# Examining the co-movement between cryptocurrency uncertainty and central bank digital currency uncertainty

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**ABSTRACT**

This paper investigates the dynamic co-movement between the Cryptocurrency Uncertainty indices and the Central Bank Digital Currency Uncertainty indices. We apply the wavelet coherence framework using weekly data from January 13, 2017, to December 30, 2022. The empirical results reveal the significant co-movement between the Cryptocurrency Uncertainty Indices and the Central Bank Digital Currency Uncertainty Indices. Our findings suggest that the Cryptocurrency Policy Uncertainty index is highly correlated with the Central Bank Digital Currency Uncertainty index in the medium and long term but with the Central Bank Digital Currency Attention index in the short term. Our findings thus indicate that the Cryptocurrency Policy Uncertainty index can be used to predict the Central Bank Digital Currency Uncertainty index. On the other hand, the Cryptocurrency Environmental Attention index has historically correlated with the Central Bank Digital Currency Uncertainty indices in terms of long frequency.

## 1. Introduction

In a world of unpredictability, the past two decades have been tumultuous. Significant financial and political events, such as the 2008 - 2009 Global Financial Crisis, the Eurozone's sovereign debt crisis, terrorist attacks in 2015, and Brexit in 2016, have shaken the global stage (Tooze, 2018). Recent occurrences like the Covid-19 pandemic, the conflict in Ukraine, and the war between Palestine and Iran have further demonstrated their direct global impacts. These consecutive events have emphasized the pivotal role of uncertainty in today's economies, shaping the enactment of fiscal and monetary policies in financial markets and subsequently impacting the real economy. Given the interconnectedness among various world markets and countries, uncertainties in one market or country can easily spread to others (Kang & Yoon, 2019). For instance, previous studies indicate that Economic Policy Uncertainty (EPU) affects stock markets (Yuan et al., 2022), commodities markets (Mokni et al., 2020), and the real estate market (Xia et al., 2020).

Researchers have shifted to examining the connectedness between economic policy uncertainty and cryptocurrencies for the past few years. A stream of research examines whether cryptocurrencies can act as diversifiers and hedging assets against economic policy uncertainty (Demir et al., 2018). On the other hand, critical events such as the DeFi boom and attacks on cryptocurrency exchanges also increase the attention and uncertainty in the cryptocurrency markets (Lucey et al., 2022). Despite extensive research, there are gaps in the current literature on the EPU-cryptocurrency relationship. First, most studies have focused on the in-sample effects of EPU on cryptocurrency volatility.

In contrast, the out-of-sample predictive power of EPU on cryptocurrency volatility still needs to be verified. Secondly, the national EPU index does not align with the super-sovereign nature of cryptocurrency as it may only affect a portion of cryptocurrency owners. This issue can be mitigated using the global EPU, but the relationship between global EPU and cryptocurrency is unclear. Lastly, the EPU data is usually available at a relatively low frequency (i.e., monthly).

Lucey et al. (2022) recently introduced novel indices for cryptocurrency policy and price uncertainty (UCRY Policy and UCRY Price) derived from an analysis of 726.9 million news articles. Their study offers a fresh perspective on uncertainty within cryptocurrency markets, suggesting that the movements of UCRY indices differ from those of other risk and uncertainty indices such as US Economic Policy Uncertainty (US EPU), the Global EPU index, and the Volatility Index (VIX), potentially resulting in distinct impacts on financial markets. Several studies (Elsayed et al., 2022; Xia et al., 2023) have examined the effectiveness of these indices in predicting cryptocurrency volatility.

Moreover, research has explored the relationship between Central Bank Digital Currency (CBDC) uncertainty, cryptocurrency returns and volatility, and other uncertainty indices. For example, Wang et al. (2022a) develop CBDC uncertainty and attention indices using news articles from the LexisNexis database. These CBDC-related indices are strongly associated with cryptocurrencies, potentially affecting other asset classes. Through Dynamic Conditional Correlation (DCC) modeling, Wang et al. (2022a) find that CBDC uncertainty is negatively correlated with the MSCI World Banks Index, the US EPU, and the FTSE All-World Index while positively correlated with cryptocurrency market volatility. Additionally, Yousaf and Goodell (2023) discover that CBDC Uncertainty tends to receive shocks, whereas cryptocurrency policy uncertainty (UCRY Policy) and cryptocurrency price uncertainty (UCRY Price) transmit them. As cryptocurrency gains global recognition, attention is shifting towards predicting its uncertainty and volatility using indicators such as geopolitical risk (Kamal et al., 2022; Triki & Maatoug, 2022) and inflation (Gambarelli et al., 2023). However, research on the relationship between cryptocurrency uncertainty and CBDC uncertainty is still nascent.

To this aim, we employ the biwavelet coherence method to explore the co-movement between the cryptocurrency uncertainty indices, namely the cryptocurrency policy uncertainty (UCRY Policy), the cryptocurrency price uncertainty (UCRY Price), the Cryptocurrency Environmental Attention (ICEA), the Non-fungible Token Attention (NFTs Attention) and the two CBDC uncertainty indices, including the Central Bank Digital Currency Uncertainty (CBDC Uncertainty) and the Central Bank Digital Currency Attention index (CBDC Attention) over the period from 13$^{th}$ January 2017 to 30$^{th}$ December 2022.

Our results reveal a strong correlation between the UCRY Policy index and CBDC Uncertainty indices in the short term. Similarly, the NFT Attention index strongly correlates with the CBDC Attention index. In contrast, only some occasional high correlations between the UCRY Price index and the CBDC Uncertainty index are observed mainly in the short and medium term. On the other hand, we observe a lower degree of co-movement between the ICEA index and the CBDC Uncertainty indices.

Our paper has two significant contributions. First, we overcome the limitations of uncertainty data usually employed in previous studies, such as the economic policy uncertainty index, which is generally available at a relatively low frequency (i.e., monthly series). This paper uses the set of uncertainty data in the weekly developed by Wang et al. (2022a), Wang (2022), Wang et al. (2022b), and Lucey et al. (2022). Doing this can provide more unmistakable evidence of spillover effects between cryptocurrency and CBDC uncertainty. Second, our paper is also the first to test the connectedness between CBDC Uncertainty and NFTs Attention. We also extend the research by Wang et al. (2022b) on the dynamic influence between the ICEA and the CBDC Uncertainty indices.

## 2. Literature review

There has been a growing interest in predicting cryptocurrency prices in recent years. This trend is driven by the volatile nature of cryptocurrencies, which can lead to significant financial gains or losses. Also, it's important to note that cryptocurrencies carry substantial risks, including high price volatility and regulatory uncertainty (see, *among others*, Akhtaruzzaman et al., 2022; Katsiampa et al., 2019).

