Digital Money Never Sleeps?
Modern qualitative-based indices in digital assets

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Wang Yizhi

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SUMMARY

What can we know about digital assets, as digital money also never sleeps? How can we measure the variations in these digital assets from a new perspective? What are the effects of digital assets on financial markets? The non-stop changes in finance caused by the financial technology revolution have deeply changed assets. Moreover, as investment tools, assets have been expanded from jewels, precious metals, real estate, stocks, bonds and others to cryptocurrencies, central bank digital currencies (CBDCs) and non-fungible tokens (NFTs). The story of Digital Money Never Sleeps is inextricably linked to how assets evolved in the FinTech area and how digital assets transformed the financial markets. This thesis creatively shows how to tap an online database to develop and evaluate new measures of interest to the three most popular digital assets: cryptocurrencies, CBDCs and NFTs. This thesis then offers useful insights into the financial implications of the three digital assets by focusing on three critical research questions motivated by a systematic literature review.

The first research question and its research activities introduce three new qualitative-based indices around cryptocurrency spaces by using 726.9 million and 778.2 million news articles separately: on cryptocurrency policy uncertainty (UCRY Policy), on cryptocurrency price uncertainty (UCRY Price) and on cryptocurrency environmental attention (ICEA). Then, around these three new issued cryptocurrency indices, this thesis further applies the vector autoregression (VAR)-based model to quantify the shocks from UCRY Policy, UCRY Price and ICEA to financial markets. Moreover, this thesis tests the impacts and predictive power of cryptocurrency uncertainties on precious metal markets.

The second research question and its investigations provide two new qualitative-based indices around the growing area of Central Bank Digital Currency (CBDC) by using 660 million news stories: the CBDC Uncertainty Index (CBDCUI) and CBDC Attention Index (CBDCAI). The application of structural vector autoregression (SVAR) and dynamic conditional correlation model (DCC)-GJR-generalised autore-
gressive conditional heteroskedasticity (GARCH) models to the second research question helps this thesis uncover how CBDC indices interact with several financial indicators, which could provide novel empirical evidence on the effects of CBDC news on financial markets.

The third research question and its studies present unique insights into the NFT market by creating the non-fungible tokens attention index (NFTsAI) based on 590 million news reports. This study uses the TVP-VAR volatility spillover connectedness model to explore the risk transmission across NFTs’ attention and financial markets. Moreover, motivated by the violent fluctuations in the NFT markets captured by the NFTsAI, this thesis further detects the price bubble in these emerging digital assets.

Ultimately, these qualitative-based indices can provide new proxies for measuring and evaluating cryptocurrencies, CBDCs and NFTs. Moreover, this thesis can offer a new methodology to develop new measures to deepen our understanding of finance and economics. The three investigations in this thesis display solid and robust results to answer the research questions identified in the literature review. Additional research directions are also determined for future research throughout the thesis.
DEDICATION

To whom it may concern.
Once again, I am writing these acknowledgments feeling excited and grateful, sitting at Trinity Business School, just like I did for my MSc dissertation in 2020.

How time flies! I have been in Ireland for three years. Looking back, I had no idea what would happen when I arrived in Dublin. It was like a dream for me. I also clearly remembered the scent, temperature and feelings when I stepped out of the aeroplane at Dublin Airport. However, now, I am heading to the terminal of my student career.

People are always joking that PhD is not the Doctor in Philosophy. It should be Pretty Hard Degree or Permeant Hair Damage. It is TRUE! I thought about giving up this degree 100 times, but for the 101st time, I chose to hold on! Just like the famous words from Human Comedy: "the innovator is supported by great confidence to have the courage to move forward in the unknown". Only you can write your own story. Many hours went into this PhD thesis, and it means so much that the work I am so passionate about also resonates with others. I started my PhD during the pandemic, and I really suffered a lot. But my supervisors always told me that anything which cannot kill you will make you stronger. Now, I feel I am making these words come true.

You would never know the impact of a well-dressed professor on a student. Professor Dr Samuel A. Vigne was the first professor I met at Trinity Business School. It was the first day of my MSc programme when Professor Vigne stood on the rostrum with a nice suit and introduced corporate finance to me. I was deeply impressed by his scholarly attainments and elegant style. I knew that he was the kind of person I also wanted to be. At that moment, I felt some invisible connections between Professor Vigne and I. Since then, he has become my PhD supervisor. To me, Professor Vigne is more like my academic father. Working with Professor Vigne was one of the most valuable experiences of my life. He is a great supervisor and gifted academic who is always passionate about education and collegiality. He not
only shares with me knowledge, but also teaches me many things that I cannot learn from books. He once told me: "Yizhi, please keep in mind that work is not everything". In academia, everyone is very intelligent. What matters just as much is your character and being a decent human. Maybe these words have faded away from the letter. However, the positive spirits from Professor Vigne have deepened in my mind. I look forward to many decades working together!

I would also like to express my immense gratitude to my co-supervisor, Professor Dr Brian M. Lucey, who assisted me in my PhD adventure with great support and care. Professor Lucey is the best academic in Ireland. I support this argument not only because of his many publications and citations but also his profound professionalism and competence. Professor Lucey understands the most straightforward and efficient way to have a successful academic career. He has acted as a true guide and listener by taking my hands and leading me to the right academic pathway. Collaborating with Professor Lucey has been a turning point in my academic career, as he has helped me gain confidence in research and inspired me to become the person I want to be. I once told Professor Lucey that I would never be able to repay him for all he has done for me. Professor Lucey’s answer was that I am not supposed to, but rather that I should carry on the favour and look after my students in the future. Here, I promise I will carry and promote your kindness and great spirits. This is the most beautiful thing in academic circles!

I would also like to thank Professor Youwei Li (University of Hull), Professor Yu Wei (Yunnan University of Finance and Economics) and Professor Dongyang Zhang (Capital University of Economics and Business) for their continuous support, guidance and understanding during my PhD adventure and many sleepless nights due to anxiety.

Without the constant support and encouragement of my parents and my girlfriend, Xuying Li, my doctoral thesis would have been impossible. PhD studies and research activities were very difficult to tolerate, but it was your mental support and wisdom words that kept me moving forward. I would also like to give many thanks to my grandfather, who set a good example for me when I was a little boy. He taught me to be rigorous, serious, diligent, practical, reliable and punctual. For several uncontrollable reasons, my grandfather did not finish his PhD degree. I know this is his regret, but now his grandson can make up for it.

A special thanks to my pets: my cat Dudley, my tortoise Scholar and my two
hamsters, Ruby and Dodo. Thanks for your company and for bringing me a lot of happiness.

I would also like to mention my gratitude to the Dean of Trinity Business School, Professor Andrew Burke. Thanks for organising and providing such a vibrant and supportive business school, which allows me to make my research ideas come true.

I will continue my efforts in digital assets and look forward to bringing positive changes in the FinTech field. In the end, I would like to say thank you to myself 10 years ago. Thank you for your hard work, resilience and ambition. And I would also like to greet myself 10 years later. I hope you can keep the same good character, and I will see you soon!
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CHAPTER 1

INTRODUCTION

What has happened in the last few years? This was the question that seemed to echo across the financial technology world and then across the entire world. The spread of the following news could reflect prosperous digital asset markets, which also indicate challenges. Cryptocurrencies collapsed 80% in September 2018 from their peak in January 2018. This crash related to cryptocurrency markets was worse than the Internet bubble in the late 1990s. Originally developed as a "joke" coin, the value of Dogecoin increased by 20,000% in one year. Bitcoin peaked on 7 November 2021 at $67,566.83, but nosedived on 27 June 2022 to $19,297.98, plummeting 250% in just eight months. Concerning the energy consumption and air pollution of cryptocurrency, Bitcoin currently could consume an estimated 150 terawatt-hours of electricity annually, more than the entire country of Argentina. Moreover, Bitcoin could emit around 65 megatons of carbon dioxide annually, a number comparable to the emissions of Greece. As another digital asset, the coming launch of Central Bank Digital Currency (CBDC) will be a historic milestone in the role of money, as many central banks are testing and issuing their own CBDCs. Non-fungible tokens (NFTs) are records on blockchains which are linked to particular digital or physical assets. Since 2021, NFTs have been the most buzzworthy digital assets, as a digital collage entitled "Everydays: The First 5000 Days" sold for a staggering $69.3 million. Furthermore, positive news such as the total sales volume of NFTs increasing 315% month-on-month in September 2021, The Sandbox reaching market capitalisation of $648.35 million in October 2021
and Bored Ape Yacht Club’s 58,118% return on investment significantly stimulated the NFT mania. With the development of financial technology, digital assets have profoundly impacted financial markets, monetary systems, cashless payment and more. Academics tend to come naturally to these revolutionary assets. This thesis innovatively proposes a qualitative method to measure the variations in the three most representative digital assets: cryptocurrency, CBDC and NFTs. It then focuses on three critical questions to quantitatively explore perspectives on cryptocurrency, CBDC and NFTs, three mysterious but truly fascinating digital assets.

1.1 Background and Motivation

1.1.1 Cryptocurrency qualitative-based indices

Firstly, since the concept of Bitcoin was first proposed in 2008, cryptocurrencies have been paid more and more attention (Urquhart and Lucey, 2022). In the finance research area, we could have plenty of methods to quantify the volatility of cryptocurrency markets. As another significant proxy, many theories indicate that uncertainty has considerable effects on the real economy and also has a sizable influence on financial decisions (Baker et al., 2016). Therefore, how could we measure the uncertainty in the cryptocurrency markets and what are the effects of these cryptocurrency uncertainties on financial markets? Based on this motivation, this thesis tries to capture the uncertainties in the cryptocurrency markets by posing a construction and analysis of two measures of policy and price uncertainty for cryptocurrencies to address the level of uncertainty that investors experience and the motivating factors of such regarding cryptocurrencies.

Secondly, how much discussion or engagement is there in mainstream and social media regarding the energy consumption and environmental impact of cryptocurrencies? More so, what drives these discussions? Surprisingly, there exists no simple answer to this. The common perception is that this awareness is high and growing. The problem recently made headlines due to the announcement made by Tesla’s CEO Elon Musk, that Bitcoin will no longer be accepted as payment due to its environmental impact. With a global agenda of making our planet greener and more sustainable, surprisingly, the impact of cryptocurrency growth and the growing energy consumption of its networks has not been included in

\footnote{https://www.ft.com/content/1aecb2db-8f61-427c-a413-3b929291c8ac}
any high-level policy debates yet, and this area remains unregulated. Adoption of Bitcoin as an official currency by El Salvador\(^2\) manifests the beginning of the legalisation of cryptocurrencies as an official method of payment, therefore the assessment of environmental impacts of this new form of money and investment asset should become one of the main priorities of the United Nations Economic and Social Council and academics worldwide.

Mining cryptocurrency takes more energy than mining gold\(^3\). It sounds like hyperbole, but it is, in fact, the truth. How can we find green solutions for cryptocurrency? Most of the studies only focus on the electricity consumption and \(CO_2\) emission issues of Bitcoin. However, we cannot forget that there are more than 4000 cryptocurrencies available on the market, which can pose a significant risk to the environment now. If one is to consider only two of the most popular cryptocurrencies, Bitcoin and Ethereum, the electricity consumption of Bitcoin has increased from 4.8Twh to 73.12Twh over the last two years (Zade et al., 2019). In October 2019, it was estimated that the energy consumption of Bitcoin mining is significantly more than the energy consumption of Austria (Malfuzi et al., 2020). As for the carbon footprint of Bitcoin transactions, each Bitcoin transaction can contribute 619 Kwt to the carbon footprint, which is equal to 350,000 bank card transactions, or the energy consumption of an average US family over 20.92 days (Badea and Mungiu-Pupazan, 2021). China has a huge cryptocurrency market and Jiang et al. (2021) estimate that without any policy regulations, the annual energy consumption of Bitcoin in China is expected to peak in 2024 at 296.59 Twh. Surprisingly, 296.59 Twh of energy consumption will generate 130.50 million metric tons of carbon emission output, which is more than the annual carbon emission output of Czechia and Qatar. As for Ethereum, in June 2017, the entire network of Ethereum had already consumed a small country’s worth of electricity, for example, Cyprus.

From a sustainability perspective, cryptocurrency mining’s negative impact on the environment is significant (Krause and Tolaymat, 2018). Motivated by this emerging challenge, this paper has identified several issues. First, there is very limited existing research on the extent or determinants of cryptocurrency’s growing energy consumption problem, precluding any conclusive scientific confirmation about its contribution to climate change (de Vries, 2020). Moreover, the few extant

\(^2\)https://www.ft.com/content/7b5b1cc4-50bb-437f-aa16-f106d2dbc1c7
\(^3\)https://www.nature.com/articles/d41586-018-07283-3
studies concerning the relationship between cryptocurrencies and environmental issues focus on how cryptocurrencies contribute to environmental issues (Corbet et al., 2021), with few studies comprehensively investigating inverse interactions. Second, no existing studies report on how environmental attention on cryptocurrencies can shock the cryptocurrency markets, not even the literature examining which financial or economic variables are susceptible to shocks transmitted by cryptocurrency environmental attention. Third, no clear and substantial regulations or policies consider the environmental issues related to cryptocurrency (Chudinovskikh and Sevryugin, 2019; Shanaev et al., 2020; Riley, 2021).

Thirdly, Finance literature has provided somewhat mixed evidence about the relationships between uncertainty measures and the gold market (Balcilar et al., 2016; Bilgin et al., 2018; Wu et al., 2019), to name but a few. Cryptocurrencies have become a significant asset class in recent years (Urquhart and Lucey, 2022), and there is rising interest focusing on linkages between the cryptocurrency and precious metal markets (Bouri et al., 2017; Klein et al., 2018; Rehman and Vo, 2020; Jalan et al., 2021; Bianchi et al., 2022). There is some evidence that from a financial market perspective, precious metals and cryptocurrencies share several common characteristics, such as safe haven, hedge and diversification for risk assets (Feng et al., 2018; Ji et al., 2020; Bouri et al., 2020; Shahzad et al., 2020). In particular, the hedging capability of precious metals is often compared to Bitcoin (Dyhrberg, 2016) and (Wu et al., 2019). Recently, Lucey et al. (2022) develop the cryptocurrency uncertainty indices (UCRY Policy and UCRY Price), which can capture policy uncertainty and price uncertainty in the cryptocurrency market beyond price volatility. Faced with high cryptocurrency uncertainty recently, investors and researchers have begun to investigate the properties of precious metals to counter cryptocurrency uncertainty shocks (Hassan et al., 2021) and (Elsayed et al., 2022b). Hassan et al. (2021) examine the time-varying interconnections between precious metals and cryptocurrency indices using a DCC-GJR-GARCH model. Their research findings show that gold has a stable and reliable safe-haven property against cryptocurrency uncertainty. Similarly, Elsayed et al. (2022b) investigate the dynamic connectedness of return- and volatility spillovers among cryptocurrency (CRIX), cryptocurrency uncertainty indices, CBOE S&P 500 Volatility Index (CBOE VIX), Global Economic Policy Uncertainty index (GEPU) and gold. The empirical results from this paper suggest that the cryptocurrency uncertainty policy index is

\footnote{For more details about cryptocurrency regulatory events, please find in (Shanaev et al., 2020).}
the main transmitter of the return spillover to gold. Elsayed et al. (2022b) discusses information spillover among the gold market and uncertainty measures. Based on these existing studies, it is worth to further exploring the impacts of cryptocurrency uncertainty on precious metal markets and further investigating the predictive power of cryptocurrency uncertainty indices on the volatility of precious metal markets.

1.1.2 CBDC qualitative-based indices

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 CBDCs 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 have 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) introduce 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 from monetary supervision and regulation. The structured currency circulation data allows the total amount of money supply to be regulated precisely (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 (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.

While a CBDC could provide some benefits, it may also bring several significant challenges to society. First, CBDCs could exacerbate financial uncertainty during periods of economic stress (Ferrari et al., 2022). 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 to the central bank balance sheet. Therefore, some scholars worry that digital currency and digitalisation could cause an inversion of the currency financial intermediation system (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. The original intention of the CBDC design is 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. 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. 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 States. 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 (Bhaskar et al., 2022). The second focuses on the design theory, technology innovation, and model optimisation of CBDC (Qian, 2019) and (Lee et al., 2021b). The third examines its security and privacy (Borgonovo et al., 2021) and (Lee et al., 2021c). The fourth analyses CBDC’s impacts on the monetary system and monetary policy (Davoodalhosseini, 2021) and (Meaning et al., 2021). The fifth group investigates the relationships between CBDC and banking, including commercial and central banking (Fernández-Villaverde et al., 2021) and (Williamson, 2021). Whereas only a few studies investigate how current CBDCs’ discussion among regulators and in the media affect the behaviour of financial markets. Considering the process of CBDCs is at the early stages of development and adoption, there is a lack of data or proxies which can reflect and stand for the CBDCs, thus hindering quantitative analyses of CBDC’s effects on financial markets.
1.1.3 NFTs qualitative-based index

A non-fungible token (NFT) is a non-interchange and secure unit of data on a blockchain, and it is a type of digital ledger. An NFT can be associated with a piece of reproducible digital media, including but not limited to digital arts, texts, photos, videos, audio and even bits of code. Many scholars have highlighted the connections between NFTs and the art market [e.g., (Horky et al., 2022)]. That is why NFTs can also be called digital collectables. Their lack of interchangeability can significantly distinguish NFTs from other blockchain-based cryptocurrencies, such as Bitcoin, Ethereum and Tether. Compared with physical collectables, NFTs can be copied perfectly, and they can be used infinitely. Because a digital ledger can only offer a public certificate of authenticity or proof of ownership, it cannot keep the blockchain-based recording from being shared and copied. This characteristic could limit the inherent value of an NFT. In addition, the value of an NFT is also determined by its scarcity, quality, liquidity and the size of the collector communities.

The first known NFT, Quantum, was created in May 2014. Then, NFTs are gaining increased popularity, starting from some images of cute digital cats called CryptoKitties. In March 2021, a digital collage named “Everydays - The First 5,000 Days” was sold as a non-fungible token at an incredible price, $69.3m\(^5\). In May 2021, a flat in Kyiv was sold as an NFT, and it even was recognised by Ukraine’s authorities\(^6\). In August 2021, NBA superstar Steph Curry jumped into the NFT market with his $180,000 purchase of a Twitter profile photo\(^7\). The NFT market hit $41bn in 2021, up from $340m in 2020\(^8\). These examples all show the crazy boom in the NFT markets. The NFT craze is similar to the initial coin offerings (ICO) in 2018 and the sneaker transaction mania in 2019, which were full of speculation and price bubbles. Some NFT asset prices are extremely decoupled from their inherent value. However, with NFT creators and investors flooding into NFT markets, now, NFTs have already received growing attention from the finance academic community.

The growing finance literature related to NFTs can be concluded into two mainstreams. Many scholars first focus on the asset pricing fields of NFTs\(^AI\). For

\(^5\)https://www.theverge.com/2021/3/11/22325054/beeple-christies-nft-sale-cost-
\everydays-69-million
\(^6\)https://cryptonews.com/news/techcrunch-founder-to-sell-his-crypto-bought-kyiv-
flat-as-an-10501.htm
\(^7\)https://markets.businessinsider.com/news/currencies/steph-curry-nft-bored-
ape-yacht-club-180000-ethereum-nba-2021-8
\(^8\)https://www.ft.com/content/e95f5ac2-0476-41f4-abd4-8a99faa7737d
example, price mechanism (Ante, 2022; Dowling, 2022; Aharon and Demir, 2022; Vidal-Tomás, 2022; Horky et al., 2022), portfolio management (Vidal-Tomás, 2022; Ko et al., 2022; Yousaf and Yarovaya, 2022), price bubble detecting (Maouchi et al., 2022; Vidal-Tomás, 2022; Wang et al., 2022c), among others. The other stream concentrates on the inter-connections between NFT markets and other financial markets, by using Vector Error Correction Model (VECM) and Granger causality test (Ante, 2022), wavelet coherence analysis (Dowling, 2021; Umar et al., 2022c; Vidal-Tomás, 2022), and spillover connectedness framework (Dowling, 2021; Aharon and Demir, 2022; Mazur, 2021; Karim et al., 2022; Ko et al., 2022; Yousaf and Yarovaya, 2022).

Considering that the NFT proxy is one of the key variables that could affect the empirical analysis findings, a reliable NFT proxy is important to get accurate results and provide useful information to decision-makers, economists, and investors. Numerous proxies have been selected to represent the NFT markets. Firstly, many contributions use hot NFT assets (Dowling, 2021; Dowling, 2022; Karim et al., 2022; Ko et al., 2022; Maouchi et al., 2022; Yousaf and Yarovaya, 2022). Secondly, several academic studies rely extensively on the average price of NFT sectors (Aharon and Demir, 2022) and (Umar et al., 2022c). Thirdly, one study employs a capitalisation-weighted composite index, NFT index\footnote{The NFTI is a capitalisation-weighted composite index designed to track the performance of the non-fungible token market. It is weighted based on each NFT asset’s circulating supply value. Underlying NFT assets in the NFTI including Polygon (Matic), Enjin, Decentraland, Sand, Axie Infinity, Aavegotchi, Rarible, and Meme.} (Wang et al., 2022c) Fourth, some studies creatively apply their own collected data-sets (Borri et al., 2022; Vidal-Tomás, 2022; Horky et al., 2022; Pinto-Gutiérrez et al., 2022).

However, NFTs are traded infrequently, and they differ in terms of quality. This characteristic of NFTs makes the development of the NFTs price composite index difficult. Only employing hot NFT asset proxies or NFT average price proxies is not sufficient, as some studies show controversial conclusions, such as (Dowling, 2021) and (Vidal-Tomás, 2022) draw a diametrically opposite result. Umar et al. (2022c) also suggest to improve the findings of (Aharon and Demir, 2022). Therefore, the lack of consistent results in the NFTs finance area indicates we may need to consider a different NFTs proxy rather than the price indices. Da et al. (2011) state that investor attention can have an impact on asset pricing statics as well as dynamics. Moreover, developing a new measure of investor attention based on online database has been proved as an accurate and efficient approach (Da
et al., 2011; Liu and Tsyvinski, 2021; Chen et al., 2022), including in the digital currency area (Lucey et al., 2022; Wang et al., 2022b; Wang et al., 2022d). In this way, following Lucey et al. (2022), this study innovatively develops and makes available a new qualitative-based NFT proxy - the NFT attention index (NFTsAI). It is based on 590m news stories collected from the LexisNexis News & Business database to track the public attention on the NFTs. The NFTsAI covers the key periods of the development of the NFT market and the most discussed events of this new asset in the media, i.e. from January 2017 to June 2022\textsuperscript{10}.

Financial spillover connectedness as a source of systemic risk and financial market instability (Diebold and Yılmaz, 2014). Investigating financial spillover connectedness could uncover information transmission channels and identify risk transmitters and receivers. From the perspective of policymakers, considering financial spillover connectedness could help to develop forward-looking monitoring regulations and to facilitate financial stability (Hamill et al., 2021). This is why, as justified above, many existing studies related to NFTs have examined the spillover connectedness between various NFT proxies and financial markets. Based on this, this study proposes the following research question. \textit{What are the volatility spillover connectedness between NFTs attention and financial markets?} To address the research question, this study empirically examines the volatility spillover connectedness between NFTsAI and financial markets. By doing so, this paper could uncover new channels of volatility transmission between NFT markets and other financial markets by using NFTsAI as a new indicator and further explore the diversification opportunities.

The new issued NFTsAI suggest that the NFT markets are characterised by high fluctuation. Motivated by this point, this thesis supposes that it is a common thought that no investor intends to hold a speculative instrument at the point when a price spiral collapses. Smart money and wise investment decisions are thought to dictate rational acting in most financial markets. Nevertheless, the history of financial markets is replete with the remains of collapsed bubbles. As of 31 January 2022, the market capitalisation of the NFT markets was $47.81bn, an increase from $340m on 1 January 2021\textsuperscript{11}, which may raise suspicion for a purely speculative character of the digital instruments. In order to better assess the likelihood of a crash, it is important to examine the price dynamics of NFT markets closely. NFT

\textsuperscript{10}The latest NFTsAI weekly data can be downloaded from https://sites.google.com/view/cryptocurrency-indices/home?authuser=0.

\textsuperscript{11}NFT market capitalisation data are obtained from https://coinmarketcap.com/
tokens are instruments in the digital space that remarkably extend the spectrum of decentralised financial assets. According to the framework of Kinlaw et al. (2017), NFTs could be characterised as instruments that display heterogeneous properties internally as well as externally with other asset classes. Nevertheless, NFTs may display differing price dynamics that are not yet fully investigated, specifically under the aspect of price explosiveness. More recently and closer to this study, Maouchi et al. (2022) investigate and predict the price bubbles of the NFT and DeFi markets in the COVID-19 pandemic by applying an optimised GSADF test with four multivariate models. They conclude that specific bubbles NFT assets occurred in the summer of 2020 that indicate distinct price dynamics for both markets in contrast to cryptocurrencies. Furthermore, NFT bubbles are less recurrent but have higher magnitudes than past cryptocurrency bubbles. However, to date, such studies have had to rely on individually selected digital assets. Therefore, we should take as merely indicative the findings of Maouchi et al. (2022), and more recently Karim et al. (2022), which examines selected representative NFT’s, DeFi and cryptocurrency assets, and further detect the explosive price behaviours in the NFT markets.

1.2 Aims and Objectives

The aim of this thesis is to creatively propose a new methodology to construct qualitative-based indices in digital asset areas, selecting cryptocurrency, CBDC and NFTs as three primary digital assets. This thesis successfully develops a series of indices related to cryptocurrency, CBDC and NFTs. Moreover, this thesis thoroughly investigates the role of the newly issued digital asset indices on the financial market.

The three different empirical analysis chapters aim to ensure that the research activities undertaken by this thesis minimise research gaps. This aim is guaranteed by the critically selected variable systems and methodologies for the three different research questions.

The three empirical analysis chapters summarise the significant and distinct objectives. The first objective is to explore straightforward and understandable results concerning the relationships between cryptocurrency policy uncertainty, cryptocurrency price uncertainty and cryptocurrency environmental attention and financial markets, including the predictive power of cryptocurrency uncertainties
on precious metal markets. By doing so, this thesis suggests that the newly issued cryptocurrency indices contain useful information and can be used for academic, policy and practice-driven research. The second objective is to provide econometric evidence of the CBDC indices associated with the volatility of financial markets, such as stock, bond and cryptocurrency markets, among others. The second objective can be valuable 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. The third objective is to offer a deep understanding of the volatility in the NFT markets and further uncover a quantitative review of the new channels of volatility transmission between NFT markets and other financial markets by using the NFTs attention index. The third objective could present insightful viewpoints to the reader on emerging NFT markets.

1.3 Contribution

The main focus of this thesis on developing new measures to reflect information in the cryptocurrency, CBDC and NFT markets. As a result, cryptocurrency policy uncertainty index (UCRY Policy), cryptocurrency price uncertainty index (UCRY Price), an index of cryptocurrency environmental attention (ICEA), central bank digital currency attention index (CBDCAI), central bank digital currency uncertainty index (CBDCUI) and non-fungible tokens attention index (NFTsAI) are developed and made available. Moreover, the overarching objective of this thesis is to contribute to a better understanding of digital assets, especially related to the effects of these new measures and digital assets on financial markets, to prove their effectiveness and present new insightful information about digital assets and financial markets. Due to the scope of analysis and the importance of digital currencies in the financial system, the target audience is not limited to academia but also includes institutional investors and policymakers.

This thesis firstly contributes to the existing literature by introducing a new methodology to develop qualitative-based indices, such as uncertainty indices and attention indices, which could capture movements in the financial markets beyond volatility. In other words, this thesis contributes to the literature by showcasing 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.
1.3. CONTRIBUTION

through systematic online empirical inquiries. Secondly, this thesis proposes and proves a new textual analysis method based on the SVAR model and its historical decomposition. This could help readers understand how financial markets could react to the shocks from positive and negative news. Thirdly, the empirical results from this thesis reveal the interconnections between financial markets and the attention/uncertainty of digital assets. In the following section, more detailed contributions of each empirical analysis chapter related to the digital asset indices are presented.

1.3.1 Cryptocurrency qualitative-based indices

Firstly, in order to track uncertainty in cryptocurrency markets, chapter 6 gathered 726.9 million news stories from the LexisNexis database spanning from January 2014 to January 2021 and then contributed to constructing the cryptocurrency policy uncertainty index (UCRY Policy) and cryptocurrency price uncertainty index (UCRY Price), two qualitative-based indices. By using the SVECM model and historical decomposition, chapter 6 found that these two uncertainty indices significantly move around the major events in the cryptocurrency space and can capture uncertainty beyond the cryptocurrency market’s volatility. Therefore, chapter 6 further contributes to proving the effectiveness of the UCRY Policy and UCRY Price and presents new proxies related to cryptocurrency for academic, policy and practice-driven research.

Secondly, concerning the environmental impacts caused by increasing cryptocurrency energy consumption and mining pollution, chapter 6 provides an efficient new proxy, the cryptocurrency environmental attention index (ICEA) for cryptocurrency and robust empirical evidence for future research concerning the impacts of environmental issues on cryptocurrency markets. Chapter 6 successfully links cryptocurrency environmental attention to financial markets, economic developments and other volatility and uncertainty measures, indicating certain novel implications for the existing cryptocurrency literature. The empirical findings of the effects of the cryptocurrency environmental attention index on financial markets could offer useful and up-to-date insights for investors, guiding policymakers, regulators and media, enabling the cryptocurrency environmental attention index to evolve into a barometer in the cryptocurrency era and play a role in, for example, environmental policy development and investment portfolio optimisation.

Thirdly, motivated by a research gap in the relationship between cryptocurrency
uncertainty and precious metal markets, chapter 6 also explores the impacts and predictive power of cryptocurrency uncertainty on precious metal markets. Then, chapter 6 contributes to extending the GARCH-MIDAS model of (Engle et al., 2013) by incorporating various uncertainty indices to identify the impacts of cryptocurrency uncertainty on the volatility of precious metal markets. Through various predictive power detecting approaches, chapter 6 also contributes to quantifying both the in-sample impacts and the out-of-sample predictive abilities of cryptocurrency uncertainty on the volatility of precious metal markets. The dependency between low-frequency cryptocurrency uncertainty and volatility in precious metal markets, however, can provide new perspectives for policymakers and investors to inform regulatorily and risk management strategies in both cryptocurrency and precious metal markets.

1.3.2 CBDC qualitative-based indices

The CBDC indices and their effects on financial markets contribute to literature on CBDCs in two main ways. Firstly, chapter 7 offers useful qualitative-based proxies of CBDCs and novel evidence for future quantitative studies into CBDCs. Secondly, chapter 7 successfully links CBDCs to financial markets and other volatility and uncertainty measures. The results provide useful insights for investors, policymakers, regulators and media on how CBDCs have evolved as a barometer in the new digital-currency era. For example, policymakers and regulators can adjust fiscal policy by referencing our CBDC indices. In addition, the CBDC indices can guide investors to increase or reduce their financial assets’ net long positions.

1.3.3 NFTs qualitative-based index

chapter 8 contributes to the growing literature related to the NFTs attention index in the following ways. Firstly, assisted by Latent Dirichlet Allocation (LDA) topic modelling, chapter 8 offers a much wider attention search string related to NFTs. chapter 8 proposes the non-fungible tokens attention index (NFTsAI) based on 590m news stories from the LexisNexis News & Business database. Moreover, NFTs attention matters to the variations of NFT markets both statistically and economically, indicating the significant role of NFTsAI as a new indicator and highlighting the important role of public attention in NFT markets in general. Secondly, chapter 8 is the first to propose an NFTs attention index and comprehensively
examine the volatility spillover connectedness between NFTsAI and other financial markets (NFTs, DeFi, cryptocurrency, stock, bond, FX, commodity, and gold). The main findings indicate that as a proxy for NFT markets, NFTsAI is consistently an essential volatility spillover receiver in the variable system. This study’s results help discover new routes of risk transmission and explore new diversification opportunities relying on NFTs attention measure. Thirdly, chapter 8 investigates the internal mechanisms between the NFTsAI and NFT markets. Chapter 8 explores the effects of NFTsAI on the NFT market by using a panel pooled regression model and a GARCH-MIDAS model. Chapter 8 confirms that NFTsAI has sufficient power to explain the return of NFT assets and suggests that NFTsAI contains useful forecasting information for both short and long-term volatility of NFT markets separately. Ultimately, in terms of the index construction methodology contribution, chapter 8 enhances and completes the methodologies used to construct a new qualitative-based index. Although many studies have proven the efficiency of referencing internet databases or newspaper archives to develop and construct new measures of financial uncertainty or attention (Baker et al., 2016; Huang and Luk, 2020; Lucey et al., 2022; Wang et al., 2022d), designing a reasonable search string to collect comprehensive data for these qualitative-based uncertainty or attention indices has remained a thorny and unresolved issue. Chapter 8 proves that LDA topic modelling could serve as a more suitable search string design method than the traditional brainstorming method, as this text analysis-based tool can improve the exactness of the designed search strings by capturing, sorting and generating more comprehensive search queries.

Motivated by the volatility spillover transmissions across the NFTsAI and financial markets, chapter 8 further detects price bubbles in the NFT markets. It is the first research to comprehensively identify price explosive behaviours in NFT markets by using SADF and GSADF tests, also using the LPPLS test being a robustness measure. In this way, chapter 8 additionally contributes to the existing literature by systematically examining the occurrence of price bubbles in a unique strand of the entire NFT market in order to reach a holistic conclusion about explosive bubble behaviour in NFT markets.
CHAPTER 1. INTRODUCTION

1.4 Structure

This chapter has introduced the research background, motivation, aims and contributions of this thesis. Following the introductory chapter, the rest of this thesis is structured as follows:

The chapter 2 provides a thorough literature review of the relevant studies in cryptocurrency, CBDC and NFTs. Moreover, it identifies the research questions and research hypotheses which have been tested.

chapter 3 illustrates the research philosophy underpinned in this thesis, and the implications of the research philosophy are also briefly assessed.

chapter 4 describes the method of constructing the qualitative-based indices and then justifies the variable selection for each research question.

chapter 5 demonstrates all the statistical tools and financial econometrics methodology used throughout this thesis in detail.

chapter 6, chapter 7 and chapter 8 thoroughly display the results of the empirical analysis obtained from the formal investigations in accordance with each articulated research question and hypothesis. Furthermore, the practical and social implications for investors, policymakers and academics from the empirical results are additionally discussed in these three empirical analysis chapters.

The doctoral thesis concludes with chapter 9, which summarises its main findings, implications and contributions. Moreover, chapter 9 also identifies several possible future research directions.

1.5 Publications from this Doctoral Thesis

1.5.1 The cryptocurrency uncertainty index

Some parts of chapter 1, chapter 2, chapter 4, chapter 5 and chapter 6 are used for an academic paper in the Finance Research Letters (ABS 2, IF: 9.848, Q1, SSCI) as:


The corresponding author*, Yizhi Wang, is also known as the author for this PhD thesis. The CRediT authorship contribution statement of Yizhi Wang in this
1.5. PUBLICATIONS FROM THIS DOCTORAL THESIS

Paper is: Data curation, Software, Methodology, Visualisation, Writing - original draft, Formal analysis, Writing - reviewing & editing.

Large parts of chapter 6 about the cryptocurrency uncertainty index are presented in the following conferences:

1.) 2021 - 7th International Young Finance Scholars’ Conference. University of Oxford and Peking University, UK.


4). 2021 - Bits and Blocks (Blockchain) Workshop 2021. Renmin University of China; American University of Sharjah; University of Manchester, China. **Yizhi Wang is an invited speaker in this conference.**

5). 2022 - 2022 AFA PhD Student Poster Session. American Finance Association, Boston. **With the AFA grant.**

1.5.2 An index of cryptocurrency environmental attention

Some parts of chapter 1, chapter 2, chapter 4, chapter 5 and chapter 6 are used for an academic paper in the *China Finance Review International* (ABS 1, IF: 3.9, Q2) as:


The first author and corresponding author*, Yizhi Wang, is also known as the author for this PhD thesis. The CRediT authorship contribution statement of Yizhi Wang in this paper is: Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualisation, Project administration, funding acquisition, Writing - Review & Editing.
CHAPTER 1. INTRODUCTION

Large parts of chapter 6 about cryptocurrency environmental attention index (ICEA) are presented in the following conferences:


3). 2021 - Bits and Blocks (Blockchain) Workshop 2021. Renmin University of China; American University of Sharjah; University of Manchester, China. Yizhi Wang is an invited speaker in this conference.


1.5.3 Cryptocurrency uncertainty and volatility forecasting of precious metal futures markets

Some parts of chapter 1, chapter 2, chapter 4, chapter 5 and chapter 6 are used for an academic paper in the Journal of Commodity Markets (ABS 3, IF: 3.317, Q1, SSCI) as:


The second author and corresponding author*, Yizhi Wang, is also known as the author for this PhD thesis. The CRediT authorship contribution statement of Yizhi Wang in this paper is: Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft,
Visualisation, Project administration, funding acquisition, Writing - Review & Editing.

1.5.4 The effects of central bank digital currencies news on financial markets

Some parts of chapter 1, chapter 2, chapter 4, chapter 5 and chapter 7 contributes to an academic paper in the Technological Forecasting and Social Change (ABS 3, IF: 10.884, Q1, SSCI) as:


The first author and corresponding author*, Yizhi Wang, is also known as the author for this PhD thesis. The CRediT authorship contribution statement of Yizhi Wang in this paper is: Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualisation, Project administration, funding acquisition, Writing - Review & Editing.

Large parts of chapter 7 about CBDC indices are presented in the following conferences:

1). 2021 - Bits and Blocks (Blockchain) Workshop 2021. Renmin University of China; American University of Sharjah; University of Manchester, China. **Yizhi Wang is an invited speaker in this conference.**


1.5.5 Volatility spillovers across NFTs news attention and financial markets

Some parts of chapter 1, chapter 2, chapter 4, chapter 5 and chapter 8 contributes to an academic paper in the International Review of Financial Analysis (ABS 3, IF: 8.235, Q1, SSCI) as:
CHAPTER 1. INTRODUCTION


This is a single author paper, Yizhi Wang, is also known as the author for this PhD thesis. The CRediT authorship contribution statement of Yizhi Wang in this paper is: All roles.

Large parts of chapter 8 about NFTs news attention are presented in the following conferences:


2). 2022 - *Cryptocurrency Research Conference 2022*. Durham University, Durham University Business School, United Kingdom.

1.5.6 Detecting and date-stamping bubble behaviour in NFT markets

Some parts of chapter 1, chapter 2, chapter 4, chapter 5 and chapter 8 contributes to an academic paper in the *Journal of Chinese Economic and Business Studies* (ABS 1, IF: 1.38, Q2) as:


The first author and corresponding author*, Yizhi Wang, is also known as the author for this PhD thesis. The CRediT authorship contribution statement of Yizhi Wang in this paper is: Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualisation, Project administration, funding acquisition, Writing - Review & Editing.

1.5.7 Financial econometrics - R tutorial guidance

Some parts of chapter 5 contributed to a book in the *Econometrics: Econometric Model Construction, Estimation & Selection* as:

The first author and corresponding author*, Yizhi Wang, is also known as the author for this PhD thesis. The CRediT authorship contribution statement of Yizhi Wang in this book is: Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualisation, Project administration, funding acquisition, Writing - Review & Editing.

Some parts of chapter 5 about financial econometrics are presented in the following conference:

A comprehensive literature review could critically evaluate the existing literature in the chosen research field and ensure that the research questions proposed can be pinpointed to the identified research gaps. This chapter provides an overview of the consulted literature in this PhD thesis. Initially, three main categorisations of the literature about the qualitative-based indices of cryptocurrency, CBDC and NFTs will be developed. Then, the ways in which the existing literature can help to find research gaps and further motivate research questions/hypotheses are also demonstrated, followed by each categorisation.

2.1 Cryptocurrency Qualitative-Based Indices

2.1.1 The cryptocurrency uncertainty indices

How uncertain are investors about cryptocurrencies, and what drives this? Yet different types of uncertainty may have varying impacts and predictive power on cryptocurrency markets. In addition, it is worth noting the difference between price volatility and price uncertainty. Cryptocurrency price volatility measures the size of variations of cryptocurrency returns, and should be the standard deviation of cryptocurrency logarithmic returns between their daily closing prices. Walther et al. (2019) use 17 different economic and financial indices to predict the volatility of cryptocurrencies. They point out that it is driven by global business and a network
of interacting driving factors. The OFR Financial Stress Index (OFR FSI) and the Chinese Economic Policy Uncertainty Index (Chinese EPU) are useful and impactful predictors for the volatility of cryptocurrencies but are overshadowed by the Global Real Economic Activity Index (GREA). Cryptocurrency price uncertainty measures the size of unpredictable disturbances in the price of cryptocurrency. Demir et al. (2018) prove that Economic Policy Uncertainty (EPU) has a predictive power on Bitcoin returns. Large moves in cryptocurrency uncertainty are less frequent but more persistent than moves in cryptocurrency price volatility.

Akyldirim et al. (2020) show that during times when investors’ fears are elevated, cryptocurrency markets experienced an increase in volatility. The authors use VIX (CBOE-traded) and VSTOXX (DAX-traded) volatility indexes as measures of the United States and European financial market risk respectively. Fang et al. (2020) further analyse the impact of the News-based Implied Volatility index (NVIX) on cryptocurrency returns, providing evidence that NVIX, developed by Manela and Moreira (2017), is a more powerful predictor of the long-term volatility in selected cryptocurrencies than the Global Economic Policy Uncertainty index (GEPU) proposed by (Davis, 2016). These results indicate that cryptocurrency market volatility might be more susceptible to price uncertainty and investors’ perceptions than to policy uncertainty.

Findings reported by Aysan et al. (2019) demonstrate that the Geopolitical Uncertainty Index (GPR) can predict Bitcoin returns and volatility. Conlon et al. (2020) further compare the impacts of GEPU and GPR indexes on cryptocurrency returns, yet find no substantial safe haven or hedging properties of cryptocurrencies against either uncertainty proxies, apart from a weak ability to hedge against GEPU during a bull market. Their results are consistent with other papers in this area, such as (Wu et al., 2019) and (Al Mamun et al., 2020). Gozgor et al. (2020) analyse the impact of Trade Policy Uncertainty (TPI) on Bitcoin returns and demonstrate a significant positive correlation between returns and uncertainty variables.

Investment sentiments have been found to be useful for predicting cryptocurrency volatility and returns. Corbet et al. (2020c) construct a sentiment index based on news stories that followed the announcements of four macroeconomic indicators: GDP, unemployment, Consumer Price Index (CPI) and durable goods. The results show that Bitcoin returns respond differently to news than to stock market returns. Furthermore, it is found that the price cryptocurrency’s reaction
2.1. CRYPTOCURRENCY QUALITATIVE-BASED INDICES

to news and announcements may vary depending on the type of digital assets. Thus, according to Corbet et al. (2020b), currency-based digital assets are likely more susceptible to the US monetary policy announcements, while applications or protocol-based digital assets are immune to these shocks. Similar differences are found for mineable and non-mineable currencies, meaning that the response to various types of uncertainty of some digital assets would be distinct from that of Bitcoin. Yarovaya and Zięba (2021) further classify cryptocurrencies with respect to multiple qualitative factors, such as geographical location of headquarters, founder’s origin, underlying platform, and the consensus algorithm. They explore the differences in patterns of interconnectedness patterns between trading volume and returns across cryptocurrencies from different categories. Benedetti and Nikbakht (2021) identify that specific heterogeneous characteristics of digital tokens affected the cryptocurrency returns. The speculative nature of cryptocurrency markets has implications for market efficiency, portfolio diversification, the contagion effect and financial stability literature, see (Corbet et al., 2018b) for a systematic review of past papers in this field.

In addition to the previously addressed indices, a few papers attempt to design new uncertainty indexes, for example, Huang and Luk (2020) introduce a new China EPU index using 10 mainland Chinese newspapers. Additionally, Trimborn and Hardle (2018) introduce the CRIX index to assess the markets volatility of cryptocurrencies. Moreover, there are further cryptocurrency market indexes available, such as the market capitalisation-weighted Bloomberg Galaxy index (BGCI). However, there is presently no designed index that captures uncertainty of cryptocurrency markets’ price and policy.

This research is motivated by three main theoretical arguments discussed in the aforementioned literature. Firstly, this study’s interest lay in exploring the effect of potential clientele in cryptocurrency markets, that is, different groups of investors who are attracted to particular kinds of cryptocurrencies. Secondly, due to their speculative nature, cryptocurrencies are attractive to amateur investors who have the potential to interpret publicly available information differently from large institutional investors. Thus, the impacts of uncertainty on cryptocurrency markets will depend on types of uncertainty and the type of digital assets. Thirdly, this study considers the importance of determinants of cryptocurrency market volatility analysis. Moreover, this study does so due to the explosivity of cryptocurrencies, which has created a new type of information asymmetry that affects other markets.
and poses a significant threat to financial stability (e.g., (Akyildirim et al., 2020)). Therefore, it is important to develop a measure that can capture uncertainty in cryptocurrency markets, so that this study proposes hypothesis 1:

\[ H_1: \text{Cryptocurrency uncertainties have impacts on financial markets} \]

### 2.1.2 Volatility and uncertainty

At here, this thesis needs to make a difference 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. 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 "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. Developing uncertainty indices not only helps one identify the uncertainty of research object themselevs, but also allow one to capture how these uncertainties can disrupt the modern economies.

### 2.1.3 An index of cryptocurrency environmental attention

Although the environmental impact of cryptocurrencies has been discussed widely in the literature, awareness of this problem among cryptocurrency investors and the general public varies, and opinions are mixed. Both mainstream and scientific literature have investigated the energy and environmental footprint of cryptocurrencies, dating back to the seminal work of O’Dwyer and Malone (2014), which focus on energy consumption and conclude that the electric power then used for Bitcoin mining is comparable to Ireland’s electricity consumption. However, this does not indicate that scholars consider cryptocurrency mining activities wasteful. For example, Wimbush (2018) suggests that mining cryptocurrencies seems significantly less wasteful because they can create more value than they consume.
The development of an electricity consumption index by the Cambridge Center for Alternative Investments is also a seminal piece of work in the field\(^1\). Meanwhile, Krause and Tolaymat (2018) indicate that cryptocurrency mining activities consume more energy than mineral mining to create an equivalent market value (with the exception of aluminium mining) and also introduce CO\(_2\) emission issues. Elsewhere, Stoll et al. (2019) examine the carbon footprint issue caused by Bitcoin, reminding the public that it could not ignore the environmental risks when evaluating the anticipated benefits of Bitcoin, and Gallersdörfer et al. (2020) select more than 500 mineable crypto coins and tokens for comprehensive and systematic research on the associated energy consumption, concluding that Bitcoin consumes two-thirds of the entire energy consumption of cryptocurrencies, with the other cryptocurrencies accounting for the remaining third. Notably, studies on cryptocurrencies and energy consumption and environmental pollution issues have continued to advance, with more recent studies considering the relationship between attention on cryptocurrency energy consumption and the performance of financial markets (Corbet et al., 2021). Interestingly, Corbet et al. (2021) apply the DCC-GARCH model to investigate the effects of Bitcoin’s volatility and cryptocurrency mining activities on energy markets and utility companies, producing results suggesting that cryptocurrency energy usage has a significantly positive relationship with the performance of some companies. Naeem and Karim (2021) further probe the interdependence of Bitcoin and green financial assets through application of time-varying optimal copula, concluding that all green assets could demonstrate Bitcoin hedge capacity.

The existing literature review confirms that cryptocurrencies—including both transactions and mining activities—are significantly associated with environmental issues, including energy consumption, environmental pollution and CO\(_2\) emissions. However, there remains controversy regarding how environmental attention and public concerns adversely affect cryptocurrency prices.

This research gap is characterised by the lack of data or proxies capable of reflecting and capturing attention on cryptocurrency environmental issues, hindering analyses of the impact of cryptocurrency environmental attention on financial markets and economic development. Therefore, building on the literature on the role of media coverage, public environmental awareness and government policy in financial markets, this paper develops an index (the ICEA) capable of capturing

\(^1\)More details can be found in: https://cbeci.org/faq/
CHAPTER 2. LITERATURE REVIEW

awareness of cryptocurrency energy consumption and sustainability issues and the consequent impacts on financial markets and economic developments. First, this paper draws on work concerning environmental awareness drivers. Both Lee et al. (2015) and Brulle et al. (2012) have observed that the changing climate and environmental issues, alongside general social educational attainment, drive awareness of climate and environmental risks in financial markets, findings that align with (Capstick et al., 2015). Second, Duijndam and van Beukering (2020) have observed that the importance of climate change and environmental issues strongly correlates with future economic and financial market uncertainty, echoing the findings of Pidgeon (2012). Third, Pianta and Sisco (2020) have demonstrated that the lagged values of extreme climate events can drive media coverage, causing financial market panic. However, many of the studies on awareness of and sensitivity to climate and environmental issues have been undertaken at individual, organisational or governmental levels, with few papers addressing longer-term macro-level drivers. For example, evaluating the effects of low-energy-consumption tax reduction policies, Dongyang (2021) observe that positive policies can improve the innovation investments of companies by alleviating financial constraints. Elsewhere, empirical findings from Zhang et al. (2021) provide evidence that air pollution in a city has a significantly positive relationship with an IPO under-pricing a company that is located in the city. Based on this gap, this paper will further examine the effects of the ICEA on financial markets or economic developments.

From a sustainability perspective, cryptocurrency mining’s negative impact on the environment is significant (Krause and Tolaymat, 2018). Motivated by this emerging challenge, this study has identified several issues. First, there is very limited existing research on the extent or determinants of cryptocurrency’s growing energy consumption problem, precluding any conclusive scientific confirmation about its contribution to climate change. Moreover, the few extant studies concerning the relationship between cryptocurrencies and environmental issues focus on how cryptocurrencies contribute to environmental issues (Corbet et al., 2021), with few studies comprehensively investigating inverse interactions. Second, no existing studies report on how environmental attention on cryptocurrencies can shock the cryptocurrency markets, not even the literature examining which financial or economic variables are susceptible to shocks transmitted by cryptocurrency environmental attention. Third, no clear and substantial regulations or policies consider the environmental issues related to cryptocurrency (Chudinovskikh and
Thus, this study has identified two research gaps in the existing literature. First, there is no proxy that reflects cryptocurrency environmental attention. Second, the impact of cryptocurrency environmental attention on long-term macro-financial markets and economic developments remains an undeveloped research field. In bridging these gaps, this study proposes the hypothesis 2:

H2: Cryptocurrency environmental attention has impacts on financial markets

### 2.1.4 UCRY indices and volatility forecasting of precious metal futures markets

The existing literature related to the inter-linkage between cryptocurrencies and precious metal markets have two major problems. On the one hand, most existing papers on the interactions between cryptocurrency and precious metal markets only use the same frequency data to conduct their empirical examinations (Hassan et al., 2021; Elsayed et al., 2022b; Bianchi et al., 2022). For example, the spillover analysis massively used in recent studies can only adopt the same frequency data, e.g., daily return or volatility series, to measure the connectedness effects. Furthermore, this method can only show the direction and intensity of the spillovers but cannot provide evidence of whether these spillover effects are statistically significant. Moreover, as we know, many uncertainty measurements, such as Economic Policy Uncertainty (EPU) of (Baker et al., 2016), Geopolitical Risk index (GPR) of (Caldara and Iacoviello, 2022), and the recently launched cryptocurrency uncertainty of (Lucey et al., 2022), are only recorded in monthly or weekly frequency, which have been proved to be very informative in explaining or predicting the fluctuations of both cryptocurrency and precious metal markets in many recent studies (Wu et al., 2019; Hassan et al., 2021; Hernandez et al., 2022; Lucey et al., 2022). Thus, ignoring these low-frequency (monthly or weekly) uncertainty measures in investigating cryptocurrency and precious metal markets will lose lots of useful information and may lead to unreliable conclusions.

On the other hand, most current studies focus only on the one-way influence of precious metals on cryptocurrencies, and ignore the possible reverse influence between them. For instance, Hassan et al. (2021) believe gold can provide a hedge against the cryptocurrency uncertainty indices, but they fail to discuss whether...
CHAPTER 2. LITERATURE REVIEW

cryptocurrency uncertainty can help to explain and forecast the volatility of the gold market. Moreover, the existing literature about the uncertainty measures and gold markets which apply a mixed data sampling model either do not consider the linkages between the newly developed cryptocurrency uncertainty indices and gold market (Feng et al., 2018) and (Wu et al., 2019), or neglects the impacts of the uncertainty of the gold market itself [CBOE Gold ETF Volatility Index (CBOE GVZCLS)] on the volatility of gold markets (Zhou et al., 2018b). To be more specific, the existing literature fails to show whether low-frequency uncertainty measures (especially the newly developed cryptocurrency uncertainty) can help to depict and forecast the volatilities of precious metal markets.

Motivated by the research gaps mentioned above, this study firstly extends the GARCH-MIDAS model of (Engle et al., 2013) by incorporating cryptocurrency uncertainty indices to identify the impacts of these uncertainty indices on the volatility of precious metal markets. Based on this, this study proposes hypothesis 3:

H₃: Cryptocurrency uncertainties have impacts on volatility of precious metal markets

Secondly, this study quantifies both the in-sample impacts and the out-of-sample predictive abilities of cryptocurrency uncertainties on the volatilities of precious metal markets. This study, therefore, proposes hypothesis 4:

H₄: Cryptocurrency uncertainties contain useful forecasting information for the volatility of precious metal markets
2.2 CBDC QUALITATIVE-BASED INDICES

2.2 CBDC Qualitative-Based Indices

2.2.1 The effects of central bank digital currencies news on financial markets

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 (Turrin, 2021). 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 (Ferrari et al., 2022; Chen and Siklos, 2022; Castrén et al., 2022). Indeed, Zams et al. (2020), using an analytic network process and the Delphi method, demonstrate 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) investigate 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) examine 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) focus 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 (Masciandaro, 2018; Li and Huang, 2021; Allen et al., 2022). While the above mentioned researchers hold positive attitudes towards CBDCs, Kirkby (2018) criticises 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) propose 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) conducts an experimental study on a Chinese prototype of a CBDC system. Qian
(2019) introduces a CBDC issuance framework designed for forward contingencies in order to prevent the currency from circulating beyond the real economy. Wagner et al. (2021) discusses and proposed a potential blueprint for a digital euro and proved its possibility. Lee et al. (2021b) propose 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. Tronnier (2021) and Borgonovo et al. (2021) demonstrate the significance of anonymity for increasing the overall attraction of CBDCs’ social medium payment. Lee et al. (2021c) conduct 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 revise CBDCs and further discussed their implications on economics, monetary policy, and legal issues. Meaning et al. (2021) discuss 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) apply a qualitative analysis of China’s CBDCs and their impacts on monetary policy and payment competition, and argue 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 argue 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 discuss CBDCs’ monetary risks, for example, Viñuela et al. (2020) list the sources of these risks, and present 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) provides 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 supports the radical proposal due to its ability to
condense the banking system and reduce the need for deposit insurance. Furthermore, some discussions centre 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 (Ferrari et al., 2022). 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., 2022), 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., 2022b). 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 this 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 study, therefore, proposes hypothesis 5:

H5: Statistically significant relationships exist between CBDC news and financial markets
2.3 NFTs Qualitative-Based Index

2.3.1 Volatility spillovers across NFTs news attention and financial markets

In the last past 12 months, NFT assets have gained significant attention and have become one of the most popular alternative investment instruments in 2022. More and more finance researchers are beginning to pay attention to the NFT research areas. Several papers concentrate on the asset pricing field of NFTs. By adopting the VECM model, Ante (2022) demonstrates that the shocks from Bitcoin prices could increase NFT sales and that active NFT wallets respond negatively to Ethereum price shocks. Furthermore, processing the Granger causality and IRF tests, Ante (2022) further finds that the NFT market has a long-run equilibrium relationship. Additionally, significant short-run relationships can also be found among NFTs’ hot assets, which indicates that the NFT market has the endogenous shock characteristic—an empirical finding consistent with (Aharon and Demir, 2022). Recently, Vidal-Tomás (2022) shows that his own selected 174 tokens have positive performance in the long run. It is worth noting that both Dowling (2022) and Aharon and Demir (2022) mention inefficiency in the pricing of the NFT market. As for the price bubble detecting in the NFT markets, Maouchi et al. (2022), Vidal-Tomás (2022) and Wang et al. (2022c) all conclude there are periods of clear bubble behaviours in the NFT markets. Mazur (2021) first investigates the risk and return profiles of NFT-based startups by using data from the cryptocurrency exchange market. He suggests that NFTs can carry more benefits than traditional investment assets. Later, based on the CryptoPunks and hedonic regression model (Rosen, 1974), Kong and Lin (2021) construct an NFT market price level index in order to analyse the pricing and NFT risk-return conditions. They suggest that NFT assets can already be valued as new alternative investment tools and could outperform traditional financial assets—the same conclusion drawn by (Mazur, 2021). Furthermore, they also observe that an NFT asset’s scarceness and an investor’s aesthetic preference can significantly impact the pricing of NFTs. In addition, Kanellopoulos et al. (2021) investigate the effects of NFTs on the pricing of physical products. They use eBay data to measure the dynamic relationships between the prices of basketball trading card collectables and an NFT asset named "NBA Top Shot (NTS)". Their findings suggest that the introduction of the NTSs’ NFT could negatively impact the prices of the collectables.
One significant stream of finance studies related to NFTs is the investigation of inter-relations between NFT asset class and other classic asset classes. Dowling (2021), Umar et al. (2022c) and Vidal-Tomás (2022) systematically examine the co-movements between NFT assets and other financial assets by employing the wavelet analysis. Umar et al. (2022c) believe that the co-movements between NFTs and other assets only can hold in a short-term horizon, which can refine the findings of (Aharon and Demir, 2022). Furthermore, Vidal-Tomás (2022) observes that his own selected 174 tokens decouple with the cryptocurrency market, which argues with the findings of Dowling (2021), who believes co-movement trend can hold between NFT and cryptocurrency markets. It is worth noting that spillover connectedness is the most popular methodology in the NFTs area, which use to examine the interconnections between the NFT markets and other financial markets.

Through applying the TVP-VAR approach, (Dowling, 2021) and (Aharon and Demir, 2022) suggest that NFTs are relatively independent and isolated. Dowling (2021) observes only limited volatility transmission effects among NFTs and cryptocurrencies. Aharon and Demir (2022) state the variations of their volatilities predominantly stem from the shocks of NFTs themselves, compared with the shocks from equities, bonds, currencies, gold, oil, and cryptocurrencies. Moreover, NFTs can be valued as transmitters of systemic risk during tranquil periods. However, NFTs can act as volatility spillover receivers during turbulent financial markets. This argument is supported by (Mazur, 2021), who find that the NFT markets contribute to the market’s recovery following the mid-2021 crash. Additionally, Dowling (2021) and Aharon and Demir (2022)’s findings are further confirmed by Karim et al. (2022), who present a strong disconnection of volatility spillover connectedness in NFT assets and other Blockchain markets by employing the quantile connectedness technique. Recently, Ko et al. (2022) and Yousaf and Yarovaya (2022) further use the TVP-VAR model to examine the volatility and/or return transmission between NFT, DeFi, cryptocurrency, stock, bond, U.S. dollar, and commodity markets. Both of them indicate that the new alternative asset class, NFTs, disconnect from other classic assets, which is also in line with the existing literature. As expected, all of the above studies suggest significant diversification benefits in the NFT asset class.

