8.4172	>	8.3713
FTSE All World Index							
	AIC	2.8813	2.9354	2.8692	2.9144	>	2.8640
	BIC	3.1183	3.1949	3.1236	3.1965	>	3.0837
	SC	2.8742	2.9269	2.8634	2.9045	>	2.8555
	HQ	2.9757	3.0388	2.9674	3.0268	>	2.9547
EUR/USD							
	AIC	2.0317	2.1001	2.0108	2.0441	>	2.0056
	BIC	2.3139	2.4048	2.2704	2.3489	>	2.3329
	SC	2.0218	2.0886	2.0024	2.0327	>	1.9925
	HQ	2.1441	2.2215	2.1656	2.1361	>	2.1142
GBP/USD							
	AIC	2.3908	2.4355	2.3660	2.4154	>	2.3630
	BIC	2.6000	2.6951	2.6504	2.6976	>	2.5804
	SC	2.3824	2.4271	2.3601	2.4055	>	2.3559
	HQ	2.4575	2.5390	2.4943	2.5278	>	2.4514
JPY/USD							
	AIC	1.9568	2.0358	1.9728	1.9931	>	1.9380
	BIC	2.1938	2.2953	2.2324	2.2752	>	2.1524
	SC	1.9497	2.0273	1.9643	1.9832	>	1.9321
	HQ	2.0512	2.1392	2.0762	2.1055	>	2.0234
RUB/USD							
	AIC	3.0287	3.0818	3.0327	3.0452	>	3.0075
	BIC	3.2657	3.3414	3.2923	3.3273	>	3.2220
	SC	3.0216	3.0733	3.0242	3.0353	>	3.0017
	HQ	3.1231	3.1852	3.1361	3.1576	>	3.0930
CNY/USD							
	AIC	0.61710	0.67858	0.65096	0.66704	>	0.60253
	BIC	0.85411	0.93816	0.91054	0.94919	>	0.81697
	SC	0.61001	0.67013	0.64251	0.65712	>	0.59668
	HQ	0.71155	0.78203	0.75441	0.77947	>	0.68799

Table 16: Discrimination among the GARCH-type models (4)

Panel B (2): GARCH-type models for CBDCAI							
		SGARCH	EGARCH	IGARCH	APARCH	Discrimination	GJRGARCH
Gold							
	AIC	3.1150	3.1835	3.1331	3.1541	>	3.0921
	BIC	3.3520	3.4430	3.3926	3.4363	>	3.3065
	SC	3.1079	3.1750	3.1246	3.1442	>	3.0863
	HQ	3.2095	3.2869	3.2365	3.2665	>	3.1776
Bitcoin							
	AIC	6.2935	6.2848	6.3016	6.3105	>	6.2708
	BIC	6.5305	6.5443	6.5611	6.5926	>	6.4852
	SC	6.2864	6.2763	6.2931	6.3006	>	6.2649
	HQ	6.3879	6.3882	6.4050	6.4229	>	6.3562
FTSE World Government Bond Index							
	AIC	1.3629	1.4259	1.3878	1.4303	>	1.3581
	BIC	1.5547	1.6404	1.6022	1.6674	>	1.5274
	SC	1.3582	1.4201	1.3820	1.4232	>	1.3544
	HQ	1.4393	1.5114	1.4733	1.5248	>	1.4256