Sosyoekonomi

2025, Vol. 33(66), 289-306

RESEARCH ARTICLE

ISSN: 1305-5577
DOI: 10.17233/sosyoekonomi.2025.04.13
Date Submitted: 26.12.2024
Date Revised: 25.03.2025
Date Accepted: 02.10.2025

An Analysis of How Economic and Monetary Policy Uncertainty Affect the Cryptocurrency Market

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Ekonomi Politika Belirsizliğinin ve Para Politikası Belirsizliğinin Kripto Para Piyasası Üzerindeki Etkisi

Abstract

This study examines how Economic Policy Uncertainty (EPU) and Monetary Policy Uncertainty (MPU) affect the returns of ten different cryptoassets using Quantile Regression (QR) and Robust Least Squares (RLS) methods. Quantile regression allows a nuanced examination of how these uncertainties affect returns at different levels under market conditions. Using monthly data from January 1, 2018, to June 1, 2024, the analysis shows that MPU has a negative impact on cryptoasset returns under normal and bull market conditions. However, this effect diminishes during bear market periods. Conversely, EPU has a significant negative impact only during bull markets. These results suggest that market conditions critically shape the sensitivity of cryptoassets to uncertainty, with such effects amplified during bull market periods.

Keywords : Monetary Policy Uncertainty, Economic Policy Uncertainty, Quantile Regression, Cryptocurrencies.

JEL Classification Codes : E44, E52, G22, G15.

Öz

Bu çalışma, on farklı kripto varlığın getirileri üzerindeki Ekonomi Politikası Belirsizliği (EPU) ve Para Politikası Belirsizliği (MPU) etkilerini, Kantil Regresyon (QR) ve Robust Least Squares (RLS) yöntemleri kullanarak değerlendirmektedir. Kantil regresyon, piyasa koşullarına göre farklı getiri düzeylerinde bu belirsizliklerin etkilerini esnek bir şekilde incelemeye olanak tanır. Elde edilen bulgular, MPU'nun normal ve boğa piyasası koşullarında kripto varlık getirileri üzerinde olumsuz bir etki yarattığını, ancak ayı piyasasında bu etkinin anlamlı olmadığını göstermektedir. EPU ise sadece boğa piyasasında belirgin bir olumsuz etki göstermektedir. Sonuçlar, piyasa koşullarının kripto varlıkların belirsizliklere tepkilerinde önemli bir rol oynadığını ve boğa piyasalarında belirsizliklerin etkisinin daha güçlü olduğunu ortaya koymaktadır.

Anahtar Sözcükler : Para Politikası Belirsizliği, Ekonomi Politikası Belirsizliği, Kantil Regresyon, Kripto Para Birimleri.

1. Introduction

These digital assets aim to transform traditional currencies and payment methods by enabling digital transactions (He et al., 2024). Since the inception of bitcoin, the first cryptocurrency, demand for and trust in cryptocurrencies have skyrocketed, leading to the stable expansion of the crypto market in recent years. Significant losses in the financial sector, particularly after the 2008 global financial crisis, eroded public confidence in conventional financial systems; this, in turn, drove the desire for decentralised currency alternatives free from government control and banking regulations, leading to the growth of the cryptocurrency market (Sharma, 2023). Following the success of Bitcoin, numerous alternative cryptoassets, or "altcoins", were introduced as competitors, leading to the creation of dedicated markets for trading these digital assets.

Cryptocurrencies have become a focal point for investors, policymakers, and academics, especially in 2017. This is due to the high returns that can be achieved with significant price increases (Umar et al., 2023). As a result of these developments, a considerable amount of research has been conducted on the dynamics of cryptocurrencies and the role of cryptocurrencies within the broader financial system, without a consensus on the subject yet (Duan et al., 2023). Some analysts view cryptocurrencies as a significant challenge to the perceived shortcomings of the current monetary and financial system, while others view them as speculative assets with minimal or no economic value (Karau, 2023). The independence of cryptocurrencies from government monetary policy and their distinct characteristics from other money market assets have been interpreted by some scholars as an immunity to policy uncertainty. However, recent studies have begun to investigate the influence of specific financial and non-financial uncertainties on cryptocurrencies (Wang et al., 2023).

The Economic Policy Uncertainty (EPU) index was constructed by Baker et al. in 2013 using articles on economic policy uncertainty in leading US newspapers. The index is based on the frequency of occurrence of specific terms related to economic policies such as "uncertainty", "economy", "congress", "budget deficit", "federal reserve", "legislation", "regulation" and was developed by Baker, et al. (2015) and Baker et al. (2016) (Korkmaz & Güngör, 2018). The Monetary Policy Uncertainty (MPU) index was constructed by Husten et al. in 2017 using articles in leading newspapers that contain keywords related to monetary policy uncertainty. The index is based on the frequency of occurrence of keywords such as "uncertainty", "monetary policy", "interest rate", "federal funds rate", "Fed funds rate", "Federal Reserve", "Fed", and "Federal Open Market Committee". In sum, economic policy uncertainty takes into account uncertainty in areas such as fiscal, monetary, trade, health, national security, regulatory policies, while monetary policy uncertainty only takes into account market-based indicators such as the volatility in interest rate option prices and intraday price movements of interest rate futures, as well as the policy decisions of the central bank (Husted et al., 2017).

A country's economic development depends on the effectiveness of its economic policies. Therefore, uncertainties in a given country may potentially harm economic growth. Existing literature suggests that heightened economic policy uncertainty (EPU) is associated with reduced financial stability, increased stock market volatility, and constrained liquidity (Zhang et al., 2024). Price fluctuations accelerate in an uncertain economic environment, especially in the highly volatile cryptocurrency market (Özkan, 2018). Moreover, EPU tends to discourage investors by increasing their risk aversion. Whether this phenomenon also manifests itself in the cryptocurrency market has recently emerged as a subject of investigation. Yen and Cheng (2021) stated that EMU creates a hedging effect on crypto market volatility. In increased uncertainty, investors will replace the assets in their portfolios with cryptocurrencies, thinking that other financial instruments will be more affected by uncertain economic conditions. As a result, cash inflows will be provided to the cryptocurrency market.

The cryptocurrency market consists of thousands of coins and is subject to fluctuations based on various factors (Sharma, 2023). Economic policy uncertainty and monetary policy uncertainty, which have been shown to adversely affect economic growth, investment decisions, and financial market volatility, have been identified in numerous studies as a significant determinant of cryptocurrency returns and volatility (Khan et al., 2021; Foglia & Dai, 2022; Umar et al., 2023; Kılıç, 2024).