The existing studies related to NFTs which apply the spillover connectedness analysis have compared NFT assets with other financial assets, measured the correlation between NFT asset class with other asset classes, and detected the
volatility and/or return spillover transmission channels between NFT markets and other classic financial markets. All of these studies utilise the average price of NFT assets or NFT sectors as proxies to represent NFT markets. However, an issue is that NFTs are traded infrequently, and they differ in terms of quality. Therefore, it is imperfect just to use average price to represent NFT markets, and it is also hard to construct a comprehensive composite NFT price index by simply looking at price differences like stock, bond and cryptocurrency composite indices. To address the issue just mentioned, this study proposes to construct a qualitative-based index to capture the public attention on NFTs as a proxy for NFT markets, as tapping newspapers or online database archives to develop and issue new measures of financial or economic activities is a widely used method and one whose accuracy and efficiency have been approved (Baker et al., 2016) and (Huang and Luk, 2020).

Social media has become a popular venue for the public to share minds on financial markets (Da et al., 2011). Several latest papers develop new measures of attention to the digital currency literature. For example, Urquhart (2018) investigates the attention of Bitcoin by using Google trends data and demonstrates that the attention of Bitcoin is impacted by the previous day’s high realised volatility and volume of Bitcoin. Then, Shen et al. (2019) examine the interconnections between investor attention and Bitcoin based on the Twitter trends, suggesting the Twitter trends can predict the next day’s trading volume and realised volume of Bitcoin. Recently, Liu and Tsyvinski (2021) construct investor attention proxies for cryptocurrency based on Google trends. This research indicates that high investor attention on cryptocurrency could predict high future returns over the one-to-six-week horizons. Still, in the cryptocurrency area, Wang et al. (2022b) collect data from LexisNexis News & Business, and develop cryptocurrency environmental attention index (ICEA). This study measures the relative extent of media discussions surrounding the environmental concerns on the volatility of cryptocurrency market. In other digital currency areas, Wang et al. (2022d) develop the CBDC attention index (CBDCAI) based on the LexisNexis News & Business database and reveal the market reactions to central bank speeches. Therefore, this study decides to construct a new NFT proxy, named NFTs Attention Index (NFTsAI), based on texting mining to reflect the public attention on NFTs for investors, policymakers and academics. Moreover, the general consensus from the studies related to investor attention is that an attention measure and the target market for this attention measure could hold causality; co-movement relationships or spillover effects (Peng and Xiong,
2.3. NFTs Qualitative-Based Index

2006; Barber and Odean, 2008; Da et al., 2015). These papers inspire this thesis to suppose that statistical and economic relationships may exist among NFT markets and the public attention related to NFT assets. Based on this, this study proposes hypothesis 6:

\[ H_6: \text{NFTsAI has financial linkages with the NFT markets.} \]

Referring to the latest studies about NFTs by using the TVP-VAR framework, they all suggest that NFT asset class is relatively isolated by other asset classes (Dowling, 2021; Aharon and Demir, 2022; Karim et al., 2022; Ko et al., 2022; Yousaf and Yarovaya, 2022). This interesting finding inspires me to further explore volatility transmission between the NFT markets and other financial markets by using NFTsAI as an indicator to represent the NFT markets, via the TVP-VAR framework. First, because the TVP-VAR framework is the most widely used econometrics model to evaluate the efficiency of a new issued qualitative-based index, from the well-known Economic Policy Uncertainty Index (EPU) (Baker et al., 2016), to the latest digital currency indices (Lucey et al., 2022; Wang et al., 2022b; Wang et al., 2022d). Second, the TVP-VAR model can estimate the volatility transmissions in both the static and time-varying two perspectives, which allows one to discover new channels of risk transmission between the emerging NFT markets and other financial markets. Furthermore, based on the theory of (Corbet et al., 2018b); (Akyildirim et al., 2020) and (Yousaf and Yarovaya, 2022), which suggest the emerging investment assets could show a significant disconnection with other classic investment instruments because of the investment information asymmetry. NFTsAI as a new proxy to reflect investor attention on the NFT asset class. This study, therefore, proposes hypothesis 7:

\[ H_7: \text{The intensity and magnitude of volatility spillover from other financial markets to NFTsAI are higher than from NFTsAI to other financial markets.} \]

2.3.2 Detecting and date-stamping bubble behaviour in NFT markets

There is a vast body of literature on the speculative price bubble formation in financial markets in the context of stocks (Pástor and Veronesi, 2009) and (Phillips et al., 2011), real estate (Kivedal, 2013) and (Jordà et al., 2015), and commodities (Sornette et al., 2009) and (Figuerola-Ferretti and McCrorie, 2016). Scholarly
work, examining the price behaviour of cryptocurrencies conversely raised evidence of explosive patterns in the price formation of several major capitalised digital currencies, pointing towards a speculative character of the digital instruments Kyriazis et al. (2020). Pioneering research by Garcia et al. (2014) first evidence two positive feedback loops that positively affect the fluctuation in Bitcoin prices and may enforce price bubbles without exogenous interference. MacDonell (2014) utilises Autoregressive Moving Average (ARMA) methodologies in combination with the Log-Periodic Power Law Singularity (LPPLS) - framework and found investor sentiment, proxied by the CBOE volatility index (VIX), to be of influential nature for changes in Bitcoin values. Cheah and Fry (2015) confirm first evidence of explosive bubble behaviour in Bitcoin prices that manifested in dramatic price rises, leading to the estimate that the fundamental value of the digital token is close to zero. Urquhart (2016) finds the Bitcoin market to be generally inefficient but acknowledges that prices do seem to approach a random distribution pattern with growing market maturity. By deploying a bubble detection methodology from the traditional financial markets, Cheung et al. (2015) conduct the PSY generalised Supremum Augmented Dickey-Fuller (GSADF) test to examine price bubbles in Bitcoin.

These findings give a first indication about inefficient pricing mechanisms in the largest capitalised cryptocurrency and spur further research intentions on other cryptocurrencies. Following the econometric test framework of the GSADF- or SADF test, several papers have detected price bubbles in Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, Stellar and Dogecoin (Su et al., 2018; Corbet et al., 2018a; Li et al., 2019; Bouri et al., 2019; Geuder et al., 2019; Li et al., 2021a; Shahzad et al., 2022.) Conversely, Wheatley et al. (2019) further explore price bubble formations in Bitcoin values by means of a combinatorial approach of applying a generalised metcalf's law in line with an LPPLS model to closer study potential bubble dynamics in Bitcoin markets. The results indicate the occurrence of four distinct bubbles, characterised by high overvaluation and LPPLS-like trajectories that entailed crashes or strong corrections [ibid.]. Further approaches containing the LPPLS approach have also been used by other scholars to capture explosive behaviour in the digital currency area (Geuder et al., 2019; Gerlach et al., 2019; Wheatley et al., 2019; Shu and Zhu, 2020; Shu and Zhu, 2020).

Numerous scholars also address the potential recurrence and degree of magnitude for price bubbles in cryptocurrency markets. Gerlach et al. (2019) study the
price dynamics of Bitcoin and specifically characterise the time duration of price bubbles based on their temporal nature. The authors evidence several long- and short-term bubbles in the time span of 2012 to 2018 that point to a multiscale character of the bubble dynamics in Bitcoin prices. Geuder et al. (2019) further underline these findings by raising evidence of frequent bubble periods in the price formation of Bitcoin and emphasise the recurring character of the bubbles. Bouri et al. (2019) detect several price explosivity periods for seven major-capitalised cryptocurrencies that suggest a re-emerging character of bubble dynamics in different markets with varying scales of magnitude and a certain degree of co-movement between the different digital assets. Conversely, Chen and Hafner (2019) test for speculative bubbles in the entire cryptocurrency market, mirrored by the CRIX index, via a profound sentiment-induced econometric framework. The authors simultaneously detect several short-term bubble phases for the market in the years 2017 to 2018 that indicate recursive regime shifts in the price explosivity potentially induced by investor sentiment.

Corbet et al. (2018a) lead a consecutive study on the price discovery of Bitcoin and Ethereum and oppositely can not find clear evidence that a persistent bubble is evolving within both markets. However, it concludes that the findings do not indicate that prices meet efficient standards and the authors attest short-term influential inter-linkages between the price formation of both cryptocurrencies and fundamental drivers such as blockchain position, liquidity, or hash-rate that could support bubble forming behaviour. Hafner (2020) argues in favour of bubble occurrences in cryptocurrency markets while studying the price properties of the 11 major-capitalised cryptocurrencies. By accounting for time-varying volatility in the price dynamics of the cryptocurrencies, the author identifies explosive bubble patterns in the index, although it constitutes that the effect is much less pronounced compared to a constantly assumed volatility component. Li et al. (2019) particularly focus on the potential formation of Bitcoin price bubbles in China and the U.S., thereby examining the nature of the bubble proliferation across time. The authors find evidence of several explosive price bubbles that accompany highly volatile economic events, suggesting spillover effects of foreign financial risk to cryptocurrency markets. As NFTs are embedded in similar blockchain ecosystems, the potential for bubble formation may be in proliferated by similar tendencies found in cryptocurrency markets.

It can be constituted that NFT markets have gained significant scholarly at-
tention in recent time and research efforts are considerably focused on examining financial properties alongside the economic attributes of the NFT markets. As novel instruments, NFTs assets specifically provoke research on the matter of market efficiency (Maouchi et al., 2022) and (Dowling, 2022), volatility dynamics (Aharon and Demir, 2022) and (Umar et al., 2022b), risk-return relationships (Borri et al., 2022) and trade network attributes (Nadini et al., 2021).

In this context the emerging literature so far has only sparsely accounted for any form of price explosive patterns in NFT markets. First studies by Dowling (2022) and Maouchi et al. (2022) assess the price behaviour of the new instruments by focusing on specific categories in the area of metaverse token. The studies reach to a common consent that NFT assets do possess inefficient and bubble-like price explosiveness at different time spans that are driven by unique price dynamics in NFT markets. Hence, the early scholarly evidence seems to indicate that bubble dynamics within the NFT markets seem to be driven by unique token pricing factors. However, current research is far from systematically explaining bubble dynamics in NFT markets. To fill this research gap, this study detects and date-stamps bubble behaviours in NFT markets. This study, therefore, proposes the research hypothesis 8:

\[ H_8: \text{NFT market exist price bubbles} \]

### 2.4 Summary of Research Questions and Research Hypotheses

This section concludes the research hypotheses that are under-considered in this thesis. This study aims to introduce a new methodology to develop and evaluate qualitative-based indices in digital assets to investors, policymakers and other researchers. Moreover, bearing in mind the identified gaps in the literature review, which are mentioned above, three research questions can be proposed precisely:

**Research question one:**

What are the impacts of media coverage of cryptocurrencies on financial markets?

**Research question two:**
2.4. SUMMARY OF RESEARCH QUESTIONS AND RESEARCH HYPOTHESES

What are the interconnections between the CBDC attention/uncertainty and financial markets?

Research question three:

Does any dynamic connectedness exist in patterns of volatility spillovers across NFTs news attention and financial markets?

Following the positivist research paradigms, the list of research hypotheses has been developed based on each research question. These research hypotheses can be examined indiscriminately by applying different methodologies. Therefore, each hypothesis regarding the particular econometric model used can be further specified in the empirical chapters. Because of the ambiguity of the definition of effect hypothesis, relationship hypothesis, spillover hypothesis, among others, this thesis specifies each research hypothesis by applying the research metaphors, concepts and other terminology. The following hypotheses are summarised to clarify more specifically what will be investigated in this thesis according to the three research questions mentioned above.

For the first research question, the following hypothesis is tested:

\[ H_1: \text{Cryptocurrency uncertainties have impacts on financial markets} \]

This hypothesis assumes that cryptocurrency policy uncertainty and cryptocurrency price uncertainty captured by tapping online databases have financial linkages with financial markets. The rejection of this hypothesis provides the opposite conclusion.

\[ H_2: \text{Cryptocurrency environmental attention has impacts on financial markets} \]

This hypothesis supposes that cryptocurrency environmental attention has financial linkages with financial markets. The rejection of this hypothesis provides the opposite conclusion.

\[ H_3: \text{Cryptocurrency uncertainties have impacts on the volatility of precious metal markets} \]
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This hypothesispresumes that the cryptocurrency policy uncertainty and cryptocurrency price uncertainty have financial linkages with the short- and long-term volatility of precious metal markets, such as gold and silver. The rejection of this hypothesis provides the opposite conclusion.

**H₄:** Cryptocurrency uncertainties contain useful forecasting information for the volatility of precious metal markets

This hypothesis postulates that the cryptocurrency policy uncertainty and cryptocurrency price uncertainty could predict the volatility of precious metal markets, such as gold and silver. The rejection of this hypothesis provides the opposite conclusion.

Further, to answer the second research question, the following research hypothesis is tested in this thesis:

**H₅:** Statistically significant relationships exist between CBDC news and financial markets

This hypothesis presumes that CBDC news has interconnections with financial markets. The rejection of this hypothesis provides the opposite conclusion. The third research question suggests the following research hypotheses that are tested in this thesis:

**H₆:** NFTs news attention has financial linkages with the NFT markets

This hypothesis supposes that statistically and economically relationships may exist among NFT markets and the public attention related to NFT assets.

**H₇:** The intensity and magnitude of volatility spillover from other financial markets to NFTsAI are higher than from NFTsAI to other financial markets

Firstly, this hypothesis postulates that cryptocurrency, DeFi, equity, bond, commodity, F.X., and gold markets are the contributors of the volatility transmissions, while the NFT markets is a receiver. This hypothesis can be confirmed or rejected by using the results of volatility spillover connectedness between NFT, cryptocurrency, DeFi, equity, bond, commodity, F.X., and gold markets. The rejection of this
2.4. SUMMARY OF RESEARCH QUESTIONS AND RESEARCH HYPOTHESES

Hypothesis provides the opposite conclusion. Secondly, this hypothesis suggests that the DeFi, equity, bond, commodity, F.X., and gold markets are more efficient channels of volatility transmission, while NFT markets are less efficient and mainly independent of other financial markets’ shocks. The rejection of this hypothesis provides the opposite conclusion.

**H₅: NFT markets do exist price bubbles**

This hypothesis assumes that NFT markets have single and multiple periodically collapsing price phenomena. The rejection of this hypothesis provides the opposite conclusion.
A PhD thesis aims to explain the development of knowledge that has been achieved through research (Gosling and Noordam, 2011) and the ways in which the philosophical assumptions of the individual researcher could have an impact on the research outputs. This chapter highlights the positivist philosophical standpoint of this thesis, followed by an explanation of the positivist research process, and demonstrates the impacts of positivism on the research output and interpretation.

3.1 Positivism

Comte (1865) explains that positivism is an approach that dispassionately observes facts and relies on empirical evidence. "Positivism has an atomistic, ontological view of the world as comprising discrete, observable elements and events that interact in an observable, determined and regular manner" (Collins, 2018). In other words, the findings are generated from experiments and statistics to reveal information about how society operates. For this reason, finance could be considered the closest of all social sciences to a natural science (Vigne, 2017). Moreover, objectivity is at the heart of positivism, with the implication that the research subject and the researcher are independent of each other. Positivists believe that although all people have their own way of learning new things, their subjective judgement and feelings do not make a significant difference to the process. Establishing an
objective knowledge system is the primary aim of positivism. The researcher is an objective analyst, and their role is limited to data collection and objectively interpreting empirical results. From the positivist perspective, the research subject can be divided into several independent variables which can each be investigated separately (Curd et al., 2014). This characteristic contributes to positivism and may be the most widely-used philosophical theory in the finance and econometrics areas.

According to the framework of the positivist approach, the research activities themselves are not dependent on any direct interactions with the facts being investigated (Booth et al., 2018). The positivist approach is rooted in a belief in the objectivity of the literature review, data, methodology and empirical analysis sections.

### 3.2 Positivist Research Principle

Positivists believe that the only reliable way to gain knowledge is through observation, including quantitative measurement (Andersen and Hepburn, 2015). The main principle of positivist research is that research is purely objective and based on facts. The researcher is independent of the research, and the world is external to them and can be objectively observed (Burrell, 1999). Therefore, positivists prefer to take a deductive approach, which in turn encourages positivists to focus on statistical analyses of quantifiable observations (Singleton and Straits, 2010).

In the financial field, the positivist approach claims that finance research is value-free and not based on common sense. Moreover, it should not be affected by the personal values, expectations, or beliefs of the researcher. As a result, when objective conditions are the same, two independent positivist researchers should always arrive at the same empirical findings and research conclusions.

### 3.3 Positivist Paradigm Criteria

Following the positivist paradigm criteria proposed by Vigne (2017), this thesis employs two criteria to evaluate the usefulness of the knowledge obtained under the positivist paradigm: generalisability and reliability.

Generalisability indicates that the results and knowledge gathered from the research activities on a sample can contribute to a general theorem which could
be used to make inferences about the whole sample (Singleton and Straits, 2010). For example, this thesis proposes a new method for developing qualitative-based indices, such as uncertainty indices and attention indices, which could be used to capture movements in the financial markets beyond volatility. Based on this qualitative-based index construction methodology, future research could develop more indices to understand broad financial and econometrics developments more comprehensively.

Reliability can be interpreted as consistency, which means the research procedures should be repeatable and produce the same or insignificantly different results. Consequently, reliable research should gain the most precise results (Gujarathi, 2022). Reliability also considers whether the inferences made from research are appropriate, meaningful, and useful. There are two ways to evaluate the reliability of research. The first one is internal reliability evaluation, which focuses on the design and implementation of the research procedures. The second one is external reliability evaluation. It assesses whether the observed findings could have been caused by other potential explanatory variables overlooked in the empirical analysis. The most straightforward method to achieve a reliability evaluation is through robust testing. A robustness test aims to check whether observed empirical findings are the same by deriving methods that gain reliable parameter estimates and associated tests, confidence intervals, distributions, and assumptions, among others (Maronna et al., 2019).
This chapter illustrates the construction method of the qualitative-based indices and presents data considered throughout the study. Different variables, time spans and data types are considered across the three different research chapters. This chapter will also justify why specific variables are considered and how these variables can help to address the three research questions. While the section starts by displaying the construction of cryptocurrency uncertainty indices, cryptocurrency environmental attention index, CBDC attention/uncertainty indices, and NFTs attention index, later sections will directly link the newly issued indices and the variables used to the individual chapters of this study.

4.1 Index Construction Method

The method of qualitative-based indices’ construction draws from the methods of Baker et al. (2016), who creates the Economic Policy Uncertainty index (EPU). However, considering the database used for the new indices’ construction, the method of this thesis differs from (Baker et al., 2016, Huang and Luk, 2020, Shen et al., 2019), who collect data from American newspapers, Chinese newspapers, Twitter trends, Baidu trends, or Google trends for constructing their indices. In contrast, this thesis chooses LexisNexis News & Business, a comprehensive digital database, as a data source 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. The rationale for using a greater range of sources, including but not limited to news-wire feeds and media news transcripts, is to acknowledge the “social” aspect of digital assets. As new phenomena, these assets have become subject to extensive discussion via not just traditional media, but alternative and social media.

One drawback of constructing an index based on any literature archive (including online database) 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. Firstly, $N_t$ denotes the weekly observed value of news articles from the LexisNexis News & Business database in time $t$ that meet the search string. Secondly, the series is then standardised to obtain a time series dataset as the initial index. In detail, compute $\mu$, the mean of the raw counts of the overall articles. Next, calculate the time-series standard deviation, $\sigma$. Then, perform $N_t$ minus $\mu$ and then divide by $\sigma$ to complete the raw counts standardisation process, $Z_t$. In the end, adding an average value of 100 for all $t$ in $Z$ to eliminate the potential negative impacts caused by the overall volume of articles varies across publication sources and time $t$, and to obtain the final normalised time-series index.

Based on the index construction method mentioned above, this thesis does not need to distinguish and sort between the important news stories and the smaller ones when it constructs the qualitative-based indices. Instead, it just needs to count the weekly observed value of news articles from LexisNexis News & Business, regardless of where the keywords from a search string are located in an article’s title, main content, comments or elsewhere. Moreover, flash events are collected according to the frequency of articles that have the same topic. During the digital assets’ high uncertainty and attention periods, there are a plethora of articles that could discuss the same topic. The flash events can then be extracted from the heated discussion topics.

This thesis builds all the qualitative-based indices related to digital assets using weekly data, and the reasons are as follows. First, Dowling (2022) confirm that the cryptocurrency and NFT markets are inefficient and rapidly rising in value. These findings indicate there to be market manipulations in cryptocurrency and NFT pricing, fraudulent behaviours and speculative transactions in cryptocurrency.
and NFT markets, thus leading to many price bubbles. Second, qualitative-based indices are all text mining-based indices, which are subject to extreme fluctuations (Baker et al., 2016). Due to these reasons, if this thesis had constructed the indices in a high-frequency index (i.e., 5 Minutes/30 Minutes/Daily), it would have been filled with outliers and could not have shown the real trend. Moreover, the famous text mining-based indices, such as EPU (Baker et al., 2016), China EPU (Huang and Luk, 2020) are all low-frequency indices (i.e., weekly/monthly).

In addition, this thesis sets the option for Group Duplicate to MODERATE or HIGH in the LexisNexis News & Business database so as to avoid duplicate results as much as possible.

### 4.2 Search String

This thesis firstly intends to develop several qualitative-based indices, and these new indices are based on text mining, meaning that the core of their constructions involved designing a rigorous and comprehensive search string to collect necessary data. Moreover, as an attention or uncertainty index, it is essential to gather as many relevant terms as possible so as to capture and reflect the trends of the aimed objective. The search string for each index is introduced as follows.

#### 4.2.1 Search string for UCRY indices

**4.2.1.1 Search string for UCRY Policy**

The text search string used to ascertain uncertainty around policy issues can be displayed as follows:

\[
(\text{uncertain or uncertainty}) \text{ and price and atl1(Bitcoin or Ethereum or ripple or litecoin or tether or cryptocurrency or cryptocurrencies) and atl1(regulator or regulators or “central bank” or government)}
\]

**4.2.1.2 Search string for UCRY Price**

The following search string can be used to gather results on price uncertainty:

\[
(\text{uncertain or uncertainty}) \text{ and price and atl1(Bitcoin or Ethereum or ripple or litecoin or tether or cryptocurrency or cryptocurrencies)}
\]
4.2.2 Search string for ICEA

Cryptocurrency environmental attention index (ICEA) relates to the cryptocurrency environmental attention. Therefore, the search string for ICEA should focus on the "cryptocurrency" and "environment". First, there is no doubt that "cryptocurrency" is set as the first search term. Second, as the two most popular cryptocurrencies (Urquhart, 2016) and (Corbet et al., 2018a), "Bitcoin" and "Ethereum" are also selected as key search terms to represent the cryptocurrency markets. Third, this study search for the most popular synonyms for "environmental" to represent "environmental attention", based on the literature review of the relationship between cryptocurrencies, environmental issues and energy consumption concerns. This study picks up "energy", "energy consumption", "energy footprint", "carbon footprint", "environment", "environmental", "environmental impact" and "climate change" to represent "environmental attention". In the end, compiling these key search terms together can successfully generate the final search string for ICEA. In addition, this study sets the option for Group Duplicate to HIGH so as to avoid duplicate results as much as possible. The queries were performed for each week from January 2014 to the beginning of May 2021. The search string for ICEA is presented as follows:

\[
[ ("cryptocurrency" \text{ or } "bitcoin" \text{ or } "ethereum") \text{ and atl1("energy" \text{ or } "energy consumption" \text{ or } "energy footprint" \text{ or } "carbon footprint" \text{ or } "environment" \text{ or } "environmental" \text{ or } "environmental impact" \text{ or } "climate change")}]
\]

4.2.3 Search string for CBDCs indices

This study conducts multiple search in LexisNexis News & Business using combinations of keywords relevant to CBDCs. There is no doubt that "Central Bank Digital Currency" and "CBDC" are set as key search terms. Moreover, due to the identification of the strongest currencies (see the literature review section), this study considers 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. Therefore, the aforementioned search terms have been translated to

\[1\text{Weekly values can be downloaded from here: https://sites.google.com/view/cryptocurrency-indices/home?authuser=0}\]

\[2\text{Although the official languages in Switzerland are German, French, Italian, and Romansh, its population is relatively small, meaning that this study considers Switzerland an English-speaking country}\]
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, this study also translates "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, this study includes "Digital currency" as another key term. Once done, this study searches for the most popular synonyms for digital currency, which finds to be "digital money", "electronic currency", "electronic money", "e-currency", and "e-money". Therefore, this study also sets these five synonyms as key search terms.

Knowing that USD, EUR, GBP, CHF, RUB, JPY, and CNY are heading towards CBDCs, this study substitutes 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, this study not only keeps the English search terms, but also translates them into the particular official languages. Considering that Germany and France have the EU’s strongest economies, this study also translates "digital euro", "electronic euro", and "e-euro" into German and French. As this study considers Switzerland an English speaking country, this study applies "digital Swiss franc", "electronic Swiss franc", "e-franc", "digital CHF", "electronic CHF", and "e-CHF". Compiling these key search terms together could generate the search string for CBDCAI. Based on the CBDCAI’s search term, this study then adds a new search term, "uncert!", with the link of "and", not "or". Therefore, this study obtains a new search string for CBDCUI. Additionally, this study sets the option for Group Duplicate to MODERATE so as to avoid duplicate results as much as possible. The search strings for CBDCUI and CBDCAI are as follows Figure 4.1 and Figure 4.2:

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3Weekly values can be downloaded from: https://sites.google.com/view/cryptocurrency-indices/the-indices/cbdc-indices?authuser=0
4.2.3.1 Search string for CBDCAI

Figure 4.1: CBDC attention index search string

Notes: This figure reports the search string for the CBDC attention index. Importing this search string to LexisNexis News & Business, 175,041 articles concerning central bank digital currency attention can be collected between January 2015 and June 2021.

4.2.3.2 Search string for CBDCUI

Figure 4.2: CBDC uncertainty index search string

Notes: This figure reports the search string for the CBDC uncertainty index. Importing this search string to LexisNexis News & Business, 10,534 articles concerning central bank digital currency uncertainty can be collected between January 2015 and June 2021.
4.2.4 Search string for NFTsAI

This study further employs bibliometric analysis and Latent Dirichlet Allocation Topic Modelling (LDA topic modelling) to design a search string for NFTsAI. Based on certain bibliometric studies (Aria and Cuccurullo, 2017), this study chooses academic papers as the optimal places for locating key terms for the NFTsAI search string due to their being straightforward, concise, and professional. Furthermore, due to its ability to extract topics from a given corpus, the LDA topic modelling is also helpful for deciding which terms could be selected for the NFTsAI search string (Blei et al., 2003). Therefore, this study uses ["("NFTs") AND ("Non-fungible tokens")]

Due to the many unpublished working papers about NFTs on SSRN, this study also applies the web crawler to download these corpora. Finally, this study combines these corpora from Scopus and SSRN, runs them into a bibliometrics analysis, and sorts them in a LDA topic modelling - the results of which are shown in Table 4.1.

<table>
<thead>
<tr>
<th>Topic 1</th>
<th>Topic 2</th>
<th>Topic 3</th>
<th>Topic 4</th>
<th>Topic 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>(&quot;Non-fungible tokens&quot;)</td>
<td>(&quot;digital art&quot;)</td>
<td>(&quot;digital collectibles&quot;)</td>
<td>(&quot;digital identity&quot;)</td>
<td>(&quot;CryptoKitties&quot;)</td>
</tr>
<tr>
<td>(&quot;NFTs&quot;)</td>
<td>(&quot;crypto art&quot;)</td>
<td>(&quot;crypto collectibles&quot;)</td>
<td>(&quot;IdToken&quot;)</td>
<td>(&quot;WCK&quot;)</td>
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<tr>
<td></td>
<td>(&quot;cryptocurrency art&quot;)</td>
<td>(&quot;cryptocurrency collectibles&quot;)</td>
<td>(&quot;token unique&quot;)</td>
<td>(&quot;CryptoPunks&quot;)</td>
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<tr>
<td></td>
<td>(&quot;artwork tokenised&quot;)</td>
<td></td>
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<td>(&quot;Axie Infinity&quot;)</td>
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<td></td>
<td>(&quot;digital image licensing&quot;)</td>
<td></td>
<td></td>
<td>(&quot;Bored Ape Yacht Club&quot;)</td>
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<td></td>
<td></td>
<td>(&quot;The Sandbox&quot;)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>(&quot;Art Blocks&quot;)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(&quot;nonfungible.com&quot;)</td>
</tr>
</tbody>
</table>

Notes: This table reports the search string for the NFTs attention index. Assisting by LDA topic modelling, 5 topics are sorted. Topic 1 relates to the official name and the abbreviation of Non-fungible tokens. Topic 2, 3 and 4 correspond to the aliases of Non-fungible tokens. Topic 5 refers to popular NFT assets and platforms. Importing this search string to LexisNexis News & Business, 590 million news items can be collected between January 2017 and May 2022.

The LDA topic modelling reveals the first topic about the official name and the abbreviation of "Non-fungible tokens". The second, third, and the fourth are related to the aliases of "Non-fungible tokens". Finally, the last topic refers to hot NFT assets and popular NFT trading platforms. Combining all of the terms from topic 1 to topic 5 allows me to generate the final searching string for NFTsAI. Once done, this study inputs the search string into the LexisNexis News & Business and collects data for the NFTsAI.

4This study should note here that this study has excluded all technical words, such as "market", "connectedness", and "investor" from the LDA topic modelling results. This study does so to optimise the results and make the final search string closer to "Non-fungible tokens".
4.3 Index Construction

Referring to the index construction methodology, which is explained in section 4.1, and also based on the data collected from the LexisNexis News & Business by using the designed search strings. The time series UCRY indices, ICEA, CBDC indices and NFTsAI, can be constructed as follows.

4.3.1 UCRY indices construction

This study selects January 2014 as the start point for constructing UCRY indices because it allows one to capture all the big events in the cryptocurrency markets.

4.3.1.1 UCRY Policy construction

The Cryptocurrency Policy Uncertainty Index (UCRY Policy) is calculated as in Equation 4.1:

\[
UCRY\ Policy_t = \left(\frac{N_{1t} - \mu_1}{\sigma_1}\right) + 100,
\]

where UCRY Policy\(_t\) is the value of the Cryptocurrency Policy Uncertainty Index in the weeks \(t\) between December 2013 and February 2021. \(N_{1t}\) is the weekly observed value of news articles on LexisNexis business concerning the uncertainty of cryptocurrency policy. If the searched terms from subsubsection 4.2.1.1 appear in one article’s title, keywords, main content, or the other parts, this study will collect this article and record it as one unit for \(N_{1t}\). \(\mu_1\) is the mean value of the collected articles related to UCRY Policy range from 30/12/2013 to 28/02/2022. This study collects 15,854 articles concerning cryptocurrency policy uncertainty in total from LexisNexis News & Business database, and there are 373 weekly observations between 30/12/2013 and 21/02/2022. Therefore, \(\mu_1 = 15,854/373 = 42.5040\). \(\sigma_1\) is the standard deviation value of such, which is equal to 31.5091. 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.

4.3.1.2 UCRY Price construction

The Cryptocurrency Price Uncertainty Index (UCRY Price) is computed as Equation 4.2:
4.3. INDEX CONSTRUCTION

\[ UCRY \ Price_t = \left( \frac{N_{2t} - \mu_2}{\sigma_2} \right) + 100, \]

where UCRY Price\(_t\) is the value of the Cryptocurrency Price Uncertainty Index in the weeks \(t\) between December 2013 and February 2021. \(N_{2t}\) is the weekly observed value of LexisNexis business news articles concerning the uncertainty of cryptocurrency price. If the searched terms from subsubsection 4.2.1.2 appear in one article’s title, keywords, main content, or the other parts, this study will collect this article and record it as one unit for \(N_{2t}\). \(\mu_2\) is the mean value of the collected articles related to UCRY Price range from 30/12/2013 to 28/02/2022. This study collects 28,066 articles concerning cryptocurrency price uncertainty in total from LexisNexis News & Business database, and there are 373 weekly observations between 30/12/2013 and 21/02/2022. Therefore, \(\mu_2 = 28,066/373 = 75.2439\). \(\sigma_2\) is the standard deviation value of such, which is equal to 59.4112. 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.

4.3.2 ICEA construction

This study selects January 2014 as the start point for constructing ICEA because it allows one to capture all the big events in the cryptocurrency markets. The Cryptocurrency Environmental Attention Index (ICEA) is expressed as Equation 4.3:

\[ ICEA_t = \left( \frac{N_{3t} - \mu_3}{\sigma_3} \right) + 100, \]

where ICEA\(_t\) is the value of the Cryptocurrency Environmental Attention Index in the weeks \(t\) between December 2013 and April 2021. \(N_{3t}\) is the weekly observed value of LexisNexis business news articles concerning the cryptocurrency environment. If the searched terms from subsection 4.2.2 appear in one article’s title, keywords, main content, or the other parts, this study will collect this article and record it as one unit for \(N_{3t}\). \(\mu_3\) is the mean value of the collected articles related to cryptocurrency environmental attention range from 30/12/2013 - 02/05/2021. This study collects 103,115 articles concerning cryptocurrency environmental attention in total from LexisNexis News & Business database, and there are 383 weekly observations between 30/12/2013 and 02/05/2021. Therefore, \(\mu_3 = 103,115/383 = 269.57\).
$\sigma_3$ is the standard deviation value of such, which is equal to 426. 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.

### 4.3.3 CBDCs indices construction

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 this study selects January 2015 as the start point for constructing the CBDC indices.

#### 4.3.3.1 CBDCAI construction

The CBDC Attention Index (CBDCAI) can be defined as Equation 4.4:

\[
CBDCAI_t = \left( \frac{N_{4t} - \mu_4}{\sigma_4} \right) + 100,
\]

where $CBDCAI_t$ is the value of the Central Bank Digital Currency Attention Index in the weeks $t$ between January 2015 and June 2021. $N_{4t}$ is the weekly observed value of LexisNexis business news articles concerning the CBDC attention. If the searched terms from Figure 4.1 appear in one article’s title, keywords, main content, or the other parts, this study will collect this article and record it as one unit for $N_{4t}$. $\mu_4$ is the mean value of the collected articles related to CBDC attention range from 29/12/2014 - 04/07/2021. This study collects 175,041 articles concerning central bank digital currency attention in total from LexisNexis News & Business database, and there are 340 weekly observations between 29/12/2014 and 04/07/2021. Therefore, $\mu_4 = 175,041 / 340 = 514.8265$. $\sigma_4$ is the standard deviation value of such, which is equal to 752.2264. 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.

#### 4.3.3.2 CBDCUI construction

The CBDC Uncertainty Index (CBDCUI) can be constructed as Equation 4.5:

\[
CBDCUI_t = \left( \frac{N_{5t} - \mu_5}{\sigma_5} \right) + 100,
\]
where $CBDCUI_t$ is the value of the Central Bank Digital Currency Uncertainty Index in the weeks $t$ between January 2015 and June 2021. $N_{4t}$ is the weekly observed value of LexisNexis business news articles concerning the CBDC uncertainty. If the searched terms from Figure 4.2 appear in one article’s title, keywords, main content, or the other parts, this study will collect this article and record it as one unit for $N_{5t}$. $\mu_5$ is the mean value of the collected articles related to CBDC attention range from 29/12/2014 - 04/07/2021. This study collects 10,534 articles concerning central bank digital currency uncertainty in total from LexisNexis News & Business database, and there are 340 weekly observations between 29/12/2014 and 04/07/2021. Therefore, $\mu_5 = 10,534/340 = 30.9824$. $\sigma_5$ is the standard deviation value of such, which is equal to 32.8131. 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.

### 4.3.4 NFTsAI construction

This study selects 01/01/2017 as the start point for constructing the NFTsAI because only one NFT can be traced back to 2015 (the Etheria launched on 21/10/2015). Furthermore, according to data from nonfungible.com - many hot NFTs were issued in 2017 (e.g., Curio Card, CryptoPunks, Moon Cats, and Decentraland). The Non-Fungible Tokens Attention Index (NFTsAI) can be denoted as Equation 4.6:

\[
NFTsAI_t = \left( \frac{N_{6t} - \mu_6}{\sigma_6} \right) + 100,
\]

where NFTsAI, is the value of the NFTs Attention Index in the week $t$ between January 2017 and May 2022. $N_{6t}$ is the weekly observed value of news articles on the LexisNexis News & Business database concerning NFTs attention. If the searched terms from Table 4.1 appear in one article’s title, keywords, main content, or the other parts, this study will collect this article and record it as one unit for $N_{6t}$. $\mu_6$ is the mean value of the collected articles related to NFTs attention range from 26/12/2016 to 05/06/2022. This study collects 292,498 articles concerning NFTs attention in total from LexisNexis News & Business database, and there are 284 weekly observations between 26/12/2016 to 05/06/2022. Therefore, $\mu_6 = 292,498/284 = 1,029.9225$. $\sigma_6$ is the standard deviation value of such, which is equal to 1,710.3515. 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.

4.4 Variable Selection

4.4.1 New cryptocurrency indices and applications

4.4.1.1 UCRY structural shock analysis

Monthly frequency data is considered for the UCRY Policy Index and UCRY Price Index structural shock analysis with six financial indices, namely, Global Economic Policy Uncertainty (GlobalEPU), Cboe Volatility Index (VIX), Bitcoin price index (Bitcoin), the United States Financial Stress (USFS), the United States Economic Policy Uncertainty (USEPU) and Gold price index (Gold). The study period runs from January 01, 2014, to January 01, 2021. The UCRY Policy Index and UCRY Price Index are generated by LexisNexis News & Business. GlobalEPU, USFS and USEPU are obtained from policyuncertainty.com and other financial indices from Bloomberg.

4.4.1.2 ICEA structural shock analysis

This study derives several explanatory variables to investigate the structural shocks of ICEA, these variables including the UCRY Policy, the UCRY Price, the GlobalEPU, the VIX, the Brent Crude Oil (BCO), the price of Bitcoin, the Global Temperature Uncertainty (GTU)⁵ and the IP. The reasons why this study chooses these variables are justified as follows:

To justify the selection of financial or economic variables for the structural shock analysis of ICEA, this study evaluates previous studies reporting variables substantially correlated with cryptocurrency environmental attention or that are susceptible to shocks transmitted by environmental concerns or, inversely, that are immunised from these shocks.

Firstly, one of this study’s research aims is to investigate the effects of the ICEA on cryptocurrency markets. Accordingly, this study selects the most important cryptocurrency assets (Corbet et al., 2020c), Bitcoin price, as one of the financial variables. As the most popular digital currency, Bitcoin is often chosen as a proxy to

⁵The GTU measure is taken from and represents the 95% confidence interval of the global temperature anomaly.
reflect trends and volatility within cryptocurrency markets (Urquhart and Lucey, 2022). Although there is an index that can represent the whole cryptocurrency markets, the Bloomberg Galaxy Crypto Index (BGCI), this study chooses not to use it because it only begins in 2017, thus not representing the entire research period.

Secondly, the ICEA is a cryptocurrency index that captures environmental attention on cryptocurrencies, enabling the assumption that ICEA could have effects on cryptocurrency prices and policy uncertainty. Accordingly, this study also includes UCRY Policy and UCRY Price indices in the variable system.

Thirdly, several studies have made overwhelmingly clear that the environmental issues caused by crude oil exploration (Zhang and Kong, 2021) can impact crude oil market volatility (Soliman and Nasir, 2019), leading to the selection of Brent Crude Oil price to represent the crude oil market (Kanamura, 2020) to examine the effects of cryptocurrency environmental attention on crude oil markets.

Fourthly, to analyse the relationships between the ICEA and other popular global economic or policy uncertainty measures, this study selects the VIX and the GlobalEPU indices, using the VIX as a "fear index" (Whaley, 2009) representing the financial price uncertainty (Whaley, 2000) and the GlobalEPU to capture economic policy uncertainty (Huang and Luk, 2020). From the literature review, no studies can directly link VIX to environmental issues and energy consumption. Only Arslan-Ayaydin and Thewissen (2016) indicate that markets do not show a positive attitude to the environmental performance of energy sector companies by using VIX. As for GlobalEPU, Ahmed et al. (2021) suggest that the GlobalEPU has a significantly negative relationship with pollutant emissions. However, the GlobalEPU has a significantly positive relationship with the $CO_2$ emissions. Yu et al. (2021) indicate that China Provincial EPU has a positive impact on the carbon emission intensity of a company. And companies prefer to use cheap and dirty fossil fuels against the rising EPU. Liao et al. (2021) select 175 companies from Shanghai and Shenzhen 300 index. Their empirical findings infer that compared with the companies with a low corporate environmental responsibility, the EPU has a lower negative impact on the stock returns of the companies with a high corporate environmental responsibility.

Fifthly, the effects of the ICEA on the output of the economy’s industrial sector is captured by including the (IP) OECD industrial production index (Feng et al., 2021). Marques et al. (2019) suggest that the investments related to ensuring a clean and safe environment can increase energy efficiency and reduce greenhouse
gas emissions by using the IP. Bozkus et al. (2020) investigate the relationships between atmospheric carbon emissions and the IP. Their empirical findings suggest that IP can cause long and short-term environmental costs. Moreover, these two variables have a strong correlation between the time domain.

Finally, this study includes the GTU index to confirm the findings of previous studies regarding the environmental issues caused by cryptocurrency mining and transactions.

### 4.4.1.3 UCRY indices and volatility forecasting of precious metal futures markets

Based on the research question, this study explores whether cryptocurrency uncertainty can forecast volatility in precious metal futures markets. Firstly, this study considers selecting the Top 2 precious metal assets with the highest trading volume to represent the precious metal market. Therefore, gold and silver these two assets are utilised. Based on the existing, this study further decides to use COMEX Gold Futures (Bailey, 1987) and COMEX Silver (Chng, 2009) as an indicator to represent the gold and silver markets, separately. Secondly, this study innovatively employs the newly issued cryptocurrency policy uncertainty index (UCRY Policy) and cryptocurrency price uncertainty index (UCRY Price) (Lucey et al., 2022) to serve as proxies for the cryptocurrency uncertainty.

According to the existing literature, this study further includes serial widely used uncertainty or volatilities indices as comparable variables. The reasons why this study chooses these comparable variables are presented as follows. Firstly, many existing studies have thoroughly discussed the effects of the equity market on the precious metal market (Baur and Lucey, 2010). Therefore, this study selects the world’s premier barometer of the equity market, the Chicago Board Options Exchange’s CBOE Volatility Index (CBOE VIX), to quantify the uncertainty of equity market (Whaley, 2009). Secondly, the volatility of the precious metal market is often discussed with the variations in the foreign exchange market (Ghonghadze and Lux, 2016), then this study includes the U.S. Dollar Index (USD Index) to represent the foreign exchange market. Thirdly, CBOE Gold ETF Volatility Index (CBOE GVZCLS) estimates the expected 30-day volatility of returns on the SPDR Gold Shares. Similar to CBOE VIX for the stock market, CBOE GVZCLS quantifies the implied volatility for the gold market and indicates people’s expectations on the gold price (Wei et al., 2020). Therefore, this study uses the CBOE GVZCLS as a
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Volatility forecasting factor to compare with other possible impactors. In the end, considering UCRY indices can capture policy uncertainty and price uncertainty in the cryptocurrency markets, this study further employs the global economic policy uncertainty index (GEPU) and geopolitical risk index (GPR) as comparable indicators.

The time span of this study ranges from 02/Jan/2014 to 13/May/2022. The reasons for selecting this sample period are as follows. Firstly, the data of all the selected variables, including the UCRY indices, are available from this date. Secondly, this time interval comprises the bull and turbulent periods in the cryptocurrency market. In the end, this sample period includes the 2018 financial crisis, recent pandemics, and the Russia-Ukraine war, among others. These special events mentioned above could significantly influence the uncertainty indices and the precious metal market. The data relating to UCRY indices are collected from their official website\(^6\). In addition, this study obtains the GEPU and GPR from Economic Policy Uncertainty\(^7\), and the other variables are all downloaded from Thomson Reuters.

4.4.2 The effects of central bank digital currencies news on financial markets

To justify the selections of financial markets in the sample, this study considers previous literature that reports which markets are susceptible to the shock transmitted from CBDCs, or reverse, are 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 (Lee et al., 2021a). This study thus hypothesizes that CBDCUI and CBDCAI may have significant effects on cryptocurrency markets. Specifically, this study assumes that debates around CBDCs may affect cryptocurrency price and policy uncertainty, therefore this study decides to also include UCRY Policy and UCRY Price indices in the 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., 2022b). 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. Moreover, Laboure et al. (2021)
already point 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. This study also selects the most important cryptocurrency markets leader, i.e. Bitcoin, as one of financial variables (Urquhart and Lucey, 2022), since this digital asset attracts the highest attention from media and general public (Wu et al., 2021), and also often used as a proxy of overall cryptocurrency market volatility (Elsayed et al., 2022a). This study omits two composite cryptocurrency indices, the Bloomberg Galaxy Crypto Index (BGCI) and the Royalton CRIX Crypto Index (CRIX), because they only begin in 2017 and 2018, respectively, and thus do not cover the entire research period. Moreover, this study applies weekly data, 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, this study selects the MSCI World Banks Index\(^8\) to represent the commercial banking sector, and investigates the impacts of CBDC indices on commercial banking. In addition, this study chooses the FTSE World Government Bond Index as a proxy for bond markets\(^9\), 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) explore the impacts of the CBDCs issuance on the GDP, compared with government bonds. It is a popular belief, that a CBDC

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\(^8\)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.

\(^9\)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.
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, 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. This study also sets the FX. 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 the USD, and vice versa.

To analyse the relationship between the new CBDC indices and other popular global uncertainty measures, this study selects the VIX and the USEPU (USA Economic Policy Uncertainty Index) indices (Umar et al., 2021). This study does not choose the EPU (global) because it contains only monthly data. While in this study, it utilises 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 the analysis and it can assign the FTSE All-World Index to represent the all-world stock markets. Lastly, this study selects gold as a safe-haven (Baur and Lucey, 2010) and (Lucey et al., 2017), because the sample in this study 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 (Chemkha et al., 2021)).

This study collects CBDCUI and CBDCAI from LexisNexis News & Business. UCRY Policy Index, UCRY Price Index, and ICEA are all collected from Cryptocurrency Indices. This study collects 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 is collected from the EPU.

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10 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.

11 https://sites.google.com/view/cryptocurrency-indices/home?authuser=0

12 https://www.policyuncertainty.com/index.html
This study tries to investigate the connectedness between NFTs attention and financial market volatility. Therefore, the first financial market this study wants to focus on is that of NFTs. (Pinto-Gutiérrez et al., 2022) study the linkages between cryptocurrency returns and NFT attention. They construct the NFT attention proxies in the Google search by using "non-fungible token", "NFT", "Cryptopunk" and "Decentraland" these four terms, separately. However, (Pinto-Gutiérrez et al., 2022) just construct the NFT attention proxies in single or double search terms, not a multidimensional search string. Therefore, these NFT attention proxies may not capture the actual social attention on the NFTs in a comprehensive way. Moreover, (Pinto-Gutiérrez et al., 2022) only focus on the effects of the NFT attention on the cryptocurrency returns but fail to explain the interconnections between the NFT attention proxies and NFT assets. Motivated by these gaps, this paper tries to study the connectedness between the NFTs attention and NFT markets. This study firstly includes the average price of Decentraland and CryptoPunks, these top two most liquid and prominent NFT assets to represent the NFT markets. NFTs are traded infrequently, and they differ in terms of quality, so some scholars suggest that we cannot simply look at price differences (Borri et al., 2022). However, NFTs can be divided and fractured, indicating that one NFT market price index could be constructed by adding partial shared ownership for this corresponding token in any market (Ko et al., 2022). Therefore, we can have strong evidence to utilise the average price of one popular NFT as a proxy to represent the NFT market. The existing literature of (Dowling, 2022; Dowling, 2021; Yousaf and Yarovaya, 2022; Maouchi et al., 2022; Pinto-Gutiérrez et al., 2022; Karim et al., 2022; Ko et al., 2022) are all use average price of popular NFTs to represent the NFT markets. Moreover, Wang et al. (2022c) creatively propose that NFT index from coinmarketcap.com can be valued as a NFTs capitalisation-weighted composite.

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13 The trading volume statistic decides the top two most liquid and prominent from www.nonfungible.com.
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However, the NFT index is only available from March 2021, which can not provide enough low-frequency observations for this study. Therefore, this study excludes the NFT index.

As another special type of digital currency, DeFi tokens are always investigated with NFTs together (Karim et al., 2022, Maouchi et al., 2022, Yousaf and Yarovaya, 2022). All of these studies believe diversification avenues exist in a portfolio containing both DeFi and NFT assets. Based on this, this study comprises the DeFi market, secondly. Following the variable selection strategy similar to NFT assets’ selection, this study secondly selects the Chainlink and Maker to represent the DeFi market. The rationales behind selecting Chainlink and Maker are also due to their trading volume and the maximum availability of data. The capitalisation-weighted composite index DeFi indices, DeFi Index from coinmarketcap.com and Bloomberg Galaxy DeFi Index are also excluded because of their limited available low-frequency observations.

Thirdly, NFTs fall within the category of crypto collectables, which are based on Blockchain technology (Regner et al., 2019), and it is widely known that NFTs are secondary assets derived from the cryptocurrencies (Dowling, 2021). One of the crucial reasons behind the soaring NFT asset prices could be the broad cryptocurrency enthusiasm. Therefore, NFTs can also be valued as crypto assets. Moreover, Dowling (2022) indicates that the price mechanism and market trading behaviours of NFTs are similar to those of cryptocurrencies. Accordingly, this could suppose that NFTsAI might have a significant relationship with the cryptocurrency market. Therefore, this study thirdly selects Bitcoin as a primary variable to represent the cryptocurrency market due to it being the most popular cryptocurrency (Urquhart and Lucey, 2022). Bitcoin has the highest price, sales volume, and market capitalisation (Demir et al., 2018). Furthermore, Bitcoin tends to be viewed as a proxy for measuring the cryptocurrency market (Corbet et al., 2018b). NFTs are based on the algorithm of Ethereum (Chirtoaca et al., 2020), which is also one of the most popular cryptocurrencies (Corbet et al., 2019). Therefore, this study lists Ethereum as another cryptocurrency proxy. The BGCI seeks to assess the performance of the largest cryptocurrencies traded in USD (Umar and Gubareva, 2020). BGCI is a comprehensive market capitalisation-weighted index that can track the cryptocurrency

15 The NFTI is a capitalisation-weighted composite index designed to track the performance of the non-fungible token market. It is weighted based on each NFT asset’s circulating supply value. Underlying NFT assets in the NFTI including Polygon (Matic), Enjin, Decentraland, Sand, Axie Infinity, Aavegotchi, Rarible, and Meme.
NFTs are attracting investors due to their high speculation and fluctuation, which can bring a high return on investment (ROI). Yousaf and Yarovaya (2022) highlights that investors have valued NFTs as essential alternative assets, which can diversify their portfolios. Moreover, Karim et al. (2022) and Ko et al. (2022) believe that NFT assets have shown the characteristics of the classic financial markets, which can bring high volatility and high return, and also can transmit risks to other financial markets. Therefore, the inter-linkages between NFTs and other classic financial sectors from investment perspectives can be confirmed, for example stocks (Aharon and Demir, 2022; Umar et al., 2022c; Yousaf and Yarovaya, 2022; Ko et al., 2022; Pinto-Gutiérrez et al., 2022), commodities (Aharon and Demir, 2022; Yousaf and Yarovaya, 2022; Umar et al., 2022c; Ko et al., 2022), bonds (Aharon and Demir, 2022; Umar et al., 2022c; Ko et al., 2022), F.X. (Aharon and Demir, 2022) and (Ko et al., 2022) and gold (Aharon and Demir, 2022; Umar et al., 2022c; Ko et al., 2022; Pinto-Gutiérrez et al., 2022). As justified above, investor attention indices have been proved to be statistically and economically significant in the financial markets (Da et al., 2011; Vozlyublennaia, 2014; Han et al., 2017; Wang et al., 2022b; Pinto-Gutiérrez et al., 2022). Therefore, there are enough theoretical and empirical supportings to allow this study to investigate the transmission effects between the relative extent of media discussions surrounding NFT assets and the other classic financial markets. For these reasons, this study further includes the stock, commodity, bond, F.X., and Gold markets. Following the selected variables in the existing literature about NFTs, this study includes FTSEAWI (Aharon and Demir, 2022; Umar et al., 2022c; Ko et al., 2022), FTSEWGBI (Umar et al., 2022c), PIMCOCORP (Aharon and Demir, 2022; Ko et al., 2022; DBC Ko et al., 2022), DXY (Aharon and Demir, 2022) and (Ko et al., 2022), and COMEX Gold (Aharon and Demir, 2022; Yousaf and Yarovaya, 2022, Umar et al., 2022c, Pinto-Gutiérrez et al., 2022) to represent stock, government bond, corporate bond, commodity, F.X. and gold markets, respectively.

As the NFT markets are beginning to emerge, it is necessary to extend the research period to collect more data to ensure the results’ accuracy. The time span of this study ranges from 05/Jan/2018 to 03/June/2022. The reasons for selecting this sample period are as follows. Firstly, the data of all the selected financial variables, including the NFTsAI, are available from this date. Secondly, this time interval comprises the bull and turbulent periods in the cryptocurrency, DeFi
and NFT markets. In the end, this sample period includes the 2018 financial crisis and recent pandemics. These special events mentioned above could have significantly influential connectedness among financial markets. The data related to the NFT and DeFi assets are obtained from nonfungible.com and coinmarketcap.com, separately. This study obtains the BGCI from the Bloomberg database and downloads Bitcoin, Ethereum, FTSEAWI, FTSEWGBI, PIMCOCORP, DBC, DXY and COMEX Gold data from Thomson Reuters.
thorough and reasonable methodology assures that the analyses undertaken align with the mathematical frameworks and rules of the finance research field. This chapter of the thesis presents and discusses all the econometric methodologies and statistical procedures considered throughout the thesis for each research question while using statistical evidence to prove why specific chosen procedures are appropriate.

5.1 Descriptive Statistic Methodology

5.1.1 Stationarity test

Stationarity (unit root test) is an essential point for time series financial econometrics (Kočenda and Černý, 2015). Unit root tests could be applied to examine whether or not the trending data should be first-differenced or regressed on deterministic functions of time to achieve the data stationary. In subsection 5.1.1, the econometrics details of unit root tests which are utilised in this thesis are introduced as follows:

5.1.1.1 Augmented Dickey-Fuller Test

Dickey-fuller test (Dickey and Fuller, 1979; Dickey and Fuller, 1981; Dickey et al., 1986; Dickey and Pantula, 1987; Fuller, 1976) is the most popular unit root test.
Dickey-fuller test can be constructed as Equation 5.1,

\begin{equation}
\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \epsilon_t,
\end{equation}

where \( \alpha \) is a constant, \( \beta \) and \( \gamma \) are the coefficient on a time trend. \( \beta t \) stands for the sum of a deterministic trend. \( \epsilon_t \) is a stationary error process.

It is only can test time series with a AR (1) process only. When a time series has a higher order autoregressive process or an autoregressive moving average model, then the residuals from the Equation 5.1 will not be white noise and autocorrelation would be shown. In order to address this issue, Dickey and Fuller (1979); Dickey and Fuller (1981); Dickey et al. (1986); Dickey and Pantula (1987) and Fuller (1976) further proposed the augmented Dickey-Fuller test (ADF test). ADF test can address the issue that autocorrelation issues exist in residuals. ADF test can be expressed as Equation 5.2:

\begin{equation}
\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \epsilon_t,
\end{equation}

where \( \alpha \) is a constant, \( \beta \) and \( \gamma \) are the coefficient on a time trend. \( \beta t \) stands for the sum of a deterministic trend. \( \delta \) is the theoretical autocorrelation. \( p \) is the lag order of the autoregressive process. \( \epsilon_t \) is a stationary error process.

The hypothesis is,

\begin{align*}
H_0 &= \text{The time series is not stationary} \\
H_1 &= \text{The time series is stationary}
\end{align*}

5.1.1.2 Phillips-Perron test

However, the weaknesses of the ADF test are that the ADF test can not distinguish between unit root and near-unit time series. In other words, a time series with a structural change will be valued as non-stationary in the ADF test. The Phillips-Perron (PP) unit test (Phillips and Perron, 1988) could solve the issues in the ADF test. The biggest differences between the ADF unit root test and the PP unit root test are how they process the serial correlation and heteroskedasticity in the errors. Specifically, a PP test does not consider any serial correlation. There are two advantages of a PP unit root test over the ADF unit root test. The first one is
5.1. DESCRIPTIVE STATISTIC METHODOLOGY

that a PP test is robust to general forms of heteroskedasticity in the error term $\varepsilon_t$. The second one is that a lag length is not required in a PP unit root test. The PP test can be defined as Equation 5.3:

\[ \Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \varepsilon_t, \]

where $\varepsilon_t$ is a simulated trend stationary and could be heteroskedastic. By modifying the test statistics $t_{\pi=0}$ and $T_{\tilde{\lambda}}$. The modified statistics $P_t$ and $P_{\pi}$ are expressed by Equation 5.4 and Equation 5.5:

\[ P_t = \left( \hat{\sigma}^2 \right) \times t_{\pi=0} - \frac{1}{2} \left( \frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\lambda^2} \right) \times \left( \frac{T \times SE(\tilde{\lambda})}{\hat{\sigma}^2} \right), \]

\[ P_{\pi} = T_{\tilde{\lambda}} - \frac{1}{2} \frac{T^2 \times SE(\tilde{\lambda})}{\hat{\sigma}^2} \left( \hat{\lambda}^2 - \hat{\sigma}^2 \right), \]

where $\hat{\varepsilon}_t$ is a consistent estimate of $\sigma^2$ and $S_T = \sum_{t=1}^{T} \times \varepsilon$.

The hypothesis is, 

- $H_0 = \text{There is a unit root}$
- $H_1 = \text{There is no unit root}$

5.1.1.3 Kwiatkowski-Phillips-Schmidt-Shin test

Another unit root test which could address the drawbacks of the ADF test is the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992). KPSS test can solve the issues in the ADF test. When a time series can be valued as stationary in the ADF test, this time series also most likely will be valued as stationary. When a time series can be valued as non-stationary in the KPSS test, then this time series almost can be valued as non-stationary in the ADF test (even do not need to observe the p-value). Based on the suggestions from (Lanne et al., 2002; Brüggemann, 2006; Kočenda and Černý, 2015). It is better to combine both the ADF test and the KPSS test in a unit root test. KPSS test can be expressed as Equation 5.6:

\[ y_t = \beta t + r_{t-1} + u_t + \varepsilon_t, \]
CHAPTER 5. METHODOLOGY

where $\beta t$ denotes the sum of a deterministic trend. $r_{t-1}$ stands for a random walk process, $u_t$ are the independent and identically distributed random variables with a zero mean and variance $\sigma^2_u$. $\varepsilon_t$ is a stationary error process.

The hypothesis is,

$H_0$ = The time series is stationary

$H_1$ = The time series is not stationary or presence of a unit root

5.1.2 Autocorrelation test

In general, regression analysis is the first step in any data analysis. One of the essential assumptions of regression analysis is that the time series data has no autocorrelation. If autocorrelation exists in the time series data, this could mislead one to believe that the econometrics model is a good fit. This thesis employs the Ljung-Box test (Box and Pierce, 1970) and (Ljung and Box, 1978) to test whether or not a time series contains an autocorrelation. The Ljung-Box test is processed to the residuals of a time series after fitting an ARMA (p,q) model to the time series data. The Ljung-Box test detects $m$ autocorrelations of the residuals. Given a time series data of length $n$, the statistic $Q$ should be calculated and can be defined as Equation 5.7:

\[
Q = n(n + 2) \sum_{k=1}^{m} \frac{r^2_k}{n - z},
\]

where $r^2_k$ is the estimated autocorrelation of the series at lag $k$, and $m$ is the number of lags which are tested.

The hypothesis is,

$H_0$ = The residuals are independently distributed

(The model does not exhibit a lack of fit)

$H_1$ = The residuals are not independently distributed so has serial correlation roots

(The model lacks fit)
5.1. DESCRIPTIVE STATISTIC METHODOLOGY

5.1.3 Cointegration test

Before 1986, economists only relied on linear regressions to identify the relationship between two or more time-series processes. In 28/11/1986, Granger and Newbold (2014) propose a new concept: spurious regression, which could happen when two or more associated variables are deemed causally related because of stochastic events. Therefore, the traditional linear regression method was not perfect anymore.

