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Asymmetric effects of global factors on return of cryptocurrencies by novel nonlinear quantile approaches

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Abstract

This study examines the asymmetric effects of global factors on the returns of cryptocurrencies. In this context, the study focuses on Bitcoin, Ethereum, and Ripple as top-traded cryptocurrencies, considers eight global factors, and uses high-frequency (i.e., daily) data between February 8, 2018, and June 21, 2022. Also, the study applies nonparametric causality in quantiles (NCQ) and quantile-on-quantile regression (QQR) as the main models and quantile regression (QR) as the robustness model. The empirical findings reveal that (i) effects of global factors on the returns of cryptocurrencies are asymmetric and generally positive; (ii) there are nonparametric causal effects from global factors to cryptocurrencies for return and volatility in most quantiles excluding some lower and higher quantiles; (iii) effects of the global factors on cryptocurrencies differentiate according to global factors, cryptocurrencies, and quantiles; (iv) the QR results confirm the robustness of the empirical findings; and (v) overall, the outcomes underline the asymmetric and varying effects of global factors on the returns of cryptocurrencies across quantiles. Hence, the results imply that traders and investors should consider the asymmetric effects of global factors on the returns of cryptocurrencies for trading, investment, and hedging purposes. Moreover, some policy recommendations are proposed.

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1 Introduction

Money and capital markets have been the main financial platforms for borrowers, lenders, investors, and lenders in traditional finance (Kartal et al. 2020; Aydoğmuş et al. 2022). Financial products in banks and stock exchanges, which are the main marketplaces in money and capital markets, have been major alternatives for both economic actors, and they have been used for borrowing, lending, investing, and trading activities on a domestic and international scale. In this context, bank products (e.g., deposit, credit) and stock market products (e.g., equity stock, debt securities) take place among financial products that are intensively used. Moreover, some other products like gold have been used as a "safe-haven" asset for a long time in turbulent times (Depren et al. 2021).

Although there are traditional financial products, such as equity stock, naturally, much newer financial products have emerged with the impact of developing technology and increasing customer needs and demands. In this context, cryptocurrencies can be evaluated as relatively new financial instruments (Dyhrberg 2016), which have had increasing trading volume recently. Depending on the increasing trading volume, cryptocurrencies have been attracting the interest of economic parties (Cheng and Yen 2020). In detail, cryptocurrencies differ from traditional financial assets due to their decentralized structure, low transaction costs, and peer-to-peer nature (Dyhrberg et al. 2018). Hence, cryptocurrencies can be considered distinct investment instruments and financial assets.

In the current literature, various studies examine cryptocurrencies from different perspectives. For instance, Kristoufek and Vosvrda (2019) and Kakinaka and Umeno (2022) focus on the market efficiency side; Alessandretti et al. (2018), Sovbetov (2018), and Kyriazis et al. (2020) uncover price changes and price discovery; Zhang and Wang (2020) investigate returns; Sabah (2020) uncover volatility; and Gurdgiev and O'Loughlin (2020) and Yen and Cheng (2021) examine uncertainty. Moreover, most studies in the literature focus on Bitcoin (e.g., Demir et al. 2018; Gözgör et al. 2019; Das et al. 2020; Bouri et al. 2022; Huang et al. 2022), whereas Ethereum (e.g., Sovbetov 2018; López-Martín et al. 2021; Erdoğan et al. 2022; Urquhart 2022) and Ripple (e.g., Malladi and Dheeriya 2021; López-Martín et al. 2021; Erdoğan et al. 2022) have been studied much lesser. In these studies, traditional econometric models, such as generalized autoregressive conditional heteroskedasticity and vector autoregression, have been mainly applied.

Overall, there are various studies that handle either a cryptocurrency or a bundle of cryptocurrencies, examine these cryptocurrencies from different perspectives, and apply mainly traditional econometric approaches. However, the current literature is not enough rich in terms of examining asymmetric effects of global factors by including the most recent available data as well as considering the potential

differences from various quantiles of cryptocurrencies. Hence, it can be stated that there is a literature gap and the current literature can be extended in this way.

By considering the literature gap and increasing trading volume of cryptocurrencies, this study focuses on top-traded three cryptocurrencies (i.e., Bitcoin, Ethereum, and Ripple), uses eight global factors, uses high-frequency (i.e., daily) return data from February 8, 2018, to June 21, 2022, and applies novel NCQ and QQR approaches as main and QR approach for robustness model. Hence, it is possible to examine the asymmetric effects of global factors at various quantiles. The empirical findings from the novel quantile approaches underline the asymmetric and varying effects of global factors on cryptocurrencies at quantiles. Moreover, some policy recommendations are discussed based on the findings.

This study contributes to the literature on the asymmetric effect of global factors on cryptocurrencies in some ways. First, this study focuses on a bundle of cryptocurrencies, such as Bitcoin, Ethereum, and Ripple, rather than considering only a cryptocurrency on a global scale. Second, the study uses a higher-frequency (i.e., daily) dataset from February 8, 2018, to June 21, 2022, which is all the intersected available data for all cryptocurrencies and global factors. Third, the study performs novel quantile approaches as recently popular approaches. Naturally, the current literature includes some studies, but this study is the leading one from the content perspective. By applying novel quantile approaches, the asymmetric effects of global factors on cryptocurrencies are examined in quantile detail.

This study consists of five parts. Part II presents a literature review. Part III introduces methods. Part IV presents the results. Part V concludes.

2 Literature review

In the literature, most of the studies focus on the return of cryptocurrencies rather than their price levels. In this context, the returns of cryptocurrencies are used as dependent variables in line with the studies of Dyhrberg et al. (2018), Aysan et al. (2019), Demir et al. (2018), Das et al. (2020), Jareño et al. (2020), Bouri et al. (2021), López-Martín et al. (2021), Malladi and Dheeriya (2021), Erdoğan et al. (2022), and Urquhart (2022).

Also, a variety of explanatory factors have been used in the current literature to examine their effect on cryptocurrencies. The first group of studies uses foreign exchange (FX) rates. For example, Corbet et al. (2018), Liang et al. (2019), Chemkha et al. (2021), Huang et al. (2022), and Rehman et al. (2022) include FX rates in their studies while examining cryptocurrencies. In line with these studies, Euro/United States (US) Dollar (USD) parity is selected as an indicator.

The second group of studies considers the geopolitical risk index. For instance, Aysan et al. (2019), Kyriazis (2021), Bouri et al. (2022), Long et al. (2022), and Nouir et al. (2023) consider geopolitical risk in investigating Bitcoin return. By considering these studies, the global geopolitical risk index is selected as an indicator because this study examines the asymmetric effect of the selected global factor on cryptocurrencies on a global scale.

The third group studies analyze interest rates. For example, Aharon et al. (2021), Zhang et al. (2021), Aboura (2022), Benigno et al. (2022), and Van Erlach (2022) include different interest rates in their studies. In line with these studies, the US 5-Year Treasury Bond yield is selected as an indicator by considering the leading characteristic of this indicator.

The fourth group of studies examines oil prices. For instance, Das and Dutta (2020), Jareño et al. (2021), Attarzadeh and Balcılar (2022), Ghabri et al. (2022), Li et al. (2022), Ren et al. (2022), and Hung (2022) include energy prices. Naturally, increasing oil prices can cause an increase in the cost of cryptocurrencies. By considering these studies, Brent crude oil prices are selected as an indicator.

