

Article

Bitcoin and Fiat Currency Interactions: Surprising Results from Asian Giants

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Abstract: This study examines the interaction of Bitcoin with fiat currencies of three developed (euro, pound sterling and yen) and three emerging (yuan, rupee and ruble) market economies. Empirical investigations are executed through symmetric, asymmetric and non-linear causality tests, and Markov regime-switching regression (MRSR) analysis. Results show that Bitcoin has a causal nexus with Chinese yuan and Indian rupee for price and various return components. The MRSR analysis justifies these findings by demonstrating the presence of interaction in contractionary regimes. Accordingly, it can be stated that when markets display a downward trend, appreciation of the Chinese yuan and Indian rupee positively and strongly affects the value of Bitcoin, possibly due to the market timing. The MRSR analysis also exhibits a transition from a tranquil to a crisis regime in March 2020 because of the pandemic. However, a shorter duration spent in the crisis regime in 2020 indicates the limited and relatively less harmful effect of the pandemic on the cryptocurrency market when compared to the turmoil that occurred in 2018.

Keywords: Bitcoin; cryptocurrency market; fiat money; causality analysis; return spillovers



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1. Introduction

The Bitcoin and cryptocurrencies market in general have had a logarithmic growth curve over the long run, making them seem uncorrelated with global markets and major fiat currencies. However, in recent years, particularly during the COVID-19 crash, as market conditions have deteriorated, Bitcoin returns have shown a positive correlation with stock markets [1,2]. This recent paradigm shift paves the way to further investigate the relationship of Bitcoin with traditional financial assets such as fiat currencies and provides some further reasoning and a comparative framework to evaluate any such interaction.

Relationships of exchange rates and their interactions with economic and financial indicators have always been a focus of interest in finance. Cryptocurrencies have also gained increasing attention in the finance literature and among investors, especially post-2018 when the price of Bitcoin soared to a then all-time high. To assess any possible relationship between cryptocurrencies and fiat currencies, this study focuses on Bitcoin as it is the most indicative asset in cryptocurrency markets. The significance of Bitcoin as a major cryptocurrency can be seen from rising exchange volumes, formation of multiple cryptocurrency price bubbles in consecutive market cycles, the rising number of Bitcoin ATMs around the globe and its increased media attention [3–6]. Further, the recent emergence of cryptocurrency-based credit/debit cards and newly emerging fields, such as decentralized finance based on a variety of cryptocurrencies and implemented through smart contracts, point to the increasing role of cryptocurrencies such as Bitcoin in mainstream financial markets [7–11]. While Bitcoin still constitutes a miniscule portion of global markets, it is arguably the asset that has the greatest potential to disrupt and reform the current financial system. A possible future dominance of Bitcoin in global markets may mean that it and

other cryptocurrencies will compete with or even replace fiat currencies, possibly leading to a framework that bypasses central banks. Whether cryptocurrencies will be disruptive or will peacefully and quietly integrate with present-day finance as an alternative means of storing and transferring value is yet to be seen. In either case, if the current trend continues, cryptocurrencies such as Bitcoin seem to be poised to be a significant part of our financial system.

Among the countries which are highly active in the cryptocurrency market, China has always been the one that is most closely associated with Bitcoin. Historically, China has been ahead of the curve, such as when the search engine giant Baidu, often tagged as Chinese Google, began accepting Bitcoin for its website security services in 2013 [12–14]. Although similar news of acceptance of cryptocurrencies on various fronts are common now, such as the recent announcement of PayPal's integration with Bitcoin in 2020, a cryptocurrency approach at the scale as adopted by China has not been seen in any other country. China has also been an early entrepreneur in Bitcoin mining and continues to be a major contributor to global Bitcoin mining. According to Kaiser et al. [14], the mining pools managed in China did constitute 80% of total mining pools, and 74% of the hash power on the Bitcoin network is accumulated under Chinese-managed mining pools. Due to the way the Bitcoin network is designed, mining dominance also translates to transaction-fee-collecting supremacy. Chinese dominance in mining may partly be attributed to low energy costs in the country. Further, according to coinmarketcap data, Binance, a major exchange with Chinese origin, is currently the most visited exchange along with having the highest trading volume.

In addition, China assumes a leading role in related technology surrounding cryptocurrencies. There are 30,000+ companies registered as blockchain businesses in China [15]. On the other hand, politically, China has been actively imposing various bans on Bitcoin, cryptocurrency in general and ICO (Initial Coin Offering), especially post-2017 [16–18]. While many countries are employing various kinds of bans on cryptocurrencies, China's actions have arguably been the most influential in cryptocurrency markets, and often are viewed as controversial. In recent years, Bitcoin had an actual use-case of wealth transport particularly in China, where traders' foreign currency acquisitions were limited to \$50,000 annually. According to the report of Chainalysis, a New York-based blockchain forensics firm, in order to circumvent this regulation, more than \$50 billion of cryptocurrency was transferred from virtual wallets in China to other parts of the world in 2019 alone [19]. Financial institutions in China are currently not allowed to facilitate Bitcoin transactions as regulations prohibit all businesses from holding or trading cryptocurrencies. However, in spite of these regulations, it is perceived that China directly or indirectly has a large impact in cryptocurrency markets as a policymaker, mining-facilitator, broker and exchange-based retail and institutional custodian [13,14,20,21].

The premise of this study was motivated by the similarity between wild price movements of Bitcoin and emerging market currencies. Literature studies depict that both Bitcoin and emerging markets have large fluctuations and require high risk premiums [10,11,22–25]. Recent events such as the US presidential elections and global trade wars have contributed to the uncertainties, particularly affecting emerging economies. As noted by Gunay [26], the global pandemic escalated the turmoil in the currency markets of these countries. However, from a financial perspective, most developed countries showed relatively better performance in coping with the outbreak. These unexpected market developments have exacerbated the divergence in the extent of risks in these two groups of economies and shifted emerging economies towards greater volatility comparable to that of cryptocurrencies. Therefore, the potential interconnectedness between emerging economies' currencies and Bitcoin is hypothesized to be more apparent due to these changes. In addition to this, cryptocurrencies, especially Bitcoin, are increasingly becoming a medium of exchange and are speculated to one day replace fiat currencies. This potential appears to be a threat to the dominance of fiat currencies of developed economies. However, from the standpoint of emerging countries, it seems to be an opportunity to overcome the hegemony of developed

economies in currency markets. Therefore, the potential of cryptocurrencies and their price developments are meticulously observed by all market participants and policymakers from both groups of countries.

To shed light on these facts and to empirically investigate the interactions of Bitcoin with both groups of fiat currencies, this study includes currencies from three developed and three emerging economies. The currencies of emerging and developed countries within this study were classified and selected following the procedures of MSCI [27] and the most recent annual trading volume report of BIS [28], respectively. Thus, we have chosen euro (EUR—€), Japanese yen (JPY—¥) and pound sterling (GBP—£) from the developed economies, and Chinese yuan (CNY—¥), Indian rupee (INR—₹) and Russian ruble (RUB—₽) from the emerging countries. The US dollar is used as the base currency. By defining the direction of causal relationships and exploring the interactions in bull and bear regimes, it can be observed whether the chosen fiat currencies have statistically significant power on Bitcoin price developments. Past studies show that contrary to the determinants of fiat currencies, token prices display highly volatile and speculative patterns [29–31]. Therefore, any evidence regarding the price formation of Bitcoin would be useful information for all market participants. In such an environment, investors can better hedge their risks stemming from the wild volatility of Bitcoin. Additionally, determining the currencies that have low/high correlations with Bitcoin would also be of use for investors who would prefer to better diversify their portfolio by adding the currencies that have a minimum degree of relationship with Bitcoin.