Most of the existing literature includes studies examining the impact of economic and monetary policy uncertainty on cryptocurrencies that focus exclusively on Bitcoin, the first and most significant cryptocurrency. The existing literature on the effects of uncertainty on various cryptocurrencies is limited. Furthermore, there is a lack of studies that address the impact of both economic policy uncertainty (EPU) and monetary policy uncertainty on multiple cryptocurrencies. Accordingly, this study addresses a significant gap in the existing literature. This study makes a substantial contribution to the existing literature by examining the impact of global economic policy uncertainty and monetary policy uncertainty on ten different cryptocurrencies (Bitcoin, Ethereum, Tether USD, BNB, Dogecoin, Cardano, Litecoin, XRP, Stellar, and TRON), as determined by market capitalisation.

Cryptocurrency markets are significantly affected by global macroeconomic uncertainties. In particular, EMU and MPU are among the key factors shaping investor risk perception. In times of economic uncertainty, investors in traditional financial markets seek safe harbours and avoid risky assets. Such uncertainties directly affect cryptocurrencies due to their high volatility and speculative investment. Economic policy uncertainty (EPU) is an essential variable due to the sensitivity of cryptocurrencies to regulatory risks. The incomplete regulatory framework of the crypto market has a negative impact on investor confidence, especially during periods of high uncertainty. This leads to significant changes in crypto asset returns depending on market conditions. EMU and MPU are considered appropriate explanatory variables for cryptocurrency returns in this context.

This study attempted to fill this critical gap in the literature by addressing the effects of uncertainty on the cryptomarket in terms of economic policy uncertainty (EPU) and monetary policy uncertainty (MPU). Earlier attempts in the literature were on single-source uncertainty; this study departs by dividing the effects between markets under dissimilar market conditions. These methods would bring out the heterogeneities in the impact that market conditions have on uncertainty and reveal more profound insight into the sensitivity of the crypto assets. From that point of view, the paper makes a theoretical and methodological contribution to understanding the dynamics of cryptocurrency markets.

2. Literature Review

A literature review shows that studies have examined the effects of central bank and economic policy uncertainty on cryptocurrency markets, focusing on Bitcoin. The impact of monetary policy announcements on cryptocurrency price fluctuations, information efficiency, and economic uncertainty on volatility has been analysed using various econometric methods and models. The results indicate that central bank announcements affect cryptocurrency prices, Bitcoin is consistent with the semi-strong form market efficiency hypothesis, economic policy uncertainty has a negative impact on cryptocurrency returns, and these uncertainties play a central role in market dynamics. Taken together, these studies underscore the vulnerability of cryptocurrency markets to economic and political uncertainty. A comprehensive overview of these studies is presented in Table 1.

Table: 1
Literature Summary

Category	Authors	Aim of the Study	Methods	Results
Effects of Central Bank & Monetary Policies on Crypto Markets	Corbet, McHugh & Meegan (2014)	Examining the impact of central bank announcements on cryptocurrency markets	GARCH model, regression analysis	Central bank policies significantly affect cryptocurrency price volatility.
	Nguyen et al. (2019)	To analyse the asymmetric effects of monetary policies on cryptocurrency markets	Regression models, asymmetric analysis	The effects of monetary policy announcements vary according to market conditions.
	Gürsoy (2021)	To investigate the impact of US and Japanese monetary policy uncertainty on Bitcoin prices	Asymmetric causality test	Monetary policy uncertainty does not have a significant effect on Bitcoin prices.
Economic Policy Uncertainty (EPU) & Cryptocurrency Volatility	Wang et al. (2019)	Measuring the effects of economic policy uncertainty on Bitcoin	Granger causality test, volatility modelling	Bitcoin volatility increases significantly when the EPU increases.
	Cheng & Yen (2020)	Analysing the impact of EPU on price movements in the cryptocurrency market	Econometric analysis, regression models	China's EPU index predicts Bitcoin returns, but other countries' EPUs are ineffective.
	Yen & Cheng (2021)	To analyse the impact of EPU changes on cryptocurrency markets	Regression analysis, time series models	Changes in the Chinese EPU negatively affect Bitcoin and Litecoin volatility.
	Mokni (2021)	To analyse the effects of economic policy uncertainty on Bitcoin on a quantile basis	Quantile regression, volatility modelling	EMU can predict Bitcoin returns under high market conditions, and volatility increases during periods of high uncertainty.
Cryptocurrency Policy Uncertainty & Price Dynamics	Karaömer (2022)	Determining the role of cryptocurrency policy uncertainty on Bitcoin prices	Econometric models, regression analysis	Cryptocurrency policy uncertainty negatively affects Bitcoin prices.
Impact of Political and Economic Uncertainties on Cryptocurrencies	Colon et al. (2021)	To investigate the impact of political and economic uncertainties on cryptocurrency markets	Regression analysis, volatility modelling	Political and economic uncertainties cause increased volatility in cryptocurrency markets.

	Shaikh (2020)	Analysing the effects of political uncertainties on Bitcoin	Quantile regression, Markov regime switching model	There are significant changes in Bitcoin returns when political uncertainty increases.
Global Economic Uncertainty and Cryptocurrency Markets	Fang et al. (2019)	Analysing the relationship between global economic uncertainty and Bitcoin volatility	Econometric models, regression analysis, and hedge effectiveness analysis	During periods of global economic uncertainty, Bitcoin volatility increases and hedging effectiveness changes.
	Khan et al. (2021)	To evaluate the impact of global economic uncertainty on Bitcoin price movements	Econometric analysis and volatility modelling	Küresel ekonomik belirsizlik, Bitcoin fiyatlarında dalgalanmalara ve volatilitenin artmasına neden olmaktadır.
Long-Term Effects of Uncertainty & Spillover Effect	Umar et al. (2023)	Measuring the impact of economic policy uncertainty on cryptocurrency markets before and after the pandemic	Panel data analyses, quantile regression	Global EPU increase has a positive effect on low cantiles and an adverse effect on high cantiles.
	Simran & Sharma (2023)	Analysing the impact of long-term economic policy uncertainty on cryptocurrencies	NARDL approach (Asymmetric ARDL model)	In the long term, all cryptocurrencies except Tether are negatively affected by EPU.
	Kılıç (2024)	To analyse the relationship between Global Economic Policy Uncertainty (GEPU) and Bitcoin	RALS cointegration tests (Residual Augmented Least Squares)	GEPU changes significantly affect Bitcoin prices and increase volatility.
Economic Uncertainty & Risk Aversion	Haq et al. (2021)	Assessing the relationship between economic uncertainty and cryptocurrency markets	Literature review, compilation study	Economic policy uncertainty affects the volatility of cryptocurrency markets, and risk aversion varies by country.
	Foglia & Dai (2022)	To analyse the relationship between economic policy uncertainty and uncertainty in the cryptocurrency market	Econometric analyses, spillover effect (spillover) models	Economic policy uncertainty increases uncertainty in cryptocurrency markets, leading to a spillover effect.