However, cryptocurrencies are increasingly viewed as a potential hedge against the risks arising from escalating inflation or geopolitical tensions. Inflation erodes the purchasing power of money over time (Adaramola & Dada, 2020), while geopolitical risks can lead to financial market volatility (Khalfaoui et al., 2022; Ndako et al., 2021; Salisu et al., 2020). As demonstrated by previous authors, cryptocurrencies, with their decentralized nature and global accessibility, offer a potential safeguard against these risks (Cheng & Yen, 2020; Melki & Nefzi, 2022; Raza et al., 2022). Their value is independent of any specific economy or political system with any single economy or political system, making them less susceptible to country-specific inflation or geopolitical events.

Given the ongoing discussion regarding the efficacy of traditional assets as safe-haven options amidst inflationary pressures, there has been a surge in interest surrounding alternative stores of value. Cryptocurrencies have come under scrutiny to determine their potential as practical hedging tools compared to conventional assets (Smales, 2024). These investigations offer empirical insights into utilizing these emerging "digital assets" to hedge against inflation. For instance, Sakurai and Kurosaki (2023) examine the correlation between cryptocurrencies and expected inflation rates in the US following the reopening of the economy post-Covid-19 pandemic. According to their findings, major cryptocurrencies show a slight improvement as inflation hedges, and the maximum supply cap of cryptocurrencies does not dictate their effectiveness as inflation-hedging instruments.

Moreover, recent scholarship has increasingly focused on the hedging capabilities of cryptocurrencies against downside risks associated with traditional financial assets such as equities, bonds, and commodities, particularly during turbulent periods like the Covid-19 pandemic (Conlon et al., 2020; Mariana et al., 2021) or geopolitical events like the Ukraine conflict (Elsayed et al., 2022). Previous research indicates that political instability negatively impacts stock market returns (Yuan et al., 2022), prompting capital flows from traditional financial markets to cryptocurrency markets. For instance, Umar et al. (2021) advocate for cryptocurrencies as a refuge against traditional markets' ineffectiveness during heightened geopolitical tensions. This finding is consistent with Fang et al. (2019), who observe that the economic policy uncertainty index enhances portfolio hedging against Bitcoin price volatility. However, another line of research presents contradictory findings regarding the safe-haven status of cryptocurrencies (Panagiotidis et al., 2019; Thampanya et al., 2020).

On the other hand, there's a growing interest in forecasting cryptocurrency returns and volatility using various indicators, including macroeconomic proxies such as interest rates, inflation, market volatility, Consumer Price Index (CPI), and even novel proxies related to the environment (Clark et al., 2023), alongside financial factors like investor sentiment (Lin, 2021), or business cycles (Wang et al., 2022a). Among these indices, a macroeconomic aspect that has garnered recent scholarly attention is uncertainty factors. For instance, Demir et al. (2018) demonstrate that Economic Policy Uncertainty (EPU) holds predictive power over Bitcoin returns. Bitcoin can serve as a hedging tool against uncertainty during extreme times due to its negative correlation with changes in EPU. Wang et al. (2020) investigate how EPU influences Bitcoin markets in the US and the UK on high and low days by constructing value-weighted BTC/GBP and BTC/USD composite indices. Additionally, Wu et al. (2021) explore the effects of two new economic policy uncertainty measures, including Twitter-based economic uncertainty and Twitter-based market uncertainty, on the returns of four cryptocurrencies: Bitcoin, Ethereum, Litecoin, and Ripple.

While EPU has frequently been studied as a predictor of cryptocurrency returns, some researchers have taken the opposite approach, examining the predictive power of UCRY Policy and CBDC Uncertainty indices in forecasting the returns/volatilities of financial assets. In their study, Hassan et al. (2021) investigate the fluctuating correlation and asymmetric impact between the volatility of precious metals and the UCRY Policy index. Employing the DCC-GJR-GARCH method, the researchers find that gold is the sole effective and safe-haven asset among the top four precious metals. In contrast, Elsayed et al. (2022) reveal that gold is susceptible to uncertainty shocks and is significantly influenced by cryptocurrency markets. This finding challenges the common perception of gold as a safe hedge against uncertainty shocks such as geopolitical risk and inflation.

Meanwhile, Karim et al. (2022) explore the safe-haven characteristic of the bond market against three UCRY uncertainty indices using the ADCC-GARCH model. They conclude that, apart from the S&P green bond, the bond market neither serves as a hedger nor a safe-haven asset against the UCRY Policy index. Karaömer (2022) also observes a negative correlation between cryptocurrency returns and three indices of cryptocurrency uncertainty, suggesting that cryptocurrencies do not function effectively as hedge instruments or safe havens against the UCRY Policy index.

Alternatively, the uncertainty surrounding CBDCs has intrigued numerous researchers. For example, Wang et al. (2022a) developed two indices related to CBDC: the CBDC Uncertainty Index and CBDC Attention Index. They find a negative correlation between these indices and the volatilities of banking sectors, stock markets, and US economic policy uncertainty. Conversely, CBDC indices positively correlate with the volatilities of cryptocurrencies, foreign exchange, gold, and bond markets. Moreover, Kamal et al. (2023) undertake a study involving three assets, USD futures, gold futures, and 1-year US bonds, to assess their potential as hedging instruments against CBDC Uncertainty indices. The findings indicate a positive correlation with the US dollar but an insignificant correlation with gold. However, US bonds only demonstrate hedging effectiveness against the CBDC Uncertainty index post-2019, consistently displaying a negative relationship with the CBDC Attention index.

Concurrently, Yousaf and Goodell (2023) investigate the interplay between CBDC uncertainty, UCRY Policy, UCRY Price, and returns and volatility of digital payment stocks. Their findings suggest uncertainty indices are more closely linked with returns than digital payment stocks' volatilities. Overall, uncertainties in the cryptocurrency market, such as CBDC Uncertainty, UCRY Policy, and UCRY Price indices, prove valuable in predicting returns and volatility of digital payment stocks. However, the relationship and co-movement between these uncertainty indices have not been explored in terms of their predictive power for cryptocurrency prices/volatility. Hence, we aim to bridge this gap by employing the wavelet coherence approach developed by Torrence and Compo (1998) and expanded by Torrence and Webster (1999) to identify and measure the co-movement between indices of cryptocurrency uncertainties and CBDC uncertainty proxies.