The fifth group of studies includes stock market indices. For example, Jiang et al. (2021), Fakhfekh et al. (2021), Maitra et al. (2022), Shahzad et al. (2022), Shanaev and Ghimire (2022), and Wang et al. (2022) consider various stock market indices. In line with these studies, SandP 500 index is selected as an indicator since the US stock market is the leading one and equity stocks are substitute investment alternatives for cryptocurrency investors and traders.

The sixth group of studies examines economic policy uncertainty. For instance, Bouri et al. (2017a), Demir et al. (2018), Yen and Cheng (2021), Ali et al. (2022), Wu et al. (2022), and Nouir et al. (2023) consider economic policy uncertainty in examining Bitcoin returns and defined that it has predictive power. By considering these studies, US economic policy uncertainty index is selected as an indicator because the USA is the biggest and leading economy in the world, and economic policy uncertainty in the USA may affect cryptocurrencies.

Moreover, Bouri et al. (2017b), Kyriazis (2021), and Leirvik (2022) investigate the volatility of various issues in terms of their effect on cryptocurrencies. Hence, the Chicago Board Options (CBOE) Exchange volatility index is selected as an indicator. That is why it reflects high market volatility and is used intensively in the current literature. Lastly, Jareño et al. (2020), Elsayed et al. (2022), Hung (2022), Nakagawa and Sakemoto (2022), Ren et al. (2022), and Shahzad et al. (2022) uncover gold prices. Thus, gold prices per ounce are selected as an indicator to be considered in the empirical analysis because gold is a substitute investment alternative for cryptocurrency investors and traders similar to equity stocks.

As a result, it is seen that the effects of various factors have been examined in terms of their effect on cryptocurrencies in different studies. Also, a variety of econometric models (e.g., autoregressive distributed lag model, generalized autoregressive conditional heteroskedasticity, and vector autoregression) are used in the context of empirical examination. In summary, although current studies examine the effect of various factors on cryptocurrencies, however, the current literature does not include a study that examines the asymmetric effect of most of the global factors on cryptocurrencies on a global scale in a single study. Also, novel quantile approaches, such as NCQ and QQR, have not been applied to make quantile-based analyses for a comprehensive study. Hence, it can be concluded that the literature has a gap. Therefore, a new study that examines the asymmetric effect of global factors on cryptocurrencies, covers most of the global factors in a single study, and applies novel quantile approaches can enrich the current literature by making a quantile-based examination.

Table 1 Explanations

Abbreviation	Explanation	Unit
BTC	Bitcoin*	USD
ETH	Ethereum*	USD
XRP	Ripple*	USD
EURUSD	Euro/USD parity	Bps
GPR	Global geopolitical risk index	Bps
INTEREST	US 5 year treasury bond yield	%
OIL	Brent crude oil per barrel	USD
SP500	SandP 500 index	Bps
UNCERT	US economic Policy uncertainty index	Bps
VIX	CBOE volatility index	Bps
XAU	Gold price per ounce	USD

*denotes the dependent variables. Bps denotes basis points

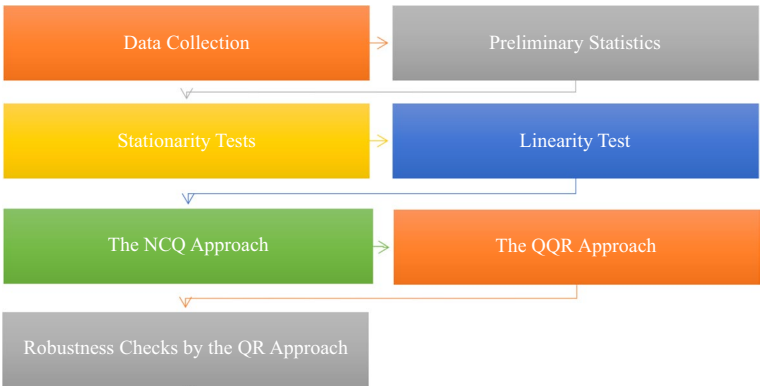

Fig. 1 The followed empirical methodology

In summary, in line with the current literature, the study considers top-traded three cryptocurrencies as dependent variables. Besides, a total of eight global factors are included as explanatory variables. Table 1 presents explanations of all these variables included.

3 Methods

3.1 Methodology

Figure 1 shows the followed empirical methodology. A seven-step empirical methodology is followed up to examine the asymmetric effect of the global indicators on the returns of cryptocurrencies. In the first step, the data are gathered from Bloomberg (2022). In the second step, the preliminary statistics are evaluated. In the third

step, the augmented Dickey–Fuller (ADF) and Phillips and Perron (PP) tests are used to discover the stationarities of the variables (Dickey and Fuller 1979; Phillips and Perron 1988). In the fourth step, the BDS test is applied to reveal the variables' nonlinearities (Broock et al. 1996). If the variables are nonlinear according to test results, asymmetric procedures are more appropriate to be applied in empirical analysis. In the fifth step, the NCQ approach is utilized (Balcılar et al. 2016). This methodology examines the nonparametric causality in quantiles for the mean (return) and variance (volatility). In the sixth step, the QQR approach is used to indicate the strength of the global indicators on the cryptocurrencies at quantiles (Sim and Zhou 2015). In the last step, the QR approach is used to investigate the robustness (Koenker 2005).

By considering traded volume, the top three-traded cryptocurrencies are selected as dependent variables and eight global economic factors are used as explanatory variables.

The methodology steps are summarized above. Not to enlarge the paper too much, the approach used in the empirical methodology is explained shortly. Thus, a detailed explanation is not given since this study does not aim to develop an econometric model. On the contrary, econometrical techniques are only applied to evaluate the asymmetric effect of global factors on cryptocurrencies. Thus, more information about the methods can be obtained from the studies that have been mentioned in the methodological flows.

3.2 Data

In this study, high-frequency (i.e., daily) data are used for all variables because daily data are available for all variables that are included in this study. In this context, data for the global risk geopolitical risk index are gathered from Matteoiacoviello (2022), while daily data for all other variables are collected from Bloomberg (2022).

The intersected dataset for all variables consists of data between February 8, 2018, and June 21, 2022, by including 1,099 observations. Dataset is transferred to logarithmic data difference series to study with return series (Sharif et al. 2021; Kartal et al. 2022a, 2022b; Depren et al. 2023). Figure 2 presents the trends of variables.

As Fig. 2 shows, the raw data seem non-stationary, whereas logarithmic difference data series seem stationary. Hence, the usage of logarithmic difference data series in the empirical analysis is much more appropriate for obtaining more robust results.