Table 1 systematically reviews the studies and includes studies examining the effects of economic and political uncertainties and central bank policies on cryptocurrency markets. These studies emphasise that monetary policy uncertainty and central bank policy announcements may increase volatility in cryptocurrency markets. It is also emphasised that this effect may vary depending on market conditions. It is also observed that EMU increases the volatility in bitcoin and various cryptocurrencies, and this effect varies according to market uncertainties that directly affect crypto markets. Still, this effect may vary depending on market dynamics, country-based factors, and regulations.

Many studies examine the impact of macroeconomic factors such as central bank policies, economic uncertainty, and policy uncertainty on cryptocurrency markets. Corbet, McHugh, and Meegan (2014) tested the hypothesis that central bank announcements increase price volatility in cryptocurrency markets and found that the market is sensitive to such policies. Similarly, Vidal-Tomás and Ibañez (2018) showed that Bitcoin prices respond quickly to market information and are consistent with the semi-strong market efficiency hypothesis. Nguyen et al. (2019) confirmed the hypothesis that monetary policy announcements have asymmetric effects depending on market conditions. Gürsoy (2021) found that the economic policy uncertainties of the US and Japan do not significantly impact Bitcoin prices. In addition, Karaömer (2022) tested the hypothesis that cryptocurrency policy uncertainty negatively affects Bitcoin prices and obtained supportive findings. Wang et al. (2019) and Fang et al. (2019) suggested that increases in economic policy uncertainty significantly increase Bitcoin volatility.

When the findings are examined, it is observed that economic and political uncertainties generally create volatility-increasing effects on cryptocurrency markets. For example, Cheng and Yen (2020) and Yen and Cheng (2021) showed that China's economic policy uncertainty (EPU) index has an adverse effect on Bitcoin and Litecoin volatility. Shaikh (2020) and Mokni (2021) found that the impact of economic policy uncertainty on Bitcoin returns varies depending on market conditions. Umar et al. (2023) showed that global EPU has a positive effect on low returns and an adverse effect on high returns. Simran and Sharma (2023) determined that all cryptocurrencies except Tether are negatively affected by economic policy uncertainty in the long run. When the effects of policy uncertainty and economic uncertainty variables on cryptocurrency markets are evaluated, it is possible to make inferences about financial development and economic complexity. When economic policy uncertainty increases, the change in demand for assets such as Bitcoin manifests differently in countries with high financial development. For example, investors' risk perceptions and orientation towards alternative investment instruments are based on more rational decision mechanisms in economies with developed financial markets. The study by Kılıç (2024) showed that changes in global economic policy uncertainty significantly affect Bitcoin prices and increase volatility. This situation indicates that portfolio diversification strategies and investor behaviours may take different forms in economies with a high level of financial development.

As a result, despite the concentration of studies on economic policy uncertainty and cryptocurrency markets in the literature, the role of financial development and economic complexity in this interaction has not been examined comprehensively. Future studies can analyse the role of economic complexity and financial development on these markets in more detail by addressing investor reactions to cryptocurrency markets in countries with different levels of financial development.

3. Methodology

3.1. Unit Root Tests

Before proceeding with regression analysis, it is imperative to first test for the presence of unit roots in the time series data. Failure to do so can result in spurious regression, where the relationships identified between variables appear significant merely due to shared trends, rather than any meaningful economic or statistical connection. Spurious regression typically arises when non-stationary time series are modelled without first addressing their stochastic properties, leading to inflated R-squared values and misleading inferences (Granger & Newbold, 1974). To mitigate this issue, unit root tests determine whether the data are stationary or contain unit roots. ADF test proposed by Dickey and Fuller (1979; 1981) and PP developed by Phillips and Perron (1989) unit root tests are widely utilised econometric tools for determining whether a time series is stationary. These tests are particularly employed in analysing macroeconomic time series to investigate the impact of long-term trends and temporary shocks. Under the assumption of stationarity, the mean, variance, and covariance of the time series are expected to remain constant over time. If this condition is violated, the series is called to contain a unit root, indicating non-stationarity. ADF test is an extension of the basic Dickey-Fuller test, which includes autoregressive (AR) terms to account for higher-order serial correlation. The ADF test checks for a unit root's presence while controlling for autocorrelation within the residuals. The test achieves this by incorporating lagged difference terms into the regression equation through three approaches (Dickey & Fuller, 1979; 1981).

$$\Delta y_t = \delta y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \varepsilon_i \text{ (none)} \tag{1}$$

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \varepsilon_i \text{ (intercept)} \tag{2}$$

$$\Delta y_t = \mu + \beta t + \delta y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \varepsilon_i \text{ (intercept\&trend)} \tag{3}$$

where μ is the intercept, t is the deterministic trend and ε_i is the error term. The test statistic is compared against a critical value, and if the calculated statistic falls below the critical threshold, the null hypothesis of non-stationarity is rejected, implying that the series does not contain a unit root (Chang & Park, 2002). On the other hand, the PP test offers a non-parametric alternative to the ADF test. The key distinction lies in its ability to account for serial correlation and heteroskedasticity in the error terms without the need for explicitly specifying lag terms. The PP test adjusts the test statistic for any autocorrelation or heteroskedasticity in the residuals, providing a more flexible approach. One of the key advantages of the PP test is its reduced reliance on the selection of lag length, thereby mitigating the risk of model misspecification. It is particularly useful in analysing time series with lower frequencies and in long-term studies where structural shifts may occur over time. Basic test equation is as follows:

$$\Delta y_t = a y_{t-1} + x_t' \delta + \varepsilon_t \tag{4}$$

In Eq. (4), α corresponds to $\rho - 1$, while x_t represents the deterministic components (either the intercept or intercept and trend), and ε_t denotes the error term. The null hypothesis suggests that the series contains a unit root (Phillips & Perron, 1989).

Both tests are highly effective for evaluating long-term equilibrium relationships and the persistence of trends in time series data. The distinct methodological approaches of the ADF and PP tests make them complementary tools in econometric analysis. In particular, ADF is a parametric test, relying on specific lag structures, while the PP test, with its non-parametric adjustments, provides broader model flexibility. As a result, the choice between these tests often depends on the data's characteristics and the analysis's specific econometric requirements.