Then, Engle and Granger (1987) formally propose the method, named cointegration vector approach. This method believes that a common stochastic trend may drive two or more non-stationary time series data. Therefore, these non-stationary time series can be integrated together and have some long-run equilibrium relationships. In details, here are the variables Equation 5.8:

\[
y_t = (y_{1t}, y_{2t}, \ldots, y_{(k-1)t}, y_{kt})'.
\]

When \( \beta = (\beta_1, \beta_2, \ldots, \beta_{k-1}, \beta_k)' \), the long-run equilibrium relation can be expressed Equation 5.9:

\[
\beta'_y t = \beta_1 y_{1t} + \beta_2 y_{2t} + \cdots + \beta_{(k-1)} y_{(k-1)t} + \beta_k y_{kt}.
\]

Due to the coincidence or stochastic events, the long-run equilibrium relation can not be satisfied sometimes. In this way, there can get Equation 5.10:

\[
\beta'_y t = S_t,
\]

where, \( S_t \) is a stochastic variable.

Now, \( y_t \) can move together and \( S_t \) is stable. However, there is a possible situation that all variables in \( y_t \) are integrated, and there is a linear combination of the stationary variables. In short words, \( y_t \) random walk as a group. In a nutshell, integrated variables with this characteristic are called cointegrated.

Many methodologies can be used to process the cointegration test. These methodologies are listed in the Table 5.1.
Table 5.1: Cointegration test methodology

<table>
<thead>
<tr>
<th>Item</th>
<th>Cointegration test methodology</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Augmented Least Squares</td>
<td>Bewley (1979); Hendry and Richard (1982)</td>
</tr>
<tr>
<td>2</td>
<td>Principal Components</td>
<td>Jolliffe (1986)</td>
</tr>
<tr>
<td>3</td>
<td>OLS</td>
<td>Engle and Granger (1987)</td>
</tr>
<tr>
<td>5</td>
<td>Canonical Cointegration Regression</td>
<td>Bossaerts (1988)</td>
</tr>
<tr>
<td>6</td>
<td>Maximum Likelihood</td>
<td>Johansen (1988)</td>
</tr>
<tr>
<td>7</td>
<td>Spectral Regression</td>
<td>Phillips et al. (1988)</td>
</tr>
<tr>
<td>8</td>
<td>Non-Parametric Canonical Cointegration</td>
<td>Park and Phillips (1989)</td>
</tr>
<tr>
<td>9</td>
<td>Instrumental Variables</td>
<td>Phillips and Hansen (1990)</td>
</tr>
<tr>
<td>10</td>
<td>Three Step Estimator</td>
<td>Engle and Granger (1991)</td>
</tr>
<tr>
<td>11</td>
<td>Modified Box-Tiao</td>
<td>Bewley et al. (1994)</td>
</tr>
</tbody>
</table>

Notes: This table presents the methodologies which can be used to a cointegration test. Eleven methodologies are listed. The left column presents the cointegration test methodologies, the right column displays the corresponding references.

Engle-Granger Two-Step Method (Engle and Granger, 1987) and Johansen Test (Johansen, 1985; Johansen, 1988; Johansen and Juselius, 1990; Johansen, 1991; Johansen et al., 1995) are the most commonly methodologies used among others for cointegration tests (Bilgili, 1998; Vigne, 2017).

According to Granger and Newbold (2014), Engle and Granger (1987), and Bilgili (1998), the first step of Engle-Granger methodology is to generate residuals by applying the static regression. In the second step, the residuals created in step one will be used to estimate a first difference residuals regression on lagged residuals for unit roots. As a result, if the time series are cointegrated, the residuals in the Engle-Granger test will show stationarity.

However, Engle-Granger Two-Step method has two backwards. The first one, in a long-run equilibrium relationship with finite data, the Engle-Granger Two-Step method test results from the first regression for unit roots in the error term sequence sometimes are not equal to the test results from another regression for unit roots in the error term sequence. In a short word, Engle-Granger Two-Step method can show more than two cointegration relationships. Second, Engle-Granger Two-Step method is a two steps methodology. Therefore, the errors contained in the first step will be automatically carried into the second step.

Fortunately, the shortcomings of the Engle-Granger Two-Step Method have been covered in the Johansen test. Johansen test can optimise the Engle-Granger Two-Step Method by applying the maximum likelihood (the largest canonical correlations) to estimate the multiple cointegrating vectors when the variables
Some Monte Carlo simulation experiments present that the Johansen test performs better than the Engle-Granger Two-Step method and also all the methods mentioned in Table 5.1 (Bilgili, 1998; Vigne, 2017).

The Johansen test construction procedures are as follows. Based on the VAR model, then, set adjustment parameters vector as $\alpha$ and cointegrating vector as $\beta$. Here can get: $\Pi = \alpha \times \beta$.

When $p > 1$, a VAR model can be expressed as Equation 5.11:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Pi_i \Delta y_{t-i} + u_t,$$

When $p = 1$, Equation 5.11 can be expressed as Equation 5.12:

$$\Delta y_t = \Pi y_{t-1} + u_t,$$

$\Pi$ is a matrix. When $\Pi = 0$, then $y_t$ are not cointegrated. One of the method to calculate whether $\Pi = 0$ is to calculate whether $\text{rank}(\Pi) = 0$. Actually, $\text{rank}(\Pi)$ is the number of cointegrating vectors. Therefore, when $\text{rank}(\Pi) \neq 0$, then $y_t$ are cointegrated. If $y_t$ has unit roots, the number of cointegrating vectors will less than the number of the variables $y_t$; If $y_t$ does not have unit roots. The number of cointegrating vectors will less than or equal to the number of the variables $y_t$.

When $\text{rank}(\Pi) < \text{the number of the variables } y_t$, the $\text{det}[\text{rank}(\Pi)] = 0$. The determinant of a square matrix equals to the product of the square matrix’s eigenvalues. Therefore, eigenvalues can solve this issue. The generalisation expression can be denoted as Equation 5.13:

$$\text{det}(\lambda I_n - A) = \lambda_1 \times \lambda_2 \times \cdots \times \lambda_{n-1} \times \lambda_n,$$

where $\lambda$ denotes the eigenvalues, $I_n$ is an $n$th order identify matrix, and $A$ is an $n \times n$ square matrix. The proofs of Equation 5.13 are as follows: Set $A$ as a $3 \times 3$ square matrix and $\lambda_1$, $\lambda_2$ and $\lambda_3$ are eigenvalues of $A$. Then, there can get:

$$\text{det}(\lambda I_n - A) = \begin{vmatrix} \lambda - A_{11} & -A_{12} & -A_{13} \\ -A_{21} & \lambda - A_{22} & -A_{23} \\ -A_{31} & -A_{32} & \lambda - A_{33} \end{vmatrix}$$

$$= (\lambda - \lambda_1)(\lambda - \lambda_2)(\lambda - \lambda_3)$$

$$= \lambda^3 - (\lambda_1 + \lambda_2 + \lambda_3)\lambda^2 + (\lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_2\lambda_3)\lambda - \lambda_1\lambda_2\lambda_3$$
Let $\lambda = 0$, then,

$$
det(\lambda I_n - A) = det(-A)
$$

$$
\lambda^3 - (\lambda_1 + \lambda_2 + \lambda_3)\lambda^2 + (\lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_2\lambda_3)\lambda - \lambda_1\lambda_2\lambda_3 = -\lambda_1\lambda_2\lambda_3
$$

$$
det(-A) = -\lambda_1\lambda_2\lambda_3
$$

$$
(-1)^3det(A) = -\lambda_1\lambda_2\lambda_3
$$

$$
det(A) = \lambda_1\lambda_2\lambda_3
$$

In Johansen test, there are $\lambda_1, \lambda_2, \ldots, \lambda_{n-1}, \lambda_n$. If $\lambda_1 = 0$, then $\text{rank}(\Pi) = 0$. So cointegrating vector $\beta = 0$. If $\lambda_1 \neq 0$, then $\text{rank}(\Pi) \geq 1$. So cointegrating vector $\beta \geq 1$.

In general, if $\lambda_{n-1} \neq 0$, then test by moving on to $\lambda_n = 0$. If $\lambda_n = 0$, then cointegrating vector $\beta = n - 1$. If $\lambda_n \neq 0$, which means the variables $y_t$ do not have unit roots.

Johansen test also can be interpreted as likelihood-ratio tests. Likelihood-ratio test can be expressed as Equation 5.15:

$$\theta_{LR} = 2[\ln l(\delta) - \ln l(\delta_r)],$$

where suppose a model has parameter space $\Theta$. The null hypothesis $H_0$ is the parameter $\theta$ is in a subset $\Theta_0$ of $\Theta$. The alternative hypothesis is parameter $\Theta$ is in the complement of $\Theta_0$. $(\delta)$ is the unconstrained maximum likelihood estimators. Based on $H_0$ and then maximize the likelihood function, $(\delta_r)$ is the restricted maximum likelihood estimators. When $\Theta_0$ can hold, the likelihood-ratio test statistic has an asymptotic $\chi^2$-distribution.

### 5.1.3.1 Johansen maximum eigenvalue test

The Johansen maximum eigenvalue test hypothesis is:

- $H_0$: $\text{rank}(\Pi) = r$
- $H_1$: $\text{rank}(\Pi) = r + 1$

According to the analysis above, Johansen maximum eigenvalue test is a likelihood-ratio test. Based on Equation 5.15, maximum eigenvalue test can be expressed as Equation 5.16:
The null hypothesis is $\text{rank}(\Pi) = r$. The alternative hypothesis is $\text{rank}(\Pi) = r + 1$. $LR(r, r + 1)$ can test whether the null hypothesis versus the alternative hypothesis. $T$ is the sample size.

Equation 5.16 can be interpreted as follows:

At first, $r = 0$ and $r + 1 = 0$. So $H_0$ is $\text{rank}(\Pi) = 0$, and $H_1$ is $\text{rank}(\Pi) = 1$. If $H_0$ can not be rejected, which mean $\text{rank}(\Pi) = r = 0$, $\lambda_{\text{max}} = \lambda_0 = 0$, and cointegrating vector $\beta = 0$. So there is no cointegration and maximum eigenvalue test can be finished. If $H_0$ can be rejected, which means $\text{rank}(\Pi) = r \geq 1$, $\lambda_{\text{max}} \geq 1$, and cointegrating vector $\beta \geq 1$. Now, $H_0$ can be written as $\text{rank}(\Pi) = 1$ and $H_1$ can be written as $\text{rank}(\Pi) = 2$. If $H_0$ can not be rejected, which means $\text{rank}(\Pi) = r = 1$, $\lambda_{\text{max}} = \lambda_1 = 0$ and cointegrating vectors $\beta = 1$. The maximum eigenvalue test can be finished now. If $H_0$ can be rejected, which means $\text{rank}(\Pi) = r \geq 2$, $\lambda_{\text{max}} \geq 2$, and cointegrating vector $\beta \geq 2$. Now, $H_0$ can be written as $\text{rank}(\Pi) = 2$ and $H_1$ can be written as $\text{rank}(\Pi) = 3$. Then, process the test in the same way. And so on until the null hypothesis $\text{rank}(\Pi) = r (\lambda_r = 0)$ can not be rejected.

In maximum eigenvalue test, the unit roots can cause nonstandard asymptotic distributions. Therefore, maximum eigenvalue test does not have an asymptotic $\chi^2$-distribution.

### 5.1.3.2 Johansen trace test

According to Johansen (1988), Johansen trace test is called as trace test because an asymptotic $\chi^2$-distribution of the Johansen trace test is the trace of a $\Pi$ based on the pedesis.

The Johansen trace test hypothesis is:

$$
H_0: \text{rank}(\Pi) = r \\
H_1: r < \text{rank}(\Pi) \leq \beta_{\text{max}}
$$

According to the analysis above, Johansen trace test is also a likelihood-ratio test. Based on Equation 5.15, Johansen trace test can be expressed as Equation 5.17:
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(5.17) \[ LR(r, \beta_{max}) = -T \sum_{n=r+1}^{\beta_{max}} \ln(1 - \lambda_n), \]

where \( \beta_{max} \) is the maximum number of possible cointegrating vectors. The hypothesis is \( \text{rank}(\Pi) = r \), and the alternative hypothesis is \( r < \text{rank}(\Pi) \leq \beta_{max} \). \( LR(r, \beta_{max}) \) can test whether the null hypothesis versus the alternative hypothesis. \( T \) is the sample size, \( \lambda_n \) denotes the maximum likelihood (the largest canonical correlations).

Equation 5.17 can be interpreted as follows:

At first, if \( r = 0 \), then \( H_0 \) is \( \text{rank}(\Pi) = 0 \), \( H_1 \) is \( \text{rank}(\Pi) \leq 1 \), and \( n = r + 1 = 1 \). If the null hypothesis can be rejected, the \( r \) will move on to \( r + 1 \), so the new null hypothesis \( H_0 \) will be \( \text{rank}(\Pi) = r + 1 \) and the alternative hypothesis \( H_1 \) will be \( r_0 + 1 < \text{rank}(\Pi) \leq \beta_{max} \). And so on until the null hypothesis, \( \text{rank}(\Pi) = 0 \) can not be rejected.

According to Lütkepohl et al. (2001) and Vigne (2017), trace statistics are more suitable if there are at least two more cointegration relations in the process because trace statistics tend to have more heavily distorted sizes, whereas their power performance is superior to the maximum eigenvalue statistic competitors.

### 5.1.4 Normal distribution test

The normality test is another essential step for data analysis. Many econometrics models and statistical tests all set normality as an underlying assumption, such as t-test, linear regression, and Monte Carol simulation, among others. If our time series data fail the normal distribution test, we may need to employ different econometrics models and statistical tools.

Please note that the normal distribution is a theoretical distribution. One could only focus on whether or not the time series data is close enough to normal. In short, the normal distribution test is not sensitive to the violation of the normality assumption. This thesis employs the Jarque-Bera (J.–B.) statistics to check the normal distribution characteristic of the data (Jarque and Bera, 1980) and (Bera and Jarque, 1981).

The J.–B. test is a goodness-of-fit test that examines whether or not the skewness and kurtosis of the time series data could be close enough to normal distribution. The formula of the J.–B. can be given as Equation 5.18:
5.1. DESCRIPTIVE STATISTIC METHODOLOGY

(5.18) \[ JB = \frac{n}{6} \left( S^2 + \frac{1}{4}(K - 3)^2 \right) \]

where, \( n \) is the number of observations, \( S \) is the sample skewness, and \( K \) is the sample kurtosis.

The hypothesis is,

\[ H_0 = \text{The time series data is normally distributed} \]
\[ H_1 = \text{The time series data does not come from a normal distribution} \]

5.1.5 Optimal lag selection

To choose the order of \( p \), the longest lag period should be identified, and it can be given by Equation 5.19:

(5.19) \[ \text{Lag.max} = 10 \times ln\left(\frac{N}{m}\right) \]

where \( N \) is the number of observations and \( m \) is the number of series. This equation can generate a default maximum lag. In addition, the number of observations and the number of series (Winker and Maringer, 2004), also should be considered when choose the default maximum lag. It should be careful if the observations have small \( N \) and comparatively large \( m \). Sometimes, one would be better to adjust the maximum lag based on the final results.

5.1.6 Information criterion

The optimal lag period could be calculated by information criteria. The information criteria including: Akaike information criterion (AIC), Hannan-Quinn criterion (HQ), Schwarz Bayes criterion (SC) and Prediction Error criterion (FPE).

The Akaike information criterion (AIC) (Akaike, 1998) can be defined as:

(5.20) \[ AIC = Tln |\Sigma_u| + 2n, \]

The Hannan-Quinn information criterion (HQ) (Hannan and Quinn, 1979) can be expressed as:

(5.21) \[ HQ = Tln |\Sigma_u| + 2(ln(lnT))n, \]
The Schwarz Bayes information criterion (SC) (Schwarz et al., 1978) can be denoted as:

\[
SC = T \ln |\Sigma_u| + (\ln T)n,
\]

The Prediction Error criterion (FPE) (Akaike, 1969) can be given as:

\[
FPE = T |\Sigma_u| \frac{T + n}{T - n},
\]

where, \(T\) is the number of observations, \(n\) is the number of parameters in all equations, and \(|\Sigma_u|\) is the determinant of covariance matrix \(\Sigma_u\) of a model’s residuals.

## 5.2 New Cryptocurrency Indices and Applications

### 5.2.1 Vector error correction model

This study develops three cryptocurrency new indices, which are the cryptocurrency policy uncertainty index (UCRY Policy), cryptocurrency price uncertainty index (UCRY Price), an index of cryptocurrency environmental attention (ICEA), and further investigates the effects of these three cryptocurrency new indices on financial and economic variables. However, it is necessary to consider the most suitable methodology for checking the effectiveness and validity of a newly issued index and further analysing the dynamic connections between the newly issued index and other variables. For this purpose, Baker et al. (2016) introduce the Economic Policy Uncertainty (EPU) Index and applied the vector autoregression model (VAR) to exploit time-series variation at log change of S&P 500, the federal funds rate, log change of employment, log change of industrial production. Elsewhere, Huang and Luk (2020) develop the China Economic Policy Uncertainty Index (China EPU) based on Chinese newspapers and using a structural vector autoregression (SVAR) model based on the VAR model used to study the responses of macroeconomic variables (e.g. log change of Shanghai Composite Index, log change of benchmark interest rate, log change of unemployment rate, log change of real GDP) to shocks in the China EPU. Meanwhile, Rice et al. (2020) develops the Ireland Economic Policy Uncertainty Index (Ireland EPU) based on the two leading Irish newspapers (Irish Times and Irish Independent) and processed historical decomposition using an SVAR model to examine the co-movement of Irish economic activities (e.g. investment, CPI, consumption, employment, financial uncertainty and European Central Bank shadow rate) with the Ireland EPU.
Building on these studies, this study selects the VAR model as the main financial econometric methodology for investigating the effects of the UCRY Policy, UCRY Price and ICEA on financial and economic variables. However, the standard VAR is a reduced form model designed for stationary data (Lütkepohl, 2005). Given these conditions, the VAR model does not perfectly suit the three cryptocurrency new indices due to the high volatility characteristic of the cryptocurrency markets. Moreover, data processing would have broken the original characteristics of variables. Thus, this study decides to not further calculate the log return, continuously compounded return or return variance (among other outcomes) of the variables, making the sample smoother. This leads to application of the vector error correction model (VECM), which is based on the VAR (Durlauf and Blume, 2016) but adds error correction features (Kočenda and Černý, 2015). The VECM is designed for the non-stationary but cointegrated sets of variables (Maronna et al., 2019).

The VECM can be expressed as Equation 5.24:

\[
\Delta y_t = \alpha \beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + \Xi^+ D_t + u_t,
\]

where \( y_t \) is a \( K \times 1 \) dimensional vector of variables observed at time \( t \). The decomposed cointegrated model \( \alpha \beta' \) has reduced rank \( r = rk(\alpha \beta') < K \). Also, \( \alpha \) is a \( K \times r \) matrix containing the loading coefficients, \( \beta \) is also a \( K \times r \) matrix containing the cointegrated vectors. \( \Gamma_j \) is a \( K \times K \) short-run coefficient matrix with \( j = 1, \cdots, p - 1 \). \( u_t \) is a \( k \)-dimensional unobservable zero mean vector white noise process, and has covariance matrix \( \Sigma_u \). \( u_t \) also denotes the reduced form disturbance (forecast errors). \( D_t \) is a vector of deterministic terms, and \( \Xi^+ \) is the coefficient matrices correspond with \( D_t \).

This study ordered variables as indicated by Equation 5.25 and Equation 5.26.

\[
(5.25) \quad y_{1t} = \begin{bmatrix} UCRYPolicy_t \\ GlobalEPU_t \\ VIX_t \\ Bitcoin_t \\ USFS_t \\ USEPU_t \\ Gold_t \\ UCRYPrice_t \end{bmatrix}
\]
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5.2. Structural shock analysis

Structural shocks on the system variables $y_t$ based on the VECM can be calculated as Equation 5.27:

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

where $\epsilon_t$ is a $K \times 1$ dimensional vector white noise process with covariance matrix $\Sigma_\epsilon$, which also means structural shocks. $A_1, A_2, \cdots, A_{p-1}, A_p$ are $K \times K$ coefficient matrices. Premultiplying the Equation 5.24 by $\bar{A}_0^{-1}$ can link the reduced form disturbance (forecast errors) $u_t$ to the underlying structural shocks $\epsilon_t$. The normal distribution $(0, I_K)$ is subject to $\epsilon_t$.

From the above, this study derives Equation 5.28:

$u_t = \bar{A}_0^{-1} \epsilon_t,$

5.2.2.1 VECM stationary test

When the reverse characteristic polynomial of a VAR (p) or VECM (p) process has no roots in or on the complex circle, which also means all eigenvalues of the companion matrix $A$ have modulus less than 1. Then, the VAR (p) or VECM (p) can be evaluated as a stability model. To check whether a VAR (p) or VECM (p) process is stable, one can calculate the eigenvalues of the companion matrix $A$ and returns by default the aim companion matrix’s modulus. It can be denoted as:
where $\det$ stands for the determinant of the matrix $A_i$, $I_K$ stands for the matrix $A_i$ is set to be an identity matrix with dimension $K$. $|z|$ stands for the moduli of the matrix $A$'s eigenvalues.

In the Equation 5.25 when set $\text{lag.\ max} = 10$, the maximal value is $1.1472438 > 1$ when $\text{lag} = 9$. Therefore, it is not a stable VECM process when the longest lag period is equal to 10. Then, test the $\text{lag.\ max}$ value from 9 to 1 in turn manually. When the $\text{lag} \leq 4$, the VECM process begin to keep stable\(^1\). The lesser the lag, the more stable the VECM process. Based on this, the statistical optimal lag is 1.

In the Equation 5.26, the lag value is set as 5, 4, 3, 2 and 1, separately. From the stability and stationarity of model test results, Eigenvalue’s moduli are all less than 1, meaning there are no roots in or on the complex circle when $\text{lag} \leq 5$. Based on this, this study can evaluate the VECM model as a stationarity model in Equation 5.26. It is worth noting that when $\text{lag} = 1^2$, the moduli are the smallest, which means when $\text{lag} = 1$, the most stationarity VECM model can be gotten.

A stationary VECM allows for three tools, which are Impulse Response Function (IRF), Forecast Error Variance Decomposition (FEVD) and Historical Decomposition (HD) to capture the dynamic and instantaneous impacts of structural shocks within the variable systems. The three tools can be defined as follows:

5.2.2.2 Impulse Response Function

The Impulse Response Function (IRF) is designed for presenting the variables’ relationships in the VECM because variables’ relationships are hard to identify just from the coefficient matrices (all the variables in VECM model are a priori endogenous).

When a VECM process is stationary, it can be said that the VECM process has a Moving-Average (MA) representation. The MA representation can be expressed as Equation 5.67:

\begin{equation}
    y_t = u_t + \sum_{i=1}^{\infty} \Phi_i u_{t-i}, \Phi_0 = I_k,
\end{equation}

\(^1\text{Detailed results are not reported here due to brevity. All test results are available upon reasonable request.}\)

\(^2\text{Detailed results are not reported here due to brevity. All test results are available upon reasonable request.}\)
where \( u_t \) is a K-dimensional unobservable zero mean vector white noise process, and has covariance matrix \( \Sigma_u \). \( \Phi_i = JA^i J' \) and \( J = [I_k : 0 : 0 : \cdots : 0] \). \( A^i \) are summable.

In the Equation 5.67, the IRF can work when tracing the marginal effect of a shock to one variable by counterfactual experiment. The IRF shows how each variable reacts to shocks or changes in each other variable, and can be used to evaluate the sensitivity of variables to each other. In details, assign 1 to one element of \( u_t \), then set other elements to 0. This process can be called as Impulse. Therefore, Response is the \( y'_t \) reactions to the Impulse as period goes on. In general, the threshold of the period will be set as 5, 10 and 20 with the needs of experiments.

### 5.2.2.3 Forecast Error Variance Decomposition

Like the IRF, the Forecast Error Variance Decomposition (FEVD) is also designed to reveal and interpret the variables’ relationships in a stationary process VECM. The FEVD is constructed in the following.

The procedures of how the error of the optimal h-step forecast error variance at origin time \( t \) can be gotten are as follows:

- In the first step, process recursively for \( h = 1, 2, 3, \ldots, p - 2, p - 1, p \), which can be expressed as Equation 5.31:

\[
(5.31) \quad y_t(h) = A_1 y_t(h-1) + A_2 y_t(h-2) + \cdots + A_{p-1} y_t(h-(p-1)) + A_p y_t(h-p),
\]

where \( A_1, A_2, \cdots, A_{p-1}, A_p \) are \( K \times K \) coefficient matrices. \( y_t(j) = y_{t+j} \) when \( j \leq 0 \).

- In the second step, the h-step forecast error variance of the \( j \)-th component of \( y_t \) can be denoted as Equation 5.32:

\[
(5.32) \quad y_{t+h} - y_t(h) = u_{t+h} + \sum_{i=1}^{h-1} \Phi_u u_{t+h-i},
\]

where the normal distribution \( (0, \Sigma_h = \Sigma_u + \sum_{i=1}^{h-1} \Phi_i \Sigma_u \Phi'_i) \) is subject to \( y_{t+h} - y_t(h) \). \( u_t \) is a k-dimensional unobservable zero mean vector white noise process, and has covariance matrix \( \Sigma_u \). The forecast errors have zero mean vector white noise process and covariance matrix \( \Sigma_h \). \( \Phi_i = JA^i J' \) and \( J = [I_k : 0 : 0 : \cdots : 0] \). \( A^i \) are summable. \( \Phi'_i \) can calculate the derivative of \( \Phi_i \).
• In the third step, from Equation 5.28, \( \Sigma_u \) can be expressed as Equation 5.33

\[
\Sigma_u = \hat{A}_0^{-1} \hat{A}_0^{-1}',
\]

(5.33)

• In the fourth step, when \( \theta_i = \Phi_i \hat{A}_0^{-1} \) and assign \((m, n)th\) element of \( \theta_i \) to \( \theta_{mn,i} \), the h-step forecast error variance can be expressed as Equation 5.34:

\[
\Sigma_h = \sum_{i=0}^{h-1} \theta_i \theta_i',
\]

(5.34)

• In the fifth step, \( j = 1, 2, \ldots, K - 1, K \). The forecast error of the j-th component can be made up of all the \( \epsilon_t \omega_{1t}, \omega_{2t}, \ldots, \omega_{(k-1)t}, \omega_t \). Therefore, the h-step forecast error variance of the j-th component of \( y_t \) can be constructed as Equation 5.35 as:

\[
y_{j,t+h} - y_{j,t}(h) = \sum_{i=0}^{h-1} (\theta_{j1,i} \omega_{1t+h-i} + \theta_{j2,i} \omega_{2t+h-i} + \cdots + \theta_{j(K-1),i} \omega_{(K-1)t+h-i} + \theta_{jK,i} \omega_{K,t+h-i}).
\]

(5.35)

• In the sixth step, the forecast error variance of the k-th element of the forecast error vector can be denoted as Equation 5.36:

\[
E(y_{j,t+h} - y_{j,t}(h))^2 = \sum_{j=1}^{K} (\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2),
\]

where \( \theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2 \) can stands for the contribution of the j-th \( \epsilon_t \) innovation to the h-step forecast error variance of variable k. \( \frac{\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2}{E(y_{j,t+h} - y_{j,t}(h))^2} \) can compute the contribution % of the j-th \( \epsilon_t \) innovation to the h-step forecast error variance of variable k. \( \omega_{k,j,h} \) can decompose the contribution of the j-th \( \epsilon_t \) innovation to the h-step forecast error variance of variable k.

The forecast error variance of the k-th element of the forecast error vector can be denoted as Equation 5.69:

\[
E(y_{j,t+h} - y_{j,t}(h))^2 = \sum_{j=1}^{K} (\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2),
\]

where \( \theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2 \) can stands for the contribution of the j-th \( \epsilon_t \) innovation to the h-step forecast error variance of variable k. \( \frac{\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2}{E(y_{j,t+h} - y_{j,t}(h))^2} \) can compute the contribution % of the j-th \( \epsilon_t \) innovation to the h-step forecast error variance of variable k. \( \omega_{k,j,h} \) can decompose the contribution of the j-th \( \epsilon_t \) innovation to the h-step forecast error variance of variable k.

The FEVD can show the decomposition of changes in a variable arising from changes in other variables.
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5.2.2.4 Historical Decomposition

Historical decomposition is the third tool used for the VECM structural shock analysis, and allows for the gathering of information on the contribution of structural shocks over time to a system of variables. IRF can only trace the response to a one-time positive or negative shock, while the variation of indices in Equation 5.26 are driven by a sequence of shocks from different levels. The historical decomposition can measure the effect of target variable shocks on the variation of Equation 5.26 under a dynamic economic environment. Furthermore, compared with the forecast error variance decomposition, the historical decomposition can analyse the relative importance of shocks in different time periods of a system’s variables. However, historical decomposition can only do this kind of analysis on a specific forecasting horizon.

In short, \( u_t \) can be decomposed into different structural components in the historical decomposition. In details, as what has been analysed above. Equation 5.67, the Moving-Average (MA) representation can be further denoted as Equation 5.38:

\[
(5.38) \quad y_t = \sum_{i=1}^{t-1} \Phi_{i,t} u_{t-i} + \sum_{i=t}^{\infty} \Phi_{i,t} u_{t-i},
\]

where the time series can be decomposed into the estimate structural shocks \( \varepsilon \) from time 1 to time \( t \), and the inestimate structural shocks \( \varepsilon \) antedating the start point of the dataset.

In a stationary VECM 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 5.39:

\[
(5.39) \quad \hat{y}_t = \sum_{i=1}^{t-1} \Phi_{i,t} u_{t-i},
\]

Therefore, the historical decomposition is equal to the weighted sums, which can be measured as the contribution of shock \( j \) on variable \( k \) in the stationary VECM process. Now, the historical decomposition can be denoted as Equation 5.40:

\[
(5.40) \quad \hat{y}_{kt}^{(j)} = \sum_{i=0}^{t-1} \Phi_{k,i} u_{j,t}
\]
5.2.3 GARCH-MIDAS-X model

This study also plans to quantify both the in-sample impacts and the out-of-sample predictive abilities of UCRY Policy and UCRY Price on the volatilities of precious metal markets. This study utilises the GARCH-MIDAS model of (Engle et al., 2013) to handle the problem in different data frequencies of daily precious metal returns and monthly uncertainty indices. Furthermore, this study extends it to a GARCH-MIDAS-X one by incorporating an additional exogenous low-frequency impactor in the simple GARCH-MIDAS model, which allows one to quantify the impacts of various uncertainties on the volatility of precious metal futures. This GARCH-MIDAS-X model can decompose total conditional volatility of asset returns into short-term and long-term components, where the short-term volatility is driven by a simple GARCH (1,1) process and the long-term one is determined by a MIDAS regression of low-frequency exogenous impactor. A standard GARCH-MIDAS model can be defined as Equation 5.41:

\( r_{i,t} - \omega = \sqrt{g_{i,t} \tau_t} \times z_{i,t}, \forall i = 1, \ldots, N_t, \)

where, \( r_{i,t} \) is the asset returns on day \( i \) of month \( t \). \( \omega \) is the unconditional mean of the return, and \( N_t \) is the number of trading days in month \( t \). \( g_{i,t} \) and \( \tau_t \) are the short-term and long-term components of the conditional volatility, respectively. The short-term volatility can be expressed as Equation 5.42:

\( g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \omega)^2}{\tau_t} + \beta g_{i-1,t}, \)

and the logarithm form of long-term component \( \tau_t \) is given by Equation 5.43:

\( log(\tau_t) = m + \theta_{RV} \sum_{k=1}^{K} \phi_k(w_{RV})RV_{t-k} + \theta_X \sum_{k=1}^{K} \phi_k(w_X)X_{t-k}, \)

where, \( K \) is the number of lags for smoothing the long-term volatility; \( RV_{t-k} = \sum_{i=1}^{N_t} r_{i,t-k}^2 \) is the realised volatility in month \( t - k \). In discussing the in-sample impacts and out-of-sample predictive abilities of uncertainty indices on the precious metal future market volatility, we should eliminate the possible effects of other factors. In order to address this potential issue, we consider adding the Realized Volatility (RV) with a lag period in our forecasting models when we detect the
predictive power of the uncertainty indices. This method is the same as adding a lag of the dependent variable Y when we do a forecasting test. And the lag of Y can include the impact of other factors on Y. This is a standard method to eliminate the potential effects of other factors when we process a forecasting test on our model. As noted early in the works of (Schwert, 1989) and (Paye, 2012), because lagged volatility captures a rich set of information regarding current economic conditions, successful forecasting variables must capture additional relevant information. Thus, in this paper, we incorporate lagged realized volatility of precious metal futures in the GARCH-MIDAS model along with those uncertainty indices. $X_{t-k}$ is the uncertainty measure that is considered in this paper and $\varphi_k(w)$ is the weighting function set by a Beta polynomial as Equation 5.44:

\begin{equation}
\varphi_k(w) = \frac{(1 - k/K)^{w-1}}{\sum_{j=1}^{K}(1 - j/K)^{w-1}},
\end{equation}

where, Equation 5.44 is used to describe the declining effect of the uncertainty index on the long-term volatility over time. Therefore, in the following analysis, this study focuses on the four major model parameters (i.e., $\alpha$, $\beta$, $\theta_{RV}$ and $\theta_{X}$) to identify the effects of different uncertainty indices on the volatility of precious metal futures.

### 5.2.4 Model evaluation methods

For the reason that different evaluation methods can test distinct predictive powers of the forecasting models, this study employs four different model evaluation methods to assess the predictive abilities of various uncertainty indices from multi-dimension criteria.

#### 5.2.4.1 Diebold and Mariano test

In model evaluation literature, the DM test proposed by (Diebold and Mariano, 2002) is a very popular and basic one, which compares the forecasting accuracy of two models by using the statistics as Equation 5.45:

\begin{equation}
DM_i = \frac{\frac{1}{H} \sum_{t=1}^{H} (Loss_{t,i} - Loss_{t,benchmark})}{\sqrt{\text{Var}(Loss_{t,j} - Loss_{t,benchmark})}},
\end{equation}
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where $i$ denotes the $i^{th}$ GARCH-MIDAS-X model incorporating different uncertainty indices, and $H$ is the length of forecasting sample. $\text{Loss}_{t,i}$ and $\text{Loss}_{t,\text{benchmark}}$ are the forecasting errors of model $i$ and benchmark model at time $t$, respectively. Following commonly used loss functions, this study uses squared error (i.e., $\sigma_{t}^2 - \hat{\sigma}_{t}^2$) and absolute error (i.e., $|\sigma_{t}^2 - \hat{\sigma}_{t}^2|$) as measures of forecasting error in the DM test, where $\hat{\sigma}_{t}^2$ is the volatility forecasts obtained by a specific model and $\sigma_{t}^2$ is the true volatility of the asset returns. The null hypothesis of a DM test is that there is no difference in predictive accuracy of model $i$ and the benchmark one. Thus, a negative DM statistic indicates higher predictive accuracy of model $i$ than that of the benchmark model. In the following evaluations, this study chooses GARCH-MIDAS-VIX as the benchmark for the tight connections between VIX and gold markets proved in many recent researches (BenSaïda et al., 2022) and (Hernandez et al., 2022).

5.2.4.2 Out-of-sample $R^2$ test

To assess the predictive ability of one model compared to a benchmark one, the out-of-sample $R^2$ test proposed by (Rapach et al., 2010) is also massively adopted in many recent literature. The out-of-sample $R^2$ ($R^2_{OOS}$) is calculated as the percentage reduction in mean squared error (MSE) of forecasting model $i$ relative to that of a benchmark Equation 5.46:

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{H}(\sigma_{t}^2 - \hat{\sigma}_{t,i}^2)^2}{\sum_{t=1}^{H}(\sigma_{t}^2 - \hat{\sigma}_{t,\text{benchmark}}^2)^2},$$

where $\sigma_{t}^2$, $\hat{\sigma}_{t,i}^2$, and $\hat{\sigma}_{t,\text{benchmark}}^2$ are the true volatility, forecasted volatility by model $i$ and forecasted volatility of the benchmark model, respectively. Clearly, a positive $R^2_{OOS}$ of model $i$ indicates that this model can outperform the benchmark model with smaller MSE. The statistical significance of the $R^2_{OOS}$ test is obtained by the method of (Clark and West, 2007) with the null hypothesis that the MSE of the benchmark model is less than or equal to that of the forecasting model $i$. Therefore, if the $R^2_{OOS}$ of one model $i$ is positive with significant rejection, it means that this model has significant smaller MSE than that of the benchmark one.
5.2.4.3 Model confidence set (MCS) test

Although the DM and out-of-sample $R^2 (R_{OOS}^2)$ tests introduced above are wildly used in recent studies, they can only compare the predictive performance between two competing models, i.e., an interested model and a benchmark one. Therefore, to get a whole picture on the forecasting accuracy across all the interested models (e.g., the GARCH-MIDAS-X models incorporating various uncertainty indices considered in this paper), this study turns to adopt the Model Confidence Set (MCS) test proposed by (Hansen et al., 2011).

This MCS test is based on some traditional model evaluation approaches, such as the DM test (Diebold and Mariano, 2002), reality check (White, 2000), and superior predictive ability (SPA) test (Hansen, 2005). However, it has several clear advantages over others. For example, firstly, the MCS test does not need a specific benchmark, while other methods, such as DM test and reality check, have to choose one. This can be highly subjective and tends to cause non-robust test results. Secondly, the p-values of MCS test are obtained by a bootstrap method, which can greatly reduce the influence of outliers in the forecasts. Lastly, the MCS test allows to select more than one best model, offering policy makers and investors more options in their decision making. The MCS process is handled as follows.

Suppose that this study wants to compare the forecasting performances of $k$ models in a model set, $M_0 = \{m_1, m_2, \ldots, m_k\}$. These models are evaluated on a forecasting sample of length $H$ and a loss function (or a criterion). In practice, this study can use different loss functions for some particular evaluation purposes. Following the suggestions of (Hansen, 2005) and (Hansen et al., 2011), this study chooses six loss functions as:

\begin{align*}
QLIKE &= \frac{1}{H} \sum_{t=1}^{H} (\ln(\hat{\sigma}_t^2) + \sigma_t^2/\hat{\sigma}_t^2), \\
MSE &= \frac{1}{H} \sum_{t=1}^{H} (\sigma_t^2 - \hat{\sigma}_t^2)^2, \\
MAE &= \frac{1}{H} \sum_{t=1}^{H} |\sigma_t^2 - \hat{\sigma}_t^2|, \\
HMSE &= \frac{1}{H} \sum_{t=1}^{H} (1 - \sigma_t^2/\hat{\sigma}_t^2)^2,
\end{align*}

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\[ HMAE = \frac{1}{H} \sum_{t=1}^{H} |1 - \frac{\sigma_t^2}{\hat{\sigma}_t^2}|, \]  

(5.51)

\[ R^2 LOG = \frac{1}{H} \sum_{t=1}^{H} [\ln(\frac{\sigma_t^2}{\hat{\sigma}_t^2})]^2 \]  

(5.52)

where QLIKE indicates the loss implied by a Gaussian likelihood. MSE and MAE are two commonly used criteria of mean square error and mean absolute error, respectively. Moreover, HMSE and HMAE are the MSE and MAE adjusted for heteroskedasticity, and \( R^2 LOG \) is similar to the \( R^2 \) of the Mincer-Zarnowitz regressions. These loss functions can serve for different practical uses. For example, in the case of value-at-risk applications, investors are more interested in the accurate forecasts of large volatilities rather than small volatilities. Thus, MSE is more suitable than MAE for risk management applications.

The MCS test is a series of significance tests in a set of forecasting models \( M_0 \), and the models with poor predictive power in the set \( M_0 \) are removed. Therefore, the null hypothesis of MCS test is that two models in \( M_0 \) have the same predictive power as Equation 5.53:

\[ H_{0,M} : E(d_{\ell,uv,t}) = 0 \text{ for all } u, v \in M < M_0, \]  

(5.53)

where \( d_{\ell,uv,t} = L_{u,t}^{\ell} - L_{v,t}^{\ell} \), and \( L_{u,t}^{\ell} \) and \( L_{v,t}^{\ell} \) are the results of loss function \( \ell \) defined in Equation 5.47 to Equation 5.52 for models \( u \) and \( v \) at time \( t \), respectively. \( E(d_{\ell,uv,t}) \) is the mathematical expectation of \( d_{uv,t} \). Then, the MCS process utilises an equivalence test (\( \delta_M \)) and an elimination rule (\( e_M \)) to continuously test the models in the model set \( M_0 \) until no model is removed from the set. Following (Hansen, 2005) and (Hansen et al., 2011), this study sets the significance level of the MCS test to be 0.1. This means that, if the p-value of one forecasting model in the MCS test is larger than 0.1, it is a surviving model in \( M_0 \). A larger p-value indicates a higher prediction accuracy of the corresponding model. In particular, a p-value equal to 1 suggests that the corresponding model has the best forecasting performance.

The above three tests are usually employed to assess the forecasting errors of different models. However, besides forecasting error, investors may also be very
interested in the accuracy in the forecasting direction for better designing their trading strategy. Thus, besides MCS test, this study further employs the Direction-of-Change (DoC) rate test utilised in (Degiannakis and Filis, 2017) to compare the accuracy in the forecasting direction of various GARCH-MIDAS-X models. The DoC calculates the proportion of forecasts that correctly predict the direction of volatility movements. That is Equation 5.54:

\[
\text{DoC} = \frac{1}{H} \sum_{t=1}^{H} D_t,
\]

where \(H\) is the number of return forecasts, and

\[
D_t = \begin{cases} 
1, & \text{if } \sigma_t^2 > \sigma_{t-1}^2 \text{ and } \hat{\sigma}_t^2 > \sigma_{t-1}^2, \\
1, & \text{if } \sigma_t^2 < \sigma_{t-1}^2 \text{ and } \hat{\sigma}_t^2 < \sigma_{t-1}^2, \\
0, & \text{otherwise.}
\end{cases}
\]

Then, a nonparametric test proposed by (Pesaran and Timmermann, 1992) is employed to test the null hypothesis that the DoC rate of an interested model is not larger than that of the benchmark.

### 5.3 The Effects of Central Bank Digital Currencies News on Financial Markets

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 the relationships between different financial variables. Applying the DCC-GARCH model, Akyldirim et al. (2020) analyse 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) investigate the time-varying co-movements between Turkish sovereign yield curve factors and oil price shocks. Xie and Zhu (2021) examine 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) use 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) analyse 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) examine 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) launch the EPU index and analyse its impact on economic activities (S&P 500 index, VIX, industrial production, and unemployment rate). Huang and Luk (2020) issue China Economic Policy Uncertainty Index (China’s EPU) to examine the impact of its shocks on macroeconomic variables (equity price, deposit rate, unemployment rate, and output volume). Lucey et al. (2022) and Wang et al. (2022b) develop the UCRY Policy, UCRY Price and ICEA. Then, these studies perform the IRF, FEVD, and HD tests to further investigate the impacts of the three indices on financial markets. This thesis uses 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, this study employs the DCC-GARCH model as the most suitable and straightforward method for achieving this goal.
5.3.1 Structural shock model specification

The main uses of the VAR model are forecasting and structural analysis Lütkepohl (2005). In order to investigate the relationship between CBDC indices and economic or financial activities, following the frameworks of the three structural shock tools, which have been discussed in subsection 5.2.2, the IRF, FEVD and HD tests are processed in this study. This study establishes 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, are selected as the system’s variables. This study orders variables as indicated by Equation 5.56:

This study adds 1 lag to the SVAR model and the three structural shock analysis tools. The optimal lag value of 1 for the variable system Equation 5.56 and SVAR model is selected based on the following procedures. First, this study calculates the maximum lag value by applying the equation of subsection 5.1.5. The calculation result suggests a maximum lag value of 13. Second, this study calculates 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 B2 SVAR stationary test results. 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, this study excludes 13, 12, 11 as the optimal lag by testing how stationary the SVAR model could stay. The statistical results in Table B3 SVAR stationary test results 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. 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, this study decides to select 1 as the optimal lag value.

5.3. THE EFFECTS OF CENTRAL BANK DIGITAL CURRENCIES NEWS ON FINANCIAL MARKETS

(5.56) \[ y_{3t} = \begin{bmatrix} \text{CBDC1}_t \\ \text{CBDC2}_t \\ \text{UCRY Policy}_t \\ \text{UCRY Price}_t \\ \text{ICEA}_t \\ \text{MSCI World Banks Index}_t \\ \text{VIX}_t \\ \text{USEPU}_t \\ \text{FTSE All World Index}_t \\ \text{EUR/USD}_t \\ \text{GBP/USD}_t \\ \text{JPY/USD}_t \\ \text{RUB/USD}_t \\ \text{CNY/USD}_t \\ \text{Gold}_t \\ \text{Bitcoin}_t \\ \text{FTSE World Government Bond Index}_t \end{bmatrix} \]

where, CBDCUI or CBDCAI is ordered first and second because this study believes 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.

5.3.2 Dynamic conditional correlation model

The key preconditions to apply a GARCH model is that the time series data is stationary with ARCH effects. The results in Table 7.2 Panel C confirms that all the time series variables are stationarity in the continuously compounded returns. Moreover, Table B6 ARCH test results\(^5\) indicates that all the variables have ARCH effects in 1, 2 and 3 orders. The above statistical evidence confirmed that the GARCH-type models are 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

\(^5\)https://www.sciencedirect.com/science/article/pii/S0040162522002414
multivariate GARCH-DCC models to estimate the DCCs. 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). This study fits 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. Discrimination among the Table B7 GARCH-type models (1), Table B8 Discrimination among the GARCH-type models (2), Table B9 Discrimination among the GARCH-type models (3) and Table B10 Discrimination among the GARCH-type models (4) 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 (Al Mamun et al., 2020).

This study first sets $r_t = [r_{1,t}, \ldots, r_{n,t}]'$ 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. $\mu$ denotes a vector of constant with length $n$. $\psi$ represents the coefficient vector of the autoregressive terms. Second, setting $h_{i,t}$ 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 5.57:

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

Second, this study sets $I_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$, otherwise $I_{t-1} = 1$. Moreover, the asymmetric effect of positive and negative shocks are identified by $\lambda$ (the leverage coefficient). Based on the GJR-GARCH (1,1) model, the conditional volatility $h^2_{i,t}$ can be expressed as Equation 5.58:

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

---

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 \( \omega, \alpha, \beta, \) and \( \lambda \) can satisfy the conditions of \( \omega > 0, \alpha, \beta, \lambda \geq 0, \) and \( \lambda + (\alpha + \beta)/2 < 1 \), Equation 5.58 can always hold for a positive and stationarity volatility process (Glosten et al., 1993) and (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 5.59:

\[
H_t = D_t \times R \times D_t,
\]

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 5.59, a simple estimate of \( R \) is the unconditional correlation matrix of the standardised residuals. When \( R \) is set as time-varying, this study can reach a dynamic correlation model, which can be denoted as Equation 5.60:

\[
H_t = D_t \times R_t \times D_t,
\]

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), this study can further reach Equation 5.61, and Equation 5.62, and Equation 5.63:

\[
R_t = (Q_t^*)^{-\frac{1}{2}} \times Q_t(Q_t^*)^{-\frac{1}{2}},
\]

\[
Q_t = (1 - \alpha - \beta)Q_s + \alpha Z_{t-1}Z_{t-1}' + \beta Q_{t-1},
\]

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

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

Finally, this study can give the element of the conditional correlation matrix \( \rho_{ij,t} \) as Equation 5.64:

\[
(5.64) \quad \rho_{ij,t} = \frac{q_{ij,t}}{q_{ii,t} \times q_{jj,t}}
\]

5.4 Volatility Spillovers Across NFTs News
Attention and Financial Markets

5.4.1 TVP-VAR

Many econometrics models can measure the interconnections between different financial markets. In the digital currency area, wavelet analysis, DCC-GARCH, and VAR are the three most popular and efficient models used to achieve this goal (Wang et al., 2022d). This study applies the time-varying parameter - vector autoregression (TVP-VAR) model for the volatility spillover connectedness analysis. Firstly, because the TVP-VAR model can estimate the volatility transmissions in both the static and time-varying two perspectives, where the GARCH models only can capture the static volatility linkages. With the help of the volatility spillovers in the time domain, the effects of flash events on volatility spillovers can be uncovered. Secondly, TVP-VAR model can capture the dynamic interconnections with a small and low-frequency dataset because the econometrics framework is based on variance decomposition of the prediction error (Primiceri, 2005; Diebold and Yilmaz, 2009; Diebold and Yilmaz, 2012). As a comparison, GARCH models are based on the a ARCH model. In this case, the conditional variance trend can rapidly fade - requires a high order of the stochastic process when measuring the conditional variance of a time series over time. Furthermore, the wavelet analysis suffers from insufficient stage information, poor directionality, and shift sensitivity (Fernandas et al., 2003). Although a few optimisation wavelet transformations can significantly reduce these disadvantages, this requires a high frequency and a large volume of data. NFT markets are still in their infancy, meaning that the research period is relatively short - not to mention that the NFTsAI is a
weekly-frequency index based on text mining. Therefore, these limitations mean that this study has to use a short time period and low-frequency dataset, which matches the TVP-VAR model’s characteristics. In the end, the TVP-VAR model allows one to examine bidirectional volatility spillover connectedness because it can achieve (a) Totally volatility spillover analysis, (2) Net directional volatility spillover analysis, (3) Directional volatility spillover from each variable to all others, (4) Directional volatility spillover to each variable from all others, (5) Net pairwise directional volatility spillover. While GARCH model and VAR-IRF (Impulse Response Function), FEVD (Forecast Error Variance Decomposition) and HD (Historical Decomposition) tests only can capture the unidirectional volatility spillover connectedness. By using the TVP-VAR model, this study can examine the effects of NFTsAI on financial markets and capture the impacts of the financial markets on NFTsAI.

5.4.1.1 VAR framework

A vector autoregression (VAR) is a standard econometric model used within a wide range of financial analyses, especially for characterising dynamic relationships (Lütkepohl, 2005). Based on the VAR framework proposed by (Sims, 1980), Primiceri (2005) further includes stochastic volatility into it, thus creating the TVP-VAR model. This model can measure prolonged time variation in the VAR model by applying coefficients and variance-covariance matrix (Nakajima et al., 2011). The TVP-VAR model framework can be denoted as follows Equation 5.65:

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

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 \( K \times K_p \) time-varying parameter coefficient matrix. \( D_t \) is a time-varying parameter vector of deterministic terms, and \( \Xi^+ \) is the time-varying parameter coefficient matrix corresponding with \( D_t \). \( u_t \) is a \( k \)-dimensional unobservable zero mean vector white noise process, and has the covariance matrix \( \Sigma_u \). \( u_t \) also denotes the reduced form disturbance.

In order to investigate the time-varying volatility spillover connectedness between the NFTsAI and financial markets. This study establishes a variable system based on the Equation 5.65, which includes the 14 variables justified and selected
in chapter 4, each of which has 230 observations. The variable system can be expressed as follow Equation 5.66:

\[ y_{4t} = \begin{bmatrix} NFTsAI_t \\ CryptoPunks_t \\ Decentraland_t \\ Chainlink_t \\ Maker_t \\ BGCI_t \\ Bitcoin_t \\ Ethereum_t \\ FTSEAWI_t \\ FTSEWGBI_t \\ PIMCOCORP_t \\ DBC_t \\ DXY_t \\ Gold_t \end{bmatrix} \]

Moreover, this study calculates the optimal lag based on the AIC, HQ, SC, and FPE information criteria. Finally, the baseline VAR specification includes one lag of all variables\(^7\). To assess the TVP-VAR spillover connectedness, three more procedure calculations are required.

5.4.1.2 Convert TVP-VAR to TVP-VMA

First, this study needs to convert the TVP-VAR model into a time-varying parameter vector moving average (TVP-VMA) representation in order to compute the impulse response function (IRF) and forecast error variance decomposition (FEVD), which can be written as follows Equation 5.67:

\[ y_t = u_t + \sum_{i=1}^{\infty} \Phi_i u_{t-i}, \Phi_0 = I_k, \]

where \( u_t \) is a k-dimensional unobservable zero mean vector white noise process and has covariance matrix \( \Sigma_u \). \( \Phi_i = JA^I JJ' \) and \( J = [I_k : 0 : 0 : \cdots : 0] \). A\(^I\) are summable.

\(^7\)The optimal lag selection process will not be detailed here for the sake of brevity. All the details are available upon reasonable request.
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5.4.1.3 Derive IRF from TVP-VMA

Second, based on the TVP-VMA in Equation 5.67, the IRF could trace the marginal effect of a shock to one variable by counterfactual experiment. Indeed, the IRF for each variable \( j \) on variable \( i \) can be computed as Equation 5.68:

\[
IRF = \sum_{p=0}^{\infty} (e'_i A P \sum e_j)^2,
\]

where both \( e'_i \) and \( e_j \) are fundamental \( N \times 1 \)-dimensional vectors with unity at \( i \) and \( j \), separately. \( A \) is still the \( K \times K_p \) time-varying parameter coefficient matrix. The impulse response is equal to the cumulative forecast error from a shock to the variable \( i \) from \( j \) at time \( t-p \).

5.4.1.4 Compute FEVD using the IRF

Third, the forecast error variance of the k-th element of the forecast error vector can be denoted as Equation 5.69:

\[
E(y_{j,t+h} - y_{j,t}(h))^2 = \sum_{j=1}^{K} (\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2),
\]

where \( \theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2 \) can represent the contribution of the j-th \( \varepsilon_t \) innovation to the h-step forecast error variance of variable \( k \). \( \theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2 \) can compute the contribution % of the j-th \( \varepsilon_t \) innovation to the h-step forecast error variance of variable \( k \). \( \omega_{kj,h} \) can decompose the contribution of the j-th \( \varepsilon_t \) innovation to the h-step forecast error variance of variable \( k \).

In order to more comprehensively understand the linkages between the FEVD Equation 5.69, the IRF Equation 5.68, and the spillover connectedness, the FEVD can also be re-written as Equation 5.70:

\[
\theta_{ij,t}(h) = \frac{\sigma_{jj}^{-1} \sum_{p=0}^{\infty} (e'_i A P \sum e_j)^2}{\sum_{p=0}^{\infty} (e'_i A P \sum A_p' e_l)} = \frac{\theta_{ij,t}(H)}{\sum_{j=1}^{N} \theta_{ij,t}(H)}, H = 1, 2, 3 \ldots ,
\]

where \( \sigma_{jj}^{-1} \) represents the standard deviation of the j-th \( \varepsilon_t \) innovation to the h-step forecast error variance of variable \( k \). \( \tilde{\theta}_{ij,t}(h) \) is the standardised results of \( \theta_{ij,t}(h) \), and can provide the magnitude of pairwise-directional spillover connectedness from
to j at horizon h. Based on Equation 5.70, we can propose that \( \sum_{j=1}^{N} \hat{\theta}_{ij,t}(h) = 1 \), and \( \sum_{i,j=1}^{N} \hat{\theta} = N \). Following (Karim et al., 2022), and also considering this study uses short-term and low-frequency data, \( H \) is set to be 10.

### 5.4.1.5 Total spillover index

As the mathematical framework of spillover connectedness has now been clearly explained, this study can now (according to the FEVD in Equation 5.70) construct the total spillover connectedness index (TSCI) as Equation 5.71:

\[
TSCI(h) = \frac{\sum_{i,j=1}^{N} \hat{\theta}_{ij,t}(h)}{\sum_{i,j=1}^{N} \hat{\theta}_{ij,t}(h)} \times 100 = \frac{\sum_{i,j=1}^{N} \hat{\theta}_{ij,t}(h)}{N} \times 100
\]

The TSCI can reveal the dynamic interconnection between a system’s variables. It is similar to the system shock analysis. For example, one unit \( A_1 \) has the highest amount of momentum, and can transfer momenta to those units closest to it. These units then subsequently pass the momenta to those nearest them, and so on. The whole process can propagate fast (high values) or attenuate slow (low values).

### 5.4.1.6 Directional spillover connectedness indices

According to the Equation 5.70 and Equation 5.71, this study could still partially compute directional spillover connectedness (DSC). DSC refers to the directional spillovers received by each variable i “From” all other variables in a variable system, or those transmitted by each variable i “To” all other variables in a variable system. Put simply, DSC can be valued as processing a decomposition on the TSCI “From” or “To” a particular source.

There are four different measures of DSC: from-spillover connectedness \( (DSC^f) \), to-spillover connectedness \( (DSC^t) \), net-spillover connectedness \( (DSC^n) \), and net-pairwise directional spillover connectedness \( (DSC^{np}) \). It is worth noting that the \( DSC^n \) is the difference between \( DSC^f \) and \( DSC^t \). Moreover, the \( DSC^{np} \) between variable i and j is the difference between the directional spillovers transmitted from variables i to j, as well as those transmitted from j to i. The formula details of the four different DSC measures are shown as follows:
The $DSC^f$ can be expressed as Equation 5.72:

\[
DSC^f_{i\rightarrow j,t}(h) = \frac{\sum_{j=1,j\neq i}^N \tilde{\theta}_{ji,t}(h)}{\sum_{j=1}^N \tilde{\theta}_{ji,t}(h)} \times 100 = \frac{\sum_{j=1,j\neq i}^N \tilde{\theta}_{ji,t}(h)}{N} \times 100
\]

The $DSC^t$ can be defined as Equation 5.73:

\[
DSC^t_{i\rightarrow j,t}(h) = \frac{\sum_{j=1,i\neq j}^N \tilde{\theta}_{ij,t}(h)}{\sum_{j=1}^N \tilde{\theta}_{ij,t}(h)} \times 100 = \frac{\sum_{j=1,i\neq j}^N \tilde{\theta}_{ij,t}(h)}{N} \times 100
\]

The $DSC^n$ can be written as Equation 5.74:

\[
DSC^n_{i,j,t}(h) = DSC^t_{i\rightarrow j,t}(h) - DSC^f_{i\rightarrow j,t}(h) = \left(\frac{\sum_{j=1,i\neq j}^N \tilde{\theta}_{ij,t}(h)}{N} - \frac{\sum_{j=1,j\neq i}^N \tilde{\theta}_{ji,t}(h)}{N}\right) \times 100
\]

The $DSC^{np}$ can be given as Equation 5.75:

\[
DSC^{np}_{i,j,t}(h) = \left(\frac{\tilde{\theta}_{ij,t}(h)}{\sum_{j=1}^N \tilde{\theta}_{ij,t}(h)} - \frac{\tilde{\theta}_{ji,t}(h)}{\sum_{j=1}^N \tilde{\theta}_{ji,t}(h)}\right) \times 100 = \frac{\tilde{\theta}_{ij,t}(h)}{N} \times 100
\]

### 5.4.2 Price bubble detecting

#### 5.4.2.1 Asset pricing equation

Asset price bubble detecting models are all based on an asset pricing equation, which can be expressed as Equation 5.76:

\[
P_t = \sum_{i=0}^\infty \left(\frac{1}{1+r_f}\right)^i \mathbb{E}_t(D_{t+i} + U_{t+i}) + B_t,
\]

where $P_t$ is the after-dividend. Or, where dividends do not exist. The price of the financial asset, $r_f$ is the risk-free interest rate, $\mathbb{E}_t$ is the expected return, $D_t$ is the investment return received from the financial asset, $U_t$ denotes the unobservable fundamentals. In the end, $B_t$ represents the bubble component, and it satisfies the sub-martingale property, which can be defined as: $\mathbb{E}_t(B_{t+1}) = (1 + r_f)B_t$. Market fundamental can be measured as: $P^f_t = P_t - B_t$.

