Dynamic price and volatility relationships between crypto returns and Twitter-based Economic Uncertainty

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Received: 20 November 2022; Accepted: 23 May 2025.

Abstract

In this study we examined the mean and the volatility transmissions of Twitter-based uncertainty and returns of Bitcoin, Ethereum, BNB, XRP, and Cardano in a time-varying context and considered the structural changes. The availability of the data directs us to have a different starting date for the analysis of five cryptocurrencies. However, our data span for all types of cryptocurrencies ended on August 31, 2022. We made several findings. First, our findings indicate that Twitter-based uncertainty has a more robust predictive power on cryptocurrency returns in the time-varying context compared with the standard Fourier-Granger causality results. Second, the empirical findings of the volatility transmission analysis also provide similar results. Third, the findings of the dynamic Fourier variance causality analysis exhibit robust evidence for the bidirectional volatility spillovers between the uncertainty indicator and the cryptocurrency returns, which in turn suggests a significant risk transmission.

Keywords: Twitter-based uncertainty, cryptocurrency returns, dynamic volatility spillovers
JEL: C22, G11, G15.

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1. Introduction

The US–China trade war, Brexit process, Eurozone crisis, and particular conflicts worldwide have significantly affected monetary and fiscal policies in advanced and emerging economies. Increased uncertainty in economic policies has fostered volatility in financial markets, affected real returns, and altered relative prices in precious metal markets (Imlak Shaikh 2020). These developments have created lost confidence in governments' economic policies and the financial system and directed investors to seek alternative financial instruments independent of conventional regulations (Jessica Paule-Vianez, Camilo Prado-Roman, and Raul Gomez-Martınez 2020).

Under these circumstances, Satoshi Nakamoto (2008) introduced Bitcoin, a new digital currency that provides an online open-source payment system. This new system uses cryptography to control and manage transactions and prevent fraud (Jinan Liu and Apostolos Serletis 2019). Following the release of Bitcoin and the rapid increase in the volume of transactions in the market, several new cryptocurrencies have been introduced.

In this study we investigate the causality between Twitter-based economic uncertainty and cryptocurrency returns and their volatility connectedness in a time-varying context, and we consider the structural changes. Therefore, we intend to provide valuable information for market participants on the transmission of Twitter-based uncertainty to cryptocurrency returns. The study covers the returns of Bitcoin, Ethereum, BNB, XRP, and Cardano. The start date for the analysis differs for these cryptocurrencies, and the end date is August 31, 2022. The study contributes to the literature by providing empirical evidence on the dynamic volatility connectedness and risk spillovers between uncertainty measures and cryptocurrency returns, unlike most studies in the literature addressing the causality relationship between uncertainty and cryptocurrency returns. Specifically, we employ dynamic Fourier Toda-Yamamoto and Fourier variance causality tests to consider both instabilities and structural changes in the causality relationships, revealing the periods in which a causality relationship or risk transmission exists.

The organization of the study is as follows. In the following section we review the literature, in the third section we introduce data and empirical methodology, in the fourth section we give the empirical results, and in the fifth section we draw our conclusions.

2. Literature Review

Cryptocurrencies have rapidly attracted attention because they might offer unique features to potential users and investors. Contrary to fiat money and conventional payment systems, cryptocurrencies are not subject to monetary authorities' traditional supervision (Khanh Hoang et al. 2020), are independent of sovereign government regulations (Ender Demir et al. 2018), and their increasing liquidity facilitates easy transactions with low cost (Owais Qarni et al. 2019).

As is the case in all forms of financial instruments and financial markets, the dynamic relationship between uncertainty and cryptocurrency returns directs investors in designing their strategies in portfolio allocation and hedging activities (Khaled Mokni et al. 2020). Existing studies mainly concentrate on whether cryptocurrencies act as significant hedge instruments against rising uncertainty.

However, the way information is conveyed is changing, and social media is becoming increasingly popular as a tool for individuals to acquire more up-to-date information on any subject. In this context, Twitter is viewed as a new-generation newspaper that provides information to social media users and reflects individual sentiments (Aharon et al. 2022). For this purpose, Scott Baker et al. (2021) developed a new metric that uses massive volumes of text messages (tweets) delivered through Twitter to track people's perceptions of economic uncertainty. The Twitter-based economic uncertainty index uses the tweets, including keywords such as "economic," "economical," "economically," "economics," "economies," "economist(s)," "economy," "uncertainties," and "uncertainty," and constructs a metric (Baker et al., 2021). Because the valuation of cryptocurrencies is still unknown, it is expected that non-fundamental factors, uncertainties, and individual sentiments will play a significant role in their pricing (Aharon et al. 2022).

Academics, policymakers, and investors are paying attention to the rise in economic policy uncertainty, and the number of researchers looking at the significance of uncertainty in predicting Bitcoin returns is growing. In one vein of the literature, researchers mostly concentrated on the relationship between economic policy uncertainty and the cryptocurrency market. In another vein, researchers found links between the cryptocurrency market and other financial or commodity markets. However, only a few researchers have looked at Bitcoin returns using the Twitter-based uncertainty measure.

The first group of researchers concentrated on the role of cryptocurrencies as a hedge against geopolitical risks and the associated uncertainty in the global economy. Ahmet Faruk Aysan et al. (2019) used many econometric methods in their comprehensive investigation. According to their research, geopolitical risk is a strong predictor of Bitcoin's returns and volatility. They also found that Bitcoin might be used as a hedge against these risks on a global scale. Using the Bitcoin market as a leading indicator, Su et al. (2020) made a strong case that Bitcoin returns reduce geopolitical uncertainty, allowing for a more thorough and accurate analysis of the global geopolitical climate. According to them, investors would do well to take cues from the Bitcoin market when times of great global uncertainty and complicated geopolitical dynamics arise.

