Do uncertainties and risks have an impact on cryptocurrency returns? Evidence from the symmetric and asymmetric fourier quantile causality test*

¿Las incertidumbres y los riesgos tienen impacto en los retornos de la criptomoneda? Evidencia de la prueba de causalidad cuántica simétrica y asimétrica de Fourier

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Abstract

This paper explores the impact of uncertainties and risks on the returns of cryptocurrencies by considering the two dimensions of uncertainty sourcing from economic policy uncertainty and geopolitical risk. Therefore, we analyze whether there is a causality from the global economic policy uncertainty (GEPU) and geopolitical risk (GPR) to the cryptocurrency returns in the period from 2015:01 through 2023:05. In our analysis, we use the GEPU and GPR indexes as independent variables and the historical values of Bitcoin, Ethereum, Litecoin, Ripple, Monero, and Dash as dependent variables. We employ the Fourier augmented causality test considering the original series, and also the positive and negative components of the series. Our findings reveal that the GPR has predictive power for all cryptocurrencies while GEPU has not predictive power for only Bitcoin. Furthermore, we find evidence of the causality nexus that runs from negative shocks of GEPU to the negative shocks of Litecoin and Ripple, and from the negative shocks of GPR to the negative shocks of Litecoin and Monero indicating when there are significant decreases at the GEPU, these values can be used to predict the decreases of Litecoin and Ripple. Similarly, we can also imply it for the causality relationship from GPR to Litecoin and Monero. When we consider there might be a causal relationship not only between shocks of the same type but also between different types of shocks we find that there is unidirectional causality from negative shocks of

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GEPU to the positive shocks of Dash, Ethereum, and Monero at the high return phase, and from positive shocks of GEPU to the negative shocks of Ethereum, and from positive shocks of GPR to the negative components of Bitcoin, Ethereum, and Ripple at the bearish market conditions.

Key words: *Uncertainty; cryptocurrencies; geopolitical risk.*

JEL Classification: *C22, G15, D81.*

Resumen

Este documento explora el impacto de las incertidumbres y los riesgos en los retornos de las criptomonedas, considerando las dos dimensiones de la incertidumbre que provienen de la inseguridad de la política económica y el riesgo geopolítico. Por lo tanto, analizamos si hay causalidad de la incertidumbre de la política económica global (GEPU) y el riesgo geopolítico (GPR) a los retornos de la criptomoneda en el período de 2015:01 a 2023:05. En nuestro análisis, utilizamos los índices GEPU y GPR como variables independientes y los valores históricos de Bitcoin, Ethereum, Litecoin, Ripple, Monero y Dash como variable dependiente. Empleamos la prueba de causalidad aumentada de Fourier considerando la serie original, así como los componentes positivos y negativos de la serie. Nuestros hallazgos revelan que el GPR tiene poder de predicción para todas las criptomonedas, mientras que GEPU no tiene poder predictivo sólo para BTC. Además, encontramos evidencia del nexo de causalidad que va desde los choques negativos de GEPU hasta los choques negativos de Litecoin y Ripple, y desde los choques negativos de GPR hasta los choques negativos de Litecoin y Monero que indican que cuando hay disminuciones significativas en el GEPU, estos valores se pueden utilizar para predecir las disminuciones de Litecoin y Ripple. Del mismo modo, también podemos insinuarlo para la relación de causalidad de GPR a Litecoin y Monero. Cuando consideramos que podría haber una relación causal no solo entre choques del mismo tipo, sino también entre diferentes tipos de choques, encontramos que hay una causalidad unidireccional desde los choques negativos de GEPU hasta los choques positivos de Dash, Ethereum y Monero en la fase de alto rendimiento, y desde los choques positivos de GEPU hasta los choques negativos de Ethereum, y desde los choques positivos de GPR hasta los componentes negativos de Bitcoin, Ethereum y Ripple en las condiciones bajistas del mercado.

Palabras clave: *Incertidumbre; criptomonedas; riesgo geopolítico.*

Clasificación JEL: *C22, G15, D81.*

1. Introduction

The interest in cryptocurrencies, and the blockchain technology that sustains them, has grown considerably since the establishment of the first Bitcoin market in July 2010. Bitcoin's resilience during the 2012-2013 Cypriot banking crisis leads to the increasing attraction of Bitcoin among investors and researchers (Luther and Salter, 2017). Because it is not subject to restrictions, regulations, or central authority implications, investments in Bitcoin have risen dramatically in recent years (Bouri et al., 2017, Hasan et al., 2022). The research on Bitcoin and other cryptocurrencies also has significantly grown to better understand the features of these currencies, particularly with its dramatic increases and falls in 2017. Although Bitcoin's market share has dropped from 90 percent in its early stages to roughly 40 percent recently, it remains the most well-known cryptocurrency, followed by Ethereum and Ripple (Aysan et al., 2019). This increase in interest has coincided with an increase in the number of new crypto-assets, as well as an increase in their market values. In parallel with the significant rise of this asset class, media coverage and online search activity have exploded, creating a sentiment-rich informational environment. Several cryptocurrencies and alt-coins have been generated since the creation of Bitcoin, which remains still the most popular cryptocurrency. In this framework, subclasses of crypto-assets have arisen, including crypto coins like Bitcoin, Ethereum, and Ripple, stablecoins like Tether and Maker Dao, and tokens that are cryptocurrencies backed by specific applications and initial coin offerings. This asset class' speculative and investment motivations have gained significance over the prospect of technological improvement in payments and transaction efficiency, particularly over the previous five years (Berentsen and Schär, 2018; Corbet and Gurdgiev, 2018; Gurdgiev and O'Loughlin, 2020). Because of the volatile nature of the Bitcoin market, researchers have recently begun searching for the factors leading to fluctuations in Bitcoin market values (Cheng and Yen, 2020). Some of these studies address the role of economic policy uncertainty (EPU) or geopolitical risk index (GPR) on the excessive returns of Bitcoin (Demir et al., 2018; Wu et al., 2019; Baur and Smales, 2020; Cheng and Yen, 2020, Cheng et al., 2020) with revealing mixed findings. For instance, Demir et al. (2018), and Fang et al. (2019) found that the EPU index of the U.S. has significant predictive power for Bitcoin price volatility. Dyhrberg (2016), Gozgor et al. (2019), Shaikh (2020), Bouri et al. (2020a), and Matkovskyy et al. (2020) also confirmed that Bitcoin might perform as a safe-haven financial asset against uncertainty. On the other hand, Cheng et al. (2020) indicated that the change in the geopolitical risk has no impact on the return and trading volume of cryptocurrencies like Ripple and Ethereum.

We have noticed sharp fluctuations in the cryptocurrency market in the 2020-2023 period covering the COVID-19 pandemic. The economic and financial crisis resulting from the COVID-19 pandemic has been identified by economist and financial analysts as being the most dangerous and destructive crisis in the last century in terms of its consequences since the economic policy and uncertainty and volatility is more perceptible than ever before in today's globally interconnected financial system. Haq et al. (2021) indicate that no other pandemic or high-uncertainty events such as the Spanish Flu, the 2008-09 global financial crisis, and the Euro-Area Debt Crisis has ever had such an impact on the stock market or EPU as COVID-19 has done. Investors' fear of investment loss is commonly referred to as "risk-aversion behavior" because of the associated economic uncertainty. Investors and investment managers are drawn to risk reduction alternatives during times of financial turbulence or heightened uncertainty, such as the COVID-19 pandemic. In times of more economic uncertainty, investors either limit their investments, wait for the current conditions to settle down, or look for suitable solutions to mitigate uncertainty worldwide. To the surprise of many, the cryptocurrency market has emerged as a risk management tool for stock and commodity market participants from around the world, particularly in times of increased uncertainty. Wu et al. (2021) also emphasize that uncertainty related to economic policy can have an impact on cryptocurrency markets as well as other financial markets. Uncertainty about central banks' monetary policy and government fiscal policies, particularly during the 2008-09 Global Financial Crisis, drastically damaged the safe-haven qualities of traditional assets, leading to the promotion of Bitcoin as an alternative payment and investment tool at the time.