#### 5.4.2.2 SADF and GSADF tests

According to the price bubble sub-martingale property, when $U_t$ in Equation 5.76 are at most unit-roots (random walks) and $D_t$ is stationary without a trend after differencing, price bubbles can be captured from the explosive behaviour in
asset prices or the price-dividend ratios. For the asset pricing equation in Equation 5.76, several econometrics models can identify the price bubble components in the asset pricing models (see as examples Hall et al., 1999; Zhou and Sornette, 2003; Pástor and Veronesi, 2006; Fry and Cheah, 2016; Cagli, 2019; Cretarola and Figà-Talamanca, 2021; Waters and Bui, 2022). No matter the framework of the price bubble detecting econometrics models, explosive or mildly explosive behaviour in asset prices is a key indicator of the existence of price bubbles (Phillips and Magdalinos, 2007). More particularly, recursive right-sided unit root tests can be used as significantly effective models to detect price bubbles in financial assets (Phillips et al., 2011), with potential for near real-bubble detection (Phillips et al., 2015).

Following Phillips et al. (2011) (PWY) and Phillips et al. (2015) (PSY), this study assumes prices follow a pure random walk process in a martingale null with an asymptotically negligible drift to capture the mild drift in price processes, which can be expressed as Equation 5.77:

\begin{equation}
    y_t = d T^{-\eta} + \theta y_{t-1} + \epsilon_t, \epsilon_t \sim iid (0, \sigma^2), \theta = 1,
\end{equation}

where \(d\) is a constant, \(T\) is the sample size, \(\eta\) is a localising coefficient that controls the magnitude of the intercept and drift as \(T\) approaches infinity in the PWY test, but drift as \(T\) approaches unity in the PSY test. In the model, \(\eta > \frac{1}{2}\) because this study assumes a pure random walk process is assumed, where the drift is small relative to the order of magnitude of \(y_t\). \(\epsilon_t\) is the error term.

Next, a recursive approach with a rolling window standard ADF regression could be applied in order to capture the price bubbles in financial assets, which can be denoted as Equation 5.78:

\begin{equation}
    \Delta y_t = \alpha + \beta T + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_p - 1 \Delta y_{t-p+1} + \epsilon_t,
\end{equation}

where \(\alpha\) is a constant, \(\beta\) and \(\gamma\) are the coefficients on a time trend. \(\beta T\) stands for the sum of a deterministic trend. \(\delta\) is the theoretical autocorrelation. \(p\) is the lag order of the autoregressive process. \(\epsilon_t\) is a stationary error process. The null hypothesis is a unit root, and the alternative hypothesis is a mildly explosive process, which can be denoted as: \(H_0: \gamma = 1; H_A: \gamma > 1\).

In order to further explain the PWY and PSY price bubble detection strategies, some notations should be set. \(T\) is the sample size, and the sample interval is as
The estimated coefficient in Equation 5.78 can be denoted as: $\gamma_{c_1,c_2}$. $\text{ADF}_{c_1,c_2}$ represents the corresponding ADF value over the normalised sample $[c_1, c_2]$. Moreover, $c_w$ is the fractional window size of the ADF regression and $c_0$ is the fixed initial window. The fraction $c_1^{th}$ is the start point of the rolling window standard ADF regression, and the $c_2^{th}$ is the end point, thus resulting in $c_2 = c_1 + c_w$.

Based on Equation 5.78, a simple right-tailed version of the standard ADF unit root test, a rolling ADF (RADF) test, a PWY SADF test, and a PSY GSADF test can be further developed. Phillips et al. (2011) and Phillips et al. (2015) prove that the SADF and GSADF tests perform better in price bubble detecting than the standard ADF test, which uses the whole sample. Furthermore, by applying Monte Carlo simulations, Homm and Breitung (2012) prove that the SADF test results in higher power in the single periodically collapsing price bubble detecting, and Homm and Breitung (2012) confirm that the GSADF outperforms the other methods in the multiple periodically collapsing price bubble detecting. Nevertheless, many scholars still prefer to apply the SADF and GSADF simultaneously and compare the results to capture price bubbles. For example, see for cryptocurrency Li et al. (2021b), stocks Wang et al. (2022a), commodities Sharma and Escobari (2018). Although NFTs are young financial markets without multiple bull or bear periods, therefore multiple periodically collapses in these markets cannot be guaranteed. Therefore, this study will seek and date price bubbles based on both SADF and GSADF tests.

The SADF test is built on recursive estimation of the standard ADF regression with a fixed starting point $c_0$ and expanding window $c_w$. The window size $c_w$ ranges from $c_0$ to 1. The starting point $c_1$ is fixed at 0, so the end point of each $c_2$ equals $c_w$. In the end, the ADF regression is repeatedly calculated while increasing the window size, which is $c_2$ and variates from $c_0$ to 1. Each recursive estimation process from 0 to $c_2$ can generate an ADF statistic, which can be expressed as $\text{ADF}_{c_0}^{c_2}$. The SADF test can further be defined as a supremum statistic of the $\text{ADF}_{c_0}^{c_2}$ sequence for $c_2 \in [c_0, 1]$ relied on the forward recursive regression Equation 5.79:

\[
(5.79) \quad SADF(c_0) = \sup_{c_2 \in [c_0, 1]} \text{ADF}_{c_0}^{c_2}
\]

According to Phillips et al. (2015), the most significant advantage of the GSADF test is that it allows more flexible estimation windows. In other words, the starting point $c_1$ can vary within the range between 0 and $c_2 - c_0$. The GSADF test can be expressed as Equation 5.80:
Based on Equation 5.77, the limit distribution of the GSADF test can be denoted as Equation 5.81:

\[
\sup_{c_1 \in [0, c_2 - c_0], c_2 \in [c_0, 1]} \frac{c_0}{c_1} \leq 1
\]

As proved by Phillips et al. (2011) and Phillips et al. (2015), the date-stamping method can also be applied to the SADF and GSADF tests to consistently estimate the origin and termination of bubbles.

In the date-stamping SADF test, all the financial price data are sorted in chronological order to be viewed as time-series data. A price bubble initiating at time \(T_{c_2}\) can be measured by comparing each element of the estimated \(ADF_{c_2}^0\) sequence to the corresponding right-tailed critical values of the standard ADF statistic. \(T_{c_s}\) denotes the estimated start point of a price bubble, and it is equal to the \(ADF_{c_2}^0\) that crosses the corresponding critical value from below. \(T_{c_e}\) represents the estimated endpoint of a price bubble and is equal to the \(ADF_{c_2}^0\) that crosses the critical value from above. Based on these notations, the estimated price bubble period based on the date-stamping SADF test can be given as Equation 5.82 and Equation 5.83:

\[
\hat{c}_s = \inf_{c_2 \in [c_0, 1]} \left\{ c_2 : ADF_{c_2}^0 > cv_{c_2}^{\beta_T} \right\},
\]

\[
\hat{c}_e = \inf_{c_2 \in [c_s, 1]} \left\{ c_2 : ADF_{c_2}^0 < cv_{c_2}^{\beta_T} \right\},
\]

where \(T\) and \(\beta_T\) approaches to 0, and \(cv_{c_2}^{\beta_T}\) denotes the \(100(1 - \beta_T)\%\) critical value of the standard ADF statistic based on \([T_{c_2}]\) observations.

Similarly, the estimated price bubble period based on the date-stamping GSADF test can be given as Equation 5.84 and Equation 5.85:
5.4. VOLATILITY SPILLOVERS ACROSS NFTS NEWS ATTENTION AND FINANCIAL MARKETS

\[
\hat{c}_s = \inf_{c_2 \in [c_0, 1]} \left\{ c_2 : BSADF^{c_2}_0(c_0) > cv_{c_2}^{\beta_T} \right\},
\]

(5.84)

\[
\hat{c}_e = \inf_{c_2 \in [\hat{c}_s, 1]} \left\{ c_2 : BSADF^{c_2}_0(c_0) < cv_{c_2}^{\beta_T} \right\},
\]

(5.85)

where \( T \) and \( \beta_T \) approaches to 0, and \( cv_{c_2}^{\beta_T} \) denotes the 100(1 − \( \beta_T \))% critical value of the sup ADF statistic based on \( [T_{c_2}] \) observations. BSADF\( (c_0) \) for \( c_2 \in [c_0, 1] \) is the backward sup ADF statistic. Moreover, \( GSADF(r_0) = \sup_{c_2 \in [c_0, 1]} BSADF^{c_2}_0(c_0) \) can link BSADF\( (c_0) \) to GSADF statistic.

5.4.2.3 LPPLS model

The LPPLS (Log Periodic Power Law Singularity) model allows quantification of the extent of growth in price beyond exponential growth under positive feedback, so it can also be applied to price bubble detecting in financial markets. Furthermore, many studies have proven that the LPPLS model can precisely identify the termination time of price bubbles and measure the risk of bubble crash in stock markets (Filimonov et al., 2017), futures (Zhou et al., 2018a), and cryptocurrency (Yao and Li, 2021), among other financial markets. The LPPLS model \( LPPLS(\Phi, t) \) can be expressed as Equation 5.86:

\[
E_t[ln p(t)] = A + B(t_c - t)^m + C(t_c - t)^m \cos[\omega ln(t_c - t)] - \phi,
\]

(5.86)

where, \( E_t[ln p(t)] \) is the expected logarithm of the asset price at the date of the termination of the bubble. \( t_c \) is the critical point, and it can be interpreted as the date of termination of the bubble and transition in a new regime. \( A \) represents the expected value of the \( ln p(t) \) when the bubble at the critical point \( t_c \), \( A = ln[p(t_c)] > 0 \). \( B \) is the amplitude of the power law acceleration, and \( B = -\kappa \alpha / m \). \( B < 0 \) represents a positive bubble and \( B > 0 \) a negative bubble. \( B \) can quantify if the asset price is growing (decreasing) super-exponentially as time moves towards \( t_c \). \( m \) is a power exponent, and it represents the degree of the super-exponential growth and measures the acceleration of the asset price increase (0\(<\)m\(<\)1). \( C = -\kappa \alpha \beta / \sqrt{m^2 + \omega^2} \) can quantify the proportional amplitude of the oscillations around the power law singular growth. \( \omega \) is the scaling ratio of the angular log-frequency of
oscillations during the bubble. $0 < \phi < 2\pi$ is a phase parameter, which can represent time scale of the oscillations. $t_c - t$ in Equation 5.86 represents a price dynamic and denotes a "bubble". The first component, $A + B(t_c - t)^m$, obeys the hyperbolic power law and can quantify the super-exponential growth. The second component, $C(t_c - t)^m$, controls the amplitude of the accelerating oscillation; it fails to zero at the critical time $t_c$. The third component, $\cos[\omega \ln(t_c - t)] - \phi$, models the local frequency of the log-periodic oscillations, which approaches infinity at $t_c$. 
NEW CRYPTOCURRENCY INDICES AND APPLICATIONS

To capture the policy uncertainty and price uncertainty in the cryptocurrency market, based on more than 700 million data from LexisNexis New & Business database. This thesis firstly develops two new indices: the cryptocurrency policy uncertainty index (UCRY Policy) and the cryptocurrency price uncertainty index (UCRY Price). By using the SVECM model and historical decomposition, this thesis finds that these two uncertainty indices significantly move around the major events in the cryptocurrency space. Therefore, this thesis suggests these two indices, as new indicators, can capture uncertainty beyond cryptocurrency market volatility and can be used for academic, policy and practice-driven research.

Secondly, energy consumption and environmental pollution issues in cryptocurrencies have been paid more and more attention because society is pursuing cryptocurrency’s environmental sustainability. Many papers have confirmed this argument. However, how the discussion and engagement in social media related to the cryptocurrency environmental issues can have impacts on the cryptocurrency market or the related financial markets has not been fully investigated. Based on this research gap and to answer this research question. This study constructs the cryptocurrency environmental attention index (ICEA), based on more than 700 million data from LexisNexis News & Business database. Then, this paper selects
independent variables from the cryptocurrency market, crude oil market, global policy uncertainty, global economic uncertainty, industrial production and global temperature uncertainty. By using the Impulse Response Function (IRF), Forecast Error Variance Decomposition (FEVD) and Historical decomposition (HD). The findings from this paper suggest that the attention on cryptocurrency environmental issues can significantly contribute to the cryptocurrency market’s volatility and can negatively impact industrial production. Therefore, these results are essential for policymakers and academics because we have to notice the big issues in the negative effects of cryptocurrency on the environment and financial markets. Moreover, these results are also important for investors because it would be better to consider their investment decisions’ ethical implications and environmental impacts.

Thirdly, although the tight connections between cryptocurrency and precious metal markets have been recognised for a long time, no studies focus on whether cryptocurrency market uncertainty could help to explain and forecast volatilities in precious metal markets. This study extends the existing literature in two major aspects: on the one hand, it is the first one to extend the simple GARCH-MIDAS model of (Engle et al., 2013) by incorporating the newly developed cryptocurrency uncertainty indices (UCRY Policy and UCRY Price), and compare the in-sample impacts and out-of-sample predictive abilities of cryptocurrency uncertainty with many other commonly used uncertainty measures on the precious metal markets. On the other hand, the superior out-of-sample predictive power of cryptocurrency uncertainty is assessed by various model evaluation methods across different forecasting horizons, based not only on predicting errors but also on the accuracy of forecasting directions. In summary, the main findings of this study can be concluded as follows. First, this study finds that different uncertainty indices can indicate the different long-term components of volatility in precious metal markets. These long-term components show distinct trends over time. Second, the in-sample results demonstrate the significant impacts of cryptocurrency uncertainty on the volatilities of precious metal markets, and the out-of-sample evidence further confirms the superior volatility predictive power of cryptocurrency uncertainty over other uncertainty indices. The empirical findings from this paper highlight the importance of cryptocurrency uncertainty and can provide new insights for investors, policymakers and academics into the investment and hedging strategies related to precious metal markets across different periods.
6.1 Cryptocurrency Uncertainty Indices

This introduces a new families of indices around the digital-currency space: on cryptocurrency policy uncertainty (UCRY Policy) and on cryptocurrency price uncertainty (UCRY Price). These two indices are developed from 726.9 million news stories text mining to reflect the memetics and emergent nature of the issues. UCRY Policy and UCRY Price indices capture well movements and moments in the cryptocurrency policy and cryptocurrency price spaces. This chapter further applies the IRF and the FEVD to analyse the structure shocks of UCRY Policy and UCRY Price on the Global EPU, VIX, Bitcoin price, US Financial Stress, US EPU and Gold price, these financial or economics barometers. Moreover, this chapter decomposes the UCRY Policy’s historical evolution into various drivers.

![Figure 6.1: Cryptocurrency uncertainty indices](image)

Notes: This figure presents the cryptocurrency policy uncertainty index and cryptocurrency price uncertainty index. The blue line and orange line represent the UCRY Policy and UCRY Price, separately. These indices reflect the scaled weekly counts of articles containing the search strings in subsection 4.2.1. These two series are standardised and then add 100 from January 2014 to January 2021 based on queries. LexisNexis News & Business is the selected database.
Figure 6.2: Annotated UCRY indices

Notes: Flash events related to cryptocurrency uncertainty indices are annotated on the time series plot. Flash events are collected according to the frequency of articles that have a similar topic during week $t$. The cryptocurrency uncertainty indices capture the following big events. For example, Mt. Gox closed its website and filed for bankruptcy in February 2014; Coinbase announced a series c funding round in January 2015; The Bitfinex cryptocurrency exchange was hacked in August 2016; Bitcoin is very close to crossing $10k$ milestone in November 2017; IMF warning the risk behind Bitcoin in 2018; COVID-19 outbreaks in 2019; Cryptocurrency major bull market starts in the middle of 2020.
6.2 Summary Statistics

Table 6.1 shows the descriptive statistics for the indices of UCRY Policy, GlobalEPU, VIX, Bitcoin, USFS, USEPU, Gold and UCRY Price. As shown in Table 6.1, Bitcoin has the largest value of mean (4997.788), variance (37268690), and standard deviation (6104.809), which indicates the high fluctuations and uncertainty. Furthermore, the mean value of Bitcoin is significantly different from zero, while the standard deviation value is larger than the mean value. The skewness and kurtosis values of Bitcoin are large and positive, indicating the Bitcoin has a skewed left, fat-tailed and leptokurtic distribution. As for the UCRY Policy and UCRY Price, the mean, variance, standard deviation, skewness and kurtosis of the UCRY Price are higher than the UCRY Policy (99.9766 > 99.9755, 0.737670 > 0.714393, 0.8589 > 0.8452, 2.7865 > 2.5765, 10.8790 > 8.4451), which indicating that UCRY Price contains more uncertainty and is riskier than UCRY Policy. In addition, all the variables in Table 6.1 reject the normal distribution confirmed by Jarque-Bera (J.-B.) statistics because the p-value of these statistics is all less than 0.01 (Except for the GlobalEPU, it is equal to 0.01794 and lesser than 0.05).

Table 6.1: Descriptive statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Count</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Median</th>
<th>Variance</th>
<th>Standard deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>J.-B.</th>
</tr>
</thead>
<tbody>
<tr>
<td>UCRY Policy</td>
<td>85</td>
<td>99.1009</td>
<td>104.3415</td>
<td>99.9755</td>
<td>99.759</td>
<td>0.714393</td>
<td>0.8452</td>
<td>2.5765</td>
<td>8.4451</td>
<td>368.7</td>
</tr>
<tr>
<td>GlobalEPU</td>
<td>85</td>
<td>86.17</td>
<td>429.43</td>
<td>192.9751</td>
<td>168.95</td>
<td>6261.7666</td>
<td>79.1314</td>
<td>0.7316</td>
<td>-0.2937</td>
<td>8.0415**</td>
</tr>
<tr>
<td>VIX</td>
<td>85</td>
<td>9.5100</td>
<td>17.4523</td>
<td>15.08</td>
<td>15.08</td>
<td>55.420862</td>
<td>7.4445</td>
<td>2.2090</td>
<td>6.1422</td>
<td>214.94***</td>
</tr>
<tr>
<td>Bitcoin</td>
<td>85</td>
<td>2.296700×10^3</td>
<td>4.997788×10^3</td>
<td>2.886710×10^3</td>
<td>3.728689×10^3</td>
<td>1.048609×10^7</td>
<td>6.104860×10^3</td>
<td>2.225124</td>
<td>7.073033</td>
<td>282.15***</td>
</tr>
<tr>
<td>USFS</td>
<td>85</td>
<td>100.05</td>
<td>102.13</td>
<td>100.5342</td>
<td>100.52</td>
<td>0.1025</td>
<td>0.320221</td>
<td>1.7517</td>
<td>6.5731</td>
<td>208.92***</td>
</tr>
<tr>
<td>USEPU</td>
<td>85</td>
<td>29.32</td>
<td>55.41</td>
<td>45.4641</td>
<td>45.4641</td>
<td>9742.6910</td>
<td>98.7050</td>
<td>2.4928</td>
<td>6.9875</td>
<td>276.17***</td>
</tr>
<tr>
<td>Gold</td>
<td>85</td>
<td>1061.10</td>
<td>1975.86</td>
<td>1344.3094</td>
<td>1283.53</td>
<td>45934.2393</td>
<td>214.3228</td>
<td>1.48994</td>
<td>4.4250</td>
<td>40.887***</td>
</tr>
<tr>
<td>UCRY Price</td>
<td>85</td>
<td>99.091</td>
<td>104.8057</td>
<td>99.9766</td>
<td>99.7759</td>
<td>0.757670</td>
<td>0.8589</td>
<td>2.7865</td>
<td>10.8790</td>
<td>558.49***</td>
</tr>
</tbody>
</table>

Jarque-Bera (J.-B.) statistics can be used to check the normal distribution characteristic of the data (Jarque and Bera, 1980) and (Bera and Jarque, 1981). *p<0.1; **p<0.05; ***p<0.01.

The time series plots and descriptive statistics for UCRY indices empirical analysis are shown in Figure 6.3. UCRY Policy, Bitcoin, and UCRY Price have a similar trend. They all have a tremendous boost around 2018 and have a successive boom trend after 2020. GlobalEPU keeps a momentum of steady growth and has a peak in the initial of 2020. Vix, USFS and USEPU keep a relatively stationary trend, but they all reach a peak at the very beginning of 2020. The gold price keeps a good momentum of steady growth and gets a peak in the middle of 2020.
As for UCRY empirical analysis, Table 6.2 shows that the ADF test’s p-value of each variable was more significant than 0.05, and KPSS test’s p-value of each variable was less significant than 0.01. Based on Table 6.2, these evidences that there are unit roots in all variables and that all variables are nonstationary.

Moreover, from Table 6.3, \( r = 0 \), test for the presence of cointegration. Since the test statistic exceeds the 1% level significantly (215.11 > 177.20), there are strong evidences to reject the null hypothesis of no cointegration. Therefore, the cointegration test can pass. The variables form is cointegrated. To prove that the results are robust, Johansen maximum eigenvalue test is processed. The results can be found in Table 6.3. As the same, \( r = 0 \), tested for the presence of cointegration. Since the tested statistic exceeded the 1% level significantly (65.84 > 57.95), there are also strong evidences that the variables forms are cointegrated.
6.2. SUMMARY STATISTICS

Table 6.2: Unit root test

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DF Lag</td>
<td>p-value</td>
</tr>
<tr>
<td>UCRY Policy</td>
<td>-2.10</td>
<td>4 0.53 &gt; 0.05</td>
</tr>
<tr>
<td>GlobalEPU</td>
<td>-2.70</td>
<td>4 0.29 &gt; 0.05</td>
</tr>
<tr>
<td>Vix</td>
<td>-2.46</td>
<td>4 0.39 &gt; 0.05</td>
</tr>
<tr>
<td>Bitcoin</td>
<td>-0.44</td>
<td>4 0.98 &gt; 0.05</td>
</tr>
<tr>
<td>USFS</td>
<td>-3.25</td>
<td>4 0.08 &gt; 0.05</td>
</tr>
<tr>
<td>USEPU</td>
<td>-3.06</td>
<td>4 0.14 &gt; 0.05</td>
</tr>
<tr>
<td>Gold</td>
<td>-1.12</td>
<td>4 0.91 &gt; 0.05</td>
</tr>
<tr>
<td>UCRY Price</td>
<td>-1.60</td>
<td>4 0.74 &gt; 0.05</td>
</tr>
</tbody>
</table>

Notes: This table presents the unit root test results for the monthly price data of UCRY Policy, UCRY Price, GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold. ADF and KPSS, these two unit root tests refer to Augmented Dickey-Fuller test (Dickey and Fuller, 1979) and Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al., 1992). The methodology details of these two unit root tests can be found in chapter 5. * p<0.1; ** p<0.05; *** p<0.01. 5% Critical Values are given in parentheses.

Table 6.3: UCRY Johansen cointegration test

<table>
<thead>
<tr>
<th></th>
<th>Johansen trace test</th>
<th></th>
<th>Johansen maximum eigenvalue test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>test 10pct 5pct 1pct</td>
<td>test 10pct 5pct 1pct</td>
<td></td>
</tr>
<tr>
<td>r ≤ 7</td>
<td>3.83 7.52 9.24 12.97</td>
<td>3.83 7.52 9.24 12.97</td>
<td></td>
</tr>
<tr>
<td>r ≤ 6</td>
<td>10.58 17.85 19.96 24.60</td>
<td>6.75 13.75 15.67 20.20</td>
<td></td>
</tr>
<tr>
<td>r ≤ 5</td>
<td>22.99 32.00 34.91 41.07</td>
<td>12.41 19.77 22.00 26.81</td>
<td></td>
</tr>
<tr>
<td>r ≤ 4</td>
<td>40.32 49.65 53.12 60.16</td>
<td>17.34 25.56 28.14 33.24</td>
<td></td>
</tr>
<tr>
<td>r ≤ 3</td>
<td>66.04 71.86 76.07 84.45</td>
<td>25.72 31.66 34.40 39.79</td>
<td></td>
</tr>
<tr>
<td>r ≤ 2</td>
<td>97.06 97.18 102.14 111.01</td>
<td>31.02 37.45 40.30 46.82</td>
<td></td>
</tr>
<tr>
<td>r ≤ 1</td>
<td>149.28 126.58 131.70 143.09</td>
<td>52.21 43.25 46.45 51.91</td>
<td></td>
</tr>
<tr>
<td>r = 0</td>
<td>215.11 159.48 165.58 177.20</td>
<td>65.84 48.91 52.00 57.95</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table presents the Johansen cointegration test for the variable system Equation 5.25, which contains UCRY Policy, UCRY Price, GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold. Johansen trace test and Johansen maximum eigenvalue test are all processed. The methodology details can be found in chapter 5. 5% Critical Values are given in parentheses.
6.3 UCRY Indices Structural Shock Analysis

6.3.1 UCRY shocks on the dynamic of financial variables volatility

To get a more comprehensive understanding of the dynamic interaction between variables. The IRF tests are processed from the SVECM about the UCRY Policy and UCRY Price shocks to variable systems Equation 5.25. The statistical results could confirm the Hypothesis 1 can hold.

Figure 6.4 shows the UCRY Policy shock to GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold. Figure 6.4a presents after UCRY Policy impulses unit shocks to GlobalEPU, GlobalEPU has a positive response. The GlobalEPU response value increase gradually from the start point and get the peak value 2.97654578 in the 2nd period. Then, the GlobalEPU response value begin to decrease gradually and move to negative values. In the 4th period, GlobalEPU response value falls down to the lowest value, −1.48474101. From the 4th period, the GlobalEPU response value begin to move to positive values again. With the increasing of period, the GlobalEPU response value tend to converge and closely move around x = 0 axis. This empirical finding can verify that the Cryptocurrency Policy Uncertainty Index can increase the Global Economic Policy Uncertainty in the early stage. Still, the cryptocurrency environmental attention index also can decrease Global Economic Policy Uncertainty around the middle stage.

Figure 6.4b presents after UCRY Policy impulses unit shocks to VIX, VIX has a positive response. The VIX response value increase gradually from the start point and get the peak value 1.045204587 in the 2nd period. Then, the VIX response value begin to decrease gradually and move to negative values. In the 3rd period, VIX response value falls down to the lowest value, −0.350869774. From the 3rd period, the VIX response value begin to move to positive values again. With the increasing of period, the VIX response value tend to converge and closely move around x = 0 axis. Similar as the εUCRY Policy shocks to GlobalEPU, this empirical finding can verify that the Cryptocurrency Policy Uncertainty Index can increase the CBOE Volatility Index in the early stage. Still, the cryptocurrency environmental attention index also can decrease the CBOE Volatility Index around the middle stage.

Figure 6.4c presents after UCRY Policy impulses unit shocks to Bitcoin, Bitcoin has a positive response. The peak response value shows on the start point, which is equal to 0.0536715014. Then, the Bitcoin response value begin to fall down.
From the 4th period, the Bitcoin response value tend to converge and closely move around $x = 0$ axis. This empirical finding can verify that the Cryptocurrency Policy Uncertainty Index can increase the Bitcoin price index.

Figure 6.4d presents after UCRY Policy impulses unit shocks to USFS, USFS has a positive response. The lowest response value show on the start point, which is equal to $-0.0260634288$. Then, the USFS response value begin to rise up and get its peak value in the 2nd period, which is equal to $0.0644512297$. From the 3rd period, the USFS response value tend to converge and closely move around $x = 0$ axis. This empirical finding can verify that the Cryptocurrency Policy Uncertainty Index can increase the United States Financial Stress Index.

Figure 6.4e presents after UCRY Policy impulses unit shocks to USEPU, USEPU has a positive response. The USEPU response value increase gradually from the start point and get the peak value $12.20874780$ in the 2nd period. Then, the USEPU response value plummet to $-0.92485815$ in the 3rd period. $-0.92485815$ is also the lowest value. Among the period 4th and 6th, the USEPU response value move significantly around $x = 0$ axis between $1.02911810$ and $-0.89493257$. From 6th period, the USEPU response value tend to converge and closely move around $x = 0$ axis. This empirical finding can verify that the Cryptocurrency Policy Uncertainty Index can increase the United States Economic Policy Uncertainty.

Figure 6.4f presents after UCRY Policy impulses unit shocks to Gold, Gold has a negative response. The Gold response value increase rapidly from the 1st to its peak value $11.66622577$ in the 2nd period. Then, the Gold response value plummet to $1.67143278$ in 3rd period and also keep stable in the 4th period. Then, Gold response value begins to fall down to the lowest value, which is $-0.38583836$ in the 5th period. After that, the Gold response value tend to converge and closely move around $x = 0$ axis. This empirical finding can verify that the Cryptocurrency Policy Uncertainty Index can increase the Gold price index.

The responses of UCRY Policy are front-loaded, correspond with the phenomenon that financial markets quickly respond to news such as the shocks of monetary policy changes.
Table 6.4: IRF results: UCRY Policy to variable system

<table>
<thead>
<tr>
<th>Period</th>
<th>εGlobalEPU</th>
<th>εVix</th>
<th>εBitcoin</th>
<th>εUSFS</th>
<th>εUSEPU</th>
<th>εGold</th>
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Lower Band, CI= 0.90

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Upper Band, CI= 0.90

Notes: This table displays the IRF test from the SVEC model about the UCRY Policy shocks to the variable system Equation 5.25, which contains UCRY Policy, UCRY Price, GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold. UCRY Policy is set as impulse, and the other variables are set as response. n. ahead is the integer specifying the steps, which is set as 10. ci is the confidence interval for the bootstrapped error bands, which is set as 90%. runs is an integer, specifying the runs for the bootstrap, which is set as 1000.
6.3. UCRY INDICES STRUCTURAL SHOCK ANALYSIS

Figure 6.4: UCRY Policy to other factors

Notes: The graphs displayed above are the GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold's response to the shock from the UCRY Policy. The black line in each plot is the response curve. And the two red lines in each plot are the confidence interval for the bootstrapped error bands. 

- $n.\text{ahead}$ is the integer specifying the steps, which is set as 10.
- $ci$ is the confidence interval for the bootstrapped error bands, which is set as 90%.
- $runs$ is an integer, specifying the runs for the bootstrap, which is set as 1000.
CHAPTER 6. NEW CRYPTOCURRENCY INDICES AND APPLICATIONS

Figure 6.5 shows the UCRY Price shock to GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold. In general, while the reaction of the different variables is qualitatively similar, discernible differences in the quantitative reactions emerge.

Figure 6.5a presents after UCRY Price impulses unit shocks to GlobalEPU. There is no response in the start point. After the 1st period, the GlobalEPU begins to have a negative response. The GlobalEPU response value has a violent fluctuation around $x = 0$ axis in the range of $1.58380411$ and $-1.08761806$ from the 1st period to the 8th period. From the 8th period, the GlobalEPU response value tend to converge and closely move around $x = 0$ axis.

Figure 6.5b presents after UCRY Price impulses unit shocks to Vix. There is no response in the start point. After the 1st period, Vix has a positive and sluggish reaction. The peak response value is in the 2nd period, which is equal to $0.052673388$. The lowest response value is in the 4th, which is equal to $-0.059504321$. From the 6th period, the Vix response value tend to converge and closely move around $x = 0$ axis.

Figure 6.5c presents after UCRY Price impulses unit shocks to Bitcoin. There is no response in the start point. After the 1st period, Bitcoin has a positive response. The Bitcoin response value has a violent fluctuation around $x = 0$ axis in the range of $0.0102553916$ and $-0.0057740555$ from the 1st period to the 6th period. From the 6th period, the Bitcoin response value tend to converge and closely move around $x = 0$ axis.

Figure 6.5d presents after UCRY Price impulses unit shocks to USFS. There is no response in the start point. After the 1st period, USFS has a negative response. The USFS response value has a violent fluctuation around $x = 0$ axis in the range of $0.0087844866$ and $-0.0051017055$ from the 1st period to the 10th period. From the 10th period, the USFS response value tend to converge and closely move around $x = 0$ axis.

Figure 6.5f presents after UCRY Price impulses unit shocks to USEPU. There is no response in the start point. After the 1st period, USEPU has a negative response. The USEPU display the strongest response. The USFS response move around $x = 0$ axis in the range of $4.2470624$ and $-3.3087295$ from the 1st period to the 8th period. From the 8th period, the USEPU response value tend to converge and closely move around $x = 0$ axis.

Figure 6.5g presents after UCRY Price impulses unit shocks to Gold. There is no response in the start point. After the 1st period, Gold has a negative response.
The response value has a slightly fluctuate around $x = 0$ axis in the range of $-0.56553133$ and $0.91565210$ from the 1st period to the 6th period. From the 6th period, the Gold response value tend to converge and closely move around $x = 0$ axis.

These findings suggest that the choice of the cryptocurrency price volatility and uncertainty in previous literature and empirical analyses is not fully innocuous, although it is worth noting that the confidence bands are wide and overlapping. Furthermore, when compared the $\epsilon_{\text{UCRY}}$ Policy shocks to the variable system Equation 5.25 with the $\epsilon_{\text{UCRY}}$ Price shocks to the same variable system Equation 5.25 together. All the responses from $\epsilon_{\text{UCRY}}$ Price shocks show a more volatility trend, and there is even can not find a general increase or decrease trend. One possible explanation for this phenomenon is that UCRY Price Index is designed to capture the cryptocurrency price uncertainty. Anything related to the cryptocurrency price will tend to be extremely fluctuating and volatile. Therefore, it is not easy to draw a general trend from the variable responses. In addition, this phenomenon also can prove the accuracy of the UCRY Policy Index and the UCRY Price Index because the UCRY Policy Index can show the unique properties of the policy uncertainty. The UCRY Price Index can also show the unique properties of the price uncertainty it should have, even though those two indices are called cryptocurrency uncertainty indices. However, this phenomenon can point out a novelty future research direction, which is to analyse the variable responses from the $\epsilon_{\text{UCRY}}$ Price shocks in a specific period. For example, what are the financial market responses from $\epsilon_{\text{UCRY}}$ Price shocks during the COVID-19 period or the bull market/bear market period.
### Table 6.5: IRF results: UCRY Price to variable system

<table>
<thead>
<tr>
<th>Period</th>
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<th>$\epsilon_{\text{Vix}}$</th>
<th>$\epsilon_{\text{Bitcoin}}$</th>
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**Lower Band, CI= 0.90**

| 1 | 0.0000000 | 0.0000000 | 0.0000000 | 0.0000000 | 0.0000000 | 0.0000000 |
| 2 | -3.9297207 | -0.65142811 | -0.013781842 | -0.03730012 | -8.381641 | -6.361984 |
| 3 | -3.3339371 | -0.35086057 | -0.017401864 | -0.01328858 | -3.795793 | -3.5242534 |
| 4 | -1.3802236 | -0.47532090 | -0.005709071 | -0.021307708 | -10.218923 | -3.728301 |
| 5 | -1.4137111 | -0.17862801 | -0.009845808 | -0.008261708 | -3.090000 | -2.1658388 |
| 6 | -1.7695240 | -0.14291862 | -0.004568223 | -0.010891074 | -5.415228 | -1.7802241 |
| 7 | -0.6738874 | -0.10239792 | -0.005693236 | -0.003990735 | -2.257243 | -1.714353 |
| 8 | -0.9985594 | -0.07055399 | -0.002222877 | -0.004948192 | -2.517383 | -0.7743103 |
| 9 | -0.3431184 | -0.06545034 | -0.003309933 | -0.002394999 | -1.346996 | -0.5945672 |
| 10 | -0.4820423 | -0.04386700 | -0.001169459 | -0.002371991 | -1.235027 | -0.3516644 |

**Upper Band, CI= 0.90**

| 1 | 0.0000000 | 0.0000000 | 0.0000000 | 0.0000000 | 0.0000000 |
| 2 | 2.0817526 | 0.47417888 | 0.0309196027 | 0.01947172 | 3.9391978 | 5.4742222 |
| 3 | 5.2547559 | 0.63951766 | 0.0057098608 | 0.032606885 | 11.4665294 | 5.3203086 |
| 4 | 2.202341 | 0.30132833 | 0.0063943260 | 0.011755090 | 3.6246337 | 3.3063742 |
| 5 | 2.6769745 | 0.27610436 | 0.0059219045 | 0.031975245 | 8.1925831 | 2.7202701 |
| 6 | 1.0971185 | 0.12232319 | 0.0057463865 | 0.005847297 | 2.5972361 | 1.6911719 |
| 7 | 1.4027070 | 0.10639053 | 0.0029256512 | 0.008202495 | 3.359723 | 1.1951653 |
| 8 | 0.4790441 | 0.08093578 | 0.0042316030 | 0.002878808 | 1.781207 | 0.8295953 |
| 9 | 0.7223217 | 0.05592921 | 0.0016155239 | 0.003453479 | 1.7844031 | 0.5311463 |
| 10 | 0.2448477 | 0.05215853 | 0.0027177311 | 0.001706852 | 1.0707746 | 0.4448766 |

Notes: This table displays the IRF test from the SVEC model about the UCRY Price shocks to the variable system Equation 5.25, which contains UCRY Policy, UCRY Price, GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold. UCRY Price is set as impulse, and the other variables are set as response. n. ahead is the integer specifying the steps, which is set as 10. ci is the confidence interval for the bootstrapped error bands, which is set as 90%. runs is an integer, specifying the runs for the bootstrap, which is set as 1000.
6.3. UCRY INDICES STRUCTURAL SHOCK ANALYSIS

Figure 6.5: UCRY Price to other factors

Notes: The graphs displayed above are the GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold's response to the shock from the UCRY Price. The black line in each plot is the response curve. And the two red lines in each plot are the confidence interval for the bootstrapped error bands. n. ahead is the integer specifying the steps, which is set as 10. ci is the confidence interval for the bootstrapped error bands, which is set as 90%. runs is an integer, specifying the runs for the bootstrap, which is set as 1000.
6.3.2 Contributions of UCRY disturbances to the variation of financial variables’ volatility

To evaluate the importance of different shocks and decompose the forecast error variance into the contributions from exogenous shocks. The FEVD for UCRY Policy and UCRY Price are calculated. Figure 6.6 and Figure 6.7 depicts the FEVD of UCRY Policy and UCRY Price decomposition results, which can provide evidence to support Hypothesis 1.

In Figure 6.6 and Table 6.6, the UCRY FEVD of UCRY Policy plot and UCRY FEVD of UCRY Policy statistics can be found. In the first period, 100% of the variation in UCRY Policy is from shocks to UCRY Policy itself. The contribution of the UCRY Policy to the variations in the UCRY Policy quickly dies after the first period and become stable after the sixth period. As for the contribution of GlobalEPU, Vix and Bitcoin to the variations in the UCRY Policy begin to rise up after the first period, and the growth rates keep stable during the whole period. It is surprising that UCRY Price only can contribute around 0.19%. These findings suggest that UCRY Policy can play an essential role in the short run, and GlobalEPU, Vix and Bitcoin are more important in the long run. Furthermore, the cryptocurrency market uncertainty is more sensitive to policy adjustments. The system becomes stable around the sixth period. In the end, the contribution of UCRY Policy, GlobalEPU, Vix, Bitcoin, USFS, USEPU, Gold and UCRY Price can converge at around 72.02%, 5.5%, 8.74%, 12.40%, 0.21%, 0.47%, 0.71%, 0.1978%, respectively.

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Notes: This table presents the FEVD results for the UCRY Policy statistics. n. ahead is the integer specifying the steps, which is set as 10.
6.3. UCRI INDICES STRUCTURAL SHOCK ANALYSIS

Figure 6.6: UCRI FEVD of UCRI Policy

Notes: This table presents the FEVD results for the UCRI Policy statistics. UCRI Policy is highlighted in blue. n. ahead is the integer specifying the steps, which is set as 10.

In Figure 6.7 and Table 6.7, the UCRI FEVD of UCRI Price plot and UCRI FEVD of UCRI Price statistics can be found. In the first period, approximately 91% of the variation shocks in UCRI Price is from UCRI Policy. However, UCRI Price can only contribute around 7.43%. UCRI Policy’s contributions to the UCRI Price variations quickly decrease after the first period and become stable at 61.9% from the seventh period. And UCRI Policy can converge at around 61.92%. However, the UCRI Price always shows a stable contribution, which is around 7%, and it can converge at around 7%. Also, the contributions of Bitcoin, Vix, GlobalEPU and USEPU to the variations change fairly rapidly over the first period and become stable after the fifth period. These findings suggest that Bitcoin, Vix, GlobalEPU and USEPU all have a short-run effect on the UCRI Price, and UCRI Policy are more important for the long run. From period 2 to period 10, approximately 75% shocks are from policy-related factors, which means policy adjustments can significantly contribute to the price of the cryptocurrency. This finding matches the above analyses, which FEVD analysis for UCRI Policy. Obviously, Bitcoin is the second major factor that can shock the UCRI Price, and it can converge at around 10.97%. GlobalEPU, Vix, USFS, USEPU and Gold can converge at around 5.31%, 9.2%, 0.24%, 3.8%, 1.37%, separately.
### Table 6.7: UCRY FEVD for UCRY Price statistics

<table>
<thead>
<tr>
<th>Period</th>
<th>$\epsilon_{UCRY\ Policy}$</th>
<th>$\epsilon_{GlobalEPU}$</th>
<th>$\epsilon_{Vix}$</th>
<th>$\epsilon_{Bitcoin}$</th>
<th>$\epsilon_{USFS}$</th>
<th>$\epsilon_{USEPU}$</th>
<th>$\epsilon_{Gold}$</th>
<th>$\epsilon_{UCRY\ Price}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.913159826</td>
<td>0.004960965</td>
<td>6.85E-05</td>
<td>0.002313306</td>
<td>5.07E-05</td>
<td>0.001996079</td>
<td>0.003173323</td>
<td>0.074277726</td>
</tr>
<tr>
<td>2</td>
<td>0.670912618</td>
<td>0.057782957</td>
<td>0.67118686</td>
<td>0.11204073</td>
<td>0.000880226</td>
<td>0.027385347</td>
<td>0.002259753</td>
<td>0.062456341</td>
</tr>
<tr>
<td>3</td>
<td>0.637270396</td>
<td>0.054579125</td>
<td>0.0922774</td>
<td>0.1087446</td>
<td>0.001055535</td>
<td>0.031267433</td>
<td>0.010185323</td>
<td>0.067670269</td>
</tr>
<tr>
<td>4</td>
<td>0.626664291</td>
<td>0.053722936</td>
<td>0.090781803</td>
<td>0.110700047</td>
<td>0.002399818</td>
<td>0.034526305</td>
<td>0.011603211</td>
<td>0.069601169</td>
</tr>
<tr>
<td>5</td>
<td>0.622982275</td>
<td>0.053329417</td>
<td>0.1091087641</td>
<td>0.109931224</td>
<td>0.002393169</td>
<td>0.036709543</td>
<td>0.013240947</td>
<td>0.07048531</td>
</tr>
<tr>
<td>6</td>
<td>0.620734755</td>
<td>0.05254689</td>
<td>0.109490242</td>
<td>0.10987185</td>
<td>0.002402943</td>
<td>0.037963305</td>
<td>0.013536665</td>
<td>0.070745251</td>
</tr>
<tr>
<td>7</td>
<td>0.61975918</td>
<td>0.05189048</td>
<td>0.10957748</td>
<td>0.109743947</td>
<td>0.002400351</td>
<td>0.038527449</td>
<td>0.013684117</td>
<td>0.070839421</td>
</tr>
<tr>
<td>8</td>
<td>0.619333328</td>
<td>0.05155214</td>
<td>0.1092022024</td>
<td>0.109705272</td>
<td>0.002402701</td>
<td>0.03876413</td>
<td>0.013745861</td>
<td>0.07087147</td>
</tr>
<tr>
<td>9</td>
<td>0.619162077</td>
<td>0.051339753</td>
<td>0.1092080757</td>
<td>0.109687608</td>
<td>0.002403571</td>
<td>0.038864303</td>
<td>0.013778991</td>
<td>0.07088294</td>
</tr>
<tr>
<td>10</td>
<td>0.619091697</td>
<td>0.05113487</td>
<td>0.1092102747</td>
<td>0.109681904</td>
<td>0.002403875</td>
<td>0.038907204</td>
<td>0.013792612</td>
<td>0.0708886474</td>
</tr>
</tbody>
</table>

Notes: This table presents the FEVD results for the UCRY Price statistics. $n.\ ahead$ is the integer specifying the steps, which is set as 10.

![Figure 6.7: UCRY FEVD of UCRY Price](image)

Notes: This table presents the FEVD results for the UCRY Price statistics. UCRY Price is highlighted in orange. $n.\ ahead$ is the integer specifying the steps, which is set as 10.
6.3.3 Cumulative contributions of UCRY Policy disturbances to the financial variables’ volatility

As for the historical decomposition of UCRY Policy in Equation 5.25, the relationship between reduced form residuals $u$ and structural shocks $\varepsilon$ of the variables system Equation 5.25 are show in Equation 6.1:

$$
\begin{bmatrix}
    u_{t}^{UCRY Policy} \\
    u_{t}^{GlobalEPU} \\
    u_{t}^{Vix} \\
    u_{t}^{Bitcoin} \\
    u_{t}^{USFS} \\
    u_{t}^{USEPU} \\
    u_{t}^{Gold} \\
    u_{t}^{UCRYPrice}
\end{bmatrix}
= 
\begin{bmatrix}
    S_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    S_{21} & S_{22} & 0 & 0 & 0 & 0 & 0 & 0 \\
    S_{31} & S_{32} & S_{33} & 0 & 0 & 0 & 0 & 0 \\
    S_{41} & S_{42} & S_{43} & S_{44} & 0 & 0 & 0 & 0 \\
    S_{51} & S_{52} & S_{53} & S_{54} & S_{55} & 0 & 0 & 0 \\
    S_{61} & S_{62} & S_{63} & S_{64} & S_{65} & S_{66} & 0 & 0 \\
    S_{71} & S_{72} & S_{73} & S_{74} & S_{75} & S_{76} & S_{77} & 0 \\
    S_{81} & S_{82} & S_{83} & S_{84} & S_{85} & S_{86} & S_{87} & S_{88}
\end{bmatrix}
\begin{bmatrix}
    \varepsilon_{t}^{UCRY Policy} \\
    \varepsilon_{t}^{GlobalEPU} \\
    \varepsilon_{t}^{Vix} \\
    \varepsilon_{t}^{Bitcoin} \\
    \varepsilon_{t}^{USFS} \\
    \varepsilon_{t}^{USEPU} \\
    \varepsilon_{t}^{Gold} \\
    \varepsilon_{t}^{UCRYPrice}
\end{bmatrix}
$$

In doing so, the drivers of movements in UCRY Policy can be traced, and whether UCRY Policy shocks in the VECM are reflective of uncertainty also can be gotten. The information contained in the historical decomposition could also show the extent to which events are driving shocks to UCRY Policy.

The historical decomposition of the UCRY Index is shown in Figure 6.8, which can also suggest the validity of the Hypothesis 1. The contribution of UCRY Policy shocks to the historical decomposition of the UCRY Index is given in light blue, while contribution to the UCRY Price is in orange. These shocks match the expectations of the public to a certain extent. For example, the Brexit vote, Donald Trump winning the 2016 United States presidential election, China banning ICOs, the BTC bubble, DeFi take off and other events have been shown to have positively impacted the UCRY Policy and Price uncertainty Indices. Figure 6.8 also displays some of the largest hacking attacks of cryptocurrency exchanges, such as attacks on Bitfinex, MintPal, Crispy, and Dao exchanges. These occurred from April 2014 to December 2020, and this research has shown that the UCRY Price and UCRY Policy Indices reacted to these events. Fiscal policy adjustments contributed to the small shifts in the UCRY Policy, however, the significance of these events may increase in the future. The decomposition also displayed that UCRY Indices captured uncertainty that could be more distinctively attributed to the major events in cryptocurrencies in comparison to VIX, EPU and Global EPU index. While the price of Bitcoin, the
CHAPTER 6. NEW CRYPTOCURRENCY INDICES AND APPLICATIONS

UCRY Policy and the UCRY Price are highly correlated, these indices appear to capture uncertainty beyond Bitcoin prices as shown by the decomposition. Finally, the COVID-19 crisis increased both the UCRY Policy and Price uncertainty Indices, therefore this UCRY indices can be used as an effective measure of uncertainty during the pandemic.

Figure 6.8: UCRY Policy historical decomposition with major events

Notes: The graphs displayed above show the historical evolution of UCRY Policy and the contribution of each of the structural shocks to variations in UCRY Policy following significant historical episodes. The horizontal axis represents the time sample period, and the vertical axis represents the variations of UCRY Policy, UCRY Price, GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold in per cent after UCRY Policy shocks. Lag = 4. The variations of UCRY Policy and UCRY Price are highlighted in blue and orange separately.
6.3.4 Robustness test

UCRY Policy and UCRY Price are newly developed indices. It is essential to verify of these two indices. In this part, this research conducts robustness on UCRY Policy and UCRY Price these two benchmark indices.

Two potential issues may exist in the UCRY Policy and UCRY Price. The first one, are these three indices really can work? Based on this issue, the relationship between the UCRY Policy, UCRY Price and Bitcoin should be further proved because these two indices are designed to reflect the cryptocurrency markets. For this purpose, Pearson correlation will be applied to find the relationship between UCRY Policy, UCRY Price and Bitcoin price index firstly. Secondly, the continuously compounded returns of UCRY Policy, UCRY Price and Bitcoin price will be calculated by considering the first difference in the logarithmic values of two consecutive prices, which can be expressed as: \[ CCR_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \times 100, \] where \( CCR_{i,t} \) denotes continuously compounded returns for index \( i \) at time \( t \), and \( P_{i,t} \) stands for the price of index \( i \) at time \( t \).

Then, Pearson correlation will be applied again to find the relationship between the continuously compounded returns of UCRY Policy, UCRY Price and Bitcoin. If UCRY Policy, UCRY Price and Bitcoin still can show a significantly relationship in the continuously compounded returns, this research can have more evidence to prove the validity of UCRY indices.

The second one, are UCRY Policy and UCRY Price really can impact the financial markets? Based on this potential issue, another robustness test will be applied. This robustness test learns from (Lyu et al., 2021) to re-process stronger IRF tests. More specifically, the new IRF test will increase the confidence interval bootstrapping from 90% to 95% and increase the threshold of runs from 1000 to 2000 runs. By increasing the impulses from the UCRY Policy and UCRY Price to the financial or economics variables, the validity of the three indices’ impact on the financial markets can be further proved.

6.3.4.1 Robustness test results for indices

From Table 6.8, the correlation value of UCRY Policy and Bitcoin price is 0.847 in 99% significance level. The correlation value of the UCRY Price and Bitcoin price is 0.852 at the 99% significance level. These statistical results can prove that UCRY Policy and UCRY Price have a strong, positive, and significant correlation with the
Bitcoin price. This finding can further prove the usefulness of the UCRY Policy and UCRY Price. It is worth noting that the correlation value between UCRY Price and the Bitcoin price is strongest among the three indices. This phenomenon is because the Bitcoin price is a price-based index, and UCRY Price is designed to capture the price uncertainty in the cryptocurrency market. This small and novelty finding can reflect the accuracies of the UCRY Policy and UCRY price from the side.

Table 6.8: UCRY and Bitcoin correlation

<table>
<thead>
<tr>
<th></th>
<th>UCRY Policy Index</th>
<th>UCRY Price Index</th>
<th>Bitcoin</th>
</tr>
</thead>
<tbody>
<tr>
<td>UCRY Policy Index</td>
<td>1***</td>
<td>0.985***</td>
<td>0.847***</td>
</tr>
<tr>
<td>UCRY Price Index</td>
<td>0.985***</td>
<td>1***</td>
<td>0.852***</td>
</tr>
<tr>
<td>Bitcoin</td>
<td>0.847***</td>
<td>0.852***</td>
<td>1***</td>
</tr>
</tbody>
</table>

Notes: This is a Pearson correlation matrix between UCRY Policy, UCRY Price and Bitcoin. UCRY Policy, UCRY Price and Bitcoin are highly correlated. *p<0.1; **p<0.05; ***p<0.01.

From Table 6.9, the correlation value of $\Delta \ln(UCRY \text{ Policy})$ and $\Delta \ln(\text{Bitcoin})$ is 0.056 in 99% significance level. The correlation value of $\Delta \ln(UCRY \text{ Price})$ and $\Delta \ln(\text{Bitcoin})$ is 0.048 in 99% significance level. These statistical results also can further prove that the $\Delta \ln(UCRY \text{ Policy})$ and the $\Delta \ln(UCRY \text{ Price})$ have a positive and significant relationship with the volatility of Bitcoin. Therefore, the UCRY Policy and UCRY Price can still work in the continuously compounded returns’ perspective. Furthermore, the correlation value between $\Delta \ln(UCRY \text{ Policy})$ and $\Delta \ln(\text{Bitcoin})$ is the strongest among the three indices’ continuously compounded returns relationship just mentioned, which means the cryptocurrencies are more sensitive to the UCRY Policy. These small and interesting finding also can prove the validity of the UCRY Policy and UCRY Price.

Table 6.9: UCRY and Bitcoin volatility correlation

<table>
<thead>
<tr>
<th>$\Delta \ln(UCRY \text{ Policy})$</th>
<th>$\Delta \ln(UCRY \text{ Price})$</th>
<th>$\Delta \ln(\text{Bitcoin})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln(UCRY \text{ Policy})$</td>
<td>1***</td>
<td>0.903***</td>
</tr>
<tr>
<td>$\Delta \ln(UCRY \text{ Price})$</td>
<td>0.903***</td>
<td>1***</td>
</tr>
<tr>
<td>$\Delta \ln(\text{Bitcoin})$</td>
<td>0.056***</td>
<td>0.048***</td>
</tr>
</tbody>
</table>

Notes: This is a Pearson correlation matrix between the continuously compounded returns of UCRY Policy, UCRY Price and Bitcoin. UCRY Policy, UCRY Price and Bitcoin are highly correlated. *p<0.1; **p<0.05; ***p<0.01.
6.3.4.2 Robustness test results for empirical results

In order to check the validity of the interconnection between the UCRY Policy, UCRY Price and the financial or economics variables, the new IRF test results about the UCRY Policy shocks and UCRY Price shocks to their own variable system are shown in Figure 6.9 and Figure 6.10. From the new IRF test plots, the responses of the financial markets to the impulses from $\epsilon_{\text{UCRY Policy}}$ and $\epsilon_{\text{UCRY Price}}$ keep the same values and trends with the former IRF test results, although the confidence interval bootstrapping is 95% and the threshold of runs are 2000 now.

These robustness test results first can prove the reliability and accuracy of the interconnections between the UCRY Policy, UCRY Price and the financial or economics variables, which have been explained in the main context because the final interconnection results will not be changed by the increasing of the confidence interval bootstrapping and the threshold of runs. These robustness test results second can prove that the volume of endogenous shock and the confidence interval limitation will not impact the potential result. In other words, the responses of the financial market indices, which be described in Equation 5.25 can only be impacted by the intrinsic characteristics of UCRY Policy and UCRY Price. These robustness test findings can further prove that the interconnection relationships between UCRY Policy, UCRY Price and the financial markets, shown in the main findings, are valid and reliable.
Figure 6.9: UCry Policy to other factors robustness test

Notes: The graphs displayed above are the GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold's response to the stronger shocks from the UCry Policy. The black line in each plot is the response curve. And the two red lines in each plot are the confidence interval for the bootstrapped error bands. n. ahead is the integer specifying the steps, which is set as 10. ci is the confidence interval for the bootstrapped error bands, which is set as 95%. runs is an integer, specifying the runs for the bootstrap, which is set as 2000.
6.3. UCRY INDICES STRUCTURAL SHOCK ANALYSIS

Figure 6.10: UCRY Price to other factors robustness test

(a) $\varepsilon$UCRY Price to GlobalEPU robustness test
(b) $\varepsilon$UCRY Price to VIX robustness test
(c) $\varepsilon$UCRY Price to Bitcoin robustness test
(d) $\varepsilon$UCRY Price to USFS robustness test
(e) $\varepsilon$UCRY Price to USEPU robustness test
(f) $\varepsilon$UCRY Price to Gold robustness test

Notes: The graphs displayed above are the GlobalEPU, VIX, Bitcoin, USFS, USEPU and Gold’s response to the stronger shocks from the UCRY Price. The black line in each plot is the response curve. And the two red lines in each plot are the confidence interval for the bootstrapped error bands. $n.\text{ ahead}$ is the integer specifying the steps, which is set as 10. $ci$ is the confidence interval for the bootstrapped error bands, which is set as 95%. $runs$ is an integer, specifying the runs for the bootstrap, which is set as 2000.
6.4 An Index of Cryptocurrency Environmental Attention (ICEA)

A concern often expressed in relation to cryptocurrencies is their environmental impact associated with increasing energy consumption, cryptocurrency mining’s $CO_2$ pollution, all of which are currently unregulated. To assist researchers and policy makers, this study has developed a new index, called the Index of Cryptocurrency Environmental Attention (ICEA), based on 778.2 million news stories from the LexisNexis News & Business database. This index captures the extent to which environmental sustainability concerns are discussed in alignment with these new assets. This study shows that the ICEA index, similar to the UCRY Policy and UCRY Price, reacts to major events in the cryptocurrency space. This study believes that ICEA can be used for environmental policy development to assess environmental pressure and bring attention to the growing energy-consumption problem of this new digital payment network.

![Image](image.png)

**Figure 6.11: An Index of Cryptocurrency Environmental Attention**

Notes: This figure presents the cryptocurrency environmental attention index, which is highlighted in green. This index reflects the scaled weekly counts of articles containing the search strings in subsection 4.2.2. These two series are standardised and then add 100 from January 2014 to May 2021 based on queries. LexisNexis News & Business is the selected database.
Figure 6.12: Annotated ICEA

Notes: Flash events related to ICEA are annotated on the time series plot.
The weekly ICEA is annotated in Figure 6.12, highlighting major changes as they map to events in the cryptocurrency and environmental sustainability concerns related spaces. Some clear spikes around the Mt. Gox occur in February. Mt. Gox goes offline, suspend transactions, shut down its official website and exchange service at this time. Even more notably, Mt. Gox files for bankruptcy protection from creditors. At the end of the month of June 2017, Ethereum has already used a small country’s worth of electricity. At the end of November 2017 and in early December 2017, Bitcoin break the $10,000 barriers, and at the same time, Bitcoin’s Carbon Footprint issue and Bitcoin’s Energy Consumption issue are proposed again. At the end of January 2018, Smartcool proves that new technology could lower the energy consumption and cost for cryptocurrencies. In February 2018, many research institutions and scholars identify that Bitcoin is an absolute energy and environmental disaster, and the Bitcoin Energy Consumption Index is issued. In July 2018, the United Nations supports a start-up that aims to eliminate the carbon footprint produced by blockchains. In December 2018, the EOSIO fulfilled blockchains’ promise on social and environmental sustainability. In June 2019, Bitcoin mining pumps out as much $CO_2$ per year as Kansas City, and Bitcoin $CO_2$ emissions are comparable to Las Vegas or Hamburg. At the end year of 2019, the COVID-19 outbreak strongly shocks the cryptocurrency market and ICEA. In July 2020, the Restart Energy MWAT (MWAT) market cap hit $1.49m. Around August 2020, the bullish market of cryptocurrency begin. On April 13, 2021, Bitcoin surpasses $63,000 in a record high, rallying further growth and bringing back the heated discussion of environmental issues associated with cryptocurrency yet again.

