

## ECONOMIC POLICY UNCERTAINTY IN THE UNITED STATES: DOES IT MATTER FOR EQUITY, COMMODITY AND CRYPTOCURRENCY MARKETS?

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### ABSTRACT

*In recent years, the issue of worldwide uncertainty has gained more attention in academic literature. Therefore, the current study examines how the United States (U.S.) economic policy uncertainty (EPU) affects various stock indices, commodities and cryptocurrencies. This study takes data on stock indices and commodities from February 2005 to December 2023 and data on cryptocurrency from October 2017 to December 2023. For estimations, we employ the Quantile-on-Quantile regression (QQR) approach to investigate the impact and to understand how changes in EPU affect stock indices, commodities, and cryptocurrency returns at different levels of quantiles. The findings reveal that EPU has a negative impact on the stock indices and cryptocurrencies. For stocks, high uncertainty leads to more volatility, while EPU exhibits higher volatility for cryptocurrencies, indicating sensitivity to policy changes. Similarly, commodities react differently to the*

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*U.S. EPU, while gold tends to appreciate in uncertain times. Furthermore, we employ quantile regression for robustness check, and the findings validate the outcome of QQR at various levels of quantiles from lower to higher. Moreover, the findings of this study are helpful for investors, portfolio managers and policymakers to develop better investment strategies and effectively manage risks across different asset classes.*

**Keywords:** Economic policy uncertainty, United States, Commodity market, Cryptocurrency markets, Equity markets, Quantile-on-Quantile regression

## INTRODUCTION

With the rising interconnectedness of the global financial system, domestic financial markets are becoming more susceptible to outside shocks. Many factors, including worldwide recessions, trade and monetary policies, illnesses, natural calamities and geopolitical risk, can cause these shocks. It may cause unanticipated swings in the financial system and upset the spillover structure, eroding public trust and jeopardising financial stability (Billio et al., 2012). The index of EPU, developed by Baker et al. (2016), helps to understand how uncertain or clear the US economic policies are at any given time. The degree to which international financial markets are integrated and linked has significantly improved in recent years. More specifically, Adebola et al. (2019) document that the above-mentioned appearances have begun to be noticed during the 2008–2009 financial crisis and the European sovereign debt crisis of 2010–2013. Likewise, integration and linkages across markets lead to high spillovers of portfolio risk and reduce the benefits of diversification. Recently, the search for multiple assets for investment in precious metals (palladium, silver, gold and platinum) has attracted the attention of investors and portfolio managers (see, e.g., Canover et al., 2009; Jensen et al., 2002; Reboredo & Rivera-Castro, 2014). In recent years, the above-mentioned financial products have become increasingly prominent. Particularly, most commodities are considered safe-haven, exhibiting a strong characteristic of assets (Bouri, Gupta, et al., 2017).

Consequently, numerous studies show that these financial commodities serve as effective hedges and improve portfolio diversification by mitigating other market risks (see e.g., Bredin et al., 2015; Beckmann et al., 2015; Bouri, Jalkh, et al., 2017; Ciner et al., 2013; Coudert & Raymond-Fiengold, 2011; Demir et al., 2018; Jin et al., 2019; Lucey & Li, 2015; Rehman et al., 2018; Salisu et al., 2019; Wang et al., 2018; Wu et al., 2019; Maydybura et al., 2023). Similarly, investors in developed markets invest in precious metals and cryptocurrencies. Therefore, considering the brittle characteristics of bitcoin relative to other cryptocurrencies, bitcoin becomes vulnerable to investing risks (Rehman & Apergis, 2018; Rehman

& Vo, 2020). Consequently, cryptocurrencies have become a popular asset class, and people and businesses must frequently make cryptocurrency-related investing decisions (Lavanya & Mamilla, 2023). Economic policy uncertainty typically raises the risk premium that people and firms must deal with, which may subsequently influence how they choose to invest (Baker et al., 2016). Furthermore, the impact on safe assets is not as strong as on speculative assets during periods of significant economic policy uncertainty (Bekaert & Hoerova, 2016; Caballero & Krishnamurthy, 2008; Fasanya et al., 2021).

Similarly, global uncertainty severely influences the financial markets and could put investors at risk (Apergis et al., 2017; Kim & In, 2002; Adebayo et al., 2022). In the recent past, across nations, regions and populations, numerous studies have investigated the relationship between EPU and commodity prices (see, e.g., Jiang & Cheng, 2021; Sharif et al., 2020; Adedoyin et al., 2021; Alaali 2020; Dogan et al., 2021; Hau et al., 2020; Lyu et al., 2021). Around the globe, numerous studies examine the association between natural resources, commodity pricing, and economic growth (Baek & Young, 2021; Kumar & Prabheesh, 2023; Mukhtarov et al., 2020). Numerous studies demonstrate how cryptocurrencies greatly enhance the diversified portfolio's risk-return trade-off, and ultimately, it meets the expectation of investors in diversified returns (Anyfantaki et al., 2021; Briere et al., 2015). EPU causes a decline in financial stability (Phan et al., 2021). Several studies investigate the impact of EPU on financial markets and document that higher EPU increases the volatility in stock markets and depletes liquidity (Chen & Chiang, 2020; Kundu & Paul, 2022; Li et al., 2020; Wang et al., 2022). Similarly, around the world, investors frequently choose a widely traded commodity (gold) as a haven against EPU (Esparcia et al., 2022; Su et al., 2022; Triki & Ben Maatoug, 2021). Several researchers and academicians document that the characteristics of gold have changed dramatically during times of crisis, including pandemics and other financial crises, and it may no longer be a haven asset (see, e.g., Chai et al., 2019; Huang & Kilic, 2019; Qin et al., 2020; Akhtaruzzaman et al., 2021; Choudhry et al., 2015; Mokni et al., 2022). According to Wang et al. (2019), Bitcoin (BTC) is generally seen as a diversifier, and there is little risk of spillover from EPU to BTC. Similarly, cryptocurrencies are a good option for hedging when EPU is high (Jiang et al., 2021; Yen & Cheng, 2021).

In the same way, as investors expand their investment tentacles in pursuit of additional assets, they can easily assess the risk associated with susceptible assets. Thus, the earlier research examines how the EPU affects commodities and cryptocurrencies (Fasanya et al., 2021). Concurrently, numerous studies explore the characteristics of BTC for hedging capacities against the EPU (see, e.g., Demir et al., 2018; Wang et al., 2018; Wu et al., 2019). As a result, studies examining

the relationship between the commodities and cryptocurrency markets are limited (Klein et al., 2018; Selmi et al., 2018; Salisu et al., 2019; Rehman, 2020). Similarly, the evolving nature of economic policies and their impact on financial markets necessitates a comprehensive understanding of the implications of EPU. While there has been extensive research on the impact of EPU on individual stock markets, the burgeoning field of cryptocurrencies and tangible assets has not been as thoroughly investigated. Therefore, to bridge this gap, our study contributes threefold to the existing literature. First, we investigate the impact of EPU on stock indices (S&P 500, FTSE 100, Euro Stoxx 50, BOVESPA). Second, we analyse the impact of EPU on commodity markets (Gold, Copper, Natural Gas, Soybean and Wheat). Third, we analyse the impact of EPU on cryptocurrencies (BTC, Ethereum Classic, Ethereum, Lite Coin and Bitcoin Cash). Further, we also determine the role of EPU during the COVID-19 pandemic and its impact on markets (stocks, commodities and cryptocurrencies), which is the fourth contribution. Furthermore, applying the Quantile-on-Quantile regression (QQR) approach jointly assesses vulnerabilities in digital contracts and inter-business unit transactions is lacking (Hau et al., 2021). While traditional methodologies determine correlation or causation, the quantile-against-quantile method provides more detailed information (Rubbiani et al., 2022). Therefore, using the QQR approach of Sim and Zhou (2015), we find that EPU has a negative effect on stock market returns. Similarly, EPU adversely affects the cryptocurrencies market. Further, we find that when EPU is high, it creates higher volatility in the markets. During the sample period, commodities react differently to EPU, while gold tends to appreciate uncertainty and act as a haven asset during the volatility. Furthermore, we employ quantile regression for robustness check, and the findings support the outcome of QQR at various levels of quantiles from lower to higher. Moreover, our findings report significant implications for investors and portfolio managers to diversify their investments in uncertain conditions.