In this paper, we analyze the role of uncertainty on the returns of cryptocurrencies by considering the GEPU and GPR indexes by employing the Fourier Quantile Causality test. In our analysis, we use the monthly data from 2015 through 2023, which covers the COVID-19 pandemic, U.S-China tensions, post-Brexit period, and Russian invasion of Ukraine. In these periods, the uncertainty has increased significantly, leading to severe fluctuations in the financial markets. Our paper contributes to the existing literature in several ways. Firstly, having noticed that previous work mainly focused on Bitcoin's safe-haven role against uncertainty, emphasizing that Bitcoin might serve as an excellent hedge against economic and geopolitical uncertainty. Given the fact that the great majority of cryptocurrency research has concentrated primarily on Bitcoin, neglecting the capabilities of the whole cryptocurrency system, we extend our study by focusing not only on Bitcoin but also on a set of cryptocurrencies, including Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Monero (XMR) and DASH. In addition, our study covers the periods in which financial stress increased dramatically result from the noteworthy events such as the pandemic, U.S-China conflict, post-Brexit period, and also Russia-Ukraine war which has been still continuing and have destructive effects. In our analysis, we employ the Fourier Quantile Causality (FQC) test, which is introduced by Cheng et al. (2021). So, further distinctive contribution of this paper is that we do not only focus on the causality relationship but also take into consideration cumulative positive and negative shocks by using this recent econometric approach. This suggested test has several attractive properties; i) There is no need to compute the difference of the data in the case of integrated variables ii) By incorporating a Fourier function, multiple smooth breaks in the causality relationship are considered iii) The test allows to test the causality in quantiles. Therefore, the test provides us with more meaningful results iv) The test allows an asymmetric structure in causality relationship.

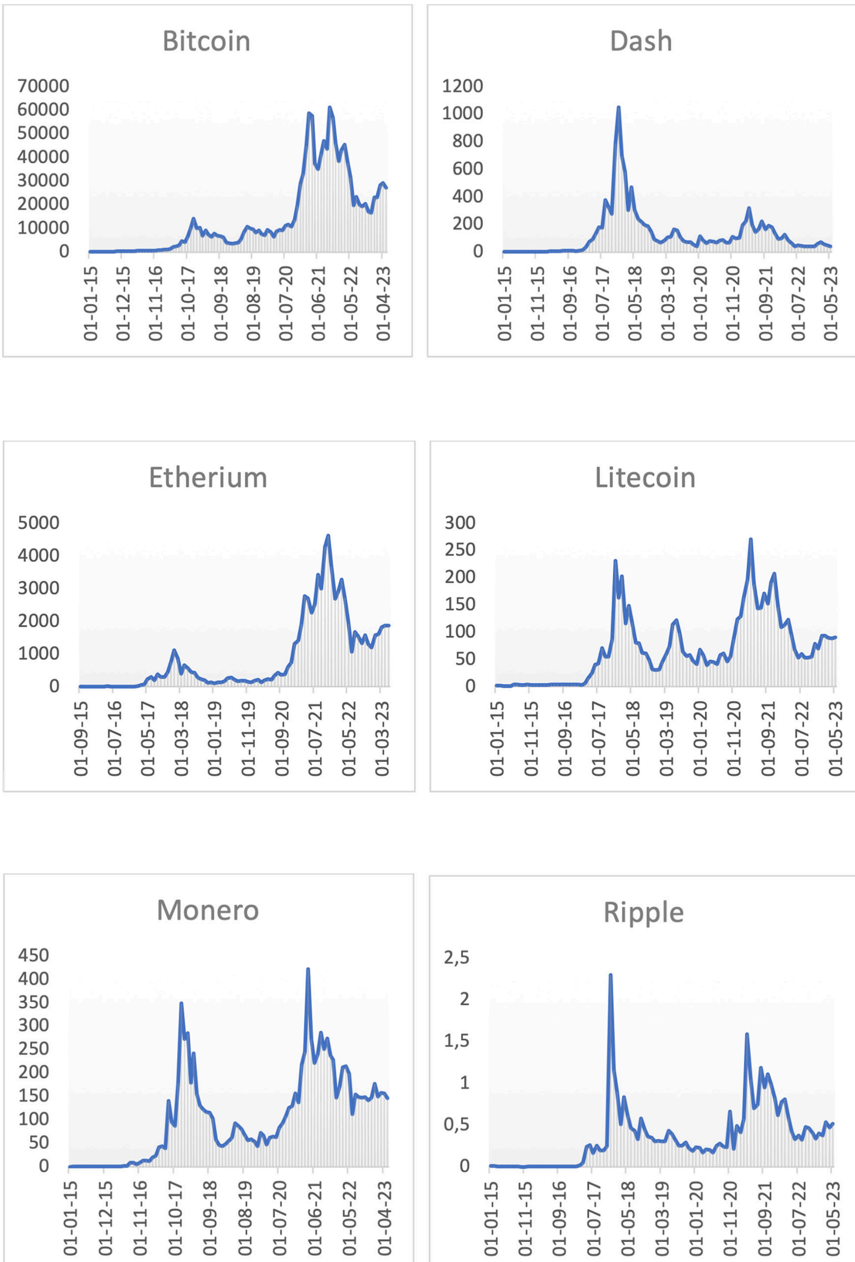
The remainder of this research is structured as follows. Section 2 discusses the research on the impact of economic policy uncertainty and geopolitical risk on the cryptocurrency markets. Section 3 introduces the econometric methodology employed in the study. Section 4 presents data and discusses the empirical findings. Finally, Section 5 concludes by giving some policy implications.

2. Theoretical Background

Tremendous focus and attention have been paid to the cryptocurrency markets in the last five years. As a result, sharp increases were experienced with the increasing demand. For instance, the first cryptocurrency, Bitcoin, was only 0.40 USD in 2010. In 2017, it exceeded 20.000 USD, and in 2021 it recorded 80.000 USD. Similarly, Ethereum, which was launched in 2015 and had a great market capitalization, was valued at 0.311 USD. It closed in the year 2017 at around 772 USD, and it recorded 4.800 USD in 2021 (CoinMarketCap, 2022). The largest cryptocurrency in the world, Bitcoin, fell below 20.000 USD in the beginning of 2023. However, the U.S. banking crisis becoming worse, the dollar index falling, and inflation slowing down has allowed Bitcoin and other digital currencies to rebound and take the lead in the path of resistance (Forbes, 2023). Figure 1 shows the market values of some cryptocurrencies in the period of 2015-2023, which is our analysis period.

FIGURE 1

HISTORICAL MARKET VALUES OF SOME CRYPTOCURRENCIES



Source: Yahoo Finance (Access date: 01.05.2023)

As seen from Figure 1, the market values of cryptocurrencies increased significantly after 2017 and experienced sharp fluctuations between 2017-2023. Here, it is of critical importance to understand which factors determine the value of a cryptocurrency. Levy (2022) indicates that cryptocurrencies' value is derived from various factors like supply and demand, production cost, exchange availability, competition, governance, and regulations considering cryptocurrencies are often decentralized. A cryptocurrency's supply mechanism is often clear; each cryptocurrency discloses its token minting and burning plans. Some, like Bitcoin, have a set maximum supply, and analysts predict that there will never be more than 21 million Bitcoins. Others, just like Ethereum, have no production limit. Increased acceptance of cryptocurrencies as investments raises demand while effectively restricting circulation supply. For instance, when institutional investors began purchasing and holding Bitcoin in early 2021, the price of Bitcoin skyrocketed as demand outpaced the rate at which new coins were generated, thereby lowering the total accessible supply of Bitcoin. As mining expenses rise, the value of the cryptocurrency increases as well. Miners do not mind if the value of the money they are mining is insufficient to cover their costs. And, because miners are required to make the blockchain operate, the price will have to rise as long as there is demand for utilizing the blockchain. Regulations might also have a detrimental influence on Bitcoin demand. If a regulatory body modifies the regulations to discourage cryptocurrency investment or use, the price of cryptocurrencies might fall. For example, in late 2021, the FED announced that it would regulate the cryptocurrency market, leading to fluctuations in the prices of cryptocurrencies (Levy, 2022).

The risk perception and trading behavior of investors, regardless of the underlying economic reasons, are expected to be effective in bubble-liked price increases experienced in cryptocurrency markets. From this perspective, speculative buying and selling of investors are seen to be effective in the sharp price increases experienced in the period 2017-2018. Furthermore, news such as companies issuing their cryptocurrencies and the cryptocurrency trading policy change in China are thought to result in increasing prices. Another factor that makes cryptocurrencies attractive and thus brings an upward trend in market values is their use in illicit financing. The absence of tax cuts is another important factor in increasing the demand and prices of cryptocurrencies. Many analysts emphasize that 2020, the COVID-19 pandemic-hit year, would be responsible for the digital currency's resurgence and rapid increase; most investors consider that the pandemic-stricken year provided an ideal atmosphere for the cryptocurrency. Digital currencies have gained momentum in 2020 since traditional currencies and assets have suffered due to the global economic crisis. The value of cryptocurrencies, notably Bitcoin, has risen as a result of large-scale stockpiling by major investors and corporations (Delhi, 2020). Urquart (2021) notes that one explanation for the significant price increase is a significant surge of investors from large-scale organizations such as pension schemes, university endowment funds, and investment trusts. It was different in 2017, the previous bull market when the price of Bitcoin recorded nearly 20.000 USD before falling down to the low of 3.000 USD a year later. Individual retail investors heavily influenced the cryptocurrency ecosystem in 2017, drawn by Bitcoin's unavailability and being remained outside the global financial system. With investors buying out of "fear of losing out", the 2017 bull market had all the characteristics of a traditional financial bubble. Recently, we see that some prominent consumer-facing payment brands have also supported Bitcoin. For instance, PayPal now enables consumers to purchase, hold, and trade Bitcoin straight from their PayPal accounts. Square, a competing digital payment startup, announced that more of its Cash App customers are purchasing digital currency in an increasing trend. The amount of companies accepting Bitcoin as payment is steadily increasing. Aside from all of this public interest, the COVID-19 pandemic's catastrophe has resulted in massive stimulus packages from governments all around the world, as well as numerous central banks providing financial support. This might cause inflation, reducing people's purchasing power. Faced with this threat, assets such as Bitcoin are being regarded as a store of value (Urquart, 2021).