## 3. Methodology and data

### *3.1. Biwavelet analysis*

The wavelet coherence method is utilized to identify both temporal and frequency domains to detect and measure the co-movement between two correlated time series variables. Torrence and Compo (1998) outline the wavelet coherence of two-time series variables by employing smoothing techniques in both temporal and frequency domains. For two time series, x(t) and y(t), with their respective cross-wavelet transforms. $W_x(u,s)$ and $W_Y\,(u,s)$, the cross-wavelet transform is represented as:

$$W_{x,y}(u,s) = W_x(u,s)W_y^*(u,s) \tag{1}$$

Here, ‘s’ denotes the scale, and ‘u’ represents the position index, $W_x(u,s)$ and $W_y^*(u,s)$ are continuous wavelet transforms of the two-time series variables x and y, respectively, with the ‘*’ sign indicating the complex conjugate. The wavelet transform captures the localized covariance between the two-time series variables. The wavelet coherence method, as proposed by Torrence and Compo (1998), calculates the cross-wavelet power to highlight areas with significant covariance between the time series variables at each scale. The wavelet coherence is employed to illustrate the temporal regions where co-movement in the time series variables exists, even if they do not exhibit high wavelet power. We adopt the approach introduced by Torrence and Webster (1999), an extension of Torrence and Compo’s (1998) method, and define the squared wavelet coherence coefficient as:

$$R^2(u,s) = \frac{\left|S(s^{-1}W_{x,y}(u,s))\right|^2}{S(s^{-1}|\,W_x(u,s)|^2)S\left(s^{-1}\left|\,W_y(u,s)\right|^2\right)} \tag{2}$$

Where ‘s’ denotes a smoothing operator across time and space, $R^2(u, s)$ represents the localized squared correlation in both time and frequency domains, and the squared wavelet coefficient falls within the range of $0 \leq R^2(u, s) \leq 1$. Higher values of the wavelet squared coherence, $R^2(u, s)$, indicate greater co-movement between the two-time series and vice versa. The wavelet squared coherence is confined to positive values between 0 and 1, preventing differentiation between negative and positive co-movements in the two-time series. To address this limitation, Torrence and Compo (1998) propose utilizing the phase difference, which aids in identifying the direction of co-movement (e.g., positive or negative co-movements between variables x and y).

The phase difference is defined as:

$$\emptyset_{x,y}(u,s) = \frac{lm\{S(s^{-1}W^{xy}(u,\ s))\}}{Re\{S(s^{-1}W^{xy}(u,\ s))\}} \tag{3}$$

Where lm and Re represent the imaginary and real parts of the smoothed cross-wavelet transform, respectively, a typical result of a cross-wavelet coherence analysis comprises five main components: black arrows with eight directions (←, →, ↑, ↓, ↘, ↗, ↙, ↖), warm and cold color patterns, black contours, two axes, and the cone. The black arrows pointing → (←) signify an in-phase (out-of-phase) relationship or positive (negative) correlation, while arrows directed ↗ (↙) indicate the leading effect of the first (second) series. For example, black arrows with the direction '↘' in wavelet coherence plots indicate an in-phase relationship or positive co-movement between two-time series, with the second series exerting maximum influence. Conversely, black arrows with the direction '↖' in wavelet coherence plots indicate an out-of-phase relationship or negative co-movement between two-time series, with the first series leading. A phase difference of zero indicates that both time series move synchronously. The black curves in the plots delineate regions of coherence significance at a 5% level, while the solid white bell-shaped line in wavelet coherence plots represents the cone of influence.

### *3.2. Data*

This research utilizes two sources of data. The first source of data corresponds to the uncertainties related to CBDC. Specifically, we adopt two proxies of CBDC uncertainties proposed by Wang et al. (2022a), namely the CBDC Uncertainty Index and the CBDC Attention Index[1]. A higher CBDC Uncertainty Index indicates more significant uncertainty about the CBDC in the financial market. Meanwhile, the CBDC Attention Index measures the level of attention or interest towards CBDC in the financial market. The higher the CBDC Attention Index, the more news correlates with CBDC and vice versa.

The second data source pertains to the unpredictability of the cryptocurrency markets. Particularly, we utilize the Cryptocurrency Policy Uncertainty Index (UCRY Policy) and the Cryptocurrency Price Uncertainty Index (UCRY Price), which were developed by Lucey et al. (2022). These indices incorporate information from various newspapers and news-wire feeds in the LexisNexis Business Database[2]. The higher the value of the UCRY Policy, the more news on the market concerning the cryptocurrency policy and regulations. The higher the value of the UCRY Price, the more news on the market related to the uncertainty of cryptocurrency price. We also employ an NFTS Uncertainty index to extend our variables and examine if CBDC and this other form of cryptocurrency uncertainty correlate. Our research paper includes the NFTs weekly data from January 13, 2017, to December 30, 2022, to match with other indices.

[1]The main purpose of these two indices is to track CBDCs' trends and variations, the authors constructed two indices using over 663 million news items, which are the combinations of keywords relevant to CBDCs from Lexis-Nexis News & Business. The authors also collected data in different languages such as English, Russian, and Chinese to cover all the news in countries leading in cryptocurrency development

[2]The researchers collected over 726.9 million news articles from the LexisNexis database between January 2014 and January 2021, demonstrating how the UCRY Policy and UCRY Price indices have influenced the historical breakdown of the index during significant events in the cryptocurrency sector

Finally, we utilize the Index of Cryptocurrency Environmental Attention (ICEA), developed by Wang et al. (2022b), which is a database capturing cryptocurrency's environmental attention concerning significant related events. Similar to the construction method of the UCRY uncertainty index by Lucey et al. (2022), Wang et al. (2022b) gather over 778.2 million news articles from LexisNexis News & Business, covering discussions on environmental sustainability alongside cryptocurrencies. This index gauges the relative extent of media discourse surrounding the environmental impact of cryptocurrencies, with higher values indicating increased coverage of significant ecological events by cryptocurrencies. These indices are all sourced from https://sites.google.com/view/cryptocurrency-indices/home?authuser=0

Notably, each index is examined in a different period. We chose January 13, 2017, as the first date for our collected data because the NFTs Attention index data has only been established since January 2017, the latest one in our data set. Therefore, all of our indices data is collected in the weekly data started on January 13, 2017. We also choose December 30, 2022, as the final date for our sample period.

Table 1 presents the descriptive statistics of the series under scrutiny. The mean value of all indices is positive, indicating a rise in their values throughout the sample period - all variables under examination exhibit stationarity at a 1% significance level. The skewness and kurtosis measures reveal that all series are leptokurtic and significantly right-skewed. Furthermore, evidence suggests that the series are autocorrelated and demonstrate ARCH errors, justifying adopting a time-varying model. Table 2 displays the correlation matrix for the variables under investigation. While most variables exhibit positive correlations, the NFTs Attention Index correlates negatively with the UCRY Policy Index, UCRY Price Index, and CBDC Uncertainty Index. Moreover, Table 2 reveals a negative correlation between the UCRY Price Index and the CBDC Attention Index.