3.2. Quantile Regression

By their nature, financial time series often do not exhibit normal distribution and contain extreme outliers. Standard methods, such as the OLS estimation method, are generally insufficient for analysing such series. The OLS approach assigns equal weight to all observations in the series, disregarding outliers. Additionally, this approach only makes predictions at a specific point of the conditional distribution of the dependent variable. The quantile regression model, introduced by Koenker and Bassett (1978), offers a more flexible framework than OLS. The quantile regression model accounts for outliers in the series and allows for examining the effects of independent variables across the entire conditional distribution of the dependent variable, providing a more comprehensive analysis. In other words, quantile regression enables the evaluation of how changes in the independent variable affect the dependent variable at different distribution quantiles. Initially applied to cross-sectional data sets, quantile regression has since been extended to both time series and panel data sets (Koenker & Basset, 1978; Koenker, 2004; Koenker & Xiao, 2004; Koenker & Xiao, 2006). This paper investigates how the returns of 10 cryptocurrencies respond to monthly monetary and economic policy uncertainty changes from January 2018 to June 2024. The quantile regression model expresses this relationship as represented in Eq.(5):

$$y_t = x_t\beta(\tau) + \varepsilon(\tau)_t, Quantile_\tau(y_t|x_t) = x_t\beta(\tau) \tag{5}$$

where t represents the cryptocurrency returns at time t, x_t is the vector of independent variables, and $\beta(\tau)$ is the parameter vector. $Quantile_\tau(y_t|x_t)$ represents the conditional quantile of y_t given x_t, for the observation at t, with x_t representing the known explanatory variable vector. In other words, it refers to the τ-th quantile of the variable y_t, conditional on x_t, and is used to estimate the expected value of a variable at a certain probability level (e.g., 10%, 50%, or 90%, which falls within the range of 0 to 1). The quantile regression estimator is obtained by minimising the function in Eq. (6) and can be rewritten as demonstrated in Eq. (7):

$$\min_{\beta\epsilon R^k}\{\textstyle\sum_{t:y_t>x_t\beta}^{n} \tau|y_t - x_t\beta(\tau)| + \sum_{t:y_t<x_t\beta}(1-\tau)|y_t - x_t\beta(\tau)|\} \tag{6}$$

$$\min_{\beta\epsilon R^k} \textstyle\sum_t \rho_t(y_t - x_t\beta(\tau)) \tag{7}$$

At this stage the indicator function $\rho_\tau(\varepsilon) = (\tau - 1)_\varepsilon$ is employed when ε>0. In the simultaneous quantile regression model, the relationship between the variables is estimated simultaneously for the defined quantile vector. This model estimates the standard errors of the coefficients using the bootstrap method. In the bootstrap approach, the number of replications should be chosen as large as possible to ensure the standard errors of the coefficients are stable.

4. Data and Empirical Results

This study uses monthly data from January 2018 to June 2024. The time frame covers a period in which the cryptoasset market has attracted more institutional investors and has become more affected by policy uncertainty. In the analysis, economic policy uncertainty (EPU) and monetary policy uncertainty (MPU) variables are used to examine the effects of these uncertainties on crypto asset returns.

Table: 1
Data Information

Variables	Abbrevation	Unit	Transformation	Data Source
Economic Policy Uncertainty	EPU	Index	Natural logarithm of EPU	Policyuncertainty.com
Monetary Policy Uncertainty	MPU	Index	Natural logarithm of MPU	Policyuncertainty.com
Bitcoin	BTC	%	First Different Logarithm	https://tr.investing.com
Ether	ETH	%	First Different Logarithm	https://tr.investing.com
Tether	USDT	%	First Different Logarithm	https://tr.investing.com
Bnb	BNB	%	First Different Logarithm	https://tr.investing.com
Dogecoin	DOGE	%	First Different Logarithm	https://tr.investing.com
Card	CRD	%	First Different Logarithm	https://tr.investing.com
Lite	LT	%	First Different Logarithm	https://tr.investing.com
Xrp	XRP	%	First Different Logarithm	https://tr.investing.com
Ste	STE	%	First Different Logarithm	https://tr.investing.com
Tron	TRX	%	First Different Logarithm	https://tr.investing.com

Before proceeding with correlation and unit root analyses, we present the variables' summary statistics to provide an overview of their central tendencies, dispersion, and distributional characteristics. These statistics help us better understand the underlying properties of the data, including potential skewness, kurtosis, and asymmetries that may influence the modelling section.

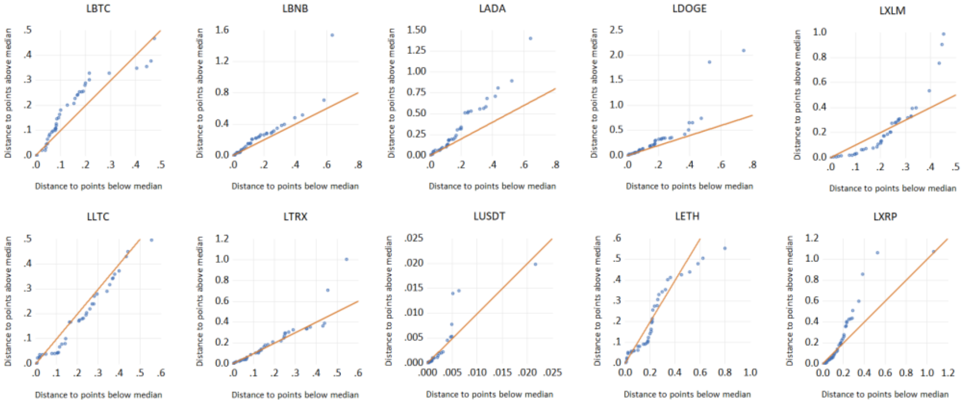
Table: 2
Summary Statistics

Variables	Mean	Median	Std. Deviation	Max.	Min.	Skewness	Kurtosis	JB
LEPU	5.5014	5.4958	0.2130	6.0676	5.0607	0.2330	2.5248	1.4027
LMPU	5.1543	5.1956	0.4701	6.0088	3.7842	-0.4627	3.0483	2.7189
BTC	0.0237	0.0037	0.2035	0.4753	-0.4672	-0.1544	2.8287	0.3951
ETH	0.0183	0.0286	0.2697	0.5787	-0.7719	-0.2664	3.2261	1.0607
USDT	0.0000	0.0000	0.0043	0.0199	-0.0217	0.0935	16.1655	548.9921***
BNB	0.0529	0.0192	0.2980	1.5570	-0.6171	1.5989	10.3122	201.6973***
DOGE	0.0397	-0.0309	0.4185	2.0663	-0.7737	2.4729	12.6523	372.4859***
CRD	0.0032	-0.0636	0.3422	1.3325	-0.7109	1.1102	5.1152	29.7794***
LT	-0.0130	0.0000	0.2384	0.4996	-0.5518	0.0175	2.3833	1.2081
XRP	-0.0082	-0.0437	0.3219	1.0310	-1.1077	0.6073	5.9356	31.9622***
STE	-0.0170	-0.0267	0.2863	0.9611	-0.4817	1.0672	4.6150	22.6864***
TRX	0.0139	0.0045	0.2549	1.0106	-0.5436	0.7593	5.3195	24.3391***