Cryptocurrencies act as a hedging mechanism during periods of increasing uncertainty in financial markets. Recently, we witnessed that uncertainty in the financial markets rose the most, particularly in the COVID-19 pandemic. In that period, the original epicenter of the shock was the Chinese financial markets, and international contagion effects rapidly expanded. Traditional flight-to-safety channels within energy markets have dissolved in the face of this turmoil, with the increase of geopolitical tensions mostly initiated by the U.S., Russia, and Saudi Arabia, leaving investors trying to locate reliable safe havens (Corbet et al., 2020). Evidently, given their relatively short history, the frequency of significant black-swan events, and the ever-increasing probability of economic divergence as a result of irregular lock-downs to mitigate ongoing pandemics, the fact that cryptocurrencies could potentially act as a financial safe-haven is quite an incredible development (Corbet et al. 2022).

Previous studies have mainly analyzed Bitcoin's hedging capacity in times of uncertainty. In this context, to the best of our knowledge, Dyhrberg (2016) investigated whether Bitcoin can be used as a hedge against stocks in the Financial Times Stock Exchange Index and the American dollar by employing the asymmetric GARCH methodology. According to their findings, Bitcoin offers strong hedging potential against the FTSE Index, and it can be used in conjunction with gold to eliminate or mitigate specific market risks, although

Bitcoin demonstrates short-term hedging potential against the American dollar. Bouri et al. (2017) also examined the role of uncertainty on the Bitcoin market by utilizing a common component, which is the first primary component of the VIXs of 14 developed and developing stock markets, as a global indicator of market uncertainty. Their findings show that short-term Bitcoin investment can help investors hedge global equity market uncertainty, particularly when the market is in a bear or bull market and when uncertainty is low or high.

From a similar perspective, Demir et al. (2018) investigated the EPU's ability to forecast daily Bitcoin returns in the period from July 18, 2010, through November 15, 2017, with the use of the Bayesian Graphical Structural Vector Autoregressive model. They discovered that the EPU could successfully anticipate Bitcoin returns. Although the changes in the EPU have a negative impact on Bitcoin returns, Bitcoin can be utilized as a hedging strategy in times of great uncertainty since they observe that the effect is positive and substantial at the higher quantiles of uncertainty. In another study, Fang et al. (2019) examined whether global EPU affects the long-term volatility of Bitcoin, global equities, commodities, and bonds. Their findings supported this idea except for bonds and suggest that Bitcoin investors can utilize information on the status of global economic uncertainty to improve their predictions of Bitcoin volatility. Emphasizing that there is no paper that investigates the impact of EPU on the interdependence of both traditional financial markets and Bitcoin markets, Matkovskyy et al. (2020) attempted to fill in this gap by looking into how EPU affects the interaction between cryptocurrencies and traditional financial markets in the period from April 27, 2015, through October 25, 2018. Selecting five stock market indices, including Euronext100, FTSE100, NASDAQ100, S&P500, and NIKKEI225, which symbolizes major traditional stock market and measuring EPU in terms of economic policy, monetary policy, taxation policy, financial regulation, and the news-based policy uncertainty index, they employ several statistical methods including multivariate EWMA models and BVAR models. The volatility correlation is also not consistent over time and eventually increases with the introduction of Bitcoin futures in December 2017.

Using the EPU index in the U.S, the U.K, Japan, China, and Hong Kong as well as monetary policy uncertainty (MPU), Shaikh (2020) tried to show how policy uncertainty affects the price of Bitcoin and the profits it generates by employing quantile regression and Markov regime-shifting models. According to the key findings is that in the U.S, China, and Japan, Bitcoin returns are more susceptible to EPU, and uncertainty has a detrimental impact on the Bitcoin market in the United States and Japan, whereas it has a favorable impact in China. The level of global MPU uncertainty is also an important factor in explaining Bitcoin exchange rates. Research on the cryptocurrency market frequently suggests that it could function as a hedge or safe-haven in times of uncertainty, yet, Colon et al. (2021) also revealed that the market reacts differently to different types of uncertainty. During such a bull market, the Bitcoin market might act as a weak hedge and safe-haven against GEPU, but it can't function as an effective safe-haven against GPR in most circumstances while it could be regarded as a strong hedge.

The analysis of the implications of the GPR index on financial markets and macroeconomic factors has sparked increased attention in the literature. In this context, Balcilar et al. (2018a), Bouri et al. (2018), Cheng and Chiu (2018), Gkillas et al. (2018), and Caldara and Iacoviello (2022) examined the impact of GPR on macroeconomic and financial indicators such as stock market returns, business cycle fluctuations, and oil prices. GPR is seen as a major determinant of investment choices and stock market dynamics by central bank officials, entrepreneurs, and market players (Caldara and Iacoviello, 2018), so Bitcoin prices are also expected to be affected by the GPR. Parallel to this view, Aysan et al. (2019) examined the predictive ability of the GPR on the daily return and price volatility of Bitcoin from 2010:07 to 2018:05. They discovered that changes in the global GPR index have predictive power on both Bitcoin returns and volatility using the Bayesian Graphical Structural Vector Autoregressive (BSGVAR) approach. Their findings reveal that the change in the GPR index has a considerable negative and positive impact on Bitcoin returns and price volatility. Furthermore, they demonstrated that changes in the global GPR index have a positive and statistically significant impact on Bitcoin price volatility and returns at the higher quantiles. Hence, they suggested that Bitcoin could be viewed as a hedging strategy against global geopolitical risks, specifically during extreme moments of global geopolitical risk. Similarly, Bouri et al. (2020b) tried to answer the question of whether cryptocurrency price fluctuations are linked to big changes in geopolitical risk. They employed logistic regressions to investigate the co-jumps between cryptocurrencies and the geopolitical risk index in order to address this issue. Using the dataset, which covers the period from April 2013 to October 2019, they find that the price behavior of all cryptocurrencies under consideration is jumpy, but only Bitcoin jumps are reliant on surges in the geopolitical risk index. This reported evidence of huge co-jumps for Bitcoin merely adds to earlier studies indicating that Bitcoin is a hedge against geopolitical risk.

Cryptocurrencies create large amounts of data that reflect investors' actual preferences from a behavioral standpoint, as stated by Gurdgiev and O'Loughlin (2020). The dynamic properties of cryptocurrencies, especially the links between investor sentiment, investor behavior, and crypto-asset values, are a major issue that impairs this new asset's market pricing in the markets. The dynamic properties of cryptocurrencies, especially the links between investor emotion, investor behavior, and crypto-asset values, are a major issue that impedes this new asset's price discovery in the markets. In this sense, Gurdgiev and O'Loughlin (2020) attempted to figure out how investor sentiment, investors' general views of financial and crypto-asset markets uncertainty, and the cryptocurrency market value are linked. They concluded that there is a strong connection between investor sentiment and the price of cryptocurrencies, suggesting that using cryptocurrencies as a stock market hedge in the presence of uncertainty is possible. Cryptocurrencies, on the other hand, don't provide a safe-haven in times of fear. There is a tendency for cryptocurrency values to rise when there is a general sense of optimism among investors, showing that there are herding biases among crypto-assets investors.

Based on investment behavior, Yen and Cheng (2021) proposed two assumptions as follows. Their first assumption implies that investors in the crypto-market might have a fear of losing their money, and investors' perception of deteriorating Bitcoin market circumstances would be exacerbated if the EPU rises. As a result, if they believe that cryptocurrency returns are negatively correlated with the EPU, they might decide to move their money out of the cryptocurrency market and into other financial markets. The cryptocurrency market becomes less liquid as a result of this capital outflow, which might increase cryptocurrency volatility in the future. Their second assumption claims that how hedging could make the price of a cryptocurrency less volatile. Investors might invest their money in a cryptocurrency if they think the cryptocurrency is a safe-haven asset when the economy is uncertain. So, the cash coming into the cryptocurrency market makes the market more liquid and makes the cryptocurrency less volatile in the future. Following investigating the role of EPU on cryptocurrency volatility and testing the assumptions above, they explore a negative correlation between EPU and Bitcoin's future volatility, which suggests that a rise in the EPU is associated with a decrease in Bitcoin volatility in the future.