Nikolaos A. Kyriazis (2020) analyzed the connectedness in both the mean and the volatility return of Bitcoin and the geopolitical uncertainty from March 2012 to March 2020. Their findings proved that rising geopolitical uncertainty boosted Bitcoin returns, and they concluded that Bitcoin could serve as a hedge against uncertainty. Colon et al. (2021) explored the asymmetric impact of geopolitical uncertainty and economic policy uncertainty on several cryptocurrency returns. Their findings indicated that the cryptocurrency market mainly acts as a haven or is an effective hedging tool in uncertain times. However, the haven and hedging roles might differ during bull and bear markets.

Another group of researchers discussed the linkage between economic policy uncertainty and the cryptocurrency market. Demir et al. (2018) used quantile-based regression and the Bayesian graphical structural vector autoregressive model and provided evidence favoring economic policy uncertainty's significant role in predicting Bitcoin returns. Their findings indicated that Bitcoin returns could act as a hedging tool against uncertainty, and there is a contemporaneous causality between Bitcoin returns and economic policy uncertainty.

Roman Matkovskyy et al. (2020) explored whether US economic policy uncertainty is a significant factor in explaining the linkage between the cryptocurrency market and traditional financial markets. Their findings suggest that Bitcoin could be an effective hedging instrument under uncertainty shocks. Similarly, Mokni et al. (2020) found that economic policy uncertainty significantly affects the dynamic conditional correlation between Bitcoin and the US stock market. Their findings also showed that the Bitcoin crash in December 2017 was a significant structural shift for investors designing their optimal portfolios. Khan Quoc Nguyen (2022) discussed the impact of the stock market on Bitcoin returns during periods of high uncertainty in the US. Their findings suggested that spillovers of stock market shocks were significant in the volatility of Bitcoin returns during the economic turmoil periods. Jihed Ben Nouir and Hayet Ben Haj Hamida (2023) provided an insightful analysis of how different sources of uncertainty impact Bitcoin volatility, effectively demonstrating that US-related uncertainty influences Bitcoin volatility in the short term, whereas uncertainty from China exerts longer-term effects. The study also highlighted that Bitcoin's volatility responds similarly to US economic policy uncertainty and global political risk but exhibits different reactions to China's economic policy uncertainty and geopolitical risk. Notably, the manuscript showed that Bitcoin serves as a hedge against extreme levels of US economic policy uncertainty and global political risk.

Hui-Pei Cheng and Kuang-Chieh Yen (2020) used a predictive regression model and evaluated economic policy uncertainty's predictive performance on cryptocurrency returns in China, the US, and other Asian countries. They found that Chinese economic policy uncertainty has significant predictive power on Bitcoin returns. At the same time, economic policy uncertainty in other sample countries is not an important tool to predict Bitcoin returns in other sample countries. Shaikh (2020) also proved that economic policy uncertainty had a negative and significant impact on Bitcoin returns in the US and Japan between July 2010 and September 2018. Paule-Vianez et al. (2020) discussed whether Bitcoin serves as a haven or speculative asset property during high uncertainty periods. Their study covered the period from July 2010 to April 2019. Their findings indicated that Bitcoin returns and volatility increase during high economic policy uncertainty periods, which in turn provided evidence favoring the role of Bitcoin as an investment asset and a haven. Matteo Foglia and Peng-Fei Dai (2022) analyzed the relationship between economic policy uncertainty spillovers and cryptocurrency prices across a group of countries between 2013 and 2021. The cross-country results suggested that economic policy uncertainty is a significant measure of predicting cryptocurrency prices. Conversely, Wang et al.

(2019) argued that the risk spillovers from economic policy uncertainty to Bitcoin returns were negligible in the US. In the same vein, Kuang-Chieh Yen and Hui-Pei Cheng (2021) found that economic policy uncertainty is not a robust indicator to predict cryptocurrency volatility in the US, Japan, and Korea. However, economic policy uncertainty in China is a valuable measure to explain cryptocurrency volatility.

Gozgor et al. (2019) found a significant impact of economic policy uncertainty on Bitcoin returns in the US between July 2010 and August 2018. Their findings demonstrated that the causal relationship between uncertainty measures and Bitcoin returns exhibited structural changes during 2010–11 and 2017–18. Similarly, Ur Koumba Calvin Mudzingiri and Jules Mba (2020) proved the cryptocurrency prices' dependence on US economic policy uncertainty from August 2016 to February 2018. Fang et al. (2019) explored whether global economic policy uncertainty affects the correlation between the returns of Bitcoin and global bonds and equities. They found that global economic policy uncertainty increases the effectiveness of Bitcoin as a hedging tool against global equities and bonds. Qarni et al. (2019) explored the time-varying dynamic volatility spillovers between US Bitcoin and the financial markets from July 2010 to December 2017. They found that the turmoil in the Bitcoin market does not become contagious to the financial markets and provides investors with an opportunity for risk hedging in portfolio diversification.

There is a dearth of research on the topic of how Twitter-based uncertainty affects cryptocurrency profits, and even less on how this uncertainty relates to the cryptocurrency market as a whole. Wu et al. (2021) examined the causal link in a rolling window framework. According to their findings, the economic policy uncertainty metric based on Twitter is a Granger cause of the returns of Bitcoin, Ethereum, and XRP, and it mostly has a positive effect in various time periods. Using data collected both before and after the COVID-19 outbreak, Joseph J. French (2021) persuasively compared the effects of Twitter-based economic uncertainty on Bitcoin. His research showed that during the pandemic, Twitter-based economic uncertainty became a much bigger influence on the conditional volatility of Bitcoin and a considerable predictor of Bitcoin returns. The findings also indicated that the Bitcoin market had a significant impact on the tweets' level of uncertainty during the pandemic. Aharon et al. (2022) made a recent contribution to the field by investigating the effect of uncertainty on the returns of different cryptocurrencies using uncertainty metrics based on Twitter. In particular, they discovered that the causal relationship is quite in sync for Bitcoin in the upper and lower quantiles.