## **LITERATURE REVIEW**

The current study examines the dynamic impact of EPU on commodities, cryptocurrencies and stock markets. The literature review provides an overview of previous studies related to this topic. We discussed studies on the impact of EPU on the stock markets, commodities, and cryptocurrencies. The uncertainty in future economic policies, including decisions made by governments and lawmakers, symbolises a lack of clarity and predictability in fiscal methods (Witt, 2021). This situation creates confusion about what might happen due to policy changes, potentially disrupting the regular functioning of businesses and currency markets (Lee et al., 2021). Measuring uncertainty in the economy is based on key

factors, such as the overall economic environment, as uncertainties can persist when significant changes or events occur, such as political shifts, international pressures or financial crises. Similarly, EPU severely affects market behaviour, risk preferences, cost of investment and consumer confidence. Recently, numerous studies have highlighted the importance and effect of EPU on market behaviour (Gutiérrez-López & Abad-González, 2020).

### **Economic Policy Uncertainty and Stock Markets**

Stock markets are driven by information provided by businesses, governments and other organisations. Similarly, investors gather information from media sources, which affects their trading decisions and ultimately causes fluctuations in stock prices (Aouadi et al., 2013; Wang, 2018). Existing literature documents the role of information in financial markets and the release of new information that impacts the stock market and trading volume (Vlastakis & Markellos, 2012). Stock prices are affected by the uncertainty in two ways. First, it lowers the projected future cash flows. Second, it increases risk aversion, which raises the risk premium in the discount rate (Andrei & Hasler, 2015; Cochrane, 2018; Smales, 2021; Aor et al., 2021). Furthermore, increased uncertainty will result in more stock price revisions, both upward and downward, and therefore increased volatility (Engle et al., 2008; Szczygielski et al., 2022; Ravinagarajan & Sophia, 2022; Kumar & Paramanik, 2022).

Similarly, Abdullah (2020) examined the effect of EPU on the Gulf Corporation Council (GCC) stock markets employing VAR models. They reported that EPU negatively affects stock returns. Using quantile regression, Kannadhasan and Das (2020) examine the impact of EPU on stock returns in Asian emerging markets. The author found that the US policy uncertainty has largely affected the markets in China, Europe and Japan. Similarly, a rise or fall in uncertainty has an adverse effect on stock returns. Further, the authors reveal that EPU negatively impacts stock returns at lower quantile levels (Chiang, 2020). Li et al. (2023) investigated the EPU spillover effect on the stock market. The authors used network analysis and the Diebold-Yilmaz (DY) spillover index to examine the effect. It shows a spillover effect on the stock markets in the U.S. and Asia, with stock indices acting as transmitters of risk spillover and EPU acting as a recipient. Sheikh et al. (2024) employed the DCC-GARCH-t copula approach and quantile time-frequency connectedness to quantify the relationship between global financial markets and uncertainty. According to the authors, the global financial stress index, trade policy uncertainty and geopolitical risk all have the greatest shock-spillover effects on Australian financial markets at the lower, medium and upper quantiles. Shaik et al. (2024) examined the relationships between the

uncertainty index, gold, BTC, oil and regional stocks regarding dynamic volatility. The authors employ the TVP-VAR-based dynamic connectedness approach and document that the properties of haven assets (such as gold, BTC and oil) decreased over the COVID-19 era because of strong dynamic connectedness with regional stock indices.

### **Economic Police Uncertainty and Commodities**

In the context of EPU and commodities, Guan et al. (2021) investigate the impact of resource prices on the economic growth of resource-dependent nations. Employing the ARDL-bound model for empirical estimation, their findings indicate that natural resources, along with gold and oil, play a vital role in driving economic growth. Similarly, Bourghelle et al. (2021) investigated the associations between stock indexes, metal prices and crude oil prices in the US economy. Their findings indicate that some metals (palladium, titanium, steel and silver) are net recipients of volatility spillovers, whereas other metals (palladium, platinum and gold) benefit from spillover. Concurrently, news about currency tariffs or disruptions in global economic activities can significantly impact agricultural product prices and market perceptions (Nchanji et al., 2021). Similarly, Bhar and Hammoudeh (2011) find that oil exhibits higher returns during uncertainty than natural resource commodities. Similarly, Liu and Chen (2022) investigate the relationships between Chinese crude oil price volatility and agricultural commodities futures using the QQR approach. It documents notable effects from the low and high quantiles of volatility in the price of oil. Hazgui et al. (2022) investigate the relationship between oil, gold, BTC and EPU, employing QQR and wavelet approach to quantify the relationship. The authors demonstrate that, at low and medium frequencies, there is negative reliance between BTC and EPU and positive interdependence between BTC and commodities.

Wu et al. (2023) explore the connectedness (time-frequency) of EPU across financial and commodity markets, employing the DY approach and regime-switching model. Their findings indicate that volatility and risk transmission among the financial and commodity markets are the shock receivers during uncertainty. Du and Zhang (2024) examined the relationship between gold, natural gas prices and EPU, using the Quantile Autoregressive Distributed Lag (QARDL) model to quantify the relationship. The authors find that EPU negatively affects gold and natural gas prices. Raza and Khan (2024) explore the relationship between climate policy uncertainty (CPU) and precious metals by employing the GARCH-MIDAS (an advanced technique) to quantify the relationship. The authors document that the CPU significantly influences the volatility of precious metal prices.

## **Economic Policy Uncertainty and Cryptocurrencies**

Cryptocurrency research has been the focus of many empirical studies in the financial literature in recent years. As the evolutionary trends of cryptocurrency research were being examined, Bouri, Gupta, et al. (2017) investigated the effect of uncertainty on BTC. The authors find that BTC serves as a safe haven during global uncertainty, and its hedging is more prevalent in bullish and bearish markets. Demir et al. (2018) investigate the impact of uncertainty on BTC using EPU as a measure. The authors find a negative relationship between the EPU movement and BTC; the effect is positive in the upper quantiles. It also provides evidence that hedging is feasible during bull markets. Fang et al. (2019) argue that considering the influence of EPU, BTC's usefulness as a hedge marginally improves for bond and equities portfolios, but only under particular economic circumstances. Wu et al. (2019) examine how BTC and gold can be safe havens and hedges against the EPU. The authors conclude that, in typical circumstances, neither BTC nor gold serves as a shelter or a viable hedge. Further, it documents that the behaviour of gold and BTC could influence market sentiments. Using different uncertainty metrics to examine the relationship between uncertainty and cryptocurrencies, Colon et al. (2021) found that every uncertainty metric has a detrimental effect on cryptocurrencies. Further, they reported that cryptocurrencies act as a robust hedge against uncertainty.

Simran and Sharma (2023) examined the asymmetric impact of EPU on the cryptocurrency market. They employed the NARDL approach, and their findings indicate that EPU negatively affects cryptocurrencies in the long run, except for Tether. He et al. (2024) examined the relationship between EPU and cryptocurrencies (BTC, Ethereum (ETH) and Tether (THT)) employing quantile regression (QR) and non-linear Autoregressive Distributed lag (NARDL) model to quantify the short and long-term effect. The authors find that BTC and ETH served as hedging tools in the short term. Further, it documents that THT shows a positive relationship with EPU. Zhang et al. (2024) investigate the relationship between global economic policy uncertainty (GEPU) and cryptocurrencies. The authors document that the stability of cryptocurrency return is higher when EPU is higher during the sample period. Further, it reveals that cryptocurrencies may be perceived as a safe-haven asset.