Cheng et al. (2020) investigated if the return and volume of cryptocurrencies are impacted by the geopolitical risk of several economies, such as Venezuela, China, and Russia. They discover that the geopolitical risk of Venezuela, rather than China or Russia, is adversely correlated with both the return on Bitcoin and the volume of Bitcoin trades, using the monthly data of three cryptocurrencies -Bitcoin, Ripple, and Ethereum- over the period of 2014:02–2019:08. Additionally, they discover that the return and trading volume of Ethereum and Ripple are unaffected by changes in the geopolitical risk. Focusing on cryptocurrencies as well as gold, oil, and stock markets, Kyriazis (2021) showed the GPR index has an adverse impact on oil price returns and volatility while increasing volatility in stock markets mostly at lower quantiles and weakening the connection between oil and stock markets. Furthermore, this index is a strong predictor of Bitcoin returns and volatility, and it is critical for identifying the diversification or hedging nature of Bitcoin and other major cryptocurrencies in portfolios. Considering two components of uncertainty, economic policy uncertainty, and geopolitical uncertainty, Colon et al. (2021) selected the top 25 cryptocurrencies which account for 94.63 percent of the total market capitalization for their analysis covering the period 2013:04-2019:08. They indicate that economic policy uncertainty (GEPU) and geopolitical risks (GPR) have an impact on the cryptocurrency market, but these effects vary depending on the kind of uncertainty. In particular, they discovered that during a bull market, the cryptocurrency market may act as a poor hedge and a safe-haven against GEPU; in most situations, however, it could not act as a safe-haven against GPR.

There are also several studies focusing on between risk and cryptocurrencies. For instance, using daily data covering the period from May 2020 to December 2022, Bouri et al. (2023) investigate the dynamic lower tail dependence and downside risk spillover between the FTX Token (FTT) and seven significant cryptocurrencies, including Bitcoin, Ethereum, Binance Coin, Tether, Ripple, Cardano, and Solana. Their research presents a thorough investigation of the tail risk and spillover effects of the FTX stress event. In another study, Delfabbro et al. (2021) evaluate the distinct psychological mechanisms that they suggest are special risk factors for excessive cryptocurrency trading, including: overestimations of the importance of knowledge or expertise, the fear of missing out, obsession, and expected regret. They additionally investigate at possible preventative and instructional measures that might be taken to safeguard novice investors in the event that this new activity grows to draw a larger proportion of retail or community investors. Focusing on co-jumps amongst cryptocurrencies, Zhang et al. (2023) study the portfolio implications of the jump transfer mechanism for a large group of cryptocurrencies. Their research demonstrates that, although Bitcoin has the most impact, co-jump heterogeneity occurs across combinations of cryptocurrencies with various market capitalizations. Finally, with the use of extreme dependence and temporal dynamic risk spillover analysis, Abid et al. (2023) compare Bitcoin to fiat currencies like EUR, GBP, and JPY utilizing different financial markets that span fixed-income, stock, and commodities indices. Their results demonstrate bearish market similarities between Bitcoin and fiat currencies, as well as their relationships with fixed-income and gold markets, using daily data from October 2010 to December 2022, which covers a number of stressful periods, which involves the COVID-19 outbreak and the war in Ukraine. On the other hand, the way that Bitcoin and fiat currencies interact with the stock and crude oil markets seems different.

3. METHODOLOGY

If we can forecast Y better by employing past values of X and Y, then just using past values Y, we conclude that X Granger-Cause Y. Over the last two decades, there have been several tests introduced to the test to examine the existence of Granger causality. While some of these tests allow examining the causality using integrated series (see Toda and Yamamoto, 1995 and Dolado and Lutkepohl, 1996), some consider structural changes in the causality relationship (Enders and Jones, 2016; Nazlioglu et al., 2016). Recently, to consider asymmetric adjustments and also non-normal distributions, quantile causality tests have been developed that are also robust to outliers in the data (see Jeong et al. (2012), Troster (2018) and Song and Taamouti (2020).

In this study, we employ the FQC test introduced by Cheng et al. (2021). This test has several attractive properties; i) There is no need to compute the difference of the data in the case of integrated variables, so there is no long-run information loss ii) The test incorporates a Fourier function which enables us to consider unknown number and form of multiple smooth breaks in the causality relationship, as Gregory and Hansen (1996) suggest neglecting breaks in the long-run relationship lead to nonrejection of the null, the same applies when the structural changes in the causality relationship ignored, so using a Fourier function we consider the structural changes and remedy the nonrejection of the null, iii) The test is sufficiently flexible to examine Granger causality in specific regions of the distribution, including the median or the tails of the distribution (either left or right). As such, we can ascertain whether extremely low or high fluctuations are significant to the causality relationship. Since the FQC test assumes that the impact of the positive and negative shocks is the same. However, especially in the financial markets, people tend to behave differently in the case of different kinds of shocks; generally, negative news tends to elicit a stronger reaction from investors than positive news (see Hong et al., 2007; Goudarzi and Ramanarayanan, 2011; Hatemi-J, 2012). To consider this asymmetric structure in the causality testing, we propose to employ the FQX causality test by considering the positive and negative shocks.

The FQC test is based on the following model:

$$(1)\quad Y_t = \beta_0 + \beta_1 \sin\left(\frac{2\pi kt}{T}\right) + \beta_2 \cos\left(\frac{2\pi kt}{T}\right) + \sum_{i=1}^{p+d\max} \alpha_{1i} Y_{t-i} + \sum_{i=1}^{p+d\max} \alpha_{2i} X_{t-i} + e_t$$

Where t, T, k, p, and $d\max$ show a trend term, number of observations, the optimal frequency of the Fourier function, and maximum integration level of the considered variables, respectively. We determine the values of k and p endogenously. To find the optimal value of k we estimate Eq. 1 for each value of $k \in \{1,2,...,5\}$ and select the k that minimizes the sum of squared residuals. After determining the k, we choose the p using Akaike information criteria. Nazlioglu et al. (2016) suggest augmenting the model with extra lags $d\max$ by following the suggestion of Toda and Yamamoto (1995) to use integrated data without differencing.

After determining the optimal values of k^*, p^* and $d\max^*$, we estimate Eq.1 by using the quantile regression approach as suggested by following Cheng et al. (2021):

(2) $$Q_{Y_t}(\tau|Z) = \beta_0(\tau) + \beta_1(\tau)\sin\left(\frac{2\pi k^* t}{T}\right) + \beta_2(\tau)\cos\left(\frac{2\pi k^* t}{T}\right) + \sum_{i=1}^{p^*+d\max^*} \alpha_{1i}(\tau) Y_{t-i} + \sum_{i=1}^{p^*+d\max^*} \alpha_{2i}(\tau) X_{t-i} + e_t$$

Where τ shows a specific quantile and Z is the covariates matrix. We use the modified Barrodale and Roberts (1973) simplex algorithm to estimate the coefficients. We can test the null of X_t does not cause Y_t in the τ th quantile ($H_0 : \alpha_{2,1}(\tau) = \alpha_{2,2}(\tau) = ... = \alpha_{2,p^*}(\tau) = 0, \ \ \forall \tau \in (0,1)$), by employing the following test statistic:

(3) $$W = \frac{\left[T\left(\hat{\alpha}_2(\tau)' \left(\hat{\Omega}(\tau) \right)^{-1} \hat{\alpha}_2(\tau) \right) \right]}{\tau(1-\tau)}$$

Where $\hat{\Omega}(\tau)$ indicates the $\hat{\alpha}_2(\tau)$'s consistent variance-covariance estimator matrix. Before applying the FQC causality test, we test the significance of the trigonometric terms ($H_0 : \beta_1 = \beta_2 = 0$) using the F test statistic, in the case of rejection the null, we apply the FQC test, else we apply bootstrap quantile causality test without a Fourier function. Cheng et al. (2021) suggest obtaining the critical values through bootstrap simulations. We employ the leveraged bootstrap technique as suggested by Hacker and Hatemi (2006).