In their comprehensive study, Remzi Gök, Elie Bouri, and Eray Gemici (2022) examined the Granger causation between economic uncertainty as expressed on Twitter and cryptocurrency, physical gold, and US 10-year Treasury notes. They used cutting-edge approaches such as causality-in-quantiles and wavelet transformations to show how Twitter-based economic uncertainty affects various haven assets differently depending on the market. They demonstrated that, particularly during the pandemic, Twitter-based economic uncertainty affected the volatility of Treasuries and Bitcoin, highlighting the impact of social media on market dynamics. An important area of research that Hajam abid Bashir and Dilip Kumar (2023) covered is the effect of investor focus on the COVID-19 pandemic, public mood, and Twitter sentiment on the performance of cryptocurrencies. The researchers employed many approaches, including linear regression, quantile regression, and the exponential generalized autoregressive conditional heteroskedastic model, to determine that investor attention and uncertainty as expressed on Twitter adversely impact volatility increases and returns on Bitcoin. This highlights the complex influence of mood on various market sectors because the quantile regression analysis shows that these impacts are more noticeable at the lower quantiles. Importantly, the results imply that cryptocurrency has not been a haven throughout the pandemic.

While some researchers have explored the relationship between Twitter-based uncertainty and cryptocurrency returns, they primarily employed static analyses that may not fully capture the dynamic nature of this relationship. Moreover, they did not explicitly consider the potential impact of recent significant events such as the COVID-19 pandemic and Russia's invasion of Ukraine. We address this gap by employing dynamic Fourier Toda-Yamamoto and dynamic Fourier variance causality tests, allowing us to investigate the time-varying nature of the relationship between uncertainty and cryptocurrency returns in the context of these recent events. This approach enables us to identify specific periods of significant causality and volatility spillovers, providing more nuanced insights into the market dynamics than previously available. Even though the literature on the relationship between uncertainty and cryptocurrency returns is growing, there is still room for further research. Applying a fresh measure of uncertainty that best matches economic agents' sentiments as well as empirical tools that account for structural changes in a time-varying setting could be a useful contribution to the literature.

3. Data, Model, and Econometric Methodology

3.1 Data and the Empirical Model

We analyze the relationship between the logarithmic returns of cryptocurrencies and Twitter-based uncertainty indices. For this purpose, we employ the five cryptocurrencies according to their market capitalization.[3] These cryptocurrencies are Binance Coin (BNB), Bitcoin (BTC), Cardano (ADA), Ethereum (ETH), and Ripple (XRP). We obtained the data on cryptocurrencies from Investing.com and data on the Twitter-based economic uncertainty index from the Economic Uncertainty Index website.[4] The beginning date of the sample changes due to data unavailability. The start date of the analysis for the ADA is January 1, 2018; for the BNB, it is November 10, 2017; for the BTC, it is June 2, 2011; for the ETH, it is March 11, 2016; and for the XRP, it is January 23, 2015. The end date of the data is August 31, 2022.

We consider the following models to examine the causality relationship:

$$\Delta \ln\left(CC\right)_t = \beta_1 + \beta_2 \Delta \ln\left(TU\right)_t + e_{1t} \tag{1}$$

[3] Considering the market cap according to https://coinmarketcap.com/

[4] https://www.policyuncertainty.com/twitter_uncert.html access date: September 9, 2022.

$$\Delta \ln\left(TU\right)_t = \alpha_1 + \alpha_2 \Delta \ln\left(CC\right)_t + e_{2t} \quad (2)$$

where $\Delta \ln\left(CC\right)_t$ shows the daily logarithmic returns of considered cryptocurrencies, $\Delta \ln\left(TU\right)_t$ is the daily changes of the Twitter-based economic uncertainty index, and e_t indicates the error term. We present the descriptive statistics of the prices considered by cryptocurrencies and the Twitter-based economic uncertainty index in Table 1.

[Table 1 about here]

As can be seen from Table 1, BTC has the highest mean, while XRP has the lowest. In addition, the price of BTC seems most spread out among all cryptocurrencies. All the prices are skewed right because all values of skewness are positive. Except for BNB, all series are leptokurtic because all values of kurtosis are higher than three. BNB is distributed as mesokurtic because the kurtosis is nearly 3. The Jarque-Bera test statistics show that all series are distributed as non-normal. Additionally, we also computed correlation coefficients between the variables. We found all coefficients to be statistically significant, and the coefficients show a low negative correlation between the uncertainty index and the cryptocurrencies' prices.[5]

3.2 Econometric Method

In this study we investigate the dynamic relationship between uncertainty and cryptocurrency returns using two complementary methodologies: the Fourier Toda-Yamamoto causality test and the Fourier variance causality test. We chose these methods for their ability to capture the cryptocurrency market's complexities, specifically its volatility and susceptibility to structural shifts and external shocks.

The Fourier Toda-Yamamoto causality test examines mean transmission, revealing whether changes in uncertainty predict future returns. Conversely, the Fourier variance causality test focuses on volatility transmission, indicating whether uncertainty influences the risk associated with those returns. By combining these tests, we gain a comprehensive understanding of both the directional impact and risk implications of uncertainty on the cryptocurrency market.

The suitability of these tests stems from their capacity to incorporate Fourier terms, effectively capturing structural changes and instabilities without requiring a priori knowledge of their timing or form. Further, their dynamic framework allows one to identify time-varying patterns of causality and volatility spillovers, which is crucial for understanding the evolving relationship between uncertainty and cryptocurrency returns, particularly in light of recent events such as the COVID-19 pandemic and

[5] The findings are not reported to conserve space but are available upon request.

Russia's invasion of Ukraine. Finally, the established nature of these tests within the econometrics literature ensures the robustness and reliability of our findings.

