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The impacts of cryptocurrency shocks on emerging market currencies: evidence from quantile regression

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Abstract

This paper employs the quantile regression model to investigate the impacts of cryptocurrency shocks on 17 emerging market currencies. The finding shows that cryptocurrency returns significantly influence the exchange rates of emerging market currencies at both lower and higher quantiles. These effects can be positive or negative during normal periods. However, during periods of turmoil, an increase in cryptocurrency returns leads to a depreciation effect on the majority of emerging market currencies.

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1. Introduction

The rapid evolution of blockchain technology has driven the emergence of cryptocurrency as a popular alternative for financial investments and online payments. Over 100 countries, including G20 members, are actively exploring the development of central bank digital currencies (CBDCs) as a response to the rise of cryptocurrencies. This development has generated significant interest in understanding the potential impact of digital currencies on the monetary system. A number of empirical studies have made on the connectedness between cryptocurrencies and fiat currencies, but their focus has largely been on the major currencies (e.g., Urquhart and Zhang 2019; Shahzad et al. 2021; Palazzi et al. 2021). Several emerging market countries, such as Kenya, Nigeria, and Vietnam, have adopted cryptocurrencies for transactions on peer-to-peer (P2P) platforms due to a lack of access to centralized exchanges. Furthermore, residents in emerging markets like Brazil, India, and Venezuela have turned to cryptocurrencies to preserve their savings in the face of inflation and significant currency devaluation. The financial instability and limited financial inclusion prevalent in emerging market and developing countries make them fertile ground for cryptocurrency adoption. Meanwhile, global equity investors have been attracted to emerging financial markets due to the potential for higher returns. The rapid economic development and integration of emerging markets into global capital markets have led to the growing presence of their currencies in the international debt market. As a result, the impact of cryptocurrencies on these emerging market currencies has become a topic of investigation. Carrick (2016) suggests that Bitcoin functions as a complement to emerging market currencies. Kinkyo (2022) finds that Bitcoin could serve as a hedge against the fluctuations of Asian currencies in the medium and long terms. However, BenSaïda (2023) finds that Bitcoin remains isolated from fiat currencies in two groups of countries: G7 and BRICS, even during five major Bitcoin crashes. Thus, this paper aims to bridge this gap in the existing literature and present an alternative viewpoint on cryptocurrencies.

This paper examines the impact of cryptocurrencies on the emerging market currencies. If the impact is positive, it tends to encourage investors to diversify their portfolios and engage in profitable speculations. In this scenario, the two markets are likely to act as complements to each other. It motivates investors to actively participate in both markets. Conversely, if the impact is negative, the two markets may compete with each other and serve as substitutes for potential investors. In such a situation, the negative effect leads investors to shift their attention and investment away from traditional currencies and towards cryptocurrencies. Moreover, this study aims to explore the effects of cryptocurrency shocks and assess the interdependence between cryptocurrencies and emerging market currencies, particularly in both stable and turbulent periods. The outcomes of this analysis will offer significant insights to enhance risk management strategies for investment portfolios. Additionally, the findings can assist monetary policymakers of emerging markets in implementing appropriate policies to mitigate volatility in the foreign exchange market triggered by cryptocurrency shocks.

The subsequent sections of this paper are structured as follows: Section 2 provides a description of the data and methodology utilized in this study. Section 3 presents the empirical findings. Section 4 concludes the paper.

2. Data and methodology

2.1 Emerging market

Chainalysis offers a crypto index that measures the level of cryptocurrency adoption in 146 countries worldwide. Table 1 displays the top 20 countries ranked in 2022. Except for the United States and the United Kingdom, all the listed countries are classified as emerging markets and developing economies by the IMF. It is evident that emerging markets dominate the index. As Ecuador uses the United States dollar as its official currency, we exclude it, along with the two advanced economies, from the sample countries. Consequently, this paper will focus on the 17 emerging and developing countries denoted by "†" in Table 1. In each country, the exchange rate of the domestic currency is quoted indirectly, representing the amount of foreign currency required to purchase one unit of the domestic currency. Consequently, a lower exchange rate indicates depreciation of the domestic currency. Additionally, cryptocurrency prices are commonly denominated in U.S. dollars. Therefore, for the purposes of this paper, the U.S. dollar will serve as the counter currency in an indirect quotation. This means that the exchange rate expresses the number of U.S. dollars per unit of the domestic currency. Table 1 also provides the codes for the fiat currencies analyzed in this study.

