ORIGINAL ARTICLE

Unveiling the Co-Movement Between Central Bank Digital Currency, Twitter EPU, Volatility Index, and Geopolitical Uncertainty

Sarah Nawazish [1]

Author's Affiliation:

[1,] Assistant Professor, Imperial College for Business Studies, Lahore (Punjab), Pakistan

Article History:

Submitted: November 03, 2025
Revised: December 27, 2025
Accepted: December 29, 2025
Published online: December 30, 2025

Corresponding author(s):

Sarah Nawazish
Email:
sara.nawazish@imperial.edu.pk

Co-author(s)Email:

ABSTRACT

Purpose—There has been a lot of international interest in the association between central bank digital currencies (CBDCs) and economic instability, as the CBDCs are gaining momentum among policymakers and investors. The CBDC Development Index (CBDCDI) is an instrument that has been used to measure the progress of the central bank digital currency projects across the globe. Each operational definition has quantifiable indicators, such as project stage, frequency of updating, and weighting of the economic size (GDP), and more so, facilitates quantitative transparency by using standardized and reproducible measures, as opposed to subjective reports. As the digital currency issued by central banks has become a competitive alternative to cash and has been discussed and announced in relation to policies, the returns of Bitcoin can be influenced.
Study Design/methodology/approach—In a bid to find out the relevance of CBDC based on Partial Wavelet Coherence (PWC) and Multiple Wavelet Coherence (MWC) on weekly data between January 2015 and December 2022, this study will analyze the co-movement of the CBDC, volatility index, Twitter-based economic policy, and geopolitical uncertainty.
Findings: The results of the study indicate that there is a positive, significant relationship between CBDC, TEP, VI, and GPU across the sample period, which means that economic shocks and uncertainty play a significant role in attracting sustainable financial instruments under different combinations of time frequencies.
Practical Implications—There are some limitations to this study, such as the limitation of the availability of data and a short time horizon. Implications: The findings may be utilized by the bank managers, legislators, and scholars to focus closer on the aspects related to CBDCs.
Originality/Value— With a unique concept that piques scholars' interest, this work offers insight into a novel research question. By combining Twitter-based policy uncertainty, volatility, and geopolitical risk with CBDC attention inside a wavelet time frequency framework, an area with little empirical research to date, the study makes a novel contribution.

Keywords: CBDC, Twitter-based economic policy, Volatility index, Geopolitical uncertainty, Wavelet connectedness.

JEL Classification Codes: C22, G15, E58, D84, G17

1 | INTRODUCTION

Central Bank Digital Currencies (CBDCs) have changed the financial scenario of the world as the most recent invention in recent years. These digital currencies are issued and controlled by central banks, which offer a viable way for financial inclusion improvement, modernize the digital payment system, and solve the inefficiencies that exist in conventional financial structures, particularly in developing and emerging economies (Morales et al., 2021). In a comparison of unregulated currencies such as cryptocurrencies, CBDCs are considered to be a new type of virtual currency, which are positioned as more liquid and safer investments. The apparent stability in the political situation and economic infrastructure guarantees resilience in times of financial crisis, which is one factor contributing to their rising popularity (Ozili, 2023). The full extent of the currency in uncertainty, especially economic and political instability, has not been thoroughly examined in scholarly literature, despite its high potential.

The aim of improving financial inclusion is one of the important reasons for the creation of CBDCs. A significant section of the world's population, especially in developing nations, still lacks access to digital currencies and uses traditional financial services. To avoid traditional banking services and provide access to digital financial services, CBDCs, being digital currencies, provide a new method to facilitate financial transactions digitally. Moreover, to address the gap in the current financial system, such as shorter processing times and exorbitant transaction costs. CBDCs enhance efficiency in cross-border payment, increase transparency, and reduce the operating risks (Tata, 2023). Therefore, CBDCs have the power to transform the functions of financial institutions, particularly where the banking sector is still infantile.

The rapid digitization of financial institutions has prompted major concerns about the value of CBDCs in the larger economic and political landscape. However, these advancements may affect financial markets for the adoption of digital currencies and the incorporation of decentralized ledger systems. Therefore, concerns regarding the outcomes of these new digital currencies are gaining the attention of regulators, investors, and scholars due to their usage as a diversifier or hedge for existing financial assets. Even though CBDCs gain more popularity, the study on their relationship to political and economic uncertainty is still under-researched, particularly the uncertainties by social media sites like Twitter (Wang et al., 2022).

While other social media trends towards digital currencies, the present debate discusses the role of the central bank in boosting the use of CBDC. In this regard, central banks have historically been crucial to maintaining financial stability by controlling the money supply, regulating currencies, and acting as clearinghouses for banks during trying times. (Choi et al., 2021). However, the rise of unregulated digital currency has made it more difficult for central banks to maintain control over monetary systems and lessen the risks associated with financial market volatility. Although CBDCs are considered to be a way to improve the stability of the financial system, little is known about how they apply to broader market circumstances. Specifically, there is a lack of empirical data regarding how CBDCs respond to various uncertainty metrics, including the geopolitical risk (GPR), volatility index (VI), and economic policy uncertainty (EPU), that are influenced by news on Twitter.

Moreover, the recent developments in digital currencies suggest that the influence of uncertainty, through social media platforms like Twitter, has become more significant and affects the performance of digital currencies. According to research, market sentiments generated by Twitter increase market volatility by amplifying both positive and negative sentiments. For example, the Twitter-based Economic Policy Uncertainty (TEPU) index has been shown to have a significant impact on financial markets, with volatility spiking in response to tweets about economic policy uncertainty (Li et al., 2022).

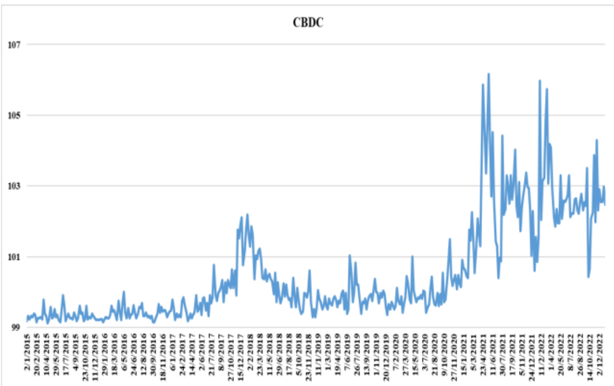
However, little research has been done on the Twitter sentiment that affects CBDC performance. In the recent era, much research has been conducted on fiat-backed digital assets, but CBDCs are a reliable investment as backed by the central banks. While it is difficult for investors and policymakers to comprehend the responsiveness of CBDC during uncertainty and volatility, specifically related to Twitter news. The investors are more concerned with CBDCs' function as a safe-haven asset during geopolitical or economic unrest. According to the financial theories, investors are risk-averse and sensitive to social media news; they are more likely to invest in safe assets than unsafe life cryptocurrencies. Consequently, the investors are more likely to invest in traditional treasury bills, government-backed assets, and bonds. Interest in CBDCs' ability to serve as a safe-haven currency in the face of global volatility has increased since their launch.

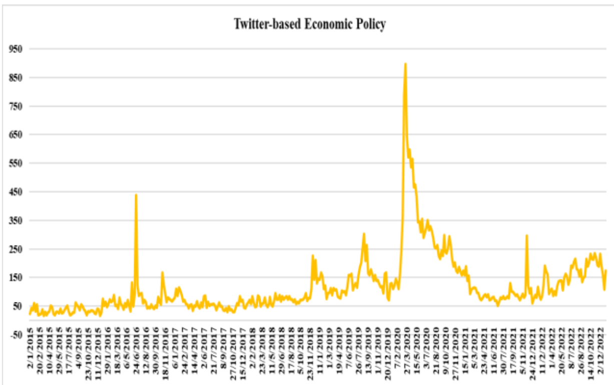
Central Bank Digital Currencies (CBDCs) have certain unique characteristics, such as being centralized and backed by the government. This makes people concerned with how well they will do compared to other assets when things remain extremely unclear. Even while more people are interested in CBDCs as possible significant financial tools, their counter-cyclical nature—especially during times of geopolitical tension or market instability—hasn't been studied in depth. The conduct of CBDCs in such crises requires additional scrutiny. Moreover, geographic variations in the response of CBDCs to uncertainty constitute a significant concern. Emerging economies, which are more politically and economically unstable than developed nations, may respond to uncertainty in different ways. Digital currencies like CBDCs are still new, and volatility indices are frequently higher in developing countries. Because of this, the effects of social media-driven uncertainty, especially on platforms like Twitter, may be stronger in these areas. So, it's important to look at how developmental and regional characteristics affect CBDC performance during times of crisis. This study seeks to examine the interaction of these parameters with uncertainty measurements, including geopolitical risk and the Volatility Index (VIX), to affect the behavior of Central Bank Digital Currencies (CBDCs).