3.2.1 Toda-Yamamoto Causality Test with a Fourier Function

One can use any causality test to reveal whether one variable precedes another. We employ the Toda-Yamamoto causality test with a Fourier function (Fourier Toda-Yamamoto) that Saban Nazlioglu, N. Alper Gormus and Ugur Soytas (2016) introduced to test the return transmission between cryptocurrencies and uncertainties. Nazlioglu et al. (2016) defined the following lag-augmented vector autoregressive model with a Fourier function:

$$y_t = \alpha_0 + \alpha_1 \sin\left(\frac{2\pi kt}{T}\right) + \alpha_2 \cos\left(\frac{2\pi kt}{T}\right) + \Pi_1 y_{t-1} + \ldots + \Pi_{p+d} y_{t-(p+d)} + e_t \quad (3)$$

where y_t denotes a $(T \times Z)$ matrix of T observations on Z endogenous variables, α_0 is a (Tx1) vector of constant terms, $\Pi = \left(\Pi_1, \ldots, \Pi_{p+d}\right)'$ shows the parameters where p is the optimal lag length, and d is the maximum lag length of the considered variables, which is included in the model to avoid differencing the series, in the case of integrated variables. e_t is a white noise disturbance term. Trigonometric terms are added to the model to consider the structural changes in the causality relationship without the need for information about the date, number, or form of the changes. k in the trigonometric terms show a particular frequency whose value is searched in the range [0.1, 0.2, 0.3, . . . , 5] and determined as the value that minimizes Akaike information criteria. t is the trend term and T is the number of observations. Finally, α_1 and α_2 show the measurement for the frequency's amplitude and displacement. We determine the optimal lag length also using Akaike information criteria. After finding the optimal lag length, the maximum integration order of the variables, and the optimal frequency, we can test the null hypothesis that no causality exists, $\mathrm{H}_0{:}\Pi_1 = \Pi_2 = \ldots = \Pi_p = 0$, using the Wald test statistic. Due to the existence of the trigonometric terms, we compute the critical values using bootstrap simulations.

Although the Fourier Toda-Yamamoto causality test enables us to consider the structural breaks in the causality relationship, there may be instabilities in this relationship, that is, the existence and/or direction of the causality may change over time. To reveal the instabilities, we also employed the causality test in a dynamic form. We first determine the number of observations in subsamples (*s*) using the following formulae (Peter CB Phillips, Shuping Shi, and Jun Yu 2015):

$$s = \left[T \left(0.01 + \frac{1.8}{\sqrt{T}} \right) \right] \quad (4)$$

After finding the value of s, we implement the causality test using the sample from the first observation to the *s*th observation. At each new stage, we exclude the first observation from the sample and include the next observation to the sample. For instance, while the first subsample includes the observations from the first to the (s) th observation, the second subsample contains the observations from the second to the ($s+1$)th observation. We proceed with this process until using the last observation in the full sample. Because the observations change in each subsample, the test statistics and the critical values that we obtained by using bootstrap simulations also change. We draw a graph with the bootstrap p values and the significance level of 0.10. The p values, which are higher than the significance level, show the non-rejection of the null hypothesis, while the p value, which is lower than 0.1, indicates the rejection of the null. So, by inspecting the figure, we can reveal the instabilities in the causality relationship.

3.2.2 Hafner and Herwartz (2006) Causality Test with a Fourier Function

To investigate the existence of a volatility spillover effect between the uncertainties and cryptocurrencies, one can employ the causality in variance test that Christian M. Hafner and Helmut Herwartz (2006) introduced to the literature. The test is based on the generalized autoregressive conditional heteroscedasticity model. The ignoring of structural breaks in the variance may lead to misleading results when testing the causality in variance (see Durmuş Çağrı Yıldırım, Emrah İsmail Cevik, Ömer Esen 2020). Therefore, to allow for structural changes in variance, we follow Razvan Pascalau Christian Thomann, and Greg N. Gregoriou (2011) and Jing Li and Walter Enders (2018) and augment the Hafner and Herwartz test using a Fourier function. To test the volatility transmission, we estimate a generalized autoregressive conditional heteroscedasticity (1,1) model for $i, j = 1, 2, 3, \ldots, N$, $i \neq j$ as follows:

$$Y_{it} = \alpha_0 + \beta Y_{t-i} + \sum_{j=1}^{q} \delta_j \varepsilon_{t-j} + \varepsilon_t \quad (5)$$

After estimating Eq. 3, Hafner and Herwartz (2006) suggested considering the following model:

$$\varepsilon_{it} = \xi_{it} \sqrt{\sigma_{it}^2 g_t}, \quad g_t = 1 + z_{jt}^{\prime} \pi, \quad z_{jt} = \left(\varepsilon_{jt-1}^2, \sigma_{jt-1}^2 \right)^{\prime} \quad (6)$$

where $\sigma_{it}^2 = \omega_{0i} + \omega_{1i} \sin\left(\frac{2\pi k_i t}{T}\right) + \omega_{2i} \cos\left(\frac{2\pi k_i t}{T}\right) + \omega_{3i}\varepsilon_{it-1}^2 + \omega_{4i}\sigma_{it-1}^2$

where σ_{it}^2 shows the conditional variance and $\sin$, $\cos$ constitute the Fourier function, which is employed to allow structural shifts in the volatility process. k, t, and T indicate a particular frequency, a trend term, and a sample size, respectively. k is determined by using Akaike or Schwarz information criteria. ξ_{it} is the standardized error for series i. So we can compute the test statistics to test $H_0 : \pi = 0$ as follows:

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right) z_{jt}^{'}\right) V\left(\theta_i\right)^{-1}\left(\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right) z_{jt}\right)\Bigg\}$$

where $V\left(\theta_i\right) = \frac{\kappa}{4T}\left(\sum_{t=1}^{T} z_{jt} z_{jt}^{'} - \sum_{t=1}^{T} z_{jt} x_{it}^{'}\left(\sum_{t=1}^{T} x_{it} x_{it}^{'}\right)^{-1}\sum_{t=1}^{T} x_{it} z_{jt}^{'}\right)$ with $\kappa = \frac{1}{T}\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right)^2$.

λ_{LM} is distributed as a chi-square with 2 degrees of freedom. We also compute the λ_{LM} in a dynamic form to reveal the instabilities in the causality relationship in variance.