2.2 Data description

To examine the effects of cryptocurrency shocks on emerging market currencies, this study utilizes daily data on cryptocurrency prices, Bitcoin (BTC) and Ethereum (ETH), and exchange rates of 17 emerging market currencies. The data covers the period from January 2, 2015, to April 19, 2023, and is obtained from Yahoo Finance (https://tw.finance.yahoo.com/). It should be noted that the data for Ethereum prices is available from November 9, 2017, to April 19, 2023. The sample periods encompass significant events such as the cryptocurrency boom in 2017, the cryptocurrency crash in 2018, the cryptocurrency bubbles during 2020-2021, and the impact of the Covid-19 pandemic.

Table 1 Cryptocurrency adoption index and the code of fiat currency

Country		**Crypto adoption index ranking***	**Fiat currency**	**Code**
Vietnam	†	1	Vietnamese đồng	VND
Philippines	†	2	Philippine peso	PHP
Ukraine	†	3	Ukrainian hryvnia	UAH
India	†	4	Indian rupee	INR
United States		5	-	-
Pakistan	†	6	Pakistani rupee	PKR
Brazil	†	7	Brazilian real	BRL
Thailand	†	8	Thai baht	THB
Russia	†	9	Russian ruble	RUB
China	†	10	Renminbi	CNY
Nigeria	†	11	Nigerian naira	NGN
Turkey	†	12	Turkish lire	TRY
Argentina	†	13	Argentine peso	ARS
Morocco	†	14	Moroccan dirham	MAD
Colombia	†	15	Colombian peso	COP
Nepal	†	16	Nepalese rupee	NPR
United Kingdom		17	-	-
Ecuador		18	-	-
Kenya	†	19	Kenyan shilling	KES
Indonesia	†	20	Indonesian rupiah	IDR

*: https://blog.chainalysis.com/reports/2022-global-crypto-adoption-index/

†: the sample countries in this paper

To accurately define and measure cryptocurrency shocks, this paper adopts the approach proposed by Rigobon and Sack (2003), which identifies periods of turmoil if the thirty-day rolling variance of the research variable exceeds one standard deviation above its average. This paper introduces dummy variables to detect these high-variance periods and capture periods of significant turbulence. Two dummy variables, denoted by $D1$ and $D2$, are employed to identify periods of major disturbance in the Bitcoin and Ethereum markets, respectively. Specifically, $D1$ ($D2$) takes a value of one when the thirty-day rolling variance of Bitcoin prices (Ethereum prices) is high, and zero otherwise. Figure 1 and Figure 2 depict the prices of Bitcoin and Ethereum, respectively, with shaded areas representing periods in which the dummy variable takes a value of one.

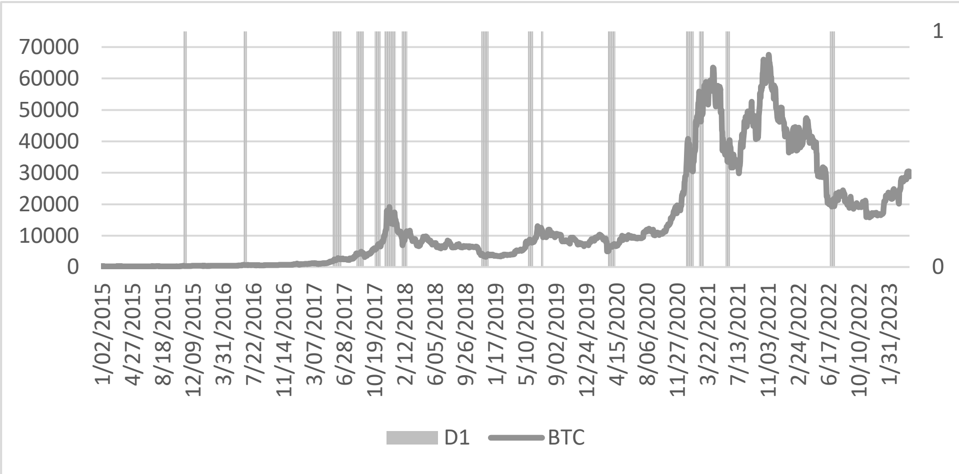

Figure 1 Bitcoin prices and the dummy variable $D1$

Note: The shaded areas represent periods in which the dummy variable takes a value of one.