## METHODOLOGY

### Data and Variables

This study employs analysis based on data collected from two primary sources. First, The U.S. Economic Policy Uncertainty (EPU) index is taken from the database created by Baker et al. (2016), accessible at <https://www.policyuncertainty.com>. Second, asset class data, e.g., stock indices, commodities, and cryptocurrencies, were taken from <https://www.investing.com>. Consequently, the Standard & Poor's 500 composite Stock Price Index, or S&P 500 Index, is a stock index that follows the share prices of 500 of the biggest publicly traded businesses whose stocks are listed on the US Nasdaq and New York Stock Exchange (NYSE). Introduced in 1957, it is frequently used as a stand-in for characterising the general state of the stock market or even the economy of the United States (Nzokem & Maposa, 2024). For EPU, stock indices and commodities, we collect data spanning from January 2005 to December 2023. Whereas for cryptocurrencies, we collect the data for two different periods. First, BTC was the first cryptocurrency launched in January 2009. Second, it is now the most valuable and well-known cryptocurrency among others. The first real-world BTC transaction occurred on 22 May 2010, a date known to Bitcoin. Therefore, we collect data on Bitcoin from mid-2010 to December 2023. Ethereum Classic (ETC) is the original Ethereum (ETH) blockchain launched in July 2015. Since Ethereum and Ethereum Classic are separate blockchains, each has its native token: ETH and ETC. Litecoin and Bitcoin Cash have taken different approaches to fix Bitcoin's scalability problem. Litecoin has taken the "Volume" route, while Bitcoin Cash has taken the "Size" route. Litecoin was created in 2011, and Bitcoin Cash was created in 2017. Therefore, we take the data for other cryptocurrencies (Ethereum Classic, Ethereum, Lite Coin and Bitcoin Cash) from October 2017 to December 2023. Further, we have included these selected cryptocurrencies in our sample because they are the largest in market capitalisation, making them representative of their respective markets. Their high trading volume increases liquidity, and the availability of extensive data facilitates easy collection and analysis of market trends. In recent years, cryptocurrencies have become more integrated into the financial system. Therefore, it is important to understand the relationship between cryptocurrencies, equities and commodities (Sebastião & Godinho, 2021). Numerous studies argued that traditional assets such as oil, silver and gold constitute risk-resistant strategies for investors (Baur & Smales, 2020; Ahmed & Huo, 2021).

Table 1 provides the equity, commodity, and cryptocurrency markets that we have selected for our study, along with the symbols of the variables.



Table 1  
*Samples and their classifications*

Variable	Symbol	Markets
Economic Policy Uncertainty	EPU	United States
Standard and Poor's 500	S&P 500	United States
Financial Times Stock Exchange 100 Index	FTSE 100	United Kingdom
Eurozone stocks	Euro Stoxx 50*	Stock Market
Brazil Stock Market	BOVESPA	Brazil
Gold	Gold	Commodities
Copper	Copper	-
Natural Gas	Natural Gas	-
Soybean	Soybean	-
Wheat	Wheat	-
Bitcoin	BTC	Cryptocurrencies
Ethereum Classic	ETC	-
Ethereum	ETH	-
Lite Coin	LTC	-
Bitcoin Cash	BSH	-

*Note:* \*The Euro Stoxx 50 index represents the 50 largest companies (based on market capitalisation and liquidity) in terms of free-float market capitalisation. The Euro Stoxx 50 index comprises eight countries: France, Germany, Spain, the Netherlands, Italy, Ireland, Belgium and Finland.

### Quantile-on-Quantile Regression Model

The purpose of this study is to analyse the impact of different quantiles of EPU on the conditional quantile returns of different asset classes. Following Sim and Zhou (2015), we employ the quantile-on-quantile regression (QQR) approach because it combines nonparametric estimation and quantile regression. Similarly, Koenker and Bassett (1978) proposed orthodox quantile regression to examine the effect of independent variables on various quantiles of dependent variables. Similarly, the local linear regression proposed by Stone (1977) and Cleveland (1979) examines the local effect of specific quantiles of an independent variable on the dependent variable. Further, the QQR approach avoids the “curse of dimensionality,” which is the problem associated with estimating non-parametric models. Similarly, the QQR combines two approaches to estimate the relationship across different quantiles of independent and dependent variables. Further, the QQR approach provides a figure for the interdependence of two variables compared to other methods (OLS and orthodox quantile regression). Furthermore, the QQR approach overcomes the limitations of the conventional quantile regression (QR) method by assessing the impact of an explanatory variable on the various quantiles of the dependent

variable (Chang et al., 2022; Sim & Zhou, 2015). Moreover, the traditional binary quantile regression (QR) approach may not yield accurate conclusions due to the possible problem of omitted variable bias (Ashley et al., 1980). To solve this issue, the QQR technique builds upon the binary QR methodology by including the moderating influence of other exogenous variables in interactions to more precisely assess the problem (Ozkan et al., 2023; Sinha et al., 2023).

Following the approach of Raza et al. (2018) and Shahbaz et al. (2018), the QQR approach is represented in the non-parametric regression equation:

$$R_i = \beta^\theta(EPU_{us}) + \alpha^\theta r_i - 1 + \mu_i^\theta \quad (1)$$

where  $R_i$  represents the returns of asset classes at time  $i$ ,  $EPU_{us}$  represent the US EPU shocks,  $\mu_i^\theta$  represent the quantile error terms whose conditional  $\theta$ th quantile is equivalent to zero, with  $\theta$  being the  $\theta$ th quantile of the conditional distribution of stock returns and  $\beta^\theta$  is an unidentified function since no previous information is known on the relationship between returns and EPU.

The main advantage of the QQR approach is that this regression specification further captures the complicated dependency relationship between EPU and returns of asset classes. Therefore, to examine the relationship between  $\theta$ th quantile of asset classes and  $\tau$ th quantile of EPU represented as  $(EPU_{us}^\tau)$ , the local linear regression used in Equation (1) in the neighborhood of  $(EPU_{us}^\tau)$ . Given the unknown value of  $\beta^\theta(\cdot)$ , the first-order Taylor expansion is employed around a quantile of  $(EPU_{us}^\tau)$ .

$$\beta^\theta(EPU_{us}) \approx \beta^\theta(EPU^\tau) + \beta^{\theta'}(EPU_{us} - EPU^\tau) \quad (2)$$

where in Equation (2),  $\beta^{\theta'}$  represent the partial derivative of  $\beta^\theta(EPU_{us})$  concerning EPU, similarly, it also describes the marginal effect or response. It also shows the slope coefficient like in the linear regression model.  $\beta^\theta(EPU^\tau)$  and  $\beta^{\theta'}(EPU^\tau)$  represent the  $\theta$  and  $\tau$  respectively.  $(EPU_{us} - EPU^\tau)$  described the unexpected EPU. Interchangeably, the term  $\beta^\theta(EPU^\tau)$  and  $\beta^{\theta'}(EPU^\tau)$  can also be written as  $\beta_0(\theta, \tau)$  and  $\beta_1(\theta, \tau)$ . Similarly, we can get the following equation:

$$\beta^\theta(EPU_{us}) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(EPU_{us} - EPU^\tau) \quad (3)$$

Therefore, by substituting the Equation (3) into Equation (1), the following Equation (4) is obtained:

$$R_i = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(EPU_{us} - EPU^\tau) + \alpha(\theta)r_i - 1 + \mu_i^\theta \quad (4)$$

where in Equation (4), the term  $\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(EPU_{us} - EPU^\tau) + \alpha(\theta)r_i - 1$  represents the  $\theta$ th conditional quantile of returns. Further, the conditional quantile describes the effect of EPU on asset class returns within each quantile, where the coefficients  $\beta_0$  and  $\beta_1$  are determined by  $\theta$  and  $\tau$ , respectively.