3.3.3 Conceptual Framework

Integrating the dynamic link between economic uncertainty and cryptocurrency returns is the conceptual foundation driving this investigation. The efficient market hypothesis and the idea of behavioral finance provide the theoretical foundation for this connection. According to behavioral finance, investor mood as recorded on Twitter and other social media platforms may impact market dynamics; in contrast, the efficient market hypothesis states that asset prices reflect all information that is accessible, including that which is shared on social media (Nicholas Barberis 2003; Eugene F. Fama 1970).

An innovative method for assessing market mood may be found in economic uncertainty indexes that are based on Twitter and compile sentiment from tweets pertaining to economic situations (Baker et al., 2021). In this study we empirically investigate the impact of such emotion on cryptocurrency returns, which are responsive to investors' actions.

In this study we use the Fourier Toda-Yamamoto and Fourier variance causality tests to experimentally examine the dynamic link between economic uncertainty as reported on Twitter and cryptocurrency returns. Taking structural breaks and time-varying dynamics into account, these approaches can discover mean and volatility spillovers.

$$Yt = \alpha + i = 1\sum p\beta iYt - i + j = 1\sum q\gamma jXt - j + \delta cos(\omega t) + \theta sin(\omega t) + \epsilon t \quad (7)$$

where Yt represents the daily logarithmic returns of the cryptocurrencies (BTC, ETH, XRP, BNB, ADA). Xt represents the changes in the Twitter-based economic uncertainty index. ω is the frequency parameter for the Fourier terms capturing structural breaks, and ϵt is the error term.

$$\sigma t2 = \alpha + \beta\sigma t - 12 + \gamma\epsilon t - 12 + \delta cos(\omega t) + \theta sin(\omega t) + \eta t \quad (8)$$

where σt2 represents the conditional variance of the cryptocurrency returns.

This generalized autoregressive conditional heteroscedasticity-based model tests for volatility spillovers from Twitter-based economic uncertainty to cryptocurrency returns by examining the impact of the Fourier terms and past shocks on the current volatility.

4. Empirical Results and Discussion
4.1 Empirical Results

The starting point in our empirical strategy is to test the variables' stationarity. The test's empirical findings imply that all variables are stationary at their levels. Therefore, we do not augment the vector autoregression model with extra lags, and we use the Fourier-Granger causality test introduced by Walter Enders and Paul Jones (2016) instead of the Fourier Toda-Yamamoto causality test to examine the causality nexus between a set of cryptocurrency returns and Twitter-based uncertainty.

The inclusion of the Fourier terms into the analysis in the Fourier-Granger causality test allows practitioners not to exactly know and describe the type and the number of structural breaks in datasets. Because financial variables exhibit many structural breaks in their nature, the Fourier-Granger causality test offers various advantages and is used as a practical tool in the causality nexus.[6] Table 2 presents the results of the Fourier causality test as follows:

[Table 2 about here]

On the one hand, the findings in Table 2 show that the null hypothesis of no causality running from economic uncertainty to cryptocurrency returns is not rejected.

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[6] The only difference between the two tests is that we accept *d = 0* in the Fourier-Granger causality test.

Therefore, our findings on the Fourier-Granger causality test exhibit no information transmission through Twitter-based uncertainty to cryptocurrency returns and provide evidence against the potential predictive power of Twitter-based uncertainty on cryptocurrency returns.

On the other hand, the Fourier-Granger causality test results in Table 2 show that there is unidirectional causality from BTC to economic uncertainty, from BNB to economic uncertainty, and from ETH to economic uncertainty. The rejection of the null hypothesis of no causality in these cases provides evidence that the returns of these cryptocurrencies have predictive power on Twitter-based uncertainty.

In addition to the mean uncertainty transmission, in the next step of our empirical configuration, we examine the volatility transmission between uncertainty and cryptocurrency returns. The analysis of the volatility spillovers provides evidence of whether there is a significant risk transmission between the uncertainty index and cryptocurrency returns.

We employ the Fourier variance causality test to examine the volatility spillovers between the uncertainty index and cryptocurrency returns. Table 3 shows the results.

[Table 3 about here]

The findings in Table 3 demonstrate that there is a significant bidirectional volatility transmission between BTC and economic uncertainty and between XRP and economic uncertainty. In addition, there exists a unidirectional volatility transmission from BNB to economic uncertainty and from ETH to economic uncertainty. These findings confirm that there is risk transmission feedback between the BTC, XRP, and economic uncertainty. Therefore, in terms of the volatility spillovers, there seems to be a significant correlation between cryptocurrency returns and the uncertainty measure.

Overall, the findings show that there is more volatility transmissions than mean transmissions between the uncertainty and cryptocurrency returns, which indicates that we observe stronger evidence of the volatility transmission from uncertainty to cryptocurrency returns.

Upon further analysis, to analyze the causality relationship and the volatility spillovers between Twitter-based uncertainty and the cryptocurrency returns in a time-varying context, we use the dynamic Fourier Toda-Yamamoto and Fourier variance causality tests. Incorporating the dynamic analysis also helps us reveal the instability in the causality relationship and the volatility transmission.

To apply the dynamic Fourier Toda-Yamamoto causality test, we follow Juan J. Dolado and Helmut Lutkepohl (1996) and add only one extra lag to the vector autoregression model instead of testing integration levels in all subsamples. Figure 1 illustrates the dynamic Fourier Toda-Yamamoto causality test results.

[Figure 1 about here]

Figure 1 demonstrates that the findings of the dynamic Fourier causality test display a different picture from the findings in Table 2. When the time-variability is considered, the information transmission from Twitter-based uncertainty to cryptocurrency returns is significant in some periods. Therefore, these findings provide evidence that the predictive power of the uncertainty on cryptocurrency returns might change over time. It should also be noted that the causality relationship in the five pairs seems to be episodic in terms of unidirectional and bidirectional information transmission between uncertainty and returns.