**Table 1**

*Summary Statistics of the Variables under Examination*

| | **Mean** | **Variance** | **Skewness** | **Excess Kurtosis** | **JB** | **ERS** | **Q(20)** | **$Q^2$(20)** |
|---|---|---|---|---|---|---|---|---|
| UCRY Policy | 4.997*** (0.122) | 3233.187*** | 17.029*** (0.000) | 293.550*** (0.000) | 1135308.499*** (0.000) | -7.730*** (0.000) | 1.594*** (1.000) | 0.045*** (1.000) |
| UCRY Price | 1.715*** (0.000) | 70.159*** | 9.951*** (0.000) | 111.101*** (0.000) | 165614.868*** (0.000) | -7.391*** (0.000) | 2.381*** (0.999) | 0.180 (1.000) |
| CBDC Uncertainty | 3.430*** (0.000) | 248.322*** | 5.691*** (0.000) | 31.502*** (0.000) | 14585.168*** (0.000) | -6.624 (0.000) | 13.458 (0.202) | 10.412 (0.461) |
| CBDC Attention | 33.490 (0.296) | 319799.405*** | 17.575*** (0.000) | 306.924*** (0.000) | 1240689.833*** (0.000) | -7.785*** (0.000) | 0.037 (1.000) | 0.037 (1.000) |
| NFTs Attention | 1.466** (0.002) | 70.690*** | 10.465*** (0.000) | 119.260*** (0.000) | 190592.858*** (0.000) | -7.496*** (0.000) | 3.330 (0.995) | 0.164 (1.000) |
| ICEA | 2.030*** (0.002) | 129.732*** | 7.956*** (0.000) | 64.694*** (0.000) | 57701.084*** (0.000) | - 6.398*** (0.000) | 22.890*** (0.005) | 26.155*** (0.001) |

*Note.* ***, **, and * denote significance at 1%, 5%, and 10% significance levels respectively. The researcher's data analysis

**Table 2**

*Correlation Matrix of the Variables under Examination*

| **Variables** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| (1) UCRY Policy | 1.000 | | | | | |
| (2) UCRY Price | 0.243 | 1.000 | | | | |
| (3) CBDC Uncertainty | 0.003 | 0.112 | 1.000 | | | |
| (4) CBDC Attention | 0.137 | -0.021 | 0.019 | 1.000 | | |
| (5) NFTs Attention | -0.008 | -0.035 | -0.017 | 0.116 | 1.000 | |
| (6) ICEA Index | 0.077 | 0.068 | 0.105 | 0.080 | 0.034 | 1.000 |

*Notes.* The researcher's data analysis

## 4. Empirical results

Figure 1a shows the wavelet coherence between cryptocurrency policy and CBDC uncertainty indexes. The chart is dominated by shades of yellow and orange, showing the medium correlation between the two variables over the sample period. We can witness a distinct difference between the periods before and after January 2020. Specifically, from January 2017 to January 2020, there are only some small, noticeable short- and medium-term correlations. After January 2020, the co-movement between the two variables is at a high degree in both the short and long term. In the short term, we can witness some co-movement with a frequency of under four weeks. The direction of the arrows (↙) points to the left and downward, indicating an out-of-phase relationship between the two variables with the leading effect of the UCRY Policy index. A similar co-movement between the UCRY Policy index and the CBDC Uncertainty index can also be witnessed in the medium and long term (08 - 64 weeks). The upward arrows (↖) describe the leading role of the UCRY Policy index over the CBDC Uncertainty index. However, the wavelet coherence shows an unstable trend in the medium term, with the arrows changing their direction to the right in the longer frequency band between January 2020 and December 2021.

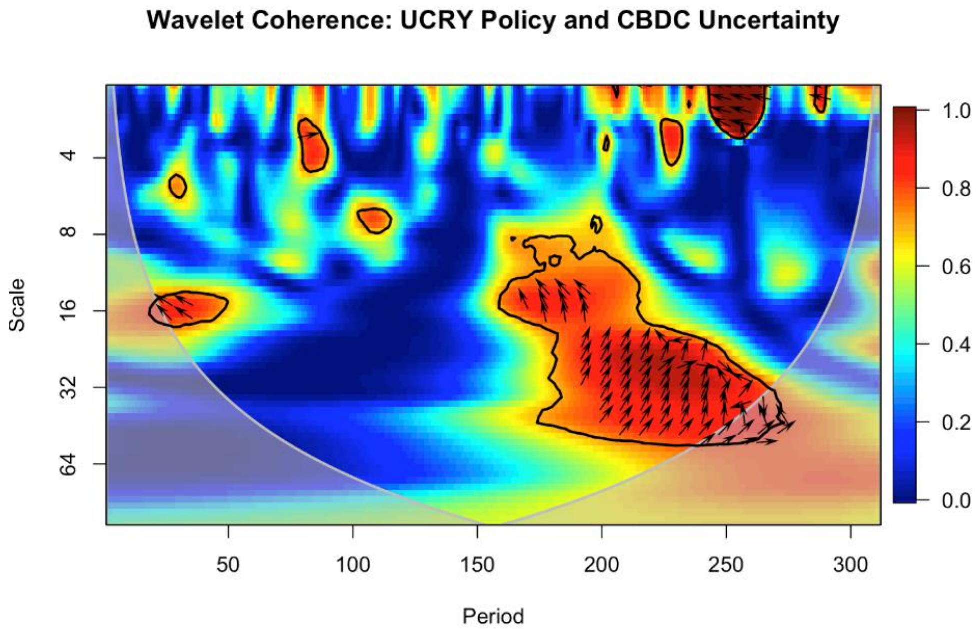
Next, we proceed with the results of the wavelet coherence between the UCRY Price index and the CBDC uncertainty index, as shown in Figure 1b. At the beginning of the examined period, the correlation is observed at the highest level over the frequency of around 8-16 weeks and becomes weaker over a longer frequency band. Occasional high correlations, demonstrated by the orange and red shades of color, are observed mainly in the short and medium term (around 01 - 16 weeks), with some remarkable co-movement in around 2021 when the Covid-19 pandemic just broke out. The upward-going direction of the arrows demonstrates the leading role of the UCRY Price index on the CBDC Uncertainty index. An out-of-phase is also noticed between the two variables.