*Note: *, ** and *** denote 0.10, 0.05 and 0.01 significance levels, respectively.*

Table 2 shows the mean, median, minimum and maximum values of economic policy uncertainty (LEPU), monetary policy uncertainty (LMPU) and cryptocurrencies. Based on the average returns, three categories are applicable for these cryptocurrencies: neutral, negative, and positive. BTC, ETR, BNB, DGC, and TRX exhibit positive averages, indicating a positive return of these cryptocurrencies over time. Cryptocurrencies such as XRP, STE, CRD, and LT have negative averages, suggesting a negative return in the long term. On the other hand, the average of ETH is very close to zero, meaning that prices have not shown a significant directional change over the long term. The JB statistics for BNB, DOGE, CRD, XRP, STE, and TRX suggest that these variables deviate significantly from a normal distribution, indicating the presence of extreme events. Assets such as BTC, ETH, and LT have relatively lower JB values, but minor outliers can still occur. The Q-Q plot further highlights this asymmetric behaviour in the data (pointing to a tendency for behaviours above the median).

Figure: 1
Quantile-Quantile (Q-Q) Plots



Descriptive statistics reveal the basic distributional characteristics of cryptocurrency returns, providing insight into the overall structure of the data. However, correlation analysis serves as a key preliminary step to move beyond the individual behaviour of variables and examine the strength and direction of linear relationships between them.

Table: 3
Spearman Correlation Coefficients

Variables	EPU	MPU	BTC	XRP	BNB	DOGE	STE	TRX	CARD	LITE	ETH	USDT
EPU	1											
MPU	0.3303	1										
BTC	0.0730	-0.2850	1									
XRP	0.0815	-0.1415	0.4364	1								
BNB	-0.1005	-0.3306	0.6299	0.3795	1							
DOGE	0.0078	-0.3674	0.4718	0.6322	0.4636	1						
STE	0.1625	-0.2390	0.6367	0.7992	0.4722	0.6438	1					
TRX	0.0432	-0.1320	0.6007	0.5260	0.5704	0.4005	0.6013	1				
CARD	0.1799	-0.2151	0.6335	0.4961	0.6642	0.5510	0.7484	0.6047	1			
LITE	0.0529	-0.2461	0.7928	0.5100	0.6385	0.5163	0.6149	0.5804	0.6143	1		
ETH	0.1276	-0.2244	0.8002	0.6232	0.5785	0.6372	0.7342	0.6592	0.7181	0.7564	1	
USDT	-0.1685	-0.0398	-0.0889	-0.1181	0.0177	0.0450	-0.1531	-0.1532	-0.0443	-0.0360	-0.0770	1

According to the Spearman correlation analysis in Table 3, a consistently negative relationship exists between MPU and cryptocurrency returns. In contrast, the relationship between EPU and cryptocurrency returns appears more ambiguous. Except for BNB and USDT, there is a positive correlation between EPU and cryptocurrency returns. The signs of the correlation coefficients detected in the correlation analysis signal the expected results in the regression analysis, as the correlation coefficient serves as a predictor of the linear relationship between variables. Since regression analysis aims to model this relationship in a more comprehensive and detailed manner, the expectations for the direction of the relationship to be derived from the regression are essentially shaped at this stage.

While the findings based on the average returns of cryptocurrencies reveal the general trends of price movements, they do not provide definitive conclusions about these trends' persistence and long-term stability. In this context, unit root tests need to be applied to determine whether the price series is stationary and to evaluate the long-term behaviour of the series more comprehensively. Unit root tests allow us to assess whether the series follows a random walk process and whether shocks are permanent. If the price series are not stationary, this indicates that shocks occurring in the long run may be permanent, weakening the predictability of market dynamics and introducing several econometric issues due to non-stationary structures. Therefore, the stationarity properties of the price series of cryptocurrencies were examined using the ADF and PP unit root tests, and the results are demonstrated in Table 4.

Table: 4
Summary of Unit Root Test Results

	ADF		**PP**	
	Test Strategies		**Test Strategies**	
Variables	Intercept (τ Stat.)	Intercept & trend (τ Stat.)	Intercept (Adj. τ Stat.)	Intercept & trend (Adj. τ Stat.)
LEPU	-4.1924***	-4.0867***	-4.1924***	-3.9784**
LMPU	-4.9598***	-4.9183***	-4.7999***	-4.7553***
BTC	-7.4967***	-7.4827***	-7.5305***	-7.5184***
ETH	-8.6169***	-8.6922***	-8.6759***	-8.7160***
USDT	-5.8260***	-5.8226***	-33.4644***	-35.9460***
BNB	-7.4860***	-7.4349***	-7.4748***	-7.4232***
DGC	-8.4901***	-8.4467***	-8.3978***	-8.3473***
CRD	-8.2814***	-8.2335***	-8.3227***	-8.2801***
LT	-7.6693***	-7.6635***	-7.6587***	-7.6533***
XRP	-12.7348	-12.7210***	-13.5009***	-13.5379***
STE	-10.5975***	-10.5472***	-10.5580***	-10.5147***
TRX	-8.8595***	-8.8699***	-9.0439***	-9.1562***

*Note: *, ** and *** denote 0.10, 0.05 and 0.01 significance levels, respectively.*

The results of the unit root tests indicate that the null hypothesis of the presence of a unit root is rejected for all variables. These findings align with our expectations since return series are technically first-difference series, often overlapping with stationary processes. Therefore, it is understood that the regression analyses between cryptocurrency returns and uncertainty indices do not include non-stationary variables, thereby eliminating the risk of spurious regression (Granger & Newbold, 1974). At this stage, selecting an appropriate estimator for the model design presented in Equation (1) is of great methodological importance. The asymmetric and non-normally distributed characteristics of assets traded in the cryptocurrency market make traditional regression methods (OLS) insufficient in representing the entire distribution of this data (see Table 2: Summary statistics, JB statistic, skewness, and kurtosis & Q-Q plot). At this point, quantile regression, as proposed by Koenker and Bassett (1978), offers two significant advantages. First, it allows for a more sensitive data analysis that deviates from normality and exhibits asymmetric behaviour. Second, as noted by Corbet et al. (2020), Raza et al. (2022), Zu et al. (2020), and Ge (2023), it enables the examination of markets under different conditions (bull, bear, and regular seasons). In this context, quantile regression can evaluate the effects of uncertainties (EPU and MPU) on cryptocurrency returns under various market conditions.