4 Results

4.1 Descriptive statistics

Table 2 presents preliminary statistics of the variables that are included in this study. Table 2 shows that BTC, SP500, XAU, and UNCERT have the highest standard deviation, respectively. Also, Jarque–Bera probability values reveal that variables do

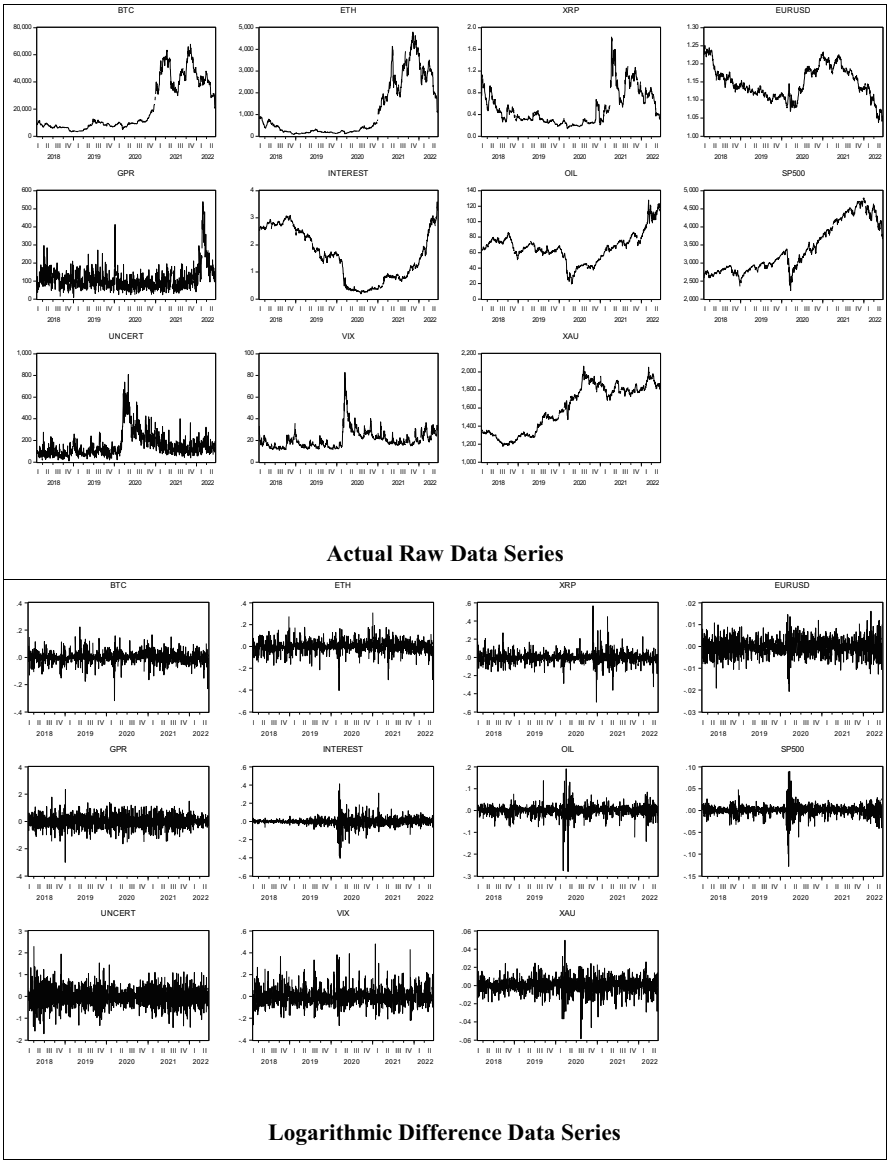

Fig. 2 Time series plots of data series

not have a normal distribution. Moreover, correlation coefficients present that SP500 and OIL variables have the highest positive correlations.

Table 2 Preliminary statistics

Variables	BTC	ETH	XRP	EURUSD	GPR	INTEREST	OIL	SP500	UNCERT	VIX	XAU
Panel A: Descriptive statistics											
Mean	20,609.17	1,120.19	0.51	1.15	111.81	1.59	66.77	3,409.29	152.27	21.04	1,598.63
Minimum	3,156.89	81.79	0.14	1.04	9.49	0.19	19.33	2,237.40	10.92	10.85	1,174.16
Maximum	67,734.04	4,799.47	1.83	1.25	539.58	3.59	127.98	4,796.56	807.66	82.69	2,063.54
Std. Dev	18,143.53	1,281.09	0.31	0.04	63.45	0.95	18.97	686.13	112.30	8.72	255.88
Jarque–Bera	177.64	244.40	334.74	22.10	5,935.49	94.57	74.14	116.24	1,959.09	6,176.37	109.92
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099
Panel B: Correlation matrix											
BTC	1.00										
ETH	0.93	1.00									
XRP	0.74	0.81	1.00								
EURUSD	0.21	0.12	0.40	1.00							
GPR	0.16	0.24	0.17	−0.20	1.00						
INTEREST	−0.32	−0.16	0.02	−0.21	0.29	1.00					
OIL	0.42	0.54	0.46	−0.17	0.51	0.61	1.00				
SP500	0.92	0.91	0.63	0.09	0.20	−0.37	0.45	1.00			
UNCERT	−0.07	−0.13	−0.29	−0.13	−0.12	−0.56	−0.55	−0.05	1.00		
VIX	0.02	0.00	−0.20	−0.21	0.02	−0.39	−0.33	0.00	0.66	1.00	
XAU	0.65	0.58	0.25	0.05	0.11	−0.71	0.01	0.77	0.40	0.40	1.00

Table 3 Stationarity test results

Variables	ADF test		PP test		Decision
	I(0)	I(1)	I(0)	I(1)	
BTC	0.6765	0.0000	0.6765	0.0000	I(1)
ETH	0.6218	0.0000	0.6472	0.0000	I(1)
XRP	0.1230	0.0000	0.1059	0.0000	I(1)
EURUSD	0.4879	0.0000	0.5736	0.0000	I(1)
GPR	0.0000		0.0000		I(0)
INTEREST	0.9498	0.0000	0.9498	0.0000	I(1)
OIL	0.8863	0.0000	0.9234	0.0000	I(1)
SP500	0.6594	0.0000	0.6384	0.0000	I(1)
UNCERT	0.0054		0.0000		I(0)
VIX	0.0013		0.0013		I(0)
XAU	0.7249	0.0000	0.7582	0.0000	I(1)

Maximum lag is determined automatically based on SIC criteria in the ADF test and based on Bartlett Kernel in the PP test

4.2 Unit root test

Table 3 presents the ADF and PP tests' results, which are applied to examine the stationarities of the variables.

Based on Table 3, the ADF and PP tests reveal that GPR, UNCERT, and VIX are stationary at I(0). Besides, all other variables are stationary at I(1). Hence, the stationarity test results demonstrate that the variables are stationary at different integrated orders.

Table 4 Linearity test results

Variables	Dimensions					Results
	2	3	4	5	6	
BTC	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
ETH	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
XRP	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
EURUSD	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
GPR	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
INTEREST	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
OIL	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
SP500	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
UNCERT	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
VIX	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear
XAU	0.0000	0.0000	0.0000	0.0000	0.0000	Nonlinear

Values indicate *p* values

4.3 BDS test

Table 4 gives the BDS test results, which are performed to investigate the variables' nonlinearities.

Based on Table 4, the BDS test results show that p values for all variables are less than 0.05, which results in the rejection of the null hypothesis (i.e., variables are linearly distributed). Hence, all variables are determined as nonlinear.

When the preliminary examination results are evaluated together, it can be summarized that variables are stationary at different integrated orders, do not have a normal distribution, and are not linear. For these reasons, applying nonlinear methods, such as NCQ and QQR in empirical analysis, is more appropriate. Hence, it is decided to apply NCQ and QQR approaches as the main models, while the QR approach is used for robustness checks.