2. Literature Review

Dynamics of currencies such as the Chinese yuan along with other economic indicators have been traditionally under focus in financial studies. Hall et al. [32] measure currency pressures upon Japanese yen, Chinese yuan and UK pound while keeping US Dollar as the reference currency. They use a model-based methodology to measure exchange market pressure and finds that conversion results are consistent with the actual market policies pursued. While Chen and Peng [33] investigate the potential of the yuan becoming an international currency, Mallaby and Wethington [34] point to difficulties in China's endeavor to internationalize the yuan. On the other hand, Dobson and Masson [35] consider the factors that contribute to the international use of currencies, and consider various aspects of China's financial system that need change in order for the yuan to emerge as an important regional or world currency. Zhang and Fung [36] use a computational general equilibrium model to observe the effects of the Chinese yuan on the consumption, investment, trade, output and welfare of individual countries or regions.

Spillovers in money markets have been thoroughly examined in the finance literature. For example, Inagaki [37] focuses on pure cross-effects between currencies such as the British pound and euro. Baba et al. [38] investigate the effects of spillovers on FX swap and long term cross-currency basis swap markets. On the other hand, Antonakakis and Kizys [39] study dynamic spillovers between currencies and commodities such as gold, silver and platinum. In addition, numerous volatility-related studies such as Nikkinen et al. [40], examine linkages in expected future volatilities of European currencies by applying autoregressive modelling to currency options on the euro, British pound and Swiss franc against the US dollar, and find that the expectations of future exchange rate volatilities are significantly linked among major European currencies. Cairns et al. [41] examine the depreciating nature of high-yielding currencies at highly volatile times of global equity and bond markets, while suggesting that low-yielding currencies tend to serve as a “safe haven”, particularly pointing to Asia-Pacific currencies.

Guesmi et al. [42], examining Portfolio diversification with cryptocurrencies, suggest that cryptocurrencies are in low correlation with financial assets. Further, Katsiampa [43] studies Bitcoin price volatility under several GARCH models and finds that the AR-CGARCH is the optimal model for goodness-of-fit to the data. Another study co-authored by Katsiampa evaluates the interactions of volatilities of cryptocurrencies, finding that

Bitcoin is not necessarily dominant while shocks from Bitcoin last the longest [23]. Katsiampa [44] also uses a Diagonal BEKK model, to study the volatility interdependencies of Bitcoin and Ether, highlighting that two cryptocurrencies' volatility and correlation depict responses to major news events and suggests Ether as a hedge against Bitcoin. On the other hand, Katsiampa et al. [45] considers volatility spillover effects in leading cryptocurrencies via a BEKK-MGARCH analysis, in which the conditional dynamic volatility and conditional correlations between major cryptocurrencies is investigated. This study finds mostly positive evidence of bi-directional shock transmission effects of Bitcoin with Ether and Litecoin. Fry and Cheah [46] study the volatile nature of cryptocurrency markets by using econo-physics models, examining shocks and crashes and finding evidence of a spillover from Ripple to Bitcoin. Another interesting study by Peng et al. [8] focuses on approaches in estimation of volatility. The authors compare machine learning for the estimation of volatility in the cryptocurrency market with other volatility models and argue that a machine learning model produces better results for low and high frequencies. Li et al. [47] measure the return risk of virtual financial assets (VFAs) by establishing a Markov regime-switching regression model, finding that the influence of speculation and investor attention on the risks of VFAs are distinguishably positive in all regimes, while under a high-risk regime, market interoperability admits a positive impact on risk. Another study suggests that cryptocurrency market returns may have an asymmetric response to market shocks, similar to that of major precious metals [48].

A recent study of Ji et al. [49] considers connectedness via return and volatility spillovers across some major cryptocurrencies and finds that Litecoin and Bitcoin are central to the connected network of returns while pointing that connectedness via negative returns is stronger than via positive ones. Another study by Ji et al. [50] focuses on information interdependence among commodities and cryptocurrencies via a time-varying entropy approach, suggesting that the nature of information spillovers changes is time-varying and argues that cryptocurrencies are integrated within broader commodity markets. Bouri et al. [51] study return and volatility spillovers between Bitcoin and major asset classes such as equities, stocks, commodities, currencies and bonds, particularly focusing on bear and bull market conditions while employing a smooth transition VAR GARCH-in-mean model pointing that Bitcoin market is not isolated completely. Another related comparative study argues that cryptocurrencies' memory is lower than stock indices [52].

Corbet et al. [53] obtain highly interesting results regarding cryptocurrency reaction to FOMC announcements, concluding that currency-based digital assets depict peculiar spillovers after US monetary policy announcements. Application or protocol-based digital assets were not as reactive to policy volatility spillover and feedback, pointing to the diverse market within the large number of cryptocurrencies, within which not all assets are equally comparable to Bitcoin. Another recent study suggests that during a financial and economic disruption, such as the covid-19 crash, Bitcoin and cryptocurrencies act more as amplifiers of contagion rather than hedge or safe havens [2]. Giudici and Pagnottoni [54] study high frequency price change spillovers in Bitcoin exchanges to specifically assess spillover effects and address lead-lag relationships among market exchanges via an extension of Diebold and Yilmaz [55] econometric connectedness measures. They also observe that connectedness of overall returns falls significantly immediately before Bitcoin price hype events. Luu Duc Huynh [56] studies spillover risks on cryptocurrency markets from quite a different perspective by using Student's-t Copulas and a SVAR (Structural Vector Autoregressive Model) Granger causality. This study find that Ether is more probable than any other cryptocurrency to be independent in this market, where Bitcoin is more inclined to be the spillover effect recipient, noting that investors must pay more attention to 'bad news'. A recent related study investigates relationship of cryptocurrency markets with US stock and gold prices by using a large variety of copula-GARCH models. By comparing the efficiencies of these models under different market conditions, it is empirically shown that S&P 500 and gold price are statistically significant in their interaction with return and volatility of Bitcoin [57].

Bohte and Rossini [58] study the forecasting ability of the time series of major cryptocurrencies in which they compare different Bayesian models, some of them with constant and time-varying volatility, such as stochastic volatility and GARCH. The authors also incorporate crypto-predictors such as S&P 500 and Nikkei 225 in the analysis and find that stochastic volatility outperforms the benchmark of VAR in point and density forecasting. Catania et al. [59] study the predictability of time series of major cryptocurrencies via univariate and multivariate models for point and density forecasting. In addition they apply crypto-predictors and dynamic model averaging in order to combine a set of univariate dynamic linear models as well as several multivariate vector autoregressive models. This allowed for improvements in point forecasting and the attainment of significant directional predictability. Bianchi et al. [60] studied the cross-sectional correlation between the returns on major cryptocurrency pairs and stablecoins while proposing a large-scale Bayesian Vector Autoregressive (BVAR) model featuring sparsity in the cross-pair returns correlations. Their study finds that price changes of the Tether (USDT) stablecoin positively correlates with future returns on major cryptocurrency pairs, yielding a strategy based on the phenomenon compared to the simple buy-and-hold investment in Bitcoin.