Furthermore, the dynamic nature of the volatility transmission is particularly evident during periods of increased global uncertainty. Observing Figure 2, the sharp increase in volatility spillover from economic uncertainty to BTC and ETH around March 2020, indicated by p values falling below the significance level of 0.1, coincides with the onset of the COVID-19 pandemic. This suggests that the pandemic-induced economic uncertainty significantly impacted investor sentiment toward cryptocurrencies, potentially driving them to seek alternative investment opportunities in a volatile traditional market. This observation aligns with Roman Matkovskyy Akanksha Jalan, and Michael Dowling (2020) who found that Bitcoin can act as a hedge during periods of economic uncertainty. Similarly, the increased volatility observed in the aftermath of Russia's invasion of Ukraine in early 2022, again evidenced by statistically significant p values, further underscores the sensitivity of cryptocurrency markets to geopolitical risks. This period also saw increased discussion on the use of cryptocurrencies to circumvent sanctions, potentially contributing to the observed volatility. These findings highlight the importance of considering external shocks and global events when analyzing the relationship between uncertainty and cryptocurrency returns. Notably, the dynamic Fourier variance causality test allows us to visualize these shifts in volatility transmission, providing a more nuanced understanding of how uncertainty and cryptocurrencies interact during turbulent times.

In the final step of our empirical strategy, we used the dynamic Fourier variance causality test and examined whether the causality in variance changes over time. Figure 2 presents the results of this test.

[Figure 2 about here]

The results in Figure 2 demonstrate that in most of the analyzed period, the null hypothesis of no causality in variance is rejected, and there is a significant volatility transmission in at least one direction in all pairs of uncertainty and returns. Figure 2 also provides evidence of the feedback volatility transmission in the uncertainty-return nexus.

4.2 Discussion

Compared with the findings of the conventional Fourier variance causality test, the dynamic analysis first highlights the dynamic nature of the volatility transmission. These findings also demonstrate that the prediction power of the uncertainty on cryptocurrency returns varies over time and shows significant long-lived and short-lived risk transmission periods in an analyzed period. In other words, findings in the dynamic Fourier variance causality analysis might suggest that volatility spillovers between Twitter-based uncertainty and the cryptocurrency returns are responsive to various international political, economic, and social factors that affect cryptocurrency returns and the uncertainty in the market.

Our findings indicate that the mean transmission and the volatility transmission between returns and the uncertainty are stronger in the time-varying context due to the dynamic nature of both the uncertainty indicator and the returns of cryptocurrencies. Furthermore, the empirical findings of our study provide valuable information for the significant role of the hedging property of cryptocurrencies during high uncertainty periods because the time-varying causality in variance test results indicate several long-lived periods of significant causal linkage in an analyzed period.

Finally, our findings on the significant predictive power of uncertainty indicators on the returns of market-dominating cryptocurrencies and the significant role these cryptocurrencies play in the hedging of investor portfolios during arousing uncertainty periods are consistent with the findings of Shu Han Hsu Chwen Sheu, and Jiho Yoon (2021), Fang et al. (2019) and Gozgor et al. (2019), in which they employed either different period or econometric techniques. Our findings on the dynamic relationship between the economic uncertainties and cryptocurrency returns based on Twitter are consistent with and build upon previous research. For instance, our research contributes to the understanding that the relationship between Twitter-based uncertainty and cryptocurrency returns is not static but rather time-varying, particularly in the context of significant global events such as the COVID-19 pandemic and Russia’s invasion of Ukraine, despite the fact that Wu et al. (2021) and Aharon et al. (2022) both identified a causal link. Additionally, our evidence of bidirectional volatility spillovers between the uncertainty index and cryptocurrencies, as demonstrated in the dynamic Fourier variance causality test, supports the conclusions of Matkovskyy et al. (2020) that cryptocurrency markets are exceedingly susceptible to economic disturbances. Our methodology differs from past static studies in that it offers a more nuanced comprehension of the dynamic relationships, underscoring the need of adding time-varying approaches into future research.

Gök et al. (2022) also discovered that economic uncertainty based on Twitter has comparable effects on haven assets. Therefore, our discovery of substantial bidirectional volatility spillovers between Twitter-based uncertainty and Bitcoin aligns with their findings. Nevertheless, in contrast to previous static models, our use of dynamic Fourier analysis paints a clearer picture of the temporal evolution of these spillovers, attracting attention to certain points in time when they are most noticeable.

5. Conclusion

Cryptocurrencies’ market capitalization has risen rapidly during the last few years, which in turn has attracted investors, scholars, and policymakers’ attention. Therefore, discovering the factors affecting cryptocurrency returns, the dynamic interconnectedness of the returns with main macroeconomic indicators, and aroused uncertainty throughout the world are becoming growing topics of discussion.

In this study, we examined the mean transmission and the volatility transmissions of Twitter uncertainty and returns of Bitcoin, Ethereum, BNB, XRP, and Cardano in a time-varying context by considering the structural changes.

Our findings first revealed that Twitter-based uncertainty has a more robust predictive power on cryptocurrency returns in the time-varying context compared with the standard Fourier-Granger causality analysis. In the next step, the empirical findings of the causality in variance analysis also provided similar results. The findings of the dynamic Fourier variance causality analysis provided robust evidence for the bidirectional volatility spillovers and indicated a significant risk transmission between the uncertainty indicator and the cryptocurrency returns. Specifically, the increased volatility observed during the COVID-19 pandemic and Russia's invasion of Ukraine, as demonstrated by the significant p values in the dynamic analysis, emphasizes the need for investors to be aware of the impact of global events on cryptocurrency markets.