4.4 NCQ results

Figures 3, 4, and 5 present the results of the NCQ approach that tell about the causal effect of global factors for return (mean) and volatility (variance) for BTC, ETH, and XRP, respectively.

In Fig. 3, there is a nonparametric causality effect from global factors to BTC for return (mean) and volatility (variance) in most quantiles at a 5% significance level. However, the causality effect does not exist at some lower and higher quantiles for some global factors. The results are almost the same for the ETH case according to Fig. 4. However, based on Fig. 5, INTEREST does not have a causal effect on XRP for return and volatility in all quantiles at a 5% significance level

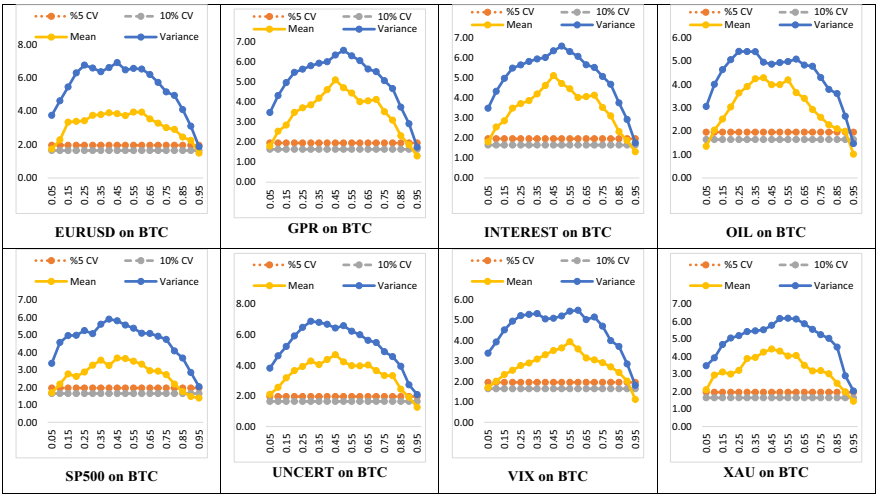

Fig. 3 NCQ results between BTC and global factors

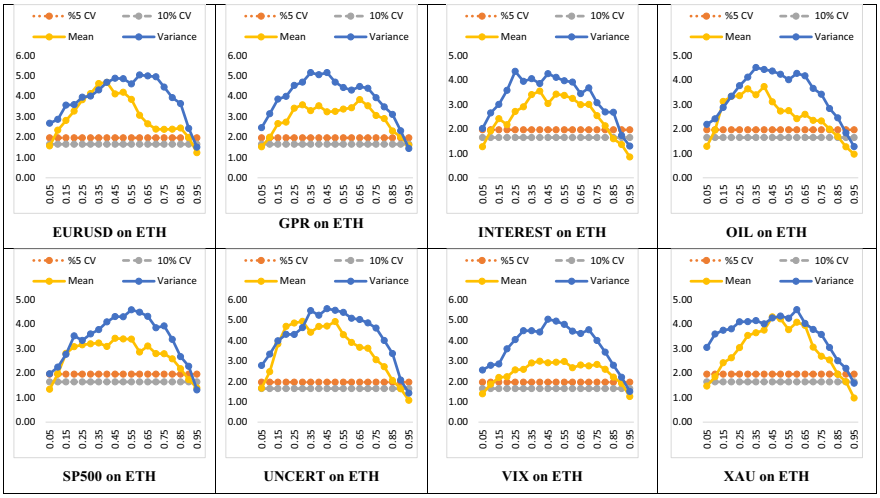

Fig. 4 NCQ results between ETH and global factors

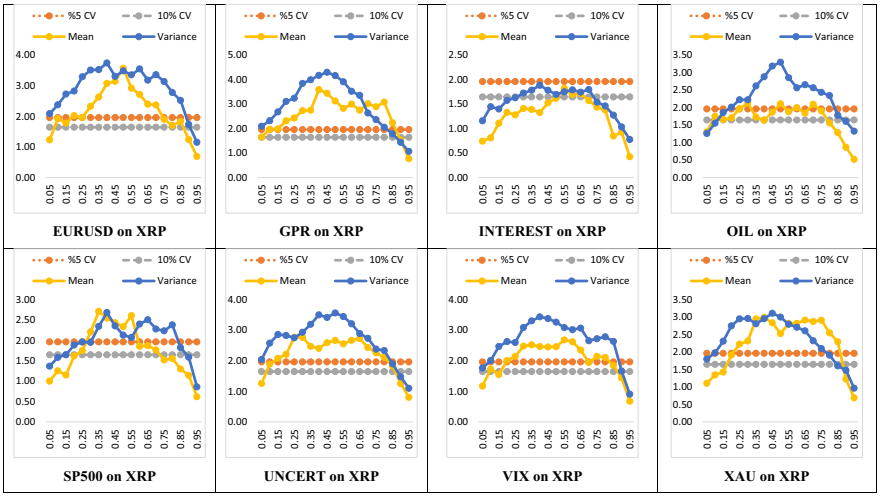

Fig. 5 NCQ results between XRP and global factors

and has only a casual effect for some quantiles at a 10% significance level, which is different from both BTC and ETH.

4.5 QQR results

After examining the causal effects of global factors on cryptocurrencies, Figs. 6, 7, and 8 present the results of the QQR approach that show the impact of global factors on BTC, ETH, and XRP, respectively.