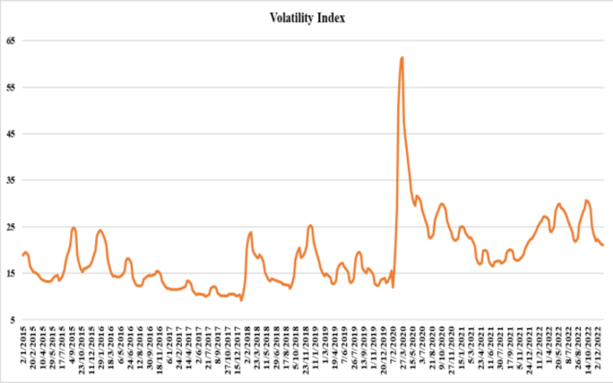
.

Figure 1

Time series variables between January 2015 and December 2022.







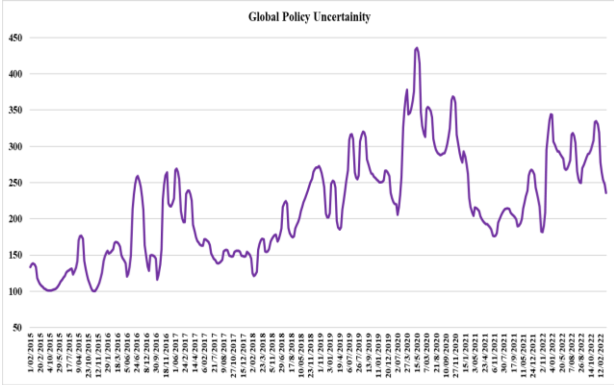


Figure 1 reveals the trends of CBDC, Twitter-based economic policy, volatility index, and global policy uncertainty.

CBDCs are becoming important, and the research currently in publication mostly ignores how they interact with other uncertainty indicators, especially when it comes to social media and geopolitical risk. This gap in the literature underscores the necessity for a more comprehensive analysis of the behavior of CBDCs in contexts characterized by heightened uncertainty. It is essential to examine in greater detail the interactions among CBDCs, Twitter-driven economic policy uncertainty, and the Volatility Index, as well as their responses to geopolitical events. The purpose of this study is to fill this gap by examining the co-movements of CBDCs, the Volatility Index, economic policy uncertainty, and geopolitical uncertainty. This study aims to comprehend the non-linear causality between these factors and the dynamic behavior of CBDCs in response to various time frequencies and economic conditions using sophisticated econometric methodologies, such as Partial and Multiple Wavelet Connectedness. This research will elucidate the role of Central Bank Digital Currencies (CBDCs) in mitigating risk during times of political and economic instability by analyzing the relationship between uncertainty and CBDCs.

Furthermore, by providing a more sophisticated knowledge of how CBDCs respond to global concerns, this study will add to the expanding corpus of scholarship on digital currencies. It will also give central banks and policymakers useful information on how to set up and run CBDCs in a way that maximizes their ability to promote financial inclusion and stabilize financial markets. The ultimate goal of this research is to add to the continuing discussion about the future of digital currencies in the global economy and offer a more thorough knowledge of the function of CBDCs in the contemporary financial system, especially during times of crisis. For investors, especially those who are risk averse and seek safe-haven assets during uncertain economic times, this study has important ramifications. Investors can make better decisions about their portfolios, especially when dealing with market volatility and political unpredictability, by being aware of the hedging and diversification capabilities of CBDCs. Additionally, the use of sophisticated analytical methods will enable a more thorough comprehension of the time-frequency relationships between uncertainty indicators and CBDCs, providing a more intricate and thorough understanding of how these digital assets behave in various market scenarios.

In conclusion, the emergence of CBDCs marks a significant turning point in the development of international financial systems. Even if they have a lot of promise to make payment systems better and make more people able to use them, we still don't know much about how they will act when there is political and economic turmoil. By examining the connection between CBDCs and uncertainty indicators, this study seeks to close this knowledge gap and offer insightful information to investors, politicians, and scholars alike. This study contributes to the ongoing discourse regarding the role of digital currencies inside the global financial system by employing advanced analytical methodologies and focusing on the interconnections between CBDCs, economic policy uncertainty, and geopolitical risk. The study objectives are as follows:

1.1 | Research Objectives

- The kind and degree of co-movement exist between Twitter-based economic policy uncertainty (TEP) and CBDC.
- The effects of Volatility Index (VI) on the behavior of the CBDC market over various time periods and frequency domains.
- The connection exists, especially during times of crisis, between CBDC performance and geopolitical uncertainty.
- In times of increased uncertainty brought on by social media trends and political unrest, do CBDCs show counter-cyclical traits?
- The differences exist between the interrelated elements of CBDC, TEP, VI, and geopolitical uncertainty in various geographical contexts and economic development levels.

1.2 | Research Questions

- What kind and degree of co-movement exists between Twitter-based economic policy uncertainty (TEP) and CBDC?
- What effects does the Volatility Index (VI) have on the behavior of the CBDC market over various time periods and frequency domains?
- What connection exists, especially during times of crisis, between CBDC performance and geopolitical uncertainty?
- In times of increased uncertainty brought on by social media trends and political unrest, do CBDCs show counter-cyclical traits?
- What differences exist between the interrelated elements of CBDC, TEP, VI, and geopolitical uncertainty in various geographical contexts and economic development levels?

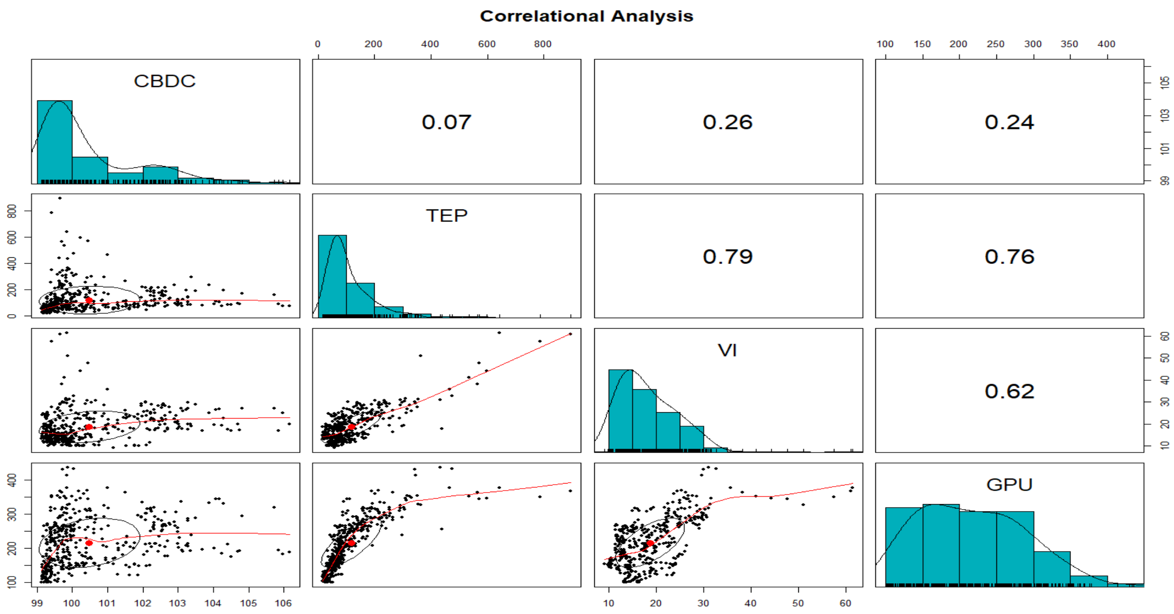
The remainder of this research is structured as follows: Section 2 reviews the literature on the current topic, while Sections 3 and 4 present the methodology and results, respectively. Ultimately, Section 5 summarizes the results.

2 | LITERATURE REVIEW

The growing interest in Central Bank Digital Currencies (CBDCs) has led to a lot of academic debate about how they could make it easier for everyone to use the financial system, update the payment system, and lessen systemic risks, especially during times of financial crisis. State-backed digital currencies, or CBDCs, offer a unique opportunity to address the limitations of traditional banking systems by enhancing payment system efficiency and mitigating settlement risks (Sinelnikova, 2020; Sissoko, 2017). CBDCs are becoming more and more popular as a way to do financial transactions that might be safe and work well. However, we don't know much about how they work with other financial issues like policy risks, market volatility, and geopolitical conflicts. Focusing on Twitter-based economic policy uncertainty (TEP), this paper critically examines the academic discourse about CBDCs in relation to volatility indices (VIX), economic policy uncertainty (EPU), and market sentiment shaped by social media.

Figure 1

Correlational analysis of study variables.