Further, in Equation (4), the lower  $\theta$ -quantile of asset returns corresponds to turbulent times, whereas the higher  $\theta$ -quantile corresponds to stable market conditions, respectively. Similarly, lower  $\tau$ -quantile of EPU imply lower degrees of policy uncertainty, while higher  $\tau$ -quantiles indicate greater uncertainty. The coefficient  $\beta_0$  and  $\beta_1$  contain the absolute information about the potential impact.  $\beta_0(\theta, \tau)$  represents the impulsive response of asset returns to a certain level of uncertainty, while the  $\beta_1(\theta, \tau)$  represent the extent and effect of unforeseen shocks of EPU on returns. Consequently,  $\beta_0$  and  $\beta_1$  are derived using linear regression, while  $b_0$  and  $b_1$  can be determined through the following equation:

$$\min_{b_0, b_1} \sum_{i=1}^n p_\theta [R_i - b_0 - b_1(\widehat{EPU}_{us} - \widehat{EPU}^\tau) - \alpha(\theta)r_i - 1] K\left(\frac{F_n(\widehat{R}_i) - \tau}{h}\right) \quad (5)$$

In Equation (5),  $p_\theta$  denotes the quantile loss function, defined as  $p_\theta(\mu) = \mu(\theta - 1)$  ( $\mu < 0$ ), in which  $i$  is the indicator function. Similarly,  $K(\cdot)$  represents the Gaussian kernel function with bandwidth  $h$ . Further, it is used to weight the observation in the neighborhood of  $EPU^\tau$ . Whereas, these weights have an inverse relation with the distance between the empirical distribution function of  $(\widehat{R}_i)$ , which is represented by  $F_n(\widehat{R}_i) = \frac{1}{n} \sum_{k=1}^n I(\widehat{R}_k < \widehat{R}_i)$ , and the value of each distribution function which corresponds with the quantile function of  $EPU^\tau$ , represented by  $\tau$ . Following the selection and choice of bandwidth  $h$  in the Gaussian kernel regression, it is, therefore, important to select the size of the area around the target point to ensure the smoothness of the result estimation. Choosing a small bandwidth  $h$  produces higher variance with smaller deviation (Wen et al., 2022). Therefore, following Sim and Zhou (2015), we choose a small bandwidth  $h$  ( $h = 0.05$ ). Further, corresponding log returns obtained for each asset as:

$$x_{it} = 100 * \left( \frac{P_{it} - P_{it-1}}{P_{it-1}} \right) \quad (6)$$

where the term  $P_{it}$  represent the current price of assets at time  $t$  and  $P_{it-1}$  represent the previous price of the assets at time  $t - 1$ .

## EMPIRICAL RESULTS

### Line Graph of the US EPU

Figure 1 exhibits the EPU level in the U.S. from February 2005 to December 2023. Over time, the line rises and falls, representing uncertainty or unpredictability in the US economic policies. A big spike, where the line shoots up dramatically, is visible around early 2020, likely reflecting the uncertainty caused by the COVID-19 pandemic. After this peak, the EPU level drops but still shows ups and downs, suggesting varying degrees of economic policy uncertainty.

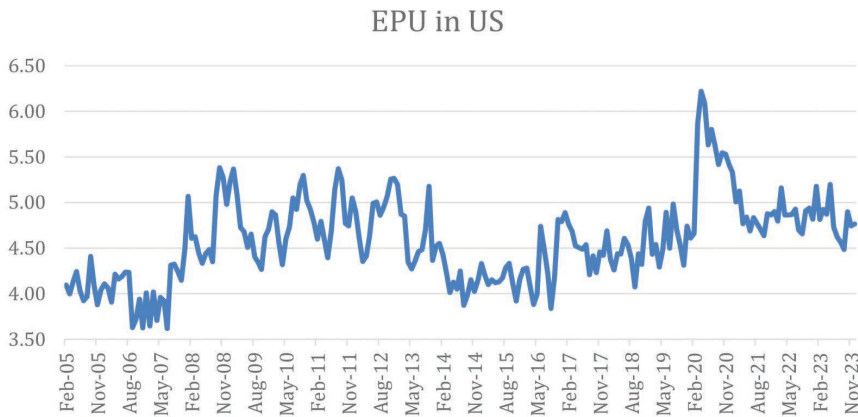


Figure 1: Movements of the US EPU index from February 2005 to December 2023

### Descriptive Statistics

Table 2 shows the summary statistics of the data. The average EPU level is about 4.8470, but this number has varied significantly over time, as shown by a Standard Deviation of approximately 0.4280. The maximum EPU level recorded was over 6.2206, pointing to a time of exceptional uncertainty, possibly around a major event like an election or the start of the COVID-19 outbreak. The S&P 500 has an average mean value of 0.0083, indicating its general performance level over the studied period. The standard deviation for the S&P 500 is quite high (0.0516), meaning its value has seen significant fluctuations, perhaps in response to changing EPU levels or other market factors. The FTSE 100's average mean value is 0.0004. The Euro Stoxx 50 has a mean value of 0.0028, while its maximum value is 0.1664. The BOVESPA has a mean value of 0.0079, and its maximum value is 0.1475.

Gold has an average mean value of 0.0065, and its price changes are less extreme than stock indices, with a Standard Deviation of 0.0372. Copper price is pretty stable with an average mean value of 0.0030 and does not change much as it only goes up or down by less than a point. Natural Gas has a negative mean value of -0.0019. Soybeans and Wheat, as agricultural commodities, present a relatively stable mean with a lower standard deviation, highlighting their lower market volatility. The kurtosis and skewness values suggest that the commodities' price changes do not deviate significantly from a normal distribution. The cryptocurrency market, represented by Bitcoin (BTC), Ethereum Classic (ETC), Ethereum (ETH), Lite Coin (LTC) and Bitcoin Cash (BSH), exhibits significantly higher mean values and standard deviations, indicative of the high-risk high-reward nature of this asset class. Bitcoin Cash has a kurtosis value that's higher than usual, which means it often has very high or very low prices more often than others. The positive skewness for most variables in Cryptocurrencies means they often have a lot of really high values. The combination of graphs and descriptive statistics provides a fundamental understanding of the behaviour of the U.S. EPU and its potential implications for various financial assets. The stark contrast in the standard deviations and kurtosis across different asset classes suggests varying degrees of risk and reaction to economic uncertainty, which would be essential to investigate further in the context of policy changes and economic events within the specified timeframe.

Table 2  
*Descriptive statistics*

Variables	Mean	Max	Min	SD	Skewness	Kurtosis	JB	ADF
S&P 500	0.0083	0.1194	-0.1336	0.0516	-0.5183	2.9674	3.3168***	-14.5736***
FTSE 100	0.0004	0.1164	-0.1480	0.0397	-0.6721	5.1662	20.0397***	-15.2096***
EURO STOXX 50	0.0028	0.1664	-0.1779	0.0527	-0.1466	4.3605	5.9725**	-14.2025***
BOVESPA	0.0079	0.1475	-0.3553	0.0713	-1.7533	10.4920	21.9782***	-13.2063***
GOLD	0.0065	0.0927	-0.0725	0.0372	0.2240	2.4445	1.5705	-16.8700***
COPPER	0.0030	0.1395	-0.1474	0.0581	-0.0154	2.9533	0.0096	-8.1876**
NATURAL GAS	-0.0019	0.4168	-0.5112	0.1789	-0.3362	3.9356	4.0931***	-15.3675***
SOYBEAN	0.0036	0.1148	-0.1669	0.0536	-0.2334	3.3758	1.1073	-14.6804***
WHEAT	0.0054	0.1987	-0.2076	0.0735	0.0139	3.2696	0.2265	-16.4432***
BTC	0.0254	0.4752	-0.4672	0.2123	-0.1210	2.6850	0.4863	-9.7424***
BSH	-0.0091	1.1041	-0.8772	0.3394	0.7487	4.5770	14.5811***	-8.0495***
ETH	0.0272	0.5787	-0.7719	0.2827	-0.2305	2.9722	0.6577	-8.0920**

*(Continued on next page)*

Table 2 (Continued)

Variables	Mean	Max	Min	SD	Skewness	Kurtosis	JB	ADF
ETC	0.0099	0.9474	-0.8415	0.3395	0.6681	4.2902	10.6378***	-8.8173**
LTC	0.0036	0.9734	-0.5518	0.2709	0.5337	3.8561	5.7724**	-7.4256**
EPU	4.8470	6.2206	4.0750	0.4280	1.1572	4.3087	21.798***	-4.466**

Note: \*\*, \* and \*\*\* shows the significance level at 10%, 5% and 1%, respectively; Min and Max show the minimum and maximum values of data, respectively. While JB and ADF stand for Jarque Bera and Augmented Dickey-Fuller.