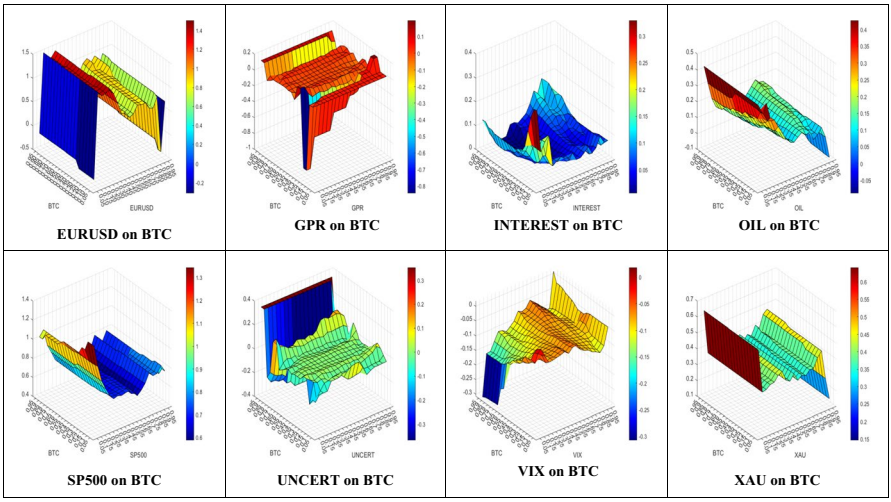

Fig. 6 QQR results between BTC and global factors

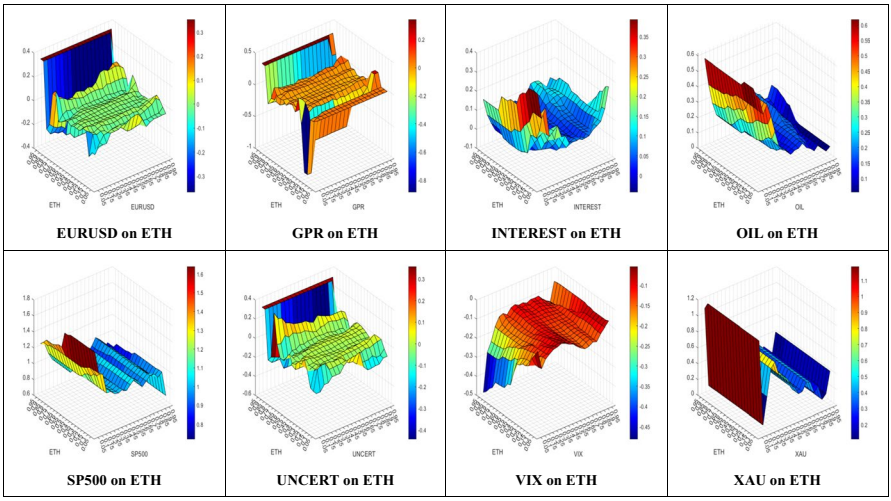

Fig. 7 QQR results between ETH and global factors

According to Fig. 6, EURUSD has a high negative impact on BTC at the lowest and highest quantiles, whereas the impact is positive at the lower, middle, and higher quantiles. On the other hand, GPR has a generally positive but low impact for most quantiles. Similar to GPR, INTEREST has generally positive and low impact on most of the quantiles. In the case of OIL, there is a negative and strong impact at the highest quantile, a positive and low impact at middle quantiles, and a positive and strong impact at lower quantiles of OIL. SP500 has a positive impact on BTC, whereas its impact is low in higher and middle quantiles, and much stronger in the

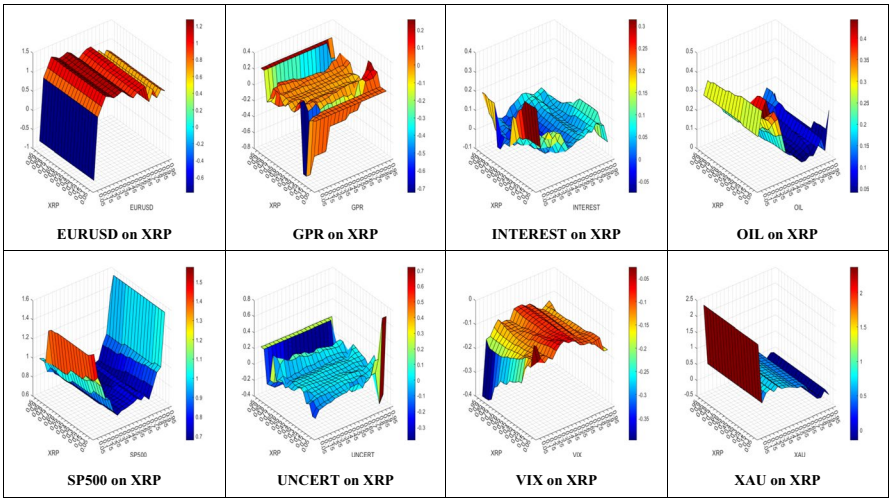

Fig. 8 QQR results between XRP and global factors

lower quantiles of SP500. Also, UNCERT has generally positive and low impact on BTC, whereas it is strong and negative in all quantiles of UNCERT and lower quantile of BTC. Moreover, VIX has generally a negative and high impact on BTC at middle and higher quantiles. Furthermore, XAU has a positive impact on BTC. In detail, XAU is much stronger in the lowest quantile of XAU, whereas it has a relatively lower impact in the middle and higher quantiles. Among all global factors, EURUSD, SP500, and XAU have the highest impact on BTC.

Based on Fig. 7, EURUSD has a positive and low impact on ETH for all quantiles except for the low quantiles of ETH where the impact is negative and strong. On the other hand, GPR has a generally positive and low impact for most of the quantiles. Similar to GPR, INTEREST has generally positive and low impact at most of the quantiles. In the case of OIL, there is a positive and strong impact in the lower quantiles, positive and low impact in the middle and higher quantiles of OIL. SP500 has a positive impact on ETH, whereas its impact is relatively low in the middle and higher quantiles of SP500. Also, UNCERT has generally positive and low impact on ETH, whereas it is strong and negative in all quantiles of UNCERT and lower quantile of ETH. Moreover, VIX has a generally negative and strong impact on ETH at middle and higher quantiles, whereas it is negative and strong in the lower quantile of VIX. Moreover, XAU has a positive impact on ETH, while the impact is much stronger in lower quantiles of XAU. Among all global factors, SP500, XAU, and OIL have the highest impact on ETH.

In Fig. 8, EURUSD has a positive and high impact on XRP at middle and higher quantiles, whereas the impact is negative at lower quantiles. On the other hand, GPR has a generally positive but low impact for most quantiles. Similar to GPR, INTEREST has generally positive and low impact on most quantiles. In the case of OIL, there is a positive and strong impact at higher quantiles and a positive and low impact at lower quantiles of OIL. SP500 has a positive and high impact on XRP

at low quantiles, whereas its impact is much lower in the middle and higher quantiles of SP500. Besides, UNCERT has generally a positive and low impact on XRP, whereas it is strong and negative in all quantiles of UNCERT and lower quantile of XRP. Moreover, VIX has a generally negative and strong impact on XRP at middle and higher quantiles. Furthermore, XAU has a positive impact on BTC and the impact is quite high in lower quantiles of XAU. Among all global factors, XAU, SP500, and EURUSD have the highest impact on XRP.

4.6 Robustness checks by QR approach

To check the robustness of the results, the QR approach is applied and the results of the QR approach are presented in Figs. 9, 10, and 11 for BTC, ETH, and XRP, respectively.

When Figs. 9, 10, and 11 are evaluated altogether, it can be seen that the results of the QQR and QR approaches are generally consistent with each other except for some variables (i.e., GPR and UNCERT mainly) for the BTC, ETH, and XRP. Also, the results differ for EURUSD in the ETH case. However, by ignoring these exceptions, it can be generalized that the results of the QQR and QR approaches are highly compatible. Hence, the QR results mainly validate the robustness of the QQR outcomes.