As presented, the above current literature omits the potential relationship between Bitcoin and fiat currencies in the domain of emerging and developed economies. By considering this observation, this study investigates the following research question: Does Bitcoin display an independent price development from fiat currencies?

Following the determination of path in relationships, an MRSR equation is set to investigate the significance of independent variables under the consideration of different market regimes (bull and bear). Additionally, contrary to the current literature, evidence is provided from both emerging and developed markets to consider the extent of economic development on the results.

3. Methodology

3.1. Symmetric and Asymmetric Causality Analysis

To investigate the causal network modified Wald test statistic (M-Wald) introduced by Toda and Yamamoto [61] was used. It is based on the augmented VAR ($p + d$) model:

$$y_t = \hat{\nu} + \hat{A}_1 y_{t-1} + \dots + \hat{A}_p y_{t-p} + \dots + \hat{A}_{p+d} y_{t-p-d} + \hat{\varepsilon}_t \quad (1)$$

y_t , $\hat{\nu}$ and $\hat{\varepsilon}_t$ are n -dimensional vectors, $\hat{A}_r$ is an $n \times n$ matrix of parameters for lag r , p is the optimal lag order that is obtained through respective information criterion in a bivariate VAR model, and d is equal to the maximum order of integration of the variables that is determined through the unit root tests of ADF, PP and BBC. The circumflex above the variables denote estimation by ordinary least squares (OLS). By following the specification of Hacker and Hatemi-J [62], and Hatemi-J [63], the M-Wald statistic for causality analysis is presented. The following definitions are specified for a sample size of T before the test statistic is introduced:

$$Y := (y_1, \dots, y_T) \quad (n \times T) \text{ matrix}, \quad (2)$$

$$\hat{D} := (\hat{\nu}, \hat{A}_1, \dots, \hat{A}_p, \dots, \hat{A}_{p+d}) \quad (n \times (1 + n(p + d))) \text{ matrix} \quad (3)$$

$$Z_t := \begin{bmatrix} 1 \\ y_t \\ y_{t-1} \\ \vdots \\ y_{t-p-d+1} \end{bmatrix} \quad ((1 + n(p + d)) \times 1) \text{ matrix, for } t = 1, \dots, T, \quad (4)$$

$$Z := (Z_0, \dots, Z_{T-1}) \quad ((1 + n(p + d)) \times T) \text{ matrix}, \quad (5)$$

$$\hat{\delta} := (\hat{\varepsilon}_1, \dots, \hat{\varepsilon}_T) \quad (n \times T) \text{ matrix} \quad (6)$$

The estimated VAR($p + d$) model can thus be compactly written as:

$$Y = \hat{D}Z + \hat{\delta} \quad (7)$$

The M-Wald statistic for testing non-Granger causality is asymptotically χ^2 distributed with the degrees of freedom equal to p , and can be compactly written as:

$$M - Wald = (C\hat{\beta})' [C((Z'Z)^{-1} \otimes S_U)C']^{-1} (C\hat{\beta}) \quad (8)$$

where $\otimes$ is the Kronecker product, C is a $p \times n(1 + n(p + d))$ matrix, S_U is the variance-covariance matrix of the unrestricted VAR model and $\hat{\beta} = vec(\hat{D})$, vec being the column-stacking operator. The null hypothesis of non-Granger causality is given by: $H_0 : C\beta = 0$.

In asymmetric causality analysis, the primary action is to generate the cumulative form of the negative and positive returns. By assuming that y_{1t} and y_{2t} follow a random walk process, positive and negative returns of their white noise error term are defined as follows: $\varepsilon_{1i}^+ = \max(\varepsilon_{1i}, 0)$, $\varepsilon_{2i}^+ = \max(\varepsilon_{2i}, 0)$, $\varepsilon_{1i}^- = \min(\varepsilon_{1i}, 0)$ and $\varepsilon_{2i}^- = \min(\varepsilon_{2i}, 0)$, respectively. Therefore,

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{i=1}^t \varepsilon_{1i}^+ + \sum_{i=1}^t \varepsilon_{1i}^- \quad (9)$$

and

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{i=1}^t \varepsilon_{2i}^+ + \sum_{i=1}^t \varepsilon_{2i}^- \quad (10)$$

The cumulative form of these returns can be expressed as follows: $y_{1t}^+ = \sum_{i=1}^t \varepsilon_{1i}^+$, $y_{1t}^- = \sum_{i=1}^t \varepsilon_{1i}^-$, $y_{2t}^+ = \sum_{i=1}^t \varepsilon_{2i}^+$ and $y_{2t}^- = \sum_{i=1}^t \varepsilon_{2i}^-$. The final step is to test causality between these variables.

3.2. Markov Regime-Switching Regression Analysis

Following Hamilton [64] and Kim et al. [65], regime-switching model for sample path of a time series $\{y_t\}_{t=1}^T$ is given by:

$$\begin{aligned} y_t &= x_t' \beta_{S_t} + \sigma_{S_t} \varepsilon_t, \\ \varepsilon_t &\sim i.i.d. N(0, 1). \end{aligned} \quad (11)$$

where y_t is scalar, x_t is a $(k \times 1)$ vector of predetermined explanatory variables, which may include lagged values of y_t , and $S_t = i$ is the state variable. Both y_t and x_t are assumed to be covariance-stationary. N denotes the number of regimes, so that $i = 1, 2, \dots, N$. Here we use two regimes ($N = 2$), representing contractionary and expansionary regimes.

Transition probabilities of the state variable according to a first-order Markov chain is given by:

$$P(S_t = i | S_{t-1} = j, z_t) = P_{ij}(z_t). \quad (12)$$

In the above equation, the transition probabilities are influenced by a $(q \times 1)$ vector of covariance-stationary variables z_t , where z_t may include elements of x_t . The Markov chain is assumed to be stationary, and to evolve independently of all observations of those elements of x_t not included in z_t .

A probit specification for S_t is used to model the influence of z_t on the $[0,1]$ transition probabilities in (12):

$$S_t = \begin{cases} 1 & \text{if } \eta_t < a_{S_{t-1}} + z_t' b_{S_{t-1}} \\ 2 & \text{if } \eta_t \geq a_{S_{t-1}} + z_t' b_{S_{t-1}} \end{cases} \quad \eta_t \sim i.i.d. N(0, 1). \quad (13)$$

Transition probabilities are then given by:

$$\begin{aligned} P_{1j}(z_t) &= P(\eta_t < a_j + z'_t b_j) = \Phi(a_j + z'_t b_j), \\ P_{2j}(z_t) &= P(\eta_t \geq a_j + z'_t b_j) = 1 - \Phi(a_j + z'_t b_j). \end{aligned} \quad (14)$$

where Φ is the standard normal cumulative distribution function.