To consider asymmetric components, we follow the suggestions of Granger and Yoon (2002) and Hatemi-j (2012) and compute the cumulative sums of positive and negative shocks as:

(4) $$Y_t^+ = \sum_{i=1}^{T} e_1^t,\ Y_t^- = \sum_{i=1}^{T} e_1^-,\ X_t^+ = \sum_{i=1}^{T} \varepsilon_1^+,\ X_t^- = \sum_{i=1}^{T} \varepsilon_1^-$$

Where,

(5) $$Y_t = Y_{t-1} + e_t = Y_0 + \sum_{i=1}^{T} e_i^+ + \sum_{i=1}^{T} e_i^- \text{ and } X_t = X_{t-1} + \varepsilon_t = X_0 + \sum_{i=1}^{T} \varepsilon_i^+ + \sum_{i=1}^{T} \varepsilon_i^-$$

Where Y_0 and X_0> show the initial values. We can apply the asymmetric FQC test by using these positive and negative shocks (Y_t^+, Y_t^-, X_t^+, and X_t^-) instead of the original series (Y_t and X_t). The critical values are obtained through bootstrap simulations.

4. Data And Findings

We test the existence of causality from the EPU and the GPR to the BTC, DASH, ETH, LTC, XMR, and XRP. We chose these cryptocurrencies because they are among the oldest and most popular cryptocurrencies. We retrieved the data of cryptocurrencies from the finance service of Yahoo[1], and the data of EPU and GPR from the website of policy uncertainty[2]. Our analysis covers the period of January 2015 to May 2023 except for ETH, which starts from September 2015. We use all variables in the logarithmic return form.

First, we present the descriptive statistics of the series in Table 1:

TABLE 1
SUMMARY STATISTICS OF THE DATA

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
GEPU	0.005	-0.013	0.625	-0.494	0.191	0.657	4.383	15.173*	0.001
GPR	0.001	-0.006	0.622	-0.600	0.209	0.253	3.885	4.334	0.114
BTC	0.048	0.042	0.528	-0.474	0.209	-0.076	2.907	0.132	0.936
DASH	0.033	-0.023	1.039	-0.648	0.330	0.788	3.667	12.189	0.002
ETH	0.085	0.054	1.152	-0.769	0.354	0.575	3.740	7.160**	0.028
LTC	0.039	0.008	0.966	-0.554	0.288	0.729	4.033	13.298	0.001
XMR	0.062	0.012	1.549	-0.593	0.347	1.199	6.362	71.028	0.000
XRP	0.036	-0.058	2.216	-1.106	0.444	1.924	9.579	242.043	0.000

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

ETH has the highest mean return (0.085), followed by XMR (0.062), BTC (0.048), and DASH (0.033) which indicates that, on average, ETH has the highest return among the assets. BTC has the highest median return (0.042), followed by ETH (0.054). XRP has the lowest median return (-0.058), indicating that it has more negative return days than the other cryptocurrencies. XRP has the highest standard deviation (0.444), followed by ETH (0.354) and XMR (0.347), indicating that these assets have the highest volatility or risk. XRP has

[1] https://finance.yahoo.com/
[2] https://www.policyuncertainty.com/

the highest skewness (1.924), followed by XMR (1.199), indicating that their return distributions are highly positively skewed. BTC has a negative skewness (-0.076), meaning that its return distribution is slightly negatively skewed, with more frequent negative returns. XRP has the highest kurtosis (9.579), followed by XMR (6.362), indicating that these cryptos have more extreme returns (fat tails) in their return distributions than the other assets. BTC has the lowest kurtosis (2.907), suggesting that its return distribution is less prone to extreme returns. XRP has the highest Jarque-Bera statistic (242.043), indicating that its return distribution is significantly different from a normal distribution. GEPU, DASH, ETH, LTC, and XMR also have significant Jarque-Bera statistics, suggesting that their return distributions are not normal either. GPR and BTC have non-significant Jarque-Bera statistics, indicating that their return distributions are more similar to a normal distribution. In summary, ETH, XMR, and XRP appear to be the most volatile and risky assets, with the highest returns and extreme values. The return distributions of most assets are not normal, with XRP and XMR having the most extreme deviations from normality.

Next, we determined the integration levels of the variables using traditional unit root tests such as Augmented Dickey-Fuller (ADF), Phillips-Perron, and advanced unit root tests such as Zivot-Andrews and Fourier ADF unit root tests[3]. Although results are mixed, we reveal that the maximal integration of variables is one, so we add an extra lag to the vector autoregressive model to test the causality relationships.

In the first step, we test the statistical significance of Fourier terms, if the Fourier function is significant, we will test the causality relationship using the FQC test else we will use bootstrap quantile causality test. The results of significance test are presented in Table 2.

[3] To conserve space, we do not present the results, which are available from the authors upon request.

TABLE 2
THE RESULTS OF THE SIGNIFICANCE OF THE FOURIER FUNCTIONS

The null hypothesis	Optimal Frequency	Optimal Lags	F Test Statistic	%10 CV	%5 CV	%1 CV
Original Series						
GEPU ↛ BTC	2.4	1	4.556	10.906	12.722	16.677
GEPU-↛ DASH	2.3	1	4.934	10.916	12.857	17.424
GEPU-↛ ETH	2.2	1	4.206	12.173	14.235	18.205
GEPU-↛ LTC	4.6	1	4.435	11.530	13.375	17.354
GEPU-↛ XMR	2.3	2	10.527***	10.475	12.287	15.455
GEPU -↛ XRP	2.5	1	3.787	8.661	10.491	14.134
GPR ↛ BTC	2.4	1	4.586	10.949	12.790	16.797
GPR-↛ DASH	2.3	1	5.088	10.926	12.840	17.198
GPR-↛ ETH	2.2	1	4.316	12.192	14.207	18.088
GPR-↛ LTC	4.3	1	3.587	10.355	12.100	16.096
GPR-↛ XMR	2.3	2	10.294***	10.190	11.786	15.155
GPR -↛ XRP	2.5	z1	4.347	8.737	10.712	14.184
The Causality Relationship for Positive Shocks						
$GEPU^{+}$ ↛ BTC^{+}	2.5	1	5.793***	5.471	5.801	6.518
$GEPU^{+}$ ↛ $DASH^{+}$	2.3	1	6.634*	5.226	5.447	6.009
$GEPU^{+}$ ↛ ETH^{+}	2.5	2	8.316	9.045	9.596	10.639
$GEPU^{+}$ ↛ LTC^{+}	2.6	2	5.378***	5.274	5.548	6.057
$GEPU^{+}$ ↛ XMR^{+}	2.2	1	5.593*	4.459	4.623	4.998
$GEPU^{+}$ ↛ XRP^{+}	2.4	1	9.167***	9.019	9.615	10.956
GPR^{+} ↛ BTC^{+}	2.5	1	6.684*	5.617	5.844	6.264
GPR^{+} ↛ $DASH^{+}$	2.4	1	6.460*	5.685	5.894	6.273
GPR^{+} ↛ ETH^{+}	2.6	2	6.622	9.213	9.676	10.641
GPR^{+} ↛ LTC^{+}	2.6	2	4.370	5.453	5.766	6.313
GPR^{+} ↛ XMR^{+}	2.2	2	7.630**	6.911	7.399	8.381
GPR^{+} ↛ XRP^{+}	2.5	1	8.992*	6.859	7.097	7.644
The Causality Relationship for Negative Shocks						
$GEPU^{-}$ ↛ BTC^{-}	2.4	1	7.184*	5.918	6.204	6.754
$GEPU^{-}$ ↛ $DASH^{-}$	2.5	1	5.204*	3.249	3.397	3.661
$GEPU^{-}$ ↛ ETH^{-}	4.3	1	5.881*	2.876	3.130	3.621
$GEPU^{-}$ ↛ LTC^{-}	0.3	1	5.444	17.307	18.559	21.621
$GEPU^{-}$ ↛ XMR^{-}	2.6	3	3.970***	3.662	3.892	4.472