4.7 Discussion and policy recommendations

The empirical examination results of the novel nonlinear quantile approaches present particular determinations about the asymmetric effect of global factors on cryptocurrencies' returns. The findings of the GCQ approach present that there is

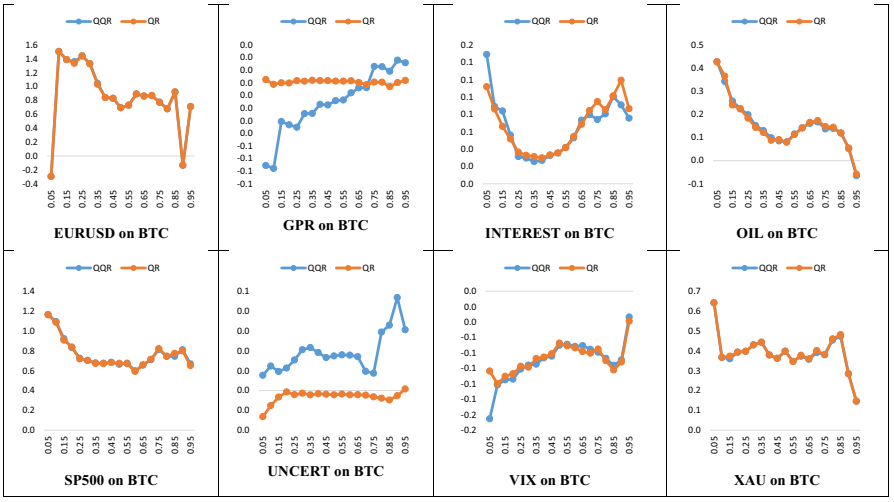

Fig. 9 QQR and QR correlations between BTC and global factors

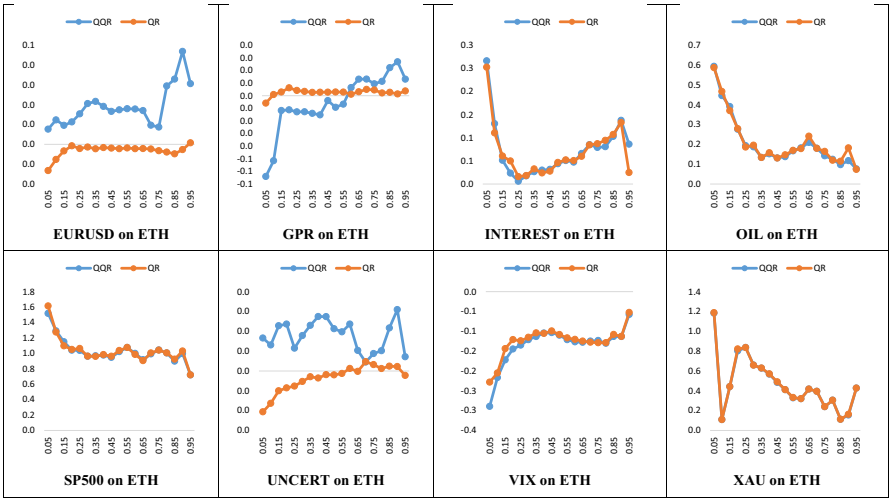

Fig. 10 QQR and QR correlations between ETH and global factors

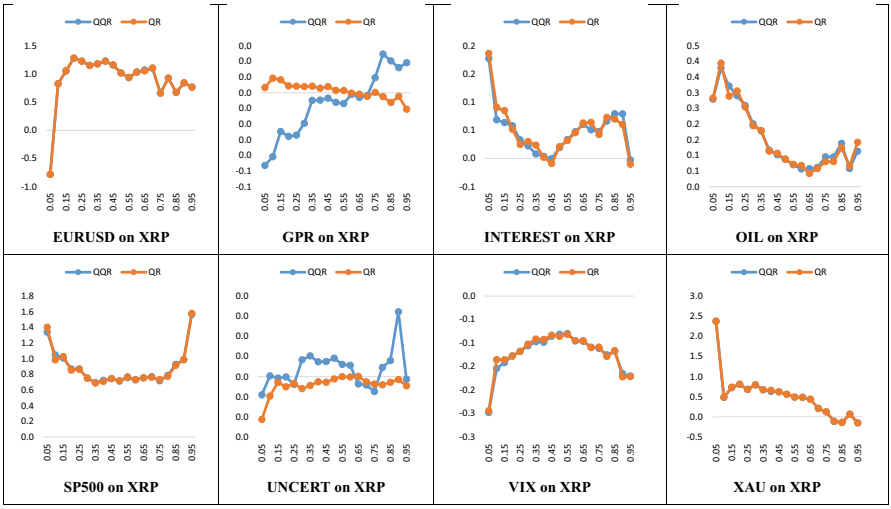

Fig. 11 QQR and QR correlations between XRP and global factors

a nonparametric causality from global factors to cryptocurrencies (i.e., Bitcoin, Ethereum, and Ripple) for return and volatility in most quantiles excluding some lower and higher ones. Also, the outcomes of the QQR approach present that the effect of global factors on cryptocurrencies is generally positive in almost all quantiles excluding some quantiles. Moreover, the results for each cryptocurrency can vary a bit based on quantiles and explanatory factors. Furthermore, the QR results validate the robustness.

The results of the novel quantile approaches reveal that global factors have an important asymmetric effect on cryptocurrencies' returns. Specifically, all global factors have a nonparametric causality on Bitcoin, Ethereum, and Ripple for return and volatility in most quantiles excluding some lower and higher ones. On the other hand, although the effects of the global factors are generally positive, however, they can be negative at some quantiles for some factors. Thus, it can be stated that the effects of the global factors on cryptocurrencies are generally positive at the causality level for the mean (return) and variance (volatility), whereas varying for some factors through quantiles. Hence, the empirical results underline the asymmetric and changing effect of global factors on cryptocurrencies at various quantiles. Furthermore, the global factors included are significant explanatory variables in the estimation of cryptocurrencies' return and volatility on a global scale, which is very crucial for traders and investors.

The results of the quantile approaches are generally consistent with the outcomes of the studies in the current literature (e.g., Chemkha et al. 2021; Kyriazis 2021; Yen and Cheng 2021; Benigno et al. 2022; Nakagawa and Sakemoto 2022). Hence, some policy recommendations can be proposed based on the results.

Firstly, economic parties dealing with cryptocurrencies such as traders and investors should consider the results of the study in their decisions. That is why because this study reveals that there is not a linear relationship between cryptocurrencies and global factors, rather, they have an asymmetric effect.

Secondly, although most global factors have a positive relationship with cryptocurrencies, the impact of the relationship has become negative for some factors at some quantiles and impacts of the global factors can vary at different quantiles. Hence, this changing effect and impact power should be also considered by related parties, especially in transactions that are made for trading, investment, and hedging.

Thirdly, by considering the changing relationship, a straight-line effect of the global factors on cryptocurrencies should not have been expected. Rather, the progress of the relationship between cryptocurrencies and global factors at various quantiles should be continuously followed up and economic decisions should be made based on this progress. Moreover, the probable interactions between cryptocurrencies and global factors should be taken into account in the decisions as well as policy development and implementation processes.

Fourthly, by considering also the high amount of traded value for cryptocurrencies, policymakers should strictly monitor cryptocurrency markets and transactions. Moreover, macro-prudential policies that would decrease potential adverse effects on cryptocurrency markets should be applied through legislation by policymakers so that any economic parties like traders and investors cannot be suffered from negative developments in cryptocurrency markets.

The policy recommendations, which are mainly developed based on the empirical results of the study, show the asymmetric and changing effect of global factors on cryptocurrencies. In this context, supervision and legislation of the cryptocurrencies and cryptocurrency markets are highly important for economic actors, especially financial ones.

In this study, relatively high-frequency (i.e., daily) data are used for the empirical examination. However, policymakers can use much more high-frequency data to

monitor cryptocurrency markets, hence developing and implementing much more policies to prevent negative developments that may arise from these markets to the financial markets and economy as a whole. Furthermore, positioning the monitoring, supervision, and legislation of new financial instruments and markets like cryptocurrencies and cryptocurrency markets as a macro-prudential concern is highly recommended. Hence, such an emerging area could be handled by high-level management of countries, and the application of harmonious policies among various regulatory authorities can be possible.