Figure 1c reports the coherence between the NFT Attention and CBDC Uncertainty indexes. The overall green-to-blue color shades denote the weak co-movement between the two variables. In the short run, there is only some notable co-movement between the NFT Attention index and the CBDC Uncertainty index at specific periods. A closer look at the arrows going in different directions at different times shows no particular trend for the co-movement between the NFT Attention Index and the CBDC Uncertainty Index. Finally,

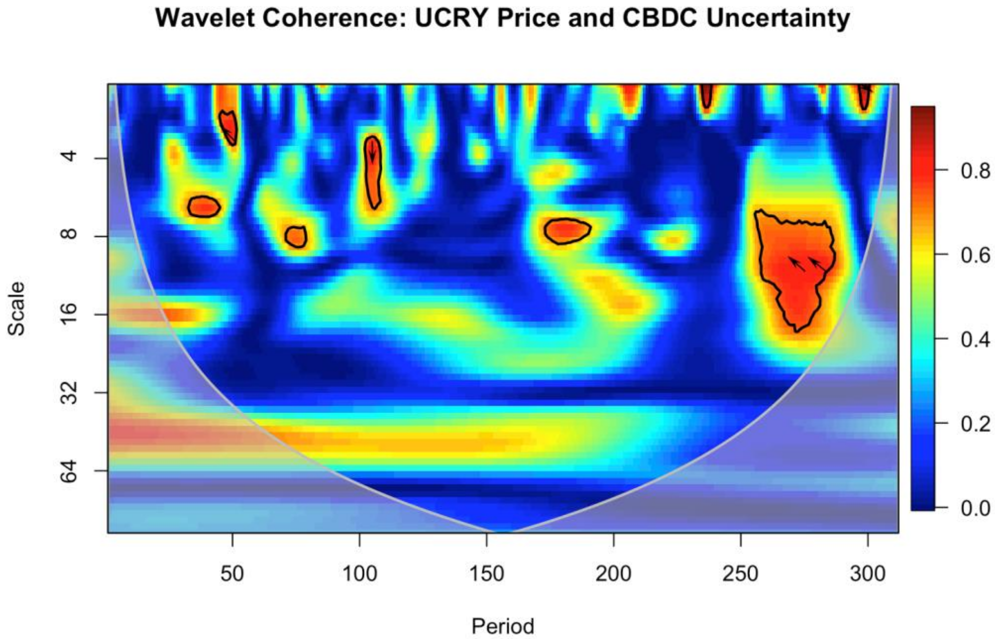
Figure 1d shows the wavelet coherence between the Cryptocurrency Environmental Attention (ICEA) index and the CBDC Uncertainty. Overall, we can observe the dominance of orange and red shades in the long term at the beginning of the sample period. We can witness high co-movement in the frequency bands of around 64 weeks. The arrows' direction tends to face downward and to the left (↙), indicating an out-of-phase relationship with the leading role of the CBDC Uncertainty index over the ICEA index. The dominance of the red color in the long term is also less visible over time. Generally speaking, we can witness lower co-movement between these two variables.

**Figure 1**

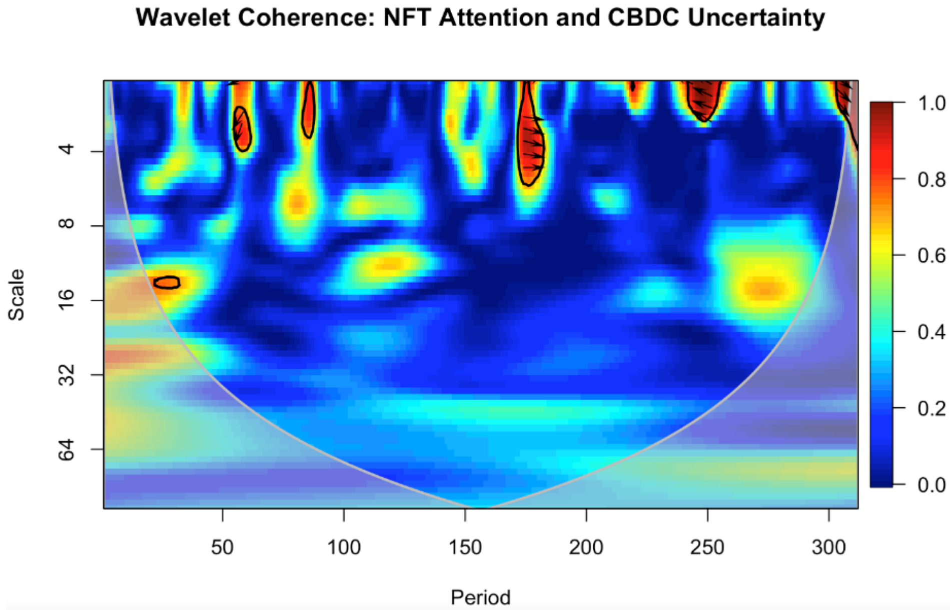
*The Wavelet Coherence between various Indices of Cryptocurrency Uncertainties and CBDC Uncertainty Index*



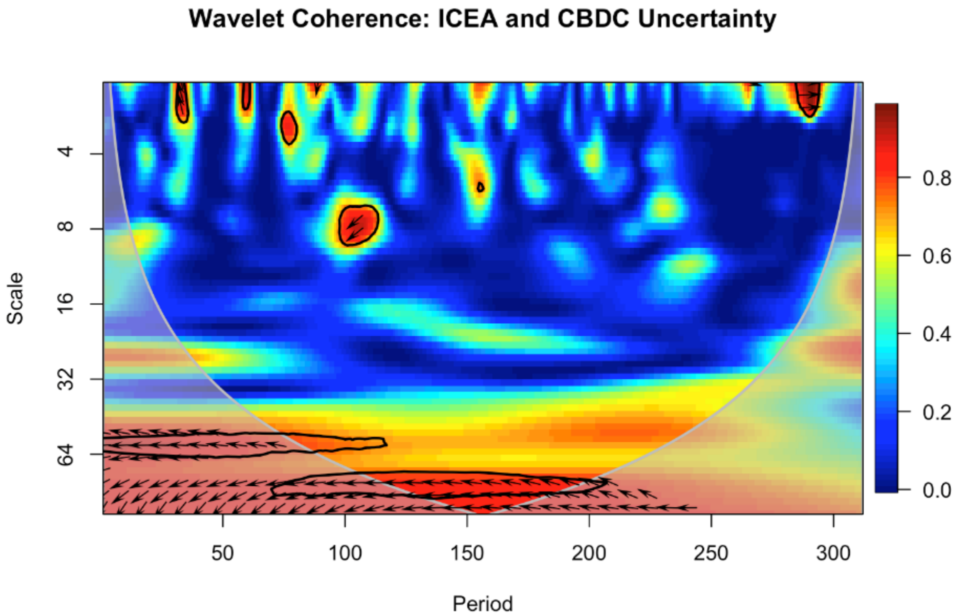

(a).




(b).




(c).




(d).

*Note.* The vertical axis depicts time in weeks, while the horizontal axis represents the scale. Colors on the right side of the main chart signify coherence levels, transitioning from blue to red, indicating higher absolute correlation values concerning $R^2(u, s)$. A solid white curved line within coherence plots denotes the cone of influence, while the black contours highlight regions of significance at a 5% level. The arrows inside the chart indicate phase differences; rightward arrows (→) signify an in-phase (positive) relationship, while the opposite direction suggests the opposite. The direction of arrows (↑ or ↓) indicates which time series leads the other. The researcher's data analysis

Figure 2a reports the wavelet coherence between the UCRY Policy and CBDC Attention indexes. Overall, the chart is dominated by shades of blue, showing little to no correlation in the medium and long term. However, after January 2021, we can witness a notable high co-movement between the two variables in the short term (0 - 12 weeks). The arrows mostly go sideways, meaning there is no leading role of any variable to the other. It also needs to be mentioned that in the longer frequency, the direction of the arrows tends to change from left to right, meaning the in-phase relationship between the two variables in the longer term.

