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Highlights

- We investigate the dynamic relationship between six foreign exchange rates and bitcoin's return
- We utilize a nonparametric causality test and apply a multivariate filter- BEKK-GARCH
- We find Interconnection and predictability in currencies and bitcoin's return
- We show evidence of CNY affecting bitcoin's return

This paper investigates whether bitcoin has a nonlinear relationship with six currencies: euro, pound sterling, Swiss franc, renminbi, yen, and ruble, each denominated in US dollars. It employs the nonparametric causality test proposed by Diks and Panchenko (2006) and applies a multivariate filtering approach using BEKK-GARCH residuals to control the conditional heteroskedasticity on daily log-returns from July 2010 to April 2020. We also split the bitcoin dataset into two samples, one before and one after a structural break. Results reveal a direct impact of the euro on bitcoin. However, in the post-break sample, there is only an effect from renminbi to bitcoin. Findings shed light on the nonlinear relationship dynamics among currencies and whether fiat currencies can help predict bitcoin's behavior.

Keywords: Bitcoin; Exchange Rate; Nonlinear Causality; BEKK-GARCH filtering
JEL: C14, F31, G15

1. Introduction

Since Nakamoto (2008) proposed a new system for electronic transactions, bitcoin (BTC) has received a great deal of attention, mainly for its skyrocketing returns and the rapid increase in its transaction volume.[1] Anyone can buy and sell bitcoin online at any time and exchange it for major currencies at a low cost (Kim, 2017).

What drives bitcoin's returns is still a puzzle—it can be used for speculative purposes or as an alternative currency not controlled by any authority. Also, there is evidence that bitcoin has frequently been associated with illegal activities (Foley, Karlsen, & Putniņš, 2019). Although we still do not fully understand bitcoin's uses, it clearly does not function like traditional fiat money. Selgin (2015) characterized it as "synthetic commodity money," while Dyhrberg (2016a) classified it as a combination of commodity and currency. Irrespective of whether bitcoin is a currency or an asset, is there a causal relationship between this cryptocurrency and conventional currencies?

A recent empirical stream of the literature has analyzed bitcoin as a currency hedge. For instance, Urquhart and Zhang (2019) showed that bitcoin can be used as an intraday hedge by currency investors. Carrick (2016) argued that bitcoin has peculiarities that can be complemented by emerging market currencies to minimize risks. Similarly, Dyhrberg (2016) exposed bitcoin's hedging capabilities, which can be used against the FTSE Index and the US dollar in the short term. On the other hand, Kristjanpoller and Bouri (2019) argued that traditional hedging between cryptocurrencies and exchange rates could be ineffective.

Another body of literature has investigated whether bitcoin meets the requirements to become a currency or a new asset class. For example, Goczek and Skliarov (2019) pointed

[1] Daily transactions increased from roughly 200 in 2010 to over 400,000 in 2018. Bitcoin's market capitalization is $221 billion, and $26 billions volume. https://coinmarketcap.com and https://coinmetrics.io (accessed on August 18, 2020).

out that the number of bitcoin transactions has no impact on its price, making its behavior distinct from conventional currency. Although bitcoin's daily volume is still small compared to major currencies, the number of transactions has risen sharply in recent years. Yermack (2015), however, argued that bitcoin cannot perform the value-storing function of a currency because it is plagued by online security problems. Glaser, Zimmermann, Haferkorn, Weber, and Siering (2014) also showed that most users consider bitcoin an alternative asset rather than a currency. Wu and Pandey (2014) also viewed bitcoin as an asset that could strengthen investors' portfolios efficiency.

Bitcoin's role as an asset class, its highly volatile behavior, and its low correlation with other assets are factors that could improve the risk-return tradeoff in a well-diversified portfolio (Brière, Oosterlinck, & Szafarz, 2015; Eisl, Gasser, & Weinmayer, 2015). Indeed, Guesmi, Saadi, Abid, and Ftiti (2019) showed that a hedging strategy that includes bitcoin in the portfolio reduces risk when compared to a portfolio without bitcoin. Considering the lack of liquidity in the bitcoin market, Kajtazi and Moro (2019) also proposed it as a speculative asset that can generate a better risk-return tradeoff.