5 Conclusion

The results of the study present mainly that there is a significant asymmetric effect of global factors on cryptocurrencies' returns; a causal effect exists in all quantiles excluding some of them, whereas cryptocurrency and explanatory factor-based results vary a bit; the empirical results have a robust structure; and overall, the effects of the global factors vary according to quantiles. Hence, the empirical results show that global factors are important for cryptocurrencies on a global scale. Also, the empirical findings of the novel nonlinear quantile approaches gathered in this study are generally consistent with the studies in the literature. By considering the findings, some policy recommendations such as positioning the monitoring, supervision, and legislation of new financial instruments and markets like cryptocurrencies and cryptocurrency markets as a macro-prudential concern are proposed. Hence, the study contributes to traders, investors, and policymakers in decisions and policy development and implementation processes by highlighting the importance of asymmetric effects of global factors on cryptocurrencies, which is crucial in decisions related to trading, investment, hedging, and regulatory legislations.

The contributions of the study can be summarized as that this study (i) is the most recent study that focuses on top-traded three cryptocurrencies (i.e., Bitcoin, Ethereum, and Ripple) by including the most recent available data; (ii) uses novel quantiles approaches, whereas current studies perform limited econometric models; (iii) includes a higher-frequency data for empirical examination; and (iv) examines the asymmetric effect of global factors on cryptocurrencies by considering quantiles.

On the other hand, this study has some drawbacks. The study focuses mainly on top-traded three cryptocurrencies (i.e., Bitcoin, Ethereum, and Ripple). However, there are also other cryptocurrencies, which may attract the attention of economic actors at different times. Hence, future studies can handle such cryptocurrencies by following up on the applied methodology of this study. Moreover, future studies can consider applying new techniques like dynamic autoregressive distributed lag model simulations and machine learning algorithms for empirical examination. Hence, the current literature about cryptocurrencies can be enriched much more.

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Declarations

Conflict of interest The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements) or non-financial interest (such as personal or professional relationships, affiliations, knowledge, or beliefs) in the subject matter or materials discussed in this manuscript.

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References

Aboura S (2022) A Note on the bitcoin and fed funds rate. Empir Econ 63:2577–2603
Aharon DY, Umar Z, Vo XV (2021) Dynamic spillovers between the term structure of interest rates, bitcoin, and safe-haven currencies. Financ Innov 7(1):1–25
Alessandretti L, ElBahrawy A, Aiello LM, Baronchelli A (2018) Anticipating cryptocurrency prices using machine learning. Complexity 2018:1–16. https://doi.org/10.1155/2018/8983590
Ali MH, Schinckus C, Uddin MA, Pahlevansharif S (2022) Asymmetric effects of economic policy uncertainty on bitcoin's hedging power. Stud Econ Financ. https://doi.org/10.1108/SEF-05-2021-0186
Attarzadeh A, Balcılar M (2022) On the Dynamic return and volatility connectedness of cryptocurrency, crude oil, clean energy, and stock markets: a time-varying analysis. Environ Sci Pollut Res 29:65185–65196
Aydoğmuş M, Gülay G, Ergun K (2022) Impact of ESG performance on firm value and profitability. Borsa Istanbul Rev. https://doi.org/10.1016/j.bir.2022.11.006
Aysan AF, Demir E, Gözgör G, Lau CKM (2019) Effects of the geopolitical risks on bitcoin returns and volatility. Res Int Bus Financ 47:511–518
Balcılar M, Gupta R, Pierdzioch C (2016) Does uncertainty move the gold price? New evidence from A nonparametric causality-in-quantiles test. Resour Policy 49:74–80
Benigno P, Schilling LM, Uhlig H (2022) Cryptocurrencies, currency competition, and the impossible trinity. J Int Econ 136:103601
Bloomberg (2022) Bloomberg terminal, Accessed on 22 June 2022
Bouri E, Gupta R, Tiwari AK, Roubaud D (2017a) Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Financ Res Lett 23:87–95
Bouri E, Azzi G, Dyhrberg AH (2017b) On the return-volatility relationship in the bitcoin market around the price crash of 2013. Economics. https://doi.org/10.5018/economics-ejournal.ja.2017-2
Bouri E, Gupta R, Vo XV (2022) Jumps in geopolitical risk and the cryptocurrency market: the singularity of bitcoin. Def Peace Econ 33(2):150–161
Bouri E, Saeed T, Vo XV, Roubaud D (2021) Quantile connectedness in the cryptocurrency market. J Int Finan Market Inst Money 71:101302
Broock WA, Scheinkman JA, Dechert WD, LeBaron B (1996) A test for independence based on the correlation dimension. Econom Rev 15(3):197–235
Chemkha R, BenSaïda A, Ghorbel A (2021) Connectedness between cryptocurrencies and foreign exchange markets: implication for risk management. J Multinatl Financ Manag 59:100666
Cheng HP, Yen KC (2020) The relationship between the economic policy uncertainty and the cryptocurrency market. Financ Res Lett 35:101308
Corbet S, Meegan A, Larkin C, Lucey B, Yarovaya L (2018) Exploring the dynamic relationships between cryptocurrencies and other financial assets. Econ Lett 165:28–34