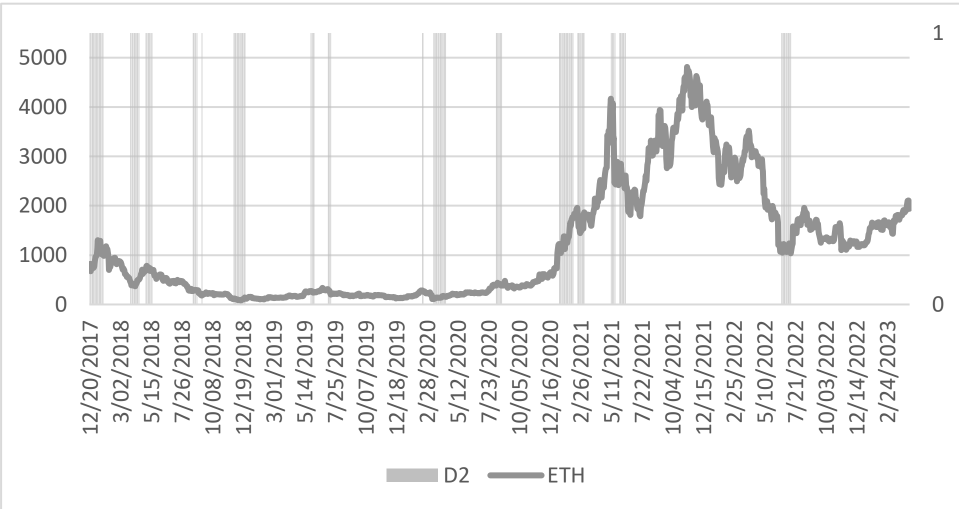

Figure 2 Ethereum prices and the dummy variable $D2$

Note: The shaded areas represent periods in which the dummy variable takes a value of one

All the variables are converted into the daily returns according to the formula $r_t = (\ln P_t - \ln P_{t-1}) \cdot 100$, where P_t denotes the exchange rate or cryptocurrency price at time *t*. Descriptive statistics for empirical variables are presented in Table 2. It is evident that the returns of Bitcoin and Ethereum exhibit higher volatility compared to the returns of all the currencies. The negative skewness statistics indicate that both the daily returns of 15 currencies and Bitcoin have a long tail in the negative direction. All the return series have a kurtosis statistic higher than 3, indicating that they demonstrate leptokurtic distributions and generate a greater number of outliers than the normal distribution. The Augmented Dickey-Fuller (ADF) test demonstrates that all return series reject the null hypothesis of a unit root at a significance level of 1%, indicating that the variables exhibit stationarity.