6.5 Summary Statistics

Time series plots of each variable are shown in Figure 6.13. Monthly frequency data is considered for further empirical analysis, and the empirical study period runs from January 01, 2014, to February 01, 2021. The ICEA, UCRY Policy and UCRY Price indices are generated by LexisNexis News & Business. GlobalEPU is obtained from policyuncertainty.com. GTU is obtained from Berkeley Earth\(^1\), and IP is collected from OECD and other financial indices from Yahoo Finance. Table 6.10

\(^1\)Data can be downloaded from: http://berkeleyearth.lbl.gov/auto/Global/Complete_TAVG_complete.txt
shows the descriptive statistics for the indices of ICEA, UCRY Policy, UCRY Price, GlobalEPU, VIX, BCO, Bitcoin price, GTU and IP. Table 6.10 shows that Bitcoin price has the largest mean value (5464.53), standard deviation (7454.22), trimmed mean (4114.64), mean absolute deviation (4226.66), and range (44908.10), which indicates the high fluctuations and uncertainty. Furthermore, the mean value of Bitcoin price is significantly different from zero, while the standard deviation value is larger than the mean value. The skewness and kurtosis values of Bitcoin price are large and positive, indicating the Bitcoin price has a skewed left, fat-tailed and leptokurtic distribution. As for the protagonist, ICEA, it features lesser fluctuations than its family members, the UCRY Policy, UCRY Price and Bitcoin price. The mean of the ICEA is 99.88, lesser than the 99.89 of the UCRY indices. The standard deviation of ICEA is 0.62, also lesser than the UCRY Policy Index (0.67) and UCRY Price Index (0.71). Furthermore, ICEA has excess skewness and kurtosis values. These findings show a certain volatility, uncertainty and overall risky related with this index. In addition, all the variables in Table 6.10 can reject the normal distribution confirmed by Jarque-Bera (J.-B.) tests because the p-values of these tests are all less than 0.01. That is, all except for the GlobalEPU and GTU. The p-value of GlobalEPU is equal to 0.0186 and less than 0.05. The p-value of GTU is equal to 0.02852 and also less than 0.05.

Table 6.10: Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Count</th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Median</th>
<th>TM</th>
<th>MAD</th>
<th>Min</th>
<th>Max</th>
<th>Range</th>
<th>Skew</th>
<th>Kurtosis</th>
<th>SE</th>
<th>J.-B.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICEA</td>
<td>86</td>
<td>99.88</td>
<td>0.62</td>
<td>99.67</td>
<td>99.76</td>
<td>0.41</td>
<td>99.39</td>
<td>102.61</td>
<td>3.22</td>
<td>1.86</td>
<td>4.03</td>
<td>0.07</td>
<td>114.75***</td>
</tr>
<tr>
<td>UCRY Policy</td>
<td>86</td>
<td>99.89</td>
<td>0.67</td>
<td>99.72</td>
<td>99.76</td>
<td>0.34</td>
<td>99.22</td>
<td>103.20</td>
<td>3.97</td>
<td>2.78</td>
<td>9.03</td>
<td>0.07</td>
<td>425.59***</td>
</tr>
<tr>
<td>UCRY Price</td>
<td>86</td>
<td>99.89</td>
<td>0.71</td>
<td>99.69</td>
<td>99.76</td>
<td>0.46</td>
<td>99.19</td>
<td>102.91</td>
<td>3.72</td>
<td>2.15</td>
<td>5.11</td>
<td>0.08</td>
<td>169.28***</td>
</tr>
<tr>
<td>GlobalEPU</td>
<td>86</td>
<td>193.29</td>
<td>78.62</td>
<td>171.36</td>
<td>186.00</td>
<td>86.14</td>
<td>86.16</td>
<td>429.60</td>
<td>343.45</td>
<td>0.73</td>
<td>-0.27</td>
<td>8.48</td>
<td>7.969**</td>
</tr>
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<td>VIX</td>
<td>86</td>
<td>17.58</td>
<td>7.49</td>
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<td>16.31</td>
<td>4.53</td>
<td>9.51</td>
<td>53.54</td>
<td>44.03</td>
<td>2.13</td>
<td>5.74</td>
<td>0.81</td>
<td>194.19***</td>
</tr>
<tr>
<td>BCO</td>
<td>86</td>
<td>61.57</td>
<td>19.46</td>
<td>57.54</td>
<td>59.33</td>
<td>13.64</td>
<td>25.27</td>
<td>111.96</td>
<td>86.69</td>
<td>1.01</td>
<td>0.64</td>
<td>2.10</td>
<td>16.972***</td>
</tr>
<tr>
<td>Bitcoin</td>
<td>86</td>
<td>5464.53</td>
<td>7454.22</td>
<td>3151.87</td>
<td>4114.64</td>
<td>4226.66</td>
<td>229.67</td>
<td>45137.77</td>
<td>44908.10</td>
<td>2.84</td>
<td>10.52</td>
<td>803.81</td>
<td>540.74***</td>
</tr>
<tr>
<td>GTU</td>
<td>86</td>
<td>0.08</td>
<td>0.02</td>
<td>0.08</td>
<td>0.08</td>
<td>0.02</td>
<td>0.05</td>
<td>0.12</td>
<td>0.08</td>
<td>0.38</td>
<td>-0.40</td>
<td>0.00</td>
<td>2.5095**</td>
</tr>
<tr>
<td>IP</td>
<td>86</td>
<td>101.92</td>
<td>3.67</td>
<td>101.56</td>
<td>102.21</td>
<td>3.18</td>
<td>84.53</td>
<td>106.47</td>
<td>21.94</td>
<td>-1.75</td>
<td>6.05</td>
<td>0.40</td>
<td>185.79***</td>
</tr>
</tbody>
</table>

Notes: Jarque-Bera (J.-B.) statistics can be used to check the normal distribution characteristic of the data (Jarque and Bera, 1980) and (Bera and Jarque, 1981). *p<0.1; **p<0.05; ***p<0.01.
In order to run a structural shock analysis, the following diagnostic tests should be processed. Firstly, unit root tests are performed on the data, in this case the Augment Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are applied\(^2\). Table 6.11 shows that the p-value of each variable is more significant than 0.05 in the ADF test and also less significant than 0.05 in the KPSS test. This evidence shows that there are unit roots in all variables and that all variables are nonstationary. Secondly, further investigation shows that stable
\(^2\)The reasons why this study chooses these two unit root tests have been discussed in chapter 5
6.5. SUMMARY STATISTICS

cointegrating relationships are present in the variable system, motivating the use of a VECM. From Table 6.12, \( r = 0 \), tested for the presence of cointegration. Since the tested statistics exceed the 1% level significantly (285.27 > 215.74), this study has strong evidence that variables forms in this study are cointegrated. To prove that the results are robust, this study also processes a Johansen maximum eigenvalue test. The results also can be found in Table 6.12. As previously displayed, \( r = 0 \), tested for the presence of cointegration. Since the tested statistic exceeded the 1% level significantly (68.01 > 63.71), this study also has strong evidence that the variables forms are cointegrated.

Table 6.11: Unit root test

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DF</td>
<td>Lag</td>
</tr>
<tr>
<td>ICEA</td>
<td>-1.33</td>
<td>4</td>
</tr>
<tr>
<td>UCRYPo</td>
<td>-2.25</td>
<td>4</td>
</tr>
<tr>
<td>EPU</td>
<td>-2.63</td>
<td>4</td>
</tr>
<tr>
<td>Vix</td>
<td>-2.54</td>
<td>4</td>
</tr>
<tr>
<td>BCO</td>
<td>-2.72</td>
<td>4</td>
</tr>
<tr>
<td>Bitcoin</td>
<td>0.37</td>
<td>4</td>
</tr>
<tr>
<td>GTU</td>
<td>-3.42</td>
<td>4</td>
</tr>
<tr>
<td>UCRYPr</td>
<td>-2.44</td>
<td>4</td>
</tr>
<tr>
<td>IP</td>
<td>-2.58</td>
<td>4</td>
</tr>
</tbody>
</table>

Notes: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01. 5% Critical Values are given in parentheses.

Table 6.12: Johansen cointegration test

<p>|  | Johansen trace test | Johansen maximum eigenvalue test |</p>
<table>
<thead>
<tr>
<th></th>
<th>test</th>
<th>10pct</th>
<th>5pct</th>
<th>1pct</th>
<th>test</th>
<th>10pct</th>
<th>5pct</th>
<th>1pct</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r \leq 8 )</td>
<td>4.88</td>
<td>7.52</td>
<td>9.24</td>
<td>12.97</td>
<td>4.88</td>
<td>7.52</td>
<td>9.24</td>
<td>12.97</td>
</tr>
<tr>
<td>( r \leq 7 )</td>
<td>14.18</td>
<td>17.85</td>
<td>19.96</td>
<td>24.60</td>
<td>9.30</td>
<td>13.75</td>
<td>15.67</td>
<td>20.20</td>
</tr>
<tr>
<td>( r \leq 6 )</td>
<td>27.56</td>
<td>32.00</td>
<td>34.91</td>
<td>41.07</td>
<td>13.37</td>
<td>19.77</td>
<td>22.00</td>
<td>26.81</td>
</tr>
<tr>
<td>( r \leq 5 )</td>
<td>49.58</td>
<td>49.65</td>
<td>53.12</td>
<td>60.16</td>
<td>22.02</td>
<td>25.56</td>
<td>28.14</td>
<td>33.24</td>
</tr>
<tr>
<td>( r \leq 4 )</td>
<td>79.90</td>
<td>71.86</td>
<td>76.07</td>
<td>84.45</td>
<td>30.33</td>
<td>31.66</td>
<td>34.40</td>
<td>39.79</td>
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<tr>
<td>( r \leq 3 )</td>
<td>112.58</td>
<td>97.18</td>
<td>102.14</td>
<td>111.01</td>
<td>32.68</td>
<td>37.45</td>
<td>40.30</td>
<td>46.82</td>
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<tr>
<td>( r \leq 2 )</td>
<td>158.53</td>
<td>126.58</td>
<td>131.70</td>
<td>143.09</td>
<td>45.95</td>
<td>43.25</td>
<td>46.45</td>
<td>51.91</td>
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<tr>
<td>( r \leq 1 )</td>
<td>217.26</td>
<td>159.48</td>
<td>165.58</td>
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<td>58.74</td>
<td>48.91</td>
<td>52.00</td>
<td>57.95</td>
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<tr>
<td>( r = 0 )</td>
<td>285.27</td>
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<td>215.74</td>
<td>68.01</td>
<td>54.35</td>
<td>57.42</td>
<td>63.71</td>
</tr>
</tbody>
</table>

Notes: 5% Critical Values are given in parentheses.

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6.6 ICEA Structural Shock Analysis

6.6.1 ICEA shocks on the dynamic of financial variables volatility

To gain a more comprehensive understanding of the dynamic interaction between variables, this study calculates the IRF from the SVECM with regards to ICEA shocks to the variable system Equation 5.26. The plots of ICEA shocks to its variable system, which contains UCRY Policy, UCRY Price, GlobalEPU, VIX, BCO, Bitcoin price, GTU, and IP can be found in Figure 6.14. More statistics can be found in Table 6.13. These statistical results could confirm the Hypothesis can hold.

Figure 6.14 presents the response of UCRY Policy after ICEA impulses unit shocks, and UCRY Policy has a positive response. The peak response value is present at the premier point, which is equal to $1.9672 \times 10^{-1}$. The response values show a decreasing tendency with the elapsing of the time period. From the 8th period, the UCRY Policy responses tend to converge and move closely around the $x=0$ axis. This empirical finding verifies that ICEA shocks can significantly increase the UCRY Policy Index. In other words, the ICEA shocks can increase the cryptocurrency policy uncertainty. Figure 6.14 presents the results after ICEA impulses unit shocks occur to UCRY Price, and UCRY Price responses show a similar response to that if $\epsilon$ICEA to UCRY Policy. The peak response value is present at the start point, which is $1.5739 \times 10^{-1}$. UCRY Price response values show a decreasing tendency with the elapsing of the time period. From the 8th period, the UCRY Price responses tend to converge and move closely around the $x=0$ axis. This empirical finding verifies that ICEA shocks can significantly increase the UCRY Price. In other words, the ICEA shocks can increase the cryptocurrency price uncertainty. Figure 6.14 presents that after ICEA impulses unit shocks to Bitcoin price, then Bitcoin price has a positive response. The peak response value shows on the start point, which is equal to 4.5325. Then, the response values begin to decay with the elapsing of the period. From the 8th period, the Bitcoin price responses tend to converge. This empirical finding verifies that the ICEA shocks can increase the Bitcoin price index.

It is worth noting that when comparing $\epsilon$ICEA to UCRY Policy, with $\epsilon$ICEA being inclusive of UCRY Price, UCRY Policy responses are slightly stronger than the UCRY Price responses. One possible explanation for this phenomenon is that the ICEA is an index focusing on environmental impacts on the cryptocurrency.
market. One of the most powerful tools to mitigate the environmental issues caused by cryptocurrencies is policy adjustments. Therefore, the UCRY Policy should be expected to be more sensitive to the ICEA shocks.

Because the ICEA focuses on cryptocurrencies, it is worth further investigating why it can increase the UCRY indices and Bitcoin price. As such, a number of potential explanations of this phenomenon are presented thusly. The rise in the ICEA can instigate speculation amongst cryptocurrency traders. These cryptocurrency speculators may increase their net long position because they believe to a certain extent in their own intellectual capabilities in the industry, and will attempt to avoid being the last to take the "hot potato" (Mnif et al., 2020). Secondly, the high cryptocurrency environmental attention can reflect the awareness of the general public’s environmental consciousness. Therefore, cryptocurrency miners may reduce the amount of cryptocurrency mining (Corbet et al., 2021). Also, new policies may be issued to regulate cryptocurrency mining activities. In this case, the decrease in the cryptocurrency supply will lead to an increase in the cryptocurrency price.

Figure 6.14 presents the results after ICEA impulses unit shocks occur to GlobalEPU, and as displayed, GlobalEPU has a negative response. The lowest response value appears in the 1st period, which is equal to -3.6055. Then, the GlobalEPU response values gradually rise with the elapsing time period. In the front-middle period, which is the 3rd period, the GlobalEPU response shows a positive value of 0.0789. However, the general trend of the GlobalEPU response to \( \varepsilon_{\text{ICEA}} \) is still negative. The GlobalEPU responses tend to converge after the 6th period. This empirical finding verifies that the ICEA shocks can decrease the Global EPU. This conclusion is consistent with Ahmed et al. (2021), who suggests that the GlobalEPU has a significantly negative relationship with the pollutant emissions but is different from Yu et al. (2021), who find that the China Provincial EPU has a positive impact on the carbon emission intensity. The reason for the inconsistent conclusion is the different characteristics of the GlobalEPU and the China Provincial EPU. One possible explanation for this phenomenon is that the GlobalEPU is spiked by negative news or policy adjusting, for example, 9/11, the Global Financial Crisis, and the Federal Reserve interest rate hike. This means, conversely, positive news or policy adjusting can significantly cool the EPU index. Substantial cryptocurrency environmental attention is likely to urge governments to launch new policies to protect the environment and mitigate pollution, which can
be considered positive policy adjusting. Accordingly, the ICEA has a significantly negative relationship with the GlobalEPU.

Figure 6.14 presents the results after ICEA impulses unit shocks occur VIX, and evidently, VIX has a positive response. The VIX response values increase gradually from the start point, where the value is 0.5646, to the peak of responses in the 2nd period, equal to 3.2476. Then, the VIX response values begin to decrease until they converge. This empirical finding verifies that the ICEA shocks can increase the VIX index. This empirical evidence reconfirms the notion of Arslan-Ayaydin and Thewissen (2016), who indicates that financial markets does not reward environmental performance of energy sector. VIX is related to the market’s expectations for the volatility in the S&P 500 over the coming 30 transaction days (Wang et al., 2019). From the characteristics of the ICEA, this study shows that the ICEA comprises the public’s concerns about environmental and energy consumption. The financial market is conductive (Leung et al., 2021) and (Shehadeh et al., 2021). Therefore, the concerns and panic about cryptocurrency environmental factors can be transmitted to the traditional financial markets. Moreover, the high environmental attention values reflect the deterioration of environmental Khan et al. (2020) and will affect the demand for some traditional energy forms Hu (2014), such as crude oil, coal and natural gas, among others. Both of the points mentioned above can cause financial market-price fluctuations. That is why ICEA can have a significantly positive relationship with the VIX.

Figure 6.14 presents the results after ICEA impulses unit shocks occur BCO, and as present in such figure, BCO has a positive response. The peak response value is present at the start point, which is equal to 2.4319. Then, the response values begin to decay over the elapsed period of time. From the 6th period, the UCRY Policy responses tend to converge. This confirms that the ICEA shocks can increase the BCO index. This phenomenon also can be explained by the ICEA can decrease the supply of BCO and provoke more BCO speculative trading activities. Moreover, \( \varepsilon \)ICEA impulses to BCO show a similar response trend as the \( \varepsilon \)ICEA impulses to Bitcoin. The only difference of note between BCO and Bitcoin’s responses is that those of Bitcoin are more violent. There are several possible reasons that can aid the explanation of this difference. Firstly, both BCO and Bitcoin are financial assets. They, therefore, have close relationships with cryptocurrencies and environmental pollution. Secondly, Bitcoin markets contain more price bubbles and fluctuate more frequently than the BCO market. Thirdly, ICEA is designed to capture the attention
of environmental issues to cryptocurrencies. Bitcoin markets hold a significant position in cryptocurrency markets, therefore, the Bitcoin price is expected to be more sensitive and responsive to the ICEA.

In a similar fashion to the ICEA on the Global EPU, Global Temperature Uncertainty (GTU) also shows a generally negative response trend to the ICEA shock. In Figure 6.14, the lowest response value is present in the 1st period, which is equal to -2.2639. Then, the GTU responses slightly rise to the peak value, which is equivalent to 0.0447. In general, the GTU responses show a "Wave-type" trend in the negative interval. From this data this study can confirm that ICEA shocks can decrease the GTU. Meanwhile, a high ICEA value indicates that people and governments are paying more attention to environmental issues and can reflect enhanced environmental awareness among the population. Governments promulgate new environmental protection policies to push entire societies to become more environmentally friendly, and heightened public environmental awareness guides more environmentally friendly behaviours. These significant steps are likely to reduce energy consumption and CO₂ emissions and achieve waste reduction, helping to mitigate the frequency and intensity of extreme weather events. Accordingly, the ICEA also demonstrates a significantly negative relationship with the GTU.

Figure 6.14 displays results after ICEA impulses unit shocks are applied to Industrial Production Index (IP). As presented, IP has a positive response in the early period (1st to 2nd), and the peak value is 0.2070. However, the IP shows a negative response in the early-mid period (around the 3rd), and the lowest value is -0.0690. After the 7th period, the IP responses tend to converge. From this, this study can state with confidence that the ICEA can increase the IP in the short-term, and the ICEA can also decrease the IP in the long-term. Importantly though, the short-term significantly positive relationship between the IP and the ICEA is leading. This empirical evidence can echo the findings of Bozkus et al. (2020) that IP can contribute to the long and short-term environmental costs. Industrial production is generally accompanied by pollution and consumption, with high industrial production values indicating high levels of pollution and consumption. The ICEA spiked in response to extreme energy consumption and pollution events, indicating it can demonstrate a significantly positive short-term relationship with the IP. However, as the environment deteriorates, governments are likely to promulgate new environmental protection policies to regulate industrial production activities, forcing enterprises to abandon high-energy-consumption and high-pollution activities and
become more environmentally friendly (Vu and Dang, 2021). Moreover, the ICEA can be cooled by new environmental protection policies, explaining its significantly negative long-term relationship with the IP.

Table 6.13: IRF results: ICEA to other factors

<table>
<thead>
<tr>
<th>Period</th>
<th>UCRI Policy</th>
<th>UCRI Price</th>
<th>GlobalEPU</th>
<th>Vix</th>
<th>BCO</th>
<th>Bitcoin</th>
<th>GTU</th>
<th>IP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Lower Band, CI = 0.90</td>
<td>Upper Band, CI = 0.90</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>0.264827892</td>
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<td>4.6880882</td>
<td>5.6219314</td>
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</tr>
<tr>
<td>2</td>
<td>9.341035e-02</td>
<td>0.168122e-01</td>
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<td>1.372655e+00</td>
<td>5.06119499</td>
<td>1.0252129</td>
<td>2.63896835</td>
</tr>
<tr>
<td>3</td>
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<td>1.46357947</td>
<td>0.08020537</td>
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</tr>
<tr>
<td>4</td>
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</tr>
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</tr>
</tbody>
</table>

Notes: This table displays the IRF test from the SVECM about the ICEA shocks to the variable system Equation 5.26, which contains UCRI Policy, UCRI Price, GlobalEPU, VIX, BCO, Bitcoin, GTU and IP. ICEA is set as impulse, and the other variables are set as response. n. ahead is the integer specifying the steps, which is set as 10. ci is the confidence interval for the bootstrapped error bands, which is set as 90%. runs is an integer, specifying the runs for the bootstrap, which is set as 1000.
Figure 6.14: Impulse from ICEA to variable system

Notes: The graphs displayed above are the UCRY Policy, UCRY Price, GlobalEPU, VIX, BCO, Bitcoin, GTU and IP’s response to the shock from the ICEA. The black line in each plot is the response curve. And the two red lines in each plot are the confidence interval for the bootstrapped error bands. \( n \text{ ahead} \) is the integer specifying the steps, which is set as 10. \( ci \) is the confidence interval for the bootstrapped error bands, which is set as 90%. \( runs \) is an integer, specifying the runs for the bootstrap, which is set as 1000.
6.6.2 Contributions of ICEA disturbances to the variation of financial variables' volatility

To evaluate the importance of different shocks and decompose the forecast error variance into the contributions from exogenous shocks, this study calculates the FEVD for ICEA. Figure 6.15 depicts the FEVD of ICEA decomposition results.

In Figure 6.15 and Table 6.14, the FEVD of ICEA plot and FEVD of ICEA statistics can be found, which also can provide evidence to support Hypothesis 2. In the first period, approximately 60% of the variation in ICEA is from shocks to ICEA itself, and most of the remaining approximately 40% is from UCRY Policy (19.17%), GlobalEPU (10.86%), Bitcoin price (4.71%) and IP (4.5%). It is surprising that UCRY Price can only contribute 0.187‰. The contribution of ICEA to the variations in the ICEA quickly dies after the first period and becomes stable after the sixth period, as is the case with the contribution of UCRY Policy to the variations in the ICEA. However, the contribution of Bitcoin price to variations in the ICEA changes fairly rapidly over the first period and eventually seems to converge at around 50%. As for the contribution of UCRY Price to variations in the ICEA, this begins to rise after the first period, and the growth rate gradually accelerates with the increase of the time period. In the end, UCRY Price to variations in the ICEA can converge at around 2.8%. These findings are also comparable to results in Lucey et al. (2022), which find that UCRY Policy and UCRY Price are more important in the short run, and the Bitcoin price is more important in the long run. The system becomes stable after the eighth period. In the end, the contribution of UCRY Policy, GlobalEPU, Vix, BCO, GTU, IP and ICEA can converge at around 11.08%, 6.73%, 1.45%, 4.15%, 1.55%, 1.87% and 20.46%, respectively.

Table 6.14: FEVD of ICEA

<table>
<thead>
<tr>
<th>Period</th>
<th>ε_UCRY Policy</th>
<th>ε_GlobalEPU</th>
<th>ε_Vix</th>
<th>ε_BCO</th>
<th>ε_Bitcoin</th>
<th>ε_GTU</th>
<th>ε_UCRY Price</th>
<th>ε_IP</th>
<th>ε_ICEA</th>
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<td>0.018770</td>
<td>0.204904</td>
</tr>
<tr>
<td>10</td>
<td>0.110785</td>
<td>0.067279</td>
<td>0.014513</td>
<td>0.041523</td>
<td>0.498608</td>
<td>0.015511</td>
<td>0.028910</td>
<td>0.018745</td>
<td>0.204626</td>
</tr>
</tbody>
</table>

Notes: This table presents the FEVD results for the ICEA statistics. *n. ahead* is the integer specifying the steps, which is set as 10.
6.6. ICÉA STRUCTURAL SHOCK ANALYSIS

Figure 6.15: FEVD of ICÉA

Notes: This figure presents the FEVD results for the ICÉA statistics. ICÉA is highlighted in green. \( n. \text{ ahead} \) is the integer specifying the steps, which is set as 10.

6.6.3 Cumulative contributions of ICÉA disturbances to the financial variables’ volatility

The historical decomposition is most interesting here as it shows how, accumulating over time, the ICÉA has changed as a consequence of changes in other variables, providing an interpretation of the relative importance over time of the various drivers. Based on the HD method introduced in the chapter 5, for example, the relationship between reduced form residuals and structural shocks of ICÉA are shown in Equation 6.2:

\[
\begin{bmatrix}
    u_{t}^{\text{ICÉA}} \\
    u_{t}^{\text{UCRY Policy}} \\
    u_{t}^{\text{GlobalEPU}} \\
    u_{t}^{\text{Vix}} \\
    u_{t}^{\text{BCO}} \\
    u_{t}^{\text{Bitcoin}} \\
    u_{t}^{\text{GTU}} \\
    u_{t}^{\text{UCRY Price}} \\
    u_{t}^{\text{IP}}
\end{bmatrix}
= 
\begin{bmatrix}
    S_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    S_{21} & S_{22} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    S_{31} & S_{32} & S_{33} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    S_{41} & S_{42} & S_{43} & S_{44} & 0 & 0 & 0 & 0 & 0 & 0 \\
    S_{51} & S_{52} & S_{53} & S_{54} & S_{55} & 0 & 0 & 0 & 0 & 0 \\
    S_{61} & S_{62} & S_{63} & S_{64} & S_{65} & S_{66} & 0 & 0 & 0 & 0 \\
    S_{71} & S_{72} & S_{73} & S_{74} & S_{75} & S_{76} & S_{77} & 0 & 0 & 0 \\
    S_{81} & S_{82} & S_{83} & S_{84} & S_{85} & S_{86} & S_{87} & S_{88} & 0 & 0 \\
    S_{91} & S_{92} & S_{93} & S_{94} & S_{95} & S_{96} & S_{97} & S_{98} & S_{99} & 0
\end{bmatrix}
\begin{bmatrix}
    \varepsilon_{t}^{\text{ICÉA}} \\
    \varepsilon_{t}^{\text{UCRY Policy}} \\
    \varepsilon_{t}^{\text{GlobalEPU}} \\
    \varepsilon_{t}^{\text{Vix}} \\
    \varepsilon_{t}^{\text{BCO}} \\
    \varepsilon_{t}^{\text{Bitcoin}} \\
    \varepsilon_{t}^{\text{GTU}} \\
    \varepsilon_{t}^{\text{UCRY Price}} \\
    \varepsilon_{t}^{\text{IP}}
\end{bmatrix}
\]

where, \( u_{t} \) denotes the reduced form disturbances (forecast errors) at time \( t \). \( \varepsilon_{t} \)
denotes the structural shocks at time $t$.

The historical decomposition of the ICEA is shown in Figure 6.16 with annotated events appended. The contribution of ICEA shocks to the historical decomposition in ICEA is given in green. These shocks match the expectations of public concerns on the environment to a certain extent, which suggests the validity of the Hypothesis $2$. ICEA and UCRY Price have a significantly positive relationship. In other words, the greater the media’s attention to cryptocurrency’s effects on the environment, the higher the cryptocurrency market value. For example: Ethereum is already using the equivalent of a small country’s worth of electricity with the rise of cryptocurrency markets’ price. Bitcoin’s Carbon Footprint and energy consumption issues gained significant attention when cryptocurrency market value reached $10k$. The ICEA increases with the start of the cryptocurrency bull market. Regulatory discussions, like UN aims to wipe out the Carbon Footprint of blockchains, negatively contributed to only small shifts in the ICEA. In contrast, technology’s type policy adjustment events - for example: Smartcool proves that technologies can lower energy consumption and costs for cryptocurrency and the creation of the Bitcoin Energy Consumption Index - positively impacted the ICEA. As for the shocks in historical decomposition from other variables, VIX and Bitcoin price have a significantly positive impact on ICEA in general. This study can assume that this is potentially due to the extreme uncertainty and volatility of Bitcoin and other financial assets. These empirical findings from the historical decomposition match the findings in the impulse response function analysis. In addition, IP does not show a significant impact on ICEA in the historical decomposition analysis. This phenomenon maybe because COVID-19 has an extremely strong cumulative shock on the IP, which will cover the shocks from ICEA.

The decomposition also shows that ICEA captures environmental attention that could be more distinctively attributed to the major environment events in cryptocurrencies. Although the price of Bitcoin, the UCRY Policy, the UCRY Price and the ICEA are highly correlated, the ICEA appears to capture environmental attention beyond the Bitcoin price, the UCRY Policy and the UCRY Price as shown by the decomposition.
Figure 6.16: ICEA index historical decomposition with major events

Notes: The graphs displayed above show the historical evolution of ICEA and the contribution of each of the structural shocks to variations in ICEA following significant historical episodes. Lag = 1. The variations of ICEA is highlighted in green.
6.6.4 The impact of the ICEA on the cryptocurrency market

ICEA is a new index, so a natural question is whether attention is paid to the environmental aspects of cryptocurrency generation in the cryptocurrency market. Based on this concern, this study investigates the relationship between the ICEA and cryptocurrency market by using a panel-pooled OLS model.

The regression model learns from the methodologies of Pastor and Veronesi (2012); Huynh et al. (2021); and Foglia and Dai (2021), who examine whether the policy uncertainty can predict the Bitcoin price return, UCRY risk and stock price volatility. The regression model can be defined as Equation 6.3:

\[
\Delta \text{Crypto}_{it} = \beta_1 \Delta \text{ICEA}_{t} + \beta_2 \Delta \text{Crypto}_{i,t-1} + \Delta \text{CV}_{it} + c + \epsilon_{it},
\]

where \(\Delta \text{Crypto}_{it}\) is the log return of cryptocurrency asset price or index at time \(t\), \(\Delta \text{ICEA}_{it}\) is the log return of cryptocurrency environmental attention index at time \(t\), \(\Delta \text{CV}_{it}\) is the \(K \times K\) matrix of control variables, \(c\) is a constant, and \(\epsilon_{it}\) is an error term. \(\Delta \text{Crypto}_{i,t-1}\) is designed to remove any serial correlation in the log return of \(\text{Crypto}_{it}\).

This study selects the Bitcoin price and the UCRY indices (UCRY Price and UCRY Policy) as the explained variables. The reasons why this study chooses these three variables are explained in the section 4.4. Ethereum is also included in the cryptocurrency assets because Ethereum is a key term in the ICEA search string. This study also adds control variables in Equation 6.3, selecting them from the left variables in Equation 5.26 because the empirical analysis mentioned above has fully demonstrated that these variables may be highly correlated with the ICEA. To eliminate the dimension divergence of the raw data in the regression results (Lütkepohl, 2005), this study calculates the log change to all the variables in Equation 5.26, including the additional Ethereum.

Table 6.15 reports the estimation results of Equation 6.3. Equation 6.3 regression results are not significantly different whether this study adds the control variables to the model or not, which indicates the robustness of the findings. All the \(\beta_1\) coefficient values in model (1) and model (2) are positive and significant, which suggests that the ICEA has a positive impact on the log change of Bitcoin price, Ethereum price and UCRY indices. From the results in model (2), when the control

---

3When Bitcoin price is the explained variable, ICEA is the explanatory variable, and the control variables are the UCRY indices, GlobalEPU, Vix, BCO, Bitcoin, GTU and IP.
variables are added to Equation 6.3, all the values of $R^2$ increase significantly, which indicates that these regressions fit better. At the same time, the $\beta_1$ values in model (2) do not decrease significantly, which shows that the explanatory power of ICEA for the cryptocurrency market can almost maintain the same level as the condition without control variables. Based on this empirical evidence, this study can infer that a single-unit ICEA log change can contribute a 147.67 Bitcoin price log change, a 206.58 Ethereum price log change, a 0.91 UCRY Policy log change and a 1.04 UCRY Price log change. Moreover, these empirical findings are in accordance with the former IRF, FEVD and HD results, which further prove the validity of the Hypothesis 2. These findings perfectly align with the previous literature Liu and Tsyvinski (2021), which finds that cryptocurrency asset returns can be predicted by some factors specific to cryptocurrency markets.
Table 6.15: The impact of the ICEA on cryptocurrency market

<table>
<thead>
<tr>
<th>∆ICEA impact</th>
<th>Model (1)</th>
<th>Model (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>∆Bitcoin</strong></td>
<td>176.2954***</td>
<td>147.6654***</td>
</tr>
<tr>
<td></td>
<td>(0.9071)</td>
<td>(0.5291)</td>
</tr>
<tr>
<td>Control variables</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>64.90%</td>
<td>88.06%</td>
</tr>
</tbody>
</table>

| **∆Ethereum**      | 211.9687*** | 206.57732*** |
|                    | (1.347)    | (0.6358)    |
| Control variables  | No         | Yes        |
| $R^2$              | 49.66%     | 88.78%     |

| **∆UCRY Policy**   | 0.9376***  | 0.9097*    |
|                    | (0.00332)  | (0.00125)  |
| Control variables  | No         | Yes       |
| $R^2$              | 75.16%     | 96.46%     |

| **∆UCRY Price**    | 1.04144*** | 1.03549*   |
|                    | (0.003049) | (0.001173) |
| Control variables  | No         | Yes       |
| $R^2$              | 81.63%     | 97.28%     |

Notes: This table displays the impacts of ICEA on cryptocurrency markets, including Bitcoin, Ethereum, UCRY Policy and UCRY Price. *p<0.1; **p<0.05; ***p<0.01. It also can show the regression results of the formula Equation 6.3. These statistical results reveal that ICEA has sufficient power to explain the return of cryptocurrency markets and can confirm that ICEA has a positive impact on the cryptocurrency markets from a fixed-effect perspective.
6.6.5 Robustness test

ICEA is a newly developed index and it is therefore essential to verify its usefulness. In this part, this study conduct a test for robustness on an ICEA benchmark.

Two potential issues may exist in the ICEA index. The first and perhaps most obvious is does this index really work? Considering this is such a significant concern, the relationships between the UCRY Policy, UCRY Price, ICEA and Bitcoin price should be definitively proved. The UCRY Policy, UCRY Price, and ICEA are designed to reflect the cryptocurrency market, and the validities of the UCRY Policy and UCRY Price have been proved by Lucey et al. (2022). For this purpose, a Pearson correlation will be applied to find the relationship between UCRY Policy, UCRY Price, ICEA and Bitcoin price index first.

Secondly, the continuously compounded returns (CCR) of UCRY Policy, UCRY Price, ICEA and Bitcoin price will be calculated by processing the first difference in the logarithmic values of two consecutive prices, which can be expressed as:

\[ CCR_{i,t} = \ln \left( \frac{P_{it}}{P_{i,t-1}} \right) \times 100, \]

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 \( t \). Then, the Pearson correlation will be applied again to find the relationship between the continuously compounded returns of the UCRY Policy, UCRY Price, ICEA and Bitcoin price index. If the ICEA, UCRY Policy Index, UCRY Price Index and Bitcoin still show a significant relationship in the continuously compounded returns, this study has further evidence to prove the validity of ICEA.

The second issue to consider is whether ICEA can actually impact the financial markets. Based on this potential issue, two further robustness tests are applied. The first test is highly influenced by (Lyu et al., 2021) to re-process stronger IRF tests. More specifically, the new IRF test increases the confidence interval bootstrapping from 90% to 95% and increase the threshold of runs from 1000 to 2000. By increasing the impulses from the ICEA to the financial markets, the validity of the ICEA’s impact on financial markets can be further assessed. This study has proved that the log change of ICEA has a significant and positive impact on the log change of Bitcoin price, Ethereum price and UCRY indices. To further examine the robustness of the impacts of ICEA on cryptocurrency markets, this study proposes an extra robustness test, which learns from the methodology of Al Mamun et al. (2020), to calculate the CCR for all the variables in Equation 5.26, including the Ethereum price. This study then re-processed the Equation 6.3 by applying the CCR results.
6.6.5.1 Robustness test results for indices

From Table 6.16 panel A, the correlation value of ICEA and UCRY Policy is 0.845 at the 99% significance level. The correlation value of ICEA and UCRY Price is 0.857 at the 99% significance level. The correlation value of ICEA and Bitcoin price is 0.818 at the 99% significance level. These statistical results prove that ICEA has a strong, positive, and significant correlation with the UCRY Policy, UCRY Price and Bitcoin price. These findings match those in the impulse response analysis and historical decomposition analysis, therefore further validating the usefulness of the ICEA. It is worth noting that the correlation value between the ICEA and the UCRY Price is the strongest value among the three correlation relationships. This phenomenon may be because the rise of the UCRY Price can awaken an environmental awareness in people, and the high cryptocurrency environmental attention may also stimulate speculations in the cryptocurrency markets. These small yet novel findings can also reflect the accuracies of the UCRY Policy, UCRY Price and ICEA from the side.

From Table 6.16 panel B, the correlation value of $\Delta \ln(\text{ICEA})$ and $\Delta \ln(\text{UCRY Policy})$ is 0.384 at a 99% significance level. The correlation value of $\Delta \ln(\text{ICEA})$ and $\Delta \ln(\text{UCRY Price})$ is 0.390 at a 99% significance level. The correlation value of $\Delta \ln(\text{ICEA})$ and $\Delta \ln(\text{Bitcoin})$ is 0.028 at a 99% significance level. These statistical results also can further prove that the $\Delta \ln(\text{UCRY Policy})$, $\Delta \ln(\text{UCRY Price})$ and $\Delta \ln(\text{ICEA})$ have a significantly relationship with $\Delta \ln(\text{Bitcoin})$. Therefore, the ICEA can still work from the continuously compounded returns’ perspective. Furthermore, the correlation value between $\Delta \ln(\text{ICEA})$ and $\Delta \ln(\text{UCRY Price})$ is still the strongest among the three ICEA continuously compounded return relationships just mentioned, which means the ICEA is more sensitive to the UCRY Price. These minor yet interesting findings also prove the validity of the UCRY Policy, UCRY Price and ICEA.
### Table 6.16: UCRY, ICEA, Bitcoin indices Pearson correlation

<table>
<thead>
<tr>
<th></th>
<th>UCRY Policy</th>
<th>UCRY Price</th>
<th>ICEA</th>
<th>Bitcoin</th>
</tr>
</thead>
<tbody>
<tr>
<td>UCRY Policy</td>
<td>1***</td>
<td>0.985***</td>
<td>0.845***</td>
<td>0.847***</td>
</tr>
<tr>
<td>UCRY Price</td>
<td>0.985***</td>
<td>1***</td>
<td>0.857***</td>
<td>0.852***</td>
</tr>
<tr>
<td>ICEA</td>
<td>0.845***</td>
<td>0.857***</td>
<td>1***</td>
<td>0.818***</td>
</tr>
<tr>
<td>Bitcoin</td>
<td>0.847***</td>
<td>0.852***</td>
<td>0.818***</td>
<td>1***</td>
</tr>
</tbody>
</table>

**Panel B: UCRY, ICEA, Bitcoin indices volatility Pearson correlation**

<table>
<thead>
<tr>
<th></th>
<th>∆ln(UCRY Policy)</th>
<th>∆ln(UCRY Price)</th>
<th>∆ln(ICEA)</th>
<th>∆ln(Bitcoin)</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆ln(UCRY Policy)</td>
<td>1***</td>
<td>0.903***</td>
<td>0.384***</td>
<td>0.056***</td>
</tr>
<tr>
<td>∆ln(UCRY Price)</td>
<td>0.903***</td>
<td>1***</td>
<td>0.390***</td>
<td>0.048***</td>
</tr>
<tr>
<td>∆ln(ICEA)</td>
<td>0.384***</td>
<td>0.390***</td>
<td>1***</td>
<td>0.028***</td>
</tr>
<tr>
<td>∆ln(Bitcoin)</td>
<td>0.056***</td>
<td>0.048***</td>
<td>0.028***</td>
<td>1***</td>
</tr>
</tbody>
</table>

Notes: This table presents the Pearson correlation of UCRY indices, ICEA and Bitcoin from a raw data level and a continuously compounded return level. ICEA is highly correlated with the other cryptocurrency indices in these two levels' data. *p<0.1; **p<0.05; ***p<0.01.

### 6.6.5.2 Robustness test results for empirical analysis

In order to check the validity of the interconnections between the ICEA and financial markets, the new IRF test results concerning ICEA shocks to the variable system Equation 5.26 are shown in Figure 6.17. From the new IRF test plots, the responses of the financial markets to the impulses from $\epsilon_{ICEA}$ still retain the same values, properties and trends as the former IRF test results, although the confidence interval bootstrapping is 95% and the threshold of runs is now at 2000. These robustness test results first prove the reliability and accuracy of the interconnections between the ICEA and financial markets, which have been explained in more detail in the main context, but essentially, the final interconnection results will not be changed by the increasing of the confidence interval bootstrapping and the threshold of runs. These robustness test results also prove that the volume of endogenous shocks and the confidence interval limitation will not impact the potential results. In other words, the responses of the financial market indices, which are described in Equation 5.26, can only be impacted by the intrinsic characteristics of ICEA. This robustness test can provide enough evidence that the former empirical findings of interconnection relationships between the ICEA and its financial markets are valid and reliable.
CHAPTER 6. NEW CRYPTOCURRENCY INDICES AND APPLICATIONS

Figure 6.17: Impulse from ICEA to other factors robustness test

(a) εICEA impulse to UCRY Policy robustness test
(b) εICEA impulse to UCRY Price robustness test
(c) εICEA impulse to GlobalEPU robustness test
(d) εICEA impulse to VIX robustness test
(e) εICEA impulse to BCO robustness test
(f) εICEA impulse to Bitcoin robustness test
(g) εICEA impulse to GTU robustness test
(h) εICEA impulse to IP robustness test

Notes: The graphs displayed above are the UCRY Policy, UCRY Price, GlobalEPU, VIX, BCO, Bitcoin, GTU and IP’s response to the stronger shocks from the ICEA. The black line in each plot is the response curve. And the two red lines in each plot are the confidence interval for the bootstrapped error bands. n. ahead is the integer specifying the steps, which is set as 10. ci is the confidence interval for the bootstrapped error bands, which is set as 95%. runs is an integer, specifying the runs for the bootstrap, which is set as 2000.

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Table 6.17 displays the Equation 6.3 estimation results at the CCR level. This study finds that all the $\beta_1$ coefficient values in model (1) and model (2) remain positive and significant, which suggests that the volatility of Bitcoin, Ethereum and UCRY indices increases when there is more attention paid to the environmental aspects of cryptocurrency generation. Based on these statistical results, this study can conclude that the impacts of ICEA on cryptocurrency assets remain robust at the CCR level. Finally, this study can confirm that ICEA has a positive impact on Bitcoin price, Ethereum price and UCRY indices.

Table 6.17: ICEA robustness test

<table>
<thead>
<tr>
<th>ΔlnICEA impact</th>
<th>Model</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>ΔlnBitcoin</td>
<td>140.311***</td>
<td>107.3383***</td>
</tr>
<tr>
<td></td>
<td>(0.285)</td>
<td>(0.242)</td>
</tr>
<tr>
<td>Control variables</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>51.84%</td>
<td>79.49%</td>
</tr>
<tr>
<td>Observations</td>
<td>85</td>
<td>85</td>
</tr>
<tr>
<td>ΔlnEthereum</td>
<td>19.1874*</td>
<td>17.1546***</td>
</tr>
<tr>
<td></td>
<td>(1.690)</td>
<td>(1.673)</td>
</tr>
<tr>
<td>Control variables</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>29.99%</td>
<td>44.01%</td>
</tr>
<tr>
<td>Observations</td>
<td>65</td>
<td>65</td>
</tr>
<tr>
<td>ΔlnUCRY Policy</td>
<td>0.9476***</td>
<td>0.9410*</td>
</tr>
<tr>
<td></td>
<td>(0.9746)</td>
<td>(0.1581)</td>
</tr>
<tr>
<td>Control variables</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>80.84%</td>
<td>97.24%</td>
</tr>
<tr>
<td>Observations</td>
<td>85</td>
<td>85</td>
</tr>
<tr>
<td>ΔlnUCRY Price</td>
<td>1.0459***</td>
<td>1.02432*</td>
</tr>
<tr>
<td></td>
<td>(0.4012)</td>
<td>(0.1488)</td>
</tr>
<tr>
<td>Control variables</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>84.51%</td>
<td>97.87%</td>
</tr>
<tr>
<td>Observations</td>
<td>85</td>
<td>85</td>
</tr>
</tbody>
</table>

Notes: This table displays the impacts of ICEA on the continuously compounded returns of the cryptocurrency markets. It also can show the regression results of the formula Equation 6.3. *$p<0.1$; **$p<0.05$; ***$p<0.01$. Model (1) shows the impacts of ΔlnICEA on cryptocurrency markets without control variables. Model (2) presents the impacts of ΔlnICEA with control variables. These statistical results reveal that ΔlnICEA has a positive impact on the volatility of cryptocurrency markets from a fixed-effect perspective.
6.7 UCRY Indices and Volatility Forecasting of Precious Metal Futures Markets

Several common properties shared by cryptocurrencies and precious metals, such as safe haven, hedge and diversification for risk assets, have been widely discussed since Bitcoin was created in 2008. However, no studies have explored whether cryptocurrency market uncertainties can help to explain and forecast volatilities in precious metal markets. By using the GARCH-MIDAS model incorporating cryptocurrency policy and price uncertainty, as well as several other commonly used uncertainty measures, this paper compares the in-sample impacts and out-of-sample predictive abilities of these uncertainties on volatility forecasts of COMEX gold and silver futures markets. The in-sample results demonstrate the significant impacts of cryptocurrency uncertainty on the volatilities of precious metal futures markets, and the out-of-sample evidence further confirms the superior predictive power of cryptocurrency uncertainty on volatility forecasting of these markets. The conclusions of this study are robust through various model evaluation approaches based not only on predicting errors but also on forecasting directions across different forecasting time horizons.

6.8 Summary Statistics

In the empirical analysis, the daily gold and silver prices are converted to logarithm returns and monthly uncertainty indices are used in their levels. Figure 6.18 shows the time evolutions of daily COMEX gold and silver prices, and other six uncertainty indices. It shows that the gold/silver prices remain relatively stable from January 2014 to January 2019/January 2020. While since then, they have maintained a rapid upward trend. Then, the monthly CBOE S&P 500 Volatility Index, CBOE Gold ETF Volatility Index, GEPU, and USD index show a significant increase after the outbreak of the COVID-19 pandemic. The Geopolitical Risk index and UCRY Policy experience a sharp increase at the end of 2021, especially after the explosion of the war in Ukraine in February 2022. Finally, after a fairly long period of flatness since January 2014, UCRY Policy index experiences a sharp rise at the end of 2020. These findings reveal that different uncertainty indices are sensitive to

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4Due to UCRY Policy and UCRY Price having very similar trends, we only display UCRY Policy here.
6.8. SUMMARY STATISTICS

different information sources, which may explain the price fluctuations in precious metal markets from multiple perspectives. The descriptive statistics are reported in Table 6.18.

Figure 6.18: Daily gold and silver futures prices and monthly uncertainty indices

![Graphs](image)

Notes: The graphs displayed above are the time evolutions of daily COMEX gold and silver prices and other six-monthly uncertainty indices, including CBOE VIX, CBOE GVZCLS, GEPU, GPR, USD Index and UCRY Policy. The sample period visualised is from 2nd January 2014 to 29th April 2022.
## Table 6.18: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>COMEX gold</th>
<th>COMEX silver</th>
<th>CBOE VIX</th>
<th>CBOE GVZCL</th>
<th>GEPU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obs.</td>
<td>2098</td>
<td>2098</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0215</td>
<td>0.0076</td>
<td>1.7654</td>
<td>1.5924</td>
<td>1.9741</td>
</tr>
<tr>
<td>Maximum</td>
<td>6.2546</td>
<td>7.9464</td>
<td>5.7740</td>
<td>3.2850</td>
<td>4.3016</td>
</tr>
<tr>
<td>Minimum</td>
<td>-5.8363</td>
<td>-16.2790</td>
<td>1.0130</td>
<td>0.9390</td>
<td>0.8631</td>
</tr>
<tr>
<td>Median</td>
<td>0.0319</td>
<td>0.0254</td>
<td>1.5700</td>
<td>1.5755</td>
<td>1.8721</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>0.9057</td>
<td>1.6788</td>
<td>0.6880</td>
<td>0.4074</td>
<td>0.7523</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.0285</td>
<td>-0.6512</td>
<td>2.6177</td>
<td>1.1121</td>
<td>0.6518</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>7.0302</td>
<td>11.7669</td>
<td>13.9895</td>
<td>5.4381</td>
<td>2.8434</td>
</tr>
<tr>
<td>J.-B.</td>
<td>1420.1167</td>
<td>6866.9199***</td>
<td>617.4047***</td>
<td>45.3819***</td>
<td>7.1823***</td>
</tr>
<tr>
<td>Q(5)</td>
<td>5.4274</td>
<td>8.6328</td>
<td>105.1256***</td>
<td>145.8673***</td>
<td>268.9158***</td>
</tr>
<tr>
<td>Q(10)</td>
<td>9.6227</td>
<td>15.1205</td>
<td>132.3274***</td>
<td>200.7231***</td>
<td>417.6058***</td>
</tr>
<tr>
<td>P-P</td>
<td>-45.7591***</td>
<td>-46.0576***</td>
<td>-4.0191***</td>
<td>-3.531***</td>
<td>-2.8231***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>GPR USD Index</th>
<th>UCRY Policy</th>
<th>UCRY Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obs.</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Mean</td>
<td>1.0033</td>
<td>1.1123</td>
<td>4.3746</td>
</tr>
<tr>
<td>Maximum</td>
<td>3.3078</td>
<td>1.2330</td>
<td>5.3929</td>
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<tr>
<td>Minimum</td>
<td>0.6068</td>
<td>0.9360</td>
<td>3.9703</td>
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<tr>
<td>Median</td>
<td>0.9252</td>
<td>1.1296</td>
<td>4.0176</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>0.3440</td>
<td>0.0681</td>
<td>0.4880</td>
</tr>
<tr>
<td>Skewness</td>
<td>3.6438</td>
<td>-1.3097</td>
<td>0.6217</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>22.5072</td>
<td>4.1946</td>
<td>1.5119</td>
</tr>
<tr>
<td>J.-B.</td>
<td>1855.9803***</td>
<td>34.5353***</td>
<td>15.6676***</td>
</tr>
<tr>
<td>Q(5)</td>
<td>48.6619***</td>
<td>344.6507***</td>
<td>51.284***</td>
</tr>
<tr>
<td>Q(10)</td>
<td>49.0409***</td>
<td>460.6627***</td>
<td>112.4792***</td>
</tr>
<tr>
<td>P-P</td>
<td>-4.21***</td>
<td>-2.3916</td>
<td>-16.7438***</td>
</tr>
</tbody>
</table>

Notes: This table reports the descriptive statistics for daily precious metal futures returns and seven uncertainty indices. For the sake of comparability of different uncertainty indices, we perform a 10-fold reduction for CBOE VIX and CBOE GVZCL, and a 100-fold reduction for the other five indices. Q(n) is the Ljung-Box Q statistics with lag length of n. P-P is the Phillips-Perron unit root statistics. *p<0.1; **p<0.05; ***p<0.01, respectively.

Table 6.18 shows that, firstly, in terms of daily precious metal returns, this study finds that COMEX gold futures return has larger mean but smaller standard deviation than those of silver futures, implying that COMEX gold futures is a safer but more profitable asset than silver futures. Then, both gold and silver returns present left skewed and leptokurtic distributions. The Jarque-Bera statistics further confirm the rejection of normal distribution for these gold and silver returns. Moreover, the Ljung-Box Q tests suggest no significant autocorrelation in the daily gold and silver returns. Secondly, regarding to monthly uncertainty indices, this study finds that all their means are positive, indicating the increasing uncertainties in stock market, economic policy, geopolitical risk, USD exchange rate, and cryptocurrency markets during the data sample. The Jarque-Bera statistics also demonstrate that all this uncertainty indices are not normally distributed, and the Ljung-Box Q tests...
show that they are auto-correlated up to 10 lags. Finally and most importantly, the Phillips-Perron unit root tests suggest that all the time series are stationary, and therefore can be modelled directly without further transformation.

6.9 UCRY Predictive Ability Test on the Metal Futures Markets

6.9.1 In-sample estimation results

In this sub-section, this study first quantifies the overall impacts of the seven monthly uncertainty indices on the volatility (especially the long-term volatility) of daily COMEX gold and silver returns. The estimation results of GARCH-MIDAS-X model fitting daily COMEX gold and silver returns incorporating various uncertainty indices are presented in Figure 6.19, Table 6.19 and Table 6.20.

For simplicity, Figure 6.19 shows estimated total and long-term volatility of daily COMEX gold futures returns by various monthly uncertainty indices. This study finds that different uncertainty indices can depict the different long-term components of volatility in gold prices, and these long-term components show distinct trends over time. These findings could confirm the Hypothesis can hold. Among them, the long-term volatilities estimated by GARCH-MIDAS incorporating CBOE VIX and GVZCLS indices seem to be very close to total volatility, indicating the information contained in these two uncertainty indices has similar impacts on the total and long-term components of COMEX gold volatilities. Furthermore, this study finds that the other four uncertainty indices, i.e., GEPU, GPR, USD index and UCRY Policy, have comparable but subtly different impacts on the long-term volatility of COMEX gold futures. These outcomes indicate that various uncertainty may capture different aspects of long-term price fluctuations in the gold market, and thus may offer policymakers and investors in gold markets a distinct perspective to design their regulatory and risk management strategies.
Figure 6.19: Estimated total and long-term volatilities of COMEX gold futures by various monthly uncertainty indices

The graphs displayed above show the estimated total and long-term volatility of daily COMEX gold futures returns by various monthly uncertainty indices, including CBOE VIX, CBOE GVZCLS, GEPU, GPR, USD Index and UCRY Policy. The green dashed line indicates the COMEX gold futures total daily volatility, and the blue line means the COMEX gold futures long-term volatility determined by the monthly uncertainty indices. The COMEX gold futures is in high-frequency daily data, and the six uncertainty indices are in low-frequency weekly data. The sample is from 2nd January 2014 to 29th April 2022.
The in-sample estimation results for GARCH-MIDAS-X model incorporating different uncertainty indices for COMEX gold and silver futures are listed in Table 6.19 and Table 6.20, respectively. First, in general, most estimated parameters quantifying GARCH-MIDAS-X model in capturing the short-term and long-term volatility of these two precious metal futures markets. Second, the $\beta$ parameters indicating the impacts of lagged RV and different uncertainty indices on the long-term volatility of COMEX gold futures returns, respectively. BIC is the Bayesian info criterion of the estimation. The bracketed numbers are the standard errors of the estimations. *$p<0.1$; **$p<0.05$; ***$p<0.01$, respectively.

<table>
<thead>
<tr>
<th>GARCH-MIDAS-X</th>
<th>$\omega$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$m$</th>
<th>$\theta_{RV}$</th>
<th>$\theta_{X}$</th>
<th>$w_{RV}$</th>
<th>$w_{X}$</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBOE VX</td>
<td>0.0302</td>
<td>0.0340</td>
<td>0.9372</td>
<td>0.2389</td>
<td>-0.0059**</td>
<td>0.5334**</td>
<td>0.0010**</td>
<td>49.9990</td>
<td>4788.3</td>
</tr>
<tr>
<td></td>
<td>(0.0307)</td>
<td>(0.0033)</td>
<td>(0.0040)</td>
<td>(0.1851)</td>
<td>(0.0009)</td>
<td>(0.0899)</td>
<td>(0.0102)</td>
<td>(88.1120)</td>
<td></td>
</tr>
<tr>
<td>CBOE GVZCLS</td>
<td>0.0221</td>
<td>0.0454</td>
<td>0.9170</td>
<td>-1.6356**</td>
<td>-0.0059**</td>
<td>1.7803**</td>
<td>6.5471**</td>
<td>49.9970</td>
<td>7465.62</td>
</tr>
<tr>
<td></td>
<td>(0.0385)</td>
<td>(0.0076)</td>
<td>(0.0144)</td>
<td>(1.2078)</td>
<td>(0.0015)</td>
<td>(1.3151)</td>
<td>(1.2645)</td>
<td>(116.8320)</td>
<td></td>
</tr>
<tr>
<td>GEPU</td>
<td>0.0274</td>
<td>0.0740</td>
<td>0.8413</td>
<td>0.4669**</td>
<td>0.0056**</td>
<td>0.0488</td>
<td>1.2136**</td>
<td>44.4490</td>
<td>7536.42</td>
</tr>
<tr>
<td></td>
<td>(0.0321)</td>
<td>(0.0085)</td>
<td>(0.0245)</td>
<td>(0.1108)</td>
<td>(0.0008)</td>
<td>(0.0597)</td>
<td>(0.3239)</td>
<td>(104.1000)</td>
<td></td>
</tr>
<tr>
<td>GPR</td>
<td>0.0272</td>
<td>0.0780</td>
<td>0.8367</td>
<td>0.6640**</td>
<td>-0.0058**</td>
<td>-0.1285</td>
<td>1.2299**</td>
<td>6.5264</td>
<td>7536.23</td>
</tr>
<tr>
<td></td>
<td>(0.0323)</td>
<td>(0.0084)</td>
<td>(0.0246)</td>
<td>(0.1799)</td>
<td>(0.0007)</td>
<td>(0.1626)</td>
<td>(0.3159)</td>
<td>(27.6940)</td>
<td></td>
</tr>
<tr>
<td>USD index</td>
<td>0.0245</td>
<td>0.0787</td>
<td>0.8277</td>
<td>1.2453**</td>
<td>0.0027**</td>
<td>-0.0016</td>
<td>1.2466**</td>
<td>1.1232</td>
<td>7536.05</td>
</tr>
<tr>
<td></td>
<td>(0.0321)</td>
<td>(0.0089)</td>
<td>(0.0255)</td>
<td>(0.5484)</td>
<td>(0.0007)</td>
<td>(0.5011)</td>
<td>(0.2911)</td>
<td>(8.1990)</td>
<td></td>
</tr>
<tr>
<td>UCRY Policy</td>
<td>0.0081**</td>
<td>0.0771</td>
<td>0.9229</td>
<td>4.0156</td>
<td>-0.0209**</td>
<td>-4.2222**</td>
<td>12.2670</td>
<td>1.0776**</td>
<td>8479.37</td>
</tr>
<tr>
<td></td>
<td>(0.0302)</td>
<td>(0.0063)</td>
<td>(0.0059)</td>
<td>(14713.00)</td>
<td>(0.0011)</td>
<td>(0.4909)</td>
<td>(14.2550)</td>
<td>(0.0651)</td>
<td></td>
</tr>
<tr>
<td>UCRY Price</td>
<td>0.0055**</td>
<td>0.0755</td>
<td>0.9243</td>
<td>-2.0827</td>
<td>-0.0022**</td>
<td>-3.0605**</td>
<td>12.2169</td>
<td>1.4980**</td>
<td>8464.25</td>
</tr>
<tr>
<td></td>
<td>(0.0311)</td>
<td>(0.0064)</td>
<td>(0.0061)</td>
<td>(3.7629)</td>
<td>(0.0011)</td>
<td>(0.5007)</td>
<td>(12.2160)</td>
<td>(0.1481)</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table reports the estimation results of GARCH-MIDAS-X models incorporating various uncertainty indices. $\theta_{RV}$ and $\theta_{X}$ indicate the impacts of lagged RV and different uncertainty indices on the long-term volatility of COMEX gold futures returns, respectively. BIC is the Bayesian info criterion of the estimation. The bracketed numbers are the standard errors of the estimations. *$p<0.1$; **$p<0.05$; ***$p<0.01$, respectively.
effect in short-term volatility are all significantly positive, ranging from about 0.82 to 0.98, indicating strong short-term volatility persistence in precious metal markets, and this persistence patterns in gold market are stronger than those in silver market. Third, most of the \( \theta_{RV} \) coefficients are significantly negative, implying that higher historical realised volatility will lead to lower long-term volatility in precious metal markets. This is also commonly observed as the mean-reversion effect in asset volatility (Engle et al., 2013) and (Bai et al., 2021). More importantly, this study focuses on the impacts of various uncertainties on the long-term volatility of precious metal markets, i.e., the estimation results of \( \theta_X \) coefficients in Table 6.19 and Table 6.20. In Table 6.19, this study finds that five uncertainty indices (i.e., CBOE VIX, CBOE GVZCLS, GEPU, UCRY Policy, and UCRY Price) have significantly positive impacts on the long-term volatility of COMEX gold futures market, while the other two (GPR and USD index) have no such significant effects, which can provide evidence to support Hypothesis 3. In terms of silver futures in Table 6.20, there are some differences from those in Table 6.19. For example, although CBOE VIX and GVZCLS still have significant positive effects on the long-term volatility of silver futures, the UCRY Policy and UCRY Price turn to have significant negative impacts on the silver market, which can provide further evidence to support Hypothesis 3. Moreover, GEPU, GRP and USD index cannot have significant effects on the long-term volatility of silver futures. These findings remind us that despite of many common attributes, gold and silver markets still have several different fundamentals. For instance, there is a difference between gold and silver in terms of value preservation. Gold has always been a reserve tool for global central banks, especially in recent years with the growing call for de-dollarisation. Therefore, central banks have increased their gold reserves, becoming an important source of growth in global gold consumption. While after World War II, silver’s monetary properties have gradually faded to zero, and its financial roles may have been transformed mainly into an investment tool. Compared to gold, the market volume of silver is much smaller, and once the fundamental changes, the volatility of silver prices can be much higher than that of gold, fueled by a large amount of speculative capital. Therefore, it is not difficult to understand that various uncertainty indices may have distinct impacts on the gold and silver markets.