### Correlation Matrix

Table 3 shows the correlation matrix of the study. The EPU negatively correlates with the stock market (S&P 500, FTSE 100, Euro Stoxx 50, BOVESPA). Similarly, EPU has a positive correlation with commodity prices (Gold, Copper, Natural Gas, Soybean, Wheat) except with natural gas. EPU positively correlates with cryptocurrencies (BTC, Ethereum Classic, Ethereum, Lite Coin and Bitcoin Cash).

Table 3  
Correlation matrix

Panel A						
	S&P 500	FTSE 100	Euro Stoxx 50	BOVESPA	EPU in U.S.	
S&P 500	1					
FTSE 100	0.767***	1				
Euro Stoxx 50	0.824***	0.835***	1			
BOVESPA	0.601***	0.593***	0.569***	1		
EPU in U.S.	-0.006	-0.076	-0.072	-0.079	1	
Panel B						
	Gold	Copper	Natural Gas	Soybean	Wheat	EPU in U.S.
Gold	1					
Copper	0.347***	1				
Natural Gas	0.004	0.069	1			
Soybean	0.196***	0.324***	0.091	1		
Wheat	0.266***	0.253***	0.085	0.536***	1	
EPU in U.S.	0.089	-0.015	-0.005	0.002	-0.032	1

(Continued on next page)

Table 3 (Continued)

<b>Panel C</b>						
	Bitcoin	Ethereum Classic	Ethereum	Lite Coin	Bitcoin Cash	EPU in U.S.
Bitcoin	1					
Ethereum Classic	0.531***	1				
Ethereum	0.643***	0.719***	1			
Lite Coin	0.73***	0.629***	0.738***	1		
Bitcoin Cash	0.774***	0.733***	0.715***	0.796***	1	
EPU in U.S.	0.052	0.05	0.093	-0.011	0.018	1

Note: \*\*\*, \*\* and \* shows the significance level at 1%, 5% and 10%, respectively

### Estimates of the QQR Model

The graphs shown in Figure 2 are visual results from a QQR analysis of major stock markets. It shows how EPU influences the returns of the stock market at different quantiles at various quantiles. In the context of the S&P 500, Figure 2(a) exhibits that the overall impact of EPU on returns is negative. However, in the area under the surface graph that combines lower to upper quantiles of EPU and lower to upper-middle quantiles of returns, the impact of EPU on returns is negative. Meanwhile, the impact is positive in the upper quantiles of returns. This implies that during a bearish market, EPU in the US negatively influences returns, whereas, during a bullish market, an increase in EPU increases returns in the U.S.

Meanwhile, in the FTSE 100 index, Figure 2(b) exhibits that the overall impact of EPU on returns is negative. Further, the region surface of the graph that combines the lower to higher quantiles of EPU and lower to middle-higher quantiles of returns, the impact of EPU on returns is strongly negative. Whereas, at the lower-upper quantiles of EPU and higher quantiles of returns, the impact of EPU is positive, but the effect is moderately strong at higher quantiles. Therefore, the findings indicate that EPU has a strong and negative effect on the returns in bearish states, whereas EPU positively affects the returns in bullish states.

In the context of Euro Stoxx 50, Figure 2(c) exhibits that the impact of EPU on returns is positive and negative. Further, the region surface of the graph, which combines the lower to higher quantiles of EPU and lower to middle quantiles of returns, the impact of EPU on returns is negative. Whereas, at the lower-upper quantiles of EPU and middle-higher quantiles of returns, the impact of EPU is positive, but the effect is observed to be strongly positive at the middle and higher

quantiles. Therefore, the findings indicate that EPU has a weak negative effect on the returns at a bearish state, whereas EPU has a strong positive effect on the returns at a bullish state.

Meanwhile, in the Brazilian stock market (BOVESPA), Figure 2(d) exhibits that the overall impact of EPU on returns is negative. Further, the region surface of the graph that combines the lower to higher quantiles of EPU and lower to middle quantiles of returns, the impact of EPU on returns is negative. Whereas, at the lower-upper quantiles of EPU and middle-higher quantiles of returns, the impact of EPU is positive at middle and higher quantiles. Therefore, the findings indicate that EPU has a negative effect on the returns in a bearish state, whereas EPU has a positive effect on the returns in a bullish state.

In summary, our findings report the different responses of the S&P 500 to EPU, where EPU exhibits more market volatility than the S&P 500. For FTSE 100, we report higher volatility in both low and high EPU metrics. Similarly, Euro Stoxx 50 shows a negative response to higher uncertainty. Interestingly, Brazil's stock market shows complex patterns at various quantiles, where we observed that low and high EPU can lead to varied returns.

The graphs in Figure 3 are visual results from a QQR analysis of major commodities markets. It shows how EPU influences the returns of different commodities at different quantiles at various levels of quantiles. Figure 3(a) exhibits that the overall impact of EPU on returns of gold is positive and negative. However, in the area under the surface graph that combines lower to upper quantiles of EPU and lower to middle quantiles of returns, the impact of EPU on returns is negative. Whereas, at the upper quantiles of returns, we observed the positive impact of EPU on Gold. It implies that during a bearish market, EPU in the US negatively influences the returns of gold, whereas, during a bullish market, EPU positively affects the returns of gold.

For Copper, Figure 3(b) exhibits that EPU has no significant effect on returns of copper at lower quantiles. Further, the region surface of the graph, which combines the lower to upper quantiles of EPU and lower to middle quantiles of returns, the impact of EPU on returns is weak negative. Whereas, at the lower-upper quantiles of EPU and middle-upper quantiles of returns, the impact of EPU is negative. Similarly, we observed a positive impact on returns at higher quantiles. Therefore, the findings indicate that EPU negatively affects the returns in a bearish state, whereas EPU positively affects the returns in a bullish state.



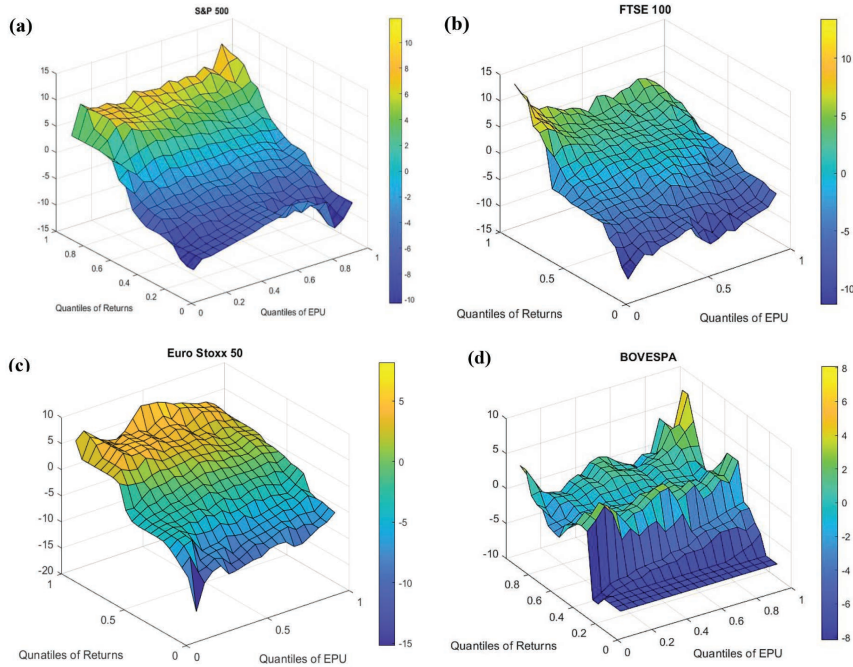


Figure 2: Impact of EPU on (a) S&P 500; (b) FTSE-100; (c) Euro Stoxx 50; and (d) BOVESPA.

Notes: Figures 2(a) to 2(d) shows the QQR estimates of the slope coefficient  $\beta_1(\theta, \tau)$  in stock markets. Where the slope coefficient  $\beta_1(\theta, \tau)$  is displayed on the z-axis of the graph, which measure the spillover effect of EPU shocks on stock returns of various markets, namely S&P 500, FTSE 100, Euro Stoxx 50 and BOVESPA.