4. Empirical Analysis

In the empirical section of the study, we examine the relationship between Bitcoin and fiat currency pairs. We utilize the log return and log price series of the corresponding time series depending on the methodology. As fiat money, we select three currencies from advanced economies (EUR—euro, GBP—British pound sterling, JPY—Japanese yen) and emerging countries (CNY—Chinese yuan, INR—Indian rupee, RUB—Russian ruble). All variables have daily frequencies and the analysis period covered from 02.01.2015 to 19.11.2020. The value of Bitcoin and the fiat currencies are expressed vis-a-vis the US dollar, meaning that in each pair the dollar is the base currency. The data is obtained from the Thomson Reuters Eikon database and www.coinmarketcap.com. The econometric investigation is executed through various methods—unit root tests, symmetric, asymmetric and nonlinear causality analyses, and return spillover methodology of Diebold–Yilmaz through E-views, Gauss and R. In Figure 1, we present the historical behavior of the raw price series of each variable. Table 1 contains the results of descriptive statistics of log return and log price series.

Table 1. Descriptive Statistics.

		USD/BTC	USD/EUR	USD/GBP	USD/JPY	USD/CNY	USD/INR	USD/RUB
Log Returns	Mean	0.0027	0.0000	0.0001	−0.0001	0.0000	0.0001	0.0002
	Std. Dev.	0.0454	0.0051	0.0064	0.0055	0.0028	0.0032	0.0102
	Skewness	−0.8387	0.0429	2.1105	−0.5534	0.9179	0.2181	0.0615
	Kurtosis	14.373	5.7030	36.255	9.1740	16.335	4.9660	7.9010
	Jarque-Bera	8.3810 *	464.00 *	7.1263 *	2.4950 *	1.1490 *	257.00 *	1.5240 *
Log Prices	Mean	3.3685	−0.0528	−0.1275	2.0467	0.8253	1.8327	1.8056
	Std. Dev.	0.6238	0.0162	0.0317	0.0210	0.0175	0.0235	0.0403
	Skewness	−0.3959	−0.4139	−0.7637	0.5029	−0.3551	0.3431	0.1645
	Kurtosis	1.5410	2.8792	2.4356	2.7817	2.0737	2.1782	3.1190
	Jarque-Bera	175.00 *	44.000 *	168.00 *	67.000 *	86.000 *	73.000 *	8.0000 *

* indicates statistical significance at the 1% level.

According to the results, except for USD/JPY all exchange rates display a positive mean return, but all are close to zero. Standard deviation statistics show the variability of return and price series. Both log return and log prices indicate that the highest volatility in the variables is observed in Bitcoin. Among the fiat currencies, USD/RUB illustrates relatively larger fluctuations. When the standard deviation is considered a risk indicator, the USD/RUB displays a higher uncertainty, that is, more risk in its price and returns. Regarding the shape of the probability distributions, skewness and kurtosis results are presented along with the Jarque-Bera test statistic. In a normal distribution, the reference values of the skewness and kurtosis are zero and three, respectively. Departures from these figures depict the presence of nonnormality. Accordingly, skewness results indicate that all return distributions are either negatively or positively skewed. For instance, while USD/BTC and USD/JPY have negative values, other variables have positive skewness statistics. Negative skewness shows that the frequency of above-average returns is higher than the frequency of below-average returns. Kurtosis suggests that all returns distributions have fat tails as the test statistics are greater than the reference number of three. The presence of the heavy tails indicates the existence of extreme values among the observations.

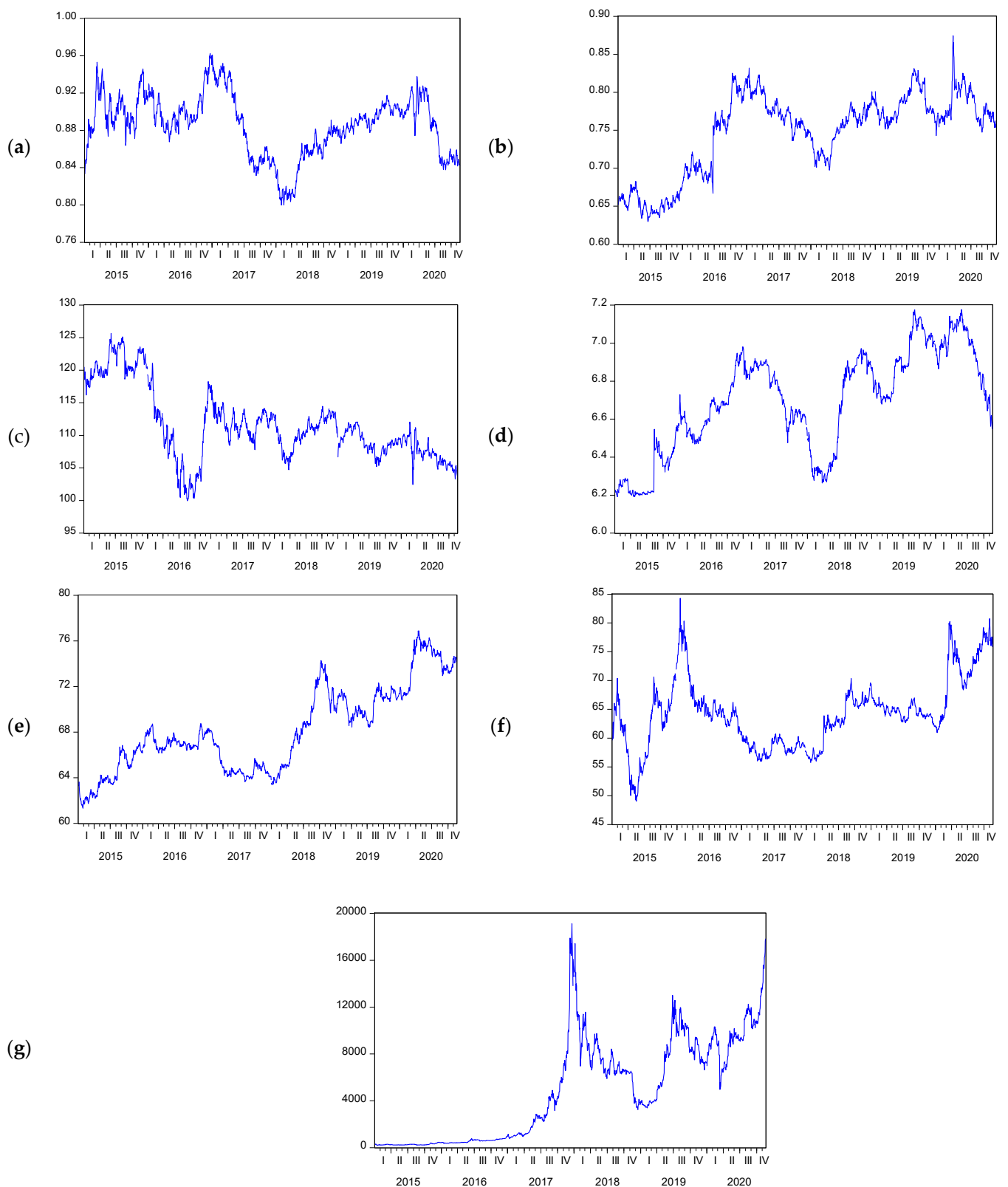


Figure 1. Price Series of Exchange Rates: (a) USDEUR; (b) USDGBP; (c) USDJPY; (d) USDCNY; (e) USDINR; (f) USDRUB; (g) BTCUSD.