The CBDC is one possible way to make sure that the economy stays stable. Researchers say that CBDCs are more stable than cryptocurrencies because they are regulated by the government and tied to a country's fiat currency. Cryptocurrencies, on the other hand, are decentralized and often unstable. Several studies indicate that CBDCs can mitigate systemic financial risk by offering an alternative to private digital currencies, especially during times of financial volatility (Tong and Jiayou, 2021; Larina & Akimov, 2020). Still, there is a lot of talk about how much CBDCs lower financial instability when the economy or politics are unpredictable. Bech and Garratt (2017) said that CBDCs might make payments safer and more efficient, but they also said that moving money from commercial banks to central banks could make banks less stable. This is especially important when it comes to retail CBDCs, because customers could move their money to the central bank's digital currency, which could make the traditional banking system less liquid. Market uncertainty, especially when it comes to economic policy, has been one of the biggest worries in CBDC research. Economic policy uncertainty, or EPU, is the term for the reality that we can't forecast what the government will do that will affect things like inflation, taxes, and regulations. There is a strong connection between EPU and financial markets. High levels of uncertainty often lead to higher asset price volatility (Bekaert et al., 2022). Some people have argued that CBDCs could help protect against this kind of volatility. Behavioral finance theories, such as prospect theory and loss aversion, suggest that investors tend to choose assets with less risk during periods of high uncertainty (Bekaert et al., 2022). Some people argue that CBDCs are a safe investment that offers stability and liquidity because they are regulated, especially in times of crisis (Rehman et al., 2024a).

The volatility index (VIX) is a common way to measure how uncertain the market is. The VIX measures how much the S&P 500 index is expected to change over the next 30 days. It is a stand-in for market mood. Studies have shown that different types of assets, including virtual currencies, have different levels of correlation with the VIX, especially when the market is most volatile (Helmi et al., 2023). While the VIX has been well studied in relation to traditional cryptocurrencies like Bitcoin, its connection to CBDCs has not been as thoroughly studied. Some scholars contend that macroeconomic elements, such as geopolitical concerns and Economic Policy Uncertainty (EPU), may influence the behavior of Central Bank Digital Currencies (CBDCs), rendering them susceptible to volatility (Chen et al., 2022). Nonetheless, there is presently a scarcity of empirical data regarding the co-movement of CBDCs and the VIX, especially concerning the role of CBDCs in risk mitigation during worldwide financial crises such as the COVID-19 pandemic (Helmi et al., 2023). In recent years, social media, notably Twitter, has become an important place for investors to get news and sentiment. Twitter-based economic policy uncertainty (TEP) shows how political discussions and economic news shared on Twitter can affect how people act in the market. Researchers have found that TEP is associated with more volatility in financial markets and less certainty among investors (Masciandaro et al., 2023). When it comes to CBDCs, Twitter has a major impact on what investors think and do. Investors' choices about CBDCs may be affected by how often they react to what they see on Twitter, which includes comments about political events and economic policy. For instance, political turmoil or the introduction of new legislation may lead to an increase in the demand for CBDCs as a safe-haven asset (Hanska & Bauchowitz, 2019). Research on the direct impact of Twitter-induced uncertainty on CBDCs remains nascent; other studies have investigated the relationship between social media trends and cryptocurrency valuations (Bekaert et al., 2022). One of the biggest problems with studying the link between social media and CBDCs is that we don't know how the transmission pathways work. Researchers remain dubious if investor sentiment is directly influenced by social media-induced uncertainty, such as TEP, or if alternative factors, including fluctuations in liquidity or market expectations, are involved (Nguyen & Nguyen, 2023). However, the growing influence of social media on financial markets cannot be overlooked, necessitating further research to ascertain the specific effects of TEP on CBDC behavior.

Even though the research gives us useful information on how CBDCs and different kinds of uncertainty are related, there are still some critical gaps in it. Most of the research done so far has looked at how economic policy uncertainty, geopolitical risk, and volatility indexes affect financial assets in different ways, often on their own. Nonetheless, insufficient focus has been directed towards the interconnections among these aspects, particularly concerning CBDCs. Rehman et al. (2024b) assert that previous studies often utilize conventional linear models, such as Granger causality and vector autoregression (VAR), which inadequately reflect the frequency-dependent, time-varying nature of financial markets in periods of crisis. Wavelet-based connectivity techniques have been used to study how cryptocurrency markets change over time, allowing researchers to look at how different time scales affect co-movements (Rehman et al., 2024b). There exists a significant methodological deficiency, as these methodologies have yet to be applied to CBDCs. Moreover, most current studies do not take into consideration the different geographic and developmental contexts in which CBDCs are being put into use. There is a shortage of research on the consequences of CBDCs in emerging nations, where aspirations for financial inclusion are often given more weight (Morales et al., 2021). This is, although established economies like the US and China have gotten a lot of attention. The acceptance and utilization of CBDCs in these markets are significantly affected by institutional backing, financial literacy levels, and regulatory frameworks (Ozili, 2023). Consequently, this literature review underscores several significant research problems related to CBDCs and their interaction with uncertainty metrics. CBDCs can reduce financial risk and provide stability during times of economic uncertainty, but their behavior in response to market volatility, especially when influenced by social media and geopolitical events, remains largely unknown. Previous research has primarily focused on conventional cryptocurrencies, utilizing linear models that inadequately capture the complex, dynamic interrelations across many sources of uncertainty. The lack of research on CBDCs in developing nations and this methodological gap show that more studies are needed that look at the many worldwide situations in which CBDCs are being used and use more advanced analytical tools. Future research can provide a more comprehensive understanding of how CBDCs enhance risk mitigation and bolster financial stability in the modern digital economy by addressing these deficiencies.

2.1 | Hypothesis

H1: *There is a strong non-linear causation relationship between Twitter-based economic policy uncertainty and the dynamics of the CBDC market.*

H2: *When there is more political upheaval and economic instability, CBDC acts countercyclically, especially when social media trends are involved.*

H3: *The performance of the CBDC market is negatively correlated with increased geopolitical uncertainty and volatility indices, suggesting a linear negative relationship.*

H4: *CBDC is a safer place to store money during times of political and economic instability than unregulated cryptocurrencies.*

H5: *The patterns of co-movement between CBDC and uncertainty indicators are very different depending on the time frequency and level of economic development.*

H6: *Because there is more uncertainty in the baseline, Twitter-based economic uncertainty has a bigger impact on CBDC markets in developing countries than in developed ones.*

CBDCs are new digital currencies that need to be studied in depth to understand how they work and how valuable they are in different economic situations, especially in developing nations. The connection between CBDCs and policy uncertainty on Twitter has mostly been disregarded in the literature, which is a big vacuum in knowledge that this study tries to fill. Additionally, risk-averse investors globally necessitate accurate information on CBDC's hedging and diversification potential, especially during periods of volatile political and economic circumstances. It's crucial to understand how these changes affect CBDC markets since social media sites, notably Twitter, have a big effect on how investors respond and how volatile the financial markets are. Central banks and regulators need to know how CBDCs react to different measures of uncertainty to effectively create and carry out digital currency policies that promote stability and financial inclusion.

3 | METHODOLOGY & DESIGN

This research examines the co-movement among Central Bank Digital Currency (CBDC), Geopolitical Policy Uncertainty (GPU), Twitter-based Economic Policy Uncertainty (TEPU), and the Volatility Index (VI) from January 2015 to December 2022. The main purpose is to look at how these factors interact when there is uncertainty and volatility in financial markets. The focus is on how CBDC reacts to geopolitical concerns, changes in economic policy, and social media-driven emotion.

3.1 | Data Sources and Frequency Harmonization

The information for this study comes from PolicyUncertainty.com, which gives weekly updates on different economic uncertainty measures. These include the Geopolitical Policy Uncertainty (GPU) index, the Twitter-based Economic Policy Uncertainty (TEPU) index, and the Volatility Index (VI). Weekly reports also provide CBDC data, which means that the data frequencies don't match up. To solve this problem, the study changes monthly variables (GPU, TEPU, and VI) into weekly data using the Kalman filtering method and state-space models, as Brook (2019) explains. This change makes the dataset more consistent and lets us analyze high-frequency market dynamics in a useful way. The Kalman filtering approach was chosen because it can keep the random features of the original data while making weekly predictions that match monthly totals. Kalman filtering is better at dealing with the data's inherent uncertainties than linear interpolation, which can smooth out patterns of volatility.

3.2 | Wavelet Analysis

This study employs wavelet-based techniques, particularly the Morlet wavelet, to investigate the time-frequency dynamics of the relationship between the variables. The Morlet wavelet is the best choice for finding lead-lag correlations in financial time series because it has the best time-frequency localization features. This method is often employed in financial research since it may find both amplitude and phase connections in data. The study also uses different wavelets, like the Paul and Mexican Hat wavelets, to do robustness checks and make sure the results are consistent. To look at how CBDC, GPU, VI, and TEPU move together over different time scales (short-term, medium-term, and long-term), we use Wavelet Transform Coherence (WTC), Partial Wavelet Coherence (PWC), and Multiple Wavelet Coherence (MWC). These methods let you look closely at how the factors affect each other throughout different investment periods (2–8 weeks, 8–32 weeks, and 32–64 weeks).