As previously mentioned, the literature has investigated bitcoin's role as a currency hedge, a currency, or an asset to improve asset allocation. However, it is unclear whether bitcoin and foreign exchange markets are interconnected or if there is a dependence, even considering market size differences. The empirical literature has evidenced the interrelation among financial markets. The deregulation of capital movements in the 1990s led to this interconnection, indicating that major financial markets behave similarly towards macroeconomic policies or financial crisis episodes (Bekiros, 2014). For example, Huang and Yang (2002) found an increase in the linkage effects of the exchange rate volatility in G-5 countries after the European monetary system crisis of 1992, the Mexican peso crisis of 1994, and the Asian crisis of 1997. The spillover effects are also seen in other financial markets; in a recent work, Bouri, Das, Gupta, and Roubaud (2018) found spillover effects between bitcoin and conventional asset returns, indicating a closer interconnection between these markets.

Regarding the linear and nonlinear nature of the foreign exchange market, Meese and Rogoff (1983) described a failure of linear exchange rate models, so later studies investigated nonlinear approaches. For instance, Kwek and Koay (2006) examined the time-varying and volatility asymmetries of six exchange rate returns; their results suggested that symmetric GARCH models were inadequate to explain the asymmetry in the volatility process. Hsieh (1989) investigated the nonlinear dependence in five significant foreign exchange rates and found nonlinearity in all currencies. Bekiros and Diks (2008) also examined the linear and nonlinear causal linkages among six currencies, and their results suggest the nonlinearity approach was more appropriate to understand the dynamic relationship among currencies. Additionally, Hsieh (1991) showed that nonlinear models can better capture financial markets' behavior, such as sudden bursts of volatility and occasional large movements. From this standpoint, bitcoin and currencies can be suitably modeled using nonlinear methods. Furthermore, a nonparametric approach is more appropriate than a linear functional form when predicting causality behavior.

This paper innovates by investigating nonlinear causal linkages between bitcoin and six major currencies—euro (EUR), pound sterling (GBP), Swiss franc (CHF), the renminbi (CNY), yen (JPY), and ruble (RUB)—denoted in US dollars,[2] in a three-step framework. First, we applied a nonparametric causality test proposed by Diks and Panchenko (2006); then, to control the conditional heteroskedasticity, we used the BEKK-GARCH model to filter residuals, enabling the variance-covariance interconnection of the currency to be incorporated (Bekiros, 2014). Further, we split the bitcoin series using the one-break LM test

[2] The US dollar is still the most frequently traded and significant anchor currency worldwide (Ilzetzki, Reinhart, & Rogoff, 2019); thus, we analyze the currencies denoted in US dollars.

from Lee and Strazicich (2013) to reapply the test before and after the break. This work's novelty lies not only in its analysis of the influence of foreign exchange markets on bitcoin (or vice versa) but also in the directional predictability and the interdependencies among foreign exchange markets. Furthermore, our results highlight the bitcoin market's inefficiency since it is challenging to forecast returns when the market is efficient (Kristoufek, 2018; B. S. Lee, Rui, & Wang, 2004). This study will appeal to a wide range of readers: policymakers and financial market regulators, as one market can induce volatility in another, thus affecting monetary policy or market returns; portfolio managers who must make hedging decisions, optimize portfolio strategies, and reduce risk exposure; bitcoin users; and foreign exchange traders.

2. Data description

We collected the exchange rate daily closing prices[3] between July 2010 and April 2020 for BTC, EUR, GBP, CHF, CNY, JPY, and RUB from the Bloomberg platform. All data were transformed into the log-return form $r_i = \ln P_t - \ln P_{t-1}$.

Table 1 shows the descriptive statistics of the series. The ARCH-LM test shows evidence of ARCH effects for all variables except CHF. We checked for stationarity using ADF, PP, KPSS, and ERS tests. All unit root tests suggest that the series are stationary. We employed the BDS test (Broock, Scheinkman, Dechert, & LeBaron, 1996) to determine whether the series are defined by nonlinearities. Hence, results are statistically significant for all currencies except CHF, indicating nonlinearity in the univariate time series.[4]

Table 1. Summary statistics of daily log-returns (2,532 observations).

	BTC	**CHF**	**CNY**	**EUR**	**GBP**	**JPY**	**RUB**
Mean	0.004	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.002	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.517	0.091	0.018	0.030	0.030	0.035	0.120
Minimum	-0.601	-0.194	-0.012	-0.024	-0.084	-0.038	-0.117
Std. Dev.	0.065	0.007	0.002	0.005	0.006	0.006	0.010

[3] Bitcoin operates 24 hours a day, seven days a week. We excluded weekend days to match with foreign exchange business days (GMT). Urquhart and Zhang (2019) showed that the trading volumes of currencies and bitcoin are small when foreign exchange markets are closed.
[4] For conciseness, the results are not reported here. However, they are available upon request.