For Natural Gas, Figure 3(c) exhibits that the overall impact of EPU on returns of natural gas is positive and negative. Further, the region surface of the graph that combines the lower to higher quantiles of EPU and middle-higher quantiles of returns, the impact of EPU on returns is strongly negative at middle quantiles (0.20–0.40). Whereas, at the lower-upper quantiles of EPU and higher quantiles of returns, the impact of EPU is positive. However, the effect is observed to be moderately strong at higher quantiles. Therefore, the findings indicate that EPU has a strong and negative effect on the returns of natural gas at a bearish state. In contrast, EPU positively affects the returns of natural gas at a bullish state.

In the context of Soybean, Figure 3(d) exhibits interesting findings, and we observed that the impact of EPU on Soybean returns is positive and negative. Further, the region surface of the graph, which combines the lower to higher quantiles of EPU and middle to higher quantiles of returns, the impact of EPU on returns is negative. Whereas, at the lower-upper quantiles of EPU and middle-higher and higher quantiles of returns (0.55–0.90), the impact of EPU is positive.

However, the effect is strongly positive at the middle and higher quantiles. Therefore, the findings indicate that EPU has a weak negative effect on the returns of Soybeans at a bearish state. In contrast, EPU has a strong positive effect on the returns of Soybeans in a bullish state.

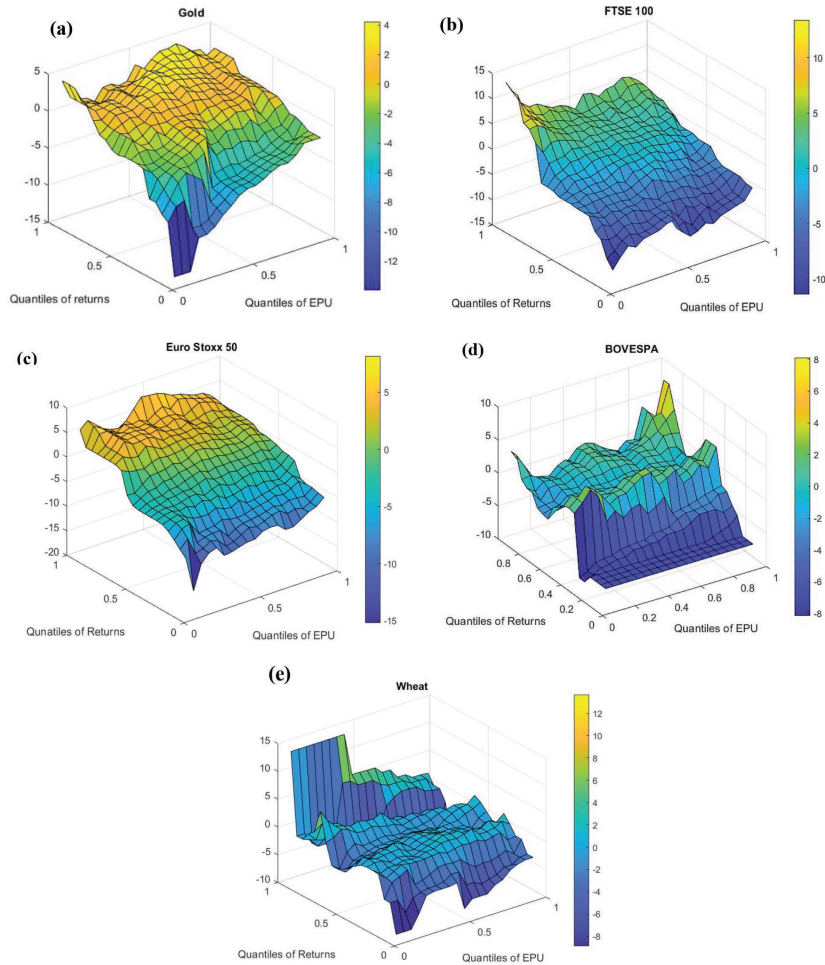


Figure 3: Impact of EPU on (a) Gold; (b) Copper; (c) Natural gas; (d) Soybean; and (e) Wheat.

Notes: Figures 3a to 3e shows the QQR estimates of the slope coefficient  $\beta_1(\theta, \tau)$  in commodities markets. Where the slope coefficient  $\beta_1(\theta, \tau)$  is displayed on the z-axis of the graph, which measure the spillover effect of EPU shocks on commodities returns of various markets, namely Gold, Natural Gas, Copper, Soybean and Wheat.

Whereas in Wheat, Figure 3(e) exhibits that the overall impact of EPU on wheat returns is strongly negative. Further, the region surface of the graph that combines the lower to higher quantiles of EPU and lower to higher quantiles of returns,

the impact of EPU on returns is strongly negative. Whereas, at the lower-upper quantiles of EPU and lower to higher quantiles of returns, the impact of EPU is strongly negative at lower, middle, and higher quantiles. Therefore, the findings indicate that EPU has a strong negative effect on wheat returns at a bearish state, whereas EPU has no significant effect on the returns at a bullish state.

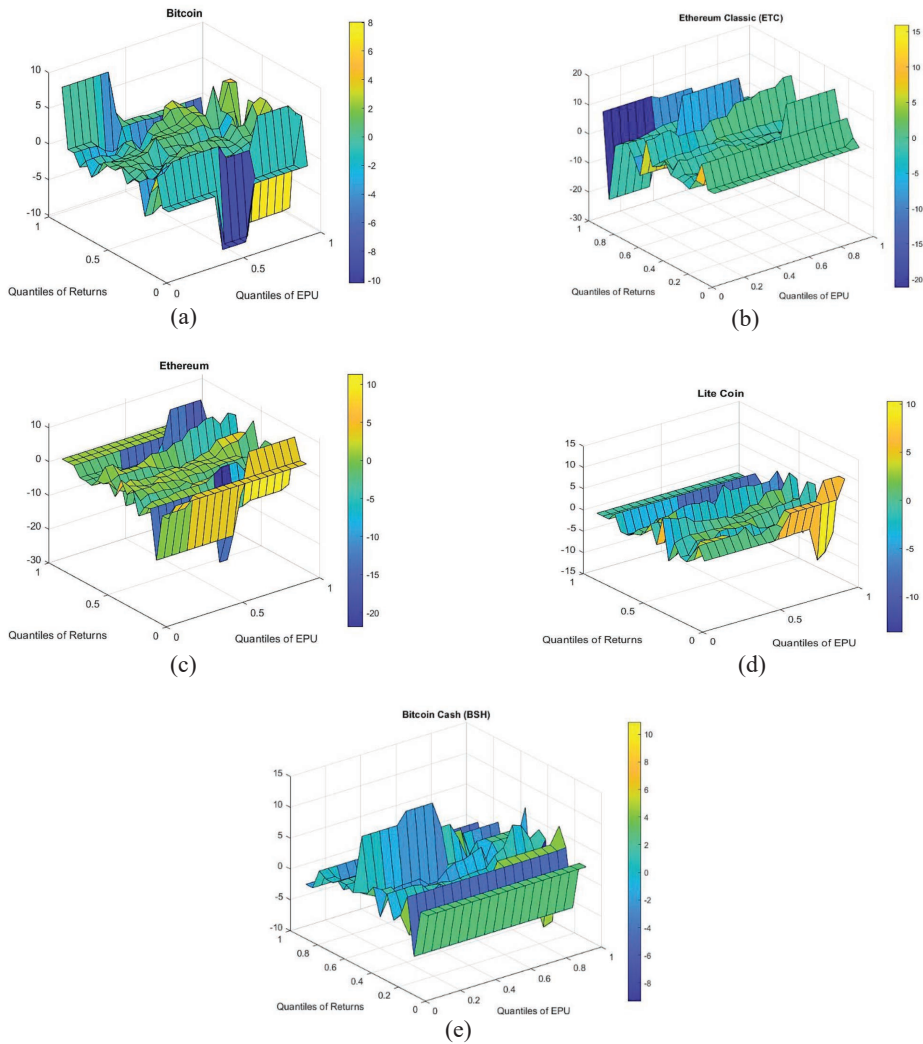


Figure 4: Impact of EPU on (a) Bitcoin; (b) Ethereum Classic; (c) Ethereum; (d) Lite Coin; and (e) Bitcoin Cash.