Table 2 Descriptive statistics

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	ADF test
ARS	-0.151	5.098	-30.450	1.129	-12.265	289.544	-10.115***
BRL	-0.029	6.224	-7.250	1.136	-0.165	6.161	-51.682***
CNY	-0.005	1.822	-1.841	0.275	0.136	8.825	-15.750***
COP	-0.031	9.596	-10.657	1.184	-0.764	10.560	-29.632***
IDR	-0.009	3.864	-4.578	0.650	-0.116	9.282	-10.545***
INR	-0.013	1.871	-2.937	0.395	-0.415	6.847	-13.594***
KES	-0.018	3.206	-2.511	0.504	0.126	7.900	-7.056***
MAD	-0.005	5.720	-5.520	1.515	-0.028	4.179	-11.014***
NGN	-0.042	14.788	-34.391	1.413	-6.681	188.019	-39.904***
NPR	-0.012	2.975	-3.720	0.514	-0.360	7.585	-22.726***
PHP	-0.011	11.518	-12.375	0.558	-0.901	199.738	-33.169***
PKR	-0.048	14.871	-14.537	1.008	-0.663	54.313	-8.848***
RUB	-0.015	11.337	-24.430	1.605	-3.088	56.297	-9.979***
THB	-0.002	2.902	-2.539	0.450	-0.032	10.597	-10.569***
TRY	-0.098	20.904	-20.538	1.233	-0.220	87.113	-9.215***
UAH	-0.040	28.493	-40.971	1.890	-5.788	214.185	-12.133***
VND	-0.006	3.476	-3.594	0.535	-0.103	10.784	-9.570***
BTC	0.308	25.247	-37.170	4.462	-0.136	9.332	-20.363***
ETH	0.308	42.426	-42.347	5.944	0.093	8.893	-25.443***
D1	0.112	1.000	0.000	0.316	2.456	7.032	-10.115***
D2	0.149	1.000	0.000	0.356	1.973	4.895	-51.682***

Note: *** denotes significance at the 1% level.

2.3 Econometric model

This study employs the quantile regression (QR) model pioneered by Koenker and Bassett (1978) to examine the interdependence among variables. The econometric model is written as follows:

$$Q_{y_t}(\tau \mid x_t) = \alpha_1(\tau) + \beta_1(\tau) \cdot BTC_t + \delta_1(\tau) \cdot BTC_t \cdot D1_t \tag{1}$$

$$Q_{y_t}(\tau \mid x_t) = \alpha_2(\tau) + \beta_2(\tau) \cdot ETH_t + \delta_2(\tau) \cdot ETH_t \cdot D2_t \tag{2}$$

where $0 < \tau < 1$, y_t represents the daily return of the emerging market currencies. The coefficients with the differenced term of cryptocurrency prices, $\beta_1(\tau)$ and $\beta_2(\tau)$, measure the impacts of cryptocurrency returns on exchange rates of emerging market currencies across different quantiles. Additionally, the coefficients associated with the interaction term, $\delta_1(\tau)$ and $\delta_2(\tau)$, determine whether these impacts differ between normal periods and turmoil periods. The significance of the estimated value for the interaction term suggests that the relationship between cryptocurrency and emerging market currency is more pronounced during periods of turmoil.

3. Empirical results

3.1 Results for Bitcoin

Table 3 presents the results obtained from QR model in equation (1). The lower quantiles ($\tau = 0.1, 0.25$) represents a lower level of foreign exchange returns, indicating a bearish market. Conversely, the higher quantiles ($\tau = 0.75, 0.9$) corresponds to a higher level of foreign exchange returns, representing a bullish market. Regarding the coefficients with Bitcoin returns (β_1), significant estimates are observed for eight currencies at the lower quantiles, one currency at the middle quantiles, and five currencies at the higher quantiles. However, the signs of these coefficients are not consistent across all quantiles. Concerning the coefficients with the interaction term (δ_1), significant effects are found in six currencies at the lower quantiles, and six currencies at the higher quantiles. The sign is negative in most of these currencies, indicating the depreciating impact on theses currencies during Bitcoin turmoil periods.

The findings from Table 3 are summarized in Table 4. The discussion will focus on four scenarios: $\beta_1 \neq 0,\ \delta_1 = 0$ (region Ⅳ , Ⅵ); β_1=0, $\delta_1 \neq 0$ (region Ⅱ , Ⅷ); $\beta_1 \neq 0,\ \delta_1 \neq 0$ (region Ⅰ ,Ⅲ,Ⅶ,Ⅸ); $\beta_1 = 0,\ \delta_1 = 0$ across all quantiles (region Ⅴ). In the first scenario, where the coefficient for Bitcoin returns is significant and the interaction term is insignificant, it suggests a consistent relationship between the returns of Bitcoin and the respective currencies, regardless of normal or turmoil periods in the Bitcoin market. The positive coefficient for Bitcoin returns in four cases indicates that these currencies tend to appreciate when Bitcoin returns increase, suggesting a complementary relationship. On the other hand, the negative coefficient for Bitcoin returns in four cases illustrates the tendency of these currencies to depreciate as Bitcoin returns increase. This demonstrates a substitute relationship with Bitcoin, particularly observed in the cases of the Colombian peso and Renminbi.