Before proceeding further, the stationarity of the variables is examined. As log-returns and log-prices are used in empirical investigation, unit root tests are executed for both time series. According to the results in Table 2, while the returns series are stationary, log price series suggest the presence of unit root. As an alternative to ADF and PP tests, BBC unit root test is also executed following the study of Pippenger and Goering [66]. Literature findings demonstrate that nonlinear unit root tests outperform their linear counterparts in terms of size and power properties [67,68]. Those studies suggest using nonlinear models since the standard unit root tests might yield misleading results in the presence of nonlinear dynamics. Considering this, the multiple regime self-exciting threshold autoregressive (SETAR) model (hereafter BBC test) is employed. The model tests the joint significance of the autoregressive parameters in the outer regimes while the middle regime is allowed to follow a random walk. In execution of the test, the methodology of Bec et al. [69] is followed. This test, in fact, is a self-exciting threshold autoregression model based on the study of Tong [70]. For the given critical value of 18.4 at 95% confidence interval, the null hypothesis of a unit root is rejected for all log returns and log price series of the euro and Indian rupee. The rest of the price variables are detected as I(1). As stated by Stern [71], if there is no cointegration between the variables, causality analysis would be an appropriate methodology on a VAR in differences. Thus, we employed various causality tests after the analysis of stationarity following this study.

Table 2. Unit Root Tests.

	Method	USD/BTC	USD/EUR	USD/GBP	USD/JPY	USD/CNY	USD/INR	USD/RUB
Log Returns	ADF	−39.48 ***	−38.63 ***	−37.87 ***	−39.98 ***	−38.65 ***	−38.98 ***	−38.31 ***
	PP	−39.49 ***	−38.72 ***	−37.92 ***	−39.98 ***	−38.65 ***	−39.01 ***	−38.31 ***
	BBC test	622.15 ***	415.74 ***	467.60 ***	520.95 ***	553.18 ***	513.94 ***	548.15 ***
Log Prices	ADF	−0.5945	−2.7557 *	−2.2008	−2.2711	−1.9063	−0.9629	−1.7825
	PP	−0.6177	−2.7177 *	−2.1566	−2.2668	−1.9032	−1.0205	−1.7777
	BBC test	10.39	22.75 **	15.67	15.97	7.64	7.18	20.66 **

*, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

The existence of the unit root in log series will be considered in Hacker and Hatemi's modified Wald test [62]. Although the model is flexible in terms of the number of unit roots and does not require stationary series, this information will be utilized to determine the lag order of VAR models. In the estimation of the optimal lags, we set two-dimensional VAR models that incorporate Bitcoin in conjunction with the respective currencies. Lag orders are selected through sequential modified Likelihood Ratio, final prediction error, Akaike information criterion, Schwarz information criterion and Hannan-Quinn information criterion at the 5% significance level. Test results are presented in Appendix A. Subsequently, one period lag was selected for further analysis based on the lag order that was significant in the majority of the above tests.

To assess the causal nexus between Bitcoin and fiat currencies, the Hacker-Hatemi modified Wald test was run using the log price series of variables. Results are presented in Table 3. As a preliminary test, a VAR analysis was first conducted for each variable pair to determine the optimum lag order (p). The integration order of the variables (d) is added to this lag length (p). Critical values of the modified Wald statistics are provided in the last column of the table. According to the results, among all potential pairs, only two significant test statistics were obtained. Accordingly, results suggest the presence of a causal nexus between Bitcoin-Chinese yuan and Bitcoin-Indian rupee. The estimated causal parameters show that a unidirectional causality running from the Chinese yuan and the Indian rupee to Bitcoin does exist at 99% and 95% confidence levels, respectively.

Table 3. Hacker-Hatemi Modified Wald Test.

Causality Directions			Lag	Selection Criteria	MWALD Test Statistic	CV
BTCUSD	→	USDEUR	1	[LR, FPE, AIC, SC, HQ]	0.139	[7.458] [3.758] [2.552]
USDEUR	→	BTCUSD	1	[LR, FPE, AIC, SC, HQ]	0.595	[6.758] [3.725] [2.634]
BTCUSD	→	USDGBP	1	[LR, FPE, AIC, SC, HQ]	0.247	[6.746] [3.893] [2.752]
USDGBP	→	BTCUSD	1	[LR, FPE, AIC, SC, HQ]	3.562	[7.376] [4.125] [2.898]
BTCUSD	→	USDJPY	1	[LR, FPE, AIC, SC, HQ]	0.594	[7.197] [3.661] [2.748]
USDJPY	→	BTCUSD	1	[LR, FPE, AIC, SC, HQ]	0.001	[6.310] [3.893] [2.748]
BTCUSD	→	USDCNY	1	[LR, SC, HQ]	0.000	[6.816] [3.901] [2.766]
USDCNY	→	BTCUSD	1	[LR, SC, HQ]	9.606 ***	[7.443] [4.129] [2.862]
BTCUSD	→	USDINR	1	[LR, FPE, AIC, SC, HQ]	2.723	[5.856] [3.597] [2.590]
USDINR	→	BTCUSD	1	[LR, FPE, AIC, SC, HQ]	4.325 **	[7.525] [3.958] [2.661]
BTCUSD	→	USDRUB	1	[FPE, AIC, SC, HQ]	0.405	[7.520] [4.400] [3.045]
USDRUB	→	BTCUSD	1	[FPE, AIC, SC, HQ]	0.124	[6.286] [3.678] [2.798]

** and *** indicate statistical significance at the 5% and 1% levels, respectively.

As stated by Cont [72], financial time series might display certain stylized facts such as long-range dependence (long memory) in absolute returns, nonlinearity, volatility clustering and gain/loss asymmetry. Considering these facts, in investigation of the interactions between Bitcoin and fiat currencies, models that account for nonlinearity and asymmetry in returns were also employed. Finance literature shows the reaction of asset prices to negative and positive news varies. Asset prices are prone to display more volatility to the bad news than good news of the same magnitude. Black [73] accounts for the asymmetry in the relationship between stock returns and their volatility through the leverage effect which occurs due to the decline in the market value of firms and increase in their financial obligations, namely the rise in debt-to-equity ratios. Alternatively, this phenomenon is attributed to the volatility-feedback as discussed by French et al. [74], and Campbell and Hentschel [75]. Hatemi-J [63] takes the asymmetry phenomenon in causal relationships into account and introduces a bootstrap simulation approach with leverage adjustments. The author shows that the test is quite robust to the presence of non-gaussian innovations and conditional variance. On the other hand, Yilanci and Bozoklu [76] report that nonlinearities and asymmetry might be attributed to the existence of switching regimes in the relationships of the variables. Similarly, Flood and Marion [77] state that time series return innovations might jump to an attack equilibrium from a tranquil regime due to nonlinearities. Following this argument, after the asymmetric and nonlinear causality analyses, a Markov regime-switching regression analysis is executed to investigate a nonlinear relationship between Bitcoin and the Chinese yuan, and Bitcoin and the Indian rupee.