The significant risk transmission and volatility spillovers between Twitter-based economic uncertainty and cryptocurrency returns suggest several important policy implications. First, investors need to be aware that the volatility in cryptocurrency returns is highly sensitive to the uncertainties aroused in social media. For investors and traders, the dynamic nature of these relationships underscores the necessity for real-time monitoring of social media sentiment as an integral part of investment strategies, especially during periods of heightened global uncertainty. Policymakers should consider the potential for cryptocurrencies to act as alternative hedging instruments during economic crises, as evidenced by their behavior during the COVID-19 pandemic and geopolitical tensions. Therefore, investors must closely follow the social, economic, and global issues that might create uncertainties in economies. Second, because we found significant information and risk transformation through uncertainty to cryptocurrency returns, cryptocurrencies might be regarded as a practical hedging tool in investors' portfolio allocation decisions. This hedging potential was particularly evident during the COVID-19 pandemic and Russia's invasion of Ukraine, where significant volatility spillovers were observed, reinforcing the need for policymakers to understand the role of cryptocurrencies in investor portfolios during crises. Third, because there is a significant bidirectional risk transmission between uncertainty and cryptocurrency returns, policymakers should be aware of the role of volatility in the cryptocurrency markets to fuel uncertainties and its potential contagion to other financial markets. Thus, policymakers also should closely monitor cryptocurrency markets to deal with the risk spillovers through this market. Finally, central banks and monetary authorities should be aware of the bidirectional pass-through mechanism between uncertainty and cryptocurrency markets while designing digital currencies. In this context, regulatory bodies need to be aware of the potential for contagion effects between cryptocurrency markets and other financial markets, necessitating robust monitoring systems to preempt and mitigate systemic risks. Understanding these dynamics could assist in formulating policies that stabilize financial markets in the face of unpredictable social and economic upheavals.

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Table 1 Descriptive Statistics

Series	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations
ADA	0.507	0.141	2.965	0.023	0.651	1.527	4.535	829.102 (0)	1704
BNB	137.442	22.480	676.560	1.490	185.516	1.158	2.883	393.231 (0)	1756
BTC	8970.442	971.100	67527.900	2.000	14957.890	2.052	6.203	4640.76 (0)	4109
ETH	850.366	281.940	4808.380	6.700	1149.213	1.597	4.404	1199.79 (0)	2365
XRP	0.351	0.266	2.780	0.004	0.372	1.762	7.683	3976.05 (0)	2778
TU	105.517	81.614	1476.198	4.327	88.413	2.885	22.763	72573.72 (0)	4109

Note: Numbers in the parentheses show the p-values.

Source: Authors' calculation

Table 2 Fourier Causality Test Results

H_0	Wald Test Stat	Bootstrap p-value	Optimal Lag	Optimal Freq.
TU $\nrightarrow$ BTC	6.109	0.791	10	3
BTC $\nrightarrow$ TU	28.501 *	0.003	10	3
TU $\nrightarrow$ BNB	7.221	0.206	5	2.8
BNB $\nrightarrow$ TU	12.993 **	0.023	5	2.8
TU $\nrightarrow$ ETH	8.211	0.233	6	1.9
ETH$\nrightarrow$ TU	13.146 **	0.038	6	1.9
TU $\nrightarrow$ XRP	6.766	0.342	6	2.2
XRP $\nrightarrow$ TU	7.576	0.278	6	2.2
TU $\nrightarrow$ ADA	7.746	0.167	5	0.6
ADA $\nrightarrow$ TU	4.891	0.456	5	0.6

Note: * and ** show significance at 1% and 5% levels, respectively. Bootstrap p-values are obtained using 2000 simulations.

Source: Authors' calculation

Table 3 Fourier Variance Causality Test Results

H_0:	LMstat	p-value	Optimal Freq.
TU ↛ BTC	7.881**	0.0194	0.1
BTC ↛ TU	30.635*	0	0.8
TU ↛ BNB	1.993	0.3692	0.1
BNB ↛ TU	11.261*	0.0036	0.8
TU ↛ ETH	0.958	0.6194	0.9
ETH↛ TU	31.100*	0	0.4
TU ↛ XRP	77.486*	0	0.1
XRP ↛ TU	26.026*	0	0.9
TU ↛ ADA	1.518	0.4681	0.1
ADA ↛ TU	4.155	0.1253	1

Note: * and ** show significance at 1% and 5% levels, respectively.