Table: 5
Quantile Regression Results

Independent Variable: LMPU										
Deterministic: Intercept										
Percentiles										
Dependent Variable		**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
BTC	Coefficient	0.0111	-0.0431	-0.0362	-0.0417	-0.2150***	-0.2269***	-0.1615**	-0.1420**	-0.1121**
	Std. Error	0.1123	0.0775	0.0807	0.0896	0.0744	0.0689	0.0666	0.0573	0.0507
	t Statistic	0.0988	-0.5564	-0.4493	-0.4654	-2.8913	-3.2941	-2.4239	-2.4795	-2.2123
BNB	Coefficient	-0.1735***	-0.2056**	-0.1871**	-0.1498**	-0.1732**	-0.1666**	-0.2055**	-0.2218**	-0.2650***
	Std. Error	0.0810	0.0814	0.0784	0.0753	0.0772	0.0757	0.0811	0.0883	0.0825
	t Statistic	-2.1425	-2.5259	-2.3857	-1.9906	-2.2429	-2.2003	-2.5343	-2.5118	-3.2123
XRP	Coefficient	0.1286	0.0344	-0.0104	-0.0642	-0.0908	-0.1251	-0.1230	-0.2542*	-0.3951**
	Std. Error	0.0784	0.0794	0.0824	0.0851	0.0872	0.0914	0.0931	0.1377	0.1659
	t Statistic	1.6402	0.4332	-0.1267	-0.7542	-1.0409	-1.3698	-1.3203	-1.8463	-2.3814
DOGE	Coefficient	0.2567***	0.0623	-0.1029	-0.1434*	-0.2250***	-0.2357***	-0.2418***	-0.2258***	-0.4698***
	Std. Error	0.0894	0.0871	0.0907	0.0837	0.0833	0.0844	0.0834	0.0869	0.1274
	t Statistic	2.8717	0.7157	-1.1351	-1.7120	-2.7002	-2.7929	-2.9006	-2.5977	-3.6860
STE	Coefficient	0.0990	-0.0406	-0.1431	-0.1836**	-0.1770*	-0.1841**	-0.1856*	-0.1963*	-0.3543***
	Std. Error	0.0831	0.0926	0.0899	0.0884	0.0899	0.0905	0.0936	0.1049	0.1279
	t Statistic	1.1913	-0.4385	-1.5921	-2.0763	-1.9693	-2.0342	-1.9832	-1.8701	-2.7712
TRX	Coefficient	-0.0709	0.0134	-0.0490	-0.0581	-0.0448	-0.0606	-0.1295*	-0.1230*	-0.1390*
	Std. Error	0.1000	0.0973	0.0960	0.0970	0.0980	0.0912	0.0673	0.0647	0.0749
	t Statistic	-0.7086	0.1375	-0.5099	-0.5995	-0.4573	-0.6652	-1.9245	-1.9017	-1.8555
CARD	Coefficient	0.1375	-0.1001	-0.1249	-0.1564*	-0.0846	-0.0974	-0.1823**	-0.5311**	-0.5290***
	Std. Error	0.1814	0.0866	0.0815	0.0787	0.0781	0.0748	0.0887	0.2175	0.1901
	t Statistic	0.7579	-1.1555	-1.5319	-1.9880	-1.0834	-1.3021	-2.0568	-2.4421	-2.7833
LITE	Coefficient	0.0232	-0.0935	-0.1725*	-0.1698**	-0.1469**	-0.1795***	-0.1381**	-0.1255**	-0.0617
	Std. Error	0.1658	0.1550	0.0903	0.0813	0.0676	0.0621	0.0576	0.0523	0.0582
	t Statistic	0.1400	-0.6033	-1.9105	-2.0893	-2.1727	-2.8878	-2.3955	-2.3981	-1.0590
ETH	Coefficient	-0.0270	-0.0617	-0.1557	-0.2067**	-0.1248	-0.0872	-0.1494**	-0.1584**	-0.3253**
	Std. Error	0.1366	0.1339	0.0970	0.0823	0.0784	0.0787	0.0702	0.0686	0.1350
	t Statistic	-0.1976	-0.4607	-1.6055	-2.5105	-1.5916	-1.1078	-2.1268	-2.3072	-2.4093
USDT	Coefficient	-0.0013	-0.0001	0.0003	-1.00E-04	-1.36E-20	-6.99E-21	0.0001	0.0006	0.0023
	Std. Error	0.0017	0.0008	0.0005	0.0003	0.0003	0.0003	0.0003	0.0005	0.0016
	t Statistic	-0.7742	-0.1540	0.5505	-0.2798	-3.94E-17	-2.13E-17	0.4170	1.0761	1.4818

Note:, ** and *** denote 0.10, 0.05 and 0.01 significance levels, respectively.*

The findings in Table 5 reveal that increases in MPU (monetary policy uncertainty) have a statistically significant and negative impact on cryptocurrency returns, particularly in the middle and higher quantiles. However, significant differences were observed among the assets. Specifically, BTC and LITE stood out as the assets most adversely affected by MPU increases in the middle quantiles, i.e., under normal market conditions. A 1% increase in MPU reduced BTC returns by approximately 0.23% and LITE returns by 0.18%. However, with the transition to bull market conditions, this adverse effect gradually diminished by up to half in the higher quantiles. In contrast, assets such as BNB, XRP, DOGE, STE, TRX, CARD, and ETH were most severely impacted by MPU increases under bull market conditions. Specifically, CARD experienced the most significant loss, with a return drop of approximately 0.53% in response to a 1% increase in MPU, followed by DOGE (0.47%), XRP (0.40%), STE (0.35%), and ETH (0.33%), respectively, with the most significant return losses. Assets such as ETH, TRX, and STE were less affected by MPU increases under normal market conditions than bull markets, with the level of impact being less than half. Finally, no significant coefficients were found for USDT at any quantile, indicating that USDT was not affected by monetary policy uncertainty during the period examined.