In summary, this study finds that, besides GEPU, CBOE VIX and CBOE GVZCLS, which have been proved massively in literature to have direct or indirect
impacts on precious metal markets, uncertainty information from cryptocurrency market could additionally help one to depict the volatility (especially the long-term volatility) in gold and silver markets, and larger uncertainty in cryptocurrency market usually leads to greater/smaller long-term fluctuations in gold/silver prices. This fact offers one a new perspective to understand the long-term drivers of precious metal market volatility, and validates the protracted and deep interdependence between precious metal and cryptocurrency markets.

6.9.2 Out-of-sample volatility forecasting results

In the sub-section of subsection 6.9.1, this study has proved the significant in-sample impacts of UCRY indices, and several other commonly used uncertainty indices on the volatilities of COMEX gold and silver futures. However, policy makers and investors may be more interested in the out-of-sample predictive abilities of these uncertainty indices in forecasting volatilities of precious metal markets. Thus, in this sub-section, this study first conducts the one-day-ahead volatility forecasting of COMEX gold and silver futures by using various GARCH-MIDAS-X models, and then assesses these out-of-sample forecasts by different model evaluation approaches. Moreover, because there are no widely accepted rules for choosing the out-of-sample lengths, this study chooses 30%, 40%, 50%, and 60% of the total sample size, i.e., the last 630, 840, 1050, and 1260 days of the data sample as the out-of-sample (OOS) forecasting horizons. All the following model evaluation results are then based on the four out-of-sample forecasting horizons.

6.9.2.1 Results of Diebold and Mariano test

In this first round evaluation, this study assesses the forecasting performances of various models by using the DM test proposed by (Diebold and Mariano, 2002). Table 6.21 and Table 6.22 summarise the testing results for COMEX gold and silver futures, respectively. As discussed above, a negative DM statistic indicates higher predictive accuracy of model \( i \) over the benchmark model. Therefore, in terms of COMEX gold market, Table 6.21 shows that all the six GARCH-MIDAS-X models incorporating CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty indices can significantly beat the benchmark model (i.e., GARCH-MIDAS-VIX) across all the four OOS forecasting horizons. The statistical results could confirm the Hypothesis 4 can hold. This outcome demonstrates that CBOE
GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty indices have higher predictive abilities than that of the CBOE VIX. Moreover, the DM MSE and MAE statistics in Table 6.21 are very close within a specific forecasting time horizon, indicating the comparable predictive powers among the CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty indices. However, the empirical results in Table 6.22, depicting the forecasting performances of silver futures, showing a number of differences compared to Table 6.21. For example, the results for out-of-sample 630 days forecasts show that model with GEPU cannot against the benchmark model for the significant positive MSE and MAE statistics. Regarding to the 840-day results, both models incorporating CBOE GVZCLS and GEPU are not superior to the benchmark model. Finally, the 1260-day outcome reveals that only GARCH-MIDAS-GEPU can outperform the benchmark. These results in Table 6.21 and Table 6.22 imply that, various uncertainty have distinct predictive powers on gold and silver markets, and these predictive powers may also switch at different market environments and forecasting horizons. All in all, CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty have comparable predictive abilities and can outperform CBOE VIX in predicting the daily volatilities of COMEX gold futures, while they are not surely superior to VIX in forecasting the daily volatility of COMEX silver futures.

Table 6.21: DM tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX gold futures returns

<table>
<thead>
<tr>
<th>GARCH-MIDAS-X</th>
<th>OOS = 630 days</th>
<th>OOS = 840 days</th>
<th>OOS = 1050 days</th>
<th>OOS = 1260 days</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBOE GVZCLS</td>
<td>−5.9225***</td>
<td>−6.7849***</td>
<td>−6.6356***</td>
<td>−6.6350***</td>
</tr>
<tr>
<td>GEPU</td>
<td>−4.3906***</td>
<td>−4.8222***</td>
<td>−4.5184***</td>
<td>−4.5180***</td>
</tr>
<tr>
<td>GPR</td>
<td>−5.9398***</td>
<td>−5.8517***</td>
<td>−5.2269***</td>
<td>−5.1287***</td>
</tr>
<tr>
<td>USD index</td>
<td>−5.7360***</td>
<td>−6.9497***</td>
<td>−5.6500***</td>
<td>−5.6504***</td>
</tr>
<tr>
<td>UCRY Policy</td>
<td>−5.8952***</td>
<td>−6.7030***</td>
<td>−5.7832***</td>
<td>−5.7834***</td>
</tr>
<tr>
<td>UCRY Price</td>
<td>−5.8950***</td>
<td>−6.7011***</td>
<td>−5.6140***</td>
<td>−5.6140***</td>
</tr>
</tbody>
</table>

Note: This table presents the MSE and MAE statistics of DM tests, with the null hypothesis that there is no difference in predictive accuracy of model i and the benchmark one. Thus, a negative DM statistic indicates higher predictive accuracy of model i than that of the benchmark model. The benchmark model is set to be GARCH-MIDAS-VIX model. *p<0.1; **p<0.05; ***p<0.01, respectively.
6.9. UCRY PREDICTIVE ABILITY TEST ON THE METAL FUTURES MARKETS

Table 6.22: DM tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX silver futures returns

<table>
<thead>
<tr>
<th>GARCH-MIDAS-X</th>
<th>OOS = 630 days</th>
<th>OOS = 840 days</th>
<th>OOS = 1050 days</th>
<th>OOS = 1260 days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MSE statistic</td>
<td>MAE statistic</td>
<td>MSE statistic</td>
<td>MAE statistic</td>
</tr>
<tr>
<td>CBOE GVZCLS</td>
<td>−5.5620***</td>
<td>−5.4930***</td>
<td>−5.9308***</td>
<td>−5.4379***</td>
</tr>
<tr>
<td>GEPU</td>
<td>9.7125***</td>
<td>11.7707***</td>
<td>8.5498***</td>
<td>9.4566***</td>
</tr>
<tr>
<td>USD index</td>
<td>−5.8823***</td>
<td>−5.6005***</td>
<td>−7.9042***</td>
<td>−7.9530***</td>
</tr>
<tr>
<td>UCRY Policy</td>
<td>−8.4718***</td>
<td>−10.5196***</td>
<td>−7.9071***</td>
<td>−9.7842***</td>
</tr>
<tr>
<td>UCRY Price</td>
<td>−8.4699***</td>
<td>−10.4960***</td>
<td>−7.9071***</td>
<td>−9.6406***</td>
</tr>
</tbody>
</table>

Note: This table presents the MSE and MAE statistics of DM tests, with the null hypothesis that there is no difference in predictive accuracy of model i and the benchmark one. Thus, a negative DM statistic indicates higher predictive accuracy of model i than that of the benchmark model. The benchmark model is set to be GARCH-MIDAS-VIX model. *p<0.1; **p<0.05; ***p<0.01, respectively.

6.9.2.2 Results of out-of-sample $R^2_{OOS}$ test

Then, this study performs the out-of-sample $R^2_{OOS}$ test of (Clark and West, 2007) to further assess the predictive powers of various uncertainty models. Similarly, Table 6.23 and Table 6.24 report the results of $R^2_{OOS}$ test for COMEX gold and silver futures, respectively. In general, this study finds in Table 6.21 that all the out-of-sample $R^2$ are significantly positive, suggesting that GARCH-MIDAS models with CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty can beat the benchmark model (GARCH-MIDAS-VIX) across various forecasting horizons. These statistical results also suggest the validity of the Hypothesis 4. Nevertheless, this study still observes several differences in Table 6.22 for COMEX silver futures from the results in Table 6.21. For instance, the 630-day $R^2_{OOS}$ for GARCH-MIDAS-GEPU is about −49.4%; those values for GARCH-MIDAS-GVZCLS and GARCH-MIDAS-GEPU at 840-day evaluation are about −1.4% and −22.6%, respectively, indicating the poor predictive abilities of GVZCLS and GEPU at these two forecasting horizons. However, when considering the 1260-day results, GEPU turns to be the only one index that can outperform VIX in $R^2_{OOS}$ test.

In summary, the $R^2_{OOS}$ evaluation results are highly consistent to those in DM tests. The six uncertainty indices, i.e., CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty, are superior to VIX in forecasting daily volatility of COMEX gold futures. While the situations for COMEX silver futures are more complicated. CBOE GVZCLS and GEPU seem cannot perform well in 630- and 840-day out-of-sample evaluations, but GEPU turns to be the only one that can against VIX in 1260-day forecasting horizon.
### Table 6.23: Out-of-sample $R^2_{OOS}$ test for various GARCH-MIDAS-X models in forecasting volatilities of COMEX gold futures returns

<table>
<thead>
<tr>
<th>GARCH-MIDAS-X</th>
<th>OOS = 630 days</th>
<th>OOS = 840 days</th>
<th>OOS = 1050 days</th>
<th>OOS = 1260 days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2_{OOS}$ (%)</td>
<td>MSFE-adjusted</td>
<td>$R^2_{OOS}$ (%)</td>
<td>MSFE-adjusted</td>
</tr>
<tr>
<td>CBOE GVZCLS</td>
<td>33.4023</td>
<td>5.9192***</td>
<td>37.0966***</td>
<td>5.7057</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>97.0575</td>
<td>4.3695***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>94.5943</td>
<td>4.3659***</td>
</tr>
<tr>
<td>GEMU</td>
<td>31.9450</td>
<td>6.1214***</td>
<td>37.8915***</td>
<td>5.9383***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>97.1240</td>
<td>4.3967***</td>
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<td>5.9474***</td>
<td>37.2462***</td>
<td>5.9405***</td>
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<td>95.2338</td>
<td>4.3854***</td>
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<td>38.2994***</td>
<td>5.9646***</td>
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<td>4.3647***</td>
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<td>4.3840***</td>
</tr>
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<td>UCRY Policy</td>
<td>31.9204</td>
<td>5.8586***</td>
<td>34.0141***</td>
<td>5.7924***</td>
</tr>
<tr>
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<td>96.2145</td>
<td>4.3521***</td>
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<td>92.3140</td>
<td>4.3395***</td>
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<td></td>
<td>92.3546</td>
<td>4.3398***</td>
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</table>

Note: This table presents the out-of-sample forecasting performance based on the out-of-sample $R^2$ test of (Clark and West, 2007), with the null hypothesis that the benchmark model has obviously smaller or equal MSE compared to the interested model $i$. The benchmark model is set to be GARCH-MIDAS-VIX model. A positive value of out-of-sample $R^2$ implies that the forecasting model of interest has higher prediction accuracy than the benchmark model. * $p<0.1$; ** $p<0.05$; *** $p<0.01$, respectively.

### Table 6.24: Out-of-sample $R^2_{OOS}$ test for various GARCH-MIDAS-X models in forecasting volatilities of COMEX silver futures returns

<table>
<thead>
<tr>
<th>GARCH-MIDAS-X</th>
<th>OOS = 630 days</th>
<th>OOS = 840 days</th>
<th>OOS = 1050 days</th>
<th>OOS = 1260 days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2_{OOS}$ (%)</td>
<td>MSFE-adjusted</td>
<td>$R^2_{OOS}$ (%)</td>
<td>MSFE-adjusted</td>
</tr>
<tr>
<td>CBOE GVZCLS</td>
<td>4.3791</td>
<td>5.6491***</td>
<td>1.4065</td>
<td>1.9803</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.7007</td>
<td>2.6518</td>
</tr>
<tr>
<td>GEMU</td>
<td>49.3908</td>
<td>9.5714***</td>
<td>22.6054</td>
<td>8.7691</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>66.5027</td>
<td>7.8603***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.3511</td>
<td>2.3240***</td>
</tr>
<tr>
<td>GPR</td>
<td>1.7055</td>
<td>2.1965***</td>
<td>64.1562</td>
<td>8.6305***</td>
</tr>
<tr>
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<td>73.7113</td>
<td>7.8353***</td>
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<td>10.2995</td>
<td>6.2963</td>
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<td>5.9600***</td>
<td>58.2845</td>
<td>8.5473***</td>
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<td>67.8488</td>
<td>7.7702***</td>
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<td></td>
<td></td>
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<td>−3.0321</td>
<td>−2.5239</td>
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<tr>
<td>UCRY Policy</td>
<td>60.7139</td>
<td>8.9235***</td>
<td>26.9135</td>
<td>8.2189***</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td>63.8418</td>
<td>7.8412***</td>
</tr>
<tr>
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<td></td>
<td>−7.4455</td>
<td>−3.9659</td>
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<tr>
<td>UCRY Price</td>
<td>60.7496</td>
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<td>26.9251</td>
<td>8.2150***</td>
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<td>63.8219</td>
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<td>−7.4880</td>
<td>−3.9836</td>
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</table>

Note: This table presents the out-of-sample forecasting performance based on the out-of-sample $R^2$ test of (Clark and West, 2007), with the null hypothesis that the benchmark model has obviously smaller or equal MSE compared to the interested model $i$. The benchmark model is set to be GARCH-MIDAS-VIX model. A positive value of out-of-sample $R^2$ implies that the forecasting model of interest has higher prediction accuracy than the benchmark model. * $p<0.1$; ** $p<0.05$; *** $p<0.01$, respectively.
6.9.3 Robustness test

6.9.3.1 Results of Model Confidence Set (MCS) test

Third, both the DM and $R^2_{OOS}$ tests can only compare the forecasting performances of two single models. To get an overall evaluation on a set of competing models, this study further adopts the Model Confidence Set (MCS) test proposed by (Hansen et al., 2011). By using bootstrap method to obtain the statistical significance of the test, and with more loss functions as criteria, the MCS approach offers one a robust evaluation on predictive ability of a set of different models.

Due to MCS test does not need a benchmark model, therefore Table 6.25 and Table 6.26 report the p-values of MCS test for all the seven competing models. Those p-values larger than 0.1 are marked in bold, indicating the corresponding model can survive in a model confidence set, and this model has equal predictive accuracy to others in this model set. Additionally, a larger p-value indicates a higher predictive accuracy of the corresponding model, and the p-values equal to 1 are marked in bold and underlined, suggesting that the corresponding models have the best forecasting performance. The evaluation results in Table 6.25 indicate that under the loss functions of QLIKE and MSE, all GARCH-MIDAS-X models can survive in the MCS, implying that all the seven uncertainty indices can make accurate daily volatility forecasts for COMEX gold futures. However, under the criteria of MAE, HMSE, HMAE, and $R^2_{LOG}$, only one model can survive except for the case of 630-day out-of-sample assessment. To be more specific, in 630-day results, both UCRY Price and USD index achieve three p-values of 1.0000, suggesting their superior predictive performances over other uncertainty indices. To sum up the results over the cases of 840-, 1050- and 1260-day evaluations, GEPU gets three p-values of 1.0000, USD index obtains two p-values of 1.0000, and GPR has three p-values of 1.0000. The UCRY Price, however, achieves ten p-values of 1.0000. More notably, under the HMSE, HMAE and $R^2_{LOG}$ criteria, only UCRY Price model can survive in the MCS with p-values of 1.0000, suggesting its absolute advantage in forecasting the daily volatilities of COMEX gold futures over other uncertainty indices. The evaluation results in Table 6.26 for COMEX silver futures demonstrate similar findings to those in Table 6.26. It shows that UCRY Price model get 15 p-values of 1.0000 in total, and under the criteria of HMSE, HMAE, and $R^2_{LOG}$, it is also the only model can survive in the MCS, furthering implying its outstanding predictive power in forecasting daily volatilities of COMEX silver futures.
Table 6.25: Model confidence set (MCS) tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX gold futures returns

<table>
<thead>
<tr>
<th></th>
<th>QLIKE</th>
<th>MSE</th>
<th>MAE</th>
<th>HMSE</th>
<th>HMAE</th>
<th>R^2 LOG</th>
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<td><strong>Panel A: OOS = 630 days</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>CBOE VIX</td>
<td>0.2950</td>
<td>0.3461</td>
<td>0.2518</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>CBOE GVZCLS</td>
<td>0.2950</td>
<td>0.3461</td>
<td>0.2518</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>GEPU</td>
<td>0.2950</td>
<td>0.3461</td>
<td>0.2518</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>GPR</td>
<td>0.2950</td>
<td>0.3461</td>
<td>0.2518</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>USD index</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
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</tr>
<tr>
<td>UCry Price</td>
<td>0.2950</td>
<td>0.3461</td>
<td>0.2518</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td><strong>Panel B: OOS = 840 days</strong></td>
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<td></td>
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</tr>
<tr>
<td>CBOE VIX</td>
<td>0.3097</td>
<td>0.4277</td>
<td>0.0047</td>
<td>0.0000</td>
<td>0.0000</td>
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</tr>
<tr>
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<td>GPR</td>
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</tr>
<tr>
<td>UCry Policy</td>
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<td>0.4277</td>
<td>0.0047</td>
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<td>0.0047</td>
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<tr>
<td><strong>Panel C: OOS = 1050 days</strong></td>
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</tr>
<tr>
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<td>0.0104</td>
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<td>0.0000</td>
</tr>
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<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>GPR</td>
<td>1.0000</td>
<td>1.0000</td>
<td>0.0104</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>USD index</td>
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<td>0.2268</td>
<td>0.0104</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>UCry Policy</td>
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<td>0.0104</td>
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<tr>
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<td>0.0104</td>
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<td>1.0000</td>
<td>1.0000</td>
</tr>
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<td><strong>Panel D: OOS = 1260 days</strong></td>
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<tr>
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<td>0.2337</td>
<td>0.0060</td>
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</tr>
<tr>
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<td>0.9750</td>
<td>0.2337</td>
<td>0.0060</td>
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<tr>
<td>USD index</td>
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<td>0.0060</td>
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</tr>
<tr>
<td>UCry Policy</td>
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<td>0.2337</td>
<td>0.0060</td>
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<td>0.2337</td>
<td>0.0060</td>
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</table>

Note: This table presents the p-values of MCS tests based on six loss functions, i.e. quasi-likelihood loss (QLIKE), mean square error (MSE), mean absolute error (MAE), heteroskedasticity-adjusted MSE and MAE (HMSE and HMAE), and R^2 LOG similar to R^2 of the Mincer-Zarnowitz regressions. The p-values larger than 0.1 are marked in bold, indicating that the corresponding model can survive in the MCS. The p-values equal to 1.0000 are marked in bold and underlined, suggesting that the corresponding models have the best forecasting performance.
### 6.9. UCRY PREDICTIVE ABILITY TEST ON THE METAL FUTURES MARKETS

Table 6.26: Model confidence set (MCS) tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX silver futures returns

<table>
<thead>
<tr>
<th></th>
<th>QLIKE</th>
<th>MSE</th>
<th>MAE</th>
<th>HMSE</th>
<th>HMAE</th>
<th>$R^2$ LOG</th>
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<td></td>
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<tr>
<td>CBOE VIX</td>
<td>0.0213</td>
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<td>0.0798</td>
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</tr>
<tr>
<td>CBOE GVZCLS</td>
<td>0.0213</td>
<td><strong>0.1013</strong></td>
<td>0.0798</td>
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<td>0.0000</td>
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<tr>
<td>GEPU</td>
<td>0.0114</td>
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<td>0.0798</td>
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<td>0.0000</td>
</tr>
<tr>
<td>GPR</td>
<td>0.0114</td>
<td><strong>0.1013</strong></td>
<td>0.0798</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>USD index</td>
<td>0.0213</td>
<td><strong>0.1013</strong></td>
<td>0.0798</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
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<tr>
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<td><strong>0.1013</strong></td>
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</tr>
<tr>
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<td><strong>1.0000</strong></td>
<td><strong>1.0000</strong></td>
<td><strong>1.0000</strong></td>
<td><strong>1.0000</strong></td>
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</tr>
<tr>
<td><strong>Panel B: OOS = 840 days</strong></td>
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</tr>
<tr>
<td>CBOE VIX</td>
<td>0.0307</td>
<td><strong>0.1328</strong></td>
<td>0.0923</td>
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<tr>
<td>CBOE GVZCLS</td>
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<td><strong>0.1328</strong></td>
<td>0.0923</td>
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</tr>
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</tr>
<tr>
<td>USD index</td>
<td>0.0307</td>
<td><strong>0.1328</strong></td>
<td>0.0923</td>
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</tr>
<tr>
<td>UCRY Policy</td>
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<td><strong>0.1328</strong></td>
<td>0.0923</td>
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<td>UCRY Price</td>
<td>0.0307</td>
<td><strong>0.1328</strong></td>
<td>0.0923</td>
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</tr>
<tr>
<td><strong>Panel C: OOS = 1050 days</strong></td>
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</tr>
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<tr>
<td>CBOE GVZCLS</td>
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<td><strong>0.2268</strong></td>
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<tr>
<td>GPR</td>
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<td></td>
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</tr>
<tr>
<td>USD index</td>
<td><strong>0.7893</strong></td>
<td><strong>0.2268</strong></td>
<td>0.0104</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>UCRY Policy</td>
<td><strong>0.4060</strong></td>
<td><strong>0.2268</strong></td>
<td>0.0104</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>UCRY Price</td>
<td><strong>0.4060</strong></td>
<td><strong>0.2268</strong></td>
<td>0.0104</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel D: OOS = 1260 days</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBOE VIX</td>
<td><strong>0.2841</strong></td>
<td><strong>0.6729</strong></td>
<td><strong>0.4618</strong></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>CBOE GVZCLS</td>
<td>0.0133</td>
<td><strong>0.1599</strong></td>
<td><strong>0.1257</strong></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>GEPU</td>
<td><strong>1.0000</strong></td>
<td><strong>1.0000</strong></td>
<td><strong>1.0000</strong></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>GPR</td>
<td>0.0133</td>
<td><strong>0.1599</strong></td>
<td><strong>0.1004</strong></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>USD index</td>
<td><strong>0.2841</strong></td>
<td><strong>0.1599</strong></td>
<td><strong>0.1257</strong></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>UCRY Policy</td>
<td><strong>0.2841</strong></td>
<td><strong>0.1599</strong></td>
<td><strong>0.1217</strong></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>UCRY Price</td>
<td>0.0133</td>
<td><strong>0.1599</strong></td>
<td><strong>0.1004</strong></td>
<td><strong>1.0000</strong></td>
<td><strong>1.0000</strong></td>
<td><strong>1.0000</strong></td>
</tr>
</tbody>
</table>

Note: This table presents the p-values of MCS tests based on six loss functions, i.e. quasi-likelihood loss (QLIKE), mean square error (MSE), mean absolute error (MAE), heteroskedasticity-adjusted MSE and MAE (HMSE and HMAE), and $R^2$ LOG similar to $R^2$ of the Mincer-Zarnowitz regressions. The p-values larger than 0.1 are marked in bold, indicating that the corresponding model can survive in the MCS. The p-values equal to 1.0000 are marked in bold and underlined, suggesting that the corresponding models have the best forecasting performance.
6.9.3.2 Results of Direction-of-Change (DoC) rate test

Finally, besides evaluation of forecasting errors, this study utilises the Direction-of-Change (DoC) rate test of (Degiannakis and Filis, 2017) to compare the accuracy in the forecasting direction by various GARCH-MIDAS-X models.

Table 6.27 and Table 6.28 reveal that all the DoC rates estimated are significantly larger than 0.5 (from about 0.64 to 0.71), suggesting that all the uncertainty indices help to get better volatility forecasting direction in COMEX gold and silver futures. Moreover, the DoC rates calculated in a specific forecasting horizon are very close to each other, implying the comparable forecasting direction accuracy of various GARCH-MIDAS-X models. A point worth noting is that UCRY Price and UCRY Policy models get the largest DoC rates of about 0.71 and 0.69 in the cases of 1260-day evaluation for COMEX gold futures and 630-day assessment for silver futures, further suggesting that uncertainty information in cryptocurrency markets may provide one a new angle to understand the possible drivers of precious metal market volatility, and can really contribute to make better volatility forecasts in these markets.

Table 6.27: Direction-of-Change tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX gold futures returns

<table>
<thead>
<tr>
<th>GARCH-MIDAS-X</th>
<th>OOS = 630 days</th>
<th>OOS = 840 days</th>
<th>OOS = 1050 days</th>
<th>OOS = 1260 days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DoC rate</td>
<td>PT statistic</td>
<td>DoC rate</td>
<td>PT statistic</td>
</tr>
<tr>
<td>CBOE VIX</td>
<td>0.6741</td>
<td>10.5249***</td>
<td>0.6865</td>
<td>12.4925***</td>
</tr>
<tr>
<td>CBOE GVZCLS</td>
<td>0.6741</td>
<td>10.4766***</td>
<td>0.6913</td>
<td>12.7648***</td>
</tr>
<tr>
<td>GEPU</td>
<td>0.6852</td>
<td>10.7202***</td>
<td>0.7044</td>
<td>12.9784***</td>
</tr>
<tr>
<td>GPR</td>
<td>0.6789</td>
<td>10.6291***</td>
<td>0.6865</td>
<td>12.5037***</td>
</tr>
<tr>
<td>USD index</td>
<td>0.6900</td>
<td>11.1848***</td>
<td>0.6937</td>
<td>12.8073***</td>
</tr>
<tr>
<td>UCRY Policy</td>
<td>0.6757</td>
<td>10.5431***</td>
<td>0.6794</td>
<td>12.2579***</td>
</tr>
</tbody>
</table>

Note: This table reports the Direction-of-Change (DoC) rates and the PT statistics of (Pesaran and Timmermann, 1992) test for various forecasting models. The greater a DoC rate is, the higher directional accuracy is obtained by the corresponding model. The null hypothesis of PT test is that the volatility forecasting model does not have directional accuracy. "p<0.1; "**p<0.05; "***p<0.01, respectively.
6.10 Chapter Summary

This study firstly develops a new measure of price and policy uncertainty in cryptocurrency markets. Using 726.9 million news articles from the Lexis Nexis database, this study constructs new Cryptocurrency Uncertainty Indices that reflect policy (UCRY Policy) and price (UCRY Price) uncertainty around major cryptocurrencies. This study provides the historical decomposition of the UCRY indices with major events from 2014 to 2020, such as the COVID-19 crisis, cyberattacks on cryptocurrency exchanges and political elections. Compared to other similar indices, it is narrowly range bound, suggesting that while such uncertainty exists, it is not volatile. Nonetheless, it does show distinct movements around high-profile events in the cryptocurrency space. The empirical findings suggest that the cryptocurrency uncertainty indices can be useful for future research on the uncertainty of cryptocurrency, portfolio diversification, and contagion effect. Additionally, it can have various practical and policy-based implications for measuring the risk stemming from cryptocurrency markets.

Secondly, this study develops a new measure of attention to sustainability concerns of cryptocurrency markets’ growth. An Index of Cryptocurrency Environmental Attention (ICEA) has been constructed using 778.2 million news stories from the LexisNexis News & Business database. The ICEA demonstrates significant increases in attention to cryptocurrency environmental impacts displayed via both traditional and social media channels from 2014 to 2021. This study further analyses the main drivers of this awareness and assesses contributions of how
ICEA variations can affect various uncertainty measures (UCRY Policy, UCRY Price, GlobalEPU, Vix and GTU) and other factors that might be affected, including the extent of the attention to environmental problems in cryptocurrency markets, traditional energy markets and industrial production (Bitcoin price, BCO and IP). The results from impulse response analysis show that ICEA has a significantly positive impact on the UCRY Policy, the UCRY Price, VIX, BCO, and Bitcoin price, while ICEA has a significantly negative impact on the GlobalEPU and GTU. It is worth noting that Bitcoin has the strongest reactions to the ICEA variation shocks, and ICEA has a significantly positive impact on the IP in the short-term while having a significantly negative impact in the long-term, and the short-term positive impact is leading. However, by decomposing the forecast variance into the contributions from exogenous shocks, this study demonstrates that at the beginning of the observation period, the UCRY Policy is the largest contributor to ICEA variations (19.17%), while Bitcoin and UCRY Price contribute just 4.71% and 0.187% respectively. These findings provide strong evidence that environmental concerns originated in policy and regulation domains and, up until recently, are not the main concerns of cryptocurrency investors who have been attracted to this asset class due to the rapid growth of cryptocurrency prices. The historical decomposition of the ICEA displays higher linkages between environmental attention, Bitcoin price, UCRY Policy and UCRY Price around key events that could significantly change prices of digital assets, for example, cyberattacks on cryptocurrency exchanges, the COVID-19 crisis, ICO and DeFi booms, and Bitcoin bubble-like periods. Therefore, this study can conclude that overall attention to environmental issues of cryptocurrency will increase cryptocurrency price fluctuations. Thus, the growth, expansion and adoption of cryptocurrencies worldwide should not be ignored by regulators, and high-level debates around sustainability concerns brought by this disruptive innovation have to be originated. The assessment of the potential negative impacts of this new technology on climate change and potential mitigation strategies have to be included in the global sustainability agendas. Finally, a panel pooled OLS regression model indicates that the ICEA positively impacts Bitcoin price, Ethereum price, and UCRY indices.

Concerning the robustness test, this study applies a Pearson correlation to analyse the relationship between the UCRY Policy, UCRY Price, ICEA and Bitcoin price. This study then uses the Pearson correlation again to investigate the rela-
relationship between the CCR of UCRY Policy, UCRY Price, ICEA and Bitcoin price. These two Pearson correlation analyses could successfully prove the usefulness and effectiveness of the ICEA because the index shows a significant relationship with UCRY Policy, UCRY Price and Bitcoin price, as well as with their CCR. Therefore, this study has confidence in believing the new issuing index is robust. In addition, this study raises the confidence interval bootstrapping and threshold of runs in the IRF test to examine the interactions between the ICEA and financial markets. The new IRF tests, with the higher confidence interval bootstrapping and threshold of runs, also show the same results as the outcomes in the main context. These new IRF tests successfully prove the robustness of the findings of the ICEA’s impact on the financial markets. In the end, this study re-processes the panel pooled OLS regression model at a CCR level. The regression results confirm the former empirical findings of the ICEA and the cryptocurrency assets. The empirical findings suggest that the public is growing more concerned with the energy consumption of these innovative assets. Environmental policy makers should consider this result, and the necessity of regulation of this area should be discussed.

Thirdly, this paper quantifies both the in-sample impacts and the out-of-sample predictive abilities of cryptocurrency uncertainty indices on the volatilities of precious metal markets. This study achieves several important empirical findings. For example, this study finds that various uncertainty measures may capture different types of long-term fluctuations in precious metal prices, and cryptocurrency uncertainty has significant but inverse in-sample impacts on the long-term volatility of COMEX gold and silver futures markets. Moreover, UCRY Policy and UCRY Price uncertainty can outperform several commonly used uncertainty indices (i.e., CBOE VIX, CBOE GVZCLS, GEPU, GPR, and USD index) in forecasting the daily volatility of precious metal markets. These findings are checked robustly by various evaluation methods and different forecasting horizons.

This innovative study could provide several valuable implications for developing and improving the precious metal markets and cryptocurrency uncertainty measures. The empirical findings suggest that cryptocurrency uncertainty proxies are significant robust predictors for volatility forecasting in precious metal markets. Therefore, the empirical results from this study first can have essential implications for risk management. Referencing the empirical findings, investors and portfolio managers could make optimal and timely decisions based on forecasting the changes in precious metal prices by adjusting their long positions. This study
not only can deepen our understanding of precious metal volatility forecasting but also help to bring new sharp insights into a more accurate valuation for precious metal assets, which in turn could benefit the effectiveness of financial risk management strategies. Second, from a policy-making perspective, the empirical findings indicate that the shocks from the cryptocurrency uncertainties can exert significant effects on precious metal return dynamics. Moreover, cryptocurrency uncertainties have significant information contents that can signal impending turbulence in precious metal markets early. Therefore, cryptocurrency uncertainty indices can be used to trace unusual fluctuations in the precious metal markets in real-time by market regulators and also can raise an early warning call to policymakers to remind them to launch more effective stabilisation policies and prevent possible recessions.
Based on coverage of over 660m news stories from LexisNexis News & Business between 2015-2021, this study provides two new indices around the growing area of Central Bank Digital Currency (CBDC): the CBDC Uncertainty Index (CBDCUI) and CBDC Attention Index (CBDCAI). This study shows that both indices spiked during news related to new developments in CBDCs and in relation to digital currency news items. This study demonstrates 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. The 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.

To investigate the indices' structural shocks on cryptocurrency, foreign exchange and stock markets as well as banking sectors, uncertainty indices and safe-haven gold, this study applies the IRF, FEVD and HD tests derived from the SVAR model. By using the DCC-GJR-GARCH model, this study can further examine the interconnections between CBDC indices and financial markets. This study will...
discuss the results of these tests, including their potential underlying causes in full detail in the following subsections. This study demonstrates 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.

7.1 Central Bank Digital Currency Indices

Figure 7.1 shows the weekly values for the derived indices based on 663,881,640 news items collected between January 2015 and June 2021. The weekly CBDCUI and CBDCAI indices are annotated in Figure 7.2 and display which events can drive spikes on the indices. The plot allows one to clearly see how new CBDC developments could raise the indices, while they could also be stimulated by other significant events related to cryptocurrencies. This study has listed all of the events captured by the CBDC indices in section A.1.

![Figure 7.1: CBDCUI and CBDCAI](image)

Notes: This figure displays the CBDC Uncertainty Index and CBDC Attention Index. The red line and blue line represent the CBDCUI and CBDCAI, separately. These indices reflect the scaled weekly counts of articles containing the search strings in subsection 4.2.3. These two series are standardised and then added 100 from January 2015 to June 2021 based on queries. LexisNexis News & Business is the selected database.
7.1. CENTRAL BANK DIGITAL CURRENCY INDICES

Figure 7.2: CBDC annotated indices

Notes: Flash events related to CBDC are annotated. This study has listed all of the events captured by the CBDC indices in section A.1.


7.2 Summary Statistics

The time-varying of the dynamic returns for each variable can be seen in Figure 7.3.

Figure 7.3: The dynamics of variables returns

Notes: The graphs displayed above are the weekly continuously compounded returns across time for CBDCUI, CBDCAI, UCRY Policy, UCRY Price, 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. The sample period visualised is January 2015 to June 2021.
7.2. SUMMARY STATISTICS

Table 7.2 shows the descriptive statistics for the variable system Equation 5.56. This study opts 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. 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. This study calculates the continuously compounded returns as volatility by processing the first-difference in the logarithmic values of two consecutive prices, expressed as:

\[ CCR_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \times 100, \]

where \( CCR_{i,t} \) denotes continuously compounded returns for index \( i \) at time \( t \), and \( P_{i,t} \) stands for the price of index \( i \) at time \( t \).

As shown in Table 7.2, this study will explain the raw data from the following three perspectives: frequency distribution, central tendency, and dispersion. The indices have the same mean values - even when this study expands the decimal point to six. The value of CBDCUI's range is 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 are almost identical, and the differences in standard deviation are apparent when this study sets the decimal point to nine. The CBDCAI has higher skewness and kurtosis value than the CBDCUI. Furthermore, the skewness and kurtosis values of these two variables are positive. These results indicate that an asymmetrical probability distribution of both indices (the mean is greater than the median, and the tail is on the right side), their being leptokurtic, and rejecting the normal distribution, which is 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, indicating non-stationary.

According to Lütkepohl (2005) and Durlauf and Blume (2016), a VAR model requires every variable running in the model to be stationary. Therefore, this study calculates the log return to Equation 5.56. The results are shown in Table 7.2 in Panel B. Unfortunately, unit roots still exist in variable system Equation 5.56 confirmed by the ADF, PP, and KPSS tests. Therefore, this study calculates the continuously compounded returns to Equation 5.56. The results are shown in Table 7.2 Panel C, indicating the variables could show stationarity in the continuously
CHAPTER 7. THE EFFECTS OF CENTRAL BANK DIGITAL CURRENCIES
NEWS ON FINANCIAL MARKETS

compounded returns. Baker et al. (2016) use EPU raw data, the log of the S&P 500 Index, log of the industrial production and the employment rate to process the IRF analysis. However, Lütkepohl (2005) and Corbet et al. (2021) indicate that continuously compounded return is more suitable than the log return for analysing the volatility characteristics. As such, this study uses the continuously compounded returns of Equation 5.56 to run the VAR and DCC-GARCH models.

Table 7.1 unveils the Pearson correlation relationship between each variable. This study 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 CBDUC indices are significantly positively correlated with the volatility of VIX, 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, this study finds negative correlation between both CBDC indices and the volatility of the MSCI World Banks Index, USEPU, and the FTSE All-World Index. The statistical results could confirm the Hypothesis 5 can hold.

Table 7.1: Unconditional correlation of variables returns

<table>
<thead>
<tr>
<th>CBDCUI</th>
<th>CBDCAI</th>
<th>USEPU</th>
<th>VIX</th>
<th>FTSE WBI</th>
<th>FXE</th>
<th>BTC</th>
<th>HBD</th>
<th>FTSE WGBI</th>
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<td>1</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBDCUI</td>
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</tr>
<tr>
<td>CBDCAI</td>
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<td>0.564*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>USEPU</td>
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<td>0.557*</td>
<td>0.557*</td>
<td>0.487*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIX</td>
<td></td>
<td>0.564*</td>
<td>0.564*</td>
<td>0.484**</td>
<td>-0.129*</td>
<td>-0.087*</td>
<td>-0.430**</td>
<td>0.574**</td>
</tr>
<tr>
<td>FTSE WBI</td>
<td></td>
<td>0.506*</td>
<td>0.686*</td>
<td>0.039**</td>
<td>-0.558*</td>
<td>-0.546**</td>
<td>0.223*</td>
<td>1</td>
</tr>
<tr>
<td>EUR/USD</td>
<td></td>
<td></td>
<td>0.039**</td>
<td>-0.013</td>
<td>-0.051</td>
<td>-0.442</td>
<td>0.149**</td>
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<td>GBP/USD</td>
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<td>0.095**</td>
<td>0.015**</td>
<td>-0.013</td>
<td>-0.244*</td>
<td>0.280**</td>
<td>-0.096**</td>
</tr>
<tr>
<td>JPY/USD</td>
<td></td>
<td></td>
<td>0.096**</td>
<td>0.161**</td>
<td>0.013**</td>
<td>-0.124*</td>
<td>-0.178*</td>
<td>0.049**</td>
</tr>
<tr>
<td>RUB/USD</td>
<td></td>
<td></td>
<td>0.056**</td>
<td>0.115**</td>
<td>0.125**</td>
<td>0.192*</td>
<td>-0.195*</td>
<td>0.039**</td>
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<tr>
<td>CNY/USD</td>
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<td></td>
<td>0.096**</td>
<td>0.049**</td>
<td>-0.013</td>
<td>-0.146*</td>
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<td>0.019**</td>
</tr>
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<td>0.052**</td>
<td>-0.024</td>
<td>-0.149*</td>
<td>-0.123*</td>
<td>-0.189**</td>
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<tr>
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<td>0.015**</td>
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<td>-0.121**</td>
<td>-0.023**</td>
</tr>
<tr>
<td>FTSE WGBI</td>
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<td></td>
<td>0.072**</td>
<td>0.038**</td>
<td>-0.024</td>
<td>-0.013</td>
<td>-0.146**</td>
<td>-0.008**</td>
</tr>
</tbody>
</table>

This is a Pearson correlation matrix between CBDCUI, CBDCAI, UCRY Policy, UCRY Price, 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. - represents the negative correlation. * p<0.1; ** p<0.05; *** p<0.01.

7.3 CBDC Indices Structural Shock Analysis

7.3.1 CBDC shocks on the dynamics of financial variables volatility

184
Table 7.2: Descriptive statistics

Panel A: Price

<table>
<thead>
<tr>
<th></th>
<th></th>
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<td>Mean</td>
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<td>Std. Dev.</td>
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<td>0.001</td>
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Panel C: Continuously Compounded Returns

<table>
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Panel A: Continuously Compounded Returns

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Notes: Ljung-Box test for the distribution of residuals (Box and Pierce, 1970) and (Ljung and Box, 1978), and it can examine the autocorrelation of squared returns series, Jarque-Bera (J.B.) test and Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al., 1992). *p<0.1; **p<0.05; ***p<0.01.
In this subsection, this study examines the effects of the indices' shocks on the financial variables' volatilities in Equation 5.56 from different time horizons.

Figure 7.4 and Figure 7.5 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. Moreover, these statistical results also suggest the validity of the Hypothesis.

As for CBDCUI shocks on the dynamics of financial variables' volatility, this study can draw several inferences from Figure 7.4. First, this study has 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, this study 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.

As for CBDCAI shocks, this study can also draw several inferences from Figure 7.5. First, this study 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.

### 7.3.2 Contributions of CBDC disturbances to the variation of financial variables’ volatility

From Figure 7.6 and Table 7.3, this study 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%) is also a relatively significant variable in explaining variations in the CBDCUI FEVD.
Figure 7.4: CBDCUI shocks to other variables

Notes: The graphs displayed above are the variables’ response to the shock from the CBDCUI. The black line in each plot is the response curve. And the two red lines in each plot are the confidence interval for the bootstrapped error bands. \( n \) ahead is the integer specifying the steps, which is set as 10. \( ci \) is the confidence interval for the bootstrapped error bands, which is set as 90%. \( runs \) is an integer, specifying the runs for the bootstrap, which is set as 1000.
7.3. CBDC INDICES STRUCTURAL SHOCK ANALYSIS

Figure 7.5: CBDCAI shocks to other variables

(a) $\epsilon$CBDCAI to UCRY Policy
(b) $\epsilon$CBDCAI to UCRY Price
(c) $\epsilon$CBDCAI to ICEA
(d) $\epsilon$CBDCAI to MSCI World Banks
(e) $\epsilon$CBDCAI to VIX
(f) $\epsilon$CBDCAI to USEPU
(g) $\epsilon$CBDCAI to FTSE All World Index
(h) $\epsilon$CBDCAI to EUR/USD
(i) $\epsilon$CBDCAI to GBP/USD
(j) $\epsilon$CBDCAI to JPY/USD
(k) $\epsilon$CBDCAI to RUB/USD
(l) $\epsilon$CBDCAI to CNY/USD
(m) $\epsilon$CBDCAI to Gold
(n) $\epsilon$CBDCAI to Bitcoin

Notes: The graphs displayed above are the variables’ response to the shock from the CBDCAI. The black line in each plot is the response curve. And the two red lines in each plot are the confidence interval for the bootstrapped error bands. $n.$ ahead is the integer specifying the steps, which is set as 10. $ci$ is the confidence interval for the bootstrapped error bands, which is set as 90%. $runs$ is an integer, specifying the runs for the bootstrap, which is set as 1000.
CHAPTER 7. THE EFFECTS OF CENTRAL BANK DIGITAL CURRENCIES NEWS ON FINANCIAL MARKETS

The following statistical results can provide evidence to support Hypothesis 5. Considering the three cryptocurrency indices, the ICEA (2.4091% to 2.4482%) has a greater contribution to the CBDCUI's fluctuations. Therefore, a novel finding is cryptocurrency environmental attention contributes 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%) is the most important variable 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 7.6 and Table 7.3, 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 is 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 has the leading role. Compared with the three world indices, the MSCI World Banks Index is 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%) is 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%) is still important for the FEVD of CBDCAI among other foreign exchange rates, the RUB/USD (0.8386% to 0.8413%) has the greatest contribution to the CBDCAI's variations. Surprisingly, although China is leading the CBDC revolution, CNY/USD (0.0205% to 0.0588%) is 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, this study finds that gold (4.25E-05) does not greatly contribute to the CBDCAI's variations.
7.3. CBDC INDICES STRUCTURAL SHOCK ANALYSIS

Figure 7.6: CBDC indices FEVD

(a) CBDCUI FEVD  
(b) CBDCAI FEVD

Notes: These two figures present the FEVD results for the CBDCUI and CBDCAI statistics. CBDCUI is highlighted in red, and CBDCAI is displayed in pink blue. \( n. \text{ ahead} \) is the integer specifying the steps, which is set as 10.

Table 7.3: FEVD of variable system due to the CBDCUI and CBDCAI shocks

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Notes: This table presents the FEVD results for the CBDCUI and CBDCAI statistics. Panel A shows the FEVD of variable system due to the CBDCUI shocks. Panel B presents the FEVD of variable system due to the CBDCAI shocks. \( n. \text{ ahead} \) is the integer specifying the steps, which is set as 10.  

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7.3.3 Cumulative contributions of CBDC disturbances to the financial variables’ volatility

While Figure 7.6 and Table 7.3 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 chapter 5, for example, the relationship between reduced form residuals and structural shocks of CBDC indices are shown in Equation 7.1:

\[
\begin{bmatrix}
    u_{CBDC1}^t \\
    u_{CBDC2}^t \\
    u_{UCRY Policy}^t \\
    u_{UCRY Price}^t \\
    u_{MSCI WBI}^t \\
    u_{VIX}^t \\
    u_{USEPU}^t \\
    u_{FTSE AWI}^t \\
    u_{EUR/USD}^t \\
    u_{GBP/USD}^t \\
    u_{JPY/USD}^t \\
    u_{RUB/USD}^t \\
    u_{CNY/USD}^t \\
    u_{Gold}^t \\
    u_{Bitcoin}^t \\
    u_{FTSE WGBI}^t
\end{bmatrix} = 
\begin{bmatrix}
    S_{11} & 0_{12} & 0_{13} & \ldots & 0_{115} & 0_{116} & 0_{117} \\
    S_{21} & S_{22} & 0_{23} & \ldots & 0_{215} & 0_{216} & 0_{217} \\
    S_{31} & S_{32} & S_{33} & \ldots & 0_{315} & 0_{316} & 0_{317} \\
    S_{41} & S_{42} & S_{43} & \ldots & 0_{415} & 0_{416} & 0_{417} \\
    S_{51} & S_{52} & S_{53} & \ldots & 0_{515} & 0_{516} & 0_{517} \\
    S_{61} & S_{62} & S_{63} & \ldots & 0_{615} & 0_{616} & 0_{617} \\
    S_{71} & S_{72} & S_{73} & \ldots & 0_{715} & 0_{716} & 0_{717} \\
    S_{81} & S_{82} & S_{83} & \ldots & 0_{815} & 0_{816} & 0_{817} \\
    S_{91} & S_{92} & S_{93} & \ldots & 0_{915} & 0_{916} & 0_{917} \\
    S_{101} & S_{102} & S_{103} & \ldots & 0_{1015} & 0_{1016} & 0_{1017} \\
    S_{111} & S_{112} & S_{113} & \ldots & 0_{1115} & 0_{1116} & 0_{1117} \\
    S_{121} & S_{122} & S_{123} & \ldots & 0_{1215} & 0_{1216} & 0_{1217} \\
    S_{131} & S_{132} & S_{133} & \ldots & 0_{1315} & 0_{1316} & 0_{1317} \\
    S_{141} & S_{142} & S_{143} & \ldots & 0_{1415} & 0_{1416} & 0_{1417} \\
    S_{151} & S_{152} & S_{153} & \ldots & 0_{1515} & S_{1516} & S_{1517} \\
    S_{161} & S_{162} & S_{163} & \ldots & 0_{1615} & 0_{1616} & S_{1617} \\
    S_{171} & S_{172} & S_{173} & \ldots & S_{1715} & S_{1716} & S_{1717}
\end{bmatrix}
\]

\[
\begin{bmatrix}
    \varepsilon_{CBDC1}^t \\
    \varepsilon_{CBDC2}^t \\
    \varepsilon_{UCRY Policy}^t \\
    \varepsilon_{UCRY Price}^t \\
    \varepsilon_{MSCI WBI}^t \\
    \varepsilon_{VIX}^t \\
    \varepsilon_{USEPU}^t \\
    \varepsilon_{FTSE AWI}^t \\
    \varepsilon_{EUR/USD}^t \\
    \varepsilon_{GBP/USD}^t \\
    \varepsilon_{JPY/USD}^t \\
    \varepsilon_{RUB/USD}^t \\
    \varepsilon_{CNY/USD}^t \\
    \varepsilon_{Gold}^t \\
    \varepsilon_{Bitcoin}^t \\
    \varepsilon_{FTSE WGBI}^t
\end{bmatrix}
\]

where, \( u_t \) denotes the reduced form disturbances (forecast errors) at time \( t \), \( \varepsilon_t \) denotes the structural shocks at time \( t \).
7.3. CBDC INDICES STRUCTURAL SHOCK ANALYSIS

Figure 7.7 and Figure 7.8 present the cumulative contributions of CBDCUI and CBDCAI disturbances to the volatilities of financial variables under dynamic economic environments, giving strong evidence to support Hypothesis 5. 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 7.7 and Figure 7.8. Firstly, this study finds that both the cumulative positive and negative effects of CBDCUI disturbances on financial variables are 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. The findings reconfirm those of (Lucey et al., 2022; Wang et al., 2022b). Secondly, the contributions of the estimated CBDCUI shocks to the evolution of the financial variables’ volatilities could change over time, and this study finds that they tend 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, this study finds 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 affect the CBDCUI’s HD results. For example, the Chinese government revises its Anti-Money Laundering Law because digital currency makes Anti-Money Laundering enforcement challenging. Regarding the positive shocks in the first larger cluster, this study clearly finds 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 could yield several interesting findings. First, new CBDC developments (e.g., the digital-CAD, digital-EUR, digital-USD, etc.) significantly decrease CBDC uncertainties. However, it is also worth noting that the UK’s CBDCs perform differently, and thus increase CBDC uncertainty before the larger cluster in period four. Besides, perhaps because the Renminbi
CHAPTER 7. THE EFFECTS OF CENTRAL BANK DIGITAL CURRENCIES NEWS ON FINANCIAL MARKETS

is not a free-float currency, it is hard to place it into the first portfolio position. Alternatively, many regulators and investors concern 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 this study clearly notes that the presence of four larger clusters between May 2016, December 2017, January 2018, June 2019 to July 2019, and March 2021 to July 2021. This study also successfully captures 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 show a significantly negative impact on the CBDCAI’s HD results.

Furthermore, 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 section A.1.
Figure 7.7: CBDCUI historical decomposition

Notes: The graphs displayed above show the historical evolution of CBDCUI and the contribution of each of the structural shocks to variations in CBDCUI following significant historical episodes. The horizontal axis represents the time sample period, and the vertical axis represents the variations of the variables in Equation 5.56 in per cent after CBDCUI shocks. Lag = 1. The variations of CBDCUI are highlighted in red. More details about the historical episodes can be found in section A.1.
Figure 7.8: CBDCAI historical decomposition

Notes: The graphs displayed above show the historical evolution of CBDCAI and the contribution of each of the structural shocks to variations in CBDCAI following significant historical episodes. The horizontal axis represents the time sample period, and the vertical axis represents the variations of the variables in Equation 5.56 in per cent after CBDCAI shocks. Lag = 1. The variations of CBDCAI are highlighted in light blue. More details about the historical episodes can be found in section A.1.
7.3. Diagnostic tests for SVAR

This study processes several diagnostic tests for the SVAR to check the validity of this model and to further confirm that lag 1 is the optimal lag. This study tests 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. 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 7.4. 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, this study 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, this study can verify the correctness of the SVAR model and that lag 1 is the optimal lag.

Table 7.4: SVAR optimal lag calculation and diagnostic test results

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<th>Panel A (1): SVAR optimal lag calculation results</th>
<th>lag max = 13</th>
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<th>lag max = 11</th>
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<th>US BY Price</th>
<th>ICRA</th>
<th>MSCI World Bank Index</th>
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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.
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7.4 CBDC Indices Interconnection Analysis

7.4.1 Dynamic conditional correlations

Table 7.5 and Table 7.6 display the bivariate DCC-GJR-GARCH (1,1) model results for CBDCUI/CBDCAI and each financial variable in Equation 5.56, which also suggest the validity of the Hypothesis 5.

Regarding the interconnections between the CBDCUI and financial variables, as shown in Panel A of Table 7.5, the ARCH, GARCH and GJR parameters are 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 5.56 is appropriate and reasonable. Panel B of Table 7.5 reveals the DCC between the CBDCUI's volatility and other financial variables. This allows this study to obtain three findings. Firstly, the CBDCUI has 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). Secondly, the CBDCUI has 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 is significantly greater than a. Therefore, this study can infer that the CBDCUI has a significantly negative DCC with the MSCI World Bank Index and FTSE All-World Index in general. Third, the CBDCUI has 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 7.6, the ARCH, GARCH and GJR parameters are 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 5.56 is appropriate and reasonable. Panel B of Table 7.6 reveals the DCC between the CBDCAI and other financial variables, thus leading to three results. Firstly, the CBDCAI has 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. Secondly, the CBDCAI has 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 signifi-
cantly greater than that of a. Therefore, this study 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 has 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 are significantly stronger.

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

Figure 7.9 and Figure 7.10 displays the time-varying correlations between CBDCUI/CBDCAI and each financial variable in Equation 5.56.

Figure 7.9: CBDCUI dynamic conditional 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

Notes: Dynamic conditional correlation (DCC) between volatility in CBDCUI and the other variables in Equation 5.56 over the period January 2015 to June 2021. This figure shows the selection of GJR-GARCH-DCC models, based on minimising the values of four information criteria, AIC, HQ, SC and FPE.
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 are 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 show a significant increase trend after China's Central Banks begin to both test and launch CBDCs. 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 is due to Brexit in the second half of 2019, and the third occurs due to the cryptocurrency bull market in 2021. Regarding the CBDCUI and gold, there is 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 are both significantly partially positive and negative. From the negative dynamic correlation periods, this study finds that, generally speaking, the partial significantly positive dynamic correlations are the most significant relationships between the CBDCUI and the UCRY Policy, GBP/USD, and JPY/USD. Moreover, the partial significantly negative dynamic correlations are the foremost relationships between the CBDCUI and MSCI World Bank Index. This study finds that the degrees of dynamic correlations between changes in the CBDCUI and USEPU, and the CBDCUI and FTSE All-World Index are 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 are positive and statistically significant throughout the whole research period. These empirical results imply that one unit increases 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

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1For the sake of brevity, this study lists these negative dynamic correlation periods in the section A.2.
CBDCAI and JPY/USD, the CBDCAI and RUB/USD, the CBDCAI and UCRY Price, and the CBDCAI and FTSE World Government Bond Index are both significantly partially positive and negative\textsuperscript{2}. From the negative dynamic correlations periods, this study finds 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 are negative throughout the whole research period, thus evidencing the potential availability of the hedging strategy.

Figure 7.10: CBDCAI dynamic conditional correlation

Notes: Dynamic conditional correlation (DCC) between volatility in CBDCAI and the other variables in Equation 5.56 over the period January 2015 to June 2021. This figure shows the selection of GJR-GARCH-DCC models, based on minimising the values of four information criteria, AIC, HQ, SC and FPE.

\textsuperscript{2}For the sake of brevity, this study lists these negative dynamic correlation periods in the section A.2.
<table>
<thead>
<tr>
<th>Panel A (1): estimates of AR(1)-GARCH-DCC model</th>
<th>CBDCUI</th>
<th>UCY Price</th>
<th>CBDCUI</th>
<th>UCY Price</th>
<th>CBDCUI</th>
<th>ICRA</th>
<th>CBDCUI</th>
<th>MSCI World Banker Index</th>
<th>VIX</th>
<th>CBDCUI</th>
<th>USRPU</th>
<th>FTCRI All World Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude (1)</td>
<td>0.0607</td>
<td>0.9984</td>
<td>0.0627</td>
<td>0.9954</td>
<td>0.6582</td>
<td>0.9698</td>
<td>0.0648</td>
<td>0.06166</td>
<td>-0.0612</td>
<td>-9.4477**</td>
<td>0.0033</td>
<td>21.2849**</td>
</tr>
<tr>
<td>(0.0727)</td>
<td>(1.0020)</td>
<td>(0.0758)</td>
<td>(1.0325)</td>
<td>(0.7858)</td>
<td>(2.7389)</td>
<td>(2.8770)</td>
<td>(2.1267)</td>
<td>(3.3213)</td>
<td>(1.0016)</td>
<td>(1.0442)</td>
<td>(2.0046)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.1555</td>
<td>0.3755</td>
<td>0.1050</td>
<td>0.3209</td>
<td>0.1779</td>
<td>0.2818</td>
<td>0.0085</td>
<td>-0.0037</td>
<td>0.0117</td>
<td>0.0474**</td>
<td>0.00009</td>
<td>0.00006</td>
</tr>
<tr>
<td>(0.2603)</td>
<td>(0.9564)</td>
<td>(0.6523)</td>
<td>(0.8968)</td>
<td>(0.7353)</td>
<td>(1.8359)</td>
<td>(1.2674)</td>
<td>(1.8285)</td>
<td>(1.3062)</td>
<td>(0.0089)</td>
<td>(0.7743)</td>
<td>(0.9254)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>GARCH (1)</td>
<td>0.7099</td>
<td>0.4764</td>
<td>0.8241</td>
<td>0.5874</td>
<td>0.8869</td>
<td>0.7641**</td>
<td>0.0032</td>
<td>0.7578**</td>
<td>0.4359**</td>
<td>0.0585**</td>
<td>0.7708**</td>
<td>0.7082**</td>
</tr>
<tr>
<td>DCC probability</td>
<td>0.6377</td>
<td>0.6352</td>
<td>0.6352</td>
<td>0.6352</td>
<td>0.6352</td>
<td>0.6352</td>
<td>0.6352</td>
<td>0.6352</td>
<td>0.6352</td>
<td>0.6352</td>
<td>0.6352</td>
<td>0.6352</td>
</tr>
<tr>
<td>V (joint distribution)</td>
<td>0.0047</td>
<td>-0.324**</td>
<td>0.0047</td>
<td>-0.324**</td>
<td>0.0047</td>
<td>-0.324**</td>
<td>0.0047</td>
<td>-0.324**</td>
<td>0.0047</td>
<td>-0.324**</td>
<td>0.0047</td>
<td>-0.324**</td>
</tr>
<tr>
<td>Table 7.5: Estimate from the CBDCUI GJR-GARCH-DCC model</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01.
### Table 7.6: Estimate from the CBDCAI GJR-GARCH-DCC model

<table>
<thead>
<tr>
<th>Panel (A): estimation of AR(1)-GARCH(1,1) model</th>
<th>CBDCAI</th>
<th>UCIT-Roy</th>
<th>CBDCAI</th>
<th>UCIT Price</th>
<th>CBDCAI</th>
<th>ISEA</th>
<th>CBDCAI</th>
<th>MSCI World Banks Index</th>
<th>CBDCAI</th>
<th>VIX</th>
<th>CBDCAI</th>
<th>USGFI</th>
<th>CBDCAI</th>
<th>FTSE All World Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const. (r)</td>
<td>0.0061∗</td>
<td>0.0061</td>
<td>0.0013</td>
<td>0.0055</td>
<td>0.0029</td>
<td>0.0014</td>
<td>0.0015</td>
<td>-0.0325</td>
<td>-0.0761</td>
<td>0.0048</td>
<td>2.3537</td>
<td>-0.0345</td>
<td>-0.2424</td>
<td>-0.0304</td>
</tr>
<tr>
<td>AR1 (r)</td>
<td>(0.0061)</td>
<td>(0.0108)</td>
<td>(0.0013)</td>
<td>(0.0055)</td>
<td>(0.0029)</td>
<td>(0.0014)</td>
<td>(0.0015)</td>
<td>-0.3806</td>
<td>-0.3385</td>
<td>0.0284</td>
<td>1.0331</td>
<td>0.0096</td>
<td>-0.0948</td>
<td>-0.3712</td>
</tr>
<tr>
<td>AR2 (r)</td>
<td>0.0258∗</td>
<td>0.0258</td>
<td>0.0013</td>
<td>0.0055</td>
<td>0.0029</td>
<td>0.0014</td>
<td>0.0015</td>
<td>-0.3806</td>
<td>-0.3385</td>
<td>0.0284</td>
<td>1.0331</td>
<td>0.0096</td>
<td>-0.0948</td>
<td>-0.3712</td>
</tr>
<tr>
<td>GARCH (1,1)</td>
<td>(0.0108)</td>
<td>(0.0174)</td>
<td>(0.0055)</td>
<td>(0.0055)</td>
<td>(0.0029)</td>
<td>(0.0014)</td>
<td>(0.0015)</td>
<td>-0.3806</td>
<td>-0.3385</td>
<td>0.0284</td>
<td>1.0331</td>
<td>0.0096</td>
<td>-0.0948</td>
<td>-0.3712</td>
</tr>
<tr>
<td>GJR</td>
<td>-0.0689∗</td>
<td>-0.0455</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
<td>-0.0321</td>
</tr>
<tr>
<td>DCC probability</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
<td>0.8048</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
7.4.2 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 be 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 this study assumes that the standardised errors follow a multivariate normal distribution in the DCC-GJR-GARCH (1,1) models, this study should confirm that the residuals of the estimated models are normally distributed; (7) no serial correlation in the squared residuals. This study processes 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 7.5 and Table 7.6. 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. This study applies 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. 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.