Source: Authors' calculation

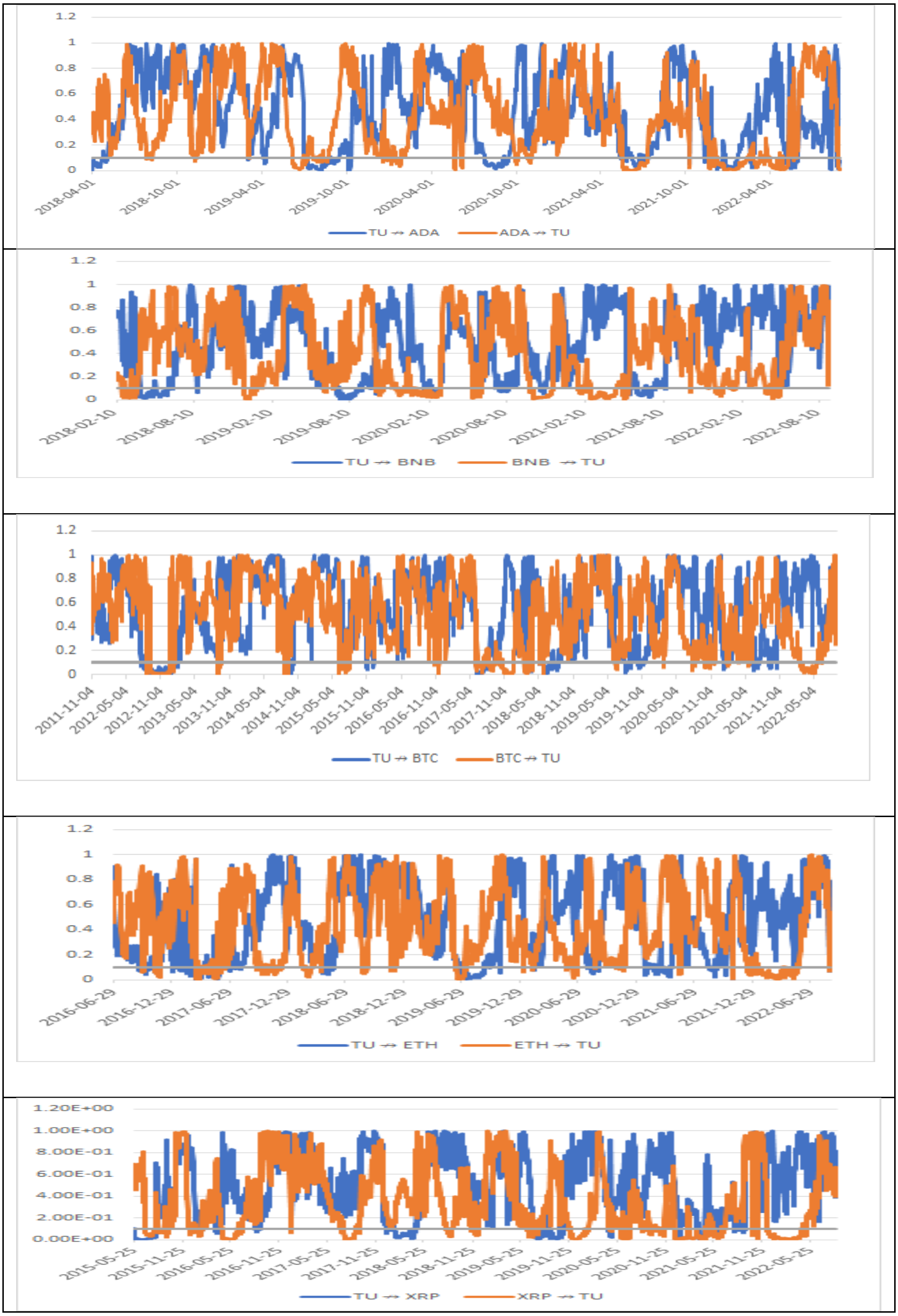

Figure 1 Dynamic FTY Causality Test Results

Source: Authors' calculation

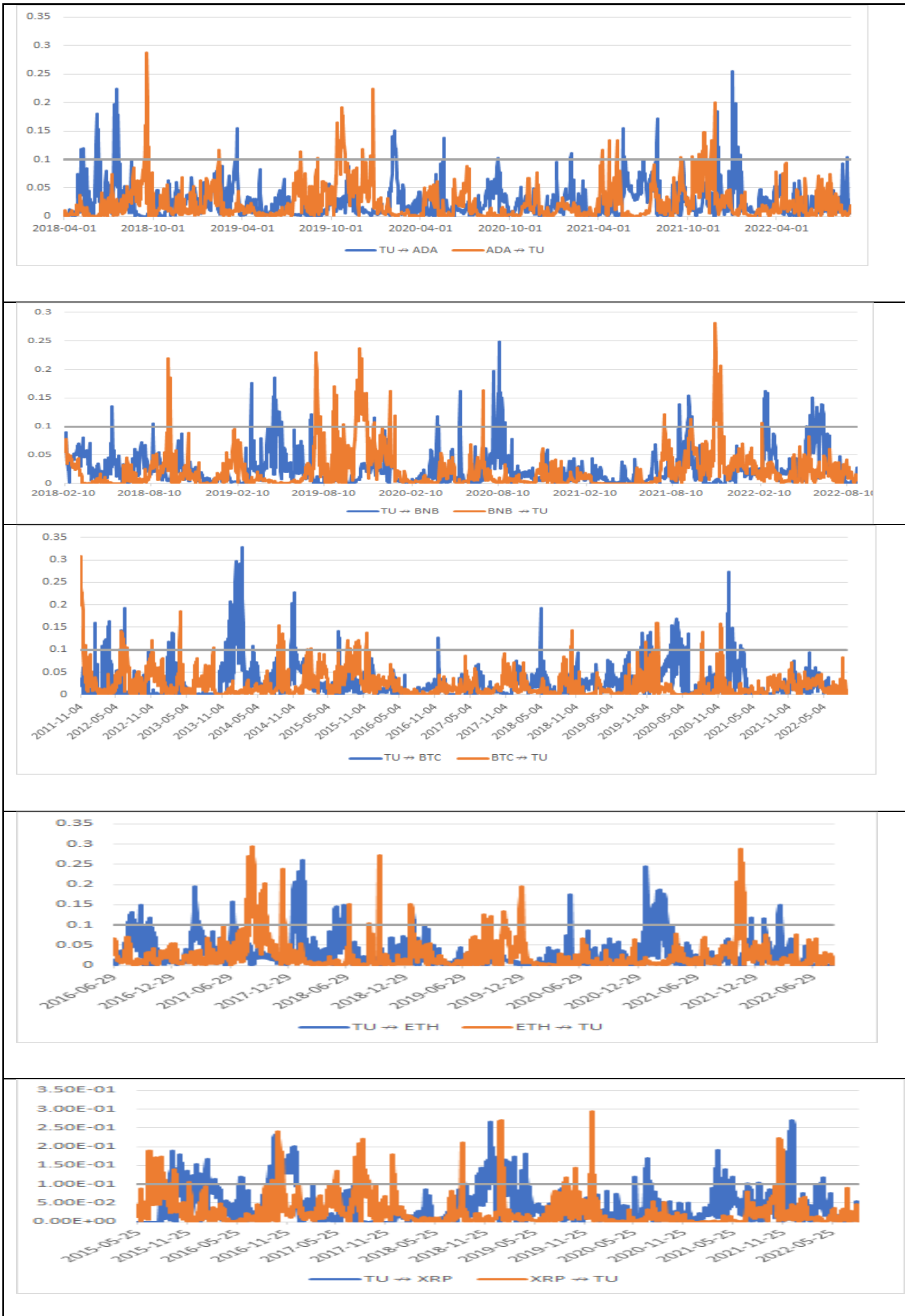

Figure 2 Dynamic FV Causality Test

Source: Authors' calculation