3.3 | Statistical Tests and Simulation

The study uses strict statistical testing to back up its results. We use 10,000 Monte Carlo simulations to make surrogate time series. This makes sure that the wavelet coherence results are strong. There are 90%, 95%, and 99% levels of significance testing, and False Discovery Rate (FDR) corrections are used to keep track of many tests. The Augmented Dickey-Fuller (ADF) test is used to see if the data is stationary, which means that the time series can be used for wavelet analysis. You can use the Ljung-Box Q-statistic to look at how the variables' autocorrelation is set up.

3.3 | Descriptive Statistics and Data Visualization

A comprehensive descriptive statistics table (N=416 weekly observations) is provided, encompassing essential metrics such as the mean, median, standard deviation, skewness, kurtosis, and stationarity results. This table gives you a basic idea of how each variable is distributed and how it acts. A correlation matrix is also used to look at how CBDC, TEPU, GPU, and VI are related to each other. The study utilizes data visualization techniques through the ggplot2 package in R to illustrate the outcomes of the wavelet coherence analysis.

Table 1.

Descriptive Statistics

Variables	CBDC	TEP	VI	GPU
N	418	418	418	418
Mean	100.484	117.653	18.775	216.488
1st Quartile	99.452	55.389	13.549	155.463
Median	99.879	83.565	17.336	211.891
3rd Quartile	101.037	145.912	22.623	266.362
SD	1.427	106.885	7.246	71.722
Min	99.117	15.645	9.106	100.036
Max	106.157	896.02	61.41	435.935
Skewness	1.483	3.079	2.05	0.407
Kurtosis	4.682	16.628	10.729	2.541

Notes*: The descriptive statistics table shows the distribution of data. N and SD stand for no. of observations and the standard deviations, respectively.*

3.4 | Methodological Limitations and Robustness Checks

This research finds some methodological constraints, especially with the frequency conversion procedure. Changing monthly data to weekly frequencies could cause biases, like weakening correlations and making volatility patterns look smoother than they really are. To deal with this, robustness checks are done, which include using alternative interpolation methods (like Chow-Lin) and frequency conversion methods (like MIDAS). To make sure the results are reliable, they also look at how sensitive they are to outliers and changes in the data. We further examine the study's strength by looking at how stable it is over time by comparing the periods before the crisis (2015–2019), during the crisis (2020–2021), and after the crisis (2022) to see whether there are any structural cracks.

3.5 | Computational Environment

The analysis is done with R version 4.3.1 and the following packages: WaveletComp, biwavelet, wavemulcor for wavelet analysis, and tseries and nortest for statistical testing. The computing environment has an 8-core CPU that runs the Monte Carlo simulations and wavelet analysis. It also keeps track of the time each computation takes so that it can be repeated.

In summary, this study utilizes sophisticated econometric techniques, such as Kalman filtering for frequency conversion, wavelet coherence for time-frequency analysis, and Monte Carlo simulations for statistical robustness, to conduct a thorough analysis of the co-movements between CBDC and diverse uncertainty indicators. These methods make sure that the results are accurate, strong, and give useful information about how CBDCs act when there is market uncertainty and geopolitical dangers.

$$R^2(m,n) \; = \; | \, N(\, N^{-1}Sxy(m,n)|^2 \, / \, N(\, N^{-1}|Sxx(m,n)|^2) \, * \, N(\, N^{-1}|Syy(m,n)|^2 \qquad (3.1)$$

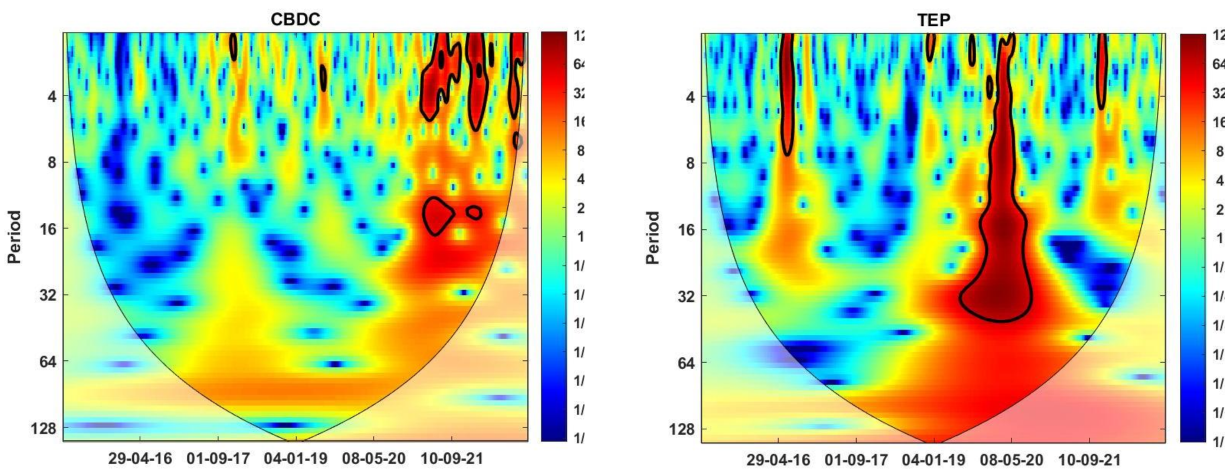
Where R^2 (m,n) is the wavelet coherence at time m with frequency n, the result values lie between 0 and 1. The closer to zero value represents absence or weak coherence between the variables, while the test results nearer to 1 show a perfect or stronger coherence between the variables. Sxy(m,n): is a cross-wavelet spectrum of two signals at time m with frequency n. Sxx(m,n): wavelet power spectrum for the first signal at time m with frequency n. Syy(m,n): wavelet power spectrum for the second signal at time m with frequency n. Wavelet technique furnishes several benefits to multiple data series: 1) relaxed the assumption of stationarity, 2) non-normal time series can be used for analysis, 3) events during the time frame can be easily captured, 4) the time-frequency perspective can be analyzed, 5) non-linear relationships can be addressed, 6) it can examine the direction and magnitude of association whether short, medium, or long-run relationship, 7) Wavelet functions and applications depend upon the nature of data, and 8) it can analyze bidirectional relationships at different time frequencies (Rej et al., 2022; Rehman et al., 2024a).

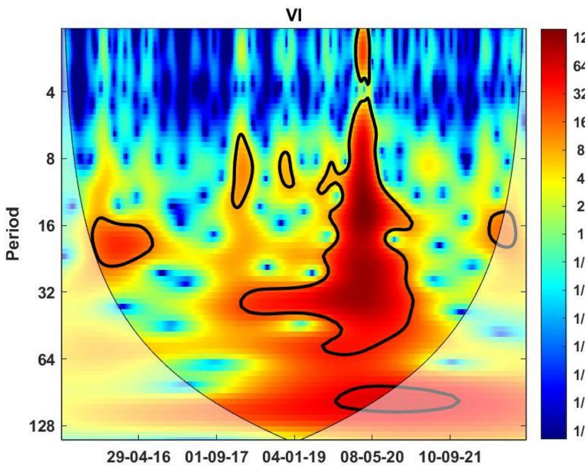
3.6 | Partial Wavelet Coherence

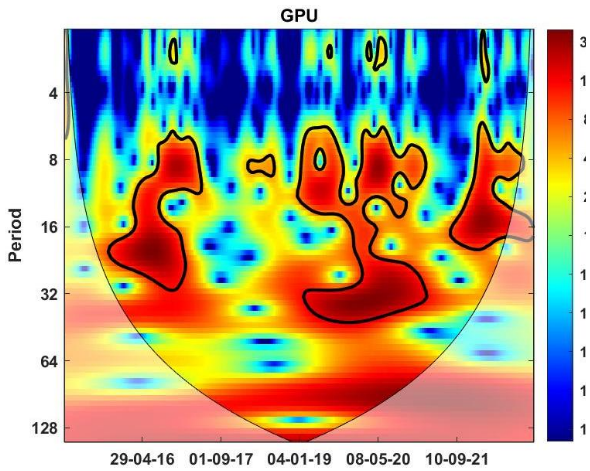
PWC is a modern version of WTC that addresses quantifying conditional dependency between two signal frequencies simultaneously by controlling the impact of other frequency signals. To evaluate the direct link between two model signals, this technique is used to rule out the indirect impacts of other signals. By excluding the impact of the third model variable, X3, PWC estimates the wavelet coherence for variables in two models, X1 and X2. As a result, the following equations give the PWC for each of the three model variables, X1, X2, and X3, by removing the impacts of each one separately:

Figure 3

Continuous Wavelet Transformation of all the study variables.







$$R(x_1, x_2) = \frac{S[W(x_1,x_2)]}{\sqrt{S[W(x_1)]\cdot S[W(x_2)]}} \tag{3.2}$$

$$R^2(x_1, x_2) = R(x_1, x_2) \cdot R(x_1, x_2) \tag{3.3}$$

$$R(x_1, x_3) = \frac{S[W(x_1,x_3)]}{\sqrt{S[W(x_1)]\cdot S[W(x_3)]}} \tag{3.4}$$

$$R^2(x_1, x_3) = R(x_1, x_3) \cdot R(x_1, x_3) \tag{3.5}$$

$$R(x_2, x_3) = \frac{S[W(x_2,x_3)]}{\sqrt{S[W(x_2)]\cdot S[W(x_3)]}} \tag{3.6}$$

$$R^2(x_2, x_3) = R(x_2, x_3) \cdot R(x_2, x_3) \tag{3.7}$$

The following PWC equation was proposed by Mihanovi et al. (2009) by removing the influence of the model variable X3:

$$RP^2(x_1, x_2, x_3) = \frac{|R(x_1,x_2) - R(x_1,x_3)\cdot R(x_1,x_2)\cdot|^2}{[1-R(x_1,x_3)]^2[1-(x_3,x_2)]^2}, \tag{3.8}$$

When the effect of X3 is eliminated among the time, m, and frequency, n, the value of the coefficient of PWC should lie between 0 and 1 inclusive. It represents a square of the partial correlation of model time series variables, X1 and X2. The closer the correlation to 0 is after eliminating the impact of X3, the weaker or absent a relation between X1 and X2 is (Kristoufek et al., 2016; Aloui et al., 2018).

3.7 | Multiple Wavelet Coherence

WTC development is also through the analysis of the coherence of the different model signals. It evaluates the level of time-frequency resemblance among different signals in order to further illuminate the association among different variables. This approach is selected to observe the co-movement of the model variable of Y and other response model variables X1 and X2. We compute MWC as follows:

$$RM^2(\mathrm{Y}, x_3, x_2) = \frac{R^2(\mathrm{Y},x_1) + R^2(\mathrm{Y},x_2) - 2\mathrm{Re}\,[R(\mathrm{Y},x_1)\cdot R(\mathrm{Y},x_2)^*\cdot R(x_1,x_2)^*]}{1-R^2(x_1,x_2)} \tag{3.9}$$

where the MWC connection between the dependent variable "Y" and the linear association of the other two response variables "X1" and "X2" is shown in $RM^2(\mathrm{Y}, x_3, x_2)$

Table 2.

Correlation Matrix

	CBDC	**TEP**	**VI**	**GPU**
CBDC	1.000			
TEP	0.075	1.000		
VI	0.256	0.787	1.000	
GPU	0.245	0.761	0.623	1.000

Table 3.

BDS Test

Variables	CBDC	TEP	VI	GPU
M2	30.5865***	27.7043***	51.1467***	69.6954***
M3	33.2384***	29.4896***	53.8725***	73.2844***
M4	36.202***	31.2275***	57.3847***	77.7816***
M5	39.9806***	33.6794***	62.6635***	84.5812***
M6	44.949***	36.9256***	69.9712***	94.2964***

*Notes: *** shows the significance level at 1%.*

3.8 | Continuous Wavelet Transform

It is an essential method to break down a signal into wavelet coefficients at both scales and time points to form a time-frequency representation of the signal. It allows the model variables to be localized to achieve accuracy in both the time and frequency domains.

CWT mends $W_x(m,n)$ to investigates a definite wavelet ψ (.) for time X(t) ∈ $L^2(\mathbb{R})$:

$$W_x(m,n) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{n}}\psi\left(\frac{t-\grave{m}}{N}\right)dt. \quad (3.10)$$

A time series model variable X(t) about the space may be successfully attenuated and then rebuilt using CWT- ∈ $L^2(\mathbb{R})$:

$$x(t) = \frac{1}{C_\psi}\int_{0}^{\infty}\left[\int_{-\infty}^{\infty} W_x(m,n)\psi m,n(t)dtu\right]\frac{dn}{N^2}, N > 0 \quad (3.11)$$

Additionally, it keeps the power of the examined time series as an integral, as indicated in Equation 3.12 below.

$$\parallel x \parallel^2 = \frac{1}{C_\psi}\int_{0}^{\infty}\left[\int_{-\infty}^{\infty} |W_x(m,n)|^2 dm\right]\frac{dn}{N^2} \quad (3.12)$$

In this empirical study, we favour using this CWT quality to investigate wavelet coherence and gauge the strength of the underlying link between two-time structures.

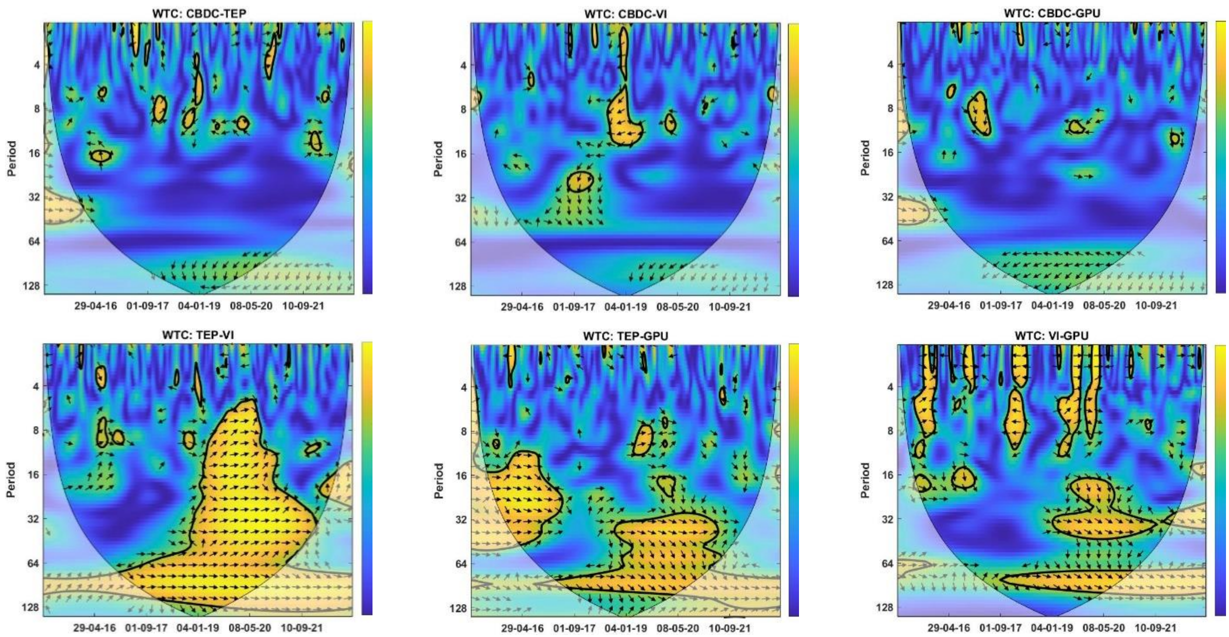
4 | RESULTS AND ANALYSIS

4.1 | Preliminary Outcomes

Before employing the wavelet technique, specific pre-estimation tests should be conducted, such as summary statistics, correlation analysis, and the BDS test to confirm the data nonlinearity. Table 1 shows the descriptive statistics, as well as the averages of the volatility index. TEP standard deviation is greater than that of other variables, meaning that there is a greater level of risk when it comes to Twitter-based policy uncertainty. The skewness is positive, with the data showing a skewed distribution, most of which are on the right. At the same time, TEP and VI data have large values of kurtosis and thin tails. Most of the values are high in the distribution. Besides, the interaction between CBDC, TEP, VI, and GPU is demonstrated in Table 2. The results show that there is a poor relationship between CBDC and TEP (0.075), and between CBDC and VI (0.256) and CPU (0.245). TEP has a great correlation with VI and GPU, with VI and GPU having a correlation of 0.623. Figure 2 represents the graphical representation of correlation analysis. The volatility and uncertainty have a strong positive correlation, as investigated in the available research.

Figure 4

Wavelet Transform Coherence of all the study variables.