Skewness	-0.323	-7.288	0.821	-0.029	-1.397	0.062	-0.469
Kurtosis	17.317	234.906	14.654	4.927	25.374	7.898	23.487
Jarque-Bera	21,668	5,696,239	14,614	392	53,637	2,533	44,373
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARCH-LM	312***	2.48	103***	139***	93***	134***	786***

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

Figure 1 depicts the log-returns for all currencies, while Figure 2 illustrates the cross-correlations for the log-returns. BTC shows a low correlation with each of the currencies, while EUR and GBP have the highest and positive correlation.

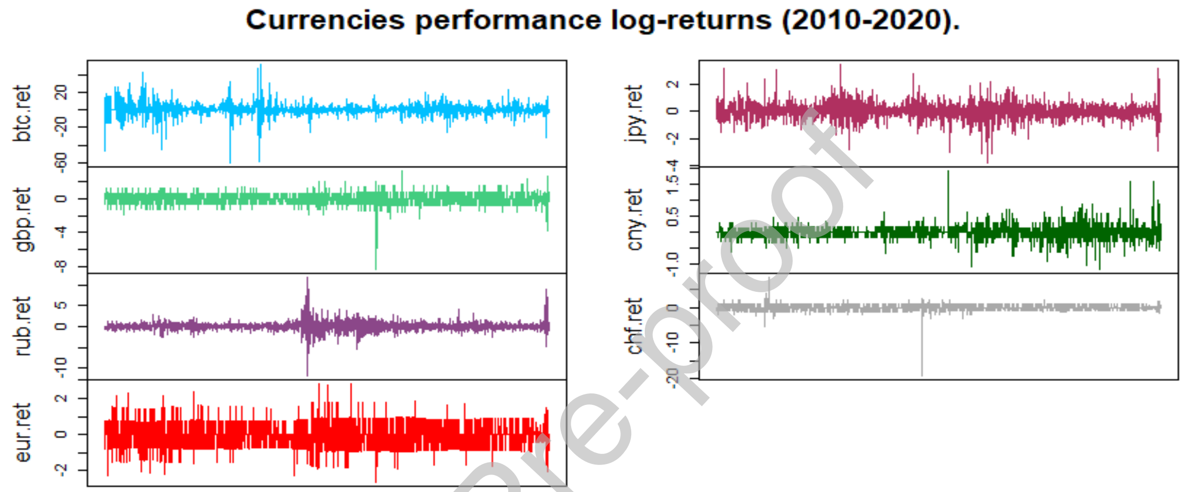

Figure 1. Time series plots of log-returns daily currencies prices (BTC, GBP, RUB, EUR, JPY, CNY, and CHF).

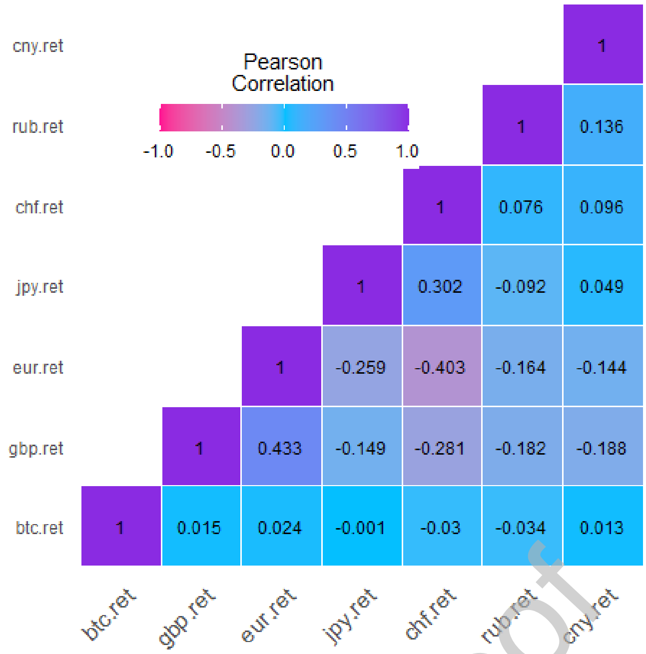

Figure 2. Pearson correlations of log-returns currencies prices (BTC, GBP, RUB, EUR, JPY, CNY, and CHF).