Das D, Dutta A (2020) Bitcoin's energy consumption: Is it the achilles heel to miner's revenue? Econ Lett 186:108530
Das D, Le Roux CL, Jana RK, Dutta A (2020) Does bitcoin hedge crude oil implied volatility and structural shocks? A comparison with gold, commodity and the US dollar. Financ Res Lett 36:101335
Demir E, Gözgör G, Lau CKM, Vigne SA (2018) Does economic policy uncertainty predict the bitcoin returns? An empirical investigation. Financ Res Lett 26:145–149
Depren Ö, Kartal MT, Depren SK (2021) Changes of gold prices in COVID-19 pandemic: daily evidence from turkey's monetary policy measures with selected determinants. Technol Forecast Soc Chang 170:120884
Depren Ö, Kartal MT, Ayhan F, Depren SK (2023) Heterogeneous impact of environmental taxes on environmental quality: tax domain based evidence from the nordic countries by nonparametric quantile approaches. J Environ Manage 329:117031
Dickey DA, Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 74(366a):427–431
Dyhrberg AH (2016) Bitcoin, gold and the dollar-a GARCH volatility analysis. Financ Res Lett 16:85–92
Dyhrberg AH, Foley S, Svec J (2018) How investible is bitcoin? Analyzing the liquidity and transaction costs of bitcoin markets. Econ Lett 171:140–143
Elsayed AH, Gozgor G, Yarovaya L (2022) Volatility and return connectedness of cryptocurrency, gold, and uncertainty: evidence from the cryptocurrency uncertainty indices. Financ Res Lett 47:102732. https://doi.org/10.1016/j.frl.2022.102732
Erdoğan S, Ahmed MY, Sarkodie SA (2022) Analyzing asymmetric effects of cryptocurrency demand on environmental sustainability. Environ Sci Pollut Res 29(21):31723–31733
Fakhfekh M, Jeribi A, Ghorbel A, Hachicha N (2021) Hedging stock market prices with WTI, gold, VIX and cryptocurrencies: a comparison between DCC, ADCC and GO-GARCH models. Int J Emerg Mark. https://doi.org/10.1108/IJOEM-03-2020-0264
Ghabri Y, Rhouma OB, Gana M, Guesmi K, Benkraiem R (2022) Information transmission among energy markets, cryptocurrencies, and stablecoins under pandemic conditions. Int Rev Financ Anal 82:102197. https://doi.org/10.1016/j.irfa.2022.102197
Gözgör G, Tiwari AK, Demir E, Akron S (2019) The relationship between bitcoin returns and trade policy uncertainty. Financ Res Lett 29:75–82
Gurdgiev C, O'Loughlin D (2020) Herding and anchoring in cryptocurrency markets: investor reaction to fear and uncertainty. J Behav Exp Financ 25:100271
Huang GY, Gau YF, Wu ZX (2022) Price discovery in fiat currency and cryptocurrency markets. Financ Res Lett 47:102615
Hung NT (2022) Asymmetric connectedness among SandP 500, crude Oil. Gold Bitcoin Manag Financ 48(4):587–610
Jareño F, González MDLO, López R, Ramos AR (2021) Cryptocurrencies and Oil price shocks: A NARDL analysis in the COVID-19 pandemic. Resour Policy 74:102281
Jareño F, González MDLO, Tolentino M, Sierra K (2020) Bitcoin and gold price returns: a quantile regression and NARDL analysis. Resour Policy 67:101666
Jiang Y, Lie J, Wang J, Mu J (2021) Revisiting the roles of cryptocurrencies in stock markets: a quantile coherency perspective. Econ Model 95:21–34
Kakinaka S, Umeno K (2022) Cryptocurrency market efficiency in short-and long-term horizons during COVID-19: an asymmetric multifractal analysis approach. Financ Res Lett 46:102319
Kartal MT, Depren Ö, Depren SK (2020) The Determinants of main stock exchange index changes in emerging countries: evidence from turkey in COVID-19 pandemic age. Quant Financ Econ 4(4):526–541
Kartal MT, Ali U, Nurgazina Z (2022a) Asymmetric effect of electricity consumption on CO_2 emissions in the USA: analysis of end-user electricity consumption by nonlinear quantile approaches. Environ Sci Pollut Res 29(55):83824–83838
Kartal MT, Kılıç Depren S, Ayhan F, Depren Ö (2022b) Impact of renewable and fossil fuel energy consumption on environmental degradation: evidence from USA by nonlinear approaches. Int J Sust Dev World. https://doi.org/10.1080/13504509.2022.2087115
Koenker R (2005) Quantile Regression. Cambridge University Press, Cambridge
Kristoufek L, Vosvrda M (2019) Cryptocurrencies market efficiency ranking: not so straightforward. Physica A 531:120853
Kyriazis NA (2021) The effects of geopolitical uncertainty on cryptocurrencies and other financial assets. SN Bus Econ 1(1):1–14

Kyriazis N, Papadamou S, Corbet S (2020) A Systematic review of the bubble dynamics of cryptocurrency prices. Res Int Bus Financ 54:101254
Leirvik T (2022) Cryptocurrency returns and the volatility of liquidity. Financ Res Lett 44:102031
Li D, Hong Y, Wang L, Xu P, Pan Z (2022) Extreme risk transmission among bitcoin and crude oil markets. Resour Policy 77:102761
Liang J, Li L, Chen W, Zeng D (2019) Towards an understanding of cryptocurrency: a comparative analysis of cryptocurrency, foreign exchange, and stock. In: 2019 IEEE international conference on intelligence and security informatics. pp 137–139
Long H, Demir E, Będowska-Sójka B, Zaremba A, Shahzad SJH (2022) Is geopolitical risk priced in the cross-section of cryptocurrency returns? Financ Res Lett 49:103131
López-Martín C, Benito Muela S, Arguedas R (2021) Efficiency in cryptocurrency markets: new evidence. Eurasian Econ Rev 11(3):403–431
Maitra D, Ur Rehman M, Dash SR, Kang SH (2022) Do cryptocurrencies provide better hedging? Evidence from major equity markets during COVID-19 pandemic. North Am J Econ Financ 62:101776. https://doi.org/10.1016/j.najef.2022.101776
Malladi RK, Dheeriya PL (2021) Time series analysis of cryptocurrency returns and volatilities. J Econ Financ 45(1):75–94
Matteoiacoviello (2022) Geopolitical risk index, https://www.matteoiacoviello.com/gpr.htm, Accessed on 22 June 2022
Nakagawa K, Sakemoto R (2022) Cryptocurrency network factors and gold. Financ Res Lett 46:102375
Nouir JB, Hamida HBH (2023) How do economic policy uncertainty and geopolitical risk drive bitcoin volatility? Res Int Bus Financ 64:101809
Phillips PC, Perron P (1988) Testing for A unit root in time series regression. Biometrika 75(2):335–346
Rehman MU, Katsiampa P, Zeitun R, Vo XV (2022) Conditional dependence structure and risk spillovers between bitcoin and fiat currencies. Emerg Market Rev. https://doi.org/10.1016/j.ememar.2022.100966
Ren X, Wang R, Duan K, Chen J (2022) Dynamics of the sheltering role of bitcoin against crude oil market crash with varying severity of the covid-19: a comparison with gold. Res Int Bus Financ 62:101672
Sabah N (2020) Cryptocurrency accepting venues, investor attention, and volatility. Financ Res Lett 36:101339
Shahzad SJH, Bouri E, Rehman MU, Roubaud D (2022) The hedge asset for brics stock markets: bitcoin. Gold VIX World Econ 45(1):292–316
Shanaev S, Ghimire B (2022) A Generalised seasonality test and applications for cryptocurrency and stock market seasonality. Q Rev Econ Financ 86:172–185
Sharif A, Bhattacharya M, Afshan S, Shahbaz M (2021) Disaggregated renewable energy sources in mitigating CO2 emissions: new evidence from the USA using quantile regressions. Environ Sci Pollut Res 28(41):57582–57601
Sim N, Zhou H (2015) Oil prices, US STOCK return, and the dependence between their quantiles. J Bank Financ 55:1–8
Sovbetov Y (2018) Factors influencing cryptocurrency prices: evidence from bitcoin, ethereum, dash, litcoin, and monero. J Econ Financ Anal 2(2):1–27
Urquhart A (2022) Under the hood of the ethereum blockchain. Financ Res Lett 47:102628
Van Erlach J (2022) How the fed caused negative real ınterest rates, ıts effects, and policy ımplications for stock, bond, gold and bitcoin returns. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4021747
Wang H, Wang X, Yin S, Ji H (2022) The asymmetric contagion effect between stock market and cryptocurrency market. Financ Res Lett 46:102345
Wu CC, Ho SL, Wu CC (2022) The determinants of bitcoin returns and volatility: perspectives on global and national economic policy uncertainty. Financ Res Lett 45:102175
Yen KC, Cheng HP (2021) Economic policy uncertainty and cryptocurrency volatility. Financ Res Lett 38:101428
Zhang W, Wang P (2020) Investor attention and the pricing of cryptocurrency market. Evolut Inst Econ Rev 17(2):445–468
Zhang S, Hou X, Ba S (2021) What determines interest rates for bitcoin lending? Res Int Bus Financ 58:101443