Notes: Figure 4a-4e shows the QQR estimates of the slope coefficient  $\beta_1(\theta, \tau)$  in commodities markets. Where the slope coefficient  $\beta_1(\theta, \tau)$  is displayed on the z-axis of the graph, which measure the spillover effect of EPU shocks on cryptocurrencies returns, namely Bitcoin, Ethereum, Ethereum Classic, Lite coin and Bitcoin Cash

The graphs shown in Figure 4 are visual results from a QQR analysis of major cryptocurrencies. It shows how EPU influences the returns of different cryptocurrencies at different quantiles at various levels of quantiles. Figure 4(a) exhibits that the overall impact of EPU on the returns of BTC is positive and negative. However, in the area under the surface graph that combines middle to upper quantiles of EPU and middle to upper quantiles of returns, the impact of EPU on returns is negative. At the upper quantiles of returns, we observed the positive impact of EPU on BTC. The findings indicate that during a bearish market, EPU in the U.S. negatively influences the returns of Bitcoin, whereas during a bullish market, EPU positively affects the returns of Bitcoin.

For Ethereum Classic, Figure 4(b) exhibits that EPU has a positive and significant effect on returns of Ethereum Classic at lower quantiles. Further, the region surface of the graph which combines the middle to upper quantiles of EPU and middle to upper quantiles of returns, the impact of EPU on returns is positive and negative. Whereas, at the lower-upper quantiles of EPU and upper quantiles of returns, the impact of EPU is negative. Similarly, we observed a positive impact on returns at middle and higher quantiles. Therefore, the findings indicate that EPU positively affects the returns in a bearish state, whereas EPU negatively affects the returns in a bullish state.

For Ethereum, Figure 4(c) exhibits that the overall impact of EPU on returns of Ethereum is positive and negative. Further, the region surface of the graph that combines the middle to higher quantiles of EPU and middle-higher quantiles of returns, the impact of EPU on returns is positive at lower-middle quantiles (0.30–0.44) and middle-higher quantiles (0.5–0.95). Interestingly, we observed that EPU positively affects the returns at middle-higher quantiles and negatively affects the return at higher quantiles. The findings indicate that EPU positively affects the returns at a bearish state, whereas EPU positively and negatively affects the returns at a bullish state.

In the context of Litecoin, Figure 4(d) exhibits interesting findings, we observed that the impact of EPU on the returns of Litecoin is positive and negative. Further, the region surface of the graph, which combines the middle to higher quantiles of EPU and middle to higher quantiles of returns, shows that the impact of EPU on returns is positive. Whereas, at the middle-higher quantiles of EPU and middle-higher and higher quantiles of returns (0.55–0.90), the impact of EPU is negative but the effect is observed strongly negative at higher quantiles. Therefore, the findings indicate that EPU has a weak and strong positive effect on the returns of Lite Coin at bearish state, whereas EPU has a negative effect on the returns of Lite Coin at bullish state.

In Bitcoin Cash, Figure 4(e) exhibits that the overall impact of EPU on returns of Bitcoin Cash is positive and negative. Further, the region surface of the graph that combines the lower to higher quantiles of EPU and lower to higher quantiles of returns, the impact of EPU on returns is positive. Whereas, at the lower-upper quantiles of EPU and lower to higher quantiles of returns, the impact of EPU is negative at lower, middle, and higher quantiles. Therefore, the findings indicate that EPU has a positive effect on the returns of Bitcoin Cash in a bearish state, whereas EPU has a negative effect on the returns of Bitcoin Cash in a bullish state.

### **Robustness Check: Quantile Regression**

To validate the consistency of our preliminary estimations using the QQR approach, we use quantile regression to assess the robustness of QQR results. Tables 4 to 6 show the estimation output of quantile regression between EPU and returns of stock markets, cryptocurrencies and commodities markets across different quantiles (0.1, 0.5 and 0.9). Furthermore, 0.1 represents the lower quantile, while 0.5 and 0.9 represent the middle and higher quantiles. Moreover, Table 4 values indicate that EPU has a time-varying effect on stock markets at various quantiles. We observed that EPU has a negative effect on stock markets (S&P 500, FTSE 100 and Euro Stoxx 50) at lower quantiles, while EPU positively affects the stock markets at higher quantiles. Furthermore, the findings indicate that EPU has a pronounced effect on stock markets from lower to higher quantiles. Whereas for commodities, Table 5 reported that EPU negatively affects the returns of commodities at lower quantiles and positively affects the returns at middle and higher quantiles. Furthermore, we report that EPU has a moderate to strong effect on Soybean and Wheat at higher quantiles. For cryptocurrencies, Table 6 reported that EPU positively affects the return at lower quantiles, while we observed negative effects at higher quantiles. Moreover, we also report that EPU significantly (positive and negative) affects the return of cryptocurrencies at middle quantiles.

Furthermore, Figures 5 to 7 show the graphical representation of quantile regression, which exhibits that EPU has a time-varying effect on returns of stocks, commodities, and cryptocurrencies from lower to higher levels of quantiles. Moreover, it is concluded that the effect of EPU is not uniform across all quantiles. Whereas the positive impact of EPU on cryptocurrencies at lower and middle quantiles indicates that cryptocurrencies could also serve as a diversifier in hedging effectiveness in the short-term, while we observed that the effect of EPU diminishes in higher quantiles. Similarly, quantile regression estimation validates QQR regression outcomes across various quantiles from lower to higher.

Table 4  
*Quantile regression: Stock markets*

Markets	Independent variable	0.1	0.5	0.9
S&P 500	EPU	-0.05661***	0.00684	0.03365***
FTSE 100	EPU	-0.03766***	-0.00081	0.01907**
Euro Stoxx 50	EPU	-0.06422***	-0.00642	0.02485***
BOVESPA	EPU	-0.01144	0.002	0.00658

Note: \*\*\*(significance at 1%), \*\*(significance at 5%), \*(significance at 10%)

Table 5  
*Quantile regression: Commodity markets*

Markets	Independent variable	0.1	0.5	0.9
Gold	EPU	-0.0022	0.01806*	0.01973**
Copper	EPU	-0.02417	0.02053**	0.02704**
Natural Gas	EPU	-0.01949	-0.02027	0.04105
Soybean	EPU	-0.01466	0.0104	0.00373
Wheat	EPU	-0.00924	-0.00475	0.0028

Note: \*\*\*(significance at 1%), \*\*(significance at 5%), \*(significance at 10%)

Table 6  
*Quantile regression: Cryptocurrencies markets*

Markets	Independent variable	0.1	0.5	0.9
BTC	EPU	0.20735***	0.07915	-0.01899
ETC	EPU	0.13163*	0.09495	-0.06981
ETH	EPU	0.23026***	0.24477***	0.0568
LTC	EPU	0.11332	0.07058	-0.02694
BSH	EPU	0.22617***	0.13597	-0.21488

Note: \*\*\*(significance at 1%), \*\*(significance at 5%), \*(significance at 10%)

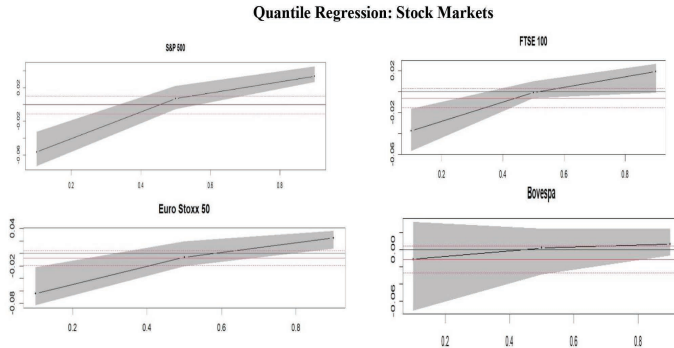


Figure 5: The time-varying effect of EPU on stock markets using quantile regression.