3. Methodology

In his seminal work on causality, Granger (1969) assumes a parametric and linear relationship for the conditional mean; it fails to detect nonlinear relationships over time, such as asymmetry, persistence, and structural breaks (Baek & Brock, 1992). To resolve this issue, Baek and Brock (1992) proposed a nonparametric test. Hiemstra and Jones (1994) modified this test by relaxing the hypothesis that the time series is independent and identically distributed. Diks and Panchenko (2005, 2006) showed that Hiemstra and Jones's test could lead to spurious rejection of the null hypothesis, so they proposed a test to overcome over-rejection.

According to DP (2006), the purpose of the non-causality test is to identify evidence against the null hypothesis

$$H_0\colon \{X_t\}\ is\ not\ Granger\ causing\ \{Y_t\},$$

under the null hypothesis, past observations of $\{X_t\}$ do not contain additional information on Y_{t+1}. To reformulated in terms of joint distribution, the conditional distribution of Z given (X, Y) = (x, y) equals to Z given Y=y. Hence, the joint probability density function

$f_{X,Y,Z}(x,y,z)$ and marginal distributions must satisfy:

$$H_0: \frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_Y(y)} \quad (1)$$

DP consider $Z_t = Y_{t+1}$ and remove the time indices t. Thus, X and Z are conditionally independent in $Y = y$ for each fixed value of y. DP demonstrates another way of writing the

$$H_0: q \equiv E\left[f_{X,Y,Z}(X,Y,Z)\, f_Y(Y) - f_{X,Y}(X,Y)\, f_{Y,Z}(Y,Z)\right] = 0 \quad (2)$$

Let $\hat{f}_W(W_i)$ be a local density estimate of a random vector d_W - variate $\boldsymbol{W}$ in $\boldsymbol{W_i}$, defined by $\hat{f}_W(W_i) = \frac{(2\varepsilon_n)^{-d_W}}{n-1} \sum_{j j \neq i} I_{ij}^W$, where $I_{ij}^W = I\left(\left\|W_i - W_j\right\| < \varepsilon_n\right)$, $I(\cdot)$ is the indicator function, and ε_n is the bandwidth parameter dependent on n (number of observations); the statistical test is:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \sum_i \left(\hat{f}_{X,Z,Y}(X_i, Z_i, Y_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i)\hat{f}_{Y,Z}(Y_i, Z_i)\right) \quad (3)$$

Asymptotic properties are developed under the “mixing” conditions (Denker & Keller, 1983). When $\varepsilon_n = Cn^{-\beta}$, where C is a positive constant and $\beta \in (1/4\,, 1/3)$, we obtain:

$$\sqrt{n}\frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{D} N(0,1) \quad (4)$$

where $\xrightarrow{D}$ denotes convergence in the distribution, and S_n is the estimator of the asymptotic variance of T_n. DP (2006) recommend a truncation,

$$\varepsilon\_n = min\left(Cn^{-2/7};\ 1.5\right) \quad (5)$$

We set the bandwidth at $1(\varepsilon_n = 1)$. The value of the bandwidth is crucial in determining the presence of nonlinear causality. Since the bandwidth values smaller (larger) than one normally results in larger (smaller) p-values (Nazlioglu, 2011).

To avoid conditional heteroskedasticity, we applied (G)ARCH specification models. We chose the best model based on the statistical significance of the parameters using the

Bayesian information criteria (BIC) (Schwarz, 1978). We selected Student's t-test, generalized error distribution (GED) or normal distribution (Gaussian) to test the conditional distribution of the error term, according to the best model by the statistical significance of the parameters using BIC (Bollerslev, 1986; Bollerslev, Engle, & Wooldridge, 1988). Next, we filtered the residuals using the BEKK-GARCH multivariate model, using the following form (Engle & Kroner, 1993):

$$H_t = C'C + \sum_{i=1}^{q} A_i' \epsilon_{t-i} \epsilon_{t-i}' A_i + \sum_{j=1}^{p} B_j' H_{t-j} B_j \quad (6)$$

where C, A_i and B$_j$ are N x N matrices, and C is the lower triangular. Notably, a multivariate GARCH model allows us to identify a posited model appropriate to describe the relationship among the series when using a nonlinear test on filtered data. Thus, Diks and Panchenko's (2006) nonlinear analysis is reapplied on the filtered data to guarantee that any causality is strictly nonlinear in nature (Bekiros, 2014).