Table 4 contains the results of Hatemi-J [63] asymmetric causality analysis. Based on the findings in Table 3, the yuan and rupee's causal nexus with Bitcoin is further investigated. The test is carried out with the cumulative sums of the negative and positive shocks in each variable. Aligning with the symmetric causality analysis, the modified Wald test statistic suggests that Bitcoin and Chinese yuan have a causal nexus in asymmetric return components. This finding is observed between negative returns of the yuan and both return signs of Bitcoin. In addition, a significant causality is detected running from negative returns of the Indian rupee to negative returns of Bitcoin, and positive returns of Bitcoin to negative returns of the Indian rupee.

Table 4. Hacker-Hatemi Asymmetric Modified Wald Test.

Causality Directions			Lag	Selection Criteria	MWALD Test Statistic	CV
+BTCUSD	→	+USDCNY	1	[FPE, AIC, SC, HQ]	0.072	[7.354] [3.523] [2.477]
+USDCNY	→	+BTCUSD	1	[FPE, AIC, SC, HQ]	1.243	[7.106] [3.616] [2.586]
−BTCUSD	→	−USDCNY	1	[FPE, AIC, SC, HQ]	1.546	[7.678] [3.918] [2.719]
−USDCNY	→	−BTCUSD	1	[FPE, AIC, SC, HQ]	8.021 ***	[6.784] [3.602] [2.565]
+BTCUSD	→	−USDCNY	1	[FPE, AIC, SC, HQ]	0.095	[7.609] [3.731] [2.565]
−USDCNY	→	+BTCUSD	1	[FPE, AIC, SC, HQ]	6.549 **	[7.790] [3.988] [2.884]
−BTCUSD	→	+USDCNY	1	[FPE, AIC, SC, HQ]	0.844	[6.721] [3.706] [2.624]
+USDCNY	→	−BTCUSD	1	[FPE, AIC, SC, HQ]	1.627	[8.398] [3.656] [2.504]
+BTCUSD	→	+USDINR	1	[LR, FPE, AIC, SC, HQ]	1.396	[6.903] [4.071] [2.868]
+USDINR	→	+BTCUSD	1	[LR, FPE, AIC, SC, HQ]	0.012	[6.909] [4.175] [2.757]
−BTCUSD	→	−USDINR	1	[LR, FPE, AIC, SC, HQ]	0.663	[6.665] [3.925] [2.830]
−USDINR	→	−BTCUSD	1	[LR, FPE, AIC, SC, HQ]	8.044 ***	[6.579] [3.681] [2.493]
+BTCUSD	→	−USDINR	1	[LR, FPE, AIC, SC, HQ]	5.809 **	[6.951] [3.594] [2.565]
−USDINR	→	+BTCUSD	1	[LR, FPE, AIC, SC, HQ]	2.560	[6.752] [4.163] [2.939]
−BTCUSD	→	+USDINR	1	[LR, FPE, AIC, SC, HQ]	0.149	[6.508] [3.558] [2.463]
+USDINR	→	−BTCUSD	1	[LR, FPE, AIC, SC, HQ]	1.533	[7.898] [3.943] [2.701]

** and *** indicate statistical significance at the 5% and 1% levels, respectively.

In addition to the asymmetry, nonlinearity is also one of the stylized facts of financial time series as stated by Cont [72]. Considering this, following the asymmetric methodology of Hatemi-J [63], the nonlinear causality analysis of Hmamouche [78] is employed. Hmamouche's analysis is the extension of the Granger approach, which utilizes feed-forward artificial neural networks. F test statistics for the potential causal nexus are presented in Table 5. As the results indicate, the null hypothesis of no causal relationship is rejected in three out of four pairs. Accordingly, it is seen that Bitcoin and the yuan have bidirectional causal nexus at the 5% significance level. The rupee presents a unidirectional causality running from the rupee to Bitcoin at the same significance level under the consideration of the nonlinear return innovations.

Table 5. Non-linear Causality Test.

Causality Directions			Lag	Selection Criteria	F Test Statistic
BTCUSD	→	USDCNY	1	[FPE, AIC, SC, HQ]	58.7563 ***
USDCNY	→	BTCUSD	1	[FPE, AIC, SC, HQ]	3.1501 ***
BTCUSD	→	USDINR	1	[LR, FPE, AIC, SC, HQ]	1.3667
USDINR	→	BTCUSD	1	[LR, FPE, AIC, SC, HQ]	2.0684 **

** and *** indicate statistical significance at the 5% and 1% levels, respectively.

To measure the magnitude of the yuan and rupee's impact on Bitcoin, a MRSR analysis was executed with two regimes with the Chinese yuan and the Indian rupee as switching regressors. The error variance was assumed to be common across the two regimes. Two alternative models are presented in this analysis, one with constant transition probabilities in regimes and the other with time-varying transition probabilities based on one-period lag of Bitcoin returns. This formulation suggests that past returns of Bitcoin affect the transition probabilities between bull and bear regimes that are observed in Bitcoin and fiat currency interactions. Wild and persistent volatilities observed in the returns of Bitcoin make this assumption plausible. Table 6 contains the results of MRSR analysis for both the yuan and rupee. In each model, Bitcoin returns were employed as the dependent variable. Estimations are executed for constant and time-varying transition probabilities. According to the Akaike, Schwarz and Hannan-Quinn information criterion, while the constant transition probability model is the best fitting model where the yuan is the independent variable; for the rupee, however, the time-varying transition probabilities exhibit better performance.

Table 6. MRSR Analysis Results.

		Yuan/Const	Yuan/TV	Rupee/Const	Rupee/TV
Regime 1	c	0.0058	0.0037	−0.1303 ***	−0.1236 ***
		0.0011	(0.0011)	(0.0084)	(0.0074)
	Fiat currency	0.4432	0.6582 **	−15.3414 ***	−16.5784 ***
		(0.3730)	(0.3872)	(2.5000)	(2.2457)
Regime 2	c	−0.1399 ***	−0.0742 ***	0.0063 ***	0.0065 ***
		(0.0101)	(0.0111)	(0.0011)	(0.0011)
	Fiat currency	−25.3499 ***	−60.7281 ***	0.3157	0.3050
		(3.3208)	(4.3024)	(0.3228)	(0.3228)
	AIC	−3.4692	−3.4369	−3.4741	−3.4780
	SC	−3.4447	−3.4054	−3.4496	−3.4465
	HQ	−3.4601	−3.4252	−3.4650	−3.4662

** and *** indicate statistical significance at the 5% and 1% levels, respectively.

Similar to the asymmetric causality analysis results, MRSR also suggests that statistically significant interaction of the variables occurs during contractionary regimes (regime two in the yuan's model and regime one in the rupee's model). Contractionary regime by its nature accommodates downward trends in price developments, and thus includes higher frequency of negative returns. It is worth mentioning that while a negative return in Bitcoin refers to a loss in its value, this indicates an appreciation in the yuan and rupee as per the quotation of the exchange rate. Therefore, the coefficients in contractionary regimes show that an increase in the yuan's and rupee's value strongly and positively affects the value of Bitcoin in downturn periods of the market. Hypothetically, we can explain this finding from the perspective of market timing. As reported by Hileman and Rauchs [79], the Chinese yuan represented up to 90% of global Bitcoin trading volume until the regulations and bans executed by the Peoples Bank of China in 2017. While the unavailability of data due to these regulations does not allow us to share the most recent statistics, our results suggest that the Chinese investor and Chinese yuan is still a non-negligible fact in the price development of Bitcoin. Transition probabilities of each model are given in Table 7.