Table 6 presents the findings on the effects of economic policy uncertainty on cryptocurrency returns. Although EPU is a broader, overarching index compared to MPU, it has a distinctly different impact on cryptocurrency returns. First, it was found that EPU has no statistically significant effect on LITE, XRP, and BTC returns at any quantile. Increases in economic policy uncertainty have a statistically significant adverse impact on high cryptocurrency returns (high quantiles 0.80 and 0.90). However, no significant effect of fluctuations in economic policy uncertainty was observed on normal or low returns. The most devastating impact of EPU increases was observed on the CARD asset, with a 1% increase in EPU leading to a 1.14% return loss. DOGE and TRX followed this with declines of 0.86%, BNB with a 0.72% drop, and ETH with a 0.42% loss. These findings suggest that cryptocurrency assets are negatively affected by increases in economic policy uncertainty during bull markets. At the same time, improvements in economic policy uncertainty can potentially boost cryptocurrency returns.

Table: 6
Quantile Regression Results

Independent Variable: LEPU										
Deterministic: Intercept										
Percentiles										
Dependent Variable		**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
BTC	Coefficient	0.0348	0.0287	0.0787	0.0492	0.1401	0.0354	0.0838	0.1309	0.0119
	Std. Error	0.1743	0.1831	0.1567	0.1606	0.1530	0.1517	0.1399	0.1380	0.1412
	t Statistic	0.1996	0.1567	0.5025	0.3061	0.9158	0.2335	0.5989	0.9484	0.0846
XRP	Coefficient	0.1656	0.1340	0.1706	0.1661	0.1394	-0.0588	0.0175	0.0697	0.1023
	Std. Error	0.1282	0.1460	0.1619	0.1736	0.1879	0.2345	0.2511	0.2844	0.3307
	t Statistic	1.2918	0.9179	1.0539	0.9566	0.7419	-0.2509	0.0698	0.2453	0.3093
BNB	Coefficient	-0.0739	-0.0984	-0.1163	-0.1180	-0.1735	-0.1615	-0.3087	-0.6010***	-0.7153***
	Std. Error	0.1877	0.1512	0.1792	0.1821	0.1908	0.1879	0.2088	0.2432	0.2604
	t Statistic	-0.3940	-0.6509	-0.6491	-0.6480	-0.9094	-0.8592	-1.4783	-2.4713	-2.7463
DOGE	Coefficient	0.1010	0.2308	0.1861	0.1017	-0.0941	-0.1911	-0.3663	-0.7247**	-0.8565**
	Std. Error	0.2428	0.2107	0.2392	0.2222	0.2220	0.2292	0.3270	0.3620	0.4382
	t Statistic	0.4160	1.0952	0.7782	0.4577	-0.4238	-0.8338	-1.1202	-2.0022	-1.9545
STE	Coefficient	0.1967	0.2039	0.1492	0.3035	0.1435	0.0682	0.0804	0.1912	0.5498**
	Std. Error	0.1415	0.1619	0.1890	0.1981	0.2742	0.2861	0.2875	0.3664	0.2668
	t Statistic	1.3899	1.2592	0.7894	1.5324	0.5233	0.2382	0.2796	0.5218	2.0607
TRX	Coefficient	0.3046	0.1439	0.1893	0.1294	0.0788	0.0753	-0.1437	-0.1549	-0.8591***
	Std. Error	0.2150	0.1344	0.1394	0.1638	0.1936	0.2339	0.2276	0.2081	0.2901
	t Statistic	1.4169	1.0706	1.3584	0.7899	0.4071	0.3218	-0.6313	-0.7445	-2.9612
CARD	Coefficient	0.2260	0.2644	0.4065	0.3995	0.1769	0.2341	0.2142	0.1807	-1.1375**
	Std. Error	0.1542	0.1745	0.2006	0.2053	0.2581	0.2613	0.2603	0.2826	0.4691
	t Statistic	1.4661	1.5158	2.0264	1.9459	0.6854	0.8958	0.8230	0.6396	-2.4246
LITE	Coefficient	0.0603	0.1237	0.2314	0.1143	-0.0282	-0.0034	-0.1285	-0.0448	0.1573
	Std. Error	0.2337	0.2327	0.2203	0.2490	0.2178	0.2025	0.1589	0.1436	0.1525
	t Statistic	0.2581	0.5316	1.0504	0.4591	-0.1293	-0.0166	-0.8086	-0.3123	1.0319
ETH	Coefficient	-0.0279	0.0794	0.0798	0.1699	0.2831	0.1581	0.0591	0.1063	-0.4133**
	Std. Error	0.1690	0.1517	0.1829	0.1897	0.2038	0.2225	0.2718	0.2389	0.2333
	t Statistic	-0.1651	0.5234	0.4362	0.8958	1.3888	0.7105	0.2173	0.4449	-1.7713
USDT	Coefficient	-0.0048	-0.0010	-0.0012	-0.0005	-2.17E-19	-0.0003	1.08E-19	-0.0111***	-0.0129***
	Std. Error	0.0042	0.0008	0.0008	0.0008	0.0009	0.0009	0.0008	0.0046	0.0033
	t Statistic	-1.1391	-1.3599	-1.5612	-0.6774	-2.52E-16	-0.3082	1.41E-16	-2.4368	-3.8527

*Note: *, ** and *** denote 0.10, 0.05 and 0.01 significance levels, respectively.*

In conclusion, economic policy uncertainty (EPU) and monetary policy uncertainty (MPU) negatively affect cryptocurrency returns. However, the impact of EPU on crypto markets is more substantial and destructive. Notably, EPU leads to larger declines in returns, and this effect is only observed during bull markets. This suggests that economic policy uncertainty becomes a more pronounced risk factor only during the market's strong growth and optimism periods. The fact that EPU causes significant losses in returns, even during the market's highest-performing periods, indicates that policy uncertainty can create more fragile market dynamics during such times. Thus, the impact of EPU on markets is more limited than that of MPU, but it is more profound and destructive. A different technique was employed to robustly check the adverse effects of MPU and EPU on cryptocurrency returns. Although quantile regression provides essential insights into the heterogeneous structure of the market by revealing the responses of cryptocurrencies to uncertainties across different return percentages, the question of whether homogeneous effects exist across the entire dataset remains. At this point, the Robust Least Squares (RLS) method comes into play to prevent the distortion of regression results due to outliers or extreme observations in the data. The RLS findings are represented in Table 7.