4. Empirical Results

The empirical framework consisted of three steps. The first was to test nonlinear causality among the involved variables—bitcoin and the six exchange rates; second, we applied the multivariate BEKK-GARCH filtering on the residuals; third, we divided the bitcoin data into two samples, before and after the structural break, using the LM unit root test from Lee and Strazicich (2013), then repeated the first and second steps.

Table 2a shows the results from applying nonlinear causality; Table 2b displays the BEKK-GARCH filtering results. The volatility transmission can be examined after the filtering process. In some cases, the discrepancy in statistical significance in the results before and after filtering implies that nonlinear causality is due to volatility effects (S. Bekiros, 2014).

The overall results indicate that EUR influences foreign exchange rates the most and vice versa, which suggests the euro's strength as an anchor currency in the international monetary system (Bénassy-Quéré & Lahrèche-Révil, 2000). EUR shows a unidirectional impact on BTC and CNY, revealing it as a feasible predictor. Also, we find a direct effect from GBP to CNY, CHF to GBP, and JPY to RUB. Conversely, a bidirectional nonlinear causality for BTC–CHF, CHF–JPY, CHF–RUB, JPY–GBP, GBP–RUB, and CNY–RUB was observed. The bidirectional causality implies that foreign exchange markets can react similarly to new information (i.e., change in monetary or macroeconomic policy by the European Central Bank) without one specific foreign exchange market influencing the other; thus, there is no indication of a relationship (Bekiros & Marcellino, 2013).

Table 2. a. DP nonlinear causality test (Log-Returns)

X	Y	Lags 1	2	3	4	5	6
BTC→	CNY	-	-	-	-	-	-
	EUR	-	-	-	-	-	-
	CHF	***	***	***	***	***	***
	JPY	-	*	**	**	*	-
	GBP	-	-	-	*	-	-
	RUB	-	-	-	-	-	-
CNY→	EUR	-	-	-	-	-	-
	CHF	-	-	-	-	-	-
	JPY	-	-	-	-	-	-
	GBP	-	-	-	-	-	-
	RUB	*	**	**	**	**	**
EUR→	CHF	***	***	***	***	***	***
	JPY	*	***	***	***	***	***
	GBP	***	***	**	**	*	**
	RUB	***	***	**	**	-	**
CHF→	JPY	**	***	***	***	***	***
	GBP	***	***	***	***	***	***
	RUB	**	-	-	-	-	-
JPY→	GBP	**	***	**	***	**	**
	RUB	-	-	-	-	-	-
GBP→	RUB	***	**	*	-	-	-

X	Y	Lags 1	2	3	4	5	6
CNY→	**BTC**	*	-	-	-	-	-
EUR→		***	***	**	-	-	-
CHF→		-	***	***	**	-	-
JPY→		-	-	-	-	-	-
GBP→		-	-	-	-	-	-
RUB→		-	-	-	-	-	-
EUR→	**CNY**	**	-	-	-	-	-
CHF→		-	-	-	-	-	-
JPY→		-	-	-	-	-	-
GBP→		***	***	***	***	-	-
RUB→		*	***	***	***	***	**
CHF→	**EUR**	***	***	***	***	***	**
JPY→		***	***	***	***	***	***
GBP→		-	**	**	*	-	**
RUB→		***	***	***	***	**	***
JPY→	**CHF**	*	***	***	***	***	***
GBP→		-	-	-	-	-	-
RUB→		**	***	***	**	**	**
GBP→	**JPY**	**	**	*	*	**	*
RUB→		**	***	**	**	**	*
RUB→	**GBP**	**	**	-	-	-	-

Notes: Nonlinear causality DP (2006) T_n statistic. (X) → (Y) denotes the independent variable does not cause the dependent variable. *, **, and *** show statistical significance at the 10%, 5%, and 1% level, respectively. Bandwidth set at ε_n= 1 and ℓag-length = 1,2,3,4,5, and 6.