$GEPU^- \nrightarrow XRP^-$	2.8	3	3.763	6.277	6.812	7.965
$GPR^- \nrightarrow BTC^-$	2.4	1	10.387	10.546	11.086	12.083
$GPR^- \nrightarrow DASH^-$	2.5	1	5.780**	5.233	5.510	5.935
$GPR^- \nrightarrow ETH^-$	0.1	2	1.814	2.898	3.179	3.718
$GPR^- \nrightarrow LTC^-$	0.4	1	2.383	5.558	6.014	6.995
$GPR^- \nrightarrow XMR^-$	2.6	3	3.687	5.289	5.604	6.406
$GPR^- \nrightarrow XRP^-$	2.6	2	7.677	10.027	10.655	11.854
The Causality Relationship from Positive Shocks to Negative Shocks						
$GEPU^+ \nrightarrow BTC^-$	2.4	1	8.125*	6.851	7.118	7.689
$GEPU^+ \nrightarrow DASH^-$	2.5	1	6.018*	4.476	4.683	5.038
$GEPU^+ \nrightarrow ETH^-$	2.3	1	7.117	7.133	7.442	8.020
$GEPU^+ \nrightarrow LTC^-$	2.5	1	6.100*	4.890	5.090	5.516
$GEPU^+ \nrightarrow XMR^-$	2.5	3	6.687	7.571	7.965	8.692
$GEPU^+ \nrightarrow XRP^-$	0.2	2	8.400	9.846	10.623	12.119
$GPR^+ \nrightarrow BTC^-$	2.4	1	5.881*	4.114	4.345	4.782
$GPR^+ \nrightarrow DASH^-$	2.6	1	4.136*	2.249	2.386	2.661
$GPR^+ \nrightarrow ETH^-$	1.5	1	8.711	9.921	10.607	11.860
$GPR^+ \nrightarrow LTC^-$	1.2	1	7.522	9.317	9.940	11.106
$GPR^+ \nrightarrow XMR^-$	1.3	3	6.037	8.538	9.165	10.432
$GPR^+ \nrightarrow XRP^-$	2.8	2	8.879**	7.997	8.482	9.417
The Causality Relationship from Negative Shocks to Positive Shocks						
$GEPU^- \nrightarrow BTC^+$	2.5	1	5.152**	4.458	4.756	5.257
$GEPU^- \nrightarrow DASH^+$	0.1	1	8.278**	7.698	8.102	8.826
$GEPU^- \nrightarrow ETH^+$	2.6	3	10.249*	8.044	8.450	9.472
$GEPU^- \nrightarrow LTC^+$	2.7	1	5.242*	3.918	4.110	4.549
$GEPU^- \nrightarrow XMR^+$	0.4	2	8.821	11.468	12.195	13.517
$GEPU^- \nrightarrow XRP^+$	2.5	1	9.032*	7.199	7.637	8.608
$GPR^- \nrightarrow BTC^+$	2.4	1	8.103*	5.875	6.145	6.664
$GPR^- \nrightarrow DASH^+$	2.4	1	6.078*	4.100	4.250	4.563
$GPR^- \nrightarrow ETH^+$	2.5	2	5.906	7.810	8.277	9.094
$GPR^- \nrightarrow LTC^+$	2.5	1	5.885*	4.459	4.648	5.069
$GPR^- \nrightarrow XMR^+$	2.2	2	7.328**	6.322	6.793	7.774
$GPR^- \nrightarrow XRP^+$	2.4	1	8.431**	7.489	7.878	8.679

Note: *, **, and *** show the significance at the 1%, 5%, and 10% levels, respectively. + and – denote the positive and negative shocks, respectively. The critical values are obtained using 5000 simulations.

According to the findings in Table 2, the Fourier function is significant for only two relationships when analyzing the original series. However, when considering the positive and negative components, we found more significant Fourier functions in the causality relationships. Besides the optimal frequency is found as fractional which indicates that the structural changes that influence the causality relationship is not temporary. So, we employ FQTY test for the causality relationship for which we find the Fourier function as significant and use bootstrap quantile causality test for the remaining relationships. Test results of the symmetric and asymmetric causality tests test, in which the null hypothesis is rejected, are presented in Table 3[4].

TABLE 3
RESULTS OF THE CAUSALITY TESTS

The Causality Relationship for Original Series					
H_0	**Quantile**	**Test Statistic**	**10% CV**	**5% CV**	**1% CV**
GEPU $\nrightarrow$ ETH	0.7	3.399***	2.982	4.383	8.536
GEPU $\nrightarrow$ XRP	0.4	3.128**	1.723	2.405	4.556
GEPU $\nrightarrow$ XRP	0.5	4.498**	1.734	2.569	4.598
GEPU $\nrightarrow$ XRP	0.6	5.890**	2.370	3.504	5.897
GEPU $\nrightarrow$ XRP	0.7	10.763*	3.537	4.963	8.281
GEPU $\nrightarrow$ XRP	0.8	9.407**	4.048	5.652	9.617
GPR $\nrightarrow$ DASH	0.7	5.844**	3.108	4.611	7.867
GPR $\nrightarrow$ XRP	0.3	2.073***	1.862	2.602	4.442
The Causality Relationship for Positive Shocks					
H_0	**Quantile**	**Test Statistic**	**10% CV**	**5% CV**	**1% CV**
$GEPU^+ \nrightarrow XMR^+$	0.7	10.222**	7.446	9.052	12.603
$GPR^+ \nrightarrow XMR^+$	0.8	7.580**	5.100	6.732	10.999
$GPR^+ \nrightarrow XRP^+$	0.9	9.741**	6.859	9.275	15.400
The Causality Relationship for Negative Shocks					
H_0	**Quantile**	**Test Statistic**	**10% CV**	**5% CV**	**1% CV**
$GEPU^- \nrightarrow LTC^-$	0.1	9.093**	4.877	6.749	11.551
$GEPU^- \nrightarrow XRP^-$	0.1	25.502**	16.294	20.278	29.132

4 We presented only the significant causality relationship, the results for the remaining causality relationships all available, upon request.

$GEPU^{-} \nrightarrow XRP^{-}$	0.2	15.944**	11.942	15.359	22.290
$GEPU^{-} \nrightarrow XRP^{-}$	0.3	14.011**	9.764	12.284	17.657
$GEPU^{-} \nrightarrow XRP^{-}$	0.4	8.783***	8.344	10.217	14.601
$GPR^{-} \nrightarrow LTC^{-}$	0.1	12.211***	11.230	14.755	22.965
$GPR^{-} \nrightarrow XMR^{-}$	0.1	31.450**	24.033	28.882	38.592
The Causality Relationship from Negative Shocks to Positive Shocks					
H_0	**Quantile**	**Test Statistic**	**10% CV**	**5% CV**	**1% CV**
$GEPU^{-} \nrightarrow DASH^{+}$	0.6	8.950**	7.265	8.821	12.053
$GEPU^{-} \nrightarrow DASH^{+}$	0.8	26.984*	11.076	13.555	19.464
$GEPU^{-} \nrightarrow DASH^{+}$	0.9	26.044*	11.664	14.774	24.004
$GEPU^{-} \nrightarrow ETH^{+}$	0.6	20.196**	16.545	19.647	27.748
$GEPU^{-} \nrightarrow ETH^{+}$	0.9	28.235***	26.345	33.276	48.051
$GEPU^{-} \nrightarrow XMR^{+}$	0.7	8.649**	6.612	8.086	10.890
$GPR^{-} \nrightarrow DASH^{+}$	0.8	5.676***	5.191	6.822	10.651
$GPR^{-} \nrightarrow LTC^{+}$	0.9	11.779**	7.561	10.259	16.624
$GPR^{-} \nrightarrow XMR^{+}$	0.7	4.776***	4.565	5.853	9.395
The Causality Relationship from Positive Shocks to Negative Shocks					
H_0	**Quantile**	**Test Statistic**	**10% CV**	**5% CV**	**1% CV**
$GEPU^{+} \nrightarrow ETH^{-}$	0.1	15.220**	11.149	14.290	22.443
$GEPU^{+} \nrightarrow ETH^{-}$	0.2	12.821***	10.451	12.349	17.968
$GPR^{+} \nrightarrow BTC^{-}$	0.1	26.209***	21.223	26.435	38.414
$GPR^{+} \nrightarrow BTC^{-}$	0.4	12.658***	10.896	12.782	17.512
$GPR^{+} \nrightarrow ETH^{-}$	0.1	15.527***	13.745	16.942	23.475
$GPR^{+} \nrightarrow ETH^{-}$	0.2	25.910*	9.771	12.615	18.719
$GPR^{+} \nrightarrow ETH^{-}$	0.3	12.809**	10.697	12.432	16.979
$GPR^{+} \nrightarrow XRP^{-}$	0.1	24.426**	13.104	16.815	26.416
$GPR^{+} \nrightarrow XRP^{-}$	0.4	15.033***	12.985	15.362	20.702

Note: *, **, and *** show the significance at the 1%, 5%, and 10% levels, respectively. + and – denote the positive and negative shocks, respectively. The critical values are obtained using 5000 simulations.

For the original series, the quantile intervals [0.1, 0.2], [0.2, 0.4], [0.6, 0.8], and [0.8, 0.9] correspond to the extremely bearish, bearish, bullish, and extremely bullish market conditions (see Albulescu et al. 2020, and Balcilar et al. 2018b), while the quantile 0.5 corresponds to the normal market states. The findings of the symmetric FQC test show that the GEPU has predictive power for ETH in the bullish states, and for XRP in the normal, bearish, and extremely bullish periods. Besides, the findings also reveal the existence of the unidirectional causality from the GPR to the DASH in the bearish states, and to the XRP in the bearish periods.

Since people generally overact in the case of negative news than positive news, testing the causality by assuming the effect of a positive shock is the same as the effect of a negative one may be misleading. So, we also test the existence of a causality relationship by decomposing the series into positive and negative shocks. The results are also summarized in Table 3. The findings support the evidence of causality from the GEPU to the XMR, and from GPR to the XMR, and XRP at high quantiles. These results show that when there are high positive changes in the GEPU, and GPR these values can be used as a prediction tool for the high positive returns of XMR, and XRP.