Table 3 The estimation result for Bitcoin

		Quantile regression				
		0.1	0.25	0.5	0.75	0.9
ARS	β_1	0.009	0.002	0.001	0.001	0.001
	δ_1	0.018*	0.006	0.002	0.0004	0.015
BRL	β_1	0.016*	0.006	-0.005	-0.012	-0.0004
	δ_1	-0.020	-0.013	0.007	-0.007	-0.005
CNY	β_1	-0.005*	-0.004**	-0.0002	-0.003**	-0.004
	δ_1	-0.003	0.001	-0.001	-0.0002	-0.001
COP	β_1	-0.011	-0.013*	-0.010*	-0.013*	-0.002
	δ_1	-0.007	0.005	0.006	-0.010	-0.003
IDR	β_1	0.003	0.002	-0.0004	-0.001	0.006
	δ_1	-0.027**	-0.007	-0.003	-0.017***	-0.026**
INR	β_1	0.005	0.002	0.0003	-0.002	-0.006**
	δ_1	-0.019**	-0.004	-0.001	-0.003	-0.009
KES	β_1	-0.002	0.002	0.001	0.005***	0.017**
	δ_1	-0.014	-0.007	-0.001	-0.007**	-0.002
MAD	β_1	-0.013	-0.003	0.000	-0.002	0.007
	δ_1	0.031	0.0005	-0.003	-0.003	-0.040*
NGN	β_1	0.007*	-0.0002	0.000	-0.002	-0.002
	δ_1	-0.003	0.009	0.000	0.007	0.002
NPR	β_1	0.009**	0.0003	0.001	0.000	-0.001
	δ_1	0.001	-0.006	0.006	-0.0003	0.011
PHP	β_1	-0.001	-0.003	-0.002	-0.003	-0.003
	δ_1	-0.004	-0.005	0.001	0.012**	0.010
PKR	β_1	0.002	0.001	0.000	0.013**	0.010
	δ_1	0.035***	0.010	0.000	-0.014*	-0.015
RUB	β_1	0.034*	0.003	0.004	0.003	-0.005
	δ_1	-0.055**	-0.016	-0.004	-0.014	0.005
THB	β_1	-0.001	0.001	-0.0001	0.003	-0.001
	δ_1	-0.014	-0.003	-0.003	-0.010**	-0.010
TRY	β_1	0.014	0.004	0.003	0.002	0.013
	δ_1	-0.018	-0.013	-0.004	-0.002	-0.007
UAH	β_1	0.024***	0.007	0.001	0.004	-0.003
	δ_1	-0.024**	0.000	-0.001	-0.002	0.016
VND	β_1	-0.013***	-0.001	0.000	-0.001	-0.012
	δ_1	0.008	-0.001	0.000	-0.001	0.008

Note: ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

In the second scenario, where the coefficient for Bitcoin returns is insignificant and the interaction term is significant, it indicates that the significant relationship between the returns of Bitcoin and the respective currencies only occurs during turmoil periods. During these periods, three currencies appreciate, while four currencies depreciate as Bitcoin returns increase. Notably, this negative relationship suggests the safe haven property of Bitcoin for the Indonesian rupiah, regardless of whether the market is bearish or bullish.

In the third scenario, where both the coefficients for Bitcoin returns and the interaction term are significant, it indicates that the currencies demonstrate different responses during normal and turmoil periods. As Bitcoin returns increase, four currencies tend to appreciate during normal periods but shift to depreciation during Bitcoin turmoil periods. Specifically, as tensions between Russia and Ukraine escalate, Bitcoin may serve as a substitute and a safe haven for the Russian ruble and Ukrainian hryvnia.

In the final scenario, where both the coefficients for Bitcoin returns and the interaction term are insignificant across all quantiles, it suggests a lack of significant relationship between Bitcoin returns and the individual currency under consideration. The Turkish lira is the only currency that appears to be unaffected by the Bitcoin market, irrespective of whether the overall market conditions are normal or in a state of turmoil.