Table 2. b. Multivariate BEKK-GARCH Residuals

X	Y	Lags 1	2	3	4	5	6
BTC→	CNY	-	-	-	-	-	-
	EUR	-	-	-	-	-	-
	CHF	***	***	***	***	***	***
	JPY	-	-	**	*	*	-
	GBP	-	-	-	-	-	-
	RUB	-	-	-	-	-	-
CNY→	EUR	-	-	-	-	-	-
	CHF	-	-	-	-	-	-
	JPY	-	-	-	-	-	-
	GBP	-	-	-	-	-	-
	RUB	*	**	**	**	**	**
EUR→	CHF	**	***	***	***	**	**
	JPY	*	***	**	***	***	***
	GBP	***	***	**	**	*	**
	RUB	***	***	**	**	-	**
CHF→	JPY	**	***	***	***	***	***
	GBP	***	***	***	***	***	***
	RUB	**	-	-	-	-	-
JPY→	GBP	**	***	**	***	**	**
	RUB	-	-	-	-	-	-
GBP→	RUB	***	**	*	-	-	-

X	Y	Lags 1	2	3	4	5	6
CNY→	**BTC**	*	-	-	-	-	-
EUR→		**	***	**	-	-	-
CHF→		*	***	***	**	-	-
JPY→		-	-	-	-	-	-
GBP→		-	-	-	-	-	-
RUB→		-	-	-	-	-	-
EUR→	**CNY**	-	-	-	-	-	-
CHF→		-	-	-	-	-	-
JPY→		-	-	-	-	-	-
GBP→		***	**	**	**	-	-
RUB→		-	**	***	***	**	**
CHF→	**EUR**	***	***	***	***	***	**
JPY→		***	***	***	***	***	***
GBP→		-	**	**	*	-	**
RUB→		***	***	***	***	***	***
JPY→	**CHF**	**	**	***	***	***	***
GBP→		-	-	-	-	-	-
RUB→		**	***	***	**	**	**
GBP→	**JPY**	**	***	*	*	**	*
RUB→		**	***	**	**	**	*
RUB→	**GBP**	**	**	*	-	-	*

Notes: GARCH-BEKK filtering was performed, and the residuals were reapplied on the nonlinear causality test. T_n statistic. (X) → (Y) denotes the independent variable does not cause the dependent variable. *, **, and *** show statistical significance at the 10%, 5%, and 1%, respectively. Bandwidth set at $\varepsilon_n = 1$ and ℓag-length = 1,2,3,4,5, and 6.

4.1 Structural Break Analysis

According to Mensi et al. (2019), investors should consider using structural breaks to enhance volatility prediction, as the absence of structural breaks in predictive models can lead to persistent overestimation of volatility in the bitcoin market. To capture the bitcoin market's dynamic nature, we employed the unit root test with one structural break developed by Lee and Strazicich (2013), generating one sample before the structural break and another after it, and then reapplied the causality test. The one-break unit root test overcomes the problems in Zivot and Andrews's (1992) unit root test: size distortions in the presence of a break under the null hypothesis and incorrect estimation under the null and alternative hypotheses.

Table 3. Lee Strazicich LM unit root test

Null hypothesis: BTC has a unit root with a break

Minimum test statistic (tau)		-7.38
Break point		8/14/2014
Selected lag		10
Test critical values	1% level	-3.80

Notes: One-break LM_{τ} test of the Bitcoin log-returns series.

Table 4a. Nonlinear causality results pre-break (before 8/14/2014)

Log-return						Multivariate BEKK-GARCH residuals					
	Lags	1	2	1	2		**Lags**	1	2	1	2
X	Y	*X*→*Y*		*Y*→*X*		*X*	Y	*X*→*Y*		*Y*→*X*	
BTC →	CNY	-	-	-	-	BTC →	CNY	-	-	-	-
	EUR	*	*	***	***		EUR	-	*	***	**
	CHF	**	***	**	***		CHF	**	***	**	***
	JPY	*	*	-	-		JPY	*	-	-	-
	GBP	**	**	**	*		GBP	**	***	**	**
	RUB	-	-	-	-		RUB	-	-	-	-

Table 4b. Nonlinear causality results post-break (after 8/14/2014)

Log-returns						Multivariate BEKK-GARCH residuals					
	Lags	1	2	1	2		**Lags**	1	2	1	2
X	Y	*X*→*Y*		*Y*→*X*		*X*	Y	*X*→*Y*		*Y*→*X*	
BTC →	CNY	*	-	**	**	BTC →	CNY	-	-	**	**
	EUR	-	-	-	-		EUR	-	-	-	-
	CHF	-	-	-	-		CHF	-	-	-	-
	JPY	-	-	-	-		JPY	-	-	-	-
	GBP	-	-	-	-		GBP	-	-	-	-
	RUB	-	-	-	-		RUB	-	-	-	-

Notes: (X) → (Y) denotes the independent variable does not cause the dependent variable, and vice-versa. *, **, and *** show statistical significance at the 10%, 5%, and 1%, respectively. Bandwidth set at ε_n= 1 and lags ℓ=1,2.