The results of the causality test in the case of negative shocks show that (i) the causality relationship exists in the low quantiles, and (ii) most of the causal relationships that exist are due to the GEPU. We find evidence of the causality nexus that runs from negative shocks of GEPU to the negative shocks of LTC, and XRP, and from the negative shocks of GPR to the negative shocks of LTC and XMR. These findings show when there are significant decreases at the GEPU, these values could be used to predict the decreases of LTC, and XRP. The same can be stated for the causality relationship from GPR to LTC and XMR.

There may be a causal relationship not only between shocks of the same type but also between different types of shocks. To consider this situation, we also consider testing the causality from negative shocks of risk to positive shocks of cryptocurrencies, and from positive shocks of risks to the negative shocks of considered cryptocurrencies. The results show that there is unidirectional causality from negative shocks of GEPU to the positive shocks of DASH, ETH, and XMR at the high return phase, and from positive shocks of GEPU to the negative shocks of ETH, and from positive shocks of GPR to the negative components of BTC, ETH, and XRP at the bearish market conditions. Finally, our empirical findings are in line with those of Demir et al. (2018), Fang et al. (2019), Bouri et al. (2020a, 2020b), and Colon et al. (2021), suggesting that cryptocurrencies could be used as a safe-haven against economic policy uncertainty and geopolitical risk.

Our empirical findings show that cryptocurrencies act as strong hedging tools against high GEPU and GPR. High GEPU and GPR signal noteworthy uncertainty in financial markets, thus altering the investor's anticipations and market volatility. Investors are shifting their money to cryptocurrencies and increasing prices in cryptocurrencies. Since investors place more weight on events that are deemed certain than on those that are just plausible, high GEPUs cause the stock market to experience violent fluctuations, prompting many to resort to cryptocurrencies as a hedge. Cryptocurrency market returns offer hedging and safe-haven characteristics, but their reactions vary on the source of uncertainty. Hence, determining the source of uncertainty is of critical importance. For instance, in our analysis, we find that the GEPU leads to more causality relationships than GPR. When the positive shocks of cryptocurrencies are taken into consideration, causality relationships always take place in high quantiles, that is, in the extreme bull markets, while the causality relationship occurs in extreme bear markets for the negative shocks. Analyzing the general outlook of the causality relationships, we can note that Monero acts differently than the other cryptocurrencies.

There were several incidents that may affect the causality relationship between cryptocurrencies over the analysis period. To reveal the changes in the existence of causality relationship, we also test the causality relationship in a time-varying framework. Fig. A in the Appendix reveals that there exists a causality relationship from GEPU to the cryptocurrencies in the last months of 2021 and first months of 2022 which indicate effect the acceptation of Bitcoin as the official currency in El Salvador and Russian invasion of Ukraine, respectively. Besides, we also find a causality that runs from GPR to the cryptocurrencies. In the beginning of 2020, there seems a causality for BTC and DASH which is mostly due to 2020 Russia–Saudi Arabia oil price war that cause a 65% quarterly fall in the oil price. There is also a causality from GPR to the cryptocurrencies in last months of 2020s, which is due to Second Nagorno-Karabakh War.

5. Conclusions and Policy Implications

The cryptocurrencies, particularly Bitcoin and Ethereum experienced huge price appreciation since 2020. There was a significant inflow of investors from large institutions, including pension plans, university endowment funds, and investment trusts. The demand for cryptocurrencies, particularly for Bitcoin, was supported by a few major consumer-facing payment brands like PayPal and Square and a rising number of businesses accepting Bitcoin as payment. Aside from all this public excitement, the devastation caused by the COVID-19 pandemic has prompted major stimulus packages from governments worldwide and increased money creation by several central banks. In the face of growing inflation and reducing purchasing power, investments like cryptocurrencies are viewed as a store of value. Countries including China, Russia, the EU, and Canada are working or planning to develop central bank digital currencies. It seems clear that cryptocurrencies are perceived as the future by traditional powers in the global financial system.

Throughout their quick growth and development, cryptocurrencies have seen several times significant price volatility. As mentioned above, cryptocurrencies, notably Bitcoin, have taken on a new role as a possible safe-haven during times of huge financial market panic since the outbreak of the COVID-19 pandemic. This was encouraged by the significant challenges in determining the degree of global problems, such as ongoing COVID-19 and geopolitical pressures. Bitcoin's performance in recent years has taken the attention of several researchers, and the number of studies focusing on Bitcoin has increased notably. In this sense, our study contributes to previous research efforts by extending the discussion on the hedging and safe-haven properties of not only Bitcoin but also the other major cryptocurrencies including Ethereum, Litecoin, Ripple, Monero, and Dash against uncertainty. In our analysis, we try to examine the causality relationship from global economic policy uncertainty and geopolitical risk to the returns of cryptocurrencies including Bitcoin, Dash, Ethereum, Litecoin, Monero, and Ripple in 2015-2023, which covers the COVID 19 pandemic, US-China tension, post-Brexit period, and Russia-Ukraine war. We employ the FQC test proposed by Cheng et al. (2021), which allows us more significant results. In our analysis, we demonstrate that the cryptocurrency market actively reacts to economic policy uncertainty (GEPU) and geopolitical risk (GPR), but the reactions to uncertainty by cryptocurrencies are heterogeneous. Specifically, we find that the GEPU has predictive power for Ethereum in the bullish states, and for ripple in the normal, bearish, and extremely bullish periods. Besides, our findings also reveal the GPR has predictive power for Dash in the bearish states, and for Ripple in the bearish periods. Therefore, we can conclude that the cryptocurrency market could serve as a hedge and safe haven against GEPU and GPR in most cases.

Our results have implications not only for researchers but also for investors, cryptocurrency users, and policymakers. Therefore, this paper might help investors in their decision-making process, and portfolio allocations also help policymakers regulate crypto-market trading. As traditional currencies and assets took a hit as a result of the global economic crisis resulting from the COVID-19 pandemic, digital currency popularity grew in the period 2020-2021. The value of cryptocurrencies has risen as many major investors and corporations bought digital money. The fact that interest rates on traditional assets hit rock bottom throughout the year also contributed to the ascent of cryptocurrencies as more investors put their money into the coin. The majority of analysts had the opinion that investors don't fully comprehend how cryptocurrencies function and that they were in a bubble. A key concern for several institutional investors was the high price volatility. Following the cryptocurrencies' outstanding performance in 2021, the year 2022 was disappointing, as the market prices of the cryptocurrencies significantly declined. In 2023, the cryptocurrencies experienced fluctuations again. In this context, Khalfaoui et al. (2023) investigating the influence of public attention on the Russia-Ukraine war find that co-movements of war attention and cryptocurrencies relies on investment horizon and market condition. Their findings coincide with cryptocurrency investors seeking liquidity in response to the war's attention, with decreases in prices interpreted as sell-offs by major holders. In another research, The Russia-Ukraine war's impact on Bitcoin and Etherium liquidity is examined by Theiri et al. (2023) in order to determine if this impact is temporary or long-lasting. Their research shows that the Russia-Ukraine conflict had a considerable, albeit transient, influence on Bitcoin and Ethereum liquidity. Liquidity levels have risen at first, then fallen back to where they were before to the occurrence.

It seems that the fluctuations might continue in the future. On the other hand, launching financial instruments like Bitcoin futures and options, in addition to blockchain-related funds, can make it possible for investors who do not participate in the market because of volatility fears to do so. With the use of Bitcoin futures, speculators might take short positions on cryptocurrencies and speculate on their price falling. All these developments imply that cryptocurrencies will continue to have importance in the future. As conflict and instability may upset markets, safe-haven assets often do well during periods of heightened geopolitical stress. Cryptocurrencies are often viewed as safe-haven instruments even though they are highly volatile. Considering cryptocurrencies did actually do well when geopolitical conflict or economic policy uncertainty rose in the past, we might anticipate that the demand might continue for cryptocurrencies in the following term as the Russia-Ukraine war is continuing. According to most investors, the sharp decline in the value of cryptocurrencies might suggest that it could be a good time to trade them. In this sense, cryptocurrency supporters have many reasons to be optimistic about the future of digital assets despite the recent difficult months, especially given the uncertainty surrounding economic policy and the seeming all-time high in geopolitical tensions.