### 7.5 A Comprehensive Interpretation of Empirical Findings

To start, this study wants 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 7.2 and Figure 7.7, this study finds that the high CBDCUI values are aroused by unfavourable news regarding CBDC or cryptocurrency flash events. As this study 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 (Akyldirim et al., 2020) and (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 7.2 and Figure 7.8, this study 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) and (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) and (Yan et al., 2022). Fourth, this study also desires 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, this study 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 (Fantacci and Gobbi, 2021), 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 estimation 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 7.2 and Figure 7.8, this study can see that excellent news about CBDCs spikes the high CBDC attention value (e.g., the CBDCs’ new developments). As this study 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, this study wants to explain the relationships between CBDC and uncertainty indices (i.e., VIX and USEPU). Moreover, this study will further elucidate
7.5. A COMPREHENSIVE INTERPRETATION OF EMPIRICAL FINDINGS

on the inconsistency between the two sets of relationships. The 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 (McLaughlin, 2021) and (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 the unconditional correlation table Table 7.1 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, the 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, this study knows 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, this study wants to illustrate that why CBDC indices have a significant positive relationship with the safe-haven, gold. This empirical evidence confirms the 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) and (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 (Williamson, 2021; Fernández-Villaverde et al., 2021; 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 curren-
cies, 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, this study seeks 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 (Copeland, 2020; McLaughlin, 2021; Buckley et al., 2021). Moreover, this empirical proof is consistent with (Tong and Jiayou, 2021) and (Barrdear and Kumhof, 2021), who suggest that CBDCs can improve financial inclusion, mitigate systemic financial risk and raise GDP. In point three, this study has 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, this study needs 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.
7.6 Robustness Test

As this study seeks to identify the effects of CBDC indices on financial markets, this study selects the SVAR and DCC-GJR-GARCH models as the two econometrics models that would most effectively help to achieve the research aim. In order to obtain a more rigorous conclusion, this study considers 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 the empirical analysis, this study concludes that both CBDC indices have a significantly negative relationship with the MSCI World Bank Index, USEPU, and FTSE All-World Index. Moreover, both CBDC indices have a significantly positive relationship with the other financial variables. Therefore, the 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, this study only selects Bitcoin as a proxy to represent the broader cryptocurrency market in the main empirical analysis. In the robustness test, this study considers including a more comprehensive cryptocurrency proxy, CRIX (Trimborn and Hardle, 2018), to capture the cryptocurrency market. It allows to closely track of the evolution of the diverse, abnormal volatile, and frequently changing in cryptocurrency market with a small number of constituents (a minimum of five cryptocurrency assets, which are verified as investable). CRIX is widely used as a broad cryptocurrency market indicator to investigate the relationships between the cryptocurrency market and other financial markets (Trimborn and Hardle, 2018). This study collects the CRIX from S&P Global.

In order to evaluate the reliability of the empirical results, this study first further analyses the relationship between CBDC indices risk and financial variables’ volatility. The hypothesis is as follows:

\[ H_0: \text{CBDC indices risk increases, financial variables’ volatility also increases.} \]

Or

\[ H_0: \text{CBDC indices risk increases, financial variables’ volatility decreases.} \]

To evaluate the significance of the relationship, this study follows the methodologies of (Pástor and Veronesi, 2013) and (Al Mamun et al., 2020). The regression model is as follows Equation 7.2:
CHAPTER 7. THE EFFECTS OF CENTRAL BANK DIGITAL CURRENCIES
NEWS ON FINANCIAL MARKETS

\[ FV_t = \beta_1 + \beta_2 CBDC_t + \beta_3 FV_{t-1} + \epsilon_t, \]

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 \( FV_t \). \( \epsilon \) is the error term.

This study tests 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 7.7 columns (1) and (2).

The results in columns (1) and (2) show the significance of the results at the 10% level. The \( \beta_2 \) values of the MSCI World Bank Index, USEPU, and FTSE All-World Index in the CBDCUI and CBDCAI are less than zero, thus implying that the volatility of these three financial variables have 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 \( \beta_2 \) values of the other financial variables (except for the three just discussed) are greater than zero, thereby indicating a positive relationship between these financial variables and the CBDCUI or CBDCAI. These additional results accord with the former empirical analysis, thus proving the main findings’ robustness.

Second, while this study still follows the formula of Equation 7.2, this study calculates 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 \( \overline{r}_{t+i} = 100 \times \ln(S_{t+i}/S_{t+i-1}) \) are the one-period return and the average return for \( T \) periods. The results are shown in Table 7.7 columns (3) and (4).

From the results in columns (3) and (4), although this study calculates all of the variables in a realised variance, the relationships between the financial variables and the CBDC indices (which this study demonstrates in the former empirical analysis) still hold in the Equation 7.2. Moreover, the MSCI World Banks Index, USEPU, and FTSE All-World Index could show 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 are also still at the 10% level. The results from this Equation 7.2 further prove the robustness of the main empirical findings.

Secondly, the robustness test of the results can be confirmed using the methodology of Whaley (2009). When $CBDC_t$ displayed a negative relationship with $FV_t$, this study finds that the changes in $CBDC_t$ rise at a higher absolute rate when the $FV_t$ falls than when it increases. In other words, when $CBDC_t$ shows 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 7.3:

\[
CBDC_t = \beta_1 + \beta_2 FV_t + \beta_3 FV^t - + \epsilon_t,
\]

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

First, if CBDC has a positive relationship with $FV$, both of the slope coefficients of $FV$ and $FV^t$ 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 $FV^t$ less than, but the coefficient value of $FV$ would be greater than that of $FV^t$. If CBDC has a negative relationship with $FV$, both of the slope coefficients of $FV$ and $FV^t$ should be less than zero.

The results are shown in Table 7.7 columns (5) and (6). The results of the robustness test could confirm the empirical results reported earlier. Moreover, the results allow one 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 markets. Moreover, this finding can further confirm the positive relationship between the CBDC indices and Bitcoin, which has been proved above.

Table 7.7: Uncertainty risk and volatility structure risk

<table>
<thead>
<tr>
<th>CBDC risk (CCR)</th>
<th>CBDC risk (RV)</th>
<th>CBDC risk (R)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CBDCUI</strong> (1)</td>
<td><strong>CBDCUI</strong> (2)</td>
<td><strong>CBDCUI</strong> (3)</td>
</tr>
<tr>
<td>UCRY Policy</td>
<td>0.7003***</td>
<td>0.6334***</td>
</tr>
<tr>
<td></td>
<td>(0.0529)</td>
<td>(0.0995)</td>
</tr>
<tr>
<td>UCRY Price</td>
<td>0.6555***</td>
<td>0.6366***</td>
</tr>
<tr>
<td></td>
<td>(0.0526)</td>
<td>(0.0963)</td>
</tr>
<tr>
<td>ICEA</td>
<td>0.3969***</td>
<td>0.7964***</td>
</tr>
<tr>
<td></td>
<td>(0.0461)</td>
<td>(0.0681)</td>
</tr>
<tr>
<td>MSCI WBI</td>
<td>−0.0985*</td>
<td>−0.5429*</td>
</tr>
<tr>
<td></td>
<td>(0.3749)</td>
<td>(0.6023)</td>
</tr>
<tr>
<td>VIX</td>
<td>0.1592**</td>
<td>0.1531**</td>
</tr>
<tr>
<td></td>
<td>(0.0538)</td>
<td>(0.0543)</td>
</tr>
<tr>
<td>USEPU</td>
<td>−0.2394**</td>
<td>−0.2406***</td>
</tr>
<tr>
<td></td>
<td>(0.0528)</td>
<td>(0.0522)</td>
</tr>
<tr>
<td>FTSE AWI</td>
<td>−0.0995**</td>
<td>−0.2122*</td>
</tr>
<tr>
<td></td>
<td>(0.2267)</td>
<td>(0.4129)</td>
</tr>
<tr>
<td>EUR/USD</td>
<td>0.1238*</td>
<td>0.0216*</td>
</tr>
<tr>
<td></td>
<td>(0.1323)</td>
<td>(0.2124)</td>
</tr>
<tr>
<td>GBP/USD</td>
<td>0.1800*</td>
<td>0.3351*</td>
</tr>
<tr>
<td></td>
<td>(0.1607)</td>
<td>(0.2573)</td>
</tr>
<tr>
<td>JPY/USD</td>
<td>0.2524*</td>
<td>0.1240*</td>
</tr>
<tr>
<td></td>
<td>(0.1316)</td>
<td>(0.2120)</td>
</tr>
<tr>
<td>RUB/USD</td>
<td>0.0281*</td>
<td>0.1526*</td>
</tr>
<tr>
<td></td>
<td>(0.2429)</td>
<td>(0.3894)</td>
</tr>
<tr>
<td>CNY/USD</td>
<td>0.0411*</td>
<td>0.0305*</td>
</tr>
<tr>
<td></td>
<td>(0.0664)</td>
<td>(0.1064)</td>
</tr>
<tr>
<td>Gold</td>
<td>0.3893*</td>
<td>0.0704*</td>
</tr>
<tr>
<td></td>
<td>(0.2329)</td>
<td>(0.3747)</td>
</tr>
<tr>
<td>Bitcoin</td>
<td>0.4789*</td>
<td>0.6257*</td>
</tr>
<tr>
<td></td>
<td>(1.2138)</td>
<td>(1.9506)</td>
</tr>
<tr>
<td>FTSE WGBI</td>
<td>0.1049*</td>
<td>0.0174*</td>
</tr>
<tr>
<td></td>
<td>(0.0968)</td>
<td>(0.1554)</td>
</tr>
<tr>
<td>CRIX</td>
<td>1.3877**</td>
<td>0.7933**</td>
</tr>
<tr>
<td></td>
<td>(1.196)</td>
<td>(1.792)</td>
</tr>
</tbody>
</table>

This table presents the results of the impacts of CBDC indices on UCRY Policy, UCRY Price, 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. Columns (1), (2), (3) and (4) are the regression results of the formula: \( FV_t = \beta_1 + \beta_2 CBDC_t + \beta_3 FV_{t-1} + \varepsilon_t \). All the variables are calculated by the continuously compounded returns in Columns (1) and (2). All the variables are calculated by the realised variance in Columns (3) and (4). Columns (5) and (6) are the regression results of the formula: \( CBDC_t = \beta_1 + \beta_2 FV_t + \beta_3 FV_{t-1} + \varepsilon_t \). All the variables are calculated by the continuously compounded returns in Columns (5) and (6). *p<0.1; **p<0.05; ***p<0.01.
7.7 Chapter Summary

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

The new CBDC Uncertainty Index (CBDCUI) and the CBDC Attention Index (CBDCAI) have been constructed and made available for the period from January 2015 to June 2021. This study employs the empirical test to examine the behaviour of CBDC indices 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.

The 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 CBDCs can bring significant changes to the economy. The 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.
While early research suggests that Bitcoin is by far the most influential cryptocurrency (Corbet et al., 2020b) and (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) and (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.
The aim of this study is to investigate the volatility spillover connectedness between NFTs attention and financial markets. This study firstly proposes a new direct proxy for the public’s attention in the NFT market: the non-fungible tokens attention index (NFTsAI), based on 590m news stories from the LexisNexis News & Business database and applies the historical decomposition to assess the historical variations of the NFTsAI. Then the empirical analysis is performed via a TVP-VAR volatility spillover connectedness model. The empirical results show that NFTsAI indicates NFT markets are dominated by cryptocurrency, DeFi, equity, bond, commodity, F.X. and gold markets. And NFT markets are volatility spillover receivers. In addition, NFT assets could impede financial contagion and have significant diversification benefits. Employing a panel pooled OLS regression model as a supplementary analysis and a GARCH-MIDAS model as a robustness test. This study reveals that NFTsAI has sufficient power to explain the return of NFT assets from a fixed effect perspective, and NFTsAI contains useful forecasting information for both short and long-term volatility of NFT markets, separately. The new NFTsAI and the empirical findings contain useful insights for risk-averse investors, portfolio managers, institutional investors, academics and financial policy regulators on how NFTsAI could act as an indicator in the new digital currency era.
CHAPTER 8. VOLATILITY SPILLOVERS ACROSS NFTS NEWS ATTENTION AND FINANCIAL MARKETS

8.1 NFTs Attention Index

Figure 8.1 shows the weekly values for the derived indices based on 590,440,560 news items collected between January 2017 and May 2022. This study also annotates which NFT flash events cause spikes on the NFTsAI in Figure 8.1 and the flash events are collected according to the frequency of articles that have the same topic. These annotated events allow readers to understand new NFT developments or major events that could stimulate the newly-constructed NFT index. From the plot, NFTsAI can divide the developments of NFTs into five stages. It is worth noting that the highest value of NFTsAI is recorded in the fourth stage, wherein some hot NFTs events like the Sandbox reached a market capitalisation of $648.35 million, Bored Ape Yacht Club 58,118% ROI, and an NFT sales volume of $3 billion significantly heighten the NFTsAI. These events serve to indicate the NFT market’s extreme prosperity and heat during this period.

8.2 Summary Statistics

NFTsAI is a weekly frequency index, and the TVP-VAR model requires one to process this model in the same frequency data series. Moreover, the daily return of NFTs and cryptocurrencies contain significant outliers (Dowling, 2022; Ko et al., 2022; Urquhart, 2016), but the weekly average price can address this issue. In the end, (Diebold and Yilmaz, 2009) and (Diebold and Yilmaz, 2012) have proven that TVP-VAR can generate solid and reliable empirical results by using the low-frequency data. Based on the above reasons, this study applies weekly frequency data for all the collected variables.

Table 8.1 Panel A-1 and Panel A-2 display the descriptive statistics for the raw data. As a key NFT asset in the NFT markets, CryptoPunks has the largest mean and standard deviation value, even higher than the well-known high fluctuation asset, Bitcoin (Urquhart and Lucey, 2022). These results reflect the prosperity and fluctuation of the NFT markets. There is no skewness value equal to 0, which indicates asymmetry. The kurtosis values of NFTsAI, CryptoPunks, Decentraland, Chainlink, Maker, and DBC are greater than 0, especially for Decentraland and CryptoPunks, indicating a leptokurtic distribution. The kurtosis values of the other variables are all negative, which means that the distributions of these variables

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1For more details about the NFTsAI and relevant big events, please see the section B.1.
8.2 SUMMARY STATISTICS

Figure 8.1: NFTs Attention Index with annotated events

Notes: This index reflected scaled weekly counts of articles containing "Non-fungible tokens" OR "NFTs" OR "digital art" OR "crypto art" OR "cryptocurrency art" OR "artwork tokenised" OR "digital image licensing" OR "digital collectibles" OR "crypto collectibles" OR "cryptocurrency collectibles" OR "digital identity" OR "IdToken" OR "token unique" OR "unique digital property" OR "CryptoKitties" OR "WCK" OR "CryptoPunks" OR "Axie Infinity" OR "Bored Ape Yacht Club" OR "The Sandbox" OR "Art Blocks" OR "nonfungible.com". This series is standardised and then 100 from 26/12/2016 to 05/06/2022 based on queries. LexisNexis News & Business is the selected database. Flash events related to NFTsAI are annotated on the time series plot. Flash events are collected according to the frequency of articles that have a similar topic during week t.
have lighter tails than the normal distributions. The Jarque-Bera (J.-B.) test also confirms these findings. The statistical results from the Ljung-Box test indicate that all of the variables’ residuals are not independently distributed and confirm the presence of serial correlations in all return series. Considering the results of the ADF, KPSS, and PP unit root tests, this study can confirm the presence of unit roots in all the variables.

In the VAR model, all the variables should keep stationary without unit roots (Lütkepohl, 2005). Moreover, volatility spillover connectedness analysis requires one to use data in its logarithm return level (Diebold and Yilmaz, 2012). To measure the logarithm return (volatility) for each variable, I calculate the logarithm returns by processing the first-difference in the logarithmic values of two consecutive prices, denoted as: \( CCR_{i,t} = \ln(P_{i,t}/P_{i,t-1}) \times 100 \), where \( CCR_{i,t} \) denotes the logarithm percentage returns for variable \( i \) at time \( t \), while \( P_{i,t} \) denotes the price level of variable \( i \) at time \( t \).

Table 8.1 Panel B-1 and Panel B-2 show the descriptive statistics for the logarithm returns of the variables used for empirical analysis. CryptoPunks still has the largest value of mean and standard deviation. Decentraland is ranked as the second, indicating the risk-return trade-off in the NFT markets. All return series are still asymmetry distributed, and all of them have a peak and thick tail. Serial correlations are not present in the BGCI, Bitcoin, Ethereum, FTSEAWI, FTSEWGBI and DBC these six variables at their logarithm return levels. Finally, the three different unit root tests can confirm that all the return series are stationary without unit-roots. Figure 8.2 shows the weekly price and logarithm return on each asset. NFT markets skyrocketed in late 2021, and then NFT markets took a nosedive in 2022, indicating that NFT markets exhibit higher fluctuations and uncertainties than the other financial markets.
Table 8.1: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>NFTsAI</th>
<th>CryptoPunks</th>
<th>Decentraland</th>
<th>Chainlink</th>
<th>Maker</th>
<th>BGCI</th>
<th>Bitcoin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observation</td>
<td>231</td>
<td>231</td>
<td>231</td>
<td>231</td>
<td>231</td>
<td>231</td>
<td>231</td>
</tr>
<tr>
<td>Mean</td>
<td>100.70</td>
<td>63326.13</td>
<td>2833.57</td>
<td>9.55</td>
<td>1197.99</td>
<td>1098.98</td>
<td>20404.71</td>
</tr>
<tr>
<td>Min</td>
<td>99.51</td>
<td>23.46</td>
<td>15.25</td>
<td>0.19</td>
<td>240.46</td>
<td>197.59</td>
<td>3258.84</td>
</tr>
<tr>
<td>Max</td>
<td>108.67</td>
<td>619540.07</td>
<td>25069.90</td>
<td>47.77</td>
<td>5361.07</td>
<td>3715.11</td>
<td>65466.84</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1.93</td>
<td>129476.99</td>
<td>4957.41</td>
<td>10.99</td>
<td>1018.51</td>
<td>953.62</td>
<td>18080.97</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.85</td>
<td>2.30</td>
<td>2.92</td>
<td>1.08</td>
<td>1.44</td>
<td>1.02</td>
<td>0.96</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.37</td>
<td>4.50</td>
<td>9.57</td>
<td>0.14</td>
<td>1.47</td>
<td>-0.31</td>
<td>-0.61</td>
</tr>
<tr>
<td>Ljung-Box</td>
<td>207.95*</td>
<td>208.11**</td>
<td>190.57***</td>
<td>225.15***</td>
<td>224.26***</td>
<td>225.96***</td>
<td>228.22***</td>
</tr>
<tr>
<td>J-B.</td>
<td>189.63***</td>
<td>406.76***</td>
<td>1234**</td>
<td>45.998***</td>
<td>102.55***</td>
<td>41.627***</td>
<td>39.035***</td>
</tr>
<tr>
<td>ADL</td>
<td>-1.3881</td>
<td>-2.5257</td>
<td>-2.3498</td>
<td>-1.6461</td>
<td>-2.1389</td>
<td>-2.2439</td>
<td>-2.369</td>
</tr>
<tr>
<td>KPSS</td>
<td>2.6885***</td>
<td>2.2605***</td>
<td>1.7326***</td>
<td>3.3172***</td>
<td>2.4178***</td>
<td>2.8496***</td>
<td>3.3723***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Ethereum</th>
<th>FTSEAWI</th>
<th>FTSEWGBI</th>
<th>PIMCCORP</th>
<th>DBC</th>
<th>DXY</th>
<th>Gold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observation</td>
<td>231</td>
<td>231</td>
<td>231</td>
<td>231</td>
<td>231</td>
<td>231</td>
<td>231</td>
</tr>
<tr>
<td>Mean</td>
<td>1119.25</td>
<td>384.11</td>
<td>999.36</td>
<td>101.49</td>
<td>16.82</td>
<td>95.25</td>
<td>1176.50</td>
</tr>
<tr>
<td>Min</td>
<td>85.26</td>
<td>262.18</td>
<td>887.46</td>
<td>88.00</td>
<td>10.70</td>
<td>89.07</td>
<td>1176.50</td>
</tr>
<tr>
<td>Max</td>
<td>4626.36</td>
<td>498.35</td>
<td>1998.56</td>
<td>113.07</td>
<td>29.88</td>
<td>104.56</td>
<td>2010.10</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1272.00</td>
<td>60.70</td>
<td>52.85</td>
<td>8.68</td>
<td>3.73</td>
<td>3.25</td>
<td>256.10</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.16</td>
<td>0.51</td>
<td>-0.05</td>
<td>-0.23</td>
<td>1.35</td>
<td>0.06</td>
<td>-0.13</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>-0.01</td>
<td>1.17</td>
<td>-1.13</td>
<td>-1.47</td>
<td>2.02</td>
<td>-0.50</td>
<td>-1.56</td>
</tr>
<tr>
<td>Ljung-Box</td>
<td>227.34***</td>
<td>227.97***</td>
<td>223.61***</td>
<td>226.79***</td>
<td>217.88***</td>
<td>212.04***</td>
<td>227.78***</td>
</tr>
<tr>
<td>J-B.</td>
<td>52.741***</td>
<td>23.136***</td>
<td>11.947***</td>
<td>22.626***</td>
<td>112.21***</td>
<td>2.3336</td>
<td>23.555***</td>
</tr>
<tr>
<td>ADL</td>
<td>-2.1138</td>
<td>-1.9971</td>
<td>0.40736</td>
<td>0.46699</td>
<td>0.585</td>
<td>-1.6664</td>
<td>-1.9632</td>
</tr>
<tr>
<td>KPSS</td>
<td>3.0493***</td>
<td>3.6678***</td>
<td>2.1362***</td>
<td>3.7443***</td>
<td>1.8593***</td>
<td>1.45573***</td>
<td>4.1705***</td>
</tr>
</tbody>
</table>

Panel B-1: volatility

<table>
<thead>
<tr>
<th></th>
<th>NFTsAI</th>
<th>CryptoPunks</th>
<th>Decentraland</th>
<th>Chainlink</th>
<th>Maker</th>
<th>BGCI</th>
<th>Bitcoin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observation</td>
<td>230</td>
<td>230</td>
<td>230</td>
<td>230</td>
<td>230</td>
<td>230</td>
<td>230</td>
</tr>
<tr>
<td>Mean(%)</td>
<td>0.02</td>
<td>2.41</td>
<td>0.21</td>
<td>0.90</td>
<td>0.05</td>
<td>-0.09</td>
<td>0.26</td>
</tr>
<tr>
<td>Min(%)</td>
<td>-5.22</td>
<td>-204.84</td>
<td>-151.65</td>
<td>-47.45</td>
<td>-45.02</td>
<td>-55.83</td>
<td>-40.79</td>
</tr>
<tr>
<td>Max(%)</td>
<td>5.76</td>
<td>222.36</td>
<td>160.69</td>
<td>42.64</td>
<td>60.69</td>
<td>34.51</td>
<td>26.07</td>
</tr>
<tr>
<td>Std. Dev.(%)</td>
<td>5.59</td>
<td>48.22</td>
<td>56.78</td>
<td>15.47</td>
<td>12.92</td>
<td>11.53</td>
<td>10.42</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.17</td>
<td>-0.12</td>
<td>0.09</td>
<td>-0.09</td>
<td>0.21</td>
<td>-0.82</td>
<td>-0.60</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>65.97</td>
<td>4.15</td>
<td>0.38</td>
<td>0.53</td>
<td>2.76</td>
<td>3.12</td>
<td>1.39</td>
</tr>
<tr>
<td>Ljung-Box</td>
<td>43.639***</td>
<td>18.741***</td>
<td>36.128***</td>
<td>16.387***</td>
<td>20.922***</td>
<td>1.4539</td>
<td>2.0992</td>
</tr>
<tr>
<td>J-B.</td>
<td>42528***</td>
<td>170.35***</td>
<td>19.328***</td>
<td>32.528***</td>
<td>77.599***</td>
<td>122.36***</td>
<td>33.637***</td>
</tr>
<tr>
<td>ADL</td>
<td>-6.9025**</td>
<td>-6.2508***</td>
<td>-5.8573***</td>
<td>-5.9406***</td>
<td>-6.8288***</td>
<td>-5.8926***</td>
<td>-5.7697***</td>
</tr>
<tr>
<td>KPSS</td>
<td>0.0997</td>
<td>0.2416</td>
<td>0.0619</td>
<td>0.1826</td>
<td>0.1074</td>
<td>0.3451</td>
<td>0.2584</td>
</tr>
<tr>
<td>PP</td>
<td>-292.29***</td>
<td>-269.46***</td>
<td>-298.66***</td>
<td>-165.87***</td>
<td>-151.73***</td>
<td>-213.47***</td>
<td>-204.71***</td>
</tr>
</tbody>
</table>

Panel B-2: volatility

Notes: Ljung-Box test for the distribution of residuals in a variable (Box and Pierce, 1970) and (Ljung and Box, 1978), and it can examine the autocorrelation of squared returns series; Jarque-Bera (J-B.) statistics can be used to check the normal distribution characteristic of the data (Jarque and Bera, 1980) and (Bera and Jarque, 1981); ADL, PP and KPSS these three unit root tests refer to Augmented Dickey-Fuller test (Dickey and Fuller, 1979), Phillips-Perron test (Phillips and Perron, 1988) and Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al., 1992). * p<0.1; ** p<0.05; *** p<0.01.
Figure 8.2: Time series of price and dynamics returns of each index on a weekly basis.

Notes: The graphs displayed above are the weekly price and logarithm return across time for each of the system variables. The sample period visualised is 26/Dec/2016 to 05/Jun/2022. CP, DL, CORP, DXY and Gold represents CryptoPunks, Decentraland, PIMCOCORP, US Dollar Index and COMEX Gold, separately.
8.3 NFTsAI Evolution

NFTsAI is a newly issued index. In order to assess the characteristics of the NFTsAI and prove it can be deeply used to further empirical analysis. It is essential to analyse the historical evolution of NFTsAI and the contribution of each of the structural shocks to variations in NFTsAI following significant historical episodes. The historical evolution of NFTsAI can be specified as Equation 8.1:

\[
\begin{bmatrix}
    u_{t}^{\text{NFTsAI}} \\
    u_{t}^{\text{CryptoPunks}} \\
    u_{t}^{\text{Decentraland}} \\
    u_{t}^{\text{Chainlink}} \\
    u_{t}^{\text{Maker}} \\
    u_{t}^{\text{BGCI}} \\
    u_{t}^{\text{Bitcoin}} \\
    u_{t}^{\text{Ethereum}} \\
    u_{t}^{\text{FTSEAWI}} \\
    u_{t}^{\text{FTSEWGBI}} \\
    u_{t}^{\text{PIMCOCORP}} \\
    u_{t}^{\text{DBC}} \\
    u_{t}^{\text{DXY}} \\
    u_{t}^{\text{Gold}}
\end{bmatrix} =
\begin{bmatrix}
    S_{11} & 0_{12} & 0_{13} & \cdots & 0_{112} & 0_{113} & 0_{114} \\
    S_{21} & S_{22} & 0_{23} & \cdots & 0_{212} & 0_{213} & 0_{214} \\
    S_{31} & S_{32} & S_{33} & \cdots & 0_{312} & 0_{313} & 0_{314} \\
    S_{41} & S_{42} & S_{43} & \cdots & 0_{412} & 0_{413} & 0_{414} \\
    S_{51} & S_{52} & S_{53} & \cdots & 0_{512} & 0_{513} & 0_{514} \\
    S_{61} & S_{62} & S_{63} & \cdots & 0_{612} & 0_{613} & 0_{614} \\
    S_{71} & S_{72} & S_{73} & \cdots & 0_{712} & 0_{713} & 0_{714} \\
    S_{81} & S_{82} & S_{83} & \cdots & 0_{812} & 0_{813} & 0_{814} \\
    S_{91} & S_{92} & S_{93} & \cdots & 0_{912} & 0_{913} & 0_{914} \\
    S_{101} & S_{102} & S_{103} & \cdots & 0_{1012} & 0_{1013} & 0_{1014} \\
    S_{111} & S_{112} & S_{113} & \cdots & 0_{1112} & 0_{1113} & 0_{1114} \\
    S_{121} & S_{122} & S_{123} & \cdots & 0_{1212} & 0_{1213} & 0_{1214} \\
    S_{131} & S_{132} & S_{133} & \cdots & 0_{1312} & 0_{1313} & 0_{1314} \\
    S_{141} & S_{142} & S_{143} & \cdots & 0_{1412} & 0_{1413} & 0_{1414}
\end{bmatrix}
\]

where, \( u_{t} \) denotes the reduced form disturbances (forecast errors) at time \( t \), \( \varepsilon_{t} \) denotes the structural shocks at time \( t \).

Figure 8.3 shows the historical variations of NFTsAI with annotated events\(^2\). The variations of NFTsAI are highlighted in purple. To identify NFTsAI disturbances’ cumulative contributions, this study sets the historical variations of NFTsAI on the right-hand axis as a secondary axis. Historical variations of the other variables’ are on the left-hand axis as the primary axis. NFTsAI is constructed based on text mining, so historical decomposition analysis in the NFTsAI takes significant historical episodes as the entry point. Several novelty findings are highlighted in the following sections:

First, there is a trend of the representative of the NFT market, CryptoPunks

\(^2\)The details of the NFTsAI related events are listed in the section B.1

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and Decentraland, co-move with NFTsAI. This finding suggests that the higher the NFTs attention, the higher NFT asset volatility. This finding also proves that NFTsAI can serve as an NFT market proxy. In this way, $H_6$ can hold. Second, the historical variations of NFTsAI reasonably match exceptions. The positive news concerning the NFT markets produces a positive shock on the historical variations of NFTsAI, and the negative news concerning the NFT markets contributes to a negative shock in the results. For example, NFTs’ $2.5$ billion sales volume and $315\%$ trading volume increased month-on-month; Bored Ape Yacht Club’s $58,118\%$ return on investment, are positive news events reflecting the prosperity of the NFT market, which, in turn, cause significant spikes in the historical variations of NFTsAI. Following NFT market hype warnings, NFT sale prices dropped, new regulations on anti-money laundering concerning trading NFTs were implemented, NFTs price bubbles popped, and the NFT platform was hacked. These negative news events reveal that the volatility and uncertainty of the NFT markets can cause the historical variations of NFTsAI to plummet. Third, the historical variation results of the NFTsAI show a volatile trend between January 2021 and June 2022. There are three potential reasons for this. Firstly, with the development of the NFT markets since 2021, more investors have seized the speculation opportunities of the NFT markets. These kinds of speculation activities in the NFT markets contribute to the volatilities of NFT markets. Secondly, the volatility cryptocurrency markets also contain a significant amount of cryptocurrency uncertainties between January 2021 and June 2022 (Lucey et al., 2022). These cryptocurrency uncertainties could transmit to the NFT markets as the speculators will reduce their net long positions in cryptocurrencies and search for alternative digital assets to hedge the uncertainty from cryptocurrency markets. These behaviours may affect the trading volume of NFT assets and bring more speculation activities to NFT markets, causing further volatilities in the NFT markets. Thirdly, NFT assets can be valued as digital art assets, and art markets always show volatility during periods of financial uncertainty (Rezaee and Sequeira, 2021).
8.4 Volatility Spillover Connectedness Analysis

8.4.1 Generalised volatility spillover connectedness table

Developing the time-varying volatility spillover connectedness econometrics framework allows one to formulate its generalised table. This table allows one to understand the various connected measures and their relationships in terms of time. The variance and spectral decomposition matrix, defined as \( A_{h,p,i,jz} \), is listed on the main upper-left \( N \times N \) block, and contains the variance and spectral decomposition results. In this type of table, the summing of columns can contribute to increasing \( A_{h,p,i,jz} = [a_{h,p,i,jz}] \) with a bottom row. The row sums are shown in the rightmost column, and the grand average can be found in the bottom-right. The generalised table can be found in Table 8.2.

Table 8.2: Generalised volatility spillover connectedness table

<table>
<thead>
<tr>
<th>NFTsAI,1</th>
<th>CryptoPunks,2</th>
<th>Decentraland,3</th>
<th>DBC,12</th>
<th>DXY,13</th>
<th>Gold,14</th>
<th>FROM OTHERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>NFTsAI,1</td>
<td>NFTsAI,1,2</td>
<td>NFTsAI,1,3</td>
<td>...</td>
<td>NFTsAI,1,13</td>
<td>NFTsAI,1,14</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 1 )</td>
</tr>
<tr>
<td>CryptoPunks,2</td>
<td>CryptoPunks,2,3</td>
<td>...</td>
<td>CryptoPunks,2,12</td>
<td>CryptoPunks,2,13</td>
<td>CryptoPunks,2,14</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 2 )</td>
</tr>
<tr>
<td>DXY,13</td>
<td>DXY,13,14</td>
<td>DXY,13,15</td>
<td>...</td>
<td>DXY,13,12</td>
<td>DXY,13,13</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 13 )</td>
</tr>
<tr>
<td>Gold,14</td>
<td>Gold,14,15</td>
<td>Gold,14,16</td>
<td>...</td>
<td>Gold,14,12</td>
<td>Gold,14,13</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 14 )</td>
</tr>
<tr>
<td>TO OTHERS</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 1 )</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 2 )</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 3 )</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 12 )</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 13 )</td>
<td>( \sum_{i=1}^{N} a_{h,i,jz} ) if ( i \neq 14 )</td>
</tr>
</tbody>
</table>

Notes: This table displays the variance decomposition matrix for this study. The 14 \( \times \) 14 matrix contains the 14 forecast error variance decomposition from a connectedness perspective. This matrix can be denoted as: \( A_{h,p,i,jz} \). The rightmost "FROM OTHERS" column presents the sums of off-diagonal row. The bottom "TO OTHERS" row displays the sums of off-diagonal column. The inter-variables' information transmission level can be found in the bottom right, as "GRAND AVERAGE".
Figure 8.3: NFTs Attention Index historical decomposition

Notes: The horizontal axis represents the time sample period, and the vertical axis represents the variations of NFTsAI, CryptoPunks, Decentraland, Chainlink, Maker, BGCI, Bitcoin, Ethereum, FTSEAWI, FTSEWGBI, PIMCO CORP, DBC, US Dollar Index and COMEX Gold volatility in per cent after NFTsAI shocks. Lag = 1. The variations of NFTsAI are highlighted in purple.
8.4. VOLATILITY SPILLOVER CONNECTEDNESS ANALYSIS

8.4.2 Static volatility spillover connectedness using the full sample

Table 8.3 summarises the static estimations of the TVP-VAR spillover connectedness model. The total spillover index can assess the systemic risk transmission. The value of the total spillover index is 50.7%, implying that the internal 14 variables’ risk transmission contributed to approximately half of the overall volatility and mutual shocks in the examined variable system. The following sections further explain the degree of system volatility spillover connectedness.

Considering the static total directional volatility spillover connectedness "FROM", its values are listed in the rightmost column of Table 8.3. "FROM" represents the volatility shocks received from the other 13 variables to each variable in the gross forecast error variance decompositions for each variable. Based on the formulas of Equation 5.72, "FROM" is equal to 100% minus the share of the gross forecast error variance decompositions. The "FROM" values in the Table 8.3 range between 4.7% (BGCI) to 1.8% (CryptoPunks). The "FROM" values of these three variables are over 4.5%, including BGCI (4.7%), Ethereum (4.6%), and Bitcoin (4.5%). These three variables all belong to cryptocurrency indices, indicating that cryptocurrency markets are significantly affected by other financial markets. This finding echoes the results of Ji et al. (2019), who believe that cryptocurrency markets are driven by global financial markets. NFT market proxies hold the lowest "FROM" values, which are NFTsAI (2.6%), Decentraland (2.3%) and CryptoPunks (1.8%). These interesting statistical results indicate that NFT markets are less affected by cryptocurrency, DeFi, equity, bond, commodity, F.X. and gold markets, which suggests the validity of the Hypothesis 7. These findings are in line with the empirical findings of Aharon and Demir (2022); Dowling (2021); Karim et al. (2022); Yousaf and Yarovaya (2022), who believe that NFT markets are relatively independent and isolated from other financial markets. The findings above suggest diversification opportunities when considering NFT assets in portfolios.

Regarding the static total directional volatility spillover connectedness "TO", which is displayed in the third-to-last row in Table 8.3. "TO" represents the total volatility spillover connectedness from each variable’s volatility to other variables’ volatility. In other words, it represents each variable’s contribution to the other’s forecast error variance decompositions. The directional spillover "TO" values can range from 6.1% (BGCI) to CryptoPunks (1.2%). The BGCI transmits the highest
level of volatility (6.1%), followed by Ethereum (5.0%) and Bitcoin (4.7%). These findings prove that NFTs are created based on the algorithm of Ethereum (Chir-toaca et al., 2020). Unsurprisingly, NFT group variables have the three lowest "TO" values, which are Decentraland (2.0%), NFTsAI (1.4%) and CryptoPunks (1.2%), and these statistical results also suggest the validity of the Hypothesis

Regarding the static "NET" total directional volatility spillover connectedness, which is displayed in the second-to-last bottom row of the Table 8.3, the "NET" values show the difference between static total directional volatility spillover connectedness to others and static total directional volatility spillover connectedness from others. The "NET" value of NFTsAI is negative at $-1.1\%$, illustrating that the impact of the NFTsAI on the other 13 variables’ volatility is less than that of the other 13 variables’ volatility. In summary, the NFT market is a volatility receiver, and this finding can be further confirmed by the representative NFT assets, CryptoPunks and Decentraland, which hold a "NET" value of $-0.6\%$ and $-0.3\%$, separately. These findings support the conclusion of (Aharon and Demir, 2022); (Karim et al., 2022); (Yousaf and Yarovaya, 2022), who find that NFTs can act as risk spillover receivers during stressful times. Conversely, BGCI is the largest volatility transmitter, contributing 6.1%, followed by Ethereum (5.0%) and Bitcoin (4.7%). The statistical results of the static "NET" total directional volatility spillover connectedness could confirm the Hypothesis can hold.

The off-diagonal elements of the $14 \times 14$ matrix in Table 8.3 illustrate the static net pairwise directional volatility spillover connectedness between the volatility of two variables. For example, the value 0.3 in row 10, column 2 stands for the percentage of forecast error variance decomposition of the volatility of Ethereum due to the shocks from NFTsAI. Regarding the shocks from NFTsAI, the static net pairwise directional volatility spillover connectedness between NFTsAI and the other financial markets is extremely low, ranging between 0.3% (Ethereum) and 4.1% (PIMCO CORP). The majority of NFTsAI volatility is attributable to endogenous shocks (64.2%), which can provide evidence to support Hypothesis. These findings are confirmed by the selected NFT assets, CryptoPunks (75.0%) and the Decentraland (72.6%). Previous studies also support this view and scholars have suggested that NFT assets may have significant diversification benefits (Aharon and Demir, 2022; Dowling, 2021; Karim et al., 2022; Yousaf and Yarovaya, 2022).

Two factors may contribute to the isolation of NFTs. First, NFTs are new investment assets with an inefficiency price mechanism (Dowling, 2022). Few
investors become involved in the NFT markets compared with the cryptocurrency markets (Mazur, 2021). The trading volume of NFT assets confirms this in nonfungible.com. Therefore, NFT has not been widely used as a hedge asset by risk-averse investors, portfolio managers or institutional investors. Second, the unique properties of NFTs also contribute to their isolation. NFTs can be valued as digital art, making these assets popular among specific culture circles (Valera et al., 2021). Therefore, NFT assets have low liquidity; this low liquidity condition reduces their impact on other financial assets.

### 8.4.3 Dynamic total volatility spillover connectedness using the rolling sample

The above empirical analysis demonstrates the static connectedness by using the full sample data. How this volatility spillover connectedness evolves in time-varying and low-frequency data should also be investigated to reveal the dynamic connectedness between NFTsAI and other financial markets. Figure 8.4 displays the time-varying dynamics of the total volatility spillover connectedness between NFT markets and the other selected financial markets and suggests how spillover effects change over time. Although the static TSCI from the Table 8.3 is 50.7%, it

<table>
<thead>
<tr>
<th>Table 8.3: Static volatility spillover connectedness table</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>From</strong></td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td>NFTsAI</td>
</tr>
<tr>
<td>CP</td>
</tr>
<tr>
<td>DL</td>
</tr>
<tr>
<td>Chainlink</td>
</tr>
<tr>
<td>Maker</td>
</tr>
<tr>
<td>BSC</td>
</tr>
<tr>
<td>Bat</td>
</tr>
<tr>
<td>ETH</td>
</tr>
<tr>
<td>FISwag</td>
</tr>
<tr>
<td>PIRMOCORP</td>
</tr>
<tr>
<td>DBC</td>
</tr>
<tr>
<td>DXY</td>
</tr>
<tr>
<td>Gold</td>
</tr>
<tr>
<td>TCI = NPDC</td>
</tr>
</tbody>
</table>

Notes: This table displays the static volatility spillover connectedness results. There are 230 observations. All of the results are given in percentages, and all of the variables are in the logarithmic return form. The model includes 1 lag based on the AIC, HQ, SC and FPE information criteria. The term “FROM” in the rightmost column indicates volatility spillover receiver. The term “TO” in the third-to-last row indicates volatility spillover contributor. The term “NET” in the second-to-last row reveals the net directional spillover connectedness. The term “NPDC” in the last row shows the net pairwise directional connectedness. The total connectedness index of the variable system is presented by the term “TCI” in the bottom right corner. CryptoPunks (CP) and Decentraland (DL).
should be noted that the actual TSCI is in the range of 39.97% and 72.18%. This is another reason why the time-varying TSCI should be fully investigated. It can provide a valuable summary of the "average" volatility spillover information to NFT investors, stakeholders and policymakers.

The highest peak in Figure 8.4 occurred in the first quarter of 2020. Considering the timespan, a plausible explanation of the high level of volatility spillover connectedness could be due to the effects of COVID-19 on financial markets (Marobhe, 2021) and (Yousaf and Yarovaya, 2022). This explanation is confirmed by the volatility plots in Figure 8.2 as COVID-19 caused fluctuations in the stock (Sharif et al., 2020), commodity (Ji et al., 2020), bond (Bouri et al., 2021), F.X. (Aslam et al., 2020), and gold (Corbet et al., 2020a) markets. In addition, total volatility transmissions also soared in the first quarter of 2021. This period matches the collapse of cryptocurrency prices, which was caused by the bear market of the cryptocurrency as a result of the crash in Bitcoin price. Interestingly, plummeting NFT prices in the first and second quarters of 2022 have aroused violent fluctuations in the total volatility spillover connectedness. Therefore, it can be inferred that price bubbles of NFT markets contributed to these fluctuations.

Figure 8.4: Total volatility spillover

Notes: The total volatility spillover connectedness index measures the connectedness of the whole variable system. The figure displays the dynamic connectedness of the variables of volatility across time using a TVP-VAR approach with AR(1) based on the information criteria. The predictive horizon for the underlying variance decomposition is 10 weeks ($H = 10$). The sample is from 26/Dec/2016 to 05/Jun/2022.
8.4. VOLATILITY SPILLOVER CONNECTEDNESS ANALYSIS

8.4.4 Dynamic directional volatility spillover connectedness using the rolling sample

To further identify the volatility spillover transmission, the dynamic net directional volatility spillover connectedness is displayed in Figure 8.5\(^3\). As a proxy for NFT markets, NFTsAI highlights the importance of media coverage on NFTs because NFTsAI is consistently an essential volatility spillover receiver in the variable system, thus indicating that NFT markets receive more volatility spillovers than it spreads and could impede the financial contagion. This finding can prove the validity of the Hypothesis\(^7\) and also is in line with the results of (Umar et al., 2022a).

NFT markets are volatility spillover receivers can be further confirmed by the represented NFT assets, CryptoPunks and Decentraland, as they keep a volatility spillover receiver role in general (Although Decentraland, one major NFT asset in the Metaverse NFT market. It plays a role as a volatility spillover transmitter in the early stage of the NFT market, but with the prosperity of the NFT market after 2020, the role of Decentraland has transferred to a volatility spillover receiver). Moreover, the statistical results in the dynamic directional volatility spillover connectedness of NFT markets match that in the static directional volatility spillover connectedness. Both of them suggest that the NFT markets can generally act as a volatility spillover receiver. In addition, regarding the popularity of NFT assets in 2021, particularly after the price of the cryptocurrency market plummeted in May 2021, the role of NFTsAI has shifted from volatility spillover receiver to transmitter, indicating that NFT markets are spreading more and more volatilities with the prosperity of the NFT markets. Please note that referring to the results of (Umar et al., 2022a), NFTsAI could serve as a better indicator for Art, Games and Utilities tokens than that for Collectibles and Metaverse tokens. Because NFTsAI, Art, Games and Utilities show a volatility spillover transmitter role from the third quarter of 2021. This has been caused by cryptocurrency market uncertainty, which is confirmed by (Lucey et al., 2022) and (Wang et al., 2022c). Investors lose confidence in cryptocurrency’s high uncertainty periods, and then they begin to search for alternative investment assets to hedge the risks of cryptocurrencies. NFT assets as new digital collectables closely related to cryptocurrencies, which can perfectly serve the aim of hedging the risks of cryptocurrencies. Furthermore, during the

\[^3\]For the sake of brevity, the plots of directional volatility spillovers from each variable i to all others and directional volatility spillovers to each variable i from all others are listed in the section B.2.
CHAPTER 8. VOLATILITY SPILLOVERS ACROSS NFTS NEWS ATTENTION AND FINANCIAL MARKETS

periods when the NFT markets can serve as a volatility spillover transmitter, the DeFi, bond, F.X. and Gold markets act as volatility spillover receivers.

In addition, BGCI is the most giant volatility transmitter across the variable system. And the cryptocurrency markets generally spreads more volatility spillovers than it receives as the cryptocurrency group variables, BGCI, Ethereum and Bitcoin, appear to have a significant positive value of dynamic net directional volatility spillovers for most of the sample time. However, as NFTs are part of the Ethereum blockchain (Nadini et al., 2021), Ethereum spread more volatilities than Bitcoin, especially after 2020 with the developments of the NFT markets. CryptoPunks, US Dollar Index, and Gold appear to be volatility spillover receivers for most of the sample span. In addition, when the COVID-19 as a time point, Decentraland, Chainlink, Bitcoin, Ethereum, and FTSE World Government Bond Index spread more volatilities than they receive before the COVID-19. However, Bloomberg Galaxy Cryptocurrency Index, FTSE All-World Index, Investment Grade Corporate Bond Index Exchange-Traded Fund and Invesco DB Commodity Index Tracking Fund spread more volatilities than they receive after the COVID-19.

To identify the linkages between NFTsAI and the volatilities of other selected financial markets, net pairwise volatility spillover connectedness should be further investigated. One advantage of this index over the other measures of directional spillover connectedness indices is that it can extract and focus on the dynamic relationships between NFTsAI and the other variables, allowing one to construct the transmitter and receiver volatility spillover connectedness framework at a net pairwise level. The net pairwise volatility spillover connectedness network results are presented in the Figure 8.6.

Figure 8.6 helps to understand the direction of directional volatility spillovers across NFTsAI and NFT, DeFi, cryptocurrency, stock, bond, F.X., commodity and Gold markets. The direction of the arrows displays a "to" or "from" connection between each variable. The size of an arrow indicates the weight of the connection between two variables (the wider the arrow, the stronger the connection). The node colour represents whether a variable is a net volatility spillover transmitter (red) or receiver (green). Node size denotes the weight of the net pairwise spillover (the higher the new pairwise spillover value, the larger the node).
8.4. VOLATILITY SPILLOVER CONNECTEDNESS ANALYSIS

Figure 8.5: Net directional volatility spillover

Notes: The net directional volatility spillover connectedness depicts the difference between dynamic total directional volatility spillover connectedness to others and dynamic total directional volatility spillover connectedness from others. Positive values imply that the variable acts as a transmitter of systemic shocks, while negative values indicate that the role of the variable is a receiver in terms of systemic risk shocks. The predictive horizon for the underlying variance decomposition is 10 weeks ($H = 10$). The sample is from 26/Dec/2016 to 05/Jun/2022.
Similar to the empirical findings which are mentioned above. Figure 8.6 shows that BGCI can dominate all the other 13 variables, and NFTsAI is dominated by all the other variables. This evidence also can confirm the validity of the Hypothesis 7. Moreover, NFTsAI receives a significant amount of volatilities from cryptocurrency markets (BGCI, Bitcoin and Ethereum), indicating that the NFT market is sensitive to shocks from cryptocurrency price volatilities. Decentraland and CryptoPunks are all spread volatilities to the NFTsAI. This finding is consistent with the former empirical analysis results. The higher the NFT attention, the higher the volatility of NFT assets. Therefore, Hypothesis 6 also can hold. Interestingly, government bond sectors (FTSE WGBI) spread more volatilities to NFTsAI than stock markets (FTSEAWI). Among the NFT group variables, the representer of the Metaverse token, Decentraland, is a prominent transmitter to the other NFT proxies. In addition, Decentraland spreads a small volume of volatilities to Bitcoin (cryptocurrency), Chainlink (DeFi), DBC (commodity market) and gold (safe-haven). Cryptocurrency group variables (including BGCI, Bitcoin and Ethereum), FTSEAWI, FTSEWGBI, DBC and Maker also play a crucial role in spreading volatility spillovers. Except for the NFTsAI, Chainlink, CryptoPunks, safe-haven (gold), F.X. markets (DXY), and corporate bond sectors (PIMCO CORP) all serve as volatility spillover receivers in the variable system.

8.5 The Impacts of NFTsAI on NFT markets

Although the previous findings suggest that the majority of NFTsAI volatility is attributable to endogenous shocks and NFT assets are relatively independent and isolated from other financial markets, there are significant spillover transmissions that exist among NFTsAI and NFT markets referring to the net pairwise spillover network. Moreover, the NFTsAI is a new index, and a natural question is whether such attention can have an impact on NFT asset prices. Therefore, it is essential to test the effects of NFTsAI on NFT markets. This study follows the methodology of Pastor and Veronesi (2012), which investigates the relationship between the economic policy uncertainty index and the stock market by utilising a panel pooled OLS regression model. The regression model for this paper can be constructed as Equation 8.2:

\[
\Delta NFT_{i,t} = \beta_1 \Delta NFT_{SAI_i,t} + \beta_2 \Delta NFT_{i,t-1} + \Delta CV_{i,t} + c + \epsilon_{i,t},
\]
8.5. THE IMPACTS OF NFTSAI ON NFT MARKETS

Figure 8.6: Net pairwise spillover network

Notes: Net pairwise spillover network can depict the dynamic relationships between NFTsAI and the other variables. It helps to understand the direction of directional volatility spillovers across the variable system. A variable that dominates the other 13 variables is marked with a red node. A variable that is dominated by the other 13 variables is marked with a green node. Node size denotes the weight of the net pairwise spillover (the higher the new pairwise spillover value, the larger the node). The direction of the arrows displays a "to" or "from" connection between each variable. The size of an arrow indicates the weight of the connection between two variables (the wider the arrow, the stronger the connection).

where the $\Delta NFT_{i,t}$ is the log return of NFT asset price at time t, the $\Delta NFTsAI_{i,t}$ is the log return of NFTs attention index at time t, $\Delta NFT_{i,t-1}$ is used to remove any potential serial correlation in the log return of NFT $\Delta CV_{i,t}$ is the $K \times K$ matrix of control variables. $\Delta CV_{i,t}$ is equal to removing the explanatory variable, $\Delta NFTsAI_{i,t}$, and one aimed explained variable, $\Delta NFT_{i,t}$, other remaining variables which are used in the volatility spillover connectedness analysis$^4$. $c$ is a constant and $\varepsilon_{i,t}$ is an error term.

$^4$Control variables are: log return of CryptoPunks, log return of Decentraland, log return of Chainlink, log return of Maker, log return of BGCI, log return of Bitcoin, log return of Ethereum, log return of FTSEAWI, log return of FTSEWGBI, log return of PIMCOCORP, log return of DBC, log return of DXY, and log return of Gold).
Due to the limitations of the research sample period in the TVP-VAR volatility spillover, the main empirical analysis only selects the CryptoPunks and Decentraland to represent NFT markets. Fortunately, a panel pooled OLS regression model does not have special requirements for the research sample period. Therefore, I select the weekly data of NFTI (2021-03-05 to 2022-06-05), All NFT segments (All) average price (2018-01-01 to 2022-06-05), Art NFT segment (Art) average price (2018-04-23 to 2022-06-05), Collectible NFT segment (Collectible) average price (2018-01-01 to 2022-06-05), Game NFT segment (Game) average price (2018-01-01 to 2022-06-05), Metaverse NFT segment (Metaverse) average price (2018-03-19 to 2022-06-05) and Utility NFT segment (Utility) average price (2018-04-30 to 2022-06-05). NFTI is collected from coinmarket.com, and All, Art, Collectible, Game, Metaverse and Utility are all can be downloaded from nonfungible.com.

The model regression results are presented in Table 8.4. These statistical results confirm that NFTsAI has a positive impact on NFT markets. The higher the attention on NFT assets, the higher the return of NFT asset prices. Model (1) in the Table 8.4 shows the impacts of NFTsAI on NFT markets without control variables. All the $\beta_1$ values in Model (1) are significant and positive. The residual standard error values are relatively low, being above 0 but below 1.7. The values of $R^2$ are approximately 50%. This statistical evidence indicates that these regression models are fitted well and that NFTsAI has sufficient power to explain the return of NFT assets. Moreover, Model (2) in the Table 8.4 presents the impacts of NFTsAI on NFT markets with control variables. The $\beta_1$ values are robust because they still keep positive at a 1% significance level. The residual standard error values in Model (2) are lower than in Model (1). The values of $R^2$ in Model (2) are significantly higher than in Model (1) at approximately 90%. These statistical numbers not only suggest that the regression models are fitted better but also indicate that NFTsAI could explain the positive return of NFT assets in a better way when the control variables are added. These findings perfectly align with the previous empirical analysis results regarding volatility spillover connectedness and can further confirm Hypothesis 6 that NFTsAI could positively impact NFT markets.
Table 8.4: The impacts of NFTsAI on NFT markets

<table>
<thead>
<tr>
<th></th>
<th>Model (1)</th>
<th>Model (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \Delta \text{NFTI} \beta_1 )</td>
<td>( \Delta \text{All} \beta_1 )</td>
</tr>
<tr>
<td></td>
<td>22.201***</td>
<td>70.691***</td>
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<tr>
<td></td>
<td>(0.4423)</td>
<td>(1.207)</td>
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<tr>
<td>Control variables</td>
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<td>Yes</td>
</tr>
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<td>( R^2 )</td>
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<td>55.8%</td>
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<tr>
<td>Observations</td>
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<td>231</td>
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<thead>
<tr>
<th></th>
<th>Model (1)</th>
<th>Model (2)</th>
</tr>
</thead>
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<tr>
<td></td>
<td>( \Delta \text{Art} \beta_1 )</td>
<td>( \Delta \text{Collectible} \beta_1 )</td>
</tr>
<tr>
<td></td>
<td>733.33***</td>
<td>124.760***</td>
</tr>
<tr>
<td></td>
<td>(1.550)</td>
<td>(1.693)</td>
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<tr>
<td>Control variables</td>
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<td>Yes</td>
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<tr>
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<td>65.78%</td>
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<td>Observations</td>
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<td>231</td>
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<table>
<thead>
<tr>
<th></th>
<th>Model (1)</th>
<th>Model (2)</th>
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</thead>
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<tr>
<td></td>
<td>( \Delta \text{Game} \beta_1 )</td>
<td>( \Delta \text{Metaverse} \beta_1 )</td>
</tr>
<tr>
<td></td>
<td>36.041***</td>
<td>1407.45***</td>
</tr>
<tr>
<td></td>
<td>(1.097)</td>
<td>(0.4495)</td>
</tr>
<tr>
<td>Control variables</td>
<td>No</td>
<td>Yes</td>
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<tr>
<td>( R^2 )</td>
<td>57.45%</td>
<td>64.89%</td>
</tr>
<tr>
<td>Observations</td>
<td>231</td>
<td>220</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Model (1)</th>
<th>Model (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \Delta \text{Utility} \beta_1 )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>27.511***</td>
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<td></td>
<td>(1.58)</td>
<td></td>
</tr>
<tr>
<td>Control variables</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>57.99%</td>
<td>88.16%</td>
</tr>
<tr>
<td>Observations</td>
<td>214</td>
<td>220</td>
</tr>
</tbody>
</table>

Notes: This table displays the impacts of NFTsAI on NFT markets, including NFTI, All NFT, Art NFT, Collectible NFT, Game NFT, Metaverse NFT, and Utility NFT segments. Weekly log return data is applied. Model (1) shows the impacts of NFTsAI on NFT markets without control variables. Model (2) presents the impacts of NFTsAI on NFT markets with control variables. Control variables are log return of CP, DL, Chainlink, Maker, BGCI, Bitcoin, Ethereum, FTSEAWI, FTSEWGBI, PIMCOCORP, DBC, DXY, and Gold. The parameter \( \beta_1 \) explicitly indicates the impacts of NFTsAI on NFT markets. *p<0.1; **p<0.05; ***p<0.01.
Supplementary Analysis

Similar to cryptocurrency markets, trading on NFT markets is highly impacted by news or flash events (Lucey et al., 2022) and (Wang et al., 2022b). Therefore, investors need to be aware of the underlying dynamics, as it is known that bubbles may burst unexpectedly. The appearance of bubbles in the NFT markets may display different formation mechanisms fostered by market hype, herding behaviour, and oscillation frequency, among others. These properties contribute to a significant level of uncertainty and volatile price behaviour in NFT markets. Therefore, it may even be crucial that market regulators and policy makers place more emphasis on risk management practices to avoid worse damage caused by price bubbles from NFT markets.