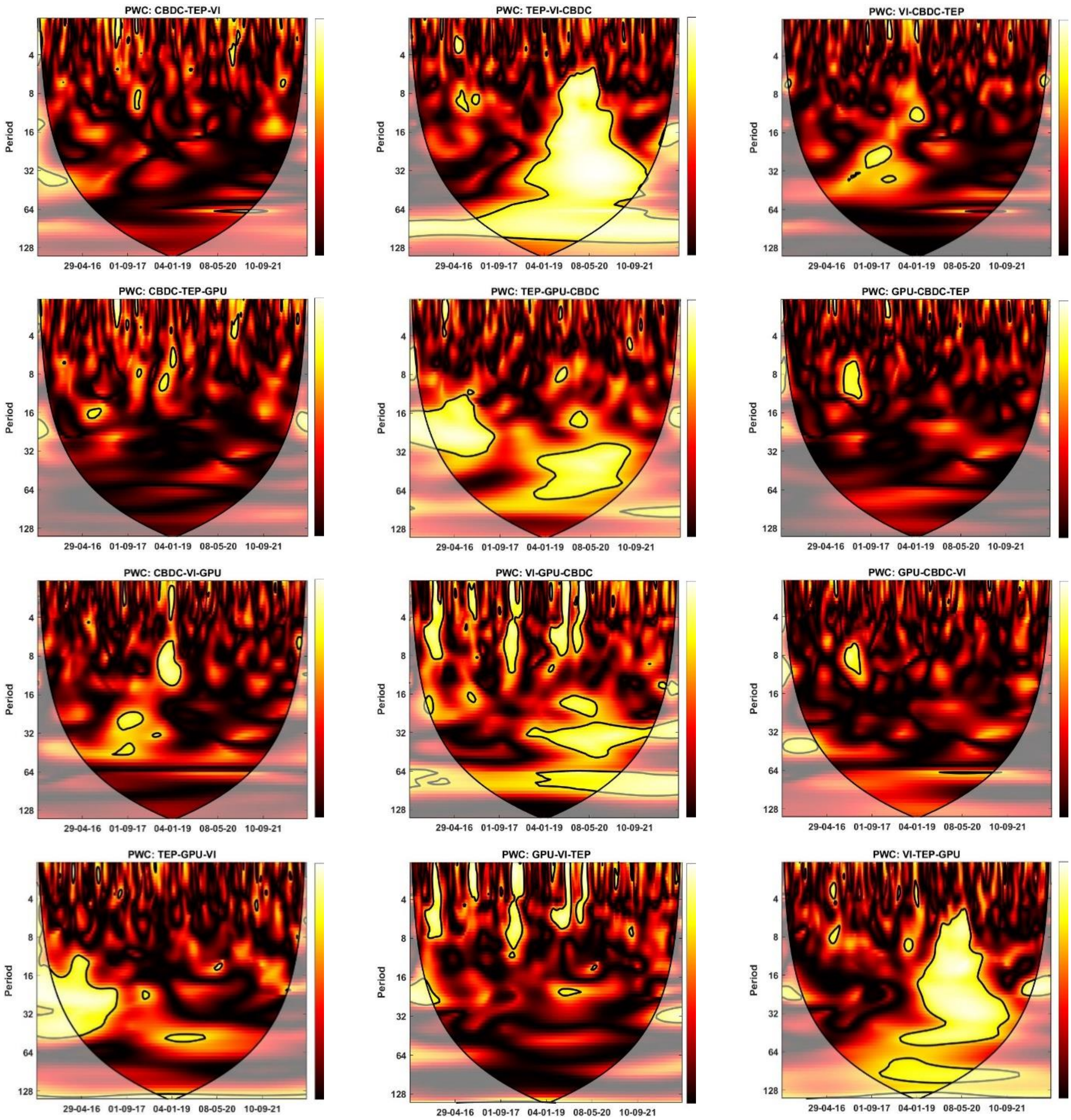
4.2 | Wavelet outcomes

A significant methodological lack in the presentation of data is its overwhelming reliance on qualitative and visual elements, lacking sufficient quantitative support from statistical measures, hypothesis testing, or effect size estimates. The narrative explaining the trends in Figures 3 and 4 employs subjective terminology such as significant disparities, greater diversity, minor fluctuation, strong collaboration, and substantial correlation, yet fails to quantify these claims with numerical coefficients, confidence intervals, or test results to maintain objectivity (Torrence and Webster, 1999). Some examples of this are the claim that CBDC-TEP is an inverse relationship because the arrows are falling, which is actually the direction of the arrows on phase diagrams. They do not include the actual size of the coherence coefficient of the wavelets or the percentage of time-frequency space that has significant coherence (more than 5 percent or 10 percent of time set by Monte

Carlo simulations) or the averages of the strength of coherence across the relevant frequency bands and time scales (Aguiar-Conraria and Soares, 2014).

Figure 5

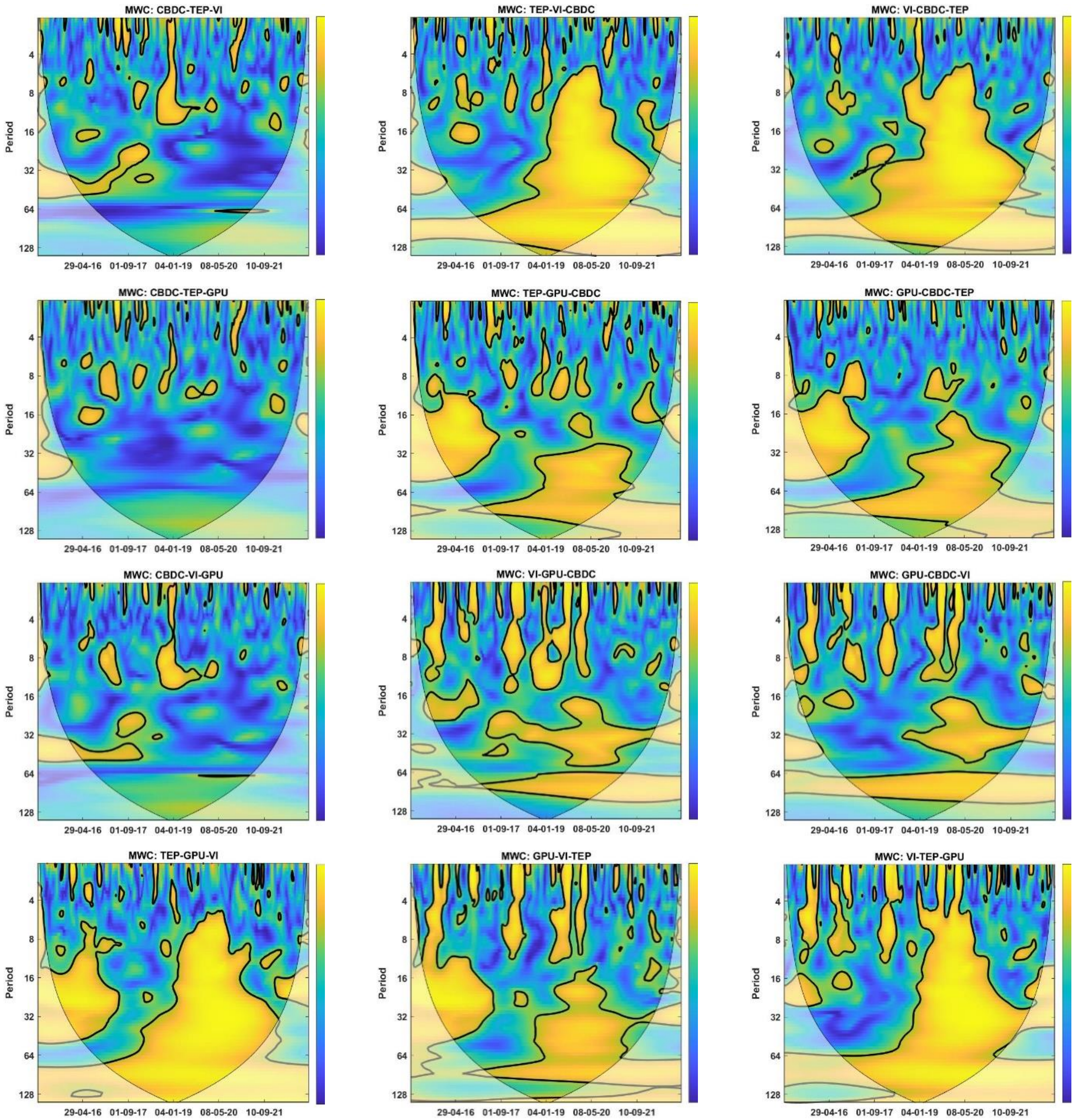
Partial Wavelet Coherence of all the study variables.



This research highlights some limitations of wavelet coherence analysis, namely the inherent subjectivity in visual pattern detection and the challenges associated with interpreting complex, multi-dimensional wavelet plots. When researchers look for patterns in these plots, they may unwittingly focus on connections that support their beliefs and ignore those that go against them. This is called confirmation bias (Simmons et al., 2011). Because of this, the direction, strength, or durability of relationships between variables is subjectively determined, which means that different researchers may come to different conclusions about the same data.

Figure 6

Multiple Wavelet Coherence of all the study variables.