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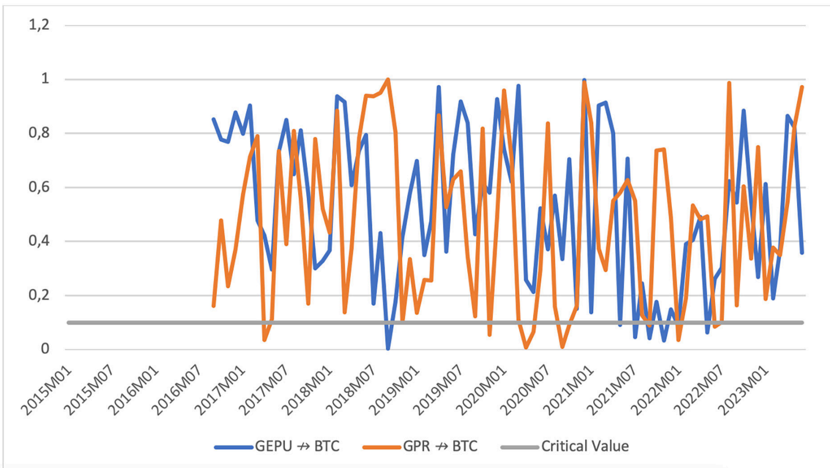
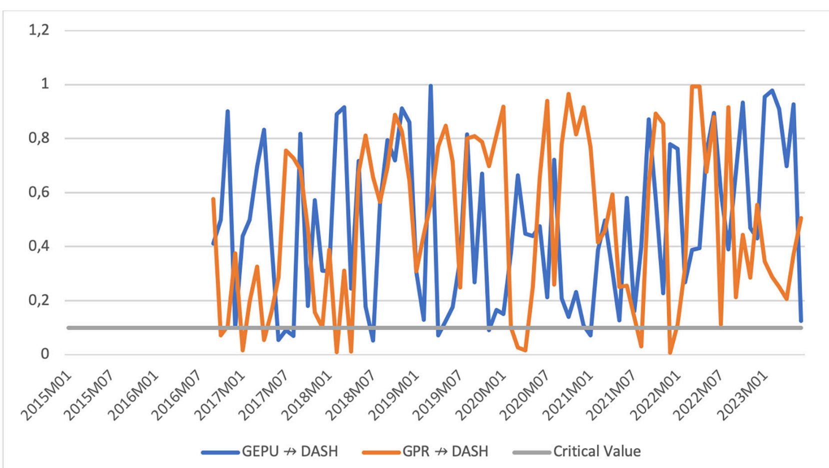
Appendix

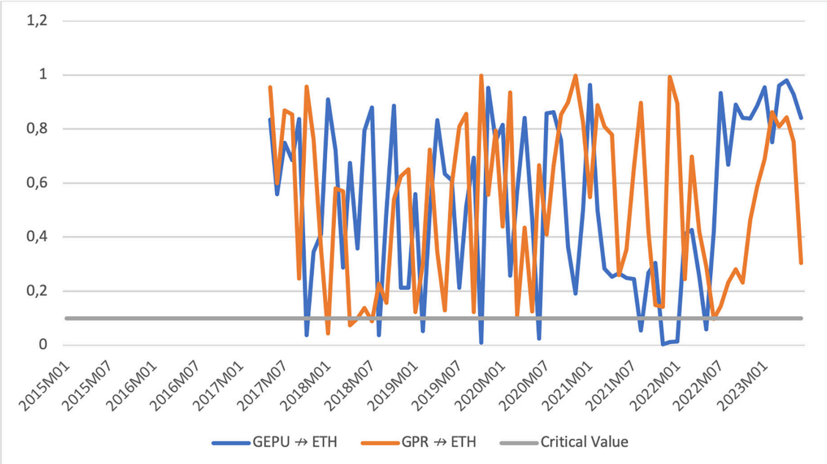
To reveal the events which cause a change in the existence of the causality relationship, we use the Fourier Toda-Yamamoto causality test in a time varying framework. We consider size of the subsample as 19 by using the formula of Phillips et al. (2015) and present the results as following:

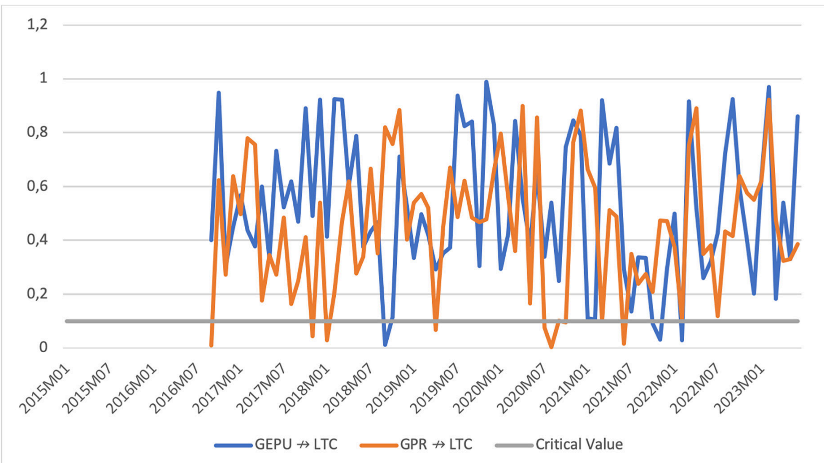
FIGURE A1

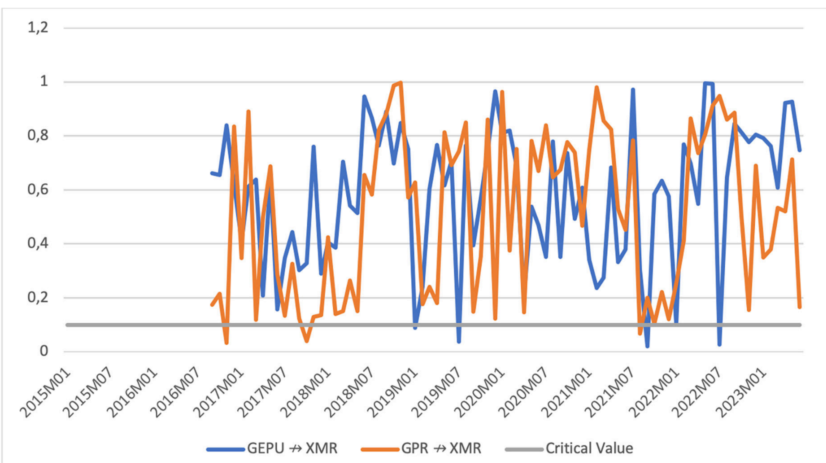
DYNAMIC FOURIER TODA-YAMAMOTO CAUSALITY ANALYSIS

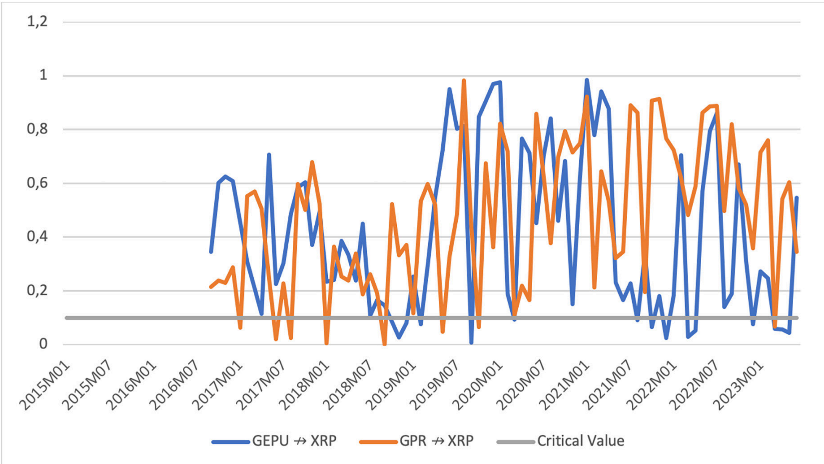





1,2
1
0,8
0,6
0,4
0,2
0
2015M01
2015M07
2016M01
2016M07
2017M01
2017M07
2018M01
2018M07
2019M01
2019M07
2020M01
2020M07
2021M01
2021M07
2022M01
2022M07
2023M01
GEPU ↛ ETH
GPR ↛ ETH
Critical Value


1,2
1
0,8
0,6
0,4
0,2
0
2015M01
2015M07
2016M01
2016M07
2017M01
2017M07
2018M01
2018M07
2019M01
2019M07
2020M01
2020M07
2021M01
2021M07
2022M01
2022M07
2023M01
GEPU ↛ LTC
GPR ↛ LTC
Critical Value


1,2
1
0,8
0,6
0,4
0,2
0
2015M01
2015M07
2016M01
2016M07
2017M01
2017M07
2018M01
2018M07
2019M01
2019M07
2020M01
2020M07
2021M01
2021M07
2022M01
2022M07
2023M01
GEPU ↛ XMR
GPR ↛ XMR
Critical Value



Note: The grey line shows the 0.10 % line. The blue and red lines show the bootstrap p-values of the relevant causality tests. The area that is below the grey line indicates the rejection of the null hypothesis of no causality