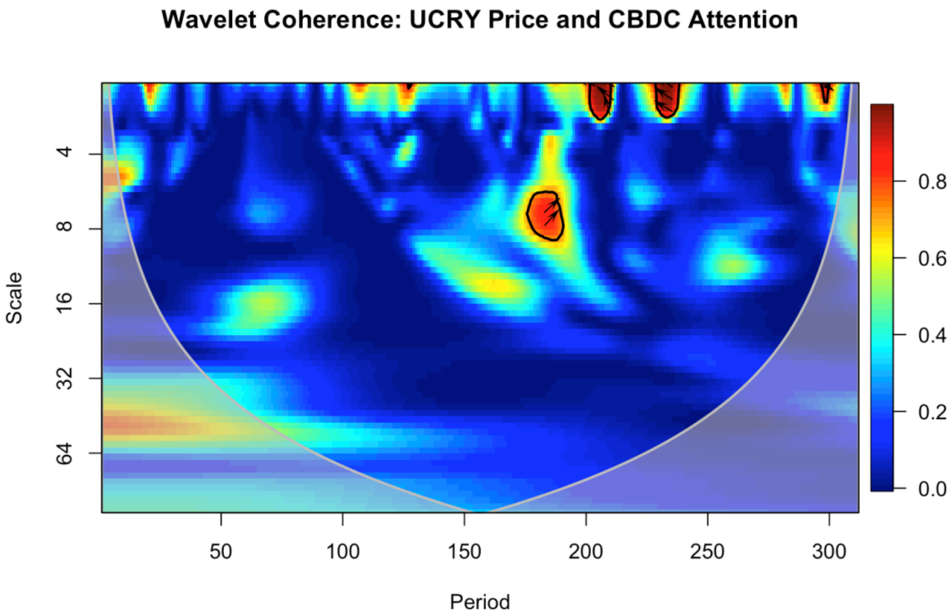
In Figure 2b, the chart is mainly dominated by the blue shade, showing almost no correlation between the two variables during the medium- and long-term. Only occasional correlations are observed in the short term (01 - 04 weeks). The upward arrows imply that the UCRY Price Index leads the CBDC Attention Index. We also notice that in the longer frequency, the arrows' direction tends to change from pointing left to right, which means two variables have positive co-movement in the longer time.

The empirical results in Figure 2c demonstrate the wavelet coherence between the NFT and CBDC Attention indexes. In the short term, 2020 marks the beginning of the high co-movement between two variables in the short run (0 - 08 weeks). While in the lower frequency (0 - 04 weeks), the arrows go sideways with no specific co-movement trend, indicating there is no leading variable to the other; then, in the more extended period (04 - 08 weeks), the direction of the arrows change to facing upward, implying that the news of NFT Attention is leading the attention around CBDC.

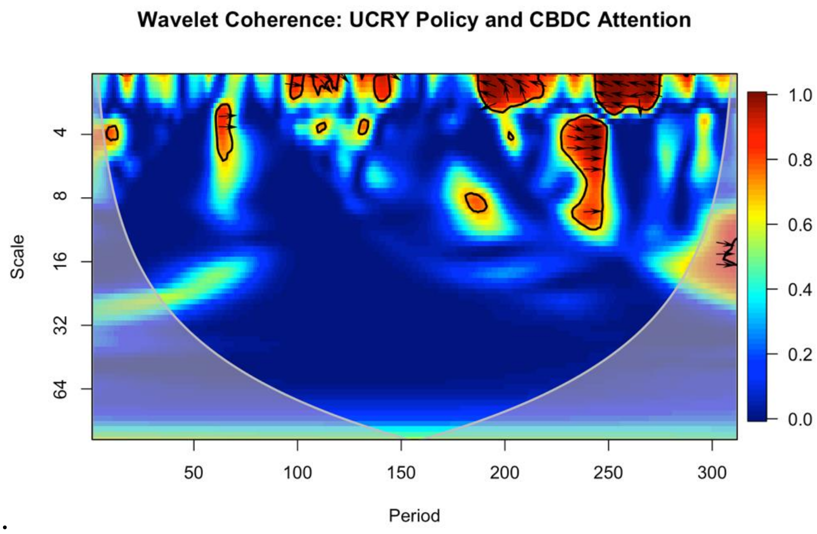
Finally, Figure 2d reports the wavelet coherence between the Index of Cryptocurrency Environmental Attention (ICEA) and the CBDC Uncertainty Index. Historically, we also witnessed high co-movement in the higher frequency band from 2017 to 2021. However, the result contradicts the wavelet coherence between the Index of Cryptocurrency Environmental Attention (ICEA) and the CBDC Uncertainty Index. Between the 16- and 64-week frequency bands, the arrows facing upward and slightly to the left show a negative relationship between the two variables. In the frequency of over 64 weeks, the direction of the arrows (↗) facing upward to the right indicates an in-phase relationship with the leading effect of the ICEA on the CBDC Attention. Similar to the result of the CBDC uncertainty, the influence of the ICEA is also weaker over the long term. It has also been noticed that in the short term (0 - 16 weeks) after January 2020, there is occasional high co-movement between ICEA and CBDC Uncertainty. The downward arrows imply that the CBDC Attention leads the ICEA.

**Figure 2**

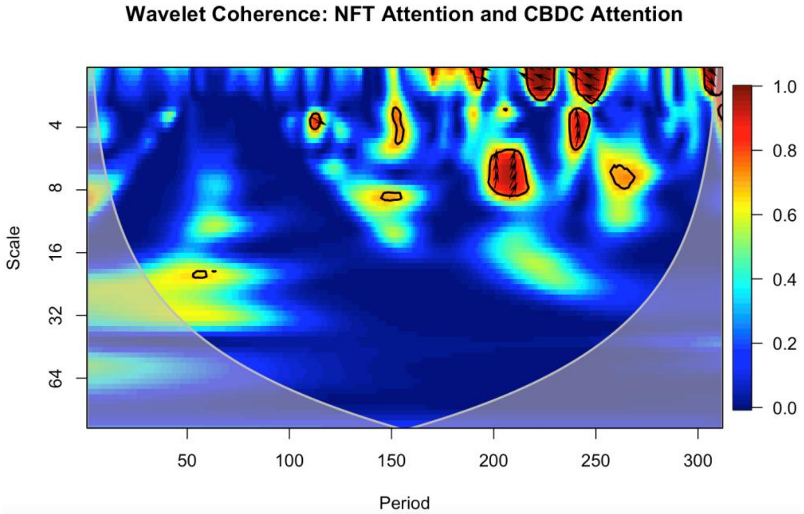
*The Wavelet Coherence between various Indices of Cryptocurrency Uncertainties and CBDC Attention*