5 | DISCUSSION

This study employed wavelet-connectedness techniques to analyze the co-movement of Central Bank Digital Currencies (CBDC), the Volatility Index (VI), Geopolitical Policy Uncertainty (GPU), and Twitter-based Economic Policy Uncertainty (TEPU). The findings yield some important new understandings regarding the conduct of CBDC markets, particularly during periods of geopolitical and economic turmoil. The investigation first showed that there was a substantial positive link between GPU and CBDC uncertainty, especially during times of crisis when things happen very quickly. But the low coherence in many time-frequency bands makes us question how important this relationship is for the economy. Even if it is statistically significant, a coherence of 0.3 means that only a small part of the fluctuation is explained. This makes it less likely that market players will find the link between CBDC and GPU useful for hedging or predicting. The fact that the association between CBDC and TEPU has changed over the course of 2017 supports this even more. This suggests that Twitter-based economic policy uncertainty may not always be beneficial for predicting changes in CBDC.

Moreover, although CBDCs exhibit significant co-movement with VI during crises, the coherence analysis between CBDC and VI indicates their ineffectiveness as safe-haven assets. Theoretical ideas say that CBDCs should be stable assets during times of uncertainty, but the high coherence shown during the COVID-19 crisis makes it possible that CBDCs won't provide the risk diversification benefits they were meant to in really bad market conditions. Another important finding is how phase angles affect the lead-lag relationships between variables. According to the temporal dynamics, Twitter-driven economic policy uncertainty (TEPU) is what makes CBDC move. But transaction costs and market frictions make the link less useful in practice and could make any trade opportunities less likely to happen. This shows how important it is to think about real-world limits when figuring out how useful predictive signals are in financial markets.

6 | CONCLUSION

The results show that we still don't know how CBDCs work as a hedge or safe-haven asset, even if they are becoming more and more linked to bigger economic and geopolitical issues. There is a statistically significant link between CBDC and other metrics of uncertainty, although these links don't always have much economic value. The notion that CBDCs serve as effective hedging instruments in volatile markets is challenged by the robust correlation between VI and CBDC, especially in times of crisis. This study underscores the necessity for a more comprehensive understanding of the response of CBDCs to external shocks and their potential for risk diversification.

6.1 | Practical Implications

The study emphasizes how important it is for investors to think about the limited diversification benefits that CBDCs offer, especially when the market is quite volatile. CBDCs may not be as good at protecting against market risk as some people think, even if they may be linked to uncertainty indexes. When times are tough, portfolio managers should carefully think about what these findings mean and consider other safe-haven assets like gold or government bonds when making portfolios. Also, because market frictions might stop the expected lead-lag relationships between uncertainty measures and CBDC markets from turning into useful trading signals, the study of high-frequency data calls for a rethinking of investment strategies.

6.2 | Theoretical Implications

This study adds to what we know about digital currencies by giving us new ways to think about how macroeconomic issues and CBDCs are related. The research interrogates the premise that CBDCs can function as reliable safe-haven assets, given their status as state-backed digital currencies. It also helps us understand better how uncertainty measurements and CBDC markets are related with time and in terms of frequency. The findings necessitate further examination of the underlying mechanisms driving these relationships, particularly the role of uncertainty exacerbated by social media and its effects on financial markets. Future research should explore alternative methodologies, such as mixed-frequency analysis and regime-switching models, to account for the non-linearities and time-varying dynamics present in the data. Additionally, the research suggests that the theoretical frameworks for understanding the behavior of CBDCs during crises need enhancement to incorporate the complex interrelations among digital asset markets, economic volatility, and geopolitical risk.

.

Acknowledgment: The authors would like to express their sincere thanks to the editor and the anonymous reviewers for their helpful comments and suggestions.

Author Contributions: Conceptualization, S.N; methodology, S.N; software, S.N.; validation, S.N.; investigation, S.N.; data curation, S.N.; writing original draft preparation, S.N.; writing—review and editing, S.N. All authors have read and agreed to the published version of the manuscript.

Declaration of Conflicting Interest: The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

Data Availability Statement: The bibliometric data utilized in this study were obtained from the Scopus database (Elsevier), which is subject to license restrictions. The data cannot be made public; however, it is available to institutions through Scopus. The studies were carried out with the freely accessible packages Biblioshiny (Bibliometrix R-package). No special code was created for this investigation.

Plagiarism Statement: This article was scanned by the plagiarism program. No plagiarism was detected.

REFERENCE

Aharon, D. Y., Demir, E., Lau, C. K. M., & Zaremba, A. (2022). Twitter-Based uncertainty and cryptocurrency returns. *Research in International Business and Finance*, *59*, 101546.

Akdag, S., İskenderoglu, Ö., & Alola, A. A. (2020). The volatility spillover effects among risk appetite indexes: insight from the VIX and the rise. *Letters in Spatial and Resource Sciences*, *13*(1), 49-65.

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID–19 crisis. *Finance research letters*, *38*, 101604.

Aloui, C., Hkiri, B., Hammoudeh, S., & Shahbaz, M. (2018). A multiple and partial wavelet analysis of the oil price, inflation, exchange rate, and economic growth nexus in Saudi Arabia. *Emerging Markets Finance and Trade*, *54*(4), 935-956.

Al-Thaqeb, S. A., & Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. *The Journal of Economic Asymmetries*, *20*, e00133.

Al-Thaqeb, S. A., Algharabali, B. G., & Alabdulghafour, K. T. (2022). The pandemic and economic policy uncertainty. *International Journal of Finance & Economics*, *27*(3), 2784-2794.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, *131*(4), 1593-1636.

Bech, M. L., & Garratt, R. (2017). Central bank cryptocurrencies. *BIS Quarterly Review September*.

Bech, M. L., Hancock, J., & Wadsworth, A. (2020). Central securities depositories and securities settlement systems.

Bekaert, G., Engstrom, E. C., & Xu, N. R. (2022). The time variation in risk appetite and uncertainty. *Management Science*, *68*(6), 3975-4004.

Bian, W., Ji, Y., & Wang, P. (2021). The crowding-out effect of central bank digital currencies: A simple and generalizable payment portfolio model. *Finance Research Letters*, *43*, 102010.

Bloom, N. (2009). The impact of uncertainty shocks. *econometrica*, *77*(3), 623-685.

Bouri, E., Shahzad, S. J. H., & Roubaud, D. (2020). Cryptocurrencies as hedges and safe-havens for US equity sectors. *The Quarterly Review of Economics and Finance*, *75*, 294-307.

Brooks, C. (2014). *Introductory econometrics for finance*. Cambridge university press.

Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. *American economic review*, *112*(4), 1194-1225.

Can Ergün, Z., Cagli, E. C., & Durukan Salı, M. B. (2023). The interconnectedness across risk appetite of distinct investor types in Borsa Istanbul. *Studies in Economics and Finance*, *40*(3), 425-444.

Chang, C. L., McAleer, M., & Wang, Y. A. (2020). Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19. *Renewable and Sustainable Energy Reviews*, *134*, 110349.

Chang, H. L., Nie, W. Y., Chang, L. H., Cheng, H. W., & Yen, K. C. (2023). Cryptocurrency Momentum and VIX premium. *Finance Research Letters*, *57*, 104196.

Chen, X., Miraz, M. H., Gazi, M. A. I., Rahaman, M. A., Habib, M. M., & Hossain, A. I. (2022). Factors affecting cryptocurrency adoption in digital business transactions: The mediating role of customer satisfaction. *Technology in Society*, *70*, 102059.

Choi, K. J., Henry, R., Lehar, A., Reardon, J., & Safavi-Naini, R. (2021). A Proposal for a Canadian CBDC. *Available at SSRN 3786426*.

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.

Demirer, R., Gkillas, K., Gupta, R., & Pierdzioch, C. (2019). Time-varying risk aversion and realized gold volatility. *The North American Journal of Economics and Finance*, *50*, 101048.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of econometrics*, *182*(1), 119-134.

Dunbar, K. (2023). CBDC uncertainty: Financial market implications. *International Review of Financial Analysis*, *87*, 102607.

Dunbar, K., & Jiang, J. (2020). What do movements in financial traders' net long positions reveal about aggregate stock returns?. *The North American Journal of Economics and Finance*, *51*, 100908.

Fatas, A. (2021). Can central bank digital currency transform digital payments?. *Central Bank Digital Currency-Considerations, Projects, Outlook*, 51-56.

Giannellis, N. (2022). Cryptocurrency market connectedness in Covid-19 days and the role of Twitter: Evidence from a smooth transition regression model. *Research in International Business and Finance*, *63*, 101801.

González-Sánchez, M., Nave, J., & Rubio, G. (2020). Effects of uncertainty and risk aversion on the exposure of investment-style factor returns to real activity. *Research in International Business and Finance*, *53*, 101236.