Table 7. Transition Probabilities of MRSR Model.

	Yuan/Const		Yuan/TV		Rupee/Const		Rupee/TV	
	R ₁	R ₂	R ₁	R ₂	R ₁	R ₂	R ₁	R ₂
R ₁	0.9813	0.0187	TV	TV	0.1652	0.8348	TV	TV
R ₂	0.7546	0.2454	TV	TV	0.0234	0.9766	TV	TV

R_i denotes regimes. TV stands for time-varying transition probabilities. The results of time-varying transition probabilities are not provided due to space considerations, however, are available upon request from the authors.

Figure 2 presents the smoothed regime probabilities for the constant and time-varying transition probabilities of the yuan and rupee's models given in Table 6. Both figures and Table 7 depict that the yuan and rupee's interactions with Bitcoin are prone to stay on tranquil regimes for most of the analysis period. The pandemic period also displays a similar behavior for both currencies. A regime shift (from tranquil to crisis regime) is observed during March 2020 in both variables. This date corresponds to a plunge in financial markets following the global pandemic announcement of the World Health Organization. However, over 2020, shifts to crisis regime are lower than the occasions seen in 2018. Indeed 2018 was a prominent bear market for Bitcoin, constituting heavy losses for investors. This finding so far suggests that the pandemic does not pose more risk for the cryptocurrency market than the turbulence in 2018.

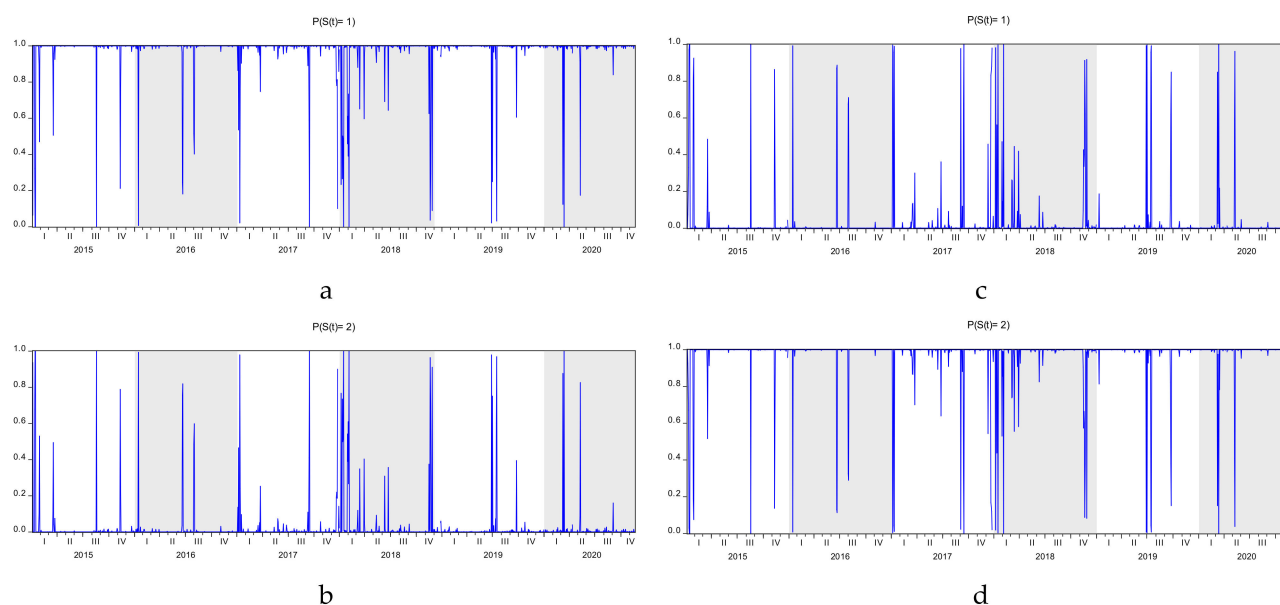


Figure 2. Markov Switching Smoothed Regime Probabilities. (a,b) indicate the regime one and regime two probabilities of yuan's model whereas (c,d) depict the regime one and regime two probabilities of rupee's model, respectively).

5. Conclusions

Empirical findings of the methods employed yield consistent results. Symmetric causality analysis reveals that only the Chinese yuan and Indian rupee Granger-cause Bitcoin. In order to consider the potential presence of asymmetry in these interactions, an asymmetric causality analysis was also executed. Results indicate that when negative and positive return components are separated the causal nexus remains significant between Bitcoin-Chinese yuan and Bitcoin-Indian rupee for various return combinations.

As causality analysis does not account for the relationship between causes and effects, as it only reports the direction of information flow between the pairs, MRSR analysis was performed in order to define the relationship between variables in contractionary and expansionary regimes. In line with the findings of asymmetric causality analysis, it was found that the relationship between the Bitcoin-Chinese yuan and Bitcoin-Indian rupee becomes significant in the contractionary regimes. By nature, this regime contains mostly negative returns. However, it should be noted that while the negative returns refer to losses in the value of Bitcoin, it denotes the appreciation of Chinese yuan and Indian rupee due to the quotation of the exchange rate. Therefore, it can be stated that when the yuan and rupee gain value during contractionary periods, it significantly and positively affects the value of Bitcoin. However, this effect does not hold in the expansionary regime. This finding can be attributed to the market timing of investors. Even though strict cryptocurrency bans were implemented by the Peoples Bank of China in 2017 and Bank of India in 2018, it seems that the Chinese yuan and the Indian rupee are still dominant currencies in the price development of Bitcoin.

The wild and speculative price development of Bitcoin necessitates the employment of respective hedging techniques. Additionally, its interactions with other financial assets can be of service for investors seeking to maximize portfolio diversification benefits. From these perspectives, our results reveal that Bitcoin displays strong causal relationships with emerging market currencies (Chinese yuan and Indian rupee) rather than with the currencies of developed economies considered in this study. This finding seems reasonable when we consider the relatively stable price movements of developed economies' currencies. However, asset prices in emerging markets, and not only the exchange rates, exhibit larger fluctuations due to the less diversified economic models, political instability and insufficient market depth. As revealed by MRSR analysis, the interactions of the variables become significant during adverse market periods. Such periods, once again, align with the nature

of emerging market economies. Wild volatilities make the future less foreseeable and cause an increasing required rate of returns in investment projects. Probable departures from the predictions, therefore, cause more severe shocks in asset prices. These shocks expand the duration and magnitude of contractionary regimes in emerging markets, contrary to the developed economies. Our results justify these theoretical facts by exhibiting a significant interaction between Bitcoin-Chinese yuan and Bitcoin-Indian rupee in the bear market regime. However, these results did not hold for the Russian ruble. It is probable that some distinctive features, which differentiate the Russian economy from the other two countries, generated this finding. Even though the Russian ruble exhibits relatively large fluctuations similar to those of other emerging economies considered in this study, it is possible that due to the relative lack of economic diversification, these fluctuations may be predominantly related to the changes in natural resource markets and other business cycles diverting out the potential nexus with the value of Bitcoin.