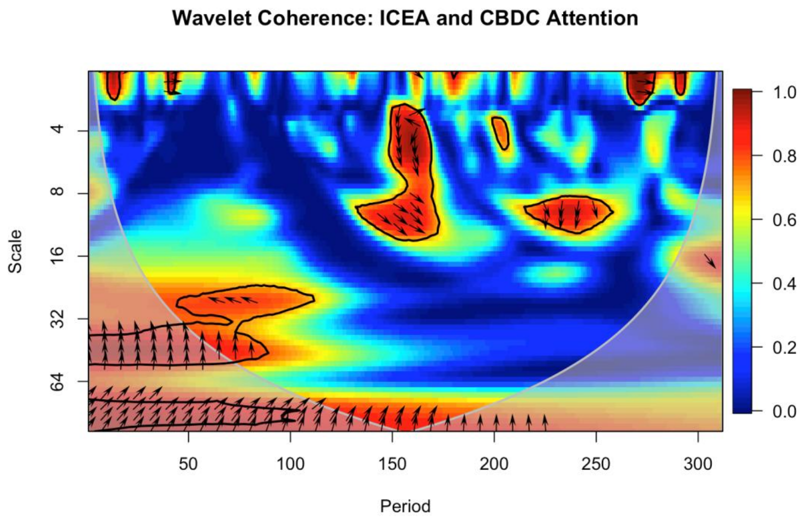

(a).




(b).




(c).




(d).

*Note*. The vertical axis depicts time in weeks, while the horizontal axis represents the scale. Colors on the right side of the main chart signify coherence levels, transitioning from blue to red, indicating higher absolute correlation values concerning $R^2(u, s)$. A solid white curved line within coherence plots denotes the cone of influence, while the black contours highlight regions of significance at a 5% level. The arrows inside the chart indicate phase differences; rightward arrows (→) signify an in-phase (positive) relationship, while the opposite direction suggests the opposite. The direction of arrows (↑ or ↓) indicates which time series leads the other. The researcher's data analysis

## 5. Conclusion

This study investigates the dynamic co-movement between the cryptocurrency uncertainty indices (UCRY Policy, UCRY Price, ICEA, NFTs Attention) and the CBDC uncertainty indices (CBDC Uncertainty, CBDC Attention) over the period between 13th January 2017 and 30th December 2022. Results from wavelet coherence analysis indicate a strong correlation between the UCRY Policy index and CBDC Uncertainty indices in the short term (less than 04 weeks), particularly following the global surge of cryptocurrencies in 2020. However, even though the UCRY Policy index primarily correlates with the CBDC Attention index in the short term, its impact on the CBDC Uncertainty index becomes apparent in the medium to long term. Overall, the CBDC Attention index is more effective at examining the UCRY Policy index in the short term, while the CBDC Uncertainty index is more adept in the long term.

Additionally, the wavelet coherence results between the UCRY Price, NFTs Attention indices, and the CBDC Uncertainty indices yield a similar outcome. We can observe occasional correlations in the short term (01 - 08 weeks), with the NFTs Attention index showing the strongest correlation with the CBDC Attention index. Finally, historically, there has been a strong correlation between the ICEA and CBDC uncertainty indices. The CBDC Uncertainty index appears to lead the ICEA index, whereas the latter seems to be a leading variable over the CBDC Attention index. Over time, the relationship between ICEA and CBDC Uncertainty indices, however, has weakened.

Our findings carry significant implications for investors interested in cryptocurrencies. Firstly, investors can utilize these findings to predict overall fluctuations in the cryptocurrency market. Specifically, they can adjust their portfolio structure across low, medium, and high frequencies throughout their investment horizons to make optimal decisions. It's worth noting that, unlike previous studies such as Ngo et al. (2024), we have incorporated NFTs as alternative investment sources for investors. In the short term, we observe a strong co-movement between the NFTs Attention and CBDC Uncertainty indices, providing investors with a reference point to adjust their portfolios.

Regulators and policymakers could also derive benefits from our findings. Our research suggests that policymakers should consider the historical impact of CBDC Uncertainty indices, particularly concerning the attention of ICEA. Conversely, for countries developing their own CBDC, awareness of the UCRY Policy Uncertainty index is crucial, as it appears to lead to CBDC Uncertainty volatility. This awareness should extend to policymakers intending to develop CBDC and investors considering CBDC as a potential future investment, potentially replacing various other market financial investments such as government bonds, stocks, or gold.

## NO CONFLICT OF INTEREST STATEMENT

All authors declare that they have no conflict of interest.

## References

Adaramola, A. O., & Dada, O. (2020). Impact of inflation on economic growth: Evidence from Nigeria. *Investment Management and Financial Innovations*, *17*(2), 1-13.

Akhtaruzzaman, M., Boubaker, S., Nguyen, D. K., & Rahman, M. R. (2022). Systemic risk-sharing framework of cryptocurrencies in the Covid-19 crisis. *Finance Research Letters*, *47*(Part B), 1-6.

Cheng, H. P., & Yen, K. C. (2020). The relationship between the economic policy uncertainty and the cryptocurrency market. *Finance Research Letters*, *35,* 1-5.

Clark, E., Lahiani, A., & Mefteh-Wali, S. (2023). Cryptocurrency return predictability: What is the role of the environment? *Technological Forecasting and Social Change, 189,* 1-9.

Conlon, T., Corbet, S., & McGee, R.J. (2020). Are cryptocurrencies a safe haven for equity markets? An international perspective from the Covid-19 pandemic. *Research in International Business and Finance*, *54*, 1-10.

Demir, E., Gozgor, G., Lau, C. K. M., & Vigne, S. A. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters*, *26*, 145-149.

Elsayed, A. H., Gozgor, G., & Yarovaya, L. (2022). Volatility and return connectedness of cryptocurrency, gold, and uncertainty: Evidence from the cryptocurrency uncertainty indices. *Finance Research Letters*, *47*(Part B), 1-11.

Fang, L., Bouri, E., Gupta, R., & Roubaud, D. (2019). Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? *International Review of Financial Analysis*, *61*, 29-36.

Gambarelli, L., Marchi, G., & Muzzioli, S. (2023). Hedging effectiveness of cryptocurrencies in the European stock market. *Journal of International Financial Markets, Institutions and Money, 84,* 1-22.

Hassan, M. K., Hasan, M. B., & Rashid, M. M. (2021). Using precious metals to hedge cryptocurrency policy and price uncertainty. *Economics Letters, 206,* 1-5.