Goodell, J. W., & Shen, D. (2021). The Chinese sovereign digital currency as a catalyst for change: A new trilemma. *Understanding cryptocurrency fraud: The challenges and headwinds to regulate digital currencies*, *2*, 177.

Gunay, S. (2019). Impact of public information arrivals on cryptocurrency market: A case of twitter posts on ripple. *East Asian economic review*, *23*(2), 149-168.

Guo, Y., Li, P., & Li, A. (2021). Tail risk contagion between international financial markets during COVID-19 pandemic. *International Review of Financial Analysis*, *73*, 101649.

Hänska, M., & Bauchowitz, S. (2019). Can social media facilitate a European public sphere? Transnational communication and the Europeanization of Twitter during the Eurozone crisis. *Social media+ society*, *5*(3), 2056305119854686.

Helmi, M. H., Çatık, A. N., & Akdeniz, C. (2023). The impact of central bank digital currency news on the stock and cryptocurrency markets: Evidence from the TVP-VAR model. *Research in International Business and Finance*, *65*, 101968.

Hoang, Y. H., Ngo, V. M., & Vu, N. B. (2023). Central bank digital currency: A systematic literature review using text mining approach. *Research in International Business and Finance*, *64*, 101889.

Huang, Y., & Luk, P. (2020). Measuring economic policy uncertainty in China. *China economic review*, *59*, 101367.

Irfan, M., Chen, Z., Adebayo, T. S., & Al-Faryan, M. A. S. (2022). Socio-economic and technological drivers of sustainability and resources management: demonstrating the role of information and communications technology and financial development using advanced wavelet coherence approach. *Resources Policy*, *79*, 103038.

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, *105*(3), 1177-1216.

Kim, Y., Lim, H., & Sohn, W. (2020). Which external shock matters in small open economies? Global risk aversion vs. US economic policy uncertainty. *Japan and the World Economy*, *54*, 101011.

Kristoufek, L., Janda, K., & Zilberman, D. (2016). Comovements of ethanol-related prices: evidence from Brazil and the USA. *Gcb Bioenergy*, *8*(2), 346-356.

Kyriazis, N., Papadamou, S., Tzeremes, P., & Corbet, S. (2023). The differential influence of social media sentiment on cryptocurrency returns and volatility during COVID-19. *The Quarterly Review of Economics and Finance*, *89*, 307-317.

Larina, O. I., & Akimov, O. M. (2020). Digital money at the present stage: Key risks and development direction. *Finance: theory and practice*, *24*(4), 18-30.

Lee, D. K. C., Yan, L., & Wang, Y. (2021). A global perspective on central bank digital currency. *China Economic Journal*, *14*(1), 52-66.

Li, Z., Yang, C., & Huang, Z. (2022). How does the fintech sector react to signals from central bank digital currencies?. *Finance Research Letters*, *50*, 103308.

Masciandaro, D. (2018). Central Bank digital cash and cryptocurrencies: insights from a new Baumol–Friedman demand for money. *Australian Economic Review*, *51*(4), 540-550.

Masciandaro, D., Peia, O., & Romelli, D. (2024). Central bank communication and social media: From silence to Twitter. *Journal of Economic Surveys*, *38*(2), 365-388.

Mihanović, H., Orlić, M., & Pasarić, Z. (2009). Diurnal thermocline oscillations driven by tidal flow around an island in the Middle Adriatic. *Journal of Marine Systems*, *78*, S157-S168.

Morales-Resendiz, R., Ponce, J., Picardo, P., Velasco, A., Chen, B., Sanz, L., ... & Hodge, A. (2021). Implementing a retail CBDC: Lessons learned and key insights. *Latin American Journal of Central Banking*, *2*(1), 100022.

Nazlioglu, S., Soytas, U., & Gupta, R. (2015). Oil prices and financial stress: A volatility spillover analysis. *Energy policy*, *82*, 278-288.

Nguyen, L. T. M., & Nguyen, P. T. (2024). Do crypto investors wait and see during policy uncertainty? An examination of the dynamic relationships between policy uncertainty and exchange inflows of Bitcoin. *Review of Behavioral Finance*, *16*(2), 234-247.

Onsare, C. (2017). Social media misinformation in Kenya: an analysis of Twitter messages during the Chase Bank collapse. *Emerging Trends in Information and Knowledge Management*, *487*.

Ozili, P. K. (2023). Central bank digital currency research around the World: a review of literature. *Journal of Money Laundering Control*, *26*(2), 215-226.

Ozturkcan, S., Senel, K., & Ozdinc, M. (2025). Framing the Central Bank digital currency (CBDC) revolution. *Technology Analysis & Strategic Management*, *37*(4), 462-479.

Peruffo, L., Cunha, A. M., & Ferrari Haines, A. E. (2023). China's central bank digital currency (CBDC): an assessment of money and power relations. *New Political Economy*, *28*(6), 881-896.

Polyzos, E. (2023). Inflation and the war in Ukraine: Evidence using impulse response functions on economic indicators and Twitter sentiment. *Research in International Business and Finance*, *66*, 102044.

Prodan, S., Dabija, D. C., & Marincean, L. (2023, July). Exploring consumer sentiment on central bank digital currencies: a Twitter analysis from 2021 to 2023. In *Proceedings of the International Conference on Business Excellence* (Vol. 17, No. 1, pp. 1085-1102). Sciendo.

Qadan, M., & Idilbi-Bayaa, Y. (2020). Risk appetite and oil prices. *Energy Economics*, *85*, 104595.

Rehman, M. A., Chopra, R., & Yadav, A. (2025). Co-moment Insights from environmental sustainability with financial markets dynamics. *Computational Economics*, *66*(4), 2959-2985.

Rehman, M. A., Sabir, S. A., Javed, M. Z., & Mahmood, H. (2024). The connectedness knowledge from investors' sentiments, financial crises, and trade policy: An economic perspective. *Journal of the Knowledge Economy*, *15*(4), 20038-20062.

Rej, S., Bandyopadhyay, A., Mahmood, H., Murshed, M., & Mahmud, S. (2022). The role of liquefied petroleum gas in decarbonizing India: fresh evidence from wavelet–partial wavelet coherence approach. *Environmental Science and Pollution Research*, *29*(24), 35862-35883.

Principe, V. A. (2024). Web3 e esportes: como a tecnologia blockchain pode auxiliar os modelos de negócios nos esportes.

Sandner, P. G., Gross, J., Grale, L., & Schulden, P. (2020). The digital programmable euro, Libra and CBDC: Implications for European banks. *Libra and CBDC: Implications for European Banks (July 29, 2020)*.

Sangeetha, S., & Latha, A. (2023, June). Sentimental analysis of CBDC tweets using machine learning and deep learning techniques. In *2023 2nd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)* (pp. 1-6). IEEE.

Scharnowski, S. (2022). Central bank speeches and digital currency competition. *Finance Research Letters*, *49*, 103072.

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International review of financial analysis*, *70*, 101496.

Shen, W., & Hou, L. (2021). China's central bank digital currency and its impacts on monetary policy and payment competition: Game changer or regulatory toolkit?. *Computer Law & Security Review*, *41*, 105577.

Sinelnikova-Muryleva, E. V. (2020). Central bank digital currencies: Potential risks and benefits. *Voprosy Ekonomiki*, (4).

Sissoko, C. (2021). The nature of money in a convertible currency world. *Review of Economic Analysis (REA)*, *13*(1), 1-43.

Tata, F. (2023). Proposing an interval design feature to Central Bank Digital Currencies. *Research in International Business and Finance*, *64*, 101898.

Tong, W., & Jiayou, C. (2021). A study of the economic impact of central bank digital currency under global competition. *China Economic Journal*, *14*(1), 78-101.

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.

Umar, Z., Jareño, F., & Escribano, A. (2021). Oil price shocks and the return and volatility spillover between industrial and precious metals. *Energy Economics*, *99*, 105291.

van Oordt, M. R. (2022). Discussion of "Central bank digital currency: Stability and information". *Journal of Economic Dynamics and Control*, *142*, 104503.

Wang, H. (2023). How to understand China's approach to central bank digital currency?. *Computer Law & Security Review*, *50*, 105788.

Wang, Y., Lucey, B. M., Vigne, S. A., & Yarovaya, L. (2022). The effects of central bank digital currencies news on financial markets. *Technological Forecasting and Social Change*, *180*, 121715.

Wang, Y., Wei, Y., Lucey, B. M., & Su, Y. (2023). Return spillover analysis across central bank digital currency attention and cryptocurrency markets. *Research in International Business and Finance*, *64*, 101896.

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*, 101478.

Xiaofen, T., Qianqian, C., & Qian, Z. (2022). Global Risk Appetite, US Economic Policy Uncertainties and Cross-Border Capital Flow. *China Economist*, *17*(5), 2-18.