Table: 7
RLS Regression Results

Independent Variable: LMPU				**Independent Variable: LEPU**		
Deterministic: Intercept				**Deterministic: Intercept**		
Dependent Variable	Coefficient	Std. Error	t Statistic	Coefficient	Std. Error	t Statistic
BTC	-0.1359***	0.0479	-2.8391	0.0646	0.1086	0.5954
XRP	-0.0931	0.0621	-1.4997	0.1001	0.1281	0.7814
BNB	-0.1677***	0.0560	-2.9970	-0.0593	0.1230	-0.4818
DOGE	-0.1857***	0.0623	-2.9820	0.0189	0.1412	0.1341
STE	-0.1329**	0.0638	-2.0838	0.1698	0.1371	1.2388
TRX	-0.1225*	0.0680	-1.8017	0.1982*	0.1162	1.7055
CARD	-0.1048	0.0740	-1.4152	0.4521***	0.1476	3.0638
LITE	-0.1415***	0.0599	-2.3617	0.0415	0.1300	0.3193
ETH	-0.1442***	0.0641	-2.2482	0.1578	0.1389	1.1367
USDT	-0.00002	0.0002	-0.0845	-0.000007	0.0005	-0.0153

*Note: *, ** and *** denote 0.10, 0.05 and 0.01 significance levels, respectively.*

To understand the effects of monetary and economic policy uncertainties on cryptocurrency returns, the RLS model, which is mean-based and capable of producing robust results despite outliers, is employed. The signs of the coefficients obtained from this model are consistent with the findings of the correlation analysis. It is important to emphasise that the RLS technique is recognised as an effective method for minimising the effects of outliers, a common phenomenon in cryptocurrency markets. In this context, the primary goal is to assess whether there is an overall trend. The findings indicate that monetary policy uncertainty significantly negatively impacts cryptocurrency returns. This result is consistent with the significant findings observed in the medium and high quantiles within the quantile regression framework and is further supported by the correlation coefficients. On the other hand, it appears that cryptocurrency returns, in general, are insensitive to economic policy uncertainty (EPU), as no statistically significant coefficient estimates are obtained. Technically, this can be considered a meaningful result, since quantile regression has revealed that responses to EPU are only substantial at stages where returns are high, while the lack of significant coefficients in mean-based techniques like RLS is quite common. In this context, in contrast to the MPU model, this study clearly highlights the critical role of quantile regression, particularly in capturing responses to EPU.

5. Conclusion

Given the cryptocurrency market's increased volatility and unpredictability compared to traditional financial markets, the effects of economic policy uncertainty (EPU) and Monetary Policy Uncertainty (MPU) are particularly significant. These uncertainties shape market behaviour and make it difficult for investors to anticipate future price movements. EPU and MPU affect investors' risk tolerance and increase market volatility and price fluctuations, directly affecting cryptoasset returns.

This study evaluates the impact of EPU and MPU on the returns of ten different cryptoassets using Quantile Regression (QR) and Robust Least Squares (RLS) techniques. As well-known robust methods, these approaches offer distinct advantages over traditional techniques. In particular, the Quantile Regression method provides the flexibility to examine the impact of EPU and MPU across different quantiles of crypto returns or different return levels. This approach allows for a detailed analysis of how low, medium, and high returns respond to market conditions. Given the volatile nature of the cryptoasset market, the flexibility offered by quantile regression is critical for analysing different market conditions.

The results suggest that the effects of EMU and MPU vary depending on market conditions. In both normal market conditions and bull markets, MPU has a statistically significant and negative impact on returns in the cryptocurrency market. The quantile regression results indicate that this effect is more pronounced at medium and high return levels. However, the impact of MPU on cryptoasset returns is not statistically significant under bear-market conditions. This result suggests that MPU has a more pronounced effect during bull markets, while this impact dissipates during bear markets.

On the other hand, the impact of EMU on cryptoasset returns was only discernible during the bull market. In particular, EMU had an adverse effect on the highest return quantiles. This suggests that investors are more sensitive to economic policy uncertainty during bull markets, and risk perceptions increase during upward market trends. Moreover, this impact is more pronounced than that of MPU regarding coefficient size.

The results suggest that market conditions (normal, bear, and bull markets) are a key factor in the cryptoasset's response to uncertainty. This differentiation based on market conditions reveals that cryptoasset markets respond asymmetrically to uncertainty. In particular, during bull markets, the impact of economic policy uncertainty (EPU) is more substantial, while monetary policy uncertainty (MPU) is a persistent risk factor.

In conclusion, EPU and MPU have different effects on the cryptocurrency market depending on market conditions. Understanding the impact of these uncertainties is of great importance for investors and policymakers. Analysing how cryptocurrency markets respond to such uncertainties is critical to improving predictions for future market dynamics.

The results of this study suggest that cryptocurrency markets' response to economic and monetary policy uncertainties varies across market conditions, and the impact of these uncertainties is powerful during bull markets. These findings provide insight into several strategic recommendations for investors and policymakers.

Cryptocurrencies are used not as a currency but as an investment instrument, and in this respect, they have become an essential financial instrument. Policymakers must meticulously address the regulations regarding the principles of the functioning of cryptocurrencies in the market. In this framework, it is vital to establish the necessary regulation and supervision mechanisms to ensure a more transparent and effective trading environment in the cryptocurrency market. In this way, it will be possible to de-risk the investment environment and make the market more secure.

Investors should receive professional support from market experts and brokerage houses on cryptocurrencies and act more consciously and carefully about the risks they face.

Structural arrangements should be implemented to protect against these risks and ensure that policymakers and investors are entirely, accurately, and quickly informed about events, situations, and developments that affect financial products' value, price, and investment decisions. This way, investors can minimise the risks and uncertainties arising from market conditions and policymakers.

Minimising the uncertainties investors face will ensure that cryptocurrency market products, which are seen as an essential investment instrument, will be more preferred by all investor groups and increase the transaction volume and depth in these markets. This will contribute to more widespread use of these products, support resource allocation in the economy and strengthen the place of cryptocurrencies among other financial products as a savings and investment instrument.

Crypto asset investors need to adapt their investment strategies to uncertain conditions. Likewise, policymakers should develop regulations that will reduce asset price volatility and increase investor confidence during periods of uncertainty. Professionals and investors operating in this market should be prepared for possible changes in market conditions by closely monitoring events, situations, and developments that increase uncertainties and affect the value and price of crypto assets and investor decisions.

In future studies on crypto financial products, the impact of uncertainties arising from policy makers and the economy on the volatility and returns of crypto assets can be investigated by expanding the study's time frame, increasing the number of crypto assets and using different methodological approaches. Such studies may contribute to rational decision-making and market stabilisation in cryptocurrency markets under uncertainty.

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