Kamal, J. B., Wohar, M., & Kamal, K. B. (2022). Do gold, oil, equities, and currencies hedge economic policy uncertainty and geopolitical risks during covid crisis? *Resources Policy, 78,* 1-14.

Kamal, J. B., Wohar, M., & Kamal, K. B. (2023). On the potential hedging instruments against central bank digital currency uncertainty and attention indices. *Asian Economics Letters*, *5*(2), 1-7.

Kang, S. H., & Yoon, S. M. (2019). Dynamic connectedness network in economic policy uncertainties. *Applied Economics Letters, 26*(1), 74-78.

Karaömer, Y. (2022). The time-varying correlation between cryptocurrency policy uncertainty and cryptocurrency returns. *Studies in Economics and Finance*, *39*(2), 297-310.

Karim, S., Naeem, M. A., Mirza, N., & Paule-Vianez, J. (2022). Quantifying the hedge and safe-haven properties of bond markets for cryptocurrency indices. *The Journal of Risk Finance*, *23*(2), 191-205.

Katsiampa, P., Corbet, S., & Lucey, B. (2019). High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money, 62,* 35-52.

Khalfaoui, R., Solarin, S. A., Al-Qadasi, A., & Ben Jabeur, S. (2022). Dynamic causality interplay from Covid-19 pandemic to oil price, stock market, and economic policy uncertainty: Evidence from oil-importing and oil-exporting countries. *Annals of Operations Research*, *313*(1), 105-143.

Lin, Z. Y. (2021). Investor attention and cryptocurrency performance. *Finance Research Letters, 40*, 1-7.

Lucey, B. M., Vigne, S. A., Yarovaya, L., & Wang, Y. (2022). The cryptocurrency uncertainty index. *Finance Research Letters*, *45*, 1-14.

Mariana, C. D., Ekaputra, I. A., & Husodo, Z. A. (2021). Are Bitcoin and Ethereum safe-havens for stocks during the Covid-19 pandemic? *Finance Research Letters*, *38*, 1-7.

Melki, A., & Nefzi, N. (2022). Tracking safe haven properties of cryptocurrencies during the Covid-19 pandemic: A smooth transition approach. *Finance Research Letters, 46*(Part A), 1-9.

Mokni, K., Hammoudeh, S., Ajmi, A. N., & Youssef, M. (2020). Does economic policy uncertainty drive the dynamic connectedness between oil price shocks and gold price? *Resources Policy, 69,* 1-13.

Ndako, U. B., Salisu, A. A., & Ogunsiji, M. O. (2021). Geopolitical risk and the return volatility of Islamic stocks in Indonesia and Malaysia: A GARCH-MIDAS approach. *Asian Economics Letters*, *2*(3), 1-5.

Ngo, T. H., Huynh, T. L. D., & Nasir, M. A. (2024). Cryptocurrencies in an uncertain world: Comprehensive insights from a wide range of uncertainty indices. *International Journal of Finance & Economics, 29*(3), 3811-3825.

Panagiotidis, T., Stengos, T., & Vravosinos, O. (2019). The effects of markets, uncertainty and search intensity on bitcoin returns. *International Review of Financial Analysis*, *63*, 220-242.

Raza, S. A., Ahmed, M., & Aloui, C. (2022). On the asymmetrical connectedness between cryptocurrencies and foreign exchange markets: Evidence from the nonparametric quantile on quantile approach. *Research in International Business and Finance*, *61*, 1-14.

Sakurai, Y., & Kurosaki, T. (2023). Have cryptocurrencies become an inflation hedge after the reopening of the US economy? *Research in International Business and Finance*, *65*, 1-24.

Salisu, A. A., Akanni, L., & Raheem, I. (2020). The Covid-19 global fear index and the predictability of commodity price returns. *Journal of Behavioral and Experimental Finance, 27,* 1-7.

Smales, L. A. (2024). Cryptocurrency as an alternative inflation hedge? *Accounting & Finance, 64*(2), 1589-1611.

Thampanya, N., Nasir, M. A., & Huynh, T. L. D. (2020). Asymmetric correlation and hedging effectiveness of gold & cryptocurrencies: From pre-industrial to the 4th industrial revolution. *Technological Forecasting and Social Change, 159,* 1-13.

Tooze, A. (2018). *Crashed: How a decade of financial crises changed the world*. Penguin.

Torrence, C., & Compo, G. P. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society, 79*(1), 61-78.

Torrence, C., & Webster, P.J. (1999). Interdecadal changes in the ENSO-monsoon system. *Journal of Climate*, *12*(8), 2679-2690.

Triki, M. B., & Maatoug, A. B. (2021). The GOLD market as a safe haven against the stock market uncertainty: Evidence from geopolitical risk. *Resources Policy*, *70*, 1-13.

Umar, Z., Jareño, F., & de la O González, M. (2021). The impact of Covid-19-related media coverage on the return and volatility connectedness of cryptocurrencies and fiat currencies. *Technological Forecasting and Social Change*, *172*, 1-16.

Wang, P., Li, X., Shen, D., & Zhang, W. (2020). How does economic policy uncertainty affect the bitcoin market? *Research in International Business and Finance*, *53*, 1-18.

Wang, Y. (2022). Volatility spillovers across NFTs news attention and financial markets. *International Review of Financial Analysis*, *83*, 1-24.

Wang, Y., Lucey, B. M., Vigne, S. A., & Yarovaya, L. (2022a). The effects of central bank digital currencies news on financial markets. *Technological Forecasting and Social Change*, *180*, 1-39.

Wang, Y., Lucey, B., Vigne, S. A., & Yarovaya, L. (2022b). An Index of Cryptocurrency Environmental Attention (ICEA). *China Finance Review International*, *12*(3), 378-414.

Wu, W., Tiwari, A. K., Gozgor, G., & Leping, H. (2021). Does economic policy uncertainty affect cryptocurrency markets? Evidence from Twitter-based uncertainty measures. *Research in International Business and Finance*, *58*, 1-14.

Xia, T., Yao, C. X., & Geng, J. B. (2020). Dynamic and frequency-domain spillover among economic policy uncertainty, stock and housing markets in China. *International Review of Financial Analysis*, *67*, 1-11.

Xia, Y., Sang, C., He, L., & Wang, Z. (2023). The role of uncertainty index in forecasting volatility of Bitcoin: Fresh evidence from GARCH-MIDAS approach. *Finance Research Letters*, *52*, 1-8.

Yousaf, I., & Goodell, J. W. (2023). Linkages between CBDC and cryptocurrency uncertainties, and digital payment stocks. *Finance Research Letters*, *54*, 1-11.

Yuan, D., Li, S., Li, R., & Zhang, F. (2022). Economic policy uncertainty, oil and stock markets in BRIC: Evidence from quantiles analysis. *Energy Economics*, *110*, 1-17.