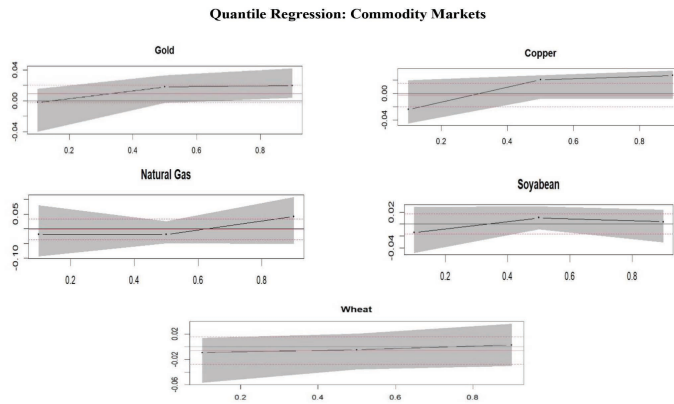


Figure 6: The time-varying effect of EPU on commodity markets using quantile regression.

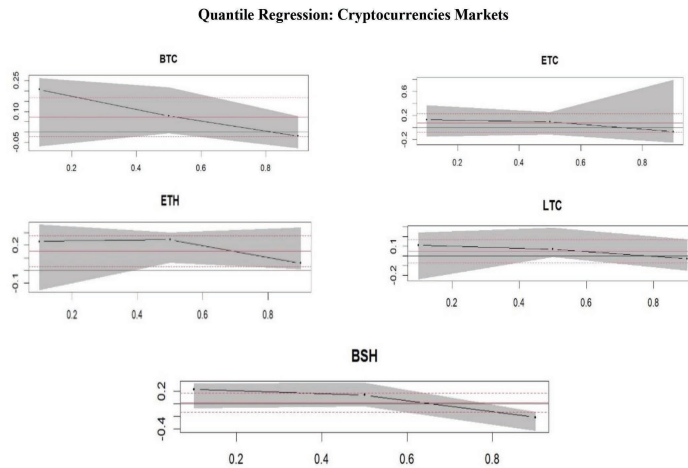


Figure 7: The time-varying effect of EPU on cryptocurrencies markets using quantile regression.

## DISCUSSION

Starting with stock markets, as illustrated by the Quantile-on-Quantile regression graphs (Figure 2), there is a general trend that higher EPU levels correspond to more volatility in stock returns. For instance, the S&P 500 showed increased return fluctuations when EPU was high. This suggests that investors could react to the perceived risks during policy uncertainty, leading to more erratic stock market movements (Arshad et al., 2024). The commodities and the impact of EPU seem diverse. Traditionally viewed as a haven, gold had its returns fluctuate at higher levels of EPU, indicating investors' tendency to flock to gold during uncertain economic times. On the other hand, assets like Copper and Wheat showed varying sensitivity to EPU, with some stability at lower EPU levels but more variability as uncertainty rose. Cryptocurrencies showed an even more pronounced response to changes in EPU (referred to as Figure 4). Bitcoin and other cryptocurrencies like Ethereum Classic and Litecoin demonstrated high volatility across all EPU levels, with drastic changes in returns. This highlights the speculative nature of cryptocurrencies and suggests that they are particularly sensitive to policy-related news and events. The descriptive statistics table (Table 2) provides a numerical backdrop to these findings. It shows the average levels and variability of returns for each asset class over the study period. Our study's conclusions are consistent with those of earlier research. According to Koutmos (1999), stock prices react to negative news quicker than positive news. However, policy changes make cryptocurrency markets more volatile. Comparably, the bearish, normal and bullish market situations are associated with the lower, middle and higher quantiles, respectively (Albulescu et al., 2020; Balcilar et al., 2018; Shafiullah et al., 2020). Lobo (2000) documents that policy rates negatively affect stock prices. Similarly, EPU captures economic fundamentals, and it drives the precious metal (Huynh, 2020; Püttmann, 2018). Numerous studies show that there is less reliance between Bitcoin and traditional financial markets in terms of return volatility (Demir et al., 2018; Panagiotidis et al., 2019; Gozgor et al., 2019; Wu et al., 2019; Shiba et al., 2023). According to Chen et al. (2021), Bitcoin can be utilised as a hedging strategy against the EPU during uncertain times. It also proves that higher returns are associated with uncertainty. According to Fasanya et al. (2021), precious metals and bitcoin may not be a haven or hedge against the US EPU. Further, their findings reveal that the medium and higher quantiles exhibit strong connectedness between EPU and markets. Similarly, during the COVID-19 pandemic, the EPU in the US significantly influence the stock markets, oil and currency, and commodity markets (Albulescu, 2019; Das et al., 2019; Shahbaz et al., 2017). Matkovskyy et al. (2020) document that in investment attractiveness, gold acts as a hedging tool during uncertainty in the US. Maquieira et al. (2023) find that each industry behaves differently when it comes to the relationship between EPU and stock



returns. Similarly, global EPU positively affects cryptocurrency returns at lower quantiles, while in upper quantiles, EPU has an adverse impact on cryptocurrency returns (Umar et al., 2023; Sayim & Quang-My, 2023). Asiri et al. (2023) argue that cryptocurrency uncertainty indices heighten in the crisis period, and they emerge as influential transmitters of shocks to other financial asset classes.

## **CONCLUSION**

In recent years, examining the interdependence between EPU, cryptocurrencies and commodities has largely gained the insight of researchers to analyse the relationships (Fasanya et al., 2021). Several studies highlight the increasing importance of the financialisation of commodity markets (Rehman, 2020) characteristics of these commodities for hedging, and the ability of haven assets (Shahbaz et al., 2018; Rehman et al., 2018). Therefore, we investigate the relationship by examining the dynamic impact of EPU on cryptocurrencies, commodities and stock markets using the QQR approach of Sim and Zhou (2015). Similarly, the US EPU greatly influences financial markets, commodities and cryptocurrencies, responding uniquely to different levels of policy uncertainty. Our findings are consistent with the broader literature that acknowledges the profound impact of policy uncertainty on market dynamics (Brogaard & Detzel, 2015). The QQR findings suggest that traditional markets like stocks and commodities may resist moderate levels of EPU because they are vulnerable to high volatility during extreme uncertainty, reaffirming the systemic risks discussed in the literature (Bekaert et al., 2013). To validate our earlier findings, we employ quantile regression for robustness check, and the findings support the primary findings of QQR at various levels of quantiles. Furthermore, our findings reveal that cryptocurrencies are extremely volatile among other financial assets due to economic policy uncertainty. Therefore, the findings are helpful for investors to better manage the risk by understanding how different asset classes respond to economic policy uncertainty. For example, the tendency of gold to become a haven during high EPU periods could inform strategies for hedging against risk. Understanding the differential impact of EPU on various assets can help investors diversify their portfolios more effectively, balancing assets sensitive to EPU with more stable ones. Investors can also make strategic investment decisions with insights into how EPU affects market volatility and can make more informed decisions on when to enter or exit positions. For instance, they might invest in cryptocurrencies when EPU is expected to rise, capitalising on potential high returns despite the risks. By recognising the patterns of market behaviour in response to EPU, investors could potentially improve market timing, identifying opportunities to buy assets at lower prices or sell them before expected downturns. Investors can monitor economic policy discussions and forthcoming decisions more closely, as these will likely influence market movements.

Similarly, our study reports some limitations. Despite the contributions of our study, we limited our scope to the US EPU and its immediate impact on stocks, commodities and cryptocurrencies without considering the impact of local and global EPU or memory lengths. Therefore, future research could expand the scope of EPU to include a more global perspective. Expanding the study to include how global EPU's affect international markets could offer a more comprehensive understanding of its impact on a wider scale. It would be valuable to look at the long-term influence of economic policy uncertainty on financial assets to see if the immediate trends observed hold over time. As news and social media significantly shape investor perception, examining their influence on the relationship between EPU and market performance would be enlightening.

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