Results of the pre-break sample exhibit bidirectional causality in BTC–CHF and BTC–GBP. The EUR has a direct effect on BTC. However, the post-break sample reveals a divergent outcome; only the CNY demonstrates an impact on BTC. Notably, the Chinese market is a significant player in cryptocurrency purchase transactions—Baidu, one of the largest e-commerce websites, began accepting bitcoin in 2013 (Kristoufek, 2015). China's growing role has significant implications for international financial markets integration (Wan, Yan, & Zeng, 2020), as well as its currency, had the largest trading volume in bitcoin until China restricted it in 2017 (Chan, Le, & Wu, 2019). Also of note, the effect from CNY to BTC can be explained by the number of buyers and sellers rather than individual currency returns, evidencing a speculative pattern (Baek & Elbeck, 2015; Gajardo, Kristjanpoller, & Minutolo, 2018).

4.2. Robustness test

To confirm our findings, we checked whether the causality test remains the same among the involved variables. To that end, we included the second most tradable cryptocurrency—Ethereum[5] (ETH), which was launched in 2015—and retested against all currencies from 2015 onwards. Overall, the results remained unaltered, although they showed that BTC affects ETH's returns. In turn, ETH showed bidirectional causality with CHF, EUR, JPY, and RUB, suggesting that ETH reacts like these currencies.

Table 5a. Nonlinear causality

	Lags	1	2	1	2
X	Y	*X→Y*		*Y→X*	
BTC →	CNY	-	-	**	*
	ETH	-	***	-	-
	EUR	-	-	-	*
	CHF	-	-	-	-
	JPY	-	-	-	-
	GBP	-	-	-	-
	RUB	-	-	-	-

[5] Ethereum's market capitalization is $48 billion, and volume is $12 billion. https://coinmarketcap.com (accessed on August 18, 2020). To conserve space, the statistics summary are not reported here, but we can provide upon request.

Table 5b. Nonlinear causality (ETH)

	Lags	1	2	1	2
X	Y	*X*→*Y*		*Y*→*X*	
ETH →	CNY	-	-	-	-
	EUR	**	***	***	-
	CHF	-	***	-	*
	JPY	-	**	*	**
	GBP	*	-	-	-
	RUB	*	**	***	***

Notes: (X) → (Y) denotes the independent variable does not cause the dependent variable, and vice-versa. *, **, and *** show statistical significance at the 10%, 5%, and 1%, respectively. Bandwidth set at ε_n= 1 and lags ℓ=1,2.

5. Conclusion

We explored the dynamic linkages between bitcoin and six currencies denoted in US dollars. The results show that the European and Chinese exchange markets have become more integrated with the cryptocurrency market. On the one hand, the transaction volume and acceptance of bitcoin as a currency in China can explain the impact of CNY on BTC returns since the Chinese market is a significant player in cryptocurrency purchase transactions (Kristoufek, 2015). On the other hand, EUR retains the greatest influence on the other currencies explored in this study, including BTC. This finding provides a better understanding of the nonlinear dynamics between currencies and bitcoin, as the improvement in predictability may guide investors, portfolio managers, and foreign exchange traders to develop optimal hedging strategies, as well as inform regulators and policymakers about high volatility in the market, which has implications for monetary policy.

Nevertheless, it is still unclear whether bitcoin will fulfill the conditions necessary to become a currency in the future. So far, bitcoin behaves as an asset rather than a currency; thus, further investigation over the next several years is crucial to identify a possible change in course. According to Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017), if investors lose confidence in fiat currencies, bitcoin could become a substitute. In China and Venezuela, for example, bitcoin has been used as a substitute currency to avoid capital controls (Bouri, Das, Gupta, & Roubaud, 2018; Kliber, Marszałek, Musiałkowska, & Świerczyńska, 2019).

Credit author statement

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