Table 4 Summary of the estimation result for Bitcoin

	$\delta_1>0$	$\delta_1=0$	$\delta_1<0$
$\beta_1>0$	I	IV BRL(l) NGN(l) NPR(l) KES(h)	VII RUB(l) UAH(l) KES(h) PKR(h)
$\beta_1=0$	II ARS(l) PKR(l) PHP(h)	V TRY(lmh)	VIII IDR(lh) INR(l) MAD(h) THB(h)
$\beta_1<0$	III	VI COP(lmh) CNY(lh) VND(l) INR(h)	IX

Note: The “l”, “m” and “h” in parentheses indicate at the lower, middle and higher quantiles, respectively.

3.2 Results for Ethereum

Table 5 presents the estimation results for equation (2). The estimates for the coefficients with Ethereum returns (β_2) are significant for eight currencies at the lower quantiles, one currency at the middle quantiles, and one currency at the higher quantiles. However, the signs of these coefficients are not all the same, indicating varying relationships between Ethereum returns and the exchange rates of these currencies. Regarding the coefficients with the interaction term (δ_2), significant effects are found in ten currencies at the lower quantiles, four currencies at the middle quantiles, and six currencies at the higher quantiles. In most cases, the signs are negative, suggesting that these currencies tend to depreciate during Ethereum turmoil periods.

Table 6 summarizes the results for Ethereum as presented in Table 5. Ethereum exhibits a complementary relationship with three currencies, and a substitute relationship with three currencies during both normal and turmoil periods. Furthermore, the second scenario includes 11 currencies. During turmoil periods, a substitution effect between Ethereum and these currencies is generally observed, particularly in the cases of the Renminbi and Thai baht. Regarding the third scenario, the relationship between Ethereum returns and three currencies is positive during normal periods but turns negative during turmoil periods. Conversely, the relationship between Ethereum returns and Nigerian naira is negative during normal periods but reverses during turmoil periods. Lastly, the Pakistani rupee is the only currency that reveals an insignificant relationship with Ethereum returns during both normal and turmoil periods.

Table 5 The estimation result for Ethereum

Currency		Quantile regression				
		0.1	0.25	0.5	0.75	0.9
ARS	β_2	0.008**	0.003	0.0004	0.000	-0.001
	δ_2	0.000	-0.002	-0.004	-0.003	0.003
BRL	β_2	0.006	-0.001	-0.006	-0.007	-0.001
	δ_2	-0.027	-0.025*	-0.004	-0.018	-0.005
CNY	β_2	-0.001	0.001	0.0002	0.0002	0.006
	δ_2	-0.007*	-0.007*	-0.007**	-0.003	-0.010**
COP	β_2	0.008	0.002	0.000	-0.001	0.008
	δ_2	-0.018	-0.029*	-0.019*	-0.011	-0.006
IDR	β_2	-0.002	-0.004	0.001	0.001	-0.028
	δ_2	-0.018**	-0.002	-0.005	-0.015***	-0.029***
INR	β_2	0.002	0.0004	0.001	0.0002	-0.004
	δ_2	-0.012	-0.005	-0.006**	-0.004	-0.005
KES	β_2	0.004	0.002	0.002*	0.001	0.001
	δ_2	-0.011	-0.001	-0.001	0.003	0.006
MAD	β_2	-0.054*	0.0001	0.000	0.004	0.014
	δ_2	0.069	-0.009	-0.003	-0.011**	-0.044
NGN	β_2	-0.011***	-0.003**	0.000	0.002	0.009
	δ_2	0.020	0.010**	0.000	0.002	0.001
NPR	β_2	0.001	-0.005*	0.002	-0.003	0.001
	δ_2	0.003	0.006	-0.0002	-0.001	-0.001
PHP	β_2	-0.003	-0.001	0.001	0.003	0.002
	δ_2	-0.018***	-0.012***	-0.005	-0.004	0.007
PKR	β_2	0.009	-0.001	0.000	0.005	0.003
	δ_2	-0.003	0.006	0.000	-0.009	-0.015
RUB	β_2	0.017**	0.002	0.000	0.006	0.007
	δ_2	-0.064***	-0.009	-0.006	-0.020	-0.042**
THB	β_2	-0.001	0.001	0.002	0.006	0.003
	δ_2	-0.022***	-0.006	-0.009**	-0.014***	-0.016***
TRY	β_2	0.011	0.012***	0.004	0.008	0.023**
	δ_2	-0.028**	-0.030***	-0.018	-0.022**	-0.034**
UAH	β_2	0.009	0.005*	0.000	0.002	-0.001
	δ_2	-0.013	-0.005	0.000	0.005	0.003
VND	β_2	-0.0001	0.001**	0.000	0.000	-0.0004
	δ_2	-0.006***	-0.003***	0.000	-0.0002	-0.005