The relationships reported between crypto and fiat currencies in this study should be interpreted within certain limitations. The number of fiat currencies selected in this study was based on the most recent annual trading volume reported by BIS [26], but the number of currencies was arbitrarily limited to three from each of the developed and emerging economies to keep the scope of this study to a manageable level. This may have limited the uncovering of potential interactions with other currencies across the globe which were not included in the present study. Future studies should explore this further in the light of the positive findings of this research. The financial development stage of each country may also be taken into consideration during the selection process for further insights. Similarly, Bitcoin was used as the representative cryptocurrency due to its dominance in trading volume and market capitalization. However, several other cryptocurrencies are quickly gaining prominence and may provide some interesting perspectives that may not be possible to detect only with Bitcoin. Future studies may consider these and other aspects to extend the findings of this research.

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Appendix A

Lag	LogL	LR	USDBTC USDEUR			
			FPE	AIC	SC	HQ
0	2881.112	NA	0.000077	−3.800808	−3.793781	−3.798192
1	10,929.14	16,064.19 *	0.000000 *	−14.41999 *	−14.39891 *	−14.41214 *
2	10,929.65	1.014806	0.000000	−14.41538	−14.38025	−14.40230
3	10,930.44	1.571077	0.000000	−14.41115	−14.36196	−14.39283
4	10,932.46	4.009429	0.000000	−14.40853	−14.34528	−14.38498
5	10934.16	3.370010	0.000000	−14.40549	−14.32819	−14.37671
6	10,935.39	2.450304	0.000000	−14.40184	−14.31048	−14.36782
7	10,937.80	4.761609	0.000000	−14.39973	−14.29432	−14.36048
8	10,940.81	5.951279	0.000000	−14.39843	−14.27896	−14.35394

* indicates lag order selected by the criterion, LR: sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion. Each test at 5% level.

USDBTC USDGBP

Lag	LogL	LR	FPE	AIC	SC	HQ
0	2097.359	NA	0.000216	−2.766151	−2.759124	−2.763534
1	10,579.65	16,931.00 *	0.000000 *	−13.95862 *	−13.93754 *	−13.95077 *
2	10,582.06	4.807086	0.000000	−13.95652	−13.92138	−13.94344
3	10,583.92	3.692400	0.000000	−13.95369	−13.90450	−13.93537
4	10,587.54	7.196135	0.000000	−13.95319	−13.88994	−13.92964
5	10,591.14	7.158725	0.000000	−13.95267	−13.87537	−13.92388
6	10,593.97	5.604220	0.000000	−13.95112	−13.85976	−13.91710
7	10,595.35	2.734897	0.000000	−13.94766	−13.84225	−13.90841
8	10,596.38	2.023126	0.000000	−13.94373	−13.82427	−13.89925

* indicates lag order selected by the criterion, LR: sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion. Each test at 5% level.

USDBTC USDJPY

Lag	LogL	LR	FPE	AIC	SC	HQ
0	2595.231	NA	0.000112	−3.423408	−3.416380	−3.420791
1	10,822.31	16,421.57 *	0.000000 *	−14.27895 *	−14.25787 *	−14.27110 *
2	10,823.13	1.644358	0.000000	−14.27476	−14.23962	−14.26168
3	10,825.00	3.729162	0.000000	−14.27195	−14.22276	−14.25364
4	10,825.78	1.550677	0.000000	−14.26770	−14.20446	−14.24415
5	10,827.91	4.223469	0.000000	−14.26523	−14.18793	−14.23645
6	10,832.33	8.770173	0.000000	−14.26579	−14.17443	−14.23177
7	10,834.17	3.638410	0.000000	−14.26293	−14.15752	−14.22368
8	10,837.06	5.709984	0.000000	−14.26146	−14.14200	−14.21698

* indicates lag order selected by the criterion, LR: sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion. Each test at 5% level.

USDBTC USDCNY

Lag	LogL	LR	FPE	AIC	SC	HQ
0	2849.837	NA	0.000080	−3.759521	−3.752493	−3.756904
1	11,836.90	17,938.53 *	0.000000	−15.61835	−15.59727 *	−15.61050 *
2	11,841.41	8.984658	0.000000 *	−15.61902 *	−15.58388	−15.60594
3	11,842.03	1.250872	0.000000	−15.61457	−15.56538	−15.59625
4	11,844.00	3.905036	0.000000	−15.61188	−15.54863	−15.58833
5	11,845.79	3.554996	0.000000	−15.60896	−15.53166	−15.58018
6	11,848.76	5.897740	0.000000	−15.60761	−15.51625	−15.57359
7	11,849.98	2.412930	0.000000	−15.60394	−15.49853	−15.56469
8	11,851.97	3.932251	0.000000	−15.60128	−15.48182	−15.55680

* indicates lag order selected by the criterion, LR: sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion. Each test at 5% level.

USDBTC USDINR						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	2435.975	NA	0.000138	−3.213168	−3.206141	−3.210552
1	11,645.42	18,382.41 *	0.000000 *	−15.36557 *	−15.34449 *	−15.35772 *
2	11,648.69	6.518171	0.000000	−15.36461	−15.32947	−15.35152
3	11,649.82	2.255323	0.000000	−15.36082	−15.31163	−15.34250
4	11,650.48	1.304369	0.000000	−15.35641	−15.29316	−15.33286
5	11,653.28	5.558456	0.000000	−15.35482	−15.27752	−15.32604
6	11,655.13	3.666487	0.000000	−15.35198	−15.26063	−15.31797
7	11,658.02	5.739961	0.000000	−15.35053	−15.24512	−15.31128
8	11,660.94	5.757218	0.000000	−15.34909	−15.22963	−15.30461

* indicates lag order selected by the criterion, LR: sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion. Each test at 5% level.

USDBTC USDRUB						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	1309.580	NA	0.000610	−1.726178	−1.719151	−1.723561
1	9902.139	17,151.09	0.000000 *	−13.06421 *	−13.04313 *	−13.05636 *
2	9902.816	1.350777	0.000000	−13.05982	−13.02469	−13.04674
3	9905.789	5.917453	0.000000	−13.05847	−13.00928	−13.04015
4	9909.513	7.404516	0.000000	−13.05810	−12.99486	−13.03455
5	9915.051	10.99546 *	0.000000	−13.06013	−12.98283	−13.03135
6	9915.408	0.708395	0.000000	−13.05532	−12.96397	−13.02131
7	9916.920	2.994092	0.000000	−13.05204	−12.94663	−13.01279
8	9918.703	3.526030	0.000000	−13.04911	−12.92965	−13.00463

* indicates lag order selected by the criterion, LR: sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion. Each test at 5% level.

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