The capitalisation-weighted composite index, NFTI is selected to represent the NFT markets. Due to the composition of the NFTI, this study is able to capture price movements in two distinctive NFT sub-markets related to the category of metaverse and game token. Additionally, several popular NFT assets are collected to further measure the price bubbles in the NFT markets in detail. Sorted by the volume all time and all-time sales thresholds, Ape, CryptoPunks, Sandbox, and ArtBlocks are selected for the NFT markets. NFT assets data are respectively obtained from CoinMarketCap and NonFungible. All the NFT assets are priced in USD. Due to NFT collections are traded infrequently, and they also differ in terms of quality, this study cannot simply look at price differences of NFT assets. Therefore, this study uses daily average price data for all the selected NFT assets, and daily average price data is widely used as a proxy to represent the NFT markets (Aharon and Demir, 2022; Dowling, 2021; Dowling, 2022; Karim et al., 2022). Also, because the NFT markets are young financial markets, no starting point for these observations is set. Data are collected in the range between the earliest available time and 31 January 2022. Descriptive statistics are shown in Table 8.5 and it is clear the NFT markets are highly volatile.

This study concentrates on the results of the SADF and GSADF tests to present the price bubbles in the NFT markets. Table 8.6 displays the two test statistics. This study follows the methodology of Phillips et al. (2015), and set the finite sample critical values threshold as 90%, 95% and 99%, separately.

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5https://nonfungible.com
8.6. SUPPLEMENTARY ANALYSIS

Table 8.5: NFTs price bubble detecting descriptive statistics

<table>
<thead>
<tr>
<th>NFT assets</th>
<th>NFT Index</th>
<th>Bored Ape Yacht Club</th>
<th>CryptoPunks</th>
<th>The Sandbox</th>
<th>Art Blocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Start point</td>
<td>2021-03-05</td>
<td>2021-04-25</td>
<td>2017-06-22</td>
<td>2019-12-02</td>
<td>2020-11-27</td>
</tr>
<tr>
<td>Observation</td>
<td>333</td>
<td>282</td>
<td>1685</td>
<td>792</td>
<td>431</td>
</tr>
<tr>
<td>Mean</td>
<td>1463.91</td>
<td>35575.74</td>
<td>46036.13</td>
<td>1960.46</td>
<td>2865.43</td>
</tr>
<tr>
<td>Min</td>
<td>353.56</td>
<td>183.62</td>
<td>22.94</td>
<td>25.35</td>
<td>19.78</td>
</tr>
<tr>
<td>Max</td>
<td>4325.82</td>
<td>94230.55</td>
<td>571998.19</td>
<td>17012.67</td>
<td>15011.11</td>
</tr>
<tr>
<td>Range</td>
<td>3972.26</td>
<td>94046.93</td>
<td>571975.25</td>
<td>16987.32</td>
<td>14991.33</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1011.78</td>
<td>27642.60</td>
<td>118850.51</td>
<td>4032.31</td>
<td>3416.70</td>
</tr>
<tr>
<td>MAD</td>
<td>764.29</td>
<td>42935.95</td>
<td>190.35</td>
<td>239.43</td>
<td>1490.62</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.94</td>
<td>0.26</td>
<td>2.85</td>
<td>2.59</td>
<td>1.56</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>-0.44</td>
<td>-1.14</td>
<td>7.00</td>
<td>5.31</td>
<td>1.69</td>
</tr>
<tr>
<td>SE</td>
<td>55.70</td>
<td>1651.96</td>
<td>2897.07</td>
<td>143.46</td>
<td>164.96</td>
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<tr>
<td>J.-B. test</td>
<td>327.17***</td>
<td>274.63***</td>
<td>1678.6***</td>
<td>787.09***</td>
<td>412.86***</td>
</tr>
<tr>
<td>Ljung-Box test</td>
<td>51.439***</td>
<td>18.091***</td>
<td>5739.6***</td>
<td>1825.9***</td>
<td>226.78***</td>
</tr>
</tbody>
</table>

Notes: Ljung-Box test for the distribution of residuals in a variable (Box and Pierce, 1970) and (Ljung and Box, 1978), and it can examine the autocorrelation of squared returns series. Jarque-Bera (J.-B.) statistics can be used to check the normal distribution characteristic of the data (Jarque and Bera, 1980) and (Bera and Jarque, 1981). *p<0.1; **p<0.05; ***p<0.01.

Table 8.6: The SADF and the GSADF tests of NFT assets

<table>
<thead>
<tr>
<th>NFT assets</th>
<th>SADF</th>
<th>GSADF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test statistic</td>
<td>Finite sample critical values</td>
<td></td>
</tr>
<tr>
<td>90%</td>
<td>95%</td>
<td>99%</td>
</tr>
</tbody>
</table>

Panel A: NFT assets SADF

| NFT Index | 3.640655*** | 1.152928 | 1.387360 | 2.009919 |
| Bored Ape Yacht Club | 6.537691*** | 1.127017 | 1.377403 | 1.915046 |
| CryptoPunks | 14.23839*** | 1.283002 | 1.570895 | 2.048547 |
| The Sandbox | 12.5281*** | 1.242486 | 1.514377 | 2.011933 |
| Art Blocks | 9.005972*** | 1.174641 | 1.450992 | 2.015503 |

Panel B: NFT assets GSADF

| NFT Index | 3.640655*** | 1.888133 | 2.112672 | 2.780311 |
| Bored Ape Yacht Club | 6.537691*** | 1.844738 | 2.070705 | 2.719613 |
| CryptoPunks | 14.23839*** | 2.196822 | 2.435595 | 2.903005 |
| The Sandbox | 12.5281*** | 2.053218 | 2.304501 | 2.853601 |
| Art Blocks | 9.005972*** | 1.931227 | 2.188845 | 2.746543 |

Notes: The smallest window contains 36, 33, 91, 58, 42, 45, 64, 45, 71 and 86 observations of the NFTI, Ape, CryptoPunks, Sandbox, and ArtBlocks, respectively.
The finite sample critical values are generated from a Monte Carlo simulation with 2000 replications. The minimum window size is chosen based on the rule $c_0 = 0.01 + 1.8/\sqrt{T}$. From Table 8.6, the SADF and GSADF statistics for each index are the same, 3.640655 which exceeds their respective 1% right-tail critical values giving strong evidence that the Hypothesis 8 of the NFT markets have explosive sub-periods and price bubbles is reasonable.

Next, this study applies the real-time price bubble date-stamping strategy for both tests with results shown in Table 8.7. Moreover, Figure 8.7 and Figure 8.8 display the SADF and GSADF tests against the corresponding 95% critical value sequence, separately. Comparing the extent of bubble periods, NFTI, BoredApe, CryptoPunks show more single periodically collapsing price bubbles (SADF > GSADF). Similarly, Sandbox, ArtBlocks show more multiple price bubbles (GSADF > SADF). Summarising NFT assets, this study could see a split with NFTI and Bored Ape Yacht Club having an average price bubble percentage rate of more than 80%, while the other NFT assets are somewhere around 20 to 30%. The reasons why the average price bubble percentage rates are significantly different between NFTI & Bored Ape Yacht Club and the other NFT assets may be caused by the different nature of the instruments. The NFTI is a capitalisation-weighted composite index for the NFT markets, and Bored Ape Yacht Club represents the single NFT asset that outperforms the wider NFT markets (Wang, 2022). Besides to the correspondence to general cryptocurrency markets (similar to DeFi), the NFT markets are especially driven by herding behaviour and media induced mania in 2021. When this study compares the percentage of bubble days in the NFT markets with that in the cryptocurrency markets (Corbet et al., 2018a) and (Maouchi et al., 2022), this study could find NFT markets contain more price explosive bubbles than cryptocurrency markets [NFT(%) > Cryptocurrency(%)], indicating the extremely price inefficiency in the NFT markets.

Referring to the magnitude of price bubbles in Table 8.7, the periods of occurrence of the highest bubble magnitude have been bolded. The highest price bubble magnitude periods in the NFT markets broadly correspond to the periods of "NFT Spring 2021" and "2021 Q4 NFT bull markets".
8.6. SUPPLEMENTARY ANALYSIS

Table 8.7: Bubbles statistics of NFT assets

<table>
<thead>
<tr>
<th>NFT assets</th>
<th>Main bubble period</th>
<th>SADF</th>
<th>GSADF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BD</td>
<td>Pct</td>
<td>HM %</td>
</tr>
<tr>
<td>NFT Index</td>
<td>285/333</td>
<td>85.59%</td>
<td>446.71%</td>
</tr>
<tr>
<td>Bored Ape Yacht Club</td>
<td>229/282</td>
<td>81.21%</td>
<td>616.11%</td>
</tr>
<tr>
<td>CryptoPunks</td>
<td>371/1685</td>
<td>22.02%</td>
<td>512.39%</td>
</tr>
<tr>
<td>The Sandbox</td>
<td>260/792</td>
<td>32.83%</td>
<td>690.97%</td>
</tr>
<tr>
<td>Art Blocks</td>
<td>134/431</td>
<td>31.09%</td>
<td>700.54%</td>
</tr>
</tbody>
</table>

Notes: Main price bubble periods are selected according to the SADF and the GSADF tests. A price bubble period can be selected only when the same price bubble lasts more than 14 days in both the SADF and GSADF tests. BD is bubble days. The bubble magnitude quantifies the percentage change between the highest and lowest prices in each price bubble period. The highest magnitude (HM %) calculates the highest record bubble magnitude. The average bubble magnitude (AM %) measures the average bubble magnitude across all bubble periods. APC% means the absolute value of average price bubble percentage change across all bubble days experienced by each digital asset.

The positive news such as NFTs sales volume surges to $2.5 billion in the first half of 2021, NFT markets have a 315% increase in total sales volume month-on-month, Bored Ape Yacht Club 58,118% return of investment in 2021, among others, could significantly heat the NFT markets. Motivated by these positive events related NFTs, more investors join these two emerging markets and look for speculative opportunities, which could cause explosive speculative bubbles in the NFT assets. However, when this study pays attention to the average bubble magnitude (AM) and the absolute value of average price bubble percentage change (APC), the statistical results reveal that NFT markets have an extremely high average bubble magnitude and average price bubble percentage change. This finding can confirm that NFT assets have the attributes of works of art, which are traded infrequently, and in terms of their quality and scarcity. Especially, some NFT assets may only be popular among specific cultural circles. Under this condition, the transactions of NFT assets are more prone to unexpected high price bubbles. Tapping the existing literature related to identifying price bubble in the cryptocurrency markets (Corbet et al., 2018a) and (Maouchi et al., 2022), this study can clearly find that both the highest bubble magnitudes and the average bubble magnitudes of NFT markets are significantly higher than that of cryptocurrency markets, indicating that there are more and stronger price explosive behaviours in the NFT markets. This finding also could prove the inefficiency of the price mechanism in the NFT markets, which could be in line with the findings of (Dowling, 2022).
Figure 8.7: Date-stamping bubble periods in the NFT assets: the SADF test

Notes: These plots show the SADF test against the corresponding 95% critical value sequence. The selected indices, SADF statistics, and 95% critical value sequence are tagged by green, blue, and red separately. The price bubble periods are highlighted in grey.
8.6. SUPPLEMENTARY ANALYSIS

Figure 8.8: Date-stamping bubble periods in the NFT assets: the GSADF test

Notes: These plots present the GSADF test against the corresponding 95% critical value sequence. The selected indices, GSADF statistics, and 95% critical value sequence are tagged in green, blue, and red. The price bubble periods are highlighted in grey.
8.7 Robustness Test

In this study, three robustness tests are designed to check the reliability of TVP-VAR empirical results, re-confirm the effects of NFTsAI on NFT markets, and infer the timing of a bubble burst in the NFT markets.

8.7.1 Robustness test one

The main econometrics model in this study is the TVP-VAR volatility spillover connectedness. The only two uncertainties in this model are the selection of the forecast horizon \(H\) and the VAR estimation thresholds. Therefore, the robustness of the TVP-VAR volatility spillover connectedness results can be verified by setting different values to the forecast horizon and parameters in the VAR model. Suppose the new forecast horizons and VAR thresholds could not significantly change the general trend of the dynamic total volatility spillover connectedness. In that case, the robustness of the main empirical findings can be confirmed. In the main empirical section, the forecast horizon is set as 10 weeks. The forecast horizon is changed by 13 weeks as 13 is a multiple of 52 (One year has 52 transaction weeks). The robustness of the main empirical findings is firstly assessed by utilising alternative forecast horizons (i.e. 13-week, 26-week, 39-week, 52-week, 65-week, 78-week, 91-week, and 104-week ahead forecast horizons). The calculated results indicate that the eight new dynamic total volatility spillover indices are quantitatively similar to that in the main empirical findings, and the static total spillover connectedness indices can always keep the same as 50.7%. In this case, this study can confirm that different forecast horizons could not change the volatility spillover connectedness and the main empirical findings are robustness in terms of the forecast horizon variations. Secondly, considering it is not easy to set different VAR parameters in the TVP-VAR spillover connectedness model as it does not require one to set rolling-windows (R). In this way, this study applies the DY-VAR spillover connectedness model to test the effects of different VAR parameters on the total spillover connectedness index (Diebold and Yilmaz, 2009). As justified above, the variations in the forecast horizon in this study will not significantly change the total volatility spillover index. Therefore, the further robustness tests could fix the forecast horizon to 10-ahead in the DY-VAR spillover connectedness model and then measure the total volatility spillover connectedness index by using a different rolling-window size (i.e. \(R = 26, 39, 52, 65, 78, 91\) or 104 weeks).
8.7. ROBUSTNESS TEST

Figure 8.9 displays the robustness test results for the TVP-VAR volatility spillover connectedness model. The TVP-VAR dynamic total volatility spillover index is highlighted in red colour. Regarding the DY-VAR dynamic total volatility spillover indices with different rolling-windows, they can co-move with the TVP-VAR dynamic total volatility spillover index, and they do not vary significantly with a variation in rolling-window sizes. Therefore, the TVP-VAR volatility spillover connectedness model can hold, and the main empirical findings of this study are robust regarding the selection of different forecast horizons and VAR thresholds.

![Figure 8.9: TVP-VAR robustness test](image)

Notes: This figure depicts the robustness test results for this study. TVP-VAR dynamic total volatility spillover index is highlighted in red colour. DY-VAR dynamic total volatility spillover connectedness indices with different rolling-windows (i.e. rolling-window = 26, 39, 52, 65, 78, 91 or 104 weeks) are in different colours. TVP-VAR and DY-VAR models are all with AR(1) based on the information criteria. The predictive horizon for the underlying variance decomposition is 10 weeks \((H = 10)\). The sample is from 26/Dec/2016 to 05/Jun/2022. Suppose the new forecast horizons and VAR thresholds could not significantly change the general trend of the dynamic total volatility spillover connectedness. In that case, the robustness of the main empirical findings can be confirmed.
8.7.2 Robustness test two

The results in section 8.6 indicate that NFTsAI has sufficient power to explain the return of NFT assets and can confirm that NFTsAI positively impacts NFT markets from a fixed effect perspective. In the robustness test, it is worth evaluating the prediction power of NFTsAI on the short and long-term volatility of the NFT markets to re-confirm the effects of NFTsAI on the NFT markets. This study still selects the NFTI to represent the NFT markets. Referring to the NFTI is a daily frequency index, but NFTsAI is constructed in weekly frequency. This study utilises the GARCH-MIDAS model of (Engle et al., 2013) to detect the predictive power of NFTsAI on the volatility of NFT markets.

Figure 8.10 displays the estimated total daily volatility and long-term volatility of GARCH-MIDAS. The green dashed line indicates the NFTI total daily volatility, and the blue line means the NFTI long-term volatility determined by NFTsAI. Figure 8.10 reveals that NFTsAI can depict the long-term components of volatility in NFT markets, and these long-term components vary significantly over time. Figure 8.10 indicates that NFTsAI could capture different aspects of long-term price fluctuations in NFT markets. Table 8.8 presents the estimation results of the GARCH-MIDAS model for NFT markets by using NFTsAI. All the coefficients in Table 8.8 are statistically significant, suggesting the capability of the GARCH-MIDAS model in capturing the short and long-term volatility of the NFT markets by using NFTsAI as a proxy.\( \beta \) parameter measuring the GARCH effects. \( \beta \) parameter is positive at 1% significance level, and the value is 0.4077, which indicates NFTsAI can cause strong short-term volatility in NFT markets. The \( \theta_{RV} \) coefficient is positive at a 1% significance level, implying that higher historical volatility of NFTsAI will lead to higher long-term volatility of NFT markets. The estimation result of \( \theta_X \) coefficient can evaluate the predictive power of the NFTsAI on the long-term volatility of NFT markets. From the statistical value of the \( \theta_X \), this study finds that NFTsAI significantly positively impacts the long-term volatility of NFT markets. In a nutshell, the empirical findings from the GARCH-MIDAS model suggest that NFTsAI contains useful forecasting information for both short and long-term volatility of NFT markets, which can further re-confirm and prove the robustness of the former empirical findings.
### 8.7. ROBUSTNESS TEST

Table 8.8: The estimation results of GARCH-MIDAS model for NFT markets

<table>
<thead>
<tr>
<th></th>
<th>( \mu )</th>
<th>( \alpha )</th>
<th>( \beta )</th>
<th>( \theta_{RV} )</th>
<th>( \theta_X )</th>
<th>( w_{RV} )</th>
<th>( w_X )</th>
<th>( m )</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>NFTI</td>
<td>0.031804***</td>
<td>0.23187***</td>
<td>0.40766***</td>
<td>0.00040289***</td>
<td>0.31497***</td>
<td>4.5163***</td>
<td>2.0731***</td>
<td>3.6846***</td>
<td>2993.79</td>
</tr>
<tr>
<td></td>
<td>(0.30402)</td>
<td>(0.060036)</td>
<td>(0.11859)</td>
<td>(0.0011817)</td>
<td>(0.13986)</td>
<td>(10.148)</td>
<td>(2.478)</td>
<td>(0.10903)</td>
<td></td>
</tr>
</tbody>
</table>

This table displays the estimation results of GARCH-MIDAS model for NFT markets by using NFTsAI. \( \theta_{RV} \) and \( \theta_X \) indicate the impacts of lagged RV and NFTsAI on the long-term volatility of NFT markets, respectively. BIC is the Bayesian info criterion of the estimation. The bracketed numbers are the standard errors of the estimations. * \( p < 0.1 \); ** \( p < 0.05 \); *** \( p < 0.01 \). NFTI estimation results have 455 sample size and the sample is from 08/Mar/2021 to 03/July/2022.

![Figure 8.10: Volatility for NFTI estimated by NFTsAI](image)

**Notes:** This plot shows the estimated total daily volatility and long-term volatility of GARCH-MIDAS. The green dashed line indicates the NFTI total daily volatility, and the blue line means the NFTI long-term volatility determined by NFTsAI. NFTI is in a high-frequency daily data, and NFTsAI is in a low-frequency weekly data. The sample is from 08/Mar/2021 to 03/July/2022.
CHAPTER 8. VOLATILITY SPILLOVERS ACROSS NFTS NEWS ATTENTION AND FINANCIAL MARKETS

8.7.3 Robustness test three

The supplementary analysis in section 8.6 discusses the price bubbles in the NFT markets. As a robustness test, here used an alternative econometric model. The LPPLS method can infer the timing of a bubble burst, as discussed above, and here shows stable results, essentially the same as the SADF and GSADF tests. LPPLS models have been used extensively as robustness checks for G/SADF tests.

Figure 8.11 presents the LPPLS confidence indicator results. The positive (resp. negative) price bubble periods are tagged in red (resp. green). The positive (negative) price bubbles indicate the process of upward (downward) accelerating prices. Moreover, the price bubble periods detected by the LPPLS model in Figure 8.11 match the main price bubble periods that are identified by the SADF and GSADF tests in Figure 8.7 and Figure 8.8. The matching of bubble periods from two sets of tests gives this study confidence in the empirical findings.

Figure 8.11: Date-stamping bubble periods in the NFT assets: the LPPLS test

Notes: These plots display the LPPLS confidence indicator results. The positive (resp. negative) price bubble periods are tagged in red (resp. green).
8.8 Chapter Summary

This study develops an NFTs attention index using over 590m news items collected from the LexisNexis News & Business database. Employing NFTsAI as a new indicator and TVP-VAR model, this study further enriches the existing NFTs literature by estimating the volatility spillover connectedness between NFT markets and other classic financial markets. Moreover, motivated by the growth of the NFT assets, this paper provides insight into the extent and timing of price bubbles. This study has examined a total of 5 individual assets/indices that represent a relevant part of the NFT markets. The empirical results of this study can be used by risk-averse investors, portfolio managers, institutional investors, researchers and financial policy regulators in their subsequent works.

Several findings can be made from the empirical analysis. Firstly, the historical decomposition results suggest that the historical variations of CryptoPunks and Decentraland could co-move with that of NFTsAI, indicating that the NFTsAI could serve as an NFT market proxy. Secondly, NFTsAI indicates that NFT markets have a relatively independent and isolated characteristic in comparison to other financial markets. In other words, NFTsAI consistently suggests that NFT markets are less affected by cryptocurrency, DeFi, equity, bond, commodity, F.X. and gold markets, and NFT markets are volatility spillover receivers. Moreover, the majority of volatility in the NFT markets is attributable to endogenous shocks, suggesting that NFT assets could impede financial contagion and have significant diversification benefits. It is also worth noting that the net dynamic volatility spillover results show that NFT markets are spreading more and more volatility to the other financial markets with the prosperity of the NFT assets. Thirdly, the net pairwise volatility spillover connectedness network uncovers that Decentraland and CryptoPunks are all spread volatilities to the NFTsAI. Fourthly, the panel pooled OLS regression model results confirm that NFTsAI has sufficient power to explain the return of NFT assets, and NFTsAI could positively impact NFT markets from a fixed-effect perspective. Moreover, NFTsAI can depict the short- and long-term components of volatility in NFT markets, which the GARCH-MIDAS model could prove. Fifthly, the NFT market shows more price bubbles than the DeFi market in general. This finding is confirmed by the robustness test based on the LPPLS test. Accordingly, it is not surprising that NFTs, as an emerging, highly heterogeneous class with many potential use cases, are in this phase subject to greater volatility than DeFi tokens.
CHAPTER 8. VOLATILITY SPILLOVERS ACROSS NFTS NEWS ATTENTION AND FINANCIAL MARKETS

Regarding the timing of the bubbles, NFTs are driven more by specific, behavioural economic factors such as media coverage and NFT-specific herding. Considering the magnitude of price bubbles, NFT markets have a higher average bubble magnitude and a higher average price bubble percentage change than the DeFi markets. In addition, both the highest bubble magnitudes and the average bubble magnitudes of NFT markets are significantly higher than that of cryptocurrency markets. In the end, robustness test results suggest that the empirical findings from the TVP-VAR are robust, and NFTsAI contains useful forecasting information for both short and long-term volatility of NFT markets.

This study’s empirical findings could interest risk-averse investors, portfolio managers, institutional investors, researchers and financial policy regulators. For risk-averse investors, considering the volatility spillover connectedness among the NFTs market and other financial markets, also with its time-varying characteristic, is helpful for forecasting and judging the trends and relationships of different financial asset prices. This information could help to identify more arbitrage opportunities, adjust net long/short positions, and avoid unacceptable investment failures. From the perspective of portfolio managers and institutional investors, the NFTsAI could help to improve portfolio performances and optimise investment portfolios because the strong/weak volatility spillover connectedness between NFT markets and other classic financial markets could affect passive and active portfolio managers. From a policy-making perspective, the empirical findings indicate that NFTsAI has significant information contents that can signal impending turbulence in the NFT markets early. Therefore, NFTsAI can be used to trace unusual fluctuations in the NFT markets in real-time by market regulators and also can raise an early warning call to policymakers to remind them to launch more effective stabilisation policies and prevent possible NFT crises. Researchers can apply the newly issued NFTsAI to the applied finance and economics fields to further enrich the research field of NFTs.

From the results of the price bubble detecting in the NFT markets, several policy implications can be derived. Firstly, the question arises whether with growing market maturity some NFT token use cases further differentiate, thus forming independent sub-markets, or whether NFTs can be continued to be treated as one common market. Date-stamping bubble behaviours identification in the NFT markets can bring policymakers (e.g. China’s central bank) an indicator and a window of opportunity to consider whether or not they should take action to adjust or control
this market. Especially for China, as China’s government banned cryptocurrency trading and mining. But at the same time, China’s government is pursuing the uses of blockchain technology and NFTs - as long as these blockchain-based technologies are under its control. Accordingly, policymakers should seek to identify valuable use cases for NFT assets and tailor any regulations to these use cases. However, overly broad regulation can destroy market potential that could be of particular interest for developing economies in general (Zhao et al., 2021). The analysis of potential actions by policymakers in the occurrence of price bubbles in the NFT markets is beyond the content of this study. Secondly, NFTs are high-risk assets, exhibiting strong bubble behaviour and the risk of substantial loss. In addition, these potential risks are significant for developing countries. As financial markets in these countries are not fully developed, the supply of alternative investment tools is limited. Investors in developing countries are prone to speculative investments with high risk and high returns, such as cryptocurrencies, P2P lending, and NFTs, among others. Given the proven evidence that the latest financial crises all originated from a bubble burst. Policymakers should seek to improve the financial literacy of the population as trading becomes more accessible to a broader segment of the population. Thirdly, although there are periods of significant bubbles, it should be noted that there are also calm periods. As these markets mature, it is expected that the price dynamics will settle to fewer bubbles and greater efficiency. However, this environment also offers profit opportunities for risk-seeking investors.

Many people still cannot grasp what value NFTs truly have, except that these assets can be used as speculation tools for making easy money. Indeed, this study has to agree that the NFTs have no fundamental or intrinsic value at first glance. Instead, the value of NFT assets is determined by the community that stands behind a certain NFT collection. That is why many people call the NFTs classical or modern art. Moreover, an NFT can also be viewed as a high-tech methodology to unbundle property. In derivatives contracts, this property divide method is common. However, it is not easy for individuals or small companies to achieve because the cost of property dividends is too high. NFTs can ameliorate this situation because these assets can define the property rights by utilising the default conditions in the crypto algorithm. NFTs also have several other advantages, for example, public records of the NFT transactions: NFT transaction records cannot be casually irrevocable and NFTs can be endorsed on blockchains and incorporated with other digital applications. Although NFTs also have several disadvantages, such as NFT
transactions being extremely complex, high energy consumption concerns, and contract enforcement issues (NFT property rights conflict), this study believes that the future of NFTs is promising and the application of NFTs will not be limited to tokens because digital currency never sleeps.
This chapter presents the conclusion of this doctoral thesis and outlines directions for future research. This thesis starts with an introduction describing the background and motivation for developing qualitative-based indices in the following three kinds of digital assets: cryptocurrency, CBDCs and NFTs. Then, a thorough literature review helps to uncover research questions, identify research gaps and propose research hypotheses. A detailed data chapter provides the methodology to construct qualitative-based indices in cryptocurrency uncertainty, cryptocurrency environmental attention, CBDCs and NFTs attention. Moreover, the data chapter justifies the variables selected for each empirical analysis chapter. Following the data chapter, a critical methodology chapter covers all the statistical and financial econometric models that are appropriately applied throughout this thesis. The two following sub-sections will synthesise the findings from the three empirical analysis chapters related to cryptocurrency qualitative-based indices, CBDC qualitative-based indices and NFTs qualitative-based index, and then open new avenues for future research.

9.1 Summary of Results

In chapter 6, it firstly introduces a new measure of price and policy uncertainty in cryptocurrency markets. Using 726.9 million news articles from the LexisNexis News & Business database, cryptocurrency policy uncertainty (UCRY Policy) and
cryptocurrency price uncertainty (UCRY Price) are developed and made available. Chapter 6 further analyses the main drivers of the UCRY indices and evaluates contributions of three uncertainty measures (GlobalEPU, USEPU and VIX) and other factors (Bitcoin price and gold price) that might have close relationships with the UCRY indices. The results from impulse response analysis show that UCRY Policy positively impacts all the variables just outlined, especially for GlobalEPU, USEPU, Bitcoin and Gold. However, compared with UCRY Policy, the shocks from UCRY Price to the variables are more fluctuating, especially for USEPU. These findings could prove that UCRY Policy and UCRY Price can successfully capture the uncertainty in the cryptocurrency markets. From the FEVD analysis, this research finds that the UCRY Policy is the largest contributor to the variations of the variable system with a long-run impact. However, UCRY Price only can contribute a few. These findings suggest that the cryptocurrency markets are highly policy-oriented. Chapter 6 also provides the historical decomposition of UCRY Policy with major events from 2014 to 2020. Compared to other similar indices, it is narrowly range bound, suggesting that while such uncertainty exists, it is not volatile. Nonetheless, it does show distinct movements around high-profile events in the cryptocurrency space, such as the COVID-19 crisis, cyberattacks on cryptocurrency exchanges and political elections. About the robustness test for cryptocurrency uncertainty indices and its empirical analysis, chapter 6 applies a Pearson correlation to analyse the relationship between the UCRY Policy, UCRY Price and Bitcoin price index. Then, chapter 6 uses the Pearson correlation again to investigate the relationship between the continuously compounded returns of UCRY Policy, UCRY Price and Bitcoin. These two Pearson correlation analyses successfully prove the usefulness and effectiveness of the UCRY Policy and UCRY Price indices because the two indices all show a significant relationship with Bitcoin, also with its continuously compounded returns. Therefore, chapter 6 has strong confidence in believing the two new issuing cryptocurrency uncertainty indices are robust. In addition, chapter 6 raises the confidence interval bootstrapping and threshold of runs in the IRF test to re-examine the reactions of the Global EPU, VIX, Bitcoin, USFS, USEPU and gold to the shocks from cryptocurrency uncertainties. In the new IRF tests, with the higher confidence interval bootstrapping and threshold of runs, the results still can keep the same trend as the results in the main empirical analysis section. These new IRF tests can successfully prove the robustness of the findings of the impact of the UCRY Policy and UCRY Price on the financial markets or macroeconomics.
Secondly, chapter 6 develops a new index for cryptocurrency environmental attention for the period 2014-2021 based on LexisNexis News & Business news coverage, namely, the ICEA. This new index captures cryptocurrency’s environmental attention in terms of the cryptocurrency’s responses to major related events and can confirm that the public is growing more concerned with the energy consumption of these innovative assets. For example, ICEA spikes alongside new developments in cryptocurrency regulation and cryptocurrency flash news. Second, investigations of the impact of the ICEA on financial markets and economic developments using SVECM structural shock analysis reveal that ICEA significantly impacts the UCRY Policy, UCRY Price, Bitcoin price, VIX, and BCO, as well as has a significantly negative impact on the GlobalEPU and GTU. Moreover, empirical findings in chapter 6 related to ICEA suggest that the ICEA has significant positive impacts on the IP in the short term while having significant negative impacts in the long term. Third, reassuring news items and positive government policies are revealed to have significant negative impacts on the ICEA's historical decomposition results. Additionally, ICEA historical decomposition results can significantly spike near significant events concerning cryptocurrencies. Ultimately, chapter 6 is able to conclude that overall attention on environmental issues concerning cryptocurrency can increase the fluctuations of cryptocurrency price, ICEA going up by one unit can positively contribute to a 147.67 Bitcoin price return change, a 206.58 Ethereum price return change, a 0.91 UCRY Policy return change and a 1.04 UCRY Price return change.

Thirdly, the predictive power tests of the cryptocurrency uncertainty on precious metal markets in chapter 6 firstly indicate that cryptocurrency uncertainty indices can reveal the different long-term components of volatility in precious metal markets. These long-term components show distinct trends over time. Secondly, the in-sample results demonstrate the significant impacts of cryptocurrency uncertainty on the volatilities of precious metal markets, and the out-of-sample evidence further confirms the superior volatility predictive power of cryptocurrency uncertainty over other uncertainty indices. The empirical findings from this paper highlight the importance of cryptocurrency uncertainty and can provide new insights for investors, policymakers and academics into the investment and hedging strategies related to precious metal markets across different periods.

Based on news coverage from LexisNexis News & Business, chapter 7 firstly develops two new indices for CBDC between 2015-2021: the CBDC uncertainty in-
index (CBDCUI) and CBDC attention index (CBDCAI), that can be used by investors, policymakers and financial regulators to monitor the impact of CBDCs-related discussions on the volatility of financial markets. CBDC indices capture CBDC trends and uncertainties as they can react to major relevant events. For example, CBDC indices spiked near new CBDC announcements, digital currency flash news, and main policy debates. Secondly, the research activities in chapter 7 around CBDC indices report that CBDCUI and CBDCAI indices significantly negatively affect the MSCI World Banks Index, USEPU, and FTSE All-World Index, where the volatilities of the financial variables react more strongly to shocks transmitted from the CBDCUI. Thirdly, by applying the historical decomposition approach to the CBDC indices, the empirical results 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 significantly negatively affect the CBDCUI historical decomposition results, i.e. decreasing the uncertainty around CBDC procedures. Besides, the empirical analysis in chapter 7 shows that both CBDCUI and CBDCAI historical decomposition results significantly spiked near key CBDC progress news and significant events regarding digital assets.

Chapter 8 firstly develops an NFTs attention index (NFTsAI) based on 590 m news stories from the LexisNexis News & Business database. NFTsAI can capture public attention on the NFT assets and serve as a useful proxy for the NFT markets. Utilising a TVP-VAR spillover connectedness model to uncover new channels of volatility transmission between NFTsAI and financial markets. chapter 8 indicates that the NFT markets could act as volatility spillover receivers in general and NFT assets could impede the financial contagion and have significant diversification benefits. Then, chapter 8 suggests that NFTsAI has sufficient power to explain the return of NFT assets from a fixed effect perspective, and NFTsAI contains useful forecasting information for the volatility of NFT markets, which obtained by a panel pooled regression model and a GARCH-MIDAS model, separately. Secondly, chapter 8 documents that NFT markets exhibit speculative bubbles, which are detected by the SADF and GSADF tests and re-confirmed by the LPPLS test. Moreover, chapter 8 reveals that NFT bubbles are more recurrent and have higher magnitudes than DeFi and cryptocurrency bubbles. The price bubbles in the NFT markets are highly correlated with market hype and with more general cryptocurrency market uncertainty. chapter 8 does find periods where bubbles are not detected, suggesting
that the NFT markets do have some intrinsic value and should not be dismissed as simply bubbles. All in all, many people still cannot grasp what value NFTs truly have, except that these assets can be used as speculation tools for making easy money. Indeed, this study has to agree that NFTs have no fundamental or intrinsic value at first glance. Instead, the value of NFT assets is determined by the community that stands behind a certain NFT collection. That is why many people call the NFTs classical or modern art. Moreover, an NFT can also be viewed as a high-tech methodology to unbundle property. In derivatives contracts, this property divide method is common. However, it is not easy for individuals or small companies to achieve because the cost of property dividends is too high. NFTs can ameliorate this situation because these assets can define property rights by utilising the default conditions in the crypto algorithm. NFTs also have several other advantages, for example, public records of the NFT transactions: NFT transaction records cannot be casually irrevocable, and NFTs can be endorsed on blockchains and incorporated with other digital applications. Although NFTs also have several disadvantages, such as NFT transactions being extremely complex, high energy consumption concerns, and contract enforcement issues (NFT property rights conflict), this study believes that the future of NFTs is promising and the application of NFTs will not be limited to tokens because digital assets never sleep.

9.2 Future Research and Outlook

The research field of digital assets is evolving quickly, and therefore the potential research questions on cryptocurrency, CBDCs and NFTs could fill decades. However, considering their importance, some research questions should be recommended and addressed more urgently than others. Moreover, identifying future research directions could also compensate for this thesis’s limitations. In the following chapters, some directions for further research will be provided, and the research areas that need further attention also will be identified.

Firstly, UCRY indices suggest that these two cryptocurrency uncertainty indices can be used for future research on the uncertainty of cryptocurrency, portfolio diversification, and contagion effect. Additionally, these two indices can have various practical and policy-based implications for measuring the risk stemming from cryptocurrency markets. Such as exploring the hedge and safe-haven properties of financial assets by using the cryptocurrency uncertainty indices, risk transmission
analysis between the cryptocurrency uncertainty indices and financial markets, and predicting the volatility of financial markets by using the cryptocurrency uncertainty indices, among others.

Secondly, ICEA is important in analysing whether cryptocurrency markets are sustainable regarding their energy consumption requirements and their negative contributions to climate change. A broader impact of the cryptocurrency environmental concern on cryptocurrency market volatility, uncertainty and environmental sustainability should be considered and developed. Moreover, this thesis wants to point out future research and policy legislation directions. Notably, this thesis poses the question of how cryptocurrency can be made more sustainable and environmentally friendly and how governments’ policies on cryptocurrency can address the cryptocurrency markets. Recently, some scholars have already argued that the societal value that Bitcoin provides is worth the resources needed to sustain it\(^1\). Therefore, discussion papers about cryptocurrency energy consumption issues and the research agenda are urgently needed. In addition, applying sentiment analysis to the corpora used to construct the ICEA also can be considered. It is worth investigating how the different tones about the cryptocurrency environment can impact the cryptocurrency markets.

Thirdly, the research on whether cryptocurrency market uncertainties can help to explain and forecast volatilities in precious metal markets in this thesis only focus on statistical evaluations. This work will be the direction of future research by further considering the tests related to economic values for volatility forecasting. Referring to the GARCH-MIDAS model, now this thesis can only achieve the volatility forecasting in 1-day-ahead. Future research could extend our research by using the HAR-RV model to forecast the volatility in 5-day- or 20-day-ahead.

Fourthly, in the CBDCs research field, this thesis believes 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, decentralisation, and disintermediation of sovereign currency. From a global monetary perspective, applying these (central bank-endorsed) digital currencies is a new step toward 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

\(^1\)More details can be found in https://hbr.org/2021/05/how-much-energy-does-bitcoin-actually-consume.
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 circulate freely and be converted into 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, their actual economic performance, and society’s acceptance of it remain to be tested and observed. Therefore, CBDCs’ problems require further investigation. First, future research could further analyse the CBDCAI and CBDCUI with firm-level data. For example, an investigation into whether 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, this thesis cannot include composite cryptocurrency indices in 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 predictive power 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.

Fifthly, this thesis provides new insights into understanding the NFT markets. However, there are some shortcomings. First, NFT markets are just beginning to emerge, and thus, the amount of research data is not large enough. This thesis has tried to extend the research sample period as much as possible. However, the relatively short research sample period due to objective reasons is unavoidable. In the future, more researchers can conduct further studies based on some of the arguments in this thesis, using the same or different econometrics models, longer research observation periods, and the same or higher-frequency data, in order to confirm or argue some of the findings and viewpoints in this study. Secondly, this thesis does not estimate the spillover connectedness in different periods and quantiles using NFTsAI. Hence, future research could concentrate on these unexplored fields. Thirdly, this thesis is limited to assessing the predictive power of NFTsAI. Future studies not only can expand the GARCH-MIDAS model to other financial markets by using the NFTsAI but also could measure whether the volatility of financial markets is driven by NFTs attention by using different prediction power evaluation methods. Fourth, in the future, it will be necessary to examine the extent to which the NFT markets continue to mature (e.g. price mechanism efficiency test). Another potential research direction is the investigation of risk transmission channels between cryptocurrency, DeFi and NFT markets, as these three digital asset markets share several common price bubble periods, and the flash events related to cryptocurrency markets can significantly stimulate NFT markets to generate price bubbles. In addition, especially against the background of new possibilities, it is important to keep an eye on different use cases. These could, if sensibly regulated and after the initial market turbulence, offer an economic added value, especially for developing countries. However, the empirical results from this thesis clearly show that currently, NFT markets are still characterised by erratic bubbles, and that caution should be exercised when operating in them.

However, digital assets are reshaping our financial markets, payment systems, payment modes and new financial orders, among other areas. The digital asset must be the main battlefield of various countries in the field of FinTech. As money never sleeps, further research into the roles and advantages of digital assets can only be beneficial, though I will pass this research to the next researcher.
A.1 Big events related to CBDC indices

A.1.0.1 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).

A.1.0.2 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).

A.1.0.3 13/07/2015 - 19/07/2015 (2015-07-17)

   Explanation: UK intellectual property office grants trade mark "GovCoin" to
APPENDIX A. APPENDIX: THE EFFECTS OF CENTRAL BANK DIGITAL CURRENCIES NEWS ON FINANCIAL MARKETS

GovCoin Limited.

   Explanation: The United States Patent and Trademark office has granted a patent to WILDTANGENT, INC, titled as "Licensing media consumption using digital currency".

3). Dollarisation 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.

A.1.0.4 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.

A.1.0.5 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.

A.1.0.6 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.

A.1.0.7 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.

A.1.0.8 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.

A.1.0.9 11/07/2016 - 17/07/2016 (2016-07-15)

   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.

A.1.0.10 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.

A.1.0.11 05/06/2017 - 11/06/2017 (2017-06-09)

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

A.1.0.12 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.
A.1.0.13  10/07/2017 - 16/07/2017 (2017-07-14)

   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.

A.1.0.14  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.

A.1.0.15  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.


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

4). CBDC testing and studying (23/12/2017).

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

A.1.0.16  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.

A.1.0.17 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.

A.1.0.18 04/06/2018 - 10/06/2018 (2018-06-08)

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

A.1.0.19 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.

A.1.0.20 26/11/2018 - 02/12/2018 (2018-11-30)

   Explanation: Sweden’s Central Bank plans to launch CBDC to against cash usage declines.

   Explanation: Central Bank of Kenya is thinking to issue CBDC of Kenyan shilling.

   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.
APPENDIX A. APPENDIX: THE EFFECTS OF CENTRAL BANK DIGITAL CURRENCIES NEWS ON FINANCIAL MARKETS

   Explanation: Bank of Korea gave a presentation about CBDC on an international symposium held by the Financial Supervisory Service.

   Explanation: Nordic central banks are considering the CBDC because of the cyber security of digital payment.

A.1.0.21 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.

   Explanation: The Turkish Central Bank is planing to launch CBDC).
A.1. BIG EVENTS RELATED TO CBDC INDICES


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.

A.1.0.23 30/03/2020 - 03/05/2020 (2020-04-03 to 2020-05-01)

1). Digital-USD new progress (30/03/2020).

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.

   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.

A.1.0.24 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.

A.1.0.25 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.

A.1.0.26 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.

   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.

   Explanation: Norges Bank’s presentation about CBDC and real-time digital
   payments.

A.1.0.27 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.*

A.1.0.28 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.*

A.1.0.29 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.*

A.1.0.30 05/04/2021 - 11/04/2021 (2021-04-09)

1). CBDC technical issues in less developed areas.

A.1.0.31 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.

A.1.0.32 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.

A.1.0.33 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).

A.1.0.34 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
A.1. BIG EVENTS RELATED TO CBDC INDICES

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.

A.1.0.35  28/06/2021 - 04/07/2021 (2021-07-02)

1). Digital currency environmental issue.
## A.2 The negative dynamic correlation periods in the CBDC indices and financial variables

### Table A.1: The negative dynamic correlation periods in the CBDC indices and financial variables

<table>
<thead>
<tr>
<th>CBDCUI &amp; Financial variables</th>
<th>Time period</th>
<th>CBDCAI &amp; Financial variables</th>
<th>Time period</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBDCUI &amp; GBP/USD</td>
<td>2015-07-03 to 2016-03-25</td>
<td>CBDCAI &amp; JPY/USD</td>
<td>2017-01-13 to 2017-07-28</td>
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<tr>
<td></td>
<td>2016-04-15 to 2017-09-15</td>
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<td>2017-08-11 to 2017-09-08</td>
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<td>2019-06-14 to 2019-06-21</td>
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<td>2017-09-22 to 2019-06-21</td>
</tr>
<tr>
<td>CBDCUI &amp; MSCI WBI</td>
<td>2015-07-10 to 2016-03-04</td>
<td>CBDCAI &amp; RUB/USD</td>
<td>2015-04-17 to 2015-06-26</td>
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<td>2016-04-29 to 2016-09-30</td>
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<td>2020-12-11</td>
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<td>2016-05-13 to 2016-09-23</td>
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<td>2021-04-30 to 2021-06-18</td>
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<td>2016-11-04</td>
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<tr>
<td>CBDCUI &amp; JPY/USD</td>
<td>2017-03-31</td>
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<td>2017-11-10 to 2018-04-27</td>
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<td>2017-05-12</td>
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<td>2018-05-18 to 2018-05-25</td>
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<tr>
<td>CBDCUI &amp; UCRY Policy</td>
<td>2020-03-20</td>
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<td>2019-04-26</td>
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<td>2019-06-07 to 2019-06-21</td>
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<td>2020-11-06 to 2020-12-04</td>
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<td>2020-04-02 to 2021-07-02</td>
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<tr>
<td>CBDCAI &amp; UCRY Price</td>
<td>2020-03-20</td>
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<td>2020-10-23</td>
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<td>2020-10-23</td>
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<tr>
<td>CBDCAI &amp; FTSE WGBI</td>
<td>2016-11-25</td>
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<td>2017-12-15</td>
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<td>2021-01-22 to 2021-01-29</td>
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<td>2021-04-09 to 2021-04-16</td>
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<td>2021-04-09 to 2021-04-16</td>
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</tbody>
</table>

Notes: This table displays the negative dynamic condition correlation (DCC) between volatility in CBDC indices and GBP/USD, MSCI World Bank Index, JPY/USD, UCRY Policy, RUB/USD, UCRY Price and FTSE World Government Bond Index. These negative DCC periods could correspond to the negative DCC values in Figure 7.9 and Figure 7.10.
APPENDIX: VOLATILITY SPILLOVERS ACROSS NFTs
NEWS ATTENTION AND FINANCIAL MARKETS

B.1 Big events related to NFTsAI

B.1.1 The first wave (26/12/2016 - 07/03/2021)

B.1.1.1 04/06/2018 - 10/06/2018

1). ERC-721 Tokens (08/06/2018).
   Explanation: ERC-721 Tokens (CryptoKitties) shake up blockchain technology.

B.1.1.2 25/06/2018 - 15/07/2018

1). ECOMI (10/07/2018).
   Explanation: ECOMI is bringing Licensed and Brand-name Collectables to Blockchain Technology.

   Explanation: HTC Blockchain phone. HTC launches the world’s first major blockchain phone - the Exodus, and cooperates with the world’s first and most popular NFT game on the blockchain, CryptoKitties.
3). Decentralized gaming economy (12/07/2018).
   Explanation: Blockchain game "War Riders" partners with WAX and OPSkins Marketplace.

B.1.1.3 06/08/2018 - 12/08/2018

1). Blockchain entertainment platform partnership (10/08/2018).
   Explanation: WAX and Terra Virtua set up strategic partnership. It is the world's first Reality/Virtual Reality blockchain entertainment platform.

2). OMI tokens (10/08/2018).
   Explanation: Ecomi launches crowd sale for OMI tokens.

B.1.1.4 15/10/2018 - 28/10/2018

1). TriForce Tokens (22/10/2018).
   Explanation: Bitcoin gaming platform TriForce Tokens developing unique blockchain ecosystem.

2). EXODUS 1 (23/10/2018).
   Explanation: HTC formally launches the Blockchain phone, EXODUS 1.

3). Greenfence Consumer teams up with Sony Pictures (22/10/2018).
   Explanation: Blockchain leader Greenfence consumer cooperates with Sony Pictures to distribute digital collectibles for Goosebumps 2: Haunted Halloween.

B.1.1.5 03/12/2018 - 23/12/2018

1). $2 million NFTs creator fund (14/12/2018).
   Explanation: the Sandbox blockchain gaming platform launches $2 million NFTs creator fund for artists.

2). Blockchain versions of Atari games (19/12/2018).
   Explanation: Atari partners with Animoca Brands to make blockchain versions of Atari games RollerCoaster Tycoon Touch and Goon Squad. The new titles will feature the integration of NFTs.
3). NFT.NYC (20/02/2019).

*NFT.NYC brings the Digital Collectibles Ecosystem to Times Square, New York City.*

**B.1.1.6 21/01/2019 - 27/01/2019**

1). P08 (22/01/2019).

*Explanation: P08, a tech company, earned the Creative Business Cup Award for innovative and impact-driven solutions in blockchain technology and NFTs.*


**B.1.1.7 11/02/2019 - 10/03/2019**

1). WAX Block Explorer (28/02/2019).

*Explanation: WAX Block Explorer takes the NFT market openness to a whole new level.*

**B.1.1.8 09/12/2019 - 26/01/2020**

1). A MOU between WAX and CWRK (19/12/2019).

*Explanation: Worldwide Asset eXchange announces the signing of a Memorandum of Understanding with CurrencyWorks. They will work together to provide a turnkey offering for NFTs.*

2). Loans backed NFTs (21/01/2020).

*Explanation: a new kind of dApp, named Rocket, that will allow DeFi users to receive undercollateralized loans by putting up (NFTs).*

**B.1.1.9 30/03/2020 - 05/04/2020**

1). Revolution in NFTs-based Gaming Metaverse (30/03/2020).

*Explanation: Atari new partnership with Animoca Brands and TSB Gaming.*

2). Emergents (30/03/2020).

*Explanation: Emergents is a crypto collectible card game that will comprise non-fungible tokens so the players will have full ownership over.*
3). NFT market 16.08% CAGR (02/04/2020).
   Explanation: NFT market is expected to achieve 16.08% compound annual growth rate.

B.1.1.10 22/06/2020 - 26/07/2020

1). Digital collectibles go mainstream (30/06/2020).
   Explanation: digital collectibles go mainstream on the WAX Blockchain.

   Explanation: the limited edition branded digital collectibles is now available on the CurrencyWorks Collectibles blockchain platform.

3). CRYPTOGRAPH (08/07/2020).
   Explanation: Cryptograph, a Blockchain based digital collectible auction platform, officially launches.

   Explanation: crypto token developers Decentraland announced that Samsung had added its token to the Samsung Blockchain Keystore.

B.1.1.11 17/08/2020 - 30/08/2020

1). VIMworld (18/08/2020).
   Explanation: 8Hours Foundation announces launch date of VIMworld, a smart NFT Collectible & Gaming platform.

2). Blockparty (19/08/2020).
   Explanation: Blockparty launches a digital collectibles marketplace for art, sports, and music that enables users to own, sell, and trade digital assets.

B.1.1.12 07/09/2020 - 27/09/2020

1). New Binance LAND NFTs Buyup (09/09/2020).
   Explanation: Blockchain technology has great potential in the gaming industry, and Blockchain gaming hits cryptoeconomy primetime.
B.1. BIG EVENTS RELATED TO NFTSAI

B.1.1.13 16/11/2020 - 29/11/2020

1). KuCoin (16/11/2020).
   KuCoin enters NFT markets with the proposal of launching NFT exchange.

B.1.1.14 14/12/2020 - 20/12/2020

1). deadmau5 digital collectibles (15/12/2020).
   Explanation: first-ever deadmau5 digital collectibles to be released on WAX Blockchain.

2). Agreement for Gibraltar NFTs (17/12/2020).
   Explanation: new agreement for Gibraltar cryptocurrency stamp and digital collectible NFTs.

B.1.1.15 21/12/2020 - 27/12/2020

1). GoldenPyrex (21/12/2020).
   Explanation: GoldenPyrex is building a sustainable and independent token ecosystem, and will lead in the next era in DeFi with a robust ecosystem.

   Explanation: Axie Infinity hits 1-Day trading volume of $8.57 million. Furthermore, market capitalisation of Axie Infinity hits $28.74 million.

   Explanation: The Federal Reserve issued the Fed Notes article about Token Accounts in the context of digital currencies.

B.1.1.16 28/12/2020 - 07/03/2020


2). Rick and Morty Creator (14/01/2020).
   Explanation: Rick and Morty Creator releases NFT artwork on Ethereum’s Blockchain.
3). Fandom (19/01/2020).
   Explanation: Fandom outlines NFTs strategy for Esports Fan rewards.

4). Hashmask (10/02/2021).
   Explanation: one kinds of digital art, hashmasks, raised about $10 million four days after its launch. A hashmask sold for $130,000.

B.1.2 The Second Wave (08/03/2021 - 22/08/2021)

B.1.2.1 08/03/2021 - 14/03/2021

1). NFTs major bull market starts (08/03/2021).

2). NFTs $250 million market value (09/03/2021).
   Explanation: investments in NFTs rose 299% in 2020, and NFTs have made nearly 1,000% profit in some cases. NFTs have a market value of $250 million. Furthermore, Christie’s auction house and Paris Hilton, these legacy auction house are involving in on the NFTs boom.

3). NFTs hype warnings (09/03/2021).
   Explanation: NFTs are also dangers attached to the current level of hysteria, and the NFT market is full of price bubbles, hypes, and speculative transactions. Some experts remind NFTs investors should be aware of volatility, illiquidity, and fraud in the NFTs budding market.

B.1.2.2 15/03/2021 - 28/03/2021

1). NFTs VS The Legal Landscape (22/03/2021).
   Explanation: concerns about NFTs could disrupt the legal landscape, especially in patent, ownership right, copyright and security fields.

2). The value of NFTs (27/03/2021).
   Explanation: questions remain over how investors should assess monetary worth of NFTs.

B.1.2.3 19/04/2021 - 25/04/2021

1). NFTs sale prices dropped (24/04/2021).
   Explanation: the average price of NFTs dropped over 60% in April compared to February highs.
B.1.2.4 10/05/2021 - 06/06/2021

1). Anti-Money Laundering (19/05/2021).
   *Explanation: a collision between the anti-money laundering and NFTs. As NFTs gain popularity, buyers and sellers should consider the potential issues related to anti-money laundering laws.*

2). NFT price bubbles pop (04/06/2021).
   *Explanation: NFT market implodes with sales falling 90% in a month as the NFTs transaction craze fades.*

B.1.2.5 28/06/2021 - 18/07/2021

1). NFTs $2.5 billion sales volume (07/07/2021).
   *Explanation: NFTs sales volume surges to $2.5 billion in the first half of the year.*

B.1.3 The Third Wave (23/08/2021 - 10/10/2021)

B.1.3.1 23/08/2021 - 29/08/2021

1). Stephen Curry $180k NFTs purchase (28/08/2021).
   *Explanation: NBA superstar Stephen Curry purchased a Bored Ape NFT for $180,000.*

B.1.3.2 06/09/2021 - 12/09/2021

1). NFTs 315% increase month-on-month (09/09/2021).
   *Explanation: according to the data from DappRadar, August was a phenomenal month for NFTs with over $5 billion in total sales volume, a 315% increase month-on-month.*

   *Explanation: a collection of BoredApes NFTs sold for $24.4 million at a Sotheby's auction.*
APPENDIX B. APPENDIX: VOLATILITY SPILLOVERS ACROSS NFTS NEWS ATTENTION AND FINANCIAL MARKETS

B.1.4 The Fourth Wave (11/10/2021 - 31/10/2021)

B.1.4.1 11/10/2021 - 17/10/2021

1). The Sandbox reaches market cap of $648.35 million (13/10/2021).

2). Bored Ape Yacht Club 58.118% ROI (13/10/2021).

3). Ether cards NFTs platform rewards (13/10/2021).
   Explanation: Ether cards NFTs platform rewards early users with dust tokens worth $10.6 million.

   Explanation: Concept Art House raises $25M to create NFT art.

5). Meta4 Capital NFTs investment (21/10/2021).
   Explanation: Meta4 Capital will invest up to $100M in rare NFTs.

6). NFTs $3 billion sales volume (26/10/2021).
   Explanation: NFTs sales volume in 2021 has exceeded $3 billion.

B.1.5 The Fifth Wave (01/11/2021 - Present)

B.1.5.1 22/11/2021 - 28/11/2021

   Explanation: AnonymousUSA Evil Dollsiu NFTs sold at Sotheby’s auction for $35.6 million.

   Explanation: Dapper Labs is developing blockchain technology and bringing it to the public, the innovative NFTs business model worth multi-billion dollar.

   Explanation: Lugano is trying to be a Blockchain & Crypto-friendly city. The digital innovation laboratory of Lugano has promoted an exhibition that explores the NFTs and Crypto Art with an exhibition, events and dedicated workshops.
B.1.5.2 13/12/2021 - 19/12/2021

1). Animoca Brands and BAYC new NFT game (14/12/2021).
   Explanation: Animoca Brands Corporation Ltd and Bored Ape Yacht Club (BAYC) have joined forces to develop and publish a blockchain game using BAYC’s popular Bored Ape non-fungible tokens (NFTs).

B.1.5.3 27/12/2021 - 02/01/2022

1). Mutant Ape Yacht Club 500% trading jump (29/12/2021).
   Explanation: Mutant Ape Yacht Club has become the hottest NFT collection. The trading volume has surged by about 500% over the past seven days. The average price of a Mutant Ape increased from about $32,000 to about $50,000 during the past seven days.

2). "REAL" or "FAKE" Bored Ape Yacht Club (31/12/2021).
   Explanation: A pair of NFT projects are testing the boundary between plagiarism and parody. Digital marketplace OpenSea has banned the PHAYC and Phunky Ape Yacht Club collections, both of which are based on the same gimmick.

B.1.5.4 07/02/2022 - 20/02/2022

1). $5 billion funding (03/02/2022).
   Explanation: The start-up behind the popular Bored Ape Yacht Club non-fungible token collection is in talks with Andreessen Horowitz for a $5 billion funding.

2). BetOnline (07/02/2022).
   Explanation: A sports betting giant, BetOnline, bought Bored Ape Yacht Club NFT for $375,000.

3). NFT avatars (10/02/2022).
   Explanation: From CryptoPunks to Bored Ape Yacht Club, avatars are providing a hit in the NFT market. A collection of images of disillusioned monkeys can sell for several hundred thousand dollars.

4). NFT passport (20/02/2022).
   Explanation: Harmony launched Bored Ape Yacht Club passport. Harmony's
Passport doesn’t move assets, but it also proves asset ownership across multiple blockchains that guarantee their authenticity.

**B.1.5.5 14/03/2022 - 10/04/2022**

1). NFTs consolidate (14/03/2022).
   *Explanation: NFTs consolidate as Bored Ape Yacht Club creator acquires CryptoPunks and Meebits.*

2). Yuga Labs and metaverse (23/03/2022).
   *Explanation: Yuga Labs, creators behind the Bored Ape Yacht Club is now stepping into the world of metaverse.*

3). Bored Ape Yacht warning (01/04/2022).
   *Explanation: Bored Ape Yacht Club warned users not to mint any NFTs after its Discord was hacked.*

**B.1.5.6 02/05/2022 - 05/06/2022**

1). NFT hack (04/06/2022).
   *Explanation: Bored Ape Yacht Club Discord server hacked, NFT stolen.*
B.2 Dynamic directional volatility spillover connectedness using the rolling sample

Figure B.1: Directional volatility spillovers from each variable i to all others

Notes: The FROM directional spillover connectedness measures the spillovers received by variable i from all other variables. The predictive horizon for the underlying variance decomposition is 10 weeks ($H = 10$). The sample is from 26/Dec/2016 to 05/Jun/2022. These figures re-confirm the existing viewpoint that NFT assets have diversification benefits (Dowling, 2021) and (Yousaf and Yarovaya, 2022)).
Figure B.2: Directional volatility spillovers to each variable i from all others

Notes: The TO directional spillover connectedness quantifies the contribution of variable i to all other variables. The predictive horizon for the underlying variance decomposition is 10 weeks (H = 10). The sample is from 26/Dec/2016 to 05/Jun/2022. These figures indicate that: 1). The cryptocurrency markets transmit more volatility spillover effects than it receives. 2). NFT markets are relatively independent and isolated. The cryptocurrency market holds the dominant role that arouses the NFT markets’ volatility, compared with the stock, commodity, bond, F.X., and gold markets.
B.3 Evolution of the price trajectories of NFT assets with optimal function results

Figure B.3: Evolution of the price trajectories of NFT assets with optimal function

(a) NFT Index  (b) Bored Ape Yacht Club

(c) CryptoPunks  (d) The Sandbox

(e) Art Blocks

The evolution of the price trajectories of NFT Index, Bored Ape Yacht Club, CryptoPunks, The Sandbox and Art Block with optimal function are visualised in this figure. This figure also can be interpreted as the visualisation of the LPPLS best fit function, which could correspond to the LPPLS robust test results in Figure 8.11.
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