Note: ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 6 Summary of the estimation result for Ethereum

	$\delta_2>0$	$\delta_2=0$	$\delta_2<0$
$\beta_2>0$	Ⅰ	Ⅳ ARS(l) UAH(l) KES(m)	Ⅶ TRY(lh) RUB(l) VND(l)
$\beta_2=0$	Ⅱ	Ⅴ PKR(lmh)	Ⅷ CNY(lmh) THB(lmh) COP(lm) TRY(lh) IDR(lh) BRL(l) PHP(l) VND(l) INR(m) RUB(h) MAD(h)
$\beta_2<0$	Ⅲ NGN(l)	Ⅵ NGN(l) NPR(l) MAD(l)	Ⅸ

Note: The “l”, “m” and “h” in parentheses indicate at the lower, middle and higher quantiles, respectively.

3.3 Discussion

To summarize the empirical findings regarding Bitcoin and Ethereum, the results show that cryptocurrency returns have a significant relationship with the exchange rates of most emerging market currencies at the lower and higher quantiles during normal periods. Furthermore, during turmoil periods, a weakening of the emerging market currency coincides with a strengthening of cryptocurrency. This outcome reveals the safe haven characteristic of cryptocurrency, which is consistent with the findings of Urquhart and Zhang (2019) at the intraday level, and Hsu et al. (2021) during the Covid-19 pandemic. However, there are differing opinions, as Hsu et al. (2021) found no spillover effects between these two markets during the 2018 cryptocurrency crash.

Let's observe the behavior of certain currencies. When the price of Bitcoin is stable, the Renminbi and Bitcoin are considered substitutes. However, when the price of Ethereum fluctuates significantly, the Renminbi and Ethereum become substitutes instead. This implies that investors may choose to hold either Renminbi or Ethereum based on their preference and market conditions. Since 2018, the Ethereum market has displayed a higher level of return and variance compared to the Bitcoin market. This means that the price of Ethereum has experienced larger fluctuations and potential gains or losses compared to Bitcoin. Such behavior in the Ethereum market has motivated investors to reconsider their portfolio allocations and potentially increase their exposure to Ethereum.

Furthermore, during normal periods, the Russian ruble and cryptocurrencies, including Bitcoin and Ethereum, are considered complements. However, during periods of turmoil, they can become substitutes. Therefore, cryptocurrencies may serve different purposes or exhibit different characteristics depending on the market environment. Investors may view cryptocurrencies as a complementary asset to the Russian ruble during stable periods, using them for diversification. However, during turbulent times, cryptocurrencies may be seen as substitutes for the Russian ruble, offering the alternative options for investment or hedging.

4. Conclusions

This paper utilizes both the OLS model and QR model to examine the effects of cryptocurrency shocks on emerging market currencies. The primary finding is that, according to the OLS model, more than half of the examined emerging market currencies exhibit no significant relationship with cryptocurrencies. In the QR model, the impact of cryptocurrencies on the emerging market currencies is observed to be significant at both lower and higher quantiles. During normal periods, the impact can be either positive or negative, while during the turmoil periods, it tends to be negative for most currencies. This negative relationship highlights the safe haven characteristics of cryptocurrencies, which holds significant implications for cryptocurrency investors